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Final Report

LYU 0404

Mobile Motion Tracking using Onboard Camera

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Abstract

This report describes the motivation, background information, algorithms related to our project, experiments done and applications/games developed by our group when participating in the final year project. The objective of our project is to use camera phone as an innovative input method for different applications on Symbian.

Firstly, we will introduce the idea of our final year project – using motion tracking as an innovative input method. Following is the introduction of Symbian OS, the major operating system used in mobile phone nowadays, which focus on image manipulations in Symbian phone. Next we will talk about the two testing platforms on PC and Symbian that we have developed. After that, we will discuss the common algorithms used in motion tracking and our proposed algorithms. These motion tracking algorithms will play an important role in our project. After that, feature selection algorithms will be discussed.

Since we aim to develop a real-time motion tracking application on the mobile phone, both the speed and precision of algorithms are very important. The report will include experimental results that we have done to evaluate the performance of different algorithms. Moreover, we performed investigations and experiments to find all possible ways so as to improve the accuracy and speed of the motion tracking.

Then we will describe the applications and games that we have developed and discuss what other possible applications can be developed using our motion tracking algorithm.

Finally, we will provide an API documentation of our motion tracking engine in the appendix.

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Chapter 1: Introduction

1.1 Motivation

Nowadays, it seems as though everyone has a mobile phone. As models with integrated CCD cameras are getting more and more popular, camera-phones have become popular networked personal image capture devices. It not only acts as a digital camera, but also provides constant wireless connectivity that allows them to exchange photo or video they captured with their friends. 3G phones even use their capabilities to make video calls as their selling point. However, other than taking pictures and capturing video, is it possible to add more values to the camera and make full use of it? This is the motivation of our FYP project.

As camera resolution improves and computation power increases, camera-phones can do more interesting things than just taking pictures and sending them out over mobile phone network. Programmable camera-phones

can actually perform image processing tasks on the device itself. With the real-time video captured by the onboard camera, we can use this information to track the motion of the phone. The result of motion tracking can then be used as an additional and innovative mean of user input, and this is our main objective of the FYP project.

1.2 Programming Capability of Symbian-based Mobile Phone

In the past, normal users were difficult to develop programs on their mobile phones. Even though users could write J2ME programs on mobile phones, J2ME does not provide phone-specific API to access the camera. Nowadays, Symbian OS makes programming on camera-phone possible. Symbian-based mobile phones allow user programs to access most of the functions provided by the phones, including the camera functions and image manipulation functions. Some 3G phones are also Symbian-based. They also allow users to develop programs on them. As Symbian OS will be the major operating system for mobile devices in the foreseeing future and its programming capability, our FYP project will use Symbian as our target platform.

Our applications will be useful for any 2G, 2.5G or 3G Symbian-based mobile phones.

1.3 Project Objective

The goal of our FYP project is to implement a real-time motion-tracking algorithm in Symbian-based mobile phones and use the tracking result as an innovative mean of user input like mouse and keyboard input. The aim of motion-tracking is not to track objects behind the camera but to track the movement of the camera, or the equivalence - the phone. This new mean of user input can give user a convenient way to operate the phone and any wireless-connected devices. For example, the phone can be used as a virtual computer mouse that allow user to control the cursor in desktop computer as if he/she is using a wireless optical mouse. Other than using the buttons or the joystick on the mobile phone as input method, users have one more choice - “motion input”, provided that the phone is programmable and camera-integrated. Users can also pre-define some gestures so that moving the phone in certain ways will trigger some events, such as making a phone call to the others. It

saves time pressing buttons to dial the phone. A more interesting application is to use it as the input method for games. For example, in a racing motorcycle game, tilting the phone can be used to control the motorcycle to tilt left or tilt right while moving the phone vertically can control the speed of the motorcycle. Using motion input is so fun and exciting that users can interact with the game.

Besides implementing a real-time motion-tracking algorithm, we planned to build an engine which provides motion-tracking functionality in Symbian OS. This engine is built using the motion-tracking algorithm and feature selection algorithm. It aims to provide a convenient way for developers to develop applications or games using phone's movement as the input method. To illustrate the usefulness of the engine and the idea of motion input, we develop some applications and games using the engine.

1.4 Project Equipment

Our project involves a Symbian mobile phone, Nokia 6600, which is equipped with Symbian OS 7.0 Series 60. Since the development cycle in Symbian mobile phone is quite long, we have decided to implement the real-time motion-tracking algorithm on PCs using web camera. Therefore, our project also involves web camera, Logitech QuickCam Pro 4000, as the video capturing device for the PCs.

Apart from Symbian based camera-phone, any other mobile devices that are programmable and camera-integrated are also the target platforms of our project. Some of the Pocket PCs, for example, are camera-integrated and are all programmable. It is also possible to develop interesting applications or games on these platforms.

Chapter 2: Symbian Operating System

Symbian OS is the global industry standard operating system for smartphones. It is structured like many desktop operating systems, with pre-emptive multitasking, multithreading and memory protection.

Because of its robust multi-tasking kernel, communications protocols (e.g. WAP and Bluetooth), data management, advanced graphics support (support of direct-access and common hardware accelerator), Symbian OS has become the major operating system for current generation of mobile phones.

In short, the functionalities of Symbian phone are summarized in the following diagram:

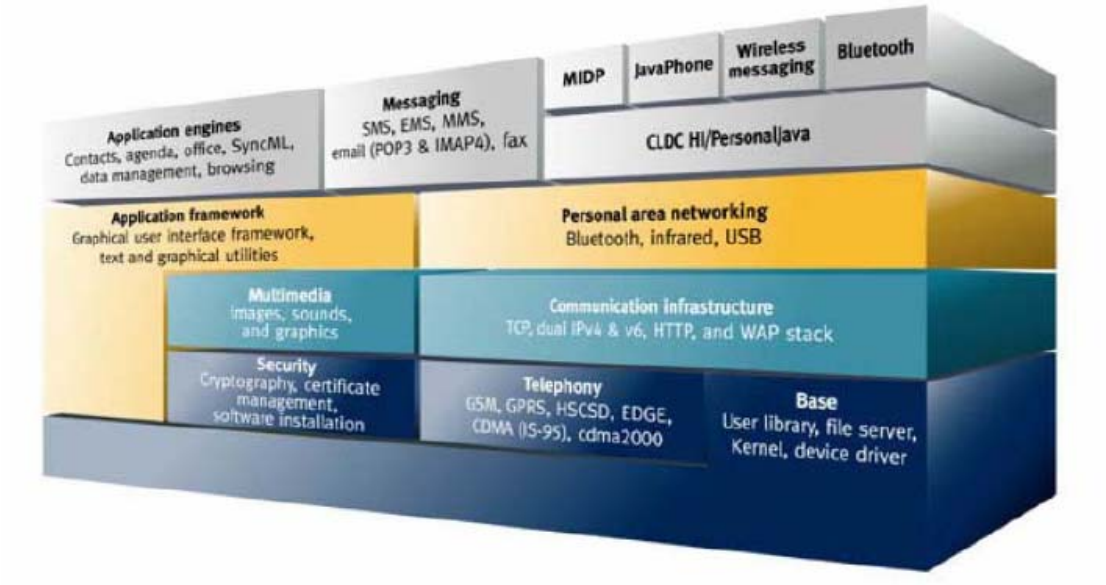


Figure 2.1 Symbian 7.0 architecture

The main focus of this chapter is to illustrate how Symbian OS provides support on image process in the phones and how we can write our program for Symbian OS effectively.

2.1 Development Environment

C++ is the native programming language of the Symbian. Symbian use its own implementation of the C++ language, optimized for small devices with memory constraints. The public C++ APIs allow access to variety of application engines, such as graphics, and camera.

Generally, the development environment is under Microsoft Visual C++ with application wizard in the SDK provided by Nokia. The development cycle can be summarized as follow:

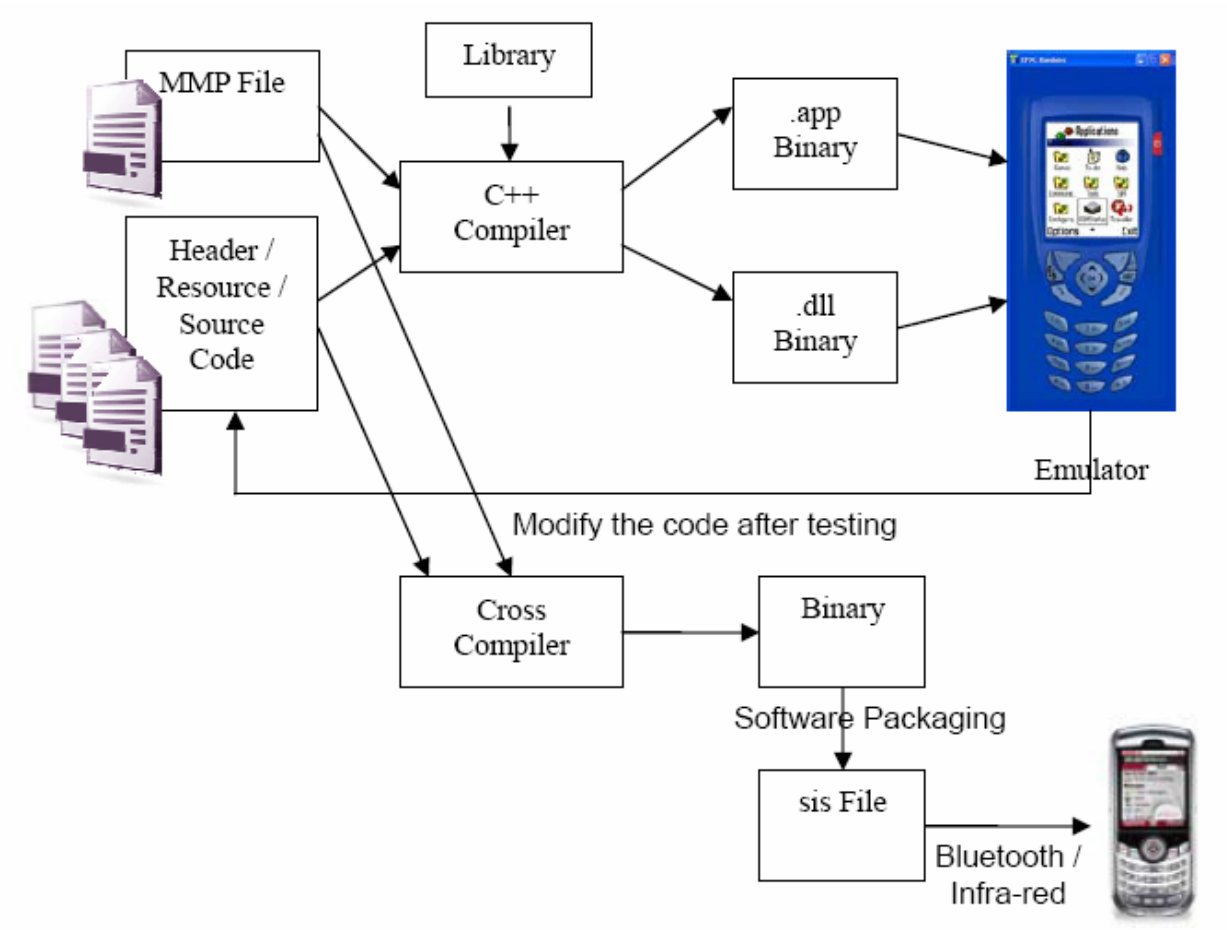


Figure 2.2 Development cycle of Symbian program

Besides source code, MMP file, which is a metadata to describe the source code and resources used (e.g. bitmaps and icons), is also supplied. Through C++ compiler, app binary (for general application) or dll binary (for building library) is then generated. Using emulator, application can be tested. After a complete testing, the source code and MMP file are compiled through cross

compiler, possibly ARM instruction compiler, to generate the binary code. All the necessary files, including bitmaps, images, icons and data file, would be grouped together through software packaging. The resulting sis file should be transferred to actual handset using any communication technologies, like Bluetooth and infra-red.

2.2 Testing environment

Although the SDK provides us the emulator for testing, we cannot rely on it. It is because we need to make use of the camera and test by moving the camera, so we mainly use MFC and OpenCV (will be discuss later) for testing and use the Symbian emulator for fine tuning the alogrithm only.

2.3 Limitations in Symbian phone

Since we are programming on handheld devices which has limited resources (limited amount of memory and limited amount of CPU speed, as shown in figure 2.3), these make programming on the Symbian phone a very difficult task.

Nokia 6600 Technical Specs	
Operating System:	Symbian OS 7.0s
Memory	Heap size: 3 MB Shared Memory for Storage: 6 MB + MMC
CPU	100 MHz

Figure 2.3 Specification of Nokia 6600

Speed is an important factor in making our real-time motion tracking. If we take too long time for the calculation of motion tracking, the frame rate will fall off, undermining the illusion of smooth movement. To get the fastest possible code we should only use, in order of preference:

1. Integer shift operations (<< and >>)
2. Integer add, subtract, and Boolean operations (&, | and ^)
3. Integer multiplication (*)

In other words, in speed-critical code we must represent all quantities (coordinates, angles, and so on) by integer types such as TInt, favor shift operations over multiplies, and avoid division entirely. We should not use floating point operation because Symbian phones do not have floating point unit. The speed constraint limits the use of optical flow algorithm (will be discuss later) for motion tracking.

2.4 Overview of Symbian Graphics Architecture

The multimedia architecture of Symbian has been designed and optimized for mobile devices. The architecture provides an environment that is akin to a desktop computing environment. With relative ease, the different components can be used for numerous tasks, ranging from drawing simple shape primitives to playing ring tones.

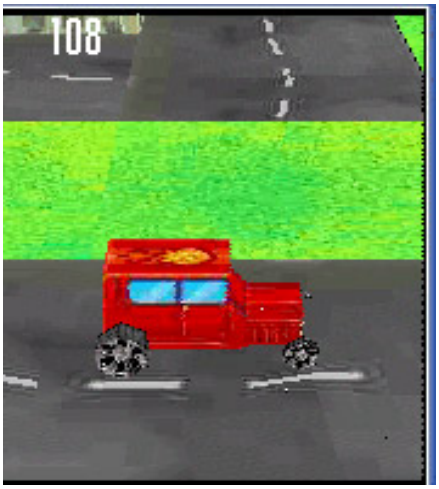


Figure 2.4 A 3D Game Engine Example (From Forum Nokia)

2.4.1 Video Capturing

Symbian OS provides camera API for developer to access the camera hardware. The camera hardware is controlled by the CCamera object which provides a simple method to control the camera.

Before we can capture the video with the camera, we need to create an instance of CCamera – this is achieved by calling the NewL( ) function:

```
iCamera = CCamera::NewL(aObserver, 0);
```

Once we have created an instance of the camera, the camera device must be reserved and power on.

```
iCamera→ Reserve( );
iCamera→PowerOn( );
```

Afterward, we need to specify the required image format and set the parameters for frame sizes, buffer sizes.

Finally, we can use the view finder to transfer frames from the camera directly to the display memory. We can then access the pixel values in the memory. The procedure for transferring video to images using view finder is shown below.

```
// Starts transfer of view finder data to the memory
iCamera->StartViewFinderBitmapsL(imageSize);
```

After the transfer of view finder data to the memory is completed, the function ViewFinderFrameReady( ) will be called. A reference (CFsBitmap &) to the view finder frame will pass as an argument to the function. We can implement our motion tracking algorithm inside ViewFinderFrameReady( ) function.

2.4.2 Image Manipulation

CfsBitmap is the class provided by the graphic architecture. By using this class, we can access the pixels of the image easily and perform some operations such as rotation, scaling, etc. However, using this class to manipulate the bitmap is not efficient way. It is because calling the functions provided by this class involved context switching. Thus the total overhead is large when you access the pixel values of the whole bitmap by the function call GetPixel(). In our application, our major concern is the speed, so we must think of other way to manipulate the bitmap instead of using the library provided by the architecture.

In order to access the pixel value effectively, we can access the bitmap array directly instead of using function calls. We can use a pointer to point to the bitmap array, and access the pixel value by de-referencing the pointer. Firstly, we need to find out the starting address of the actual bitmap:

```
TInt data_start = (TInt)iBitmap->DataAddress();
```

After getting the starting address, we declare an unsigned integer pointer to point to that location:

```
TUint16 *ptr = (TUint16 *) data_start;
```

If we want to access the pixel value at location (x,y), we increment the pointer so that we can access the value at (x,y):

```
ptr += width of bitmap*y+x;
```

Since the display mode of the view finder is 64k-colour displays, that means for the RGB values, 5 bits are allocated to red, 6 bits to green and 5 bits to blue. Therefore, we need to do bit masking to retain the R,G, B values:

```
//retain the RGB value
Red = (*ptr >>11) & 0x001f;
Green = (*ptr >> 5) & 0x003f;
Blue = *ptr & 0x001f;
```

By using this method for accessing the pixel values, we prevent the large overhead caused by context switching and thus our application can run faster.

2.5 Why Programming in Symbian

Apart from Symbian, there is another solution, J2ME, which is a cross-platform language. By using J2ME, we can develop applications for any kind of mobile devices, provided that they have the Java Virtual Machine installed.

It seems attractive to develop a cross-platform application by using J2ME. However, J2ME doesn't provide API for accessing onboard camera, and speed of java program is slow. In our project, we need to use the onboard camera to capture video and our major concern is the speed of the application. Therefore, at this stage, J2ME would not be our consideration.

2.6 Conclusion

This chapter briefly introduced the features of Symbian OS. The measures to tackle speed problem are also emphasized here. That is to use integer operations rather than floating point operations and access the bitmap array directly, instead of calling functions.

Chapter3: OpenCV Testing Platform on Window

3.1 OpenCV Library

OpenCV means Open Source Computer Vision Library. It is a collection of C functions and few C++ classes that implement many algorithms of Image Processing and Computer Vision. The library has also implemented algorithms for motion tracking; however, those algorithms use optical flow technique which is not useful to our project. OpenCV library is a high level API that consists of many useful data types and functions to manage the image window and video window. There are a few fundamental types OpenCV operates on, and several helper data types that are introduced to make OpenCV API more simple and uniform. The fundamental data types include array-like types: IplImage (IPL image), CvMat (matrix), mixed types: CvHistogram (multi-dimensional histogram). Helper data types include: CvPoint (2d point), CvSize (width and height), IplConvKernel (convolution kernel), etc.

Our project made use of some of these useful data types and functions to facilitate us to build a testing platform on window.

3.2 OpenCV Testing Platform

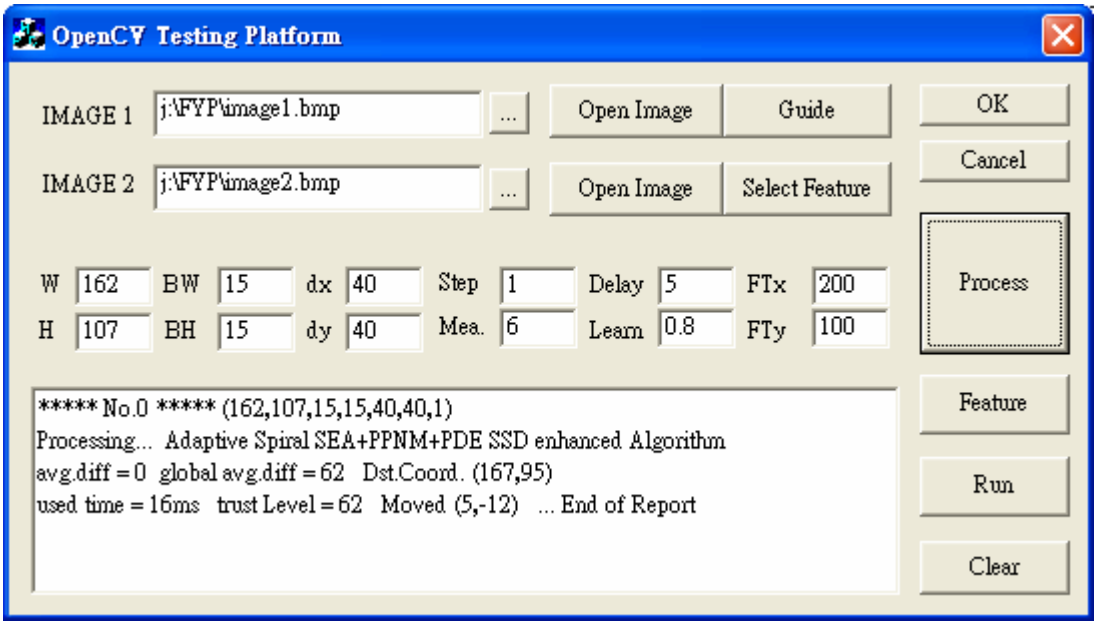


Figure 3.1 Snapshot of our OpenCV Testing Platform

Since the development cycle in Symbian is long, we decided to implement the algorithm in window environment first. In order to test the performance of our algorithms, we have written a GUI program using Window MFC and OpenCV library. The program serves mainly two functions: 1) It determines the motion vector of a pair of static frame with one of it is the shifted version of another; 2) It captures frames using web camera and real-time tracks the motion of a moving object.

Figure 3.1 show a snapshot of our program's interface. There are two "image path" input fields so that a pair of static image can be specified easily. The middle part consists of many input text fields that allow users to tune the block matching parameters of the algorithm in order to find the parameters that yield better result. The meaning of each label is listed in the following table:

Labels' Meaning

W	X-coordinate of the left top corner of the matching block
H	Y-coordinate of the left top corner of the matching block
BW	1/2 Width of matching block
BH	1/2 Height of matching block
Dx	1/2 Width of search window
Dy	1/2 Height of search window
Step	Sampling rate during matching block. Step = 1 means all pixels in a matching block is involved in calculating SAD. Step = 3 means one out of three pixels in a matching block is involved in calculating SAD and so on.
Mea.	Specifying which algorithm to be used. Mea. = 0 – ESA SAD Algorithm Mea. = 1 – ESA+PDE SAD Algorithm Mea. = 2 – Spiral ESA SAD Algorithm Mea. = 3 – Spiral ESA+PDE SAD Algorithm Mea. = 4 – SEA+PPNM SAD Algorithm Mea. = 5 – SEA+PPNM+PDE SAD Algorithm Mea. = 6 – Spiral SEA+PPNM+PDE SAD Algorithm Mea. = 7 – Adaptive Spiral SEA+PPNM+PDE SAD Algorithm
Delay	Number of time to run the algorithm before timer is stopped. Delay = 5 means the chosen algorithm is run 5 times so that the

	"time used" recorded is the time required to run the algorithm 5 times. Running the algorithm more than 1 time reduces the effect of inaccuracy of timer.
Learn	Learning rate of adaptive search window. $Learn \in [0.5,1.0]$
FTx	X-coordinate of the left top corner of the feature selection window
FTy	Y-coordinate of the left top corner of the feature selection window

Buttons' Function

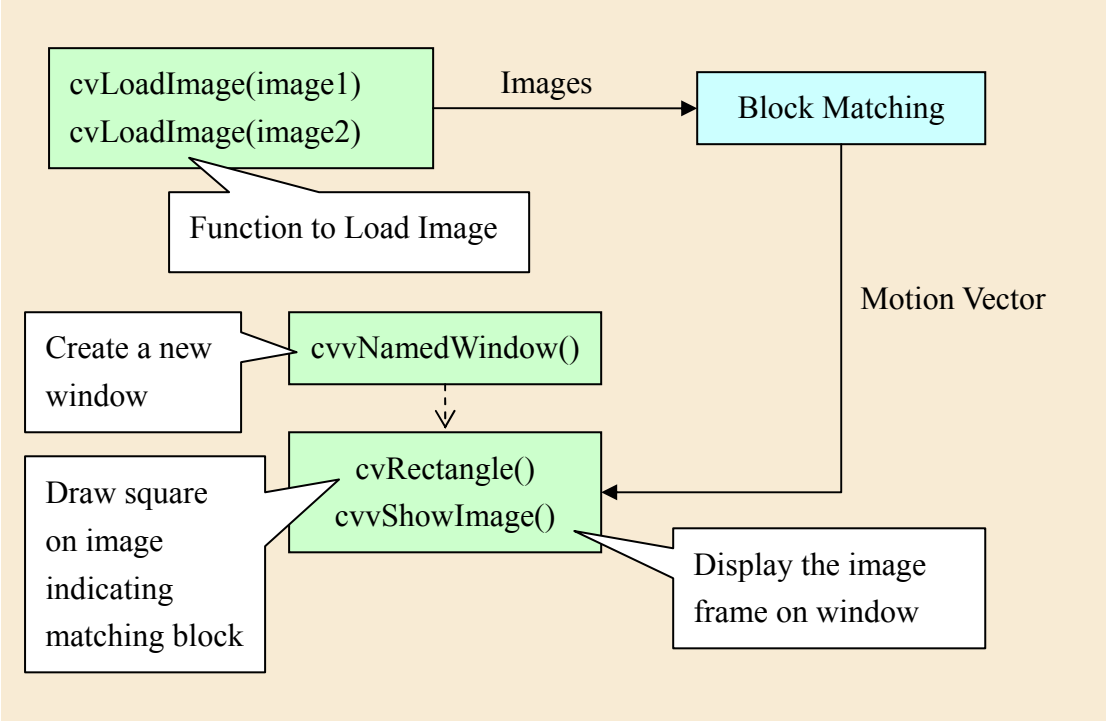
…	Open up a file explorer. Allow users to choose the image used for static frames motion tracking
Open Image	New a window and display the corresponding image on the window
Guide	Read the block matching parameters. Display a red square on image 1 denoting the previous block's location and a green square on image 2 denoting the search window's location
Select Feature	Run the feature selection algorithm and select the highest rated feature block
Process	Do static frames motion tracking by running the specified block matching algorithm on image 1 and image 2
Feature	New a window and display the video instantly captured by the web camera. Frames of the video are passed to the feature selection algorithm. Highest rated block is displayed on the window and are denoted by orange square
Run	New a window and display the video instantly captured by the web camera. A feature block is first found by the feature selection algorithm. Then do real-time motion tracking. The feature block is tracked using the specified block matching algorithm.
Clear	During the *Run* and *Process* of our algorithm, block matching result will be printed out in text format inside the Output Text Area. Press the *Clear* button can clear up the text area.
OK / Cancel	Close the application

Screenshot of *Process* window will be shown in the section "Static Frames Motion Tracking", screenshot of *Run* window will be shown in the section "Real-time Motion Tracking" while screenshot of *Feature* window will be shown in the last section of this chapter.

3.3 Static Frames Motion Tracking

3.3.1 Design and Implementation

With OpenCV library, loading images and accessing pixel of images becomes easier. Here is the flow chart of the OpenCV program for static frames motion tracking.



3.3.2 Testing our algorithms

The first main function of our program is to allow us to determine the accuracy of our implemented algorithms and time required to run them. Since the shifted images fed into the program is manually shifted using software, we know how much has the image shifted and thus the true motion vector is known. The algorithms that produce a motion vector close to this true motion vector is believed to have high accuracy, otherwise, they have low accuracy. Determining the accuracy of the algorithm also facilitates us to debug the program since some of the algorithms are supposed to have the same accuracy as others. For example, the SEA, PPNM and PDE algorithms should all have the same accuracy as the Exhaustive Search algorithm (ESA). If ESA have determined the optimum motion vector as $\vec{V}$, the SEA, PPNM and PDE algorithm should all produce the same result, with optimum motion vector $\vec{V}$; otherwise, there must be some bugs in the program. The time used to run each of the algorithms to determine the motion vector of a fixed previous block is also

shown to compare the speed of each algorithm. Since the speed of algorithm such as the SEA algorithm, depends on the image complexity of the matching block inside the search window, different locations of the previous block and different input images with different levels of noise are needed to obtain a representative computation time requirement for an algorithm.

The following is an example of a pair of input image.

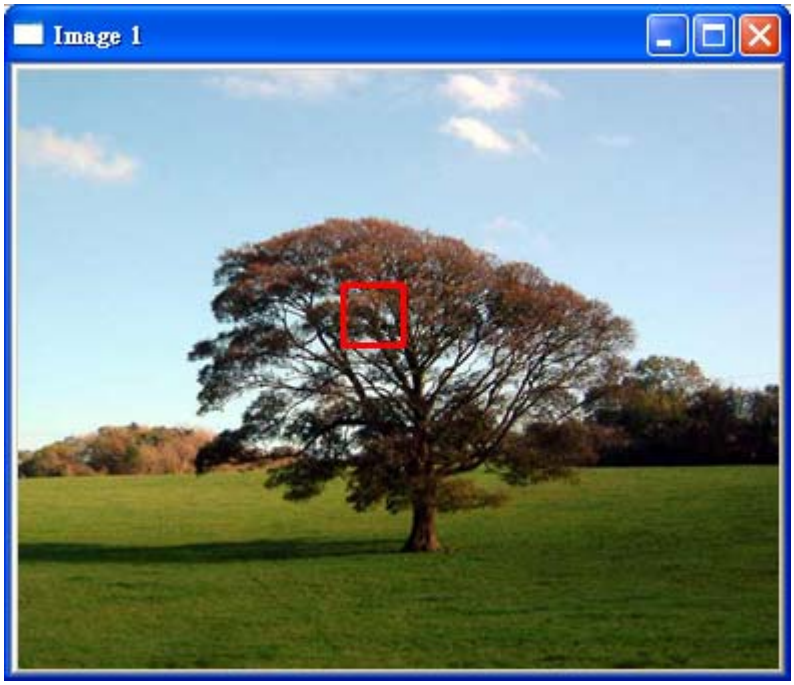


Figure 3.2 Input Image 1 and previous block marked as red square

Figure 3.2 shows the input image1, while Figure 3.3 shows the input image2. Image2 is the shifted version of Image1. In our algorithm, previous block is located at Image1 while current matching block is located at Image2 inside the search window. The previous block is marked by a red square in Image1 and the search window is marked by a green square in Image2. The figure below shows the result of block matching.

Figure 3.3 Input Image 2 and search window marked as green square

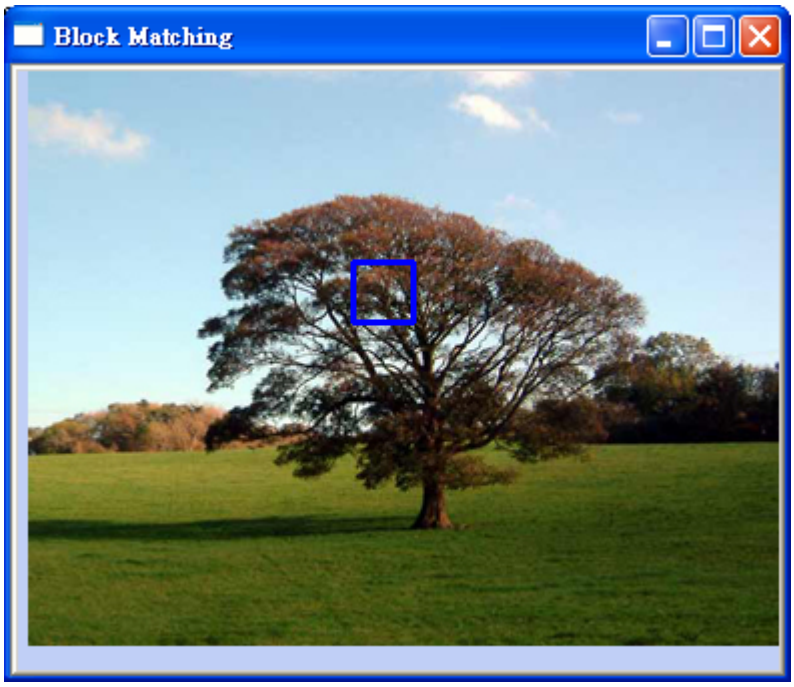


Figure 3.4 Block Matching Result, the best matched marked as blue square

In Figure 3.4, the blue square is the optimum block found by our algorithm in Image2. This block of image is the closest block to the previous block in Image1. Since the motion vector is hard to be guessed from Figure 3.4, another window showing solely the motion vector is displayed. The wider end of the arrow represents the

location of the optimum block while the narrower end represents the location of the previous block.

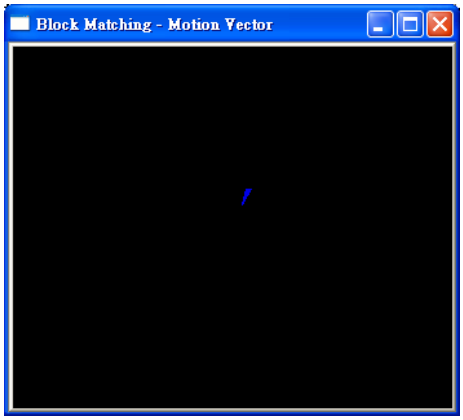
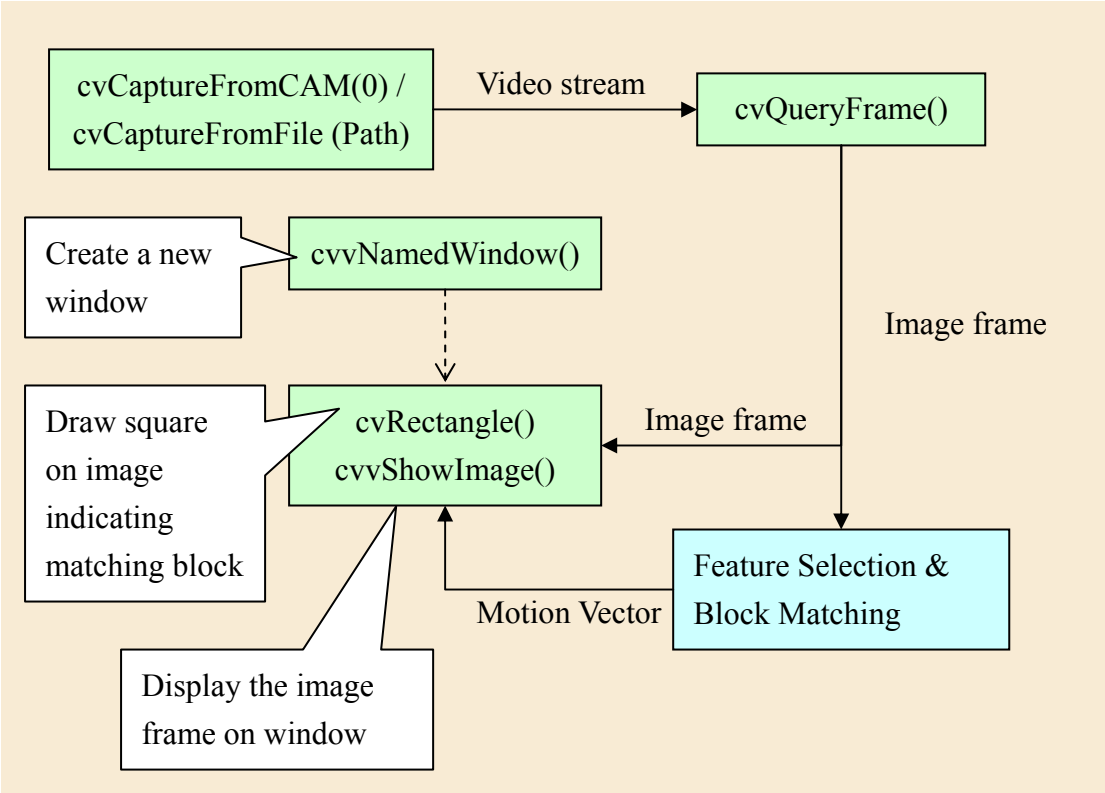


Figure 3.5 Motion Vector, pointing toward top right direction

3.4 Real-Time Motion Tracking

3.4.1 Design and Implementation

With OpenCV library, capturing video from web camera or video file and accessing frames of the video becomes easier. Here is the flow chart of the OpenCV program for real-time motion tracking part.



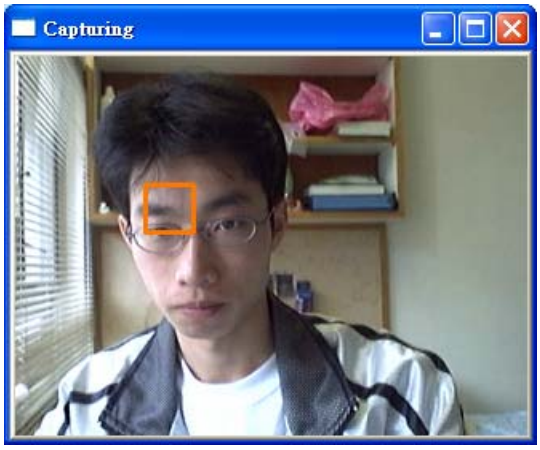
3.4.2 Difficulties on Real-time tracking

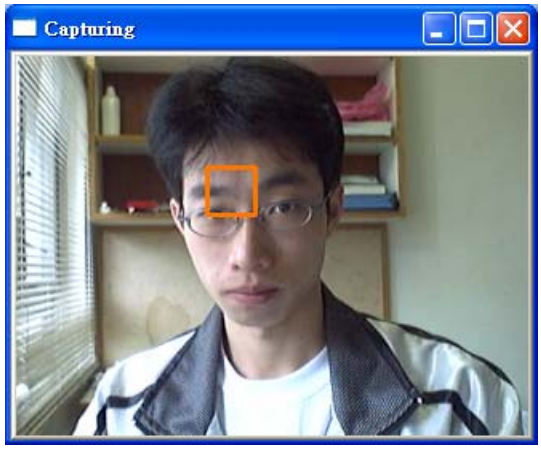
Since our goal is to real-time track the phone's motion, it is better to test real-time motion tracking first in PC using the implemented algorithm. Real-time motion tracking has many things different from static frames motion tracking.

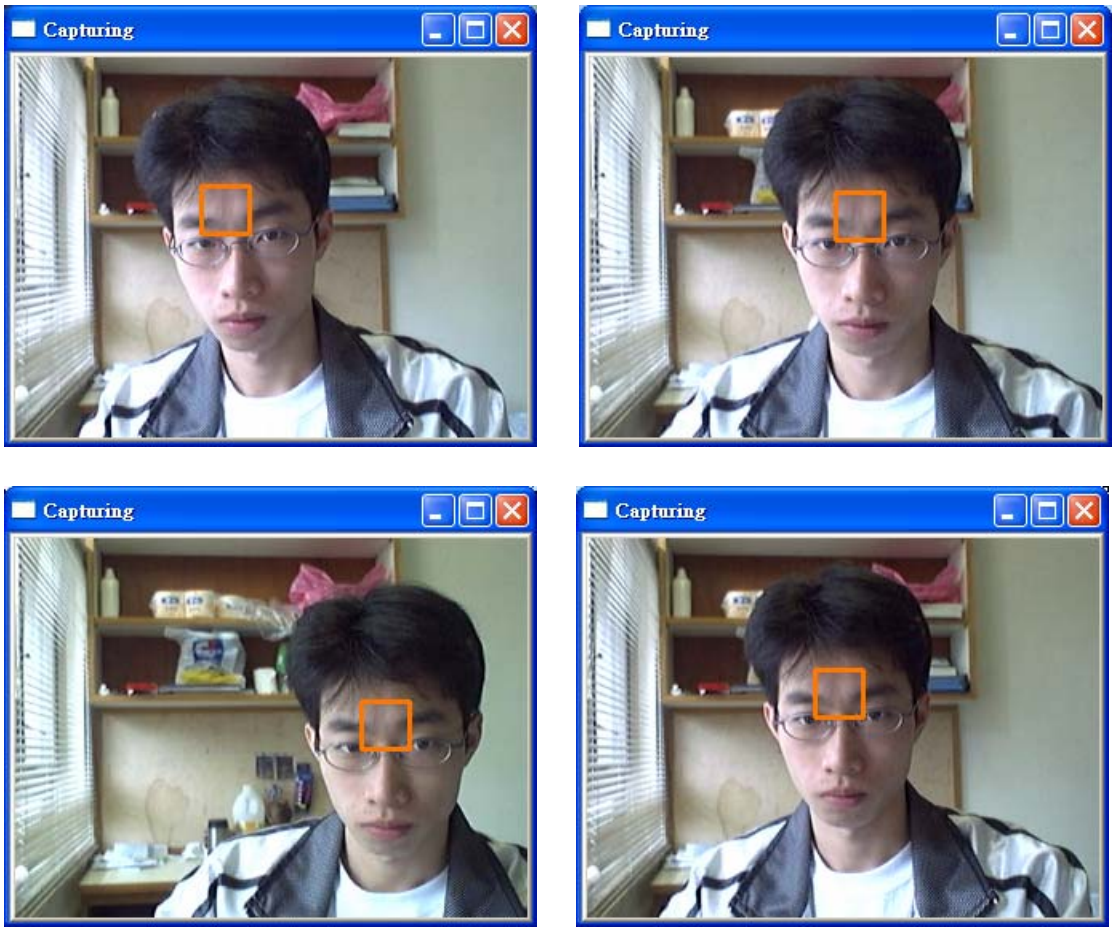
Firstly, the noise in a real-time frame is larger than that in a captured frame. This noise is called photon noise. It is due to the statistical variance of photons hitting a pixel. For a large number of photon hits per second N the standard deviation is $\sqrt{N}$. For a smaller number of photon hits per second, the standard deviation is larger. Since in real-time tracking exposure time of the CCD camera is short, smaller number of photon hits per second results. Thus the signal to noise ratio of real-time frame is lower. Noise in frames is not desirable because it produces unexpected impact on the SAD of each matching block. Block with minimum SAD may not be the true optimum block due to the noise.

Secondly, the same object in two consecutive frames may not have the same geometric shape. It may be geometrically distorted when the camera moves laterally or rotates. Geometric distortion problem is difficult to be solved, especially in real-time tracking. The impact of this problem can be reduced if time between frames is short so that geometric shape of the same object in the consecutive frame does not have big difference. Therefore, our algorithms should run as fast as possible.

Figure below is a sequence of images, showing how object is tracked and displayed in the "Capturing" window.







3.4.3 Evaluate the Performance of Real-Time Motion Tracking

In order to compare the results of different algorithms fairly, input video must be the same. Therefore, we need to use a web camera to capture a video first and use this video as a generic input to all algorithms.

The performance of the real-time motion tracking can be evaluated by observing how tight the matching block is stuck to the object. As the object moves, the matching block should keep sticking onto the object. Fail to do so mean either the accuracy of the algorithm is low or the speed of the algorithm is slow, or both.

The speed of the algorithm can be evaluated by observing the lagging level of the capturing video. Since new frame is captured only after the block matching algorithm is finished, speed of the algorithm affect the frame rate of the video. As faster algorithm finishes earlier, higher frame rate and lower lagging level result. Observation may sometimes be a

subjective measure. A more accurate method is to count how many times an algorithm has been called within a specified time limit. If an algorithm is called very frequently, it means its speed is high.

3.4.4 Relationship with Real-Time Camera Motion Tracking

The goal of our project is to implement an algorithm for tracking the motion of the camera (or say the phone). We have implemented many and have tested them on our testing platform. The way we evaluate the performance of the motion tracking algorithm is through tracking the motion of an object appears in the video. The reasons why we evaluate by tracking through moving the object instead of moving the camera are:

Firstly, results of evaluation of both methods are the same. It is because moving an object to the right in front of a web camera is just the same as moving the camera to the left with the object fixed. Their movements are relative to each other. Thus, moving camera can easily be emulated by moving the tracking object. There are no differences to use which method.

Secondly, since in testing phase we use web camera to test our algorithm, it is not convenient to move the wire-connected camera deliberately. After the algorithms are deployed into the Symbian phone, it would be more convenient to test the algorithm by moving the camera.

3.5 Feature Selection

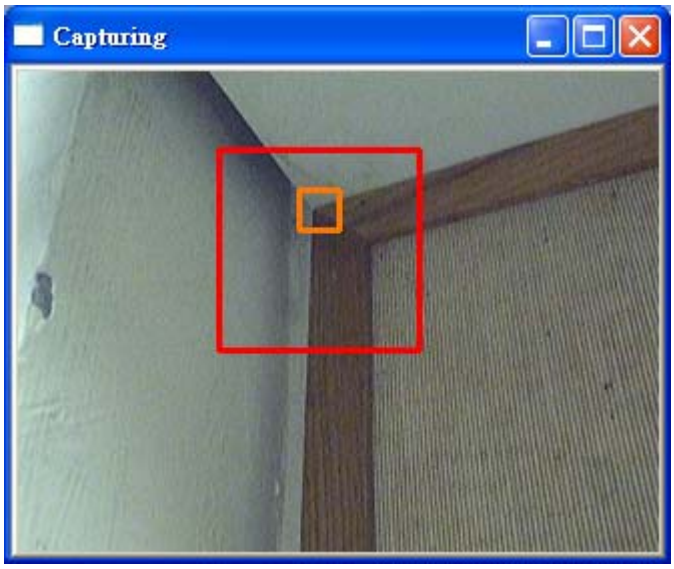


Figure 3.6 *Feature* Window

The function of *Feature* window is solely to verify if the feature selection algorithm is run correctly and the feature block selected by the algorithm is desirable.

Chapter 4: Testing Platform on Symbian

4.1 Introduction

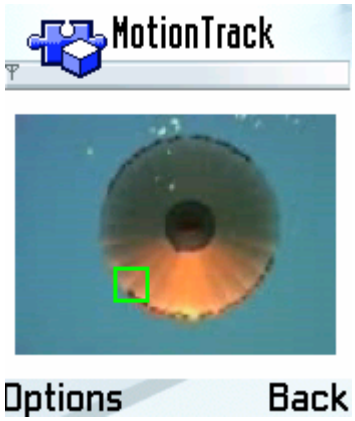
After the final algorithm was implemented and tested in window OpenCV testing platform, we finally built a platform ("MotionTrack" application) on Symbian and implemented our algorithms on it so that we can further test the performance of our algorithms on Symbian phone. Other applications can also be built on top of this program and access the motion tracking result directly.

4.2 User Interface

The application makes use of the standard Symbian OS application framework comprising the Application, Document, UI and View classes.

At the start up of the application, the following screen is displayed:

Initial application display



The Options menu displays two choices:

The Options menu

- Select *Algorithm* to choose which algorithm to use for tracking the object's movement.
- Select *Reset* to run the feature selection algorithm immediately and choose the highest rated feature block inside the feature selection window.

When *Algorithm* item is selected from the *Options* menu the application will show block matching algorithm choices of MotionTrack program as follows:

The Algorithm menu

- *Full Spiral:* Exhaustive Search Algorithm with Spiral Scanning method.
- *Partial Spiral:* Partial Distortion Elimination Algorithm with Spiral Scanning method.
- *Adaptive Sea:* Our final algorithm. The Adaptive Spiral SEA PPNM

PDE algorithm.

- *Sea:* SEA PPNM PDE algorithm with Spiral Scan method.

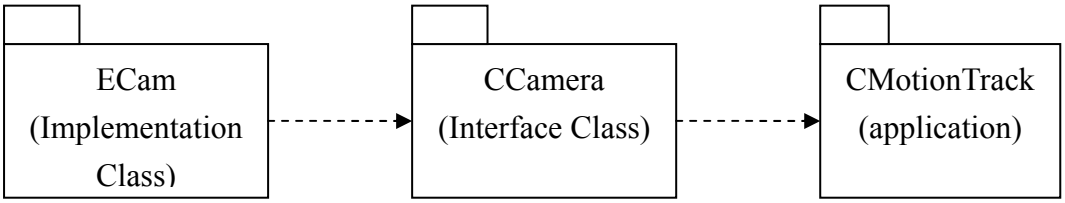
4.3 Design and Implementation

The program consists of these files:

File	Description
MotionTrack.cpp	The DLL entry point
MotionTrackApplication.cpp MotionTrackApplication.h	An Application that creates a new blank document and defines the application UID.
MotionTrackDocument.cpp MotionTrackDocument.h	A Document object that represents the data model and is used to construct the App Ui.
MotionTrackAppUi.cpp MotionTrackAppUi.h	An App Ui (Application User interface) object that handles the commands generated from menu options.
MotionTrackAppView.cpp MotionTrackAppView.h	An App View (Application View) object that displays data on the screen.
MotionTrack.rss	A resource file. This describes the menus and string resources of the application.
MotionTrackVideoEng.cpp MotionTrackVideoEng.h	An implementation of MCameraObserver Class, which must be implemented if the application needs to use the Camera function.

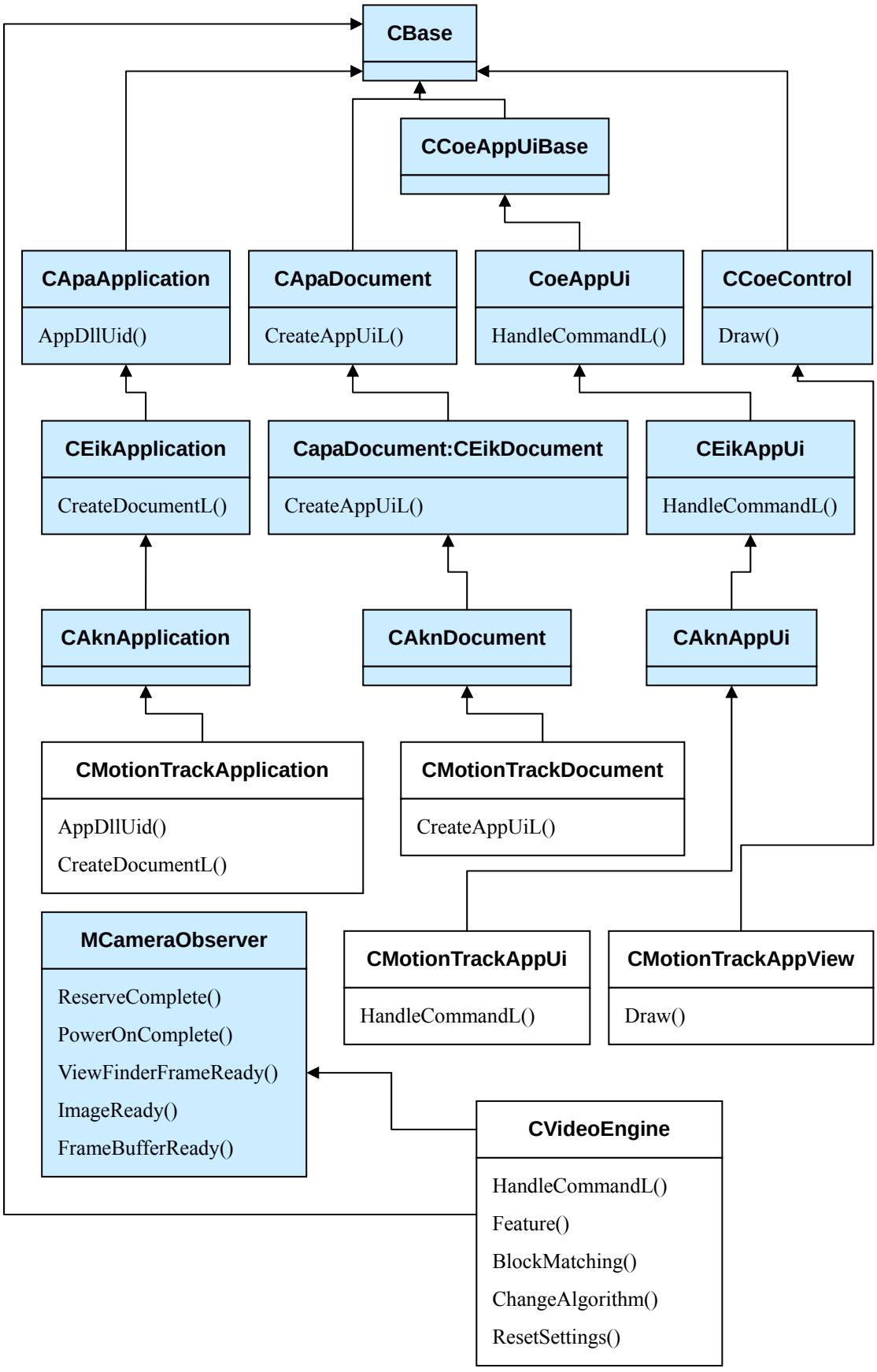
4.3.1 Class Structure

The camera API interface diagram for our MotionTrack application is shown below:



The required asynchronous virtual methods of the CCamera class are implemented in the MotionTrack classes.

A class diagram for the MotionTrack application is shown below:

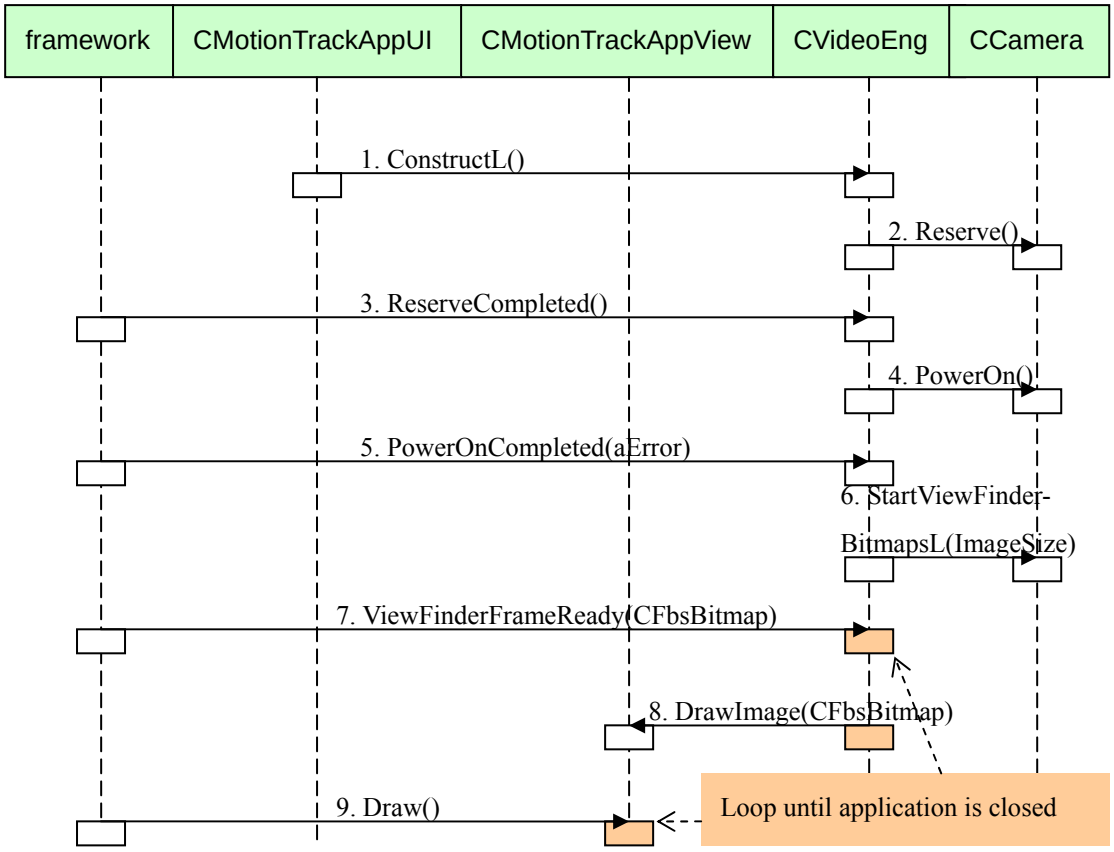


This diagram shows the classes implemented by MotionTrack application, and which files implement those classes. All the classes are derived from CBase. CBase has a number of useful features: it initialises all member data to zero, it has a virtual destructor, and it implements support for the Symbian OS cleanup stack.

4.3.2 Reserving Camera

Before the application can use the camera, it must reserve the application. The camera reservation includes two phases. First it must reserve, after the reservation is succeeded, the camera power must be switched on.

The UML sequence diagram below shows how the camera reservation is made.

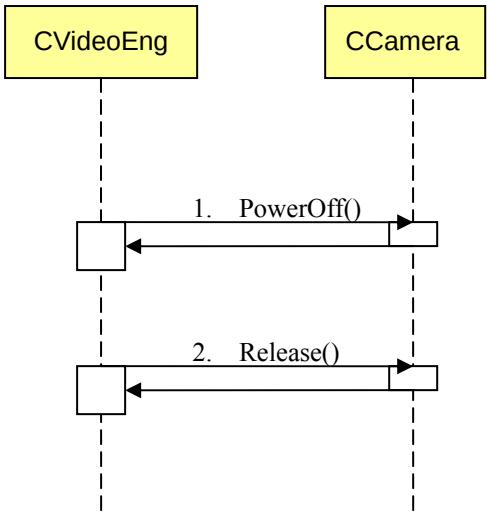


Function	Description
1	CMotionTrackAppUi calls the ConstructL method of the class CVideoEngine.
2	The CVideoEngine sends the asynchronous reserve request to the camera. If the camera is not yet reserved, the camera reserve session identification is stored.
3	The client will give the reservation answer to the overloaded Camera API method ReserveComplete. In the case of success reservation, the error code is KerrNone. In the other cases the error code is KerrNoMemory or KerrInUse.
4	Next the CVideoEngine sends the asynchronous power on request to the camera.
5	If the power on request was successful, the answer KErrNone arrives to the PowerOnComplete method. In the other cases the error code is KErrNoMemory or KerrInUse. If both reservation and power on are successfully performed, the camera is reserved for the application.
6	The CVideoEngine sends the asynchronous start viewfinder request StartViewFinderBitmapsL to the camera.
7	If the start command was successful, the camera API sends an asynchronous answer to the ViewFinderFrameReady function every time bitmap frame captured by the camera is ready. If the start command was fail, the camera API sends the error code KErrNotSupported, KErrNotReady or KErrNoMemory.
8	The camera client draws the captured image onto the display with the AppView method DrawImage.
9	The framework updates the final display when the draw functions of the AppUi are complete.
7 - 9	This loop will continue until the user/application sends the viewfinder the stop command.

4.3.3 Releasing Camera

After finished using it, application must release the camera. The camera release has two phases: First the camera power must be switched off, and then the camera can be released.

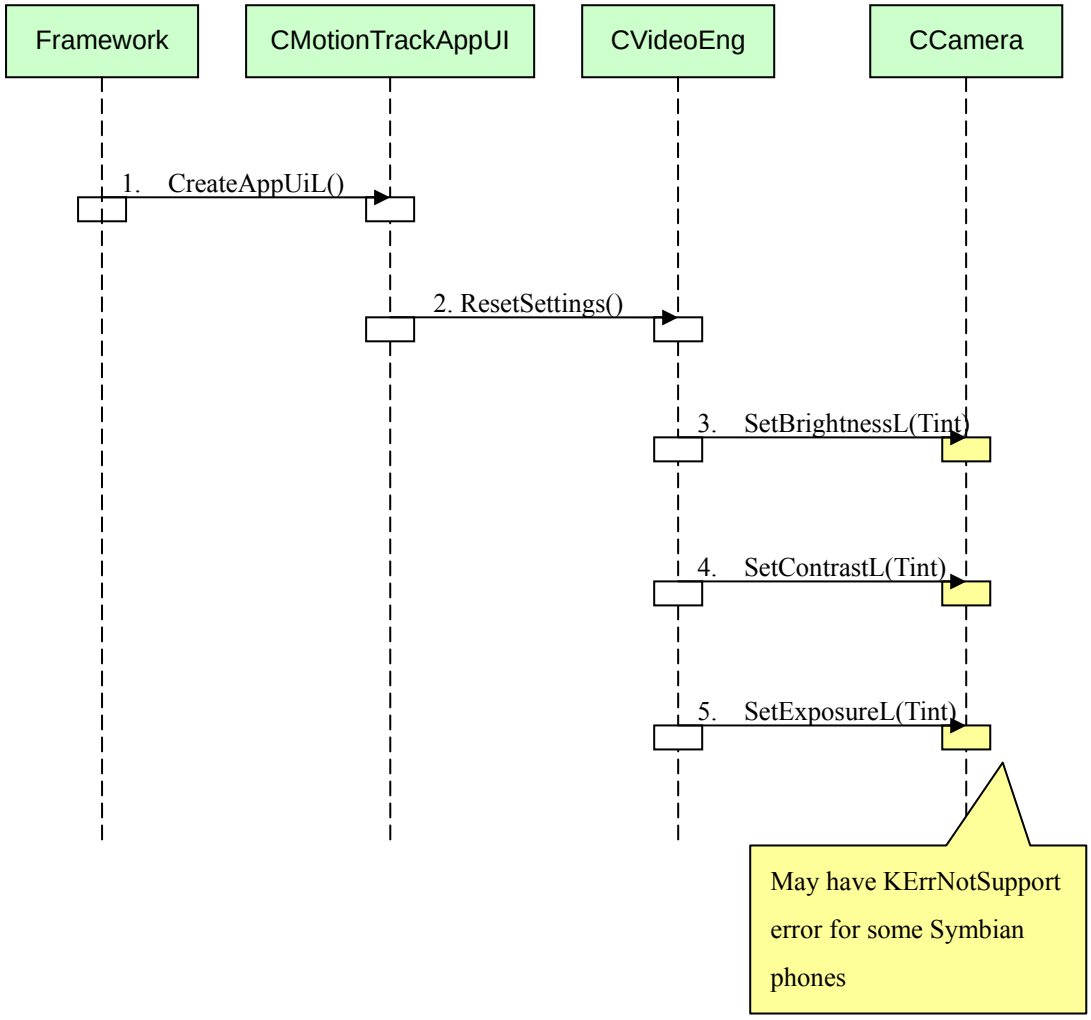
The UML sequence diagram below shows the function how the camera release is done.



Function	Description
1	The AppUi sends the *synchronous* power off request to the camera.
2	The AppUi sends the *synchronous* release request to the camera.

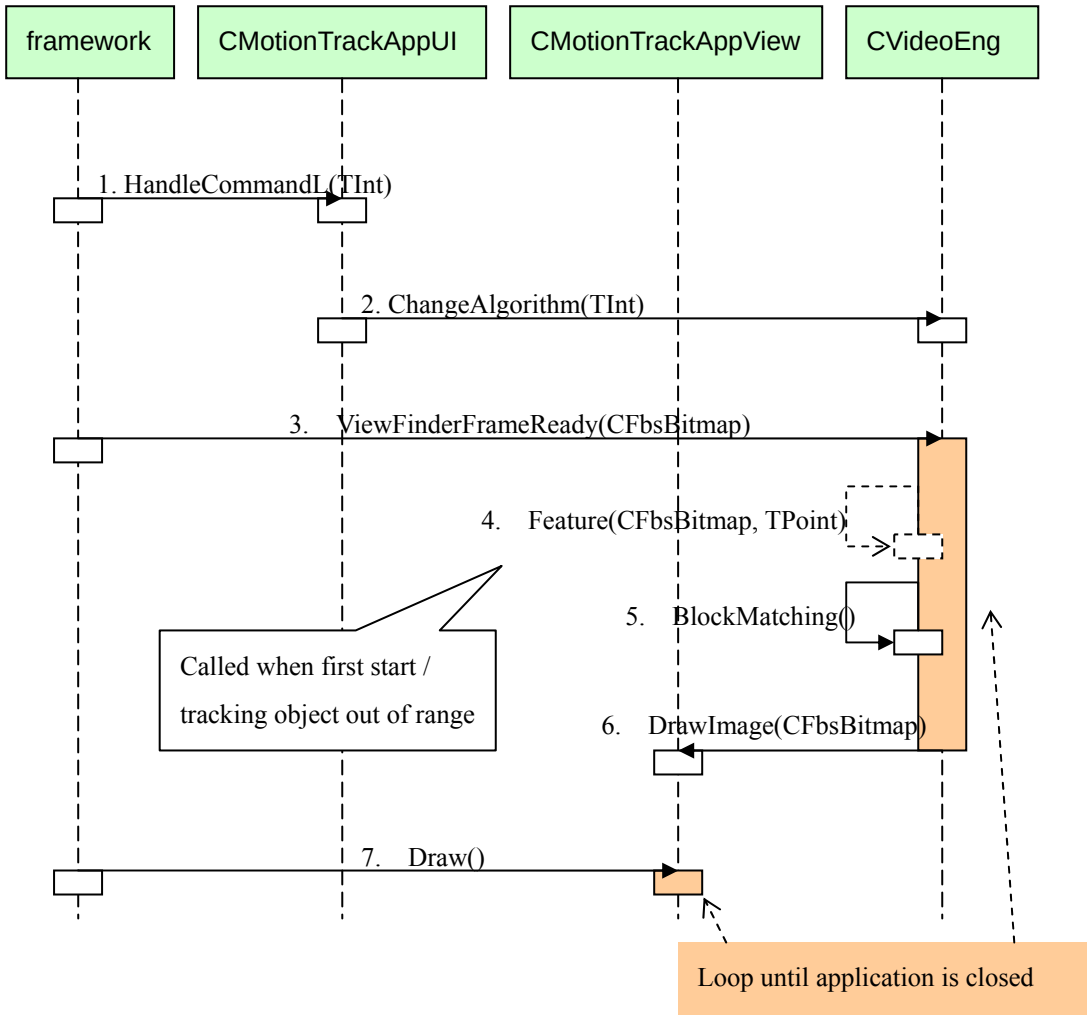
4.3.4 Reset Contrast, Brightness and Exposure Mode of camera

The camera default settings for contrast, brightness and exposure mode are all "Auto". That means the contrast, brightness and exposure level of the image frame may change from time to time. If either the contrast, brightness or exposure level of the previous video frame and the video current frame are different, the motion tracking algorithm will have significant error. Therefore, we need to fix all these levels and fortunately, most Symbian phones do support this function, e.g. Nokia 6600.



Function	Description
1	The framework calls the Document object's CreateAppUiL method. This creates the App UI object and returns a pointer to it.
2	The AppUi uses the ResetSettings method of the class CVideoEngine to restore the default settings of the camera.
3	The ResetSettings method uses the SetBrightnessL method of the class CCamera to fix the brightness of the image to certain value.
4	The ResetSettings method uses the SetContrastL method of the class CCamera to fix the contrast of the image to certain value.
5	The ResetSettings method uses the SetExposureL method of the class CCamera to fix the exposure mode to certain value.

4.3.5 Running the Block Matching Algorithm



Function	Description
1	The user selects the *Algorithm Name* item from the *Algorithm* menu. The aCommand command arrives through HandleCommandL to CMotionTrackAppUi module.
2	The App Ui calls the ChangeAlgorithm method of class CVideoEngine to specify which block matching algorithm to use for motion tracking.
3	The camera API sends an asynchronous answer to the ViewFinderFrameReady function every time bitmap frame captured by the camera is ready.
4	If motion tracking is the first time to start or the currently tracking object can't be tracked anymore, the CVideoEngine run the feature selection algorithm by calling Feature method. Object can't be tracked when it falls out of the range that can be captured by the camera
5	The CVideoEngine run the Block Matching algorithm to track the motion of feature block found by the feature selection algorithm.
6	The camera client draws the captured image onto the display with the AppView method DrawImage.
7	The framework updates the final display when the draw functions of the AppUi are complete.

Chapter 5: Translational Motion Tracking

Motion tracking is the process of determining the values of motion vector. Given a set of images in time which are similar but not identical, motion tracking identify the motion that has occurred (in 2D) between different images. Motion tracking techniques are classified into four main groups [17]:

1. gradient techniques
2. pel-recursive techniques
3. block matching techniques
4. frequency-domain techniques

Gradient techniques are typically used for analysis of image sequences. Pel-recursive techniques are applied in image sequence coding. Frequency-domain techniques are based on the relationship between transformed coefficient of shifted image, and they are not widely used for image sequence coding. Finally, block matching techniques, based on the minimizations of a specified cost functions, are the most widely used in coding application.

For motion tracking, gradient techniques (which will be discussed later) and block-matching techniques are commonly used. In our project, we use the block-matching techniques for motion tracking.

5.1 Characterization of the motion

Before discussing in more details motion tracking techniques, the notion of motion should be clarified in the framework of image sequence processing.

Formulation in terms of either instantaneous velocity or displacement is possible. The instantaneous velocity v of a pixel and its displacement d are related by a constant Δt which correspond to the temporal sampling interval. Consequently, in this case these two quantities are interchangeable. We adapt the formulation in term of displacement and thus when we talk about motion vector, we refer to displacement.

5.2 Block-Matching Motion tracking

These algorithms estimate the amount of motion on a block by block basis, i.e. for each block in the previous frame, a block from the current frame is found, that is said to match this block based on a certain criterion.

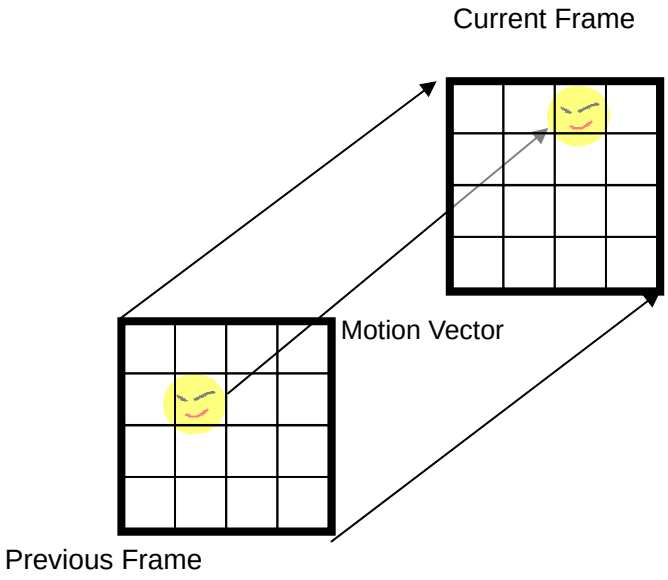


Figure 5.1 Block matching

5.2.1 Principle of Block-Matching Motion Tracking

The image is divided into small rectangular blocks. For a selected block in the image, it tries to find a similar block with same size in the second image. It searches some neighborhood of some given points in the second image. The assumption is that motion in the frame will cause most of the pixels within a block to move a consistent distance in a consistent direction.

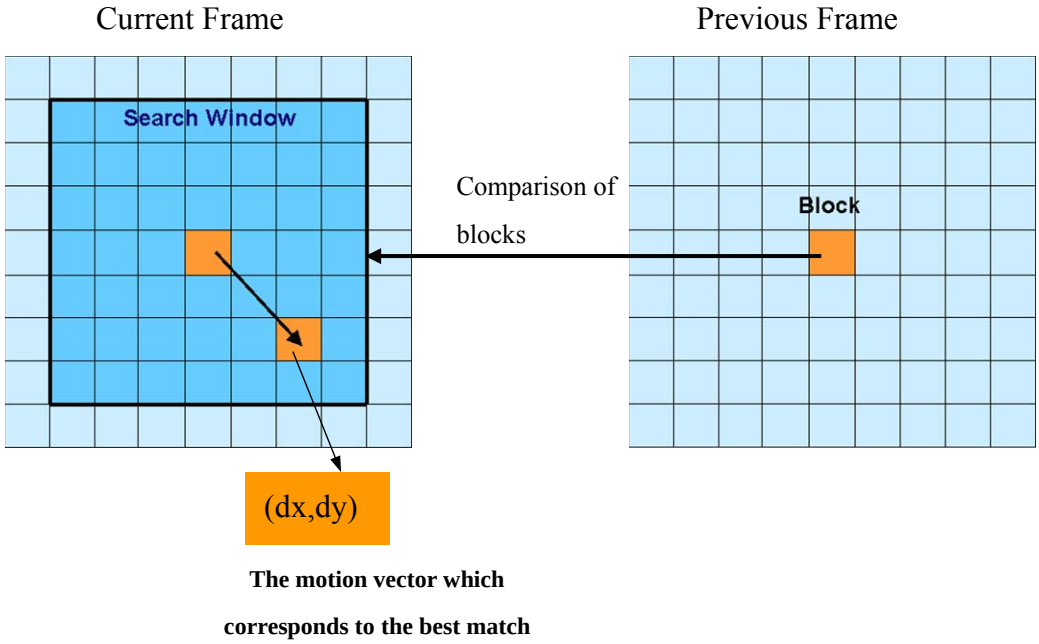


Figure 5.2 Motion tracking: a block is compared against the blocks in the search area in the current frame.
The motion vector corresponding to the best match is returned.

The basic technique used for block-matching is a search. It is subject to a tradeoff between accuracy and efficiency. The search space is defined by the search range parameter, generally referred to as W, as illustrated in Figure 5.3

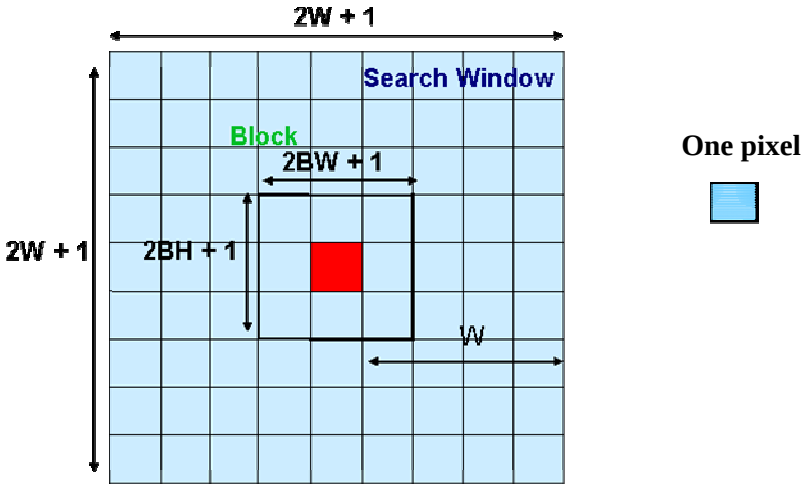


Figure 5.3 The search area in block-matching motion tracking techniques
The red grid is the center pixel of the block

The value W represents the distance between center block, and the edge of the search space. W defines the numbers of evaluations of the cost functions that would occur in only one direction. In the rest of the report, we will refer to the number of calculations of the cost function as the number of weights.

Thus, the search space can be defined in terms of W as (2W+1) x (2W+1). For example, the search ranges parameter of W = 6 would produce $(12+1)^2 = 169$ weights. Each of these weights would be the result of the application of a cost function, and the best one is chosen. The location of the weight chosen as the best match is the motion vector.

The complexity of the motion tracking techniques can then be defined by the three main characteristics: (1) search algorithm, (2) cost function, and (3) search range parameter W.

For search algorithm, many fast algorithms have been developed that they gain their efficiency by looking at only a fraction of the weights (will be discussed later).

For the cost function, there are a number of cost functions to evaluate the "goodness" of a match and some of them are:

1. Mean Absolute Difference
2. Mean Squared Difference
3. Pel Difference Classification (PDC)

Some of these criteria are simple to evaluate, while others are more involved. Different kinds of block-matching algorithms use different criteria for comparison of blocks. The block-matching algorithms obtain the motion vector by minimizing the cost functions.

5.2.2 Cost Functions

The cost function is a mapping from pixel block differences to the real numbers. In other words, cost functions are used to estimate the differences or similarities between any two given blocks. The smaller the values returned by the cost functions, the more similar the two pixel blocks

are to each other. Theses cost functions have the second largest effect on the complexity of motion tracking. The more intensive the function, the longer the search will take. Different cost functions have different accuracy and time complexity.

The Mean Absolute Difference (MAD)

$$MAD(dx, dy) = \frac{1}{MN} \sum_{i=-n/2}^{n/2} \sum_{j=-m/2}^{m/2} |F(i, j) - G(i + dx, j + dy)|$$

Where:

F(i,j) is the (MxN) block in the previous frame

G(I,j) is the reference (MxN) block in current frame and

(dx, dy) is the search location motion vector

The MAD is commonly used because of its simplicity.

The Mean Squared Difference (MSD)

$$MSD(dx, dy) = \frac{1}{MN} \sum_{i=-n/2}^{n/2} \sum_{j=-m/2}^{m/2} [F(i, j) - G(i + dx, j + dy)]^2$$

The multiplications of MSD are much more computationally intense than MAD. However, the square on the difference term causes the function to be more complex and accurate than MAD.

The Pixel Difference Classification (PDC)

In order to reduce the computational complexity of MSD, MAD, and CCF functions, Gharavi and Mills have proposed a simple block matching criterion, called Pixel Difference Classification [18]. The PDC functions is defines as:

$$PDC(dx, dy) = \sum_{i} \sum_{j} T(dx, dy, i, j)$$

for (dx,dy) = {-W,W}.

Then, T(dx, dy, i, j) is the binary = 1 if $|F(i, j) - G(i + dx, j + dy)| \leq t$
= 0 otherwise

where t is the predefined threshold value.

In this way, each pixel in a block is classified as either a matching pixel (T=1), or a mismatching pixel (T=0). The block that maximizes the PDC function is selected as the best matched block.

5.2.3 The Exhaustive Search Algorithm (SEA)

The most obvious searching algorithm for finding the best possible weights in the search area is the exhaustive search, or full search. All possible displacements in the search area are evaluated using the block-matching cost function. Therefore, no specialized algorithm is required. It is just a two-dimensional search.

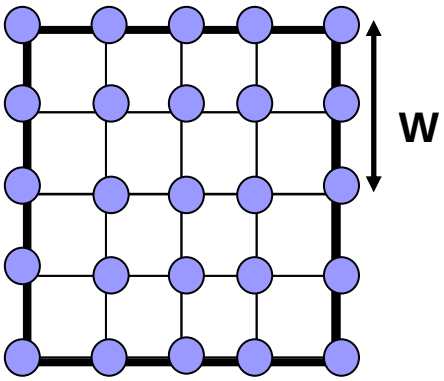


Figure 5.4 The exhaustive search evaluates the cost function in all locations in the search area

The advantage of the exhaustive search is that if we evaluate all the possible position in the search area, we can be guaranteed that we will find the absolute minimum.

The number of search locations to be evaluated by the exhaustive search is directly proportional to the square of the search range W. The total number of search locations in the search area = $(2W+1)^2$. Therefore

the exhaustive search algorithm has complexity of $O(W^2)$. As we can see, the size of W is very important to the speed of the exhaustive search algorithm.

Although, this algorithm in terms of accuracy and the simplicity of the algorithm, it is very computationally intensive. Fast exhaustive search algorithms were developed that they achieve the same quality but with less computationally intensive. They are The Successive Elimination Algorithm (SEA) proposed by W.Li and E.Salari [11] and Progressive Partial Norm Matching (PPNM). Fast exhaustive search algorithm will be discussed in detail in Section 5.2.5

5.2.4 Fast Motion tracking Algorithms

The complexity of motion tracking is affected by the search algorithm and the complexity of the selected cost function. Apart from the exhaustive search algorithm which evaluates all the possible locations in a search area, there exists fast motion tracking algorithms. In the case of fast motion tracking, only a subset of all the possible locations is evaluated.

All fast searching algorithms are based on an assumption that the matching error monotonically increases as the search position moves away from the optimal motion vector. That means the further we move away from the best position, the worst the match, and thus the higher the weight returned by the cost function. Hence, we would expect that a bowl would form around the minimum, as shown in figure 5.5 [19]

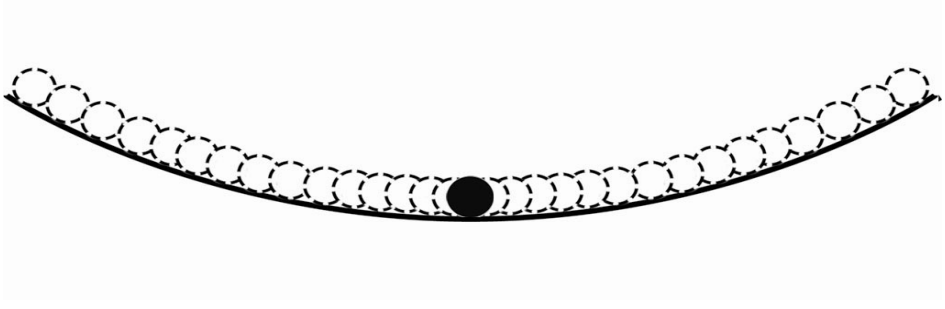


Figure 5.5 Weights generated by the cost function increase monotonically from the global minimum

If we assume that the inside of the bowl is a very smooth surface, we will reach the minimum weight by following the direction of decreasing

weights. From everyday experience, we know that if we place a marble at the edge of a bowl, it will roll to the center. In the same way, if we look for a minimum weight adjacent to our starting position and then the minimum weight adjacent to that, we will in effect be directing our marble to the center of the bowl. In other words if we follow the direction of decreasing weights, we will eventually find the minimum weight. It is that assumption, that of a smooth bowl, which is the defining characteristic of the fast search algorithms. Regardless of their implementation, all of the fast search algorithms try to find the minimum position of the bowl by following the gradient downward.

Fast Search algorithms:

1. Three-Step Search algorithm
2. Diamond Search algorithm
3. Conjugate Direction Search

5.2.4.1 Three-Step Search Algorithm

The three-step search has been proposed by Koga et al [20] and implemented by Lee et al. [21]. An example of the three-step search algorithm is shown in figure 5.6.

Step 1

The Three-Step Search begins by calculating the weight at the center of the search area. This is then set to the best match so far. A starting step size is defined as the search range divided by two: W/2. Using this step size, the 8 positions surrounding the center are searched: (0, W/2), (0,-W/2), (W/2, 0), (-W/2, 0), (W/2, W/2), (W/2,-W/2), (-W/2, W/2), and (-W/2,-W/2). The cost function of these eight locations is computed, and the resulting weights are compared to each other. The location with the lowest weight is chosen as best match and this location will become the center position of the next step. In the example of Figure 3.1, the current best location is (-4,-4).

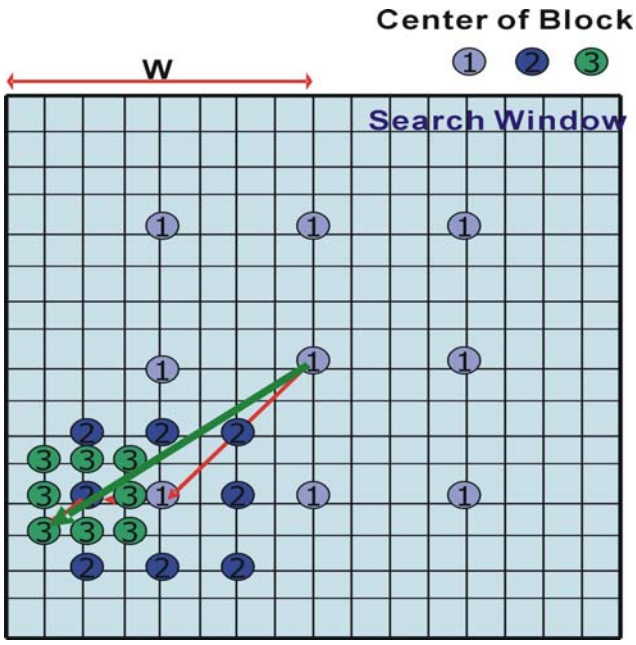


Figure 5.6 An example of the three-step search algorithm

Step 2

The step size is further divided by 2. The cost function is applied to the new eight surrounding locations around the current best match in the horizontal, vertical, and diagonal directions. Again, among these 9 points (the new eight and the current best match), the location which give the lowest value of cost function is chosen. In the example of Figure 3.1, the new best location from step 2 becomes (-6,4).

Step 3

The process of calculating the eight positions around the current best location continues until the step size = 1. In the example of Figure 3.1, the last step gives the best location (-7,5), which is the obtained motion vector.

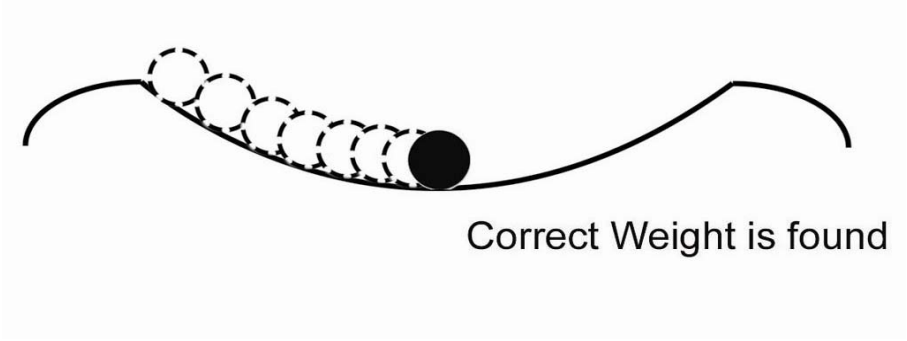
5.2.4.2 Time Complexity

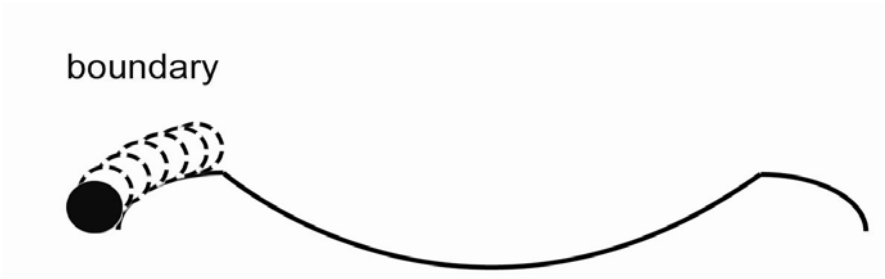
As the three-step search algorithm continuously divides the step size by two, and in each iteration, 8 points are calculated, the total complexity for the search is O(8logW). That is O(logW).

5.2.4.3 Problem of fast searching algorithms

Since all fast-search algorithms based on the assumption "The weight function in both the x and y directions increases monotonically as we move away from the minimum weight in the search area.". However, this assumption is difficult to be valid. Consider the bowl example in figure 5.5, if the "bowl" is not smooth and it contains local minimum. Then the fast-search algorithm will not found a global minimal, instead it can only obtain a local minimal.

Apart from this, the choice of origin of the searching window will also affect the accuracy. If the origin is contained within the walls of the "bowl", then by taking one step at a time, we should reach the center of the bowl, even if it is somewhat uneven. However, if the origin is located at the rim of the bowl, then the global minimum will not be found as illustrated in figure 5.6.





Correct Weight never found. Local Minimum found instead.

Figure 5.6 Bowl with extended rim illustrating the problem of selecting a wrong origin

5.2.4.4 Conclusion

In our project, we want to motion tracking to be as accurate as possible, so we decided not to use the fast-search algorithms.

5.2.5 Fast Exhaustive Search Algorithm

Since we want the motion tracking to be very accurate, we decided to use the exhaustive search. However, apart from accuracy, the speed is also our major concern, so there is a need to improve the speed of Exhaustive Search. W.Li and E.Salari have proposed a fast exhaustive search algorithm. That is the SEA algorithm.

5.2.5.1 The Successive Elimination Algorithm (SEA)

Before we talk about the principle of SEA, we need to define some terms first. The sum of absolute difference (SAD) is the most widely used matching criteria; the SAD of two NxN blocks X and Y is defined as

$$SAD(x,y) = \sum_{i=1}^{N}\sum_{j=1}^{N} | X(i,j) - Y(i,j) |$$

The SEA proposed in [11] adopted the well-known Minkowski inequality:

$$| (x_1 + x_2) - (y_1 + y_2) | \le | (x_1 - y_1) | + | (x_2 - y_2) | \quad (2)$$

To derive the following inequality:

$$| \sum_{i=1}^{N}\sum_{j=1}^{N} X(i,j) - \sum_{i=1}^{N}\sum_{j=1}^{N} Y(i,j) | \le SAD(X,Y) = | \, \| X \| - \| Y \| \, | \le | X - Y(i,j) |$$

Where:

X: reference block in previous frame

Y: candidate block in current frame

$$\|X\| = \sum_{i=1}^{N}\sum_{j=1}^{N} X(i,j)$$

That means if the difference between the block sum (summing all pixels value inside a block) of candidate Z and the block sum of reference block X is greater than the minimum SAD(X,Y), block Z must not be the best match, since its SAD must be greater than the minimum SAD(X,Y) based on the inequality (3).

As the calculation of block sum requires only N^2-1 additions and 1 subtraction for a NxN block while calculation of SAD requires N^2-1 additions and N^2 subtraction. Thus, calculating the block sum difference is much faster than calculating the SAD.

Then, by calculating the block sum difference first, we can eliminate many candidates block before the calculation of SAD. Therefore, the speed of the block matching algorithm is increased.

5.2.5.2 PPNM (Progressive Partial Norm Matching)

After the SEA has been proposed, another algorithm is proposed to improve the speed of exhaustive search algorithm. That is the PPNM which is commonly used in video coding standard H.264.

The concept of PPNM is very similar to SEA. PPNM also makes use of the Minkowski inequality to derive a matching criterion. The criterion further eliminates invalid candidate blocks before calculating the SAD of the blocks.

Based on the Minkowski inequality,

$$\left| \|X\| - \|Y\| \right| = \left|(\|X_1\| + \|X_2\|) - (\|Y_1\| + \|Y_2\|)\right| \le \left|(\|X_1\| - \|Y_1\|)\right| + \left|(\|X_2\| - \|Y_2\|)\right|$$

$$\textit{from } \left|A_1 + A_2\right| \le \left|A_1\right| + \left|A_2\right|$$

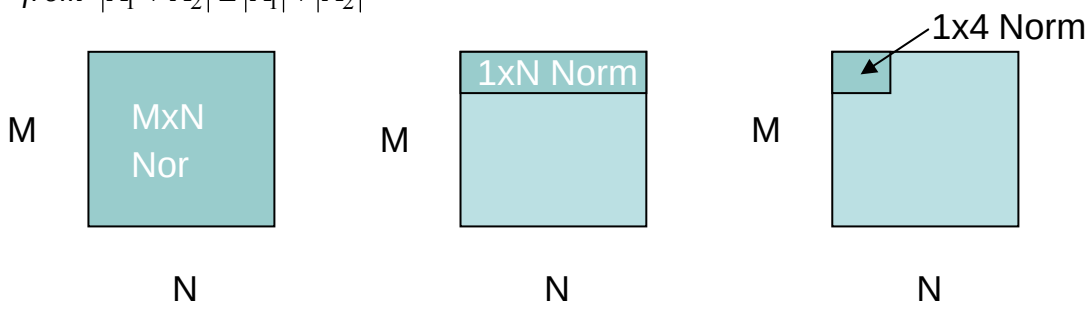


Figure 5.7 Different sizes of sub-blocks

From the above inequality, we can derive the following inequality,

$$\sum \left| \left\| X_{1x4} \right\| - \left\| Y_{1x4} \right\| \right| > \sum_{\min} \left| X - Y \right| = SAD(X, Y)$$

In the example of Figure 5.7 , PPNM calculates the sum of difference of the 1xN norms between two block X and Z. If the sum is larger than the minimum SAD(X,Y), the SAD(X,Z) must be greater than the SAD(X,Y).

PPNM further eliminates the invalid candidate blocks with the expense of higher computation load than SEA.

In conclusion, by using the following inequality, many invalid candidate blocks are eliminated. Besides, there exists fast method for calculation of block sum (which will be discussed later).Thus further increases the speed of the exhaustive search.

$$\underbrace{\left| \left\| X \right\| - \left\| Y(i,j) \right\| \right|}_{\text{SEA}} \le \underbrace{\left| \left\| X_1 \right\| - \left\| Y_1 \right\| + \left\| X_2 \right\| - \left\| Y_2 \right\| \right|}_{PNSA} \le \underbrace{\left\| X \right\| - \left\| Y(i,j) \right\|}_{SAD}$$

5.3 Fast Calculation of Block Sum

5.3.1 Objective

In SEA algorithm, we need to calculate the block sum in the current frame in order to compute this matching criterion.

$$\left| \sum_{i=1}^{N} \sum_{j=1}^{N} X(i,j) - \sum_{i=1}^{N} \sum_{j=1}^{N} Y(i,j) \right| > SAD(X, Y)$$

$\sum_{i=1}^{N} \sum_{j=1}^{N} Y(i,j)$ term is the sum of pixel values in the previous block. Since there is just one previous block, this block sum can be reused every time the matching criterion is computed.

$\sum_{i=1}^{N} \sum_{j=1}^{N} X(i,j)$ term is the sum of pixel values in a block in the current frame. The simplest way to calculate this term is that for each block, we

calculate the sum of pixel values inside that block. This method is simplest yet inefficient. Since blocks inside the search window are overlapping to each other, sum of the overlapped pixels is redundant and wasting time. There is a better way to calculate the sum without adding the pixels redundantly.

5.3.2 Methodology

Figure 5.8

Consider Figure 5.8. There are two blocks, the first block has pixel 1-9, and the second block is the neighbor of the first block, it has pixel 4-12. The two blocks are overlapping with pixel 4-9 common to each other. First block sum is calculated by adding pixel 1-9. Second block sum can be calculated by adding pixel 4-12, but it is actually redundant to add pixel 4-9 as the sum of these pixels have already be calculated in the first block sum. This sum process involves 8 addition operations. A more efficient method is to make use of the first block sum. First block sum is the sum of pixel 1-9. If we subtract pixel 1-3 from the first block sum and add pixel 10-12 to it, we yield the second block involving only 6 addition and subtraction operations. Again, subtracting pixel 1-3 one by one is not efficient enough since sum of pixel 1-3 has also been calculated in first block sum. To further reduce the operation required, we can store the pixels in column with the expense of using larger memory storage. The increase in speed is best observed when the block size is large, so we use a larger block size as an example.

Figure 5.9

Consider Figure 5.9. The summation of the column i of pixels are stored in the first column and the sum is denoted by Norm[i] where i = [0,8]. To calculate norm[0] to norm[5], 29 addition and subtraction operations are required. First block sum can be calculated by adding norm[0] to norm[4], involving 4 more additions. Second block sum can be calculated by adding norm[5] and subtracting norm[0] from the first block sum, involving 2 more addition and subtraction operations only. In total, calculation of the first 2 block sum involves 35 addition and subtraction operations. If simplest method is used, 58 (= 29 x 2) addition and subtraction operations are needed. Thus the fast method requires 23 operations less. Calculation of the remaining block sums in the same row follows the same step as that in calculating the second block sum. To calculate the block sum of the second row, the sum we have calculated in the first row can also be used.

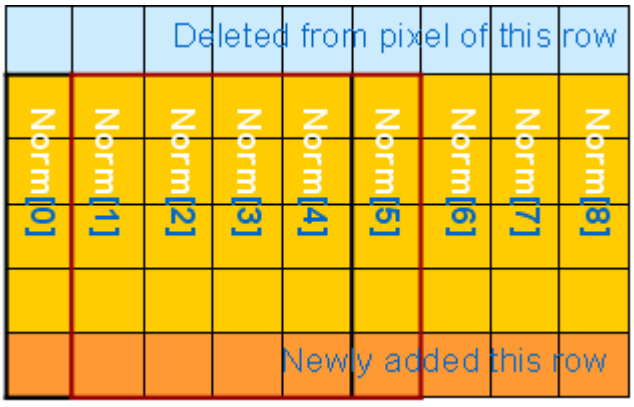


Figure 5.10

Consider Figure 5.10. To calculate the second row block sum, each norm is added one pixel below and one pixel above that column. Then the process used to calculate first row block sum is repeated in the second row, then third row, until all block sums are calculated.

5.3.3 Advantage to SEA and PPNM

As discussed above, fast calculation method involves less computation operations than the simplest method. Thus the computation time required to calculate block sum is reduced and it greatly improve the speed of SEA algorithm.

Apart from improving the speed of SEA algorithm, it can also greatly improve the speed of PPNM algorithm. In PPNM algorithm, the following matching criterion is needed to be computed.

$$\sum_{i=1}^{N} \left| \sum_{j=1}^{N} X(i,j) - \sum_{j=1}^{N} Y(i,j) \right| > SAD(X,Y)$$

$\sum_{j=1}^{N} Y(i,j)$ term, again, need to be calculated once and then reuse every time the matching criterion is computed.

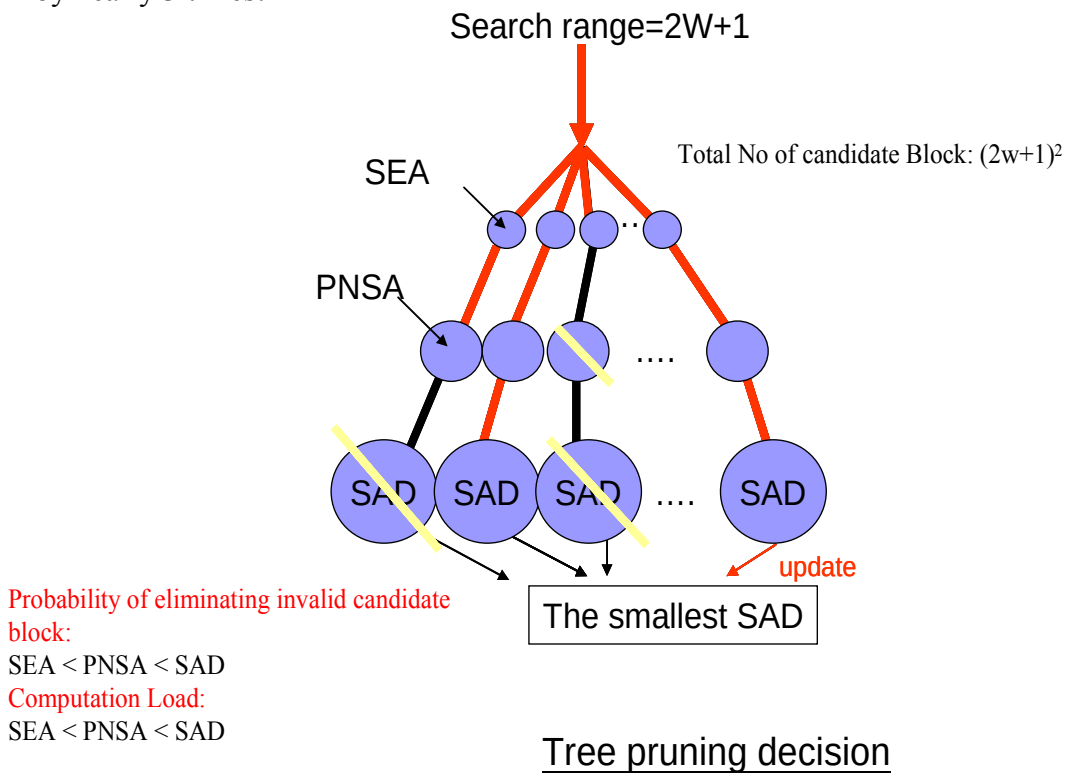
$\sum_{j=1}^{N} X(i,j)$ term is the sum of pixel values in one of the column in a block. This sum is exactly the norm of the block we calculated during the fast calculation of block sum. Therefore, if we keep the norm value in form of a 2D array, we can use that value as the $\sum_{j=1}^{N} X(i,j)$ term and thus less computation is required to compute the sum of pixel values in that column again.

5.3.4 Disadvantage

The only disadvantage of fast calculation of block sum method is that it increases the memory storage requirement. To facilitate the SEA algorithm, a (DY+DY+1) x (DX+DX+1) large block sum array is required. To facilitate the PPNM algorithm, another (DY+DY+1) x (DX+DX+BW+BW+1) large norm array is required. However, this increase in memory storage requirement is not significant when the search window size and the block size are both small.

5.4 Summary

The SEA and PPNM form a decision tree that eliminates about 50%-70% of invalid candidate blocks. The speed of the exhaustive full search is increased by nearly 3 times!



5.5 The Motion tracking Hypothesis

The previous chapter is dedicated to the current algorithms designed for motion tracking, while this chapter analyzes the underlying theory of motion tracking. We recall that motion tracking is the process used to discover the closest matching block, in the search area of the reference frame.

5.5.1 The Motion tracking Assumptions

If we attempt to describe the pitch of the motion tracking, we seem to generate three distinct concepts. Following definition of each of these ideas, we will expand on them to extract their implications.

5.5.2 Proximity Translation

The first of the concepts is a consideration of the physical properties of motion video sequences. Motion is communicated by translation of a group of pixels which resides in close physical proximity to one another. We refer to this definition as the Proximity Translation Hypothesis, and it forms the basis for block matching algorithms.

Figure 5.11 illustrating the proximity translation hypothesis. Motion is communicated by the translation of a group of pixels.

Very often, large solid objects exist in their entirety and their components move in a predictable fashion. Namely, all parts of the bottle will be moving as the same rate since they are all attached, as illustrated in Figure 5.11.

5.5.3 Intensity Stability

In order for block matching to work, we assume the intensity of objects remain unchanged during translational motion. Of course, the same argument can be made for inanimate objects appearing in the video sequence. It is common that the intensity of objects changes only slightly for a small translational movement.

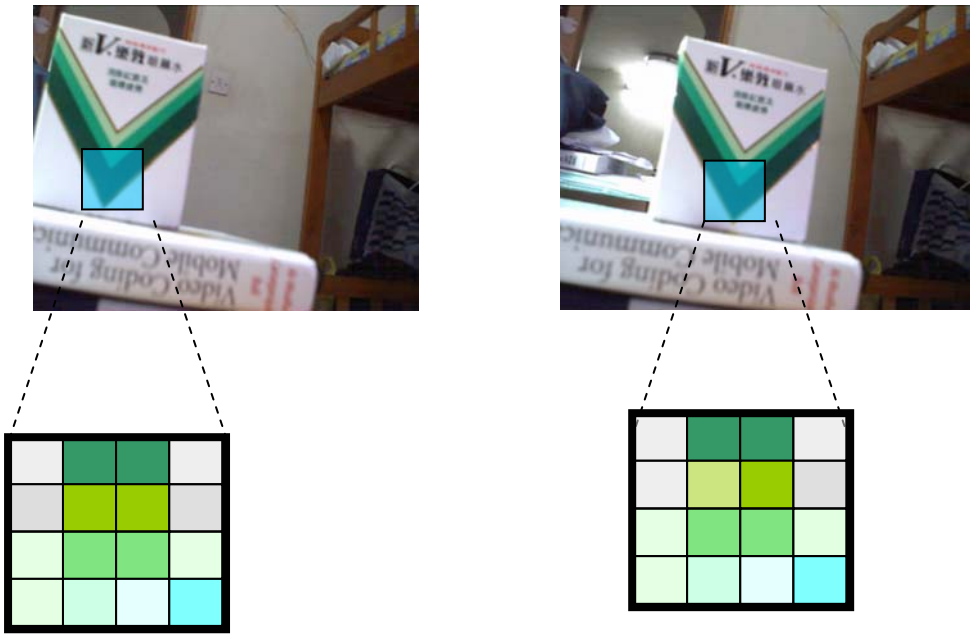


Figure 5.12 illustrating the intensity stability hypothesis.
Each region of pixels translates with little change in intensity or relative position.

5.5.4 Linear Motion Hypothesis

In most of the cases, we can assume that motion can be considered as relatively linear over short period of time. This means that an object will have a smooth continuous motion as it moves. It is quite believable that a driver would choose to drive continuously rather than applying the gas and brake in quick succession. This means that the car has a smooth continuous motion as it moves. The implication this produces is that if motion occurred at the rate of two pixels per frame between frames one and two, it is not unreasonable to assume that a motion of two pixels per frame may continue through frames two and three, three and four, etc. Though this may not last for extremely long in terms of seconds, linear motion may last over a period of several frames.

Base on the linear Motion hypothesis, we invent a new method "Adaptive Search Window" which increases the speed of the block matching algorithm.

5.6 Optical Flow

Apart from block matching, there is another method for motion tracking -- Optical Flow.

In this chapter, we will discuss briefly how optical flow work and explain why we choose block-matching algorithm instead of optical flow for motion.

5.6.1 Overview of Optical Flow

Optical Flow is defined as the apparent motion of brightness pattern in an image. That is the velocity field of every pixel. This is illustrated by the Figure 5.13 below. The sphere is rotating from left to right, generating the optical flow field shown in the center.

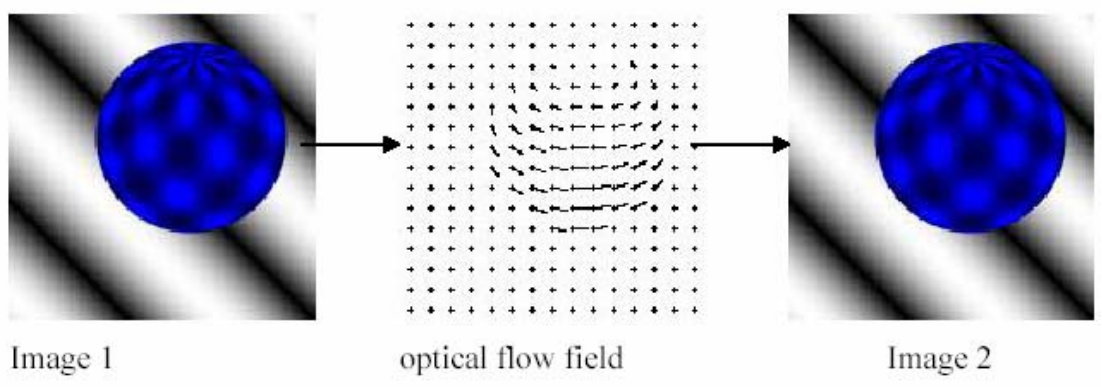


Figure 5.13 Illustration of Optical Flow

Optical flow is very similar to motion field, but it is not equal to motion field. Ideally, it will be the same as the motion field, but this is not always the case.

5.6.2 Motion Fields

A velocity vector is associated to each image point, and a collection of such velocity vectors is a 2D motion field. It tells us how the position of the image of the corresponding scene point changes over time. It is the projection of 3-D velocity field onto image plane. In figure 5.11, a point p_o on a object moves with a velocity v_o, then the image point pi can assigned a vector vi to indicate its movement on the image plane

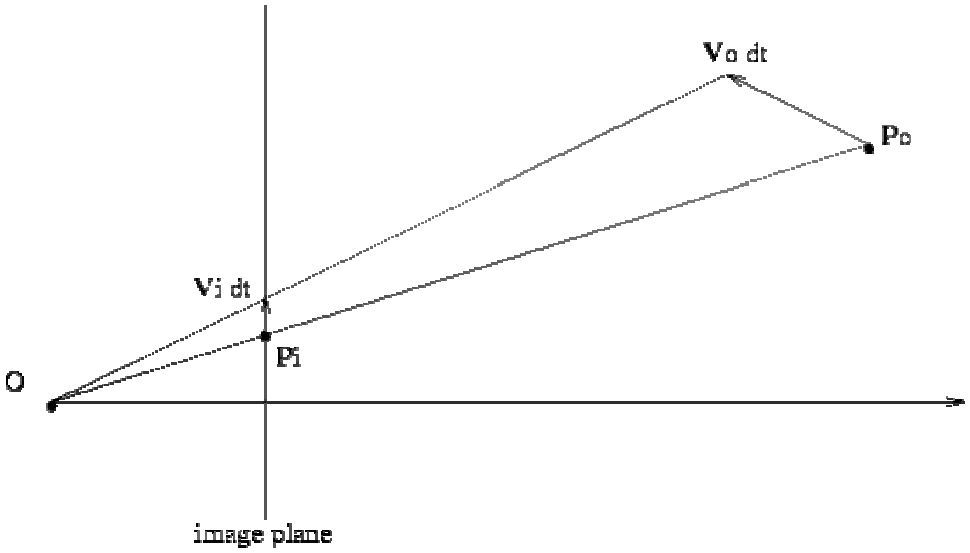


Figure 5.14 Object motion creates a motion field on the 2D image plane

5.6.3 Difference between Optical Flow and Motion Field

The difference between Optical Flow and Motion Field can be illustrated as follow. Consider a perfectly uniform sphere. There will be some shadow on the surface. When the sphere rotates, such shading pattern won't move at all. In this case, the apparent motion of the brightness pattern is zero, thus the optical flow is zero, but motion field is not zero.

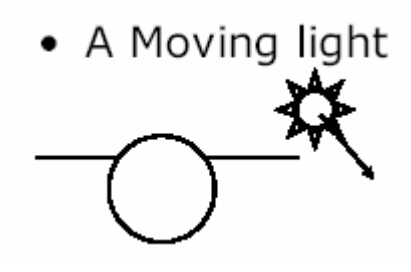


Figure 5.15

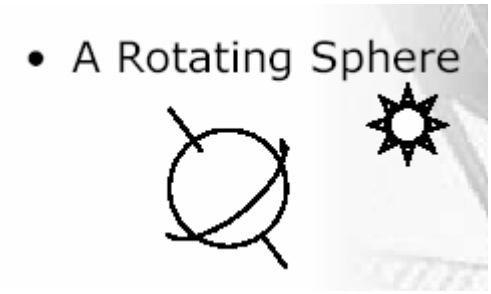


Figure 5.16

In figure 5.15, the image intensity of the object changes due to the moving light source, so there is optical flow. However, the scene objects do not move, so there is no motion field. For figure 5.16, the scene object moves, so there is motion field. However, the image intensity does not change, so there is no optical flow.

5.6.4 Optical flow computation

There are three approaches to calculate the optical flow: the gradient-based approach, the correlation-based approach, or the spatiotemporal energy-approach. In this session, we will briefly explain the principle by using gradient-based approach.

One of the most important feature of optical flow is that it can be calculated simply, using local information. Let *I (x, y, t)* be the brightness of image, which changes in time to provide an image sequence. Firstly, there are some assumptions before deriving the formula of optical flow. The assumptions are

1. The change of brightness of a point to the motion of the brightness pattern is constant (brightness constancy assumption)
2. Nearby points in the image plane move in a similar manner (velocity smoothness constraint).

From the first assumption, we can obtain:

$$I(x,y,t) = I(x+u,y+v,t+dt) \qquad \text{.....(1)}$$

Where

I(x,y,t) is the brightness of the image at location (x,y) and time t.

(u,v) is the motion field at location (x,y) and time t+dt

From equation (1), it means the change of intensity w.r.t is zero, so we can express it in another way:

$$\frac{dI(x,y,t)}{dt} = 0$$

By chain rule, it can be shown that

$$\frac{dI(x,y,t)}{dt} = 0$$

$$\frac{\partial I}{\partial x}\frac{dx}{dt} + \frac{\partial I}{\partial y}\frac{dy}{dt} + \frac{\partial I}{\partial t} = 0$$

$$\frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \frac{\partial I}{\partial t} = 0$$

$$fxu + fyv + ft = 0 \quad \text{.....(2)}$$

where

$$\text{fx} = \frac{\partial I}{\partial x}, \text{fy} = \frac{\partial I}{\partial y} \text{ and } \text{f}_\text{t} = \frac{\partial I}{\partial t}$$

From equation (2), it indicates that the velocity (u,v) of a point must lie on a line perpendicular to the vector (fx,fy) as illustrated as figure 5.17.

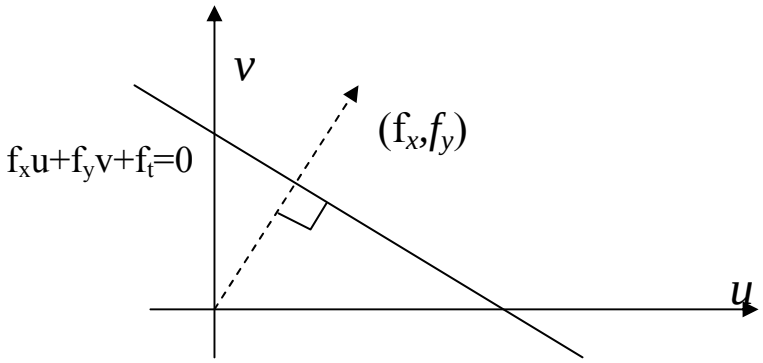


Figure 5.17 geometric explanation of equation (2)

Thus, the local constraints provide one linear equation in the variables u and v. As a result, the velocity (u,v) cannot be determined locally without applying additional constraints as illustrated by figure 5.18

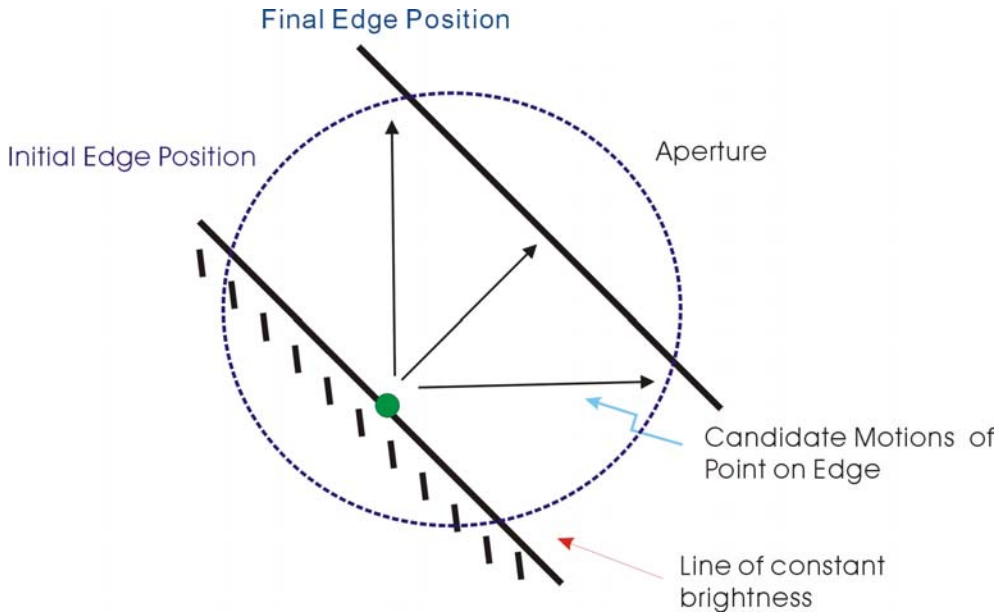


Figure 5.18 aperture problem

As we can see from the above figure, we know that the green point should move to a point on the line, but we don't know which one. This is known as aperture problem.

If we want to find a unique solution for equation (2), we need to have another constraint, which is the second assumption -- The neighboring pixels in the image should have similar optical flow. Therefore, u and v need to have low variation with its neighboring pixels, so we set $(u-u_{av}) = 0$ and $(v-v_{av}) = 0$ where u_{av} and v_{av} are the average of neighboring pixels' velocity.

In order to find a (u,v) that is as close as possible to the linear equation (2) and also is locally smooth, we can use the Lagrange multipliers to minimize the flow error

$$E^2(x,y) = (f_x u + f_y v + f_t)^2 + \lambda^2[(u- u_{av})^2 + (v- v_{av})^2]$$

Differentiating this equation w.r.t u and v provides equations for the

change in error, which must be zero for minimum.

Thus, by differentiating the flow error w.r.t u and v, this gives:

$$(\lambda^2 + f^2{}_x)u + f_x f_y v = \lambda^2 u_{av} - f_x f_t$$

$$f_x f_y u + (\lambda^2 + f_y^2)v = \lambda^2 v_{av} - f_y f_t$$

Solving the two equations gives

$$u = u_{av} - fx\frac{P}{D} \qquad \ldots\ldots(5.34)$$

$$v = v_{av} - fy\frac{P}{D} \qquad \ldots\ldots.(5.35)$$

where

$$P = fxu_{av} + fyv_{av} + ft$$

$$D = \lambda^2 + fx^2 + fy^2$$

We can solve equation 5.34 and 5.35 iteratively by using Gauss-Seidel method.

Algorithm 3.4: Optical Flow [Horn and Schunck 1980]

k=0;

Initialize all u^k and v^k to zero.

Until decrease in flow error is negligible, do

$$u^k = u_{av}{}^{k-1} - fx\frac{P}{D} \qquad \ldots\ldots\ldots\ldots (5.36)$$

$$v^k = v_{av}{}^{k-1} - fy\frac{P}{D} \qquad \ldots\ldots\ldots\ldots (5.37)$$

The derivates of brightness fx,fy and ft can be obtained from a sequence of frames

5.6.5 Comparison between optical flow and block-matching

In term of speed, optical flow is usually faster than block-matching, because the motion vector is calculated by the formulas 4.44 and 4.45. It can be solved iteratively and usually, the number of iteration is smaller than the number of candidates block that need to be evaluated for block-matching.

In term of stability, block-matching is better than optical flow. Stability here means that for block-matching, it is more resistant to lighting effect (including shadows, reflections, and highlights) while the optical flow is more susceptible to lighting effect. This is because optical flow is derived based on the assumption that the intensity of a pixel in the pattern is constant. Although block-matching is also based on the intensity stability assumption, the effects of lighting have less influence on block-matching algorithm. It is because block-matching algorithm considers a block of pixels, thus it is less susceptible to the lighting effects. Therefore, optical flow requires a stable environment to work fine.

In term of type of movement, optical flow can only measure small movement while block-matching can also measure large movement, depending on the search range. It is because for the brightness constancy assumption $I(x,y,t) = I(x+u,y+v,t+dt)$ to be true, dt usually is small. Therefore, for a large movement, usually this assumption will not hold. Comparing to optical flow, block-matching is less susceptible to lighting effect, so it can measure large movement.

Finally, we summarize the differences between the optical flow and block-matching by table 5.16

	Optical Flow	Block-Matching
Speed	**Faster**	**Slower**
Stability	**Less stable (affected by lighting effect)**	**More stable (less affected by lighting effect)**
Movement measure	**Small movement**	**Small and Large movement**
Floating point operations	**Yes**	**No**

Table 5.16 Differences between optical flow and block-matching

5.6.6 Conclusion

We decide to use block matching instead of Optical Flow, because in the calculation of Optical Flow, it involves a lot of floating point operations. Recall from chapter 2 that Symbian phones don't not have dedicated floating point unit.

Moreover, Optical Flow is affected more by the effects of lighting while the block-matching is more resistant to these effects. As we want the motion tracking to be worked in different environment, we choose block-matching for our project instead of optical flow.

5.7 Partial Distortion Elimination

Unlike fast search algorithm, which only examine a few candidate blocks in order to determine whether it is the optimum block, full search algorithm ensure all candidate blocks in the current frame will be examined and the block with highest SAD inside the search window will be selected. However, there exist some fast full search algorithms which can search for the highest SAD block faster yet still ensure all blocks are examined. One of these algorithms is the partial distortion elimination (PDE) algorithm, which is excellent in removing unnecessary computations efficiently. The PDE technique has been widely

used to reduce the computational load in full search algorithm.

5.7.1 Methodology

PDE algorithm improves the speed of searching in shortening the calculation of Square of Absolute Difference (SAD) between each currently matching block with the previous block. Its main objective is to use the partial sum of matching distortion to eliminate impossible candidates before complete calculation of SAD in a matching block. That is, if an intermediate sum of the matching distortion is larger than the minimum value of the SAD at that time, the remaining computation for the SAD is abandoned. The SAD of the matching block is calculated by:

$$SAD(x,y) = \sum_{i=1}^{N}\sum_{j=1}^{N} | X(i,j) - Y(i+x, j+y) | \qquad where\ |x,y| \le W$$

The k^{th} partial sum of matching distortion is calculated by:

$$PSAD(x,y) = \sum_{i=1}^{k}\sum_{j=1}^{N} | X(i,j) - Y(i+x, j+y) | \quad where\ k = 1,2,3,...,N\ \ and\ |x,y| \le W$$

W represents the size of search window and N the matching block size. Usually, the SAD of a block is obtained by adding the pixels inside the block in row by row basic. We can check if the partial sum of matching distortion exceeds the current minimum SAD after each row is added to the PSAD. Remaining calculation will be quit if PSAD(x, y) > SAD(x, y) and this impossible candidate block is eliminated from consideration.

Checking PSAD(x, y) > SAD(x, y) can be done every time after a pixel is added to the PSAD(x, y) or after a row of pixels is added. The latter scheme is preferred because the code overhead of checking PSAD(x, y) > SAD(x, y) is too large. If the block width and block height is N, the former scheme costs at most $N^2 - N$ comparison operations more than the latter scheme while the former scheme can at most stop the remaining calculation 3N addition operations earlier than the latter scheme. For large N, $N^2 - N$ is much larger than 3N. Since the cost outweighs the advantage, the latter scheme is used instead.

5.7.2 Result

From the experimental result we have done on OpenCV program, PDE algorithm is faster than exhaustive search algorithm (ESA) by 3 times on average. PDE algorithm does not increase the memory storage requirement, does not involve complex operation and does not increase code overhead much, yet it can effectively remove the impossible candidate blocks during calculation of SAD. Any algorithm that requires the calculation of SAD can incorporate with PDE to improve its speed in matching optimum block. And because this algorithm just affects the calculation of SAD, it is compatible with other type of algorithms, such as SEA and PPNM.

5.7.3 Possible Improvement

The speed of PDE algorithm depends on how fast computation of SAD is stopped according to the partial sum of SAD. Kim, Byun and Ahn [1] proposed some methods which can further reduce computations with the same accuracy as that of conventional full search method. They mathematically derived the relationship between spatial complexity of the previous block and the matching distortion. In the derivation, they showed that the matching distortion between the current blocks and previous block is proportional to the image complexity of the previous block. That is, larger SAD can be obtained by first calculating the matching distortions of the image area with large gradient magnitudes, that is, more complex area. Through this, unnecessary computations can further be removed. They proposed to use adaptive sequential matching start with the left, right, top or bottom and row vector based matching in which matching order is determined by the image complexity. The PDE algorithm with adaptive sequential matching and row vector based scan can be expressed as follows:

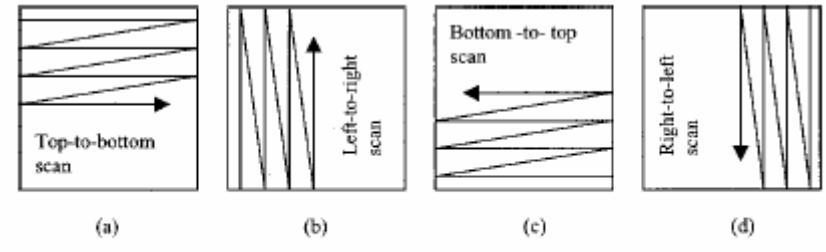


Fig. 1 Various matching scans: (a) Top-to-bottom scan, (b) left-to-right scan, (c) bottom-to-top scan, (d) right-to-left scan.

Figure from reference paper [1]

Table 6 Computational reduction ratio of TSS, NTSS, MRME, and various matching scan algorithms of full search in 10 fps.

Algorithm	Sequence					
	foreman (%)	car phone (%)	trevor (%)	claire (%)	akio (%)	grandmother (%)
Original FS	100	100	100	100	100	100
Sequential (4×4)	31.9	29.1	29.2	29.0	13.7	26.4
Dither (4×4)	29.4	27.8	28.0	26.2	12.5	25.0
Complexity (4×4)	23.5	23.0	23.5	22.2	9.8	21.3
Sequential (1×16)	31.8	29.3	29.2	28.2	13.0	25.5
Dither (1×16)	28.9	27.5	27.4	25.1	11.8	24.1
Complexity (1×16)	25.0	24.6	25.0	23.2	10.4	22.4
MRME	9.0	9.0	9.0	9.0	9.0	9.0
NTSS	10.5	9.6	7.9	7.8	7.6	8.9
TSS	11.1	11.1	11.1	11.1	11.1	11.1

Experimental result from reference paper [1]

The above table is the experimental result done by Kim, Byun and Ahn. The sequential, dither and complexity algorithms are the modified PDE algorithms. Original PDE algorithm has about 30% computation reduction over the original FS algorithm. The sequential and dither PDE algorithms have a bit better reduction than the original PDE algorithm while the complexity PDE algorithm shows greater improvement in reduction. However, the code overhead of using complexity is high and the implementation is complex, the actual improvement of speed may be not so high. We haven't incorporated this kind of adaptive matching scan method into our algorithm because of its complexity in implementing, but later we may try improving PDE algorithm using this method.

5.8 Adaptive Search Window

In our application, it is very useful to carry history of the motions. Our goal is to track the motion of the camera. If we reasonably assumed the things captured by the camera do not move, when the camera moves, all these things move together with about the same displacement. Therefore, the whole frame

can be regarded as one object. With this assumption, block at any position in the previous frame actually tracks the motion of the same object. Thus, history of motions is always useful to any candidate block.

Conventionally, search window is defined as a rectangle with the same center as block in previous frame, extended by W pixels in both directions. This definition is reasonable but it can be improved based on the history of motions. With the history, search window can be newly defined as a rectangle with its center being predicted from the previous motion vector and the previous block position.

5.8.1 Methodology

$$\vec{P} = (1 - L)\vec{P}' + L\vec{D} \quad \ldots (5.38)$$

P: Predicted Displacement of object

P': Previous Predicted Displacement of object

L: Learning Factor, range is [0.5, 1.0]

D: Previous Displacement of object

The next displacement of object is predicted using exponential averaging over previous displacement and previous predicted displacement of the object. The previous predicted displacement is involved to predict a new displacement in order to reduce the effect of detection error which may exist in the previous displacement returned from the algorithm. That is, if the object is detected to be moving to the left for a while, a sudden detection telling that it is moving up will not cause the search window to shift upward too much because it is usually due to detection error. But if there is a second detection telling that it is still moving up, the search window will shift upward much more. It is because the past previous displacement and previous displacement affect the predicted displacement seriously. Therefore, if the frames captured by a camera are noisy, the learning factor should be set to a low value, say 0.5, so that a detection error will not affect the search window much. If the frames are not so noisy, the learning factor can be set higher, say even 1.0, so that predicted displacement solely depends on the previous displacement.

5.8.2 Comparison with conventional method

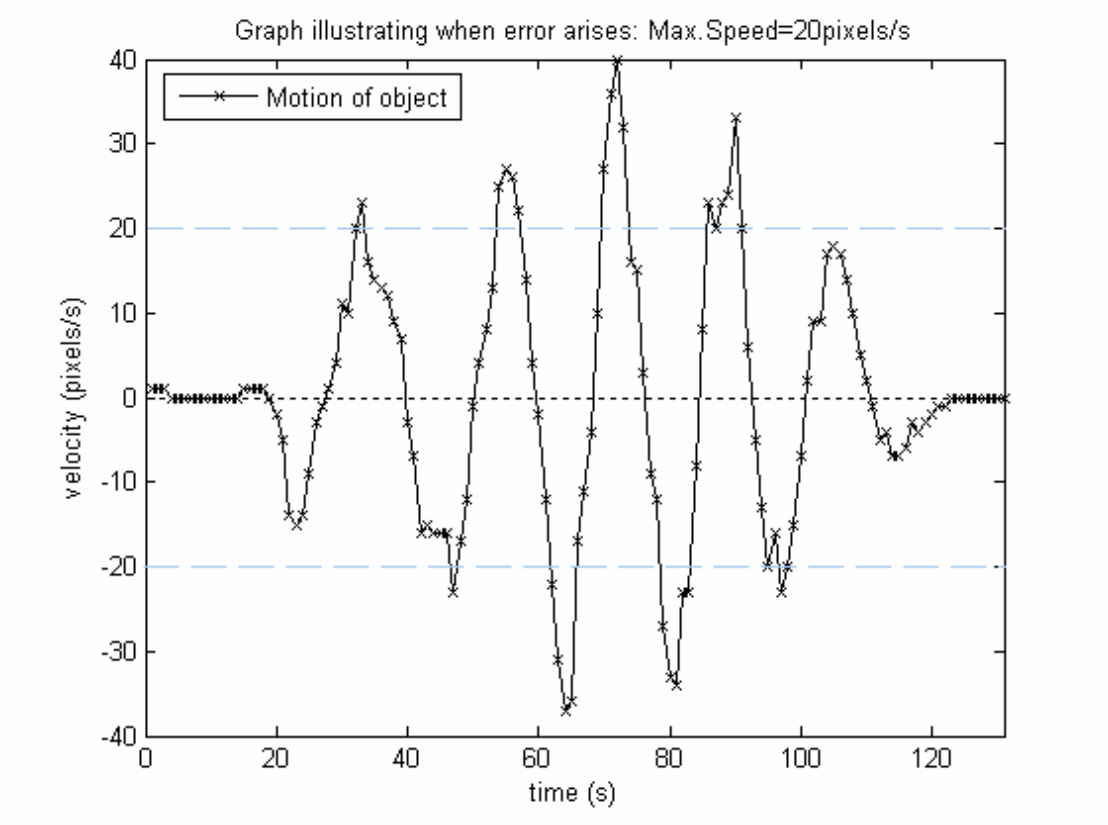


Figure 5.19

To evaluate the performance of the adaptive search window method, we used web camera to track the motion of an object and plot a graph (Figure 5.19) showing its x-axis velocity against time. The data points are collected when we run the Adaptive Spiral SEA PPNM PDE SAD Algorithm. The velocity means how many pixels the object has moved, positive value means it is moving to the right direction, negative value means to the left. The algorithm is run every second, thus the velocity just equals the magnitude of the x-component of the motion vector. The object is moving to the left and right periodically, thus the curve move up and down.

The search window size is 41 x 41 and the magnitude of the motion is 40 pixels/s, so all the true optimum points fall within the conventional search window. In this case, although the conventional search window method is possible to find the true optimum point on every run, the speed of the algorithm will not be high, it is because the average magnitude of the object's velocity is high, which means the distance between the optimum point and the initial search center is long and therefore minimum SAD is found only after many computations.

Considering the Figure 5.19, if the search window size is set to 20 x 20, conventional search window method will definitely can't find some true optimum points on some runs of algorithm since the true optimum point falls out of the search window at some points, say at time=80s. For the same search window size, the adaptive search window method does not have this error.

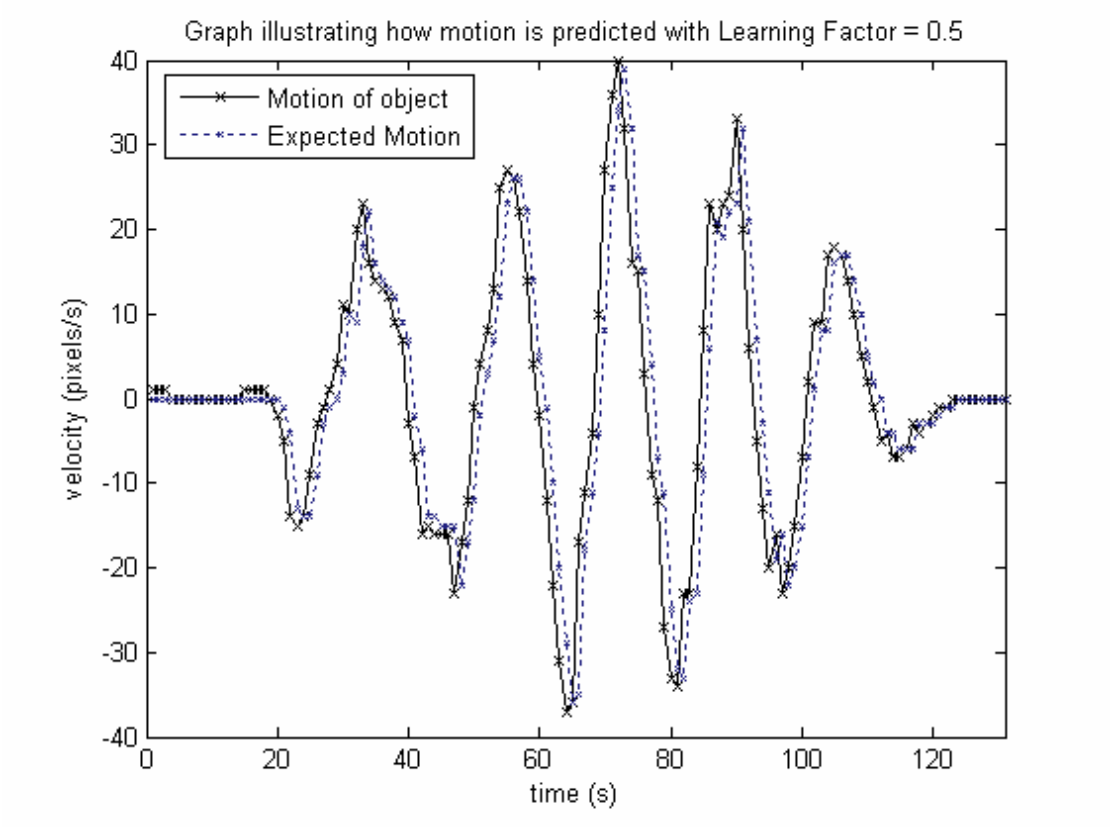


Figure 5.20

The displacement of the object is predicted using the equation (5.38) with L=0.5 during the motion tracking, the graph of predicted velocity (=displacement) over time is plotted on the Figure 5.19 to give Figure 5.20. The two curves look similar and difficult to analyze, thus another graph showing the difference between the two curves is plotted.

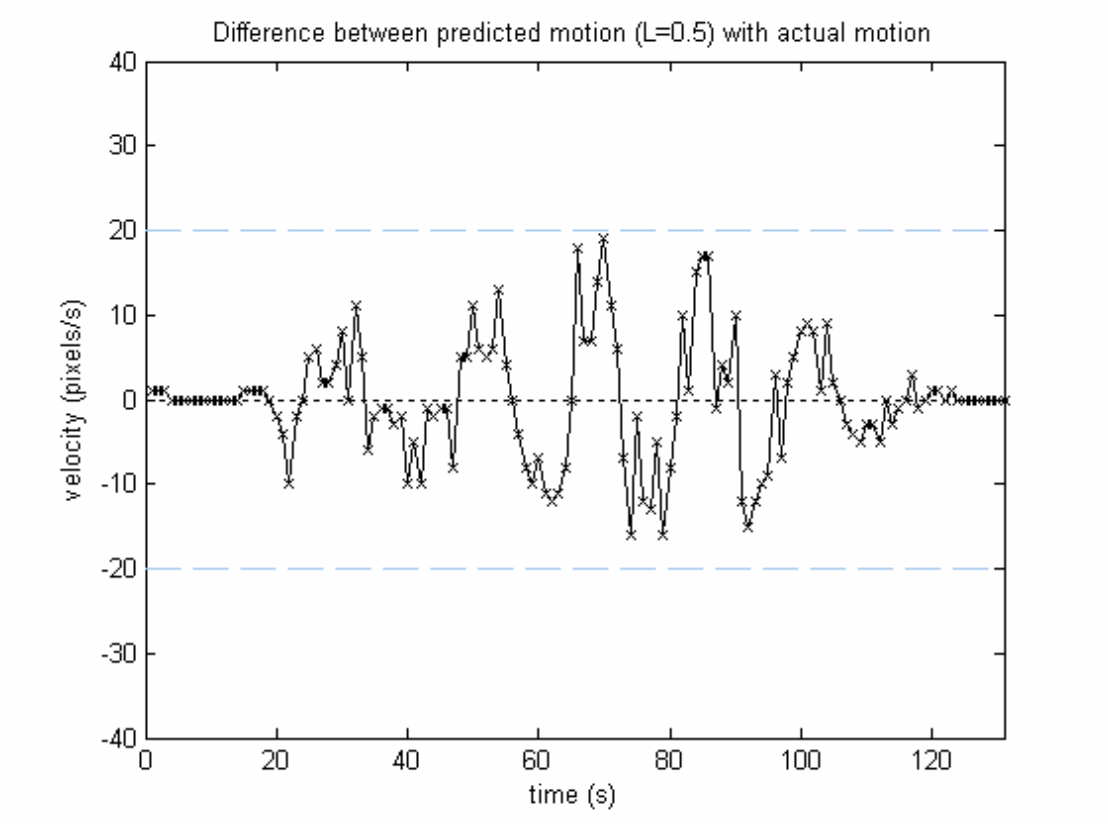


Figure 5.21

Figure 5.21 is a graph showing the relative velocity between predicted velocity and actual velocity over time. The maximum magnitude of the curve is below 20 pixels per second. The true optimum point always falls into the search window and thus no serious detection error would result even if the search window size is 20 x 20. Moreover, the average magnitude of the object's velocity is relatively lower, which means the distance between the optimum point and the initial search center is shorter and thus less computation is required.

Figure 5.22 is a graph showing the relative velocity over time using different learning factor. Since noise in the image captured by web camera is not too high, large learning factor generally gives better prediction of motion. From the graph, point curve with learning factor = 1.0 is always the closest one when compared with other curve with learning factor = 0.5 and 0.8. Thus, on PC, learning factor = 1.0 can be used, while on mobile, since the noise in the image captured by the camera on mobile phone is relatively higher, a bit lower learning factor can be used.

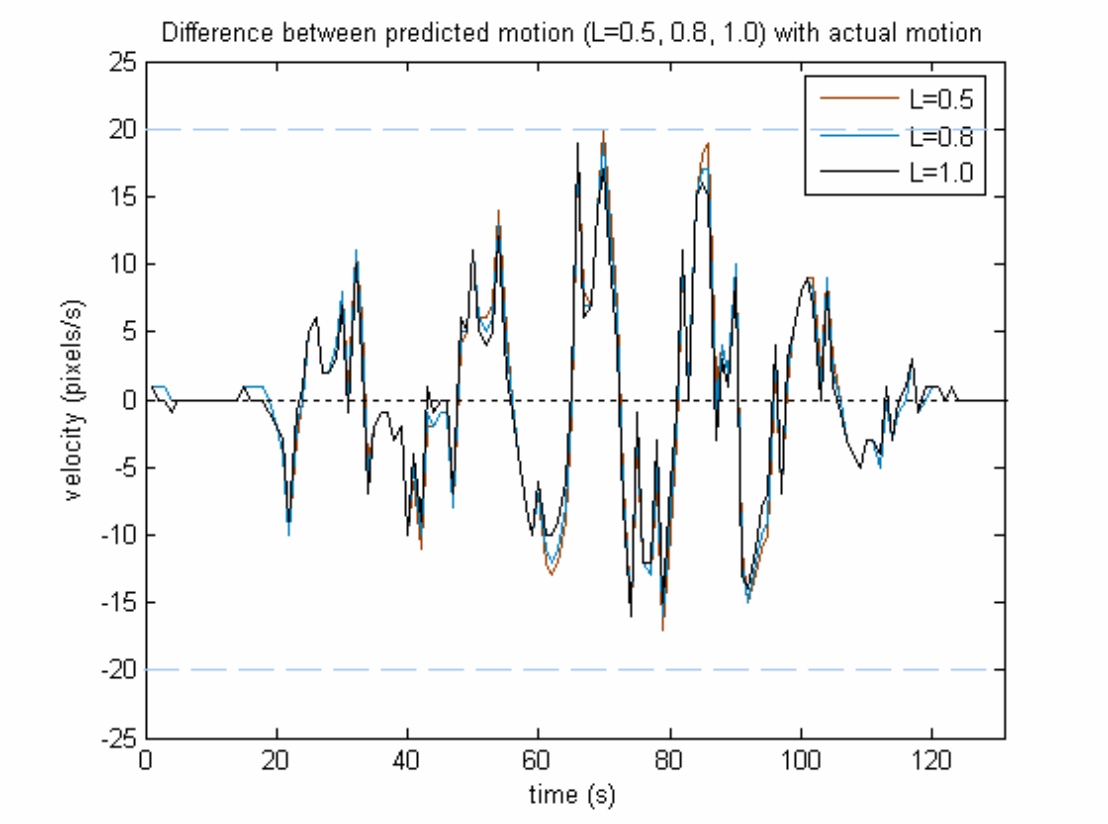


Figure 5.22

5.8.3 Constraint of each method

Accuracies of both methods are motion dependent. Based on the size of the search window, we can represent a constraint on the velocity of object by an equation. Unsatisfying this constraint leads to detection error. For the conventional search window method, the constraint for the object's velocity can be represented by:

$$| Velocity | < W \text{ pixels/s} \quad \ldots (5.39)$$

Where W is half of the search window width/height provided that the algorithm run every second.

For the adaptive search window method, the constraint becomes:

$$|Relative\ Velocity | < W \text{ pixels/s or } | Acceleration | < W \text{ pixels/s}^2 \quad \ldots (5.40)$$

5.8.4 Analysis

1. **When velocity of object is low,** both the conventional and adaptive methods will not have detection error.
2. **When velocity is high,** conventional method can't ensure the result is the true optimum point while adaptive method can ensure provided that the object is not accelerating fast at the same time.
3. **When acceleration is high,** conventional method will not have detection error if the velocity can be kept lower than W pixels/s while adaptive method will have detection error. But conventional method will also have detection error if acceleration is higher than 2W pixels/s^2 since final velocity would definitely be higher than W pixels/s. Thus, conventional method can't ensure the result is the true optimum point when acceleration is high, either.

The most important issue is how these constraints affect users' movements. Considering a user is holding a camera-equipped mobile phone and moving it. If conventional method is used, we concern constraint (5.39), which means user must move slow enough in order to ensure accurate motion detection. This is not desirable to user and very inconvenient to use. If adaptive method is used, user can move as fast as he wants but the acceleration must not be high, which is relatively easier to achieve and more desirable. If user does not shake the phone rapidly, natural motion of hand normally does not have too high acceleration. In order word, adaptive method allows user to move in a more natural way.

5.8.5 Conclusion

If user moves naturally with small acceleration, adaptive search method has two advantages over the conventional one. Firstly, it increases the chance of finding the true optimum point. Secondly, it reduces the computation steps, especially if spiral scan method is used together. Since in spiral scan method, previous block will first match the center region of the adaptive search window, which is highly probably to contain the true optimum point. As distance between the starting search point and the true optimum point becomes shorter, the previous block can match the block at optimum point earlier and thus the computation steps is reduced. The detail of spiral scan method is discussed in the next section.

5.9 Spiral Scan Method

5.9.1 Raster Scan method

Commonly used block scanning method in the field of video compensation and coding is the "Raster Scan" method. That is, when we use the previous block to find a best match in the current frame, we calculate the Sum of Absolute Difference (SAD) of the previous block with the current block C_{00} at the left top position first, and then calculate that with the current block C_{01} with center one pixel next to C_{00} in the same row. This process repeats until all SAD of the current block in the first row is calculated. Then the process repeat in the next row until all SAD of current block in the search window is calculated. In short, it scans from top to bottom, from left to right. The advantage of this method is that it is very simple to implement and code overhead is very small.

5.9.2 Analysis

The order of scanning can affect the time to reach the optimum candidate block. When SEA, PPNM and PDE method are used, this property can affect the amount of computation. The reduction of calculation in obtaining the motion vector with these algorithms depends on how fast the global minimum of SAD is detected. If we find the global minimum in the calculation of the matching error faster, complete computation of the matching error in a block is avoided more. In PDE method, calculation of the SAD stop if the sub-blocks SAD between the two block is already larger than minimum SAD. If optimum candidate block is reached earlier, global minimum SAD will be found earlier. For each current block, a smaller sub-block SAD is already larger than the minimum SAD, thus calculation of SAD stop earlier and amount of computation is reduced. In SEA method, impossible candidate block is eliminated before its PPNM and SAD are computed based on the following criterion:

$$\left|\sum_{i=1}^{N}\sum_{j=1}^{N} X(i,j) - \sum_{i=1}^{N}\sum_{j=1}^{N} Y(i,j)\right| > SAD(X,Y)$$

Thus global minimum SAD found earlier leads to less computation on PPNM and SAD. In PPNM method, impossible candidate block is eliminated before its SAD are computed based on the following criterion:

$$\sum_{i=1}^{N} \left| \sum_{j=1}^{N} X(i,j) - \sum_{j=1}^{N} Y(i,j) \right| > SAD(X,Y)$$

In order reach the optimum candidate block earlier, candidate blocks with higher probability to be an optimum block should be reached first. If all candidate blocks have equal probability to be an optimum block, order of scanning doesn't matter. But if candidate block at the center region of the search window has a higher probability to be an optimum block, scanning the center region first highly improves the speed of our algorithm. This is our motivation to use spiral scan method as the block scanning method.

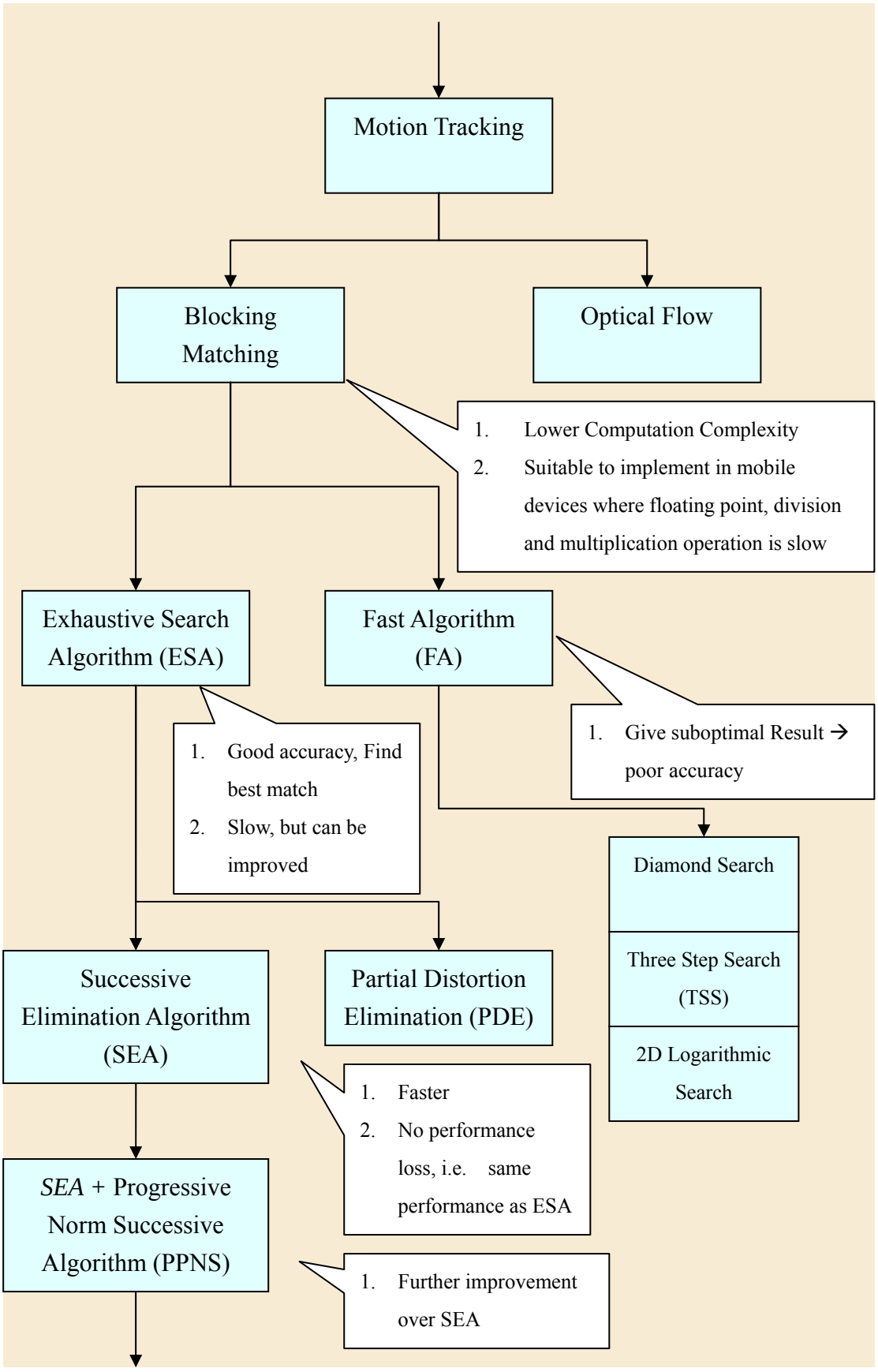
5.9.3 Spiral Scan Method

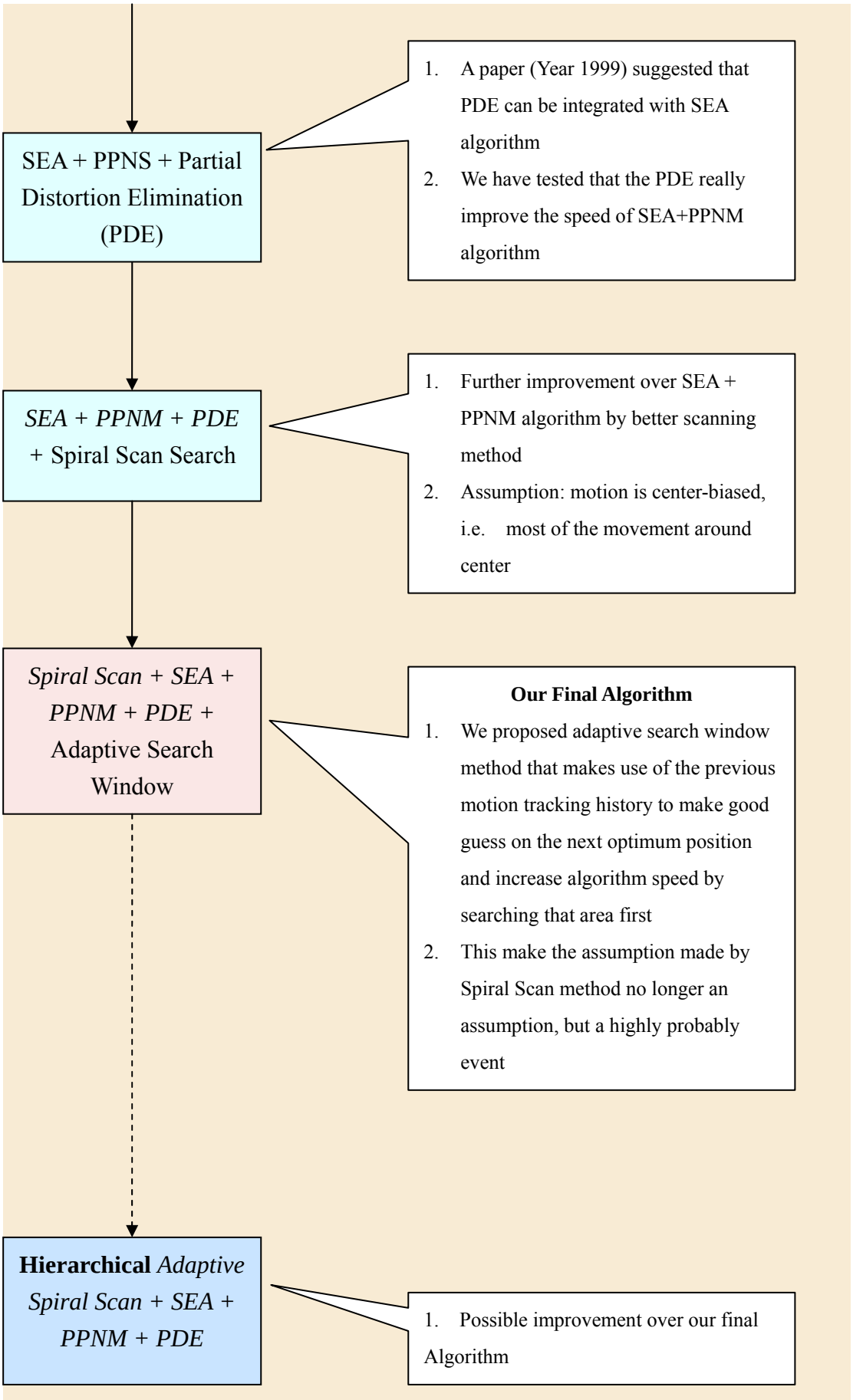
Instead of starting at the left top position, we can start finding the SAD at the center of the search window first, then finding the SAD at position that are 1 pixels away from the center, then 2 pixels away from the center, …etc. When adaptive search window method is used, most of the motion vectors are center biased. That is, the optimum point would have higher probability to locate at the center of the search window. Since spiral scan method scans the center position of the search window first, it has higher chance to reach the optimum block earlier. As discussed above, reaching the optimum block earlier improves speed of our algorithm.

5.9.4 Result

Spiral scan method requires larger memory storage than Raster Scan method if fast calculation of block sum is used together. In Raster Scan method, only a row of block sum is needed to be stored. Since SAD of current blocks is calculated row by row, the row of block sum can be updated to store the block sum of the second row after the first row is finished. However, in spiral method, since SAD of current blocks is calculated in spiral order, not row by row, the whole block sum 2D array is needed to be stored. Although larger memory storage is required, speed of algorithm not only do not degraded, but improved a lot due to earlier reaching of optimum block.

5.10 Motion Tracking Algorithm Development




SEA + PPNS + Partial Distortion Elimination (PDE)
1. A paper (Year 1999) suggested that PDE can be integrated with SEA algorithm
2. We have tested that the PDE really improve the speed of SEA+PPNM algorithm
SEA + PPNM + PDE + Spiral Scan Search
1. Further improvement over SEA + PPNM algorithm by better scanning method
2. Assumption: motion is center-biased, i.e. most of the movement around center
Spiral Scan + SEA + PPNM + PDE + Adaptive Search Window
Our Final Algorithm
1. We proposed adaptive search window method that makes use of the previous motion tracking history to make good guess on the next optimum position and increase algorithm speed by searching that area first
2. This make the assumption made by Spiral Scan method no longer an assumption, but a highly probably event
Hierarchical *Adaptive Spiral Scan + SEA + PPNM + PDE*
1. Possible improvement over our final Algorithm

5.11 Improvement of performance by SSD matching criteria

Originally, we use SAD (sum of absolute difference) as the matching criteria of block matching algorithm. SAD is commonly used because of its lower complexity which means it runs faster. However, we finally adopted SSD as the matching criteria. Apparently, SSD is more complex than SAD and should run slower. However, when SSD is used together with SEA, PPNM and PDE, the run speed of the whole algorithm is as fast as that using SAD.

The major reason for why we choose to adopt SSD matching criteria in the BM algorithm is that, algorithm runs with SSD has higher performance in term of accuracy. Tracking blocks can be tracked more firmly and less matching error results. The reason that algorithm runs with SSD has as high performance in term of speed as that with SAD is that the elimination effects from SEA, PPNM and PDE become large when SSD is used. This compensates the longer runtime of running SSD which has higher complexity.

5.11.1 Methodology

As the matching criteria changes to SSD, SEA and PPNM lower bound need to be adjusted. According to the paper "J.J. Francis and G. de Jager. *A Sum Square Error based Successive Elimination Algorithm for Block Motion Estimation* (2002) "[50], the lower bound can be derived as follow:

$$\mathrm{SAD}(\mathbf{f}, \mathbf{g}) \geq | \, \|\mathbf{f}\|_1 - \|\mathbf{g}\|_1 \, |, \qquad (6)$$

where $\|\mathbf{f}\|_1$ denotes the sum of pixels in the search block, $\|\mathbf{g}\|_1$ denotes the sum of pixels in the current best match block under consideration, and $\mathrm{SAD}(\mathbf{f}, \mathbf{g})$ is the SAD of the best match thus far. Equation 7 and 8 shows the bounds.

2.2 Attempts to bound the SSE

Wang and Mercerau [19] describe a lower bound on the MSE in terms of the difference of the averages of the search and candidate best match block. Brunig and Niehsen make use of a similar bound [2].

Given the Cauchy-Swartz inequality for vectors **a** and **b** [9]:

$$| \, \mathbf{a}^T \mathbf{b} \, | \leq \|\mathbf{a}\|_2 \|\mathbf{b}\|_2 \qquad (9)$$

If one sets **a** to be a column vector of ones, and allows **b** to be the pixel differences for the error measure, equation 9 becomes:

$$\|\mathbf{f} - \mathbf{g}\|_1 \leq \sqrt{N} \|\mathbf{f} - \mathbf{g}\|_2$$

and squaring,

$$\mathrm{SAD}^2 \leq N\mathrm{SSE} \qquad (10)$$

$$\mathrm{MAD}^2 \leq \mathrm{MSE} \qquad (11)$$

Applying the SEA lower bound (equation 6) leads to:

$$\frac{(\|\mathbf{f}\|_1 - \|\mathbf{g}\|_1)^2}{N^2} \leq \mathrm{MAD} \leq \mathrm{MSE} \qquad (12)$$

Figure 5.23 An extract from the paper

According to equation (10), $\left| \|f\|_1 - \|g\|_1 \right|^2 \leq SAD^2 \leq N \times SSD$.

$\frac{\left| \|f\|_1 - \|g\|_1 \right|^2}{N}$ is the lower bound of SSD in SEA method.

Originally, $\sum_i \left| \|f_i\|_1 - \|g_i\|_1 \right|$ is the lower bound of SAD in PPNM method. This lower bound changes as SSD is used too.

According to equation (10) and the proof in the chapter of PPNM method, the following relation can be derived:

$$\left| \|f\|_1 - \|g\|_1 \right|^2 \le (\sum_i \left| \|f_i\|_1 - \|g_i\|_1 \right|)^2 \le SAD^2 \le N \times SSD$$

Thus, the lower bound of SSD in PPNM method becomes $\frac{(\sum_i \left| \|f_i\|_1 - \|g_i\|_1 \right|)^2}{N}$.

Using the same technique described in the paper above, we can prove that $\left(\sum_i^{\sqrt{N}} \left| \|f_i\|_1 - \|g_i\|_1 \right| \right)^2 \le \sqrt{N} \times \sum_i \left| \|f_i\|_1 - \|g_i\|_1 \right|^2$. However, we can't prove that $\sqrt{N} \times \sum_i \left| \|f_i\|_1 - \|g_i\|_1 \right|^2 \le N \times SSD$. Thus, we can't tell whether $\frac{\sum_i \left| \|f_i\|_1 - \|g_i\|_1 \right|^2}{\sqrt{N}}$ is the lower bound of SSD. If it does, this bound is much tighter than the above one and will increase the elimination effect of PPNM.

5.11.2 Experiment

Experiment is done to investigate how efficient SSD is in removal of candidate blocks when compared with SAD.

Col. 1: Total number of candidate blocks

Col. 2: Number of candidate blocks removed by SSD SEA

Col. 3: Number of candidate blocks removed by SSD PPNM

Col. 4: Total # of candidate blocks removed by SSD SEA & PPNM

Col. 5: Number of un-removed candidate blocks

Col. 6: Number of candidate blocks removed by SAD SEA

Col. 7: Number of candidate blocks removed by SAD PPNM

Col. 8: Total # of candidate blocks removed by SAD SEA & PPNM

Col. 9: Number of un-removed candidate blocks

Col. 10: number in Col.4 – number in Col.8

Row: Result of each run of an algorithm

Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8	Col. 9	Col. 10
288	254	21	275	13	233	6	239	49	-36
288	261	25	286	2	244	6	250	38	-36
288	258	25	283	5	272	10	282	6	-1
288	252	17	269	19	269	10	279	9	10
288	268	17	285	3	253	3	256	32	-29
288	254	24	278	10	270	13	283	5	5
288	255	29	284	4	263	17	280	8	-4
288	268	18	286	2	265	13	278	10	-8
288	269	16	285	3	268	14	282	6	-3
288	269	16	285	3	265	14	279	9	-6
288	269	17	286	2	268	12	280	8	-6
288	262	25	287	1	269	12	281	7	-6
288	268	17	285	3	262	18	280	8	-5
288	263	17	280	8	263	12	275	13	-5
288	260	25	285	3	262	10	272	16	-13
288	267	19	286	2	266	13	279	9	-7
288	255	25	280	8	267	16	283	5	3
288	253	18	271	17	261	17	278	10	7
288	264	12	276	12	257	7	264	24	-12
288	250	19	269	19	256	10	266	22	-3
288	258	27	285	3	253	8	261	27	-24
288	256	28	284	4	262	19	281	7	-3
288	260	23	283	5	251	7	258	30	-25
288	255	28	283	5	250	3	253	35	-30
288	235	24	259	29	235	19	254	34	-5
288	214	25	239	49	219	10	229	59	-10
288	188	29	217	71	216	13	229	59	12
288	221	43	264	24	211	10	221	67	-43
288	249	29	278	10	222	13	235	53	-43
288	255	18	273	15	237	21	258	30	-15
288	260	15	275	13	236	14	250	38	-25
288	266	19	285	3	248	12	260	28	-25
288	254	29	283	5	259	15	274	14	-9

288	246	33	279	9	252	24	276	12	-3
288	250	30	280	8	249	7	256	32	-24
288	249	29	278	10	253	13	266	22	-12
288	249	31	280	8	251	10	261	27	-19
288	252	26	278	10	255	16	271	17	-7
288	243	37	280	8	254	20	274	14	-6
288	246	33	279	9	238	28	266	22	-13
288	252	33	285	3	249	21	270	18	-15
288	254	25	279	9	255	22	277	11	-2
288	253	27	280	8	242	25	267	21	-13
288	254	28	282	6	247	12	259	29	-23
288	242	27	269	19	251	21	272	16	3
288	211	36	247	41	226	23	249	39	2

As shown in Col. 10, SSD SEA and PPNM are generally more effective in removing candidate blocks during block matching.

5.11.3 Conclusion

As the matching criterion is changed to SSD, the lower bounds for SEA and PPNM are needed to be modified to keep the relation between SSD and the lower bound tight. According to the paper "J.J. Francis and G. de Jager. *A Sum Square Error based Successive Elimination Algorithm for Block Motion Estimation* (2002) ", we have successfully worked out the lower bounds for SEA and PPNM. They are $\frac{\left|\|f\|_1 - \|g\|_1\right|^2}{N}$, $\frac{(\sum_i \left|\|f_i\|_1 - \|g_i\|_1\right|)^2}{N}$ respectively. In actual implementation, inequality $\left|\|f\|_1 - \|g\|_1\right|^2 \le N \times SSD$ and $(\sum_i \left|\|f_i\|_1 - \|g_i\|_1\right|)^2 \le N \times SSD$ are used instead because division computation is much slower than multiplication.

After changing the criteria, we have tested that the accuracy of motion tracking has been increased and the performance in speed is slightly improved in Symbian phone platform.

Chapter 6: Rotational Motion Tracking

6.1 Observation

After translational motion tracking engine is finished, it is observed that the motion tracking algorithm can not only be used to track the translational movement of the phone, but also the rotational movement.

Figure 6.1

To illustrate the observation clearly, let's consider an example. The phone shown in Figure 6.1 is tracking a fish. When the phone is rotated, the scene captured by the camera and shown on the screen of the phone rotates relatively. It is observed that the object, fish, can still be tracked correctly. That is, the center of the object is roughly the same as that of the tracking box before and after the phone is rotated. It has been tested that even the phone is rotated in fast speed, the object can still be tracked firmly. The reason that the object can still be tracked firmly is that the sum of squared difference between the rotated object's block and the non-rotated object's block are very small when compared with other blocks nearby.

6.2 Motivation

Due to this observation, we have come up an idea that makes use of this property. That is to detect the rotational movement using translational motion tracking engine. The method is to track the movement of two blocks at the same time and find the slope of the line connecting the two blocks' centers.

6.3 Two-block approach

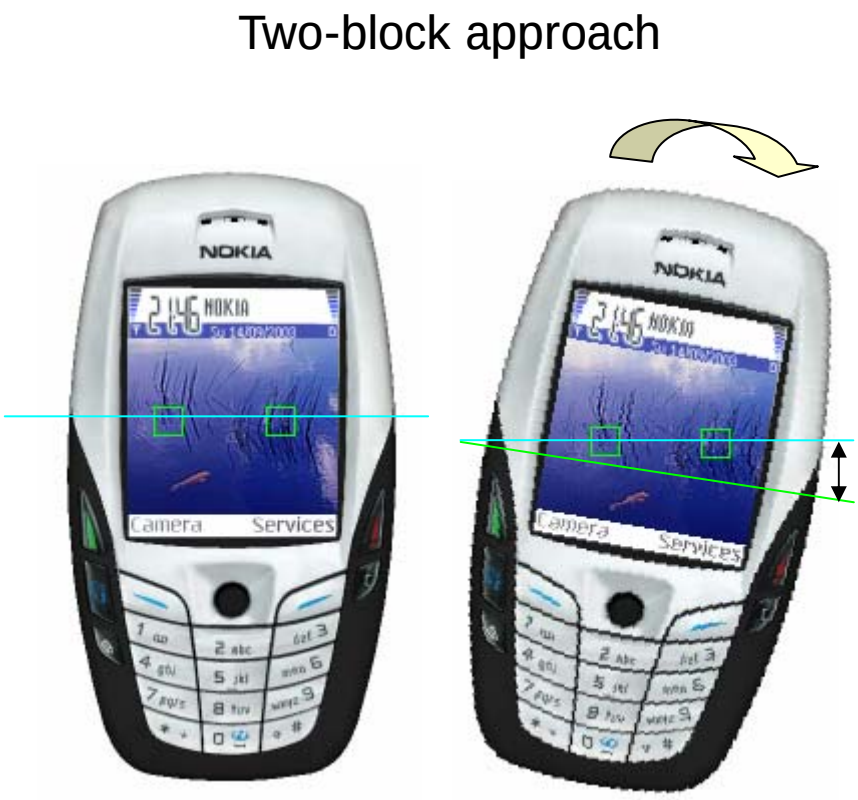


Figure 6.2

As illustrated in the Figure 6.2, two blocks are being tracked and are marked by the green square. The slope of the blue line connecting the two blocks' center can be used to estimate the tiling angle of the phone. Before the phone is rotated, the slope of the blue line is zero. As the phone is rotated, the scene is rotated relatively in the opposite direction. The two blocks can still be tracked firmly and the blue line connecting the two blocks can now tell us the tiling angle of the phone. The green line is a horizontal line relative to the phone. The included angle between the blue line and the green line is roughly equal to the tiling angle of the phone.

Advantage of this approach is its reliability. As long as the two blocks can be tracked firmly, the slope of the line connecting them indicates the rotational movement of the phone. Another advantage is that, with this approach, translational motion of phone can be tracked at the same time from the translational motion of the two blocks. Thus, rotation tracking engine can support detecting both rotational and translational movement.

6.4 Another possible approach

Figure 6.3

In this approach, translational motion tracking algorithm is still used because user must have chance to move in translational way instead of rotational way. Instead of tracking two blocks, one block is tracked in this approach. In addition to applying translational motion tracking algorithm, the previous frame's tracking block is rotated and compared with the current frame's block. As shown in figure 6.3, we call the yellow blocks the rotating frames and the white blocks the rotated blocks. As seen from the figure, the rotating frames have to be larger than the rotated blocks in order to accommodate an upright square block for block-matching with current frame's block.

Advantage of this approach is its accuracy. Measuring how much a block is rotated is the same as measuring how much the phone is rotated. However, the actual precision depends on the number of kinds of rotating frames used. Use more rotating frames can increase the maximum precision, though it doesn't mean the precision attained by this approach is increased if using more frames.

Disadvantage of this approach is its performance. Rotating a rotating frame must involve bilinear interpolation in order to obtain satisfactory result. This is computationally expensive. Moreover, the rotating frame is large which can be up to $\sqrt{2} \times sizeofBlock$. The larger the frame to rotate, the more expensive is the rotation process. Thus the performance of this approach will not be much higher than the two-block approach.

Another disadvantage is its reliability. Some objects being tracked doesn't have noticeably difference when being rotated. That means this approach may not be able to find the degree of rotation made on this object. In that case, the rotation tracking engine would fail.

Because of the reliability of the two-block approach, we currently adopted that approach for the rotation tracking engine.

6.5 Reducing error by using level

In order to make the rotation tracking output suitable for game playing, the output shouldn't show changes or even frustrate when user hasn't rotated the phone or user has just rotated it a little bit. The rotation tracking output can be made more stable by suppressing the output and cause the output to change only when the rotation is larger than a threshold.

As illustrated in Figure 6.4 below, rotation tracking output is quantized as several levels, says from level -4 to level 4. 0° or level 0 means the phone is not rotated. Each level is 40° different from its neighbor level. If the tiling angle of the phone is within -40° and 40°, level 0 will be outputted. If the tiling angle is with 40° and 80°, level 1 will be outputted, etc. Through this method, any error that will not cause a 40° changes will not cause the output to change and this make the output more stable.

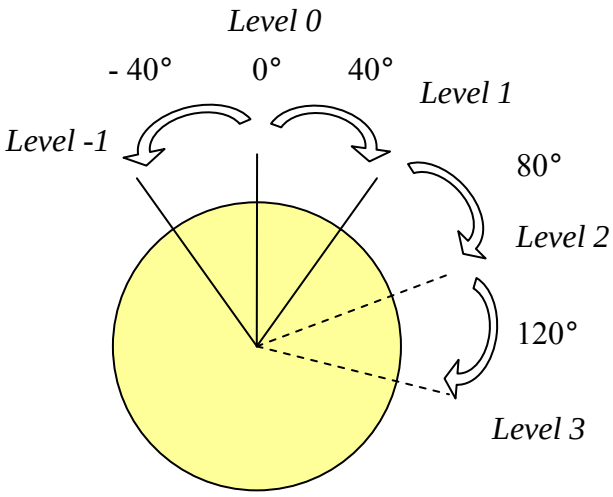


Figure 6.4

Many games doesn't allow player to have too much degree of freedom of movement in order to reduce the complexity of both producing and playing the game. Thus, quantizing rotation tracking output suits the need of these games. For example, the Skiing game allows only 7 degrees of freedom of movement such that it requires only 7 different images of skier. Our rotation tracking engine can also be tailor-made to give 7 levels of output namely -90°, -60°, -30°, 0°, 30°, 60° and 90°. Quantizing rotation tracking output gives less sensitive but more desirable output for game playing. It also reduces the difficulty of the game and increases the reliability of the engine.

6.6 Reference slope and non-reference slope method

By using the two-block approach in rotation tracking, we can obtain the slope of the line connecting two tracking blocks easily by $slope = \frac{y_1 - y_2}{x_1 - x_2}$ where (x_1, y_1) and (x_2, y_2) are the coordinates of the two blocks' center. In calculation, this slope information is converted to the angle between that line and the horizontal line by:

$$angle = \tan^{-1}(slope)$$

Notice that the $\tan^{-1}$ function return value from -90° to 90° only, which mean a line with angle 100° is regarded the same as a line with -10° by the $\tan^{-1}$ function. However, the minimum range of angle we want to find from

a line is from -180° to 180°, we can't fully rely on the angle returned to determine the actual angle we want. Two methods can be used to solve the problem. The first method is to guess the current angle based on the previous angle. For example, if the previous angle is 80° and the current (returned) angle is -10°. We can guess that the actual current angle is 100° instead of -10°. Another method is to remember the coordinates of the previous blocks and guess the actual current angle based on them.

After the correct angle information is found, rotation angle output is calculated based on the angle information. Two methods can be used to produce the correct rotation angle output from the angle information.

6.6.1 Static reference slope method

Once the rotation tracking engine is run, the first slope it found is regarded as the reference slope. The phone is assumed to be held horizontally and thus the rotation angle of the phone is 0°. As the phone rotates, the slope found changes correspondingly. The current slope is compared with the reference slope to obtain the included angle/rotation angle. In this method, only the reference slope needs to be stored to determine the rotation tracking output.

But this method suffers from a problem. It is that the detectable rotation angle is in between -180° and 180°. That is, if the phone is rotated more than 180° and less than 360°, the rotation tracking engine will regard the phone as being rotated in between 0° and -180°, which is wrong. This is the limitation of this method. However, for normal applications and games, we seldom require user to rotate the phone more than 180° in order to control something. Thus, this limitation doesn't matter in most cases. Moreover, we can solve this problem by guessing the correct rotation angle using the similar method discussed just above this subchapter.

Not all applications or games actually want the exact degree of rotation of the phone, but which direction the phone has been rotated or say the change of the rotation angle of the phone. In this case, non-reference slope method just suit the need

6.6.2 Dynamic reference slope method

Rather than remembering the initial slope and regard it as the reference slope, we choose to use the previous slope as the reference. We regard the previous as the x-axis of the new coordinates system and project the coordinates of the current block to the new coordinates system. That is, if the previous slope has t degree, the new coordinates of the current blocks are found by rotating it by t degree. Therefore, if the angle that the slope make with the x-axis is positive, that means the phone has rotated left; whereas if the angle is negative, that means the phone has rotated right. If the application or game wants to know which direction the phone is rotating, the sign of the change of rotation angle can be the output to it. If the application or game wants to know how much exactly the phone is rotated in advance, a variable can be used to store the accumulated change of rotation angle which can be outputted as the magnitude of the angle. If level is wanted, the accumulated change can further be quantized to give level output.

6.7 Adaptive window method on rotation tracking engine

In translational motion tracking algorithm, we have used adaptive window method to improve its performance (speed and accuracy). That method is designed for predicting linear motion and thus it is not applicable for predicting circular motion. Since the rotation tracking engine is designed to track both linear and circular motion, the adaptive window method has to be modified to predict the hybrid of circular and linear motion.

6.7.1 Objective

As mentioned before in the Adaptive Search Window section of the Motion Tracking chapter, it is useful to carry the history of the motions. The history of motions can then be used to predict the next possible movement of the phone and thus the next possible positions of the tracking blocks. The history of motions available is the previous coordinates of the tracking blocks and our goal is to predict the coordinates of the tracking blocks that may appear in the next frame.

6.7.2 Methodology

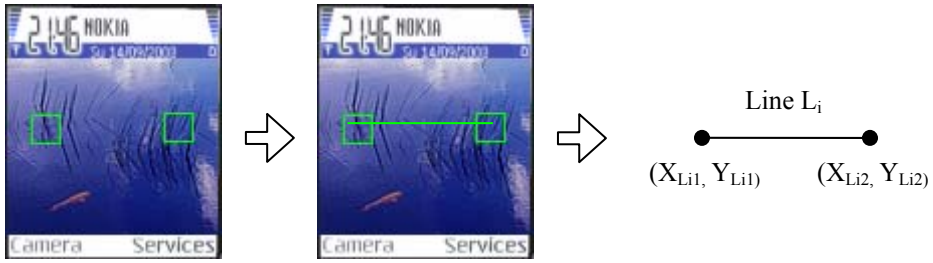


Figure 6.5

As shown in Figure 6.5, the line connecting the two tracking blocks are represented by the line Li. The two blocks are represented by the end points with coordinates (X_{Li1}, Y_{Li1}) and (X_{Li2}, Y_{Li2}).

To predict the coordinates of the tracking blocks in the next frame, we make use of their coordinates in the last two previous frames.

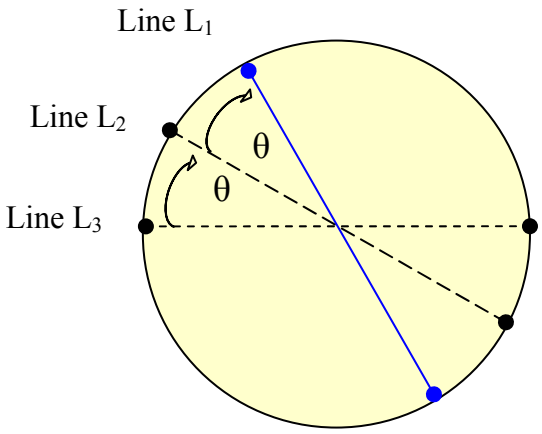


Figure 6.6 a simplified mathematic problem

In Figure 6.6, L_1, L_2 and L_3 correspond to lines in the current frame, previous frame and frame before the previous frame. The problem is simplified by making the following approximately correct assumption:

1. All the three lines pass through the circle's center
2. End points of the three lines lie on the circle

Our goal is to find the end points of the line L_1. From L_2 and L_3, we obtain the magnitude and direction of the previous rotated angle. The angle is calculated by:

$$\theta = \tan^{-1}(slope(\mathrm{L}_2)) - \tan^{-1}(slope(L_3)) \quad \ldots (6.1)$$

$$\text{Where } slope(L_i) = \frac{y_{Li1} - y_{Li2}}{x_{Li1} - x_{Li2}}, \text{ i = 1, 2.}$$

Our major assumption is that the rotation of the phone is approximately uniform. That is, L_1 can be obtained by rotating L_2 by angle θ. The coordinates of the center of the next tracking blocks (X_{L11}, Y_{L11}) and (X_{L12}, Y_{L12}) can be calculated by:

$$\begin{bmatrix} x_{L_{1}j} \\ y_{L_{1}j} \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x_{L_{2}j} \\ y_{L_{2}j} \end{bmatrix} \quad \ldots (6.2)$$

Where j = 1, 2.

This prediction only takes into account of circular motion. To take linear motion into account at the same time, the following method is used. Since translational movement doesn't affect the slopes of the lines, prediction of linear motion and circular motion can be done separately.

Horizontal displacement detected = Tx

$$Tx = (x_{L21} + x_{L22} - x_{L31} - x_{L32})/2 \quad \ldots (6.3)$$

Vertical displacement detected = Ty

$$Ty = (y_{L21} + y_{L22} - y_{L31} - y_{L32})/2 \quad \ldots (6.4)$$

The coordinates of the center of the next tracking blocks (X_{L11}, Y_{L11}) and (X_{L12}, Y_{L12}) can be calculated by:

$$\begin{bmatrix} x_{L_{1}j} \\ y_{L_{1}j} \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta & Tx \\ \sin\theta & \cos\theta & Ty \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x_{L_{j2}} \\ y_{L_{2}j} \\ 1 \end{bmatrix} \quad \ldots (6.5)$$

Where j = 1, 2.

6.8 Enhancement on rotation tracking engine

We have adopted the two-block approach to build the rotation tracking engine. Something has to be done to improve the reliability of that approach.

Firstly, the two blocks to be selected during feature selection stage should be as far away as possible. If they are too close, slope of them changes abruptly

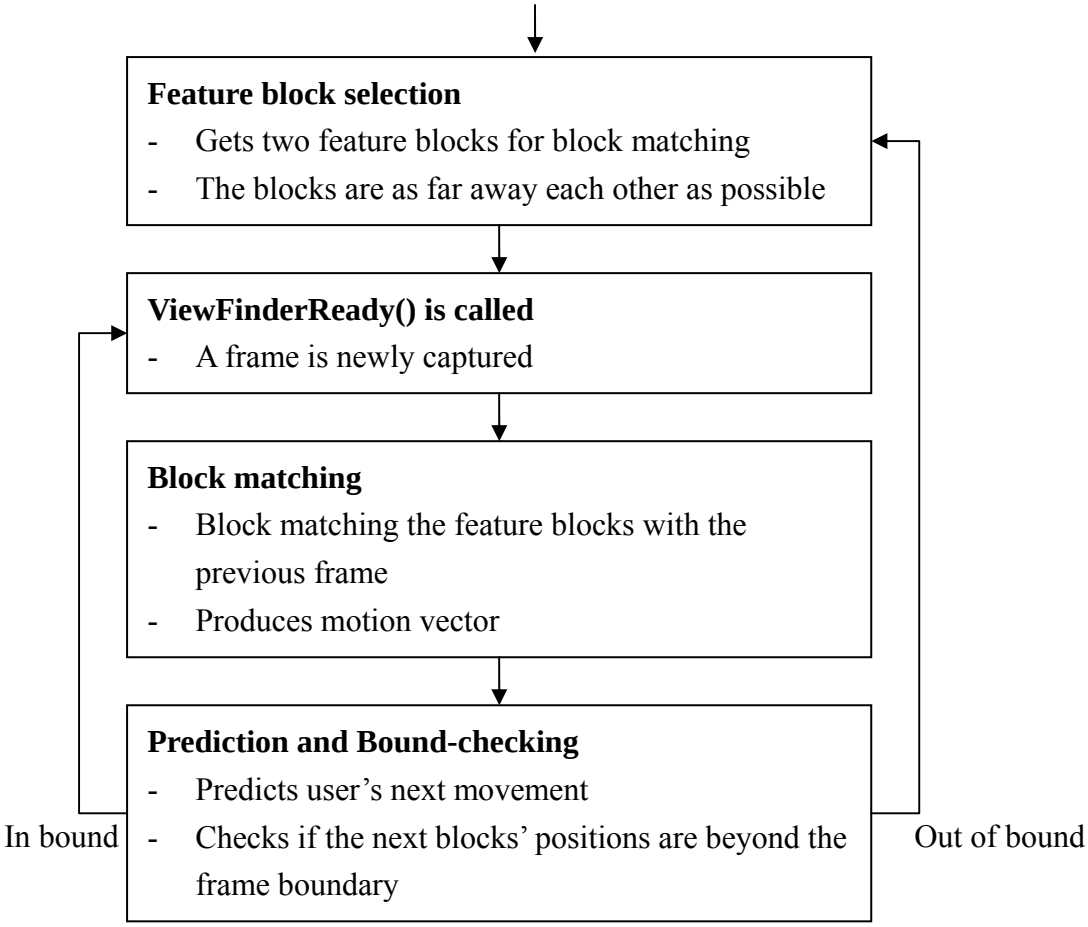
when small detection error occurs. As illustrated in Figure 6.5, it is clear that the two green blocks in right side is too close to each other. A small detection error will change the slope greatly. Because of this reason, feature selection for each block is carried out in non-overlapping region. Feature block is also search spirally such that block at center of the feature selection window has higher priority to be selected.

Figure 6.7

Secondly, after feature selection stage and during motion tracking stage, the blocks may come closer to each other due to accumulated detection error. For the same reason as above, if the two blocks are too close to each other that their distance is below certain distance, the two blocks are reselected. Motion tracking stage ends and feature selection stage begins.

6.9 Design and Implementation of the Engine

The implementation of this engine is the same as the translational motion tracking engine except the algorithm part that dealing with each captured frame. Below is the flow chart of the algorithm part of the rotation tracking engine:



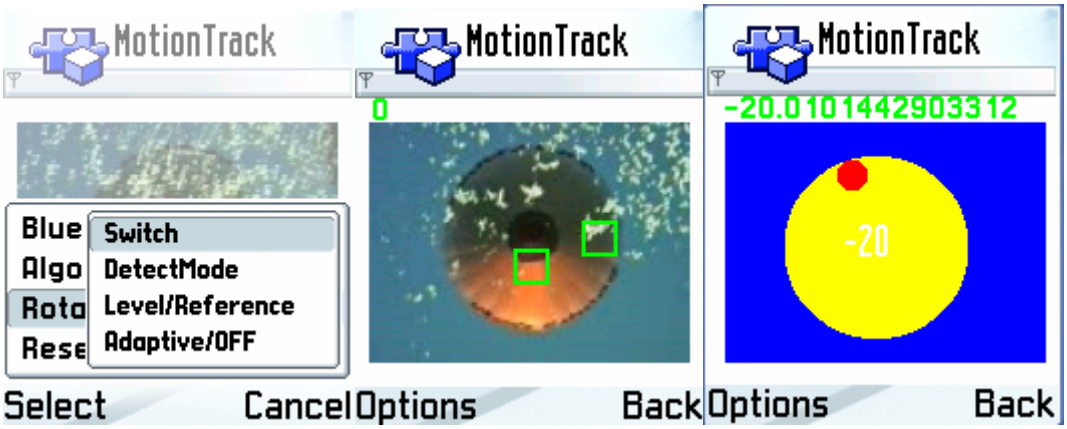


Figure 6.8 (a), (b) and (c).(a) Screenshot of switching to rotation tracking mode. (b) Screenshot of rotation tracking. (c) Screenshot of presentation of rotation tracking result.

Chapter 7: Feature Selection

We use the block matching algorithm for the motion tracking, so which block in the previous frame should be chosen for block matching? We must make a compromise between two contradictory desires. On one hand we would like features to be as descriptive as possible: The block chosen should facilitate the block matching algorithm and increase the accuracy of the algorithm. On the other hand, we also want feature extraction to be robust across thousands of video frames.

In our application, our purpose is to provide real-time tracking on the mobile device. Thus we implement our own feature selection algorithm instead of using well-known feature selection algorithms which usually have a high computation load. Our algorithm, although is simple, it bears certain level of robustness.

7.1 Implementation

Intuitively, if we want to select a good feature block for block matching, it should not select a block in the flag region. As in figure 6.1, although the window has moved to the right, we will not able to detect the movement. It is because all neighbors of the feature block have the same color, so they will have same SAD with the feature block. We can conclude that because motion is indeterminate when spatial gradient is near zero. Therefore, we cannot find a best match as all of the candidate blocks have the same SAD (Remember that we will choose the candidate block with the minimum SAD as the best match). Thus, the accuracy is decreased greatly.

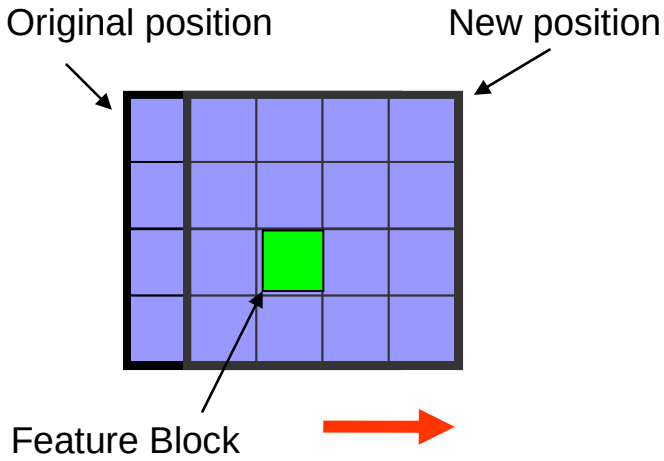


Figure 6.1 A reference block in flag region

In order to prevent the selection of a flat-region block, the block selected should be complex. We can evaluate the complexity of a block by calculating the local variance within the block Sxy. If the block is totally flat, the local variance will be 0 while the local variance will be large if the block is complex. The selection of a highly complex block will increase the chance of Partial Distortion Error (PDE) since the difference between candidate blocks and the reference block will be large even for a small movement. Thus increase the speed of the algorithm.

Apart from the complexity of a block, the feature block should have large intensity difference between neighbor blocks. Consider the figure 3.x, although either one of the block is complex, the complex block repeat itself all over the window. Hence, it affects the accuracy of block matching.

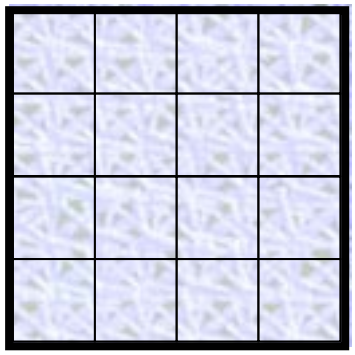


Figure 6.2 repeated pattern background

In order to solve the above problem, we can use Laplacian mask to calculate the intensity difference between the current block with its neighbors. Originally, Laplacian operator is used as edge detector that it find out how brighter the current pixel is than the neighborhood.

- Gray level discontinuity → large output
- Flat background → zero output

Firstly, we divide current frame into small rectangular blocks. For each block, sum all the pixels value, denoted as Ixy, and store it in 2D array (Intensity of the block). After that, we calculate the variance of each block which represents the complexity of the block. Apply Laplacian Mask for the 2D array (Masking). Since the Laplacian operator indicates how difference the reference block is than the neighbors, we select the block which has the largest Ixy and

large variance as feature block

7.2 Laplacian Operator

The Laplacian *L(x,y)* of an image with pixel intensity values *I(x,y)* is given by:

$$\partial^2 f = \frac{\partial^2 I}{\partial^2 x^2} + \frac{\partial^2 f}{\partial^2 y^2}$$

Where

$$\frac{\partial^2 I}{\partial x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y)$$

$$\frac{\partial^2 I}{\partial y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y)$$

Negative Definition

$$\partial^2 f = f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) - 4f(x, y)$$

Positive Definition

$$\partial^2 f = -[f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1)] + 4f(x, y)$$

Diagonal derivatives can also be included.

In our application, we use the positive definition with diagonal derivates. Then the Laplacian operator can be represented by the Laplacian mask (Figure 6.3)

-1	-1	-1
-1	8	-1
-1	-1	-1

Figure 6.3 Laplacian Mask

Then we apply the Laplacian mask to the image. For example, in figure

6.4, the mask values are multiplied by corresponding pixels values, and then summed up. The final value is returned to the output image at the position corresponding to the centre element of the window. The mask is then moved by one pixel (not the window size) to its next position and the operation is repeated.

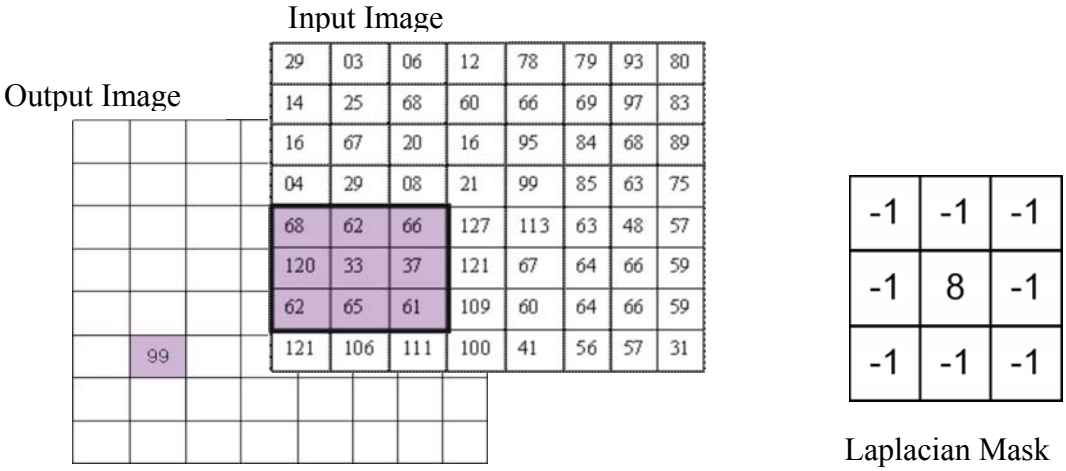


Figure 6.4

Output Value is -86, because:
(-1x68)+ (-1x62) + (-1x66) + (-1x120) + (8x80)
+ (-1x37) + (-1x62) + (-1x65) + (-1x61)
= 99

7.3 Experimental Result

We have tested our feature selection algorithm in different cases:

1. A black rectangle in a white background
2. A black rectangle in a repeated pattern background

In case 1, we want to test the performance of our feature selection algorithm on a flat region. In a white region background, we draw a black rectangle on it. Intuitively, the black rectangle should be selected as the reference block for block-matching. Our feature selection algorithm selects the corner of the black rectangle as the reference block as shown in figure 6.5. It is a good tracking location because of the brightness difference between the black and white colors.

As we can see, the block selected contains black pixel values. Hence our algorithm can prevent the selection of flat-region block as reference block.

Figure 6.5 Experiment on feature selection

In case 2, we apply the feature selection to a background of repeated pattern with a black rectangle as illustrated in figure 6.6. If we do use feature selection algorithm Again, it selects the black rectangle block as the reference block. Thus, we can see that our algorithm will never select a block that will lead to indeterminate movement. If we select a block as in figure 4.x rather than the black rectangle, when the object move to the right, the block-matching algorithm finds the best-match wrongly as illustrated in figure 6.7

Figure 6.6

Figure 6.7

Hence, we can see that if we can select a good feature block as the reference block, the performance of block-matching is guaranteed that it will not be acceptable.

7.4 Conclusion

For block matching, if we select either a block in flat region or in a repeated pattern region as the reference block, the accuracy will be affected significantly. Block mismatch always happens. After using the feature selection algorithm, it will ensure that a block selected will not be in flat region or repeated pattern region. Hence the error is reduced. Since our feature selection algorithm requires a small computation load, the speed of the block matching algorithm is not affected.

Chapter 8: Enhanced Feature Selection

8.1 Objective

We have developed a more robust feature selection. For the old feature selection algorithm, sometimes a block on the edge is found as feature block. If a block is found on an edge, then problem will be raised, as shown in the following diagram:

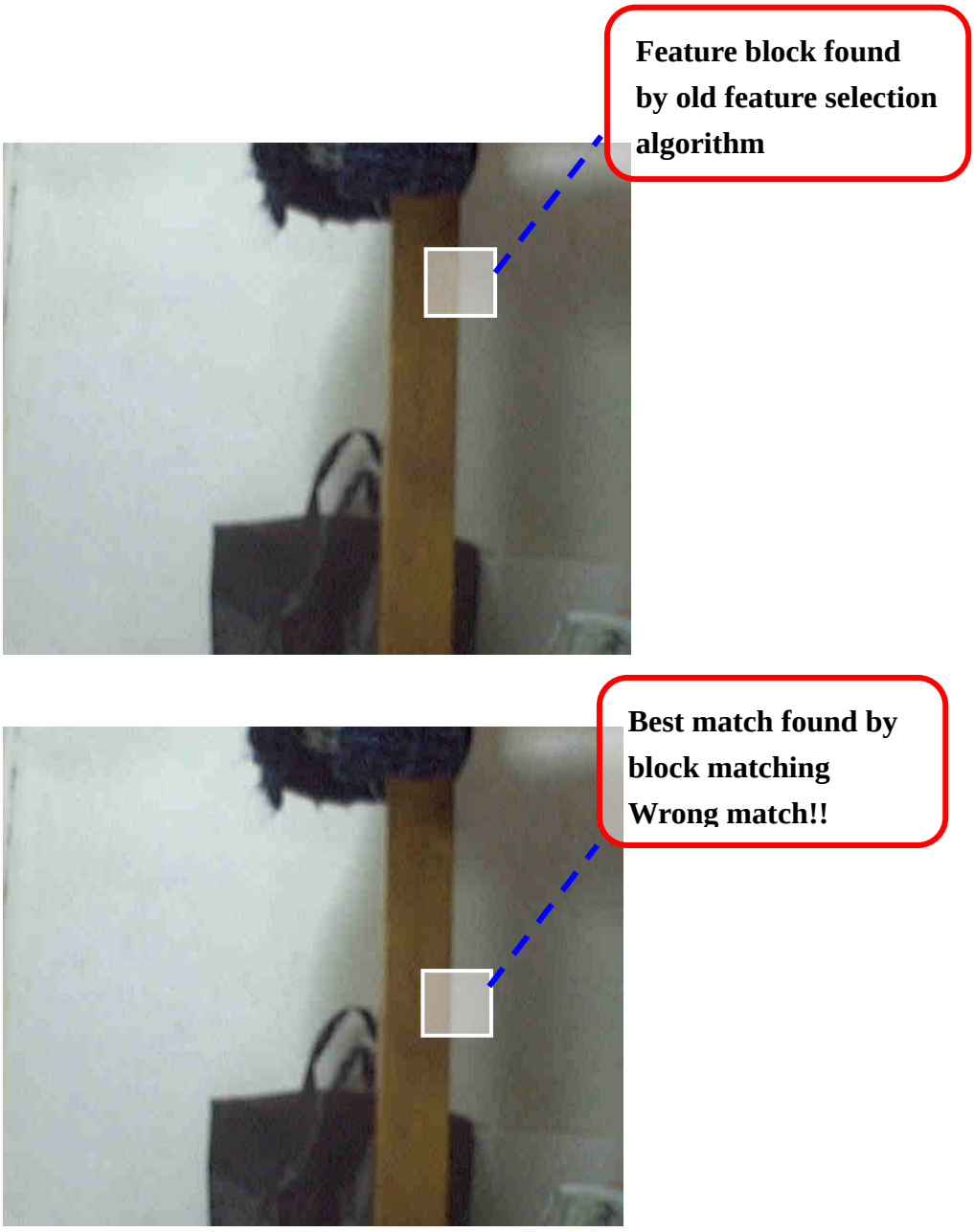


Figure 8.1 – A feature block on the edge

If a block is found on an edge, then the accuracy for finding the best match will decrease significantly. Along the edges, nearly all the blocks are the same, so we should prevent finding a block on an edge.

This motivates us to improve the feature selection algorithm. We add one more constraint to the feature block found that we will check if the block is on an edge or not. We can check it by the SSD difference in all directions of the candidate feature block. Illustrate as follow:

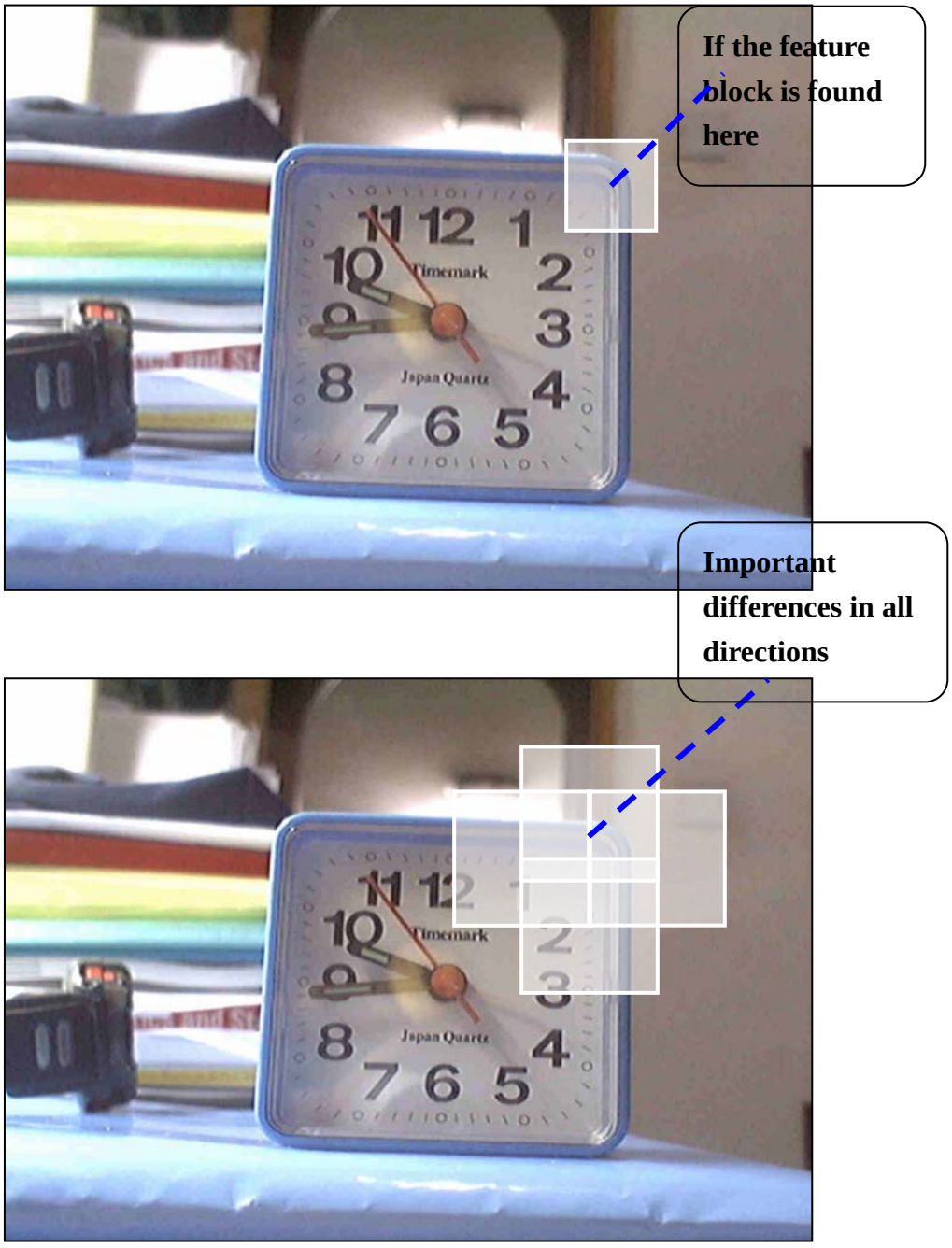


Figure 8.2 – Important difference in all directions

Therefore, now we will determine the block as a feature block in the following steps:

1. Find a block with a large variance -> which indicate the complexity of the block
2. Check if the block is on the edge or not by calculating the SSD in all four directions
3. If either one of the SSD is small -> the block is on edge -> reject
   Else the block is not on edge, and return this block as feature block.

Apart from the above modification, we also make some changes to enhance the performance of the feature selection:

1. More feature blocks are sampled
2. Search in a spiral way
3. Code more efficiently

8.2 Higher Sampling Rate

In our old feature selection, we divide the frame into squares, and examine each square to check if it is a feature block as shown in figure 8.3. However, the best feature block may appear between two squares as shown in figure 8.4.

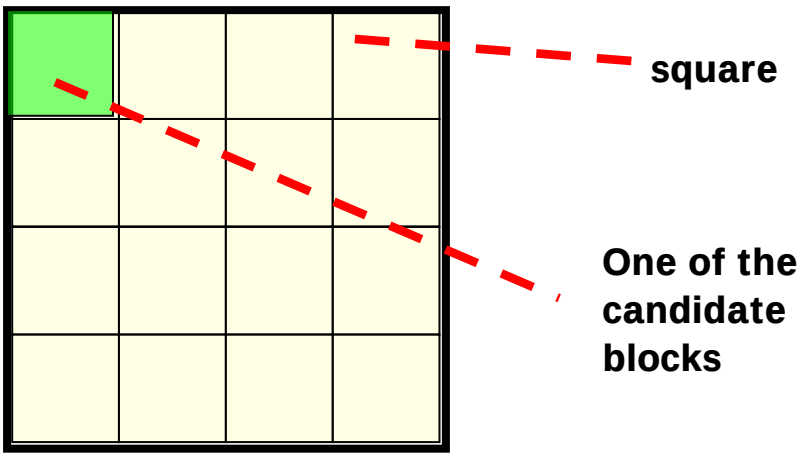


Figure 8.3 – A frame is divided into square

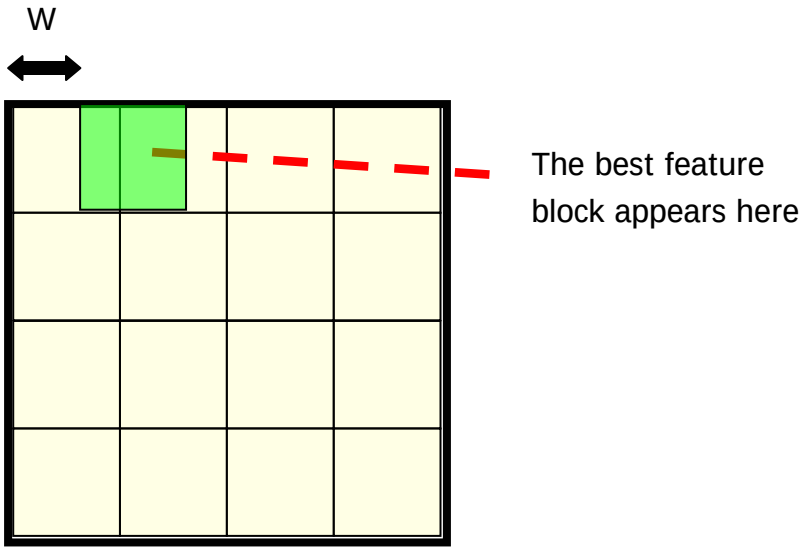


Figure 8.4 – Possible location of the best feature block

Now, blocks that appear in between the squares are also examined. Thus, it will have a higher chance to find a good feature block. Now, we sample each block with distance between each other W pixels (W = 3 in our project) Now 26x26 variances of blocks are sampled with size of each block 15x15 in a 54x54 window.

8.3 Searching in Spiral Way

When searching a feature block, we want the block locate in the center as much as possible. It is because, if a feature block is located at the boundary of the screen, when the phone moves, there is a great chance that the location of the block will exceed the boundary, and thus a new feature block need to be found. Once we find a suitable feature block, the searching will be stopped. Therefore, if we search the feature block in a spiral way, there will be a greater chance to find a feature block located at the center of the searching.

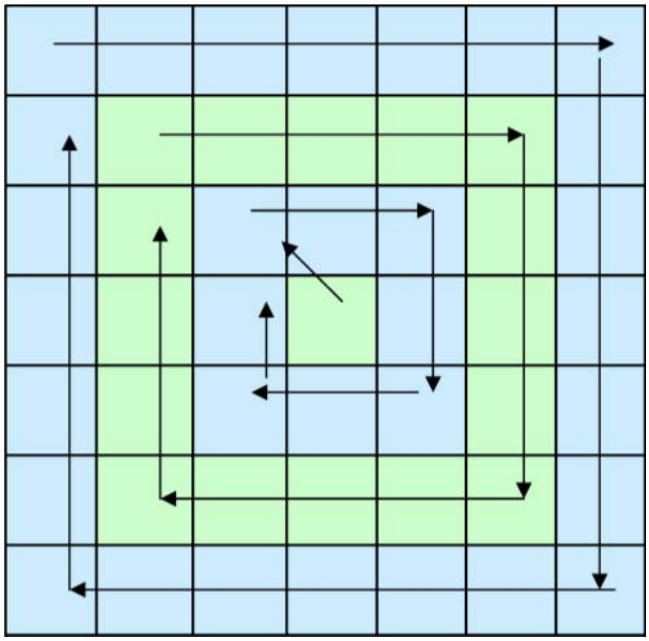


Figure 8.5 – Searching a feature block in spiral way

8.4 Code Efficiently

Since in our feature selection, we need to find the variance of the candidate blocks. In our old implementation, we use $\sigma = \sum (X_{i,j} - \mu)^2$ That means we need a for-loop to find the mean μ first, then calculate $\sum (X_{i,j} - \mu)^2$. That means two for-loops are required. Now, we use the mathematic expression $\sigma = \sum X_{i,j}^2 - \mu^2$. We can find the $\sum X_{i,j}^2$ and mean μ in a single for-loop, and only one subtraction is required finally. Thus, it reduces the computational time for find a feature block.

8.5 Condition to be a good reference background image

A reference image is said to be good if it has plenty of feature blocks. If we use this kind of image as the background image for our motion tracking engine, our engine would have less chance to lose tracking of an object. With this background image, the usability of the applications using our motion tracking engine will be increased. On the other hand, it allows us to evaluate the maximum performance of our motion tracking algorithm.

8.5.1 Requirement

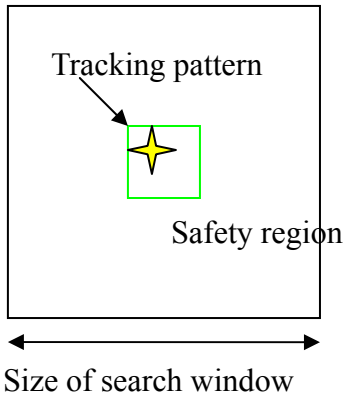


Figure 8.6

Consider Figure 8.6, the green block is the tracking block. The pattern being tracked is the tracking pattern. Safety region is roughly the same size as the search window of the motion tracking algorithm. In the view of the motion tracking algorithm, within the safety region, if the following things are satisfied, less detection error will occur. In other word, performance increases.

1. The tracking pattern doesn't appear at any other position within the safety region. Otherwise, the motion tracking algorithm would have high chance of misrecognizing the repeated pattern as the tracking pattern.

2. Patterns appear around the tracking block are very different with the tracking pattern in the sense that they have large sum of squared difference with the tracking block. In this way, those patterns would have lower possibility of being recognized as the tracking pattern, this reduces error of detection due to noise in captured image.

3. The tracking pattern/block itself should be a feature pattern/block. This makes the feature selection algorithm easier to find a good feature block.

4. The tracking pattern remains more or less the same shape even when it is rotated. Having this property is good for rotation tracking engine. The tracking pattern can be tracked more firmly as the phone is rotated and

this improves the performance of the algorithm.

8.5.2 Possible reference image

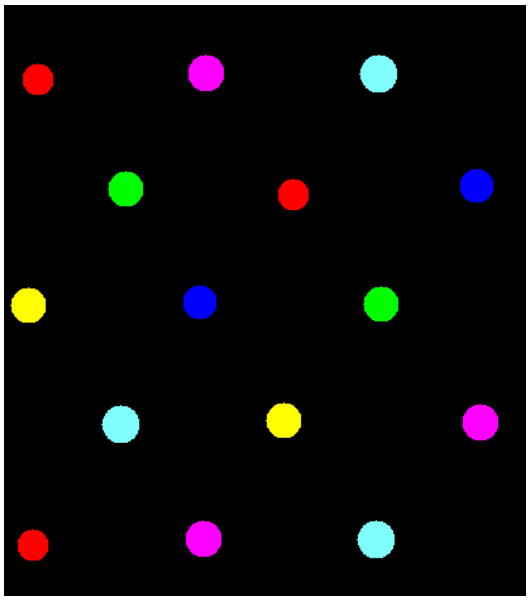


Figure 8.7 Background image 1

Figure 8.7 shows the first possible background image that satisfies the requirement above.

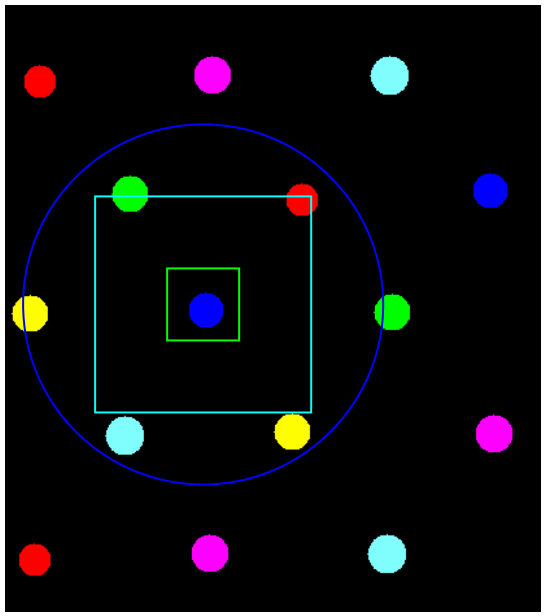


Figure 8.8 Analysis of background image 1

Background image 1 satisfies the requirement above. Figure 8.8 illustrates why background image 1 is the background image we want.

1. Within the safety region which is bound by the blue circle, the tracking pattern, green dot in the case of Figure 2.3, doesn't repeat itself. Actually, for the other three kinds of dot, there is no repeat within the safety region of itself too.

2. Within the safety region of green dot, there appear dots with different colors. Green, blue, red, cyan, magenta and yellow colors have very distinct RGB value. Thus the sum of squared difference among them is very large.

3. The color dots are very distinct with the black background. Thus, a block containing the color dot usually has high variance. Since our feature selection select feature block with high variance in the first pass, block containing the color dot is usually selected.

4. The pattern used is circle. Circle remains the same shape as it is rotated. This satisfies requirement 4.

8.6 Conclusion

After our modification, the feature selection algorithm can find a better feature block that make our motion tracking more accurate. Since we now take more samples, the time used for finding a feature block is longer than our previous feature selection algorithm. Although the time used is longer, it increases the accuracy of the motion tracking. It is worth to do so, as the feature selection algorithm will be invoked only when the block is out of the bound and thus the times of invocation are low.

Chapter 9: Applications Development

In this chapter, we will discuss what kinds of applications can be developed from motion tracking and benefits of using it.

Motion tracking has been widely used in many areas, for example video compression, robotics, video surveillance, etc. It is possible to develop different kinds of applications. Moreover, it can be used as an innovative input method to many applications, for example, games, camera mouse and gesture input. We will focus on how motion tracking can be used as an input method for different applications.

9.1 Development procedure

Before we talk about what applications can be made, we talk about how a motion-tracking application can be developed. The flow chart of developing motion-tracking application is shown below:

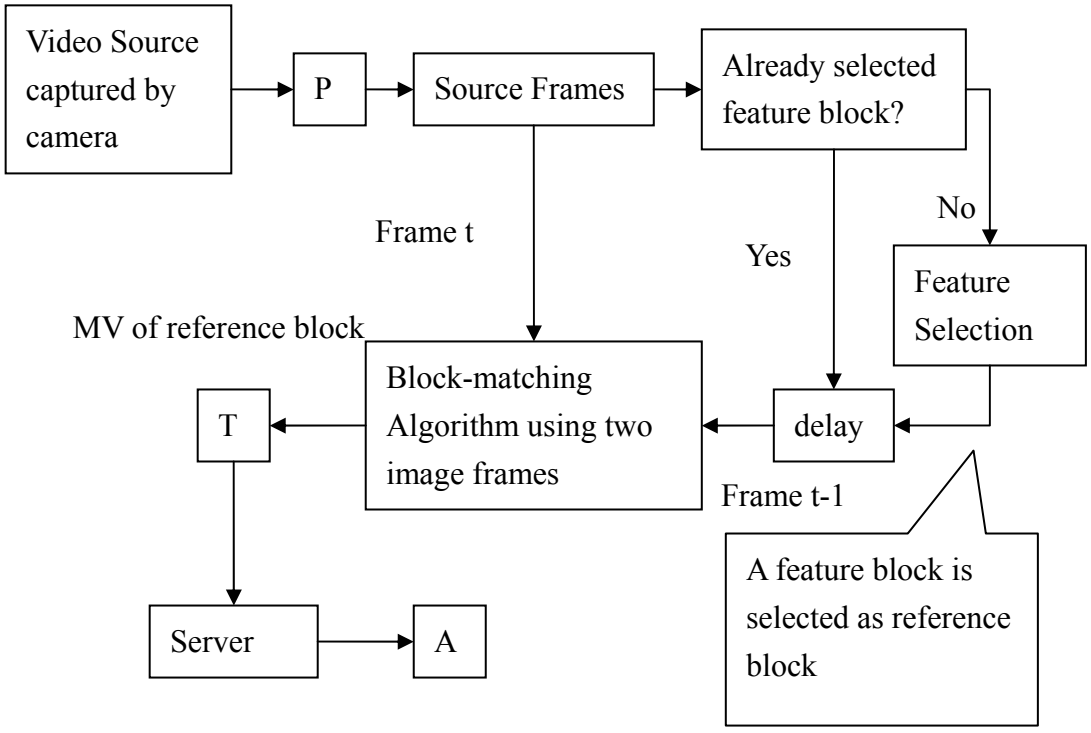


Figure 9.1 Flow Chart of developing motion tracking application

Input Stage

In order to use the motion tracking technique, we need to extract frames from video. This process is procedure "P" shown in the Figure 5.1. There are several ways to do that. In PC, we use libraries from OpenCV and in Symbian, we use the view finder to extract the frames from video.

OpenCV provides a lot of library for us to manipulate the video. Firstly, we need to reserve the camera to use. After that, by calling cvQueryFrame( ), a frame will be extracted and stored in a 2D array. Then we can get the frame data by using a pointer.

Processing Stage

After we have extracted frames from video, we use two consecutive frames Ft-1 and Ft for block-matching. If we have not selected a reference block for tracking, feature selection algorithm will be applied to find a good feature block as reference block. After that, we can use the block-matching algorithm to find the motion vector of the reference block.

Output Stage

Once a motion vector is found, it will be output to a server by using transmission medium "T". We can use different kinds of transmission medium, eg Serial Cable, USB, Bluetooth, etc. The server is responsible for receiving the motion vector and interpreting it. Finally, the server will give corresponding commands to the application "A".

Conclusion

Different kinds of application can be developed by following the flow chart above. Moreover, the motion tracking technique can be used in different platforms, eg PC, PDA, Symbian phone, provided that they support video capture and libraries for image manipulation.

9.2 Example Applications

In order to illustrate the idea of innovative input method using the motion tracking, we have implemented two applications one in the PC and one in the Symbian phone based on the block-matching algorithm that we have discussed before.

9.2.1 Pong Game

Here show the screenshot of the pong game. The left one is developed on the PC written by C# while the right one is developed on the Symbian and tested by the emulator.

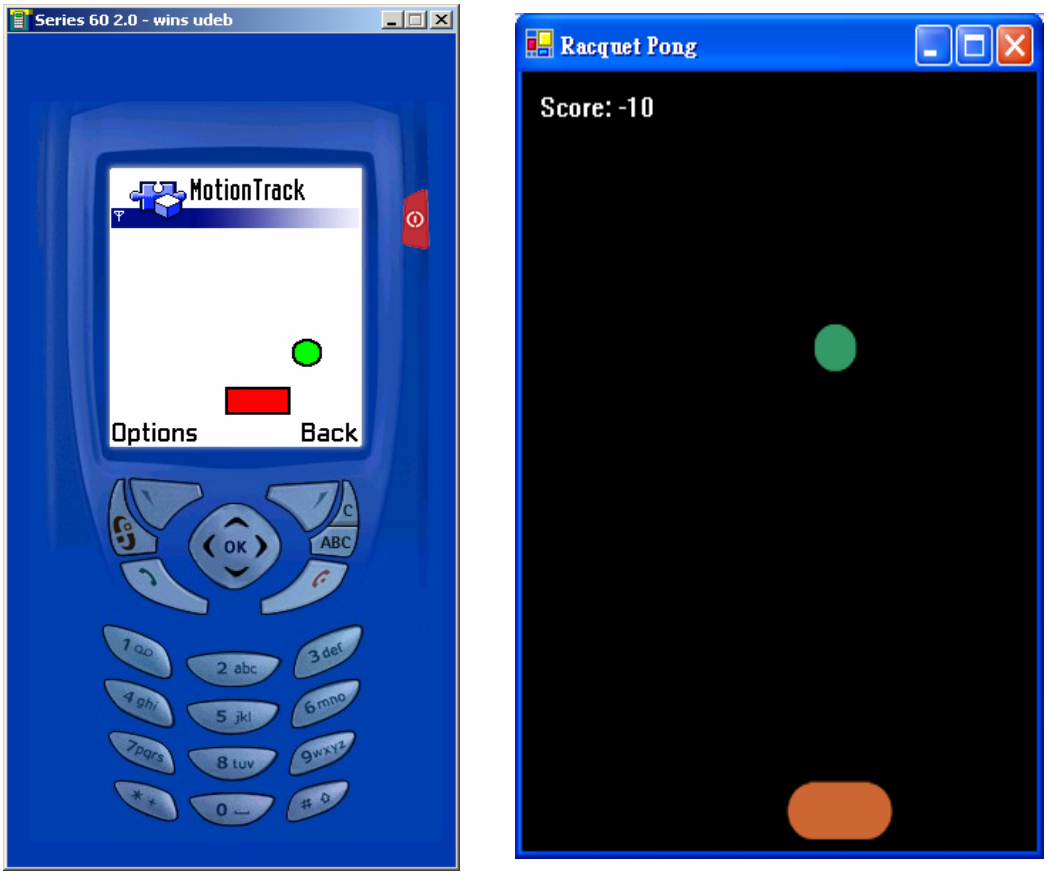


Figure 9.2 Screenshot of the pong game

Traditionally, users play the game by using the keyboard to control the movement of the paddle. It would be much more interesting if users' movements are involved in playing the game. We implemented the block-matching algorithm in the game so that the paddle could be controlled by the users' movement. When the user moves the camera or camera phone, the padding will move according to the direction of movement. Because of the motion tracking technique, the traditional pong game has

become much more interesting.

The pong game is just one of the applications to illustrate the benefits of using motion tracking technique. There are a lot of applications in which this technique can be used

9.3 Other Possible Application

9.3.1 Camera Mouse

In the society, there are people with serve disabilities that they can only move their heads. Because of their disabilities, they cannot use the computers for any purpose. Therefore, there is a need to develop a tool for the physically handicaps so that it can provide a chance for them to access the computers. Due to their limitation of movements, a motion tracking system, Camera Mouse, can helps them to access the computer. Therefore, they can acquire knowledge more actively, use the Internet, and access computer-controlled techniques such as automated wheel-chairs.

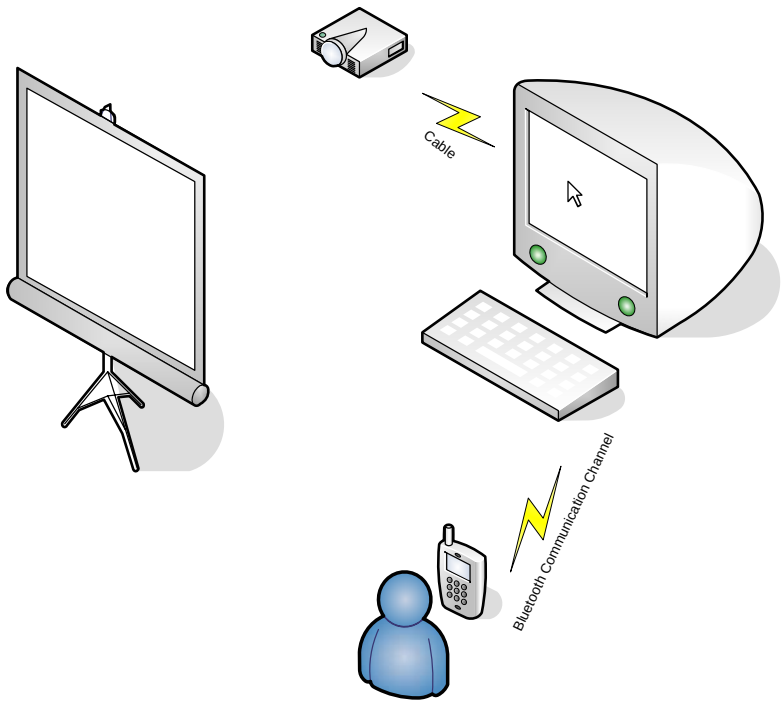
The idea of camera mouse system is that the system tracks the computer user's movements with a video camera and translates into the movements of the mouse pointer on the screen. It is particularly useful for physically handicaps. For example, people with serve disabilities can control the movements of the mouse pointer by moving their heads.

Chapter 10: Virtual Mouse Application

Virtual Mouse application is developed aiming to illustrate how our motion tracking engine can be incorporated to develop a new type of application. Virtual Mouse application also illustrate how useful is our translational motion tracking engine when compared with other conventional input method.

10.1 Brief Description of the Virtual Mouse Application

Virtual Mouse is a client-server application using Bluetooth wireless technology as the core communication channel. By this application, user can make commands on a Symbian phone to control the mouse cursor and keypress event of a specific computer through Bluetooth wireless communication channel. The server part is hosted on a desktop computer with Windows as the operating system while the client part is implemented as a Symbian program.



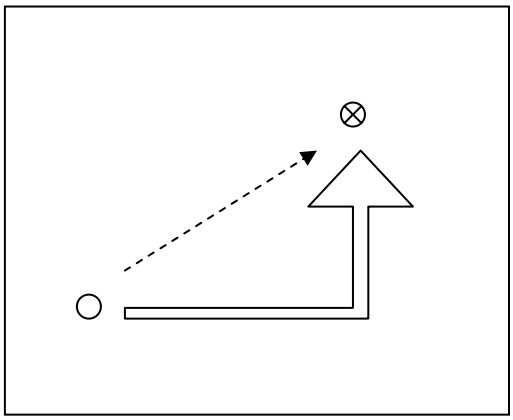
10.2 Advantage of Motion Input over Conventional Input Method

In this application, user issues commands on the phone and send out to the server. There are at least three ways for user to issues commands:

1. Moving the joystick
2. Pressing the keypad
3. Use motion input (moving the phone)

The third way, the motion input, has absolute advantage over the first two input methods. Comparison is made as follow:

1. Joysticks of most of the phones have limited freedom of movement. Usually only up, down, right and left directions can be detected. Moreover, its level of control is low. Usually joystick provides only one level of control. That is, it can detect either upward or not upward, downward or not downward, etc. We can imagine that if we can only move the cursor in only four directions and can not control the speed of the cursor, controlling will be very inefficient and slow. Imagine that we want to move the cursor from the white circle to the cross position, we have to instruct the cursor to move right and then upward instead of moving diagonally. The cursor is required to be moved in a longer distance without controllable speed. Clearly time of doing this will be longer than moving the cursor to the cross in the shortest path with controllable speed.



2. Pressing keypad is more inconvenient than moving the joystick because user needs to press at least 4 distinct buttons in order to get the same function of moving the joystick. Thus, certainly pressing keypad won't be a better input method than moving joystick in virtual mouse application.

3. Motion input has 4 advantages. *Firstly*, it allows input in all directions.

Our translational motion tracking engine is capable of tracking the phone movement in all directions. Thus, user can instruct the mouse cursor to move in any direction they like. In this way, user can always reach its desired destination through the shortest path. *Secondly*, it provides high levels of control. Motion input gives not only the phone is moving in certain direction, but also gives the information of how many pixels it has moved. Thus, user can instruct the mouse cursor to move faster or slower by moving the phone faster or slower respectively. *Thirdly*, it allows user to give commands faster. User does not need to struggle to turn the joystick or busy to hit the keypad in order to give many commands; user can just simply move the phone then he can give 12 commands per second as motion information is captured and sent to the server 12 times every second. *Fourthly*, motion input gives user a sense of moving an off-table wireless computer mouse and that's why this application is called virtual mouse. User who is accustomed of moving a real computer mouse will enjoy using this virtual mouse and will find it easy to use. Moreover, there are far more buttons available on the phone that can be used to send shortcut commands to the computer. This makes the mouse more convenient to use.

10.3 The Server

The server program is written in Windows MFC. The main task of this program is to listen on a Bluetooth virtual comm. Port for motion information message sent from the client program and resolve the message according to the predefined protocol. After motion information is resolved, this program controls the mouse cursor of the window host and emulates keypress event according to the motion information resolved.

10.4 The Client

The client program is written in Symbian. The main task of this program is to switch on the motion tracking engine and obtain the phone's motion information. The information is then sent to the pre-selected server via Bluetooth connection according to the predefined protocol.

10.5 Bluetooth Wireless Communication

Bluetooth is an industrial specification for wireless personal area networks. It provides a way to connect and exchange information between devices like PDA, mobile phones, PCs and laptops via a secure, low-cost, globally available short range radio frequency. Bluetooth lets these devices talk to each other when they come in range even if they are not in the same room, as long as they are with 10 meters of each other. Bluetooth is a wireless radio standard primarily designed for low power consumption and is suitable to be used for a long time.

Most of the Symbian phones nowadays have Bluetooth wireless facility. Thus, the virtual mouse application can be used in most of the Symbian phones.

10.6 Running the Server

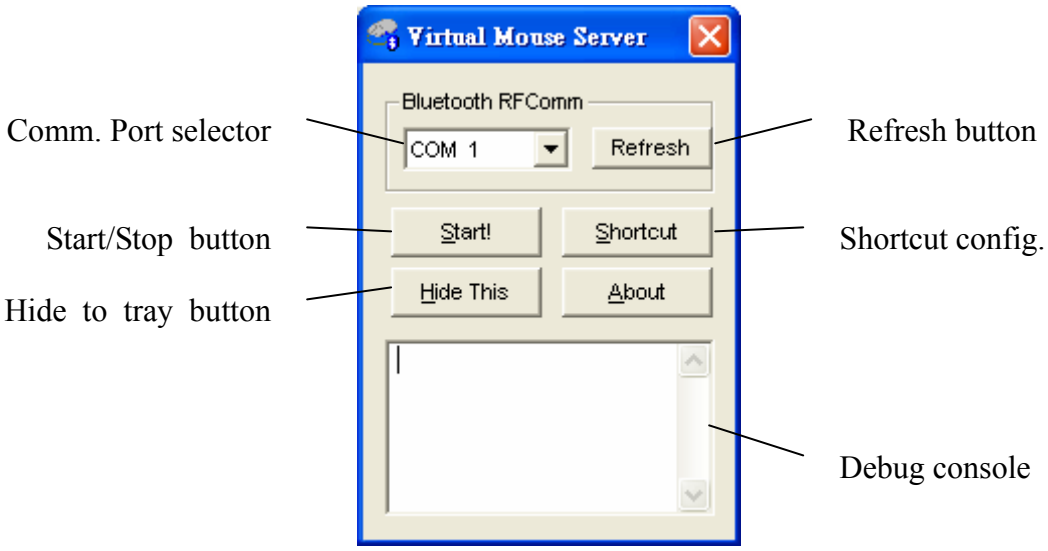


Figure 10.1 Virtual mouse server

When the server is executed, the above window will appear. The function of each component is described below:

1. Comm. Port selector

   To select the virtual comm. Port Bluetooth device has bind with. The port number has to be the same with the configuration in the Bluetooth manager.

2. Refresh button

To refresh the list of comm. Port available in the computer.

3. Start/Stop button

   To start/stop the server.

4. Hide to tray button

   Hide the application to the tray bar on the bottom right of the Windows.

5. Shortcut configuration

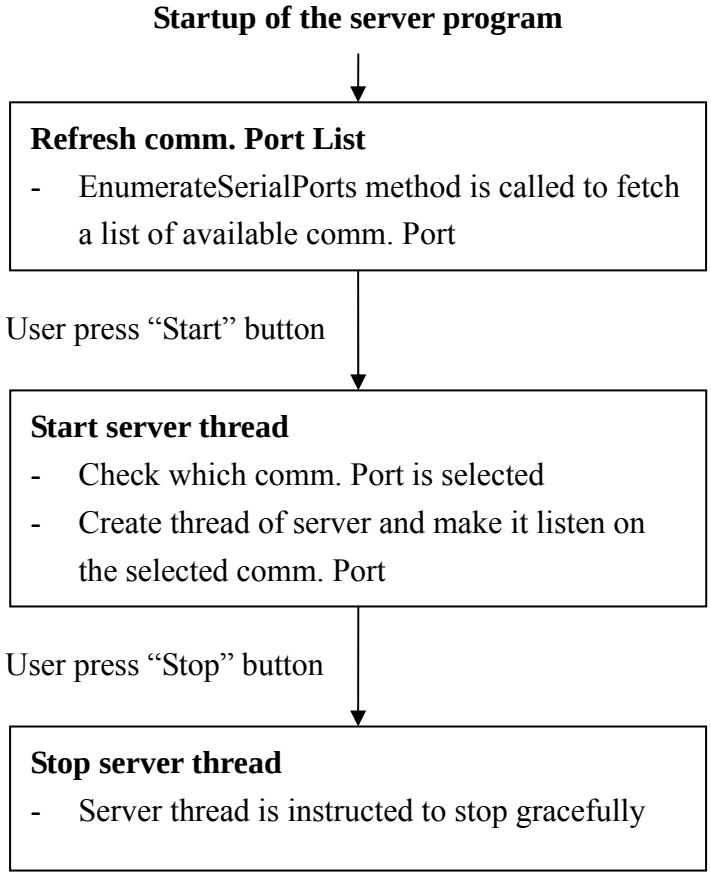
   To configure the function mapping between client message and server action.

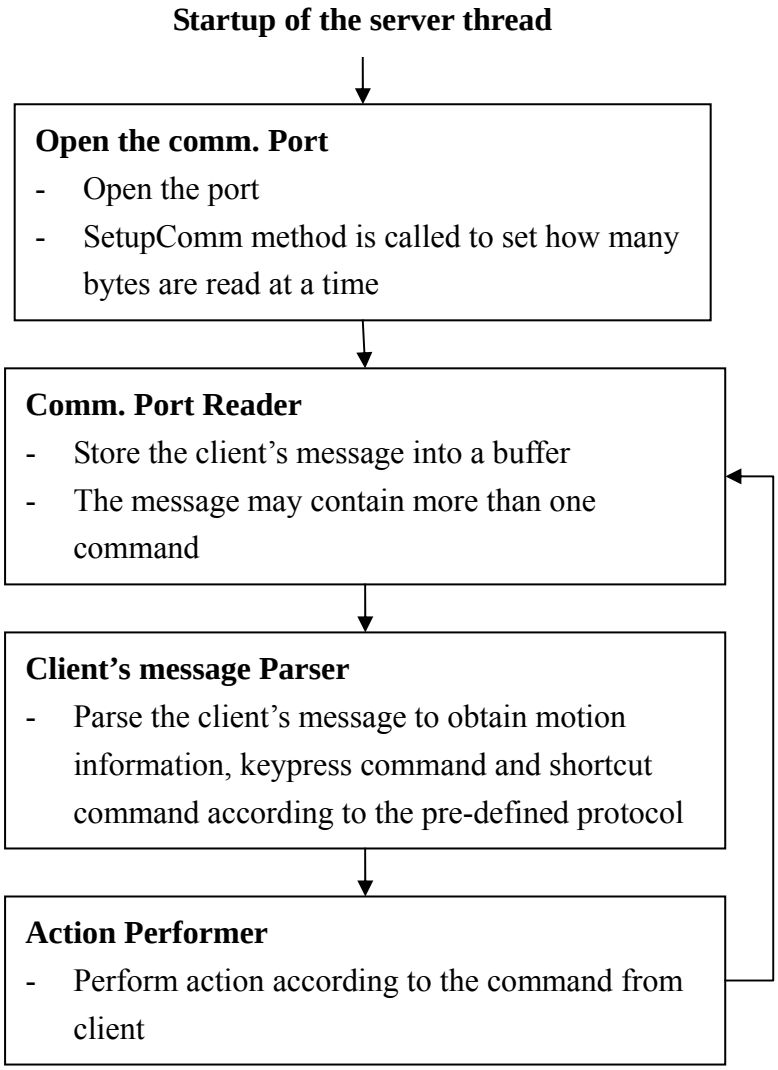
6. Debug console

   For debugging use only.

10.7 Design and Implementation of Server

Below is the flow chart of the server program and server thread:





Below is the protocol table:

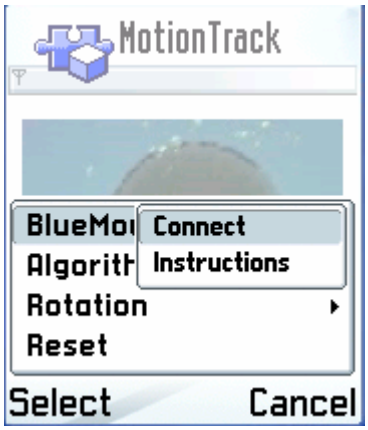
Client's Message	Server's Action	User's Action
M <a> <b>	Move cursor "a" pixels to the right and "b" pixels downward	User moves the phone
L	Coarsely move the cursor to the left by a large step	User pushes the joystick to the left
R	Coarsely move the cursor to the right by a large step	User pushes the joystick to the right
U	Coarsely move the cursor upward by a large step	User pushes the joystick upward
D	Coarsely move the cursor downward by a large step	User pushes the joystick downward

x	Emulate left mouse button down event	User presses the button
X	Emulate left mouse button up event	User release the button
z	Emulate right mouse button down event	User presses the button
Z	Emulate right mouse button up event	User release the button
y	Emulate middle mouse button down event	User presses the button
Y	Emulate middle mouse button up event	User release the button
W	Wheel up	User presses keypad 5
w	Wheel down	User presses keypad 8

10.8 Running the Client

When the application starts up, the following screen appears:

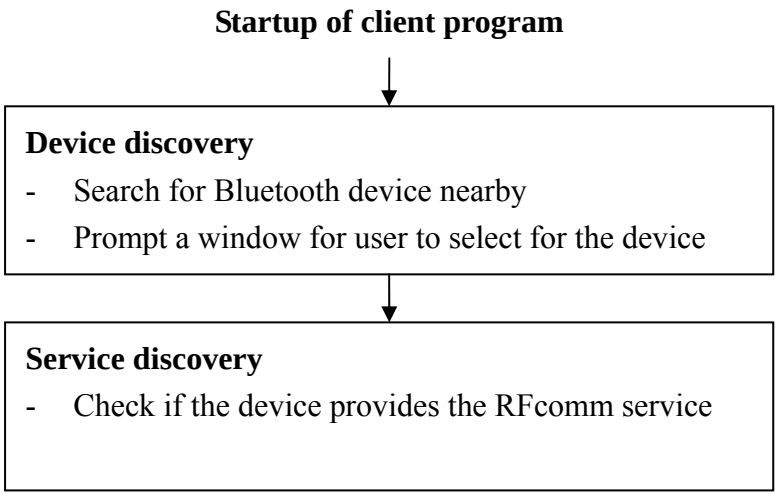
The Options menu displays four choices, select the choice “BlueMouse” then the following screen will appear:

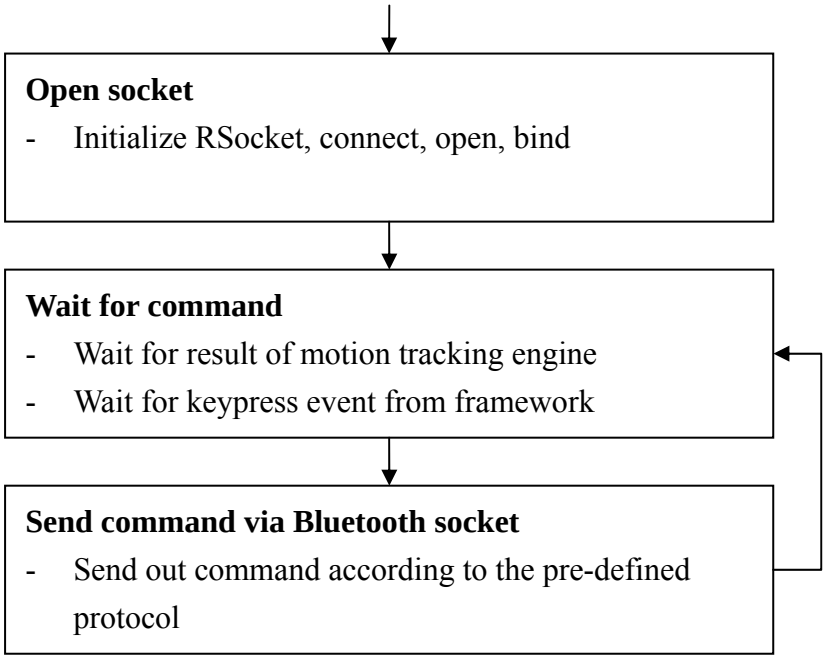


After choosing "Connect", a window will be prompted to show the searching process for Bluetooth device:

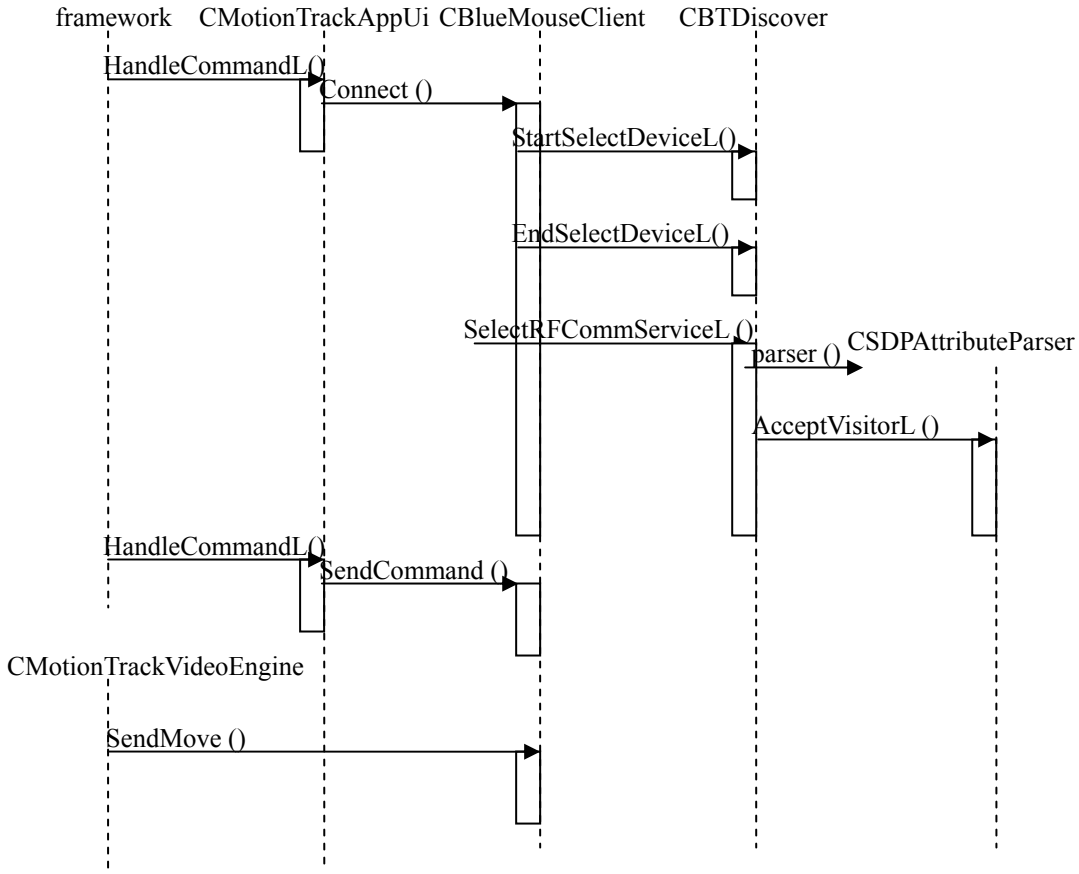
After choosing the server device, the program will setup a connection to the server and you can control the mouse cursor of the server now.

10.9 Design and Implementation of Client





The UML sequence diagram below shows the function calls that occur as a result of the user's request to discover Bluetooth device, verify Bluetooth RFComm service and send command to server.



Chapter 11: Games Development

This chapter provides an overview of the game concept, a more in-depth look how to develop motion sensing game and finally our developed game applications

11.1 Programming Games for Series 60

As the mobile devices have become more and more sophisticated in term of CPU power and technologies, they are currently well suitable as a game platform. The Series 60 Developer Platform provides a wide range of features that make game development easier. However, the small size of the display, the small keyboard, which even varies between different devices need to be taken into account when developing games.

Our goal is to develop games that make use of the Motion Tracking API that we developed. By using the Motion Tracking API, it can be used as an innovative input method for the games and design interesting games that will response differently according to player's motion.

The following figures show some existing games for Symbian phones.

Figure 11.1– A 3D motorcycle racing game

Figure 11.2 – A J2ME skiing game

Before going into detail of the motion sensor games, we will talk about some restriction in game programming in mobile phones.

11.2 Series 60 Specific Considerations

11.2.1 Memory

Memory management is very important in memory-constrained devices. This concerns both the run time memory usage and the eventual compiled code size. Most of the Symbian based devices have only several MB of memory. Therefore, all allocated memory should be unallocated as soon as possible. If you forget to free up the memory, small memory leaks might go unnoticed over a day or two's usage have the chance to accumulate over a lengthier period. The result is that the system's resources are finally exhausted and the machine, or at least the app, needs to be restarted with likely data loss in order to free up memory again.

When implementing an application, the usage of a stack memory is worth noting too. In Symbian OS, each thread has its own memory stack, which cannot grow after the thread has been launched. The default stack size for an application in Series 60 is only 8KB, and because of this, it should be use with great caution.

Due to graphical nature of games, bitmaps often form a large portion of their memory consumption. The most effective way to reduce the memory consumption, without decreasing the number of bitmaps is to reduce their color depths.

11.2.2 Processors

In addition to limited memory size, Symbian phones have other restriction when compared to PCs. Symbian phones do not have as efficient processor as PCs do, and graphics processors are rare. Math processors are also very rare in Symbian phones and hence calculations should be implemented using integers.

11.2.3 Fixed Point Mathematics

Since there are no native floating points, we cannot include a lot of floating point calculations in the games, as every emulated calculation slows things down. In order to solve this problem, we use fixed point mathematics. For example, we use a 32-bits integer with 24 bits for the number and 8 bits for the decimal.

Moreover, we can use a pre-calculated table for some mathematics like cosine or sine operation, because E32Math's Math::Sin() is both very slow and a floating point function.

11.3 Structure of Game and Game Loop

The whole life of the game is actually in the game loop. The game loop and overall structure of any game are the most important things in game development. The document-view architecture of Series 60 is already suitable for game development. The typical structure of a game is typically as follows:

- **AppUI**: Controller of the game. It controls the views of the game and menu commands, and other user inputs

- **View:** Owns the game engine (or part of it), displays the game state

from the engine, and handles the UI controls on the view and other user input.

- **Document:** Used to store the game state of the engine.

- **Engine:** The game engine. The game engine is responsible for the logic of the game. The engine is sometimes mixed together with view, so that the engine can handle the user input and drawing.

When developing a game, there are actually two ways of implementing the multiple screen of the game:

1. Using multiple views (for example, introduction, main menu, options screen, game playing).
2. Using single view.

If a single view is used throughout the game it may be easier to implement the engine so that it is owned by appUI. Since both appUI and view process user input and view displays the game state, it is usually necessary to pass a reference of the game engine to view when creating it. This makes the structure of the game somewhat obscure.

Using a single view makes handling user input and drawing messy because the single view needs to be conditional depending on the game state, especially with larger games.

When the game is divided into multiple, logical views, the user input and drawing can be capsulated clearly into separate classes, for example:

- View for the introduction of the game.

- View for the main menu.

- View for the options screen.

- View for the game playing

Since the multiple views architecture makes the structure of the game clear,

we use this approach for our games.

Figure 11.3 – Multiply views

As in figure 11.3, the game cover is one of the multiple views. After the player presses “Play”, the game will enter game playing view.

For the game loop, we use a timer to implement it. The timer updates the game state, and user input is processed independent of timer. The timer updates the game status periodically:

```
void MyGameView::MyTimer()
{
    iMyEngine->NextFrame(frameTimer);
    UpdateDisplay();
}
```

11.4 Input Device

In the past the only way of controlling the game in Series 60 devices is the keyboard. For the time being the keyboard is the only practical solution for controlling games. The variety of different keyboard layouts and the limitations of the small keyboard should be taken into account when developing games.

In our final year project, we have broken this limitation that by using the embedded camera for controlling games. Now, by making use of our motion tracking engine, developers can develop their applications not limiting by the keyboard. They can now develop innovative and creative applications that use motion as input.

Before introducing how to use the motion tracking engine, we will talk about traditional game programming using keyboard.

Key event handling in an application is simple:

1. **AppUI** receives the key event in **HandleKeyEventL.**
2. **AppUI** relays the key event to active view by calling view's **OfferKeyEventL.**

Therefore, by implement the OfferKeyEventL function, we can handle the key event.

Note that for Symbian phone, handling multiple keys simultaneously is not possible by default. Only the events from the key that is pressed first are received. This is called **key blocking**. If we want to handle multiple keys event, we can allow this by using **CAknAppUi** which provides the **SetKeyBlockMode** method to disable key blocking for the application

Below is an example of switching off key blocking:

```
void CMyGameAppUi::ConstructL()
{
    // Disable key blocking
    SetKeyBlockMode(ENoKeyBlock);
}
```

11.5 Advance Graphic Programming

In this section, we will talk about how to make your graphic programming to be more efficient. There are several techniques that can be used to improve the performance of the games.

11.5.1 Double Buffering

If a game's graphics consists of multiple moving objects which need to be updated frequently, the window server's client side buffer may be filled up and thus be flushed before all objects have been updated. To the user, this may appear as flickering. Flickering or other undesirable effects may also occur if a view that is built up over a long period of time is drawn while it is still been updated. A solution for these problems is to use double buffering where graphics are first drawn in an off-screen bitmap (back buffer), which is then drawn on the screen, thus forcing the entire frame to be drawn at once. Especially games, which redraw their screens several times in a second, practically require an off-screen bitmap.

The procedure for using double buffering is as follows:

1. Create a new bitmap, size of the game view

2. Set the color depth of the bitmap to be the same as the view's bit depth. It is because, it can avoid the time consuming conversions from one bit depth to another.
3. Create a bitmap device and the graphics context for the created back buffer bitmap. This is needed, because when graphics context is created for the bitmap, drawing onto the bitmap is possible just like drawing onto the view's graphics context.

4. Every time when the screen needs to be updated, the graphic is drawn into the back buffer. When drawing is finished, call the view's **DrawNow** or **DrawDeferred** method, **DrawDeferred** is the safer method.

5. In the view's **Draw** method the only drawing that exists is the blt operation of the back buffer bitmap into the view (front buffer).

The following illustrates the ideas of double buffering:

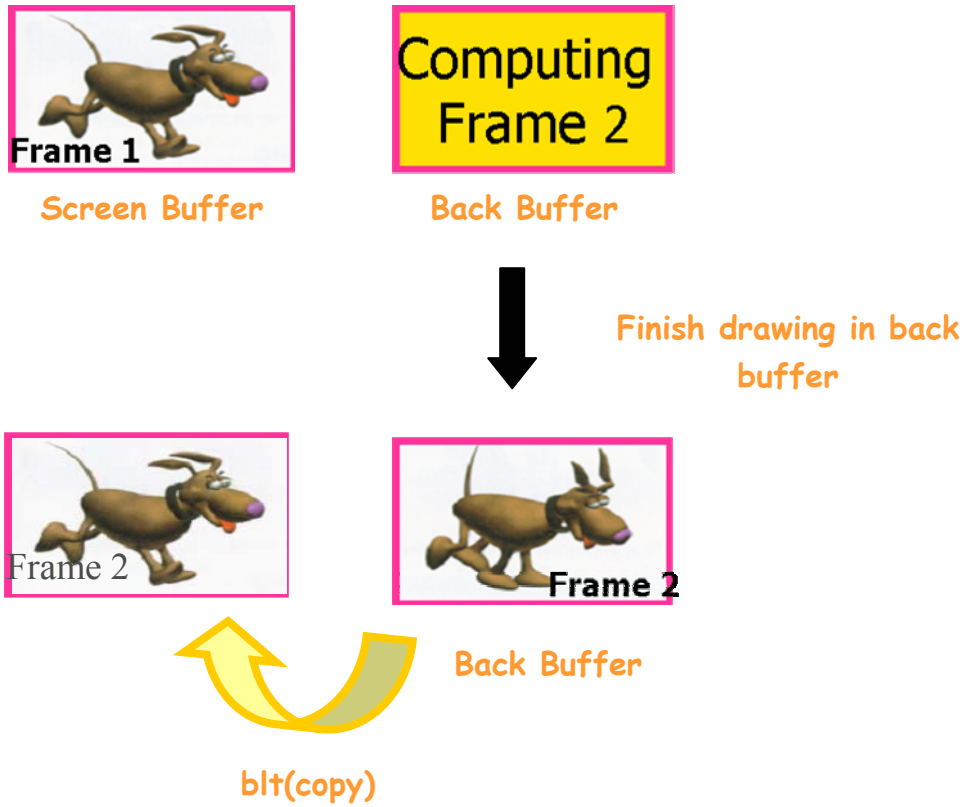


Figure 11.4 – The use of double buffering

As we can see from Figure 11.4, one frame is displayed while the other is calculating next scene to be drawn. When the drawing of the next frame is completed, the content of the back buffer is copied to the screen surface.

11.5.2 Direct Screen Access

In Symbian, if you want to draw onto the screen, you need to make use of the window server as shown in figure xxx. However, using the window server will slow down the speed because it requires context switching. To by pass the window server, and thus get rid of the context switching, an

application can access the screen directly in three ways:

- Creating and using **CfbsScreenDevice**
- Accessing screen memory directly.
- Using **CdirectScreenAccess.**

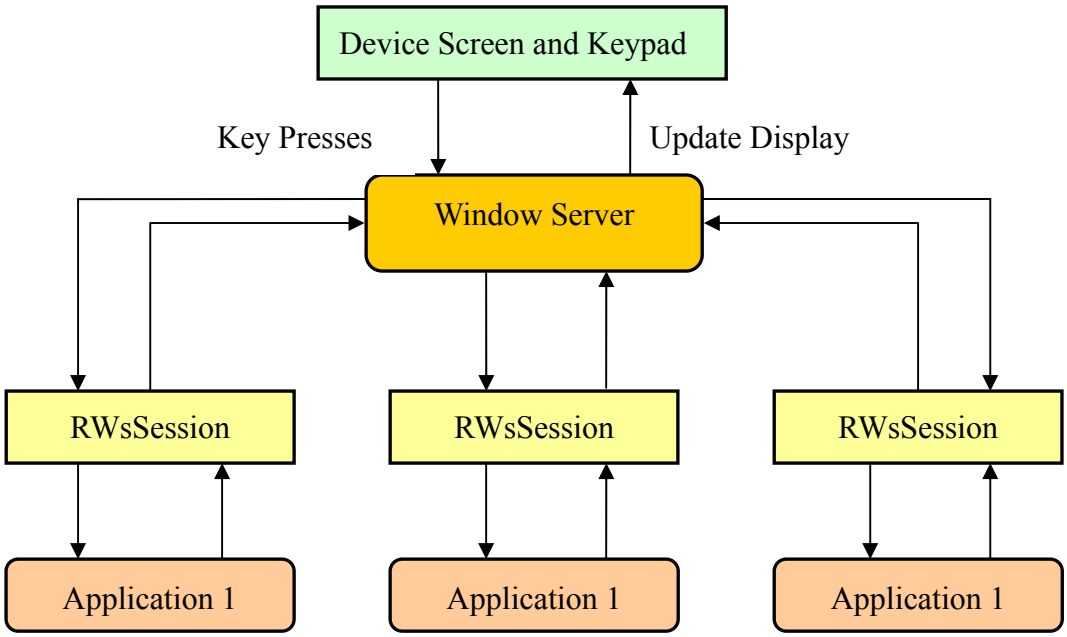


Figure 11.5 – The flow of for the applications through sessions with the Window Server.

CFbsScreenDevice is a graphics device that can be addressed to a screen driver. After creating a **CFbsBitGc** graphics context for it, it can be used like any other graphics device. However, the drawing is done directly on the screen without using the window server.

In figure 11.6, a request is issued to the Window Server to operate in Direct Screen Access mode, which if successful will provide an area on the screen that can be drawn to.

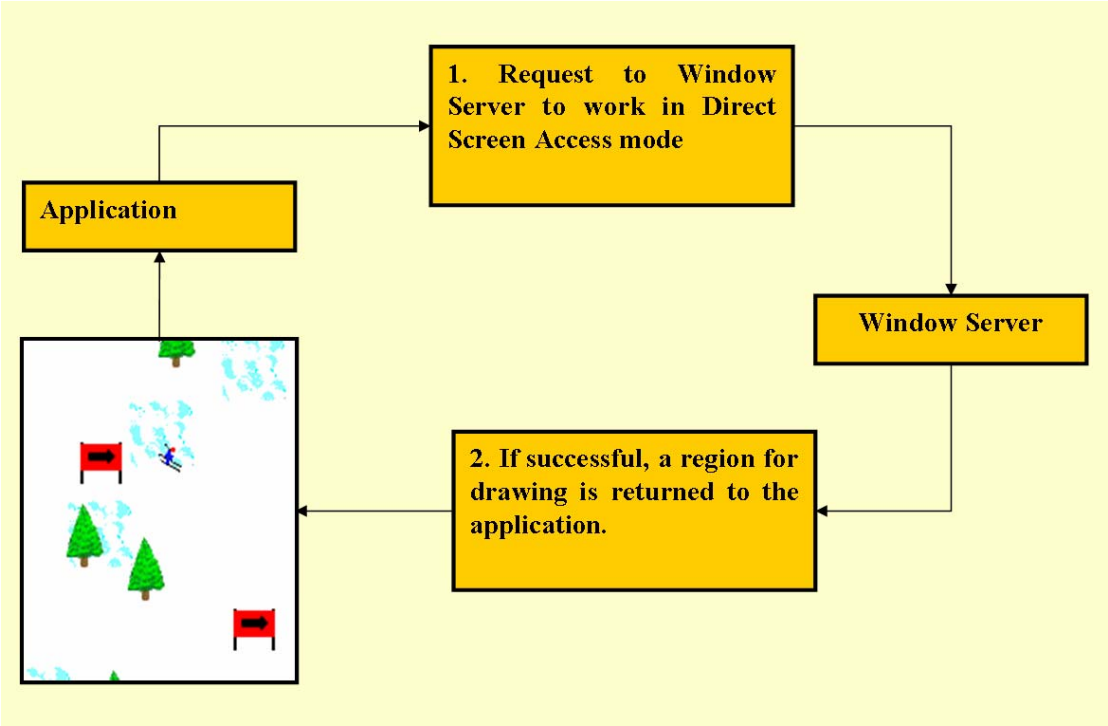


Figure 11.6 – Requesting use of direct screen access

When an external event takes place that it wants to access a portion of the screen (e.g. displaying a menu), this will result in Direct Screen Access being stopped as shown in figure 11.7. Then a new request is made to the Window Server, which will help you to access the screen.

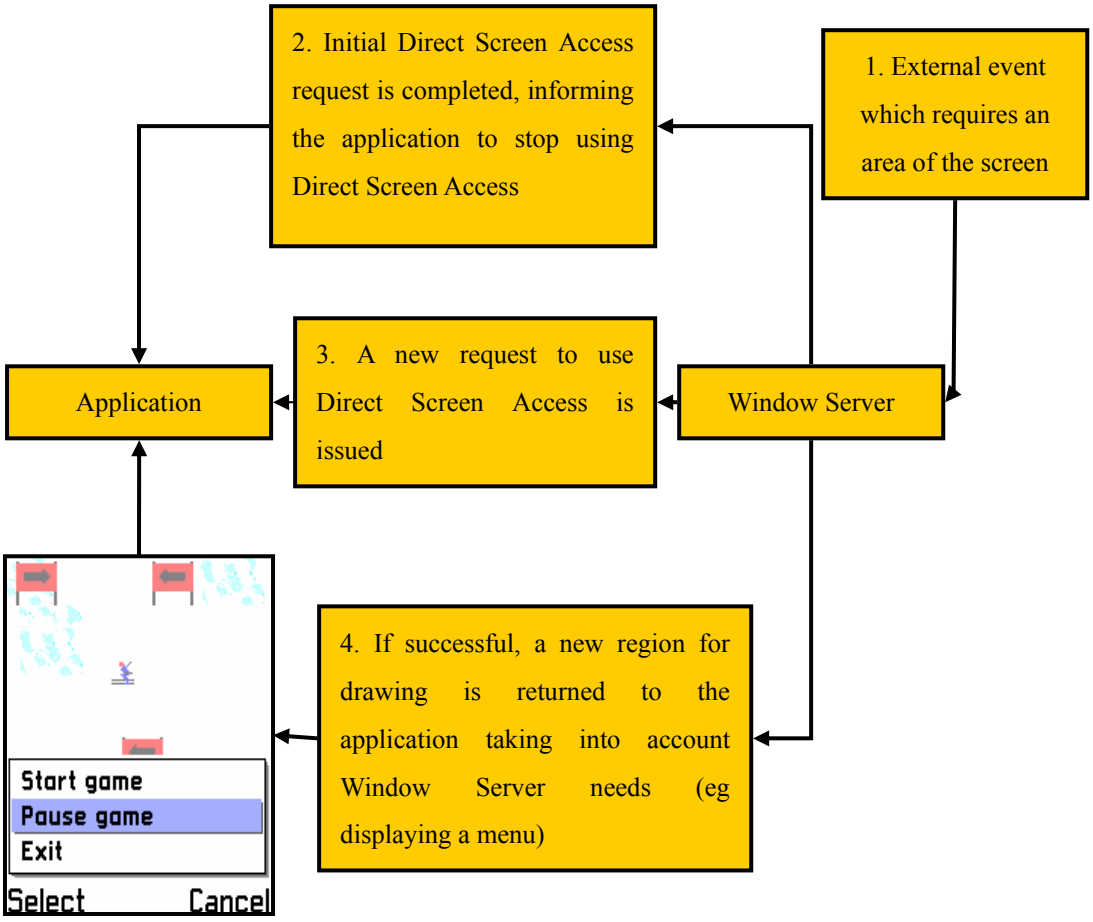


Figure 11.7 – Responding to external/window server events when using direct screen access

11.6 Conclusion

In this chapter, we provide an overview of game programming in Symbian phones. We also discuss the limitations of Symbian phones and the methods to tackle the problems. By using some efficient graphic programming algorithm, we will be able to make use of our motion tracking engine to develop other applications without affecting the performance.

Chapter 12: Car Racing Game

We have developed a Car Racing Game that illustrates the possibilities of game development using our motion tracking engine. Here, we will first introduce our game, and then talk about the structure of the game.

12.1 Overview of the Game

When the game is started, a game cover is displayed as shown in the figure 12.1.

Figure 12.1 Game Cover of Car Racing Game

After the player presses “Play”, the game will enter game playing view as shown in figure xx.

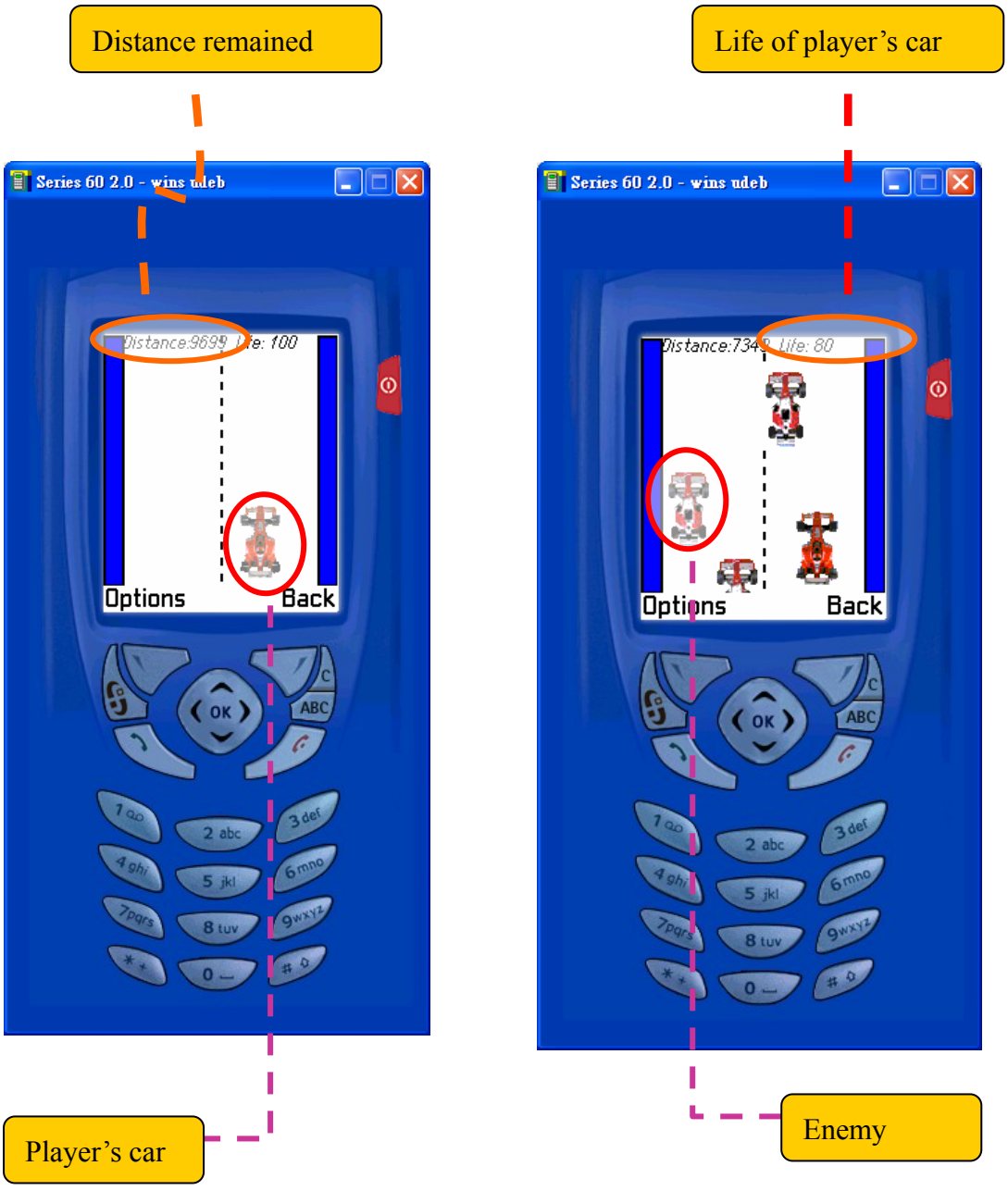


Figure 12.2 Game-play view

In this game, it makes use of the motion tracking engine to track to user's hand movement. If the user moves his hand to the left/right, then the player's car will move accordingly. If the user moves up the phone, then the player's car will accelerate for 5s. If player's car can reach the destination before the life drop to zero, then the player win the game. If the player's life drops to zero before reaching the destination, then the player loses.

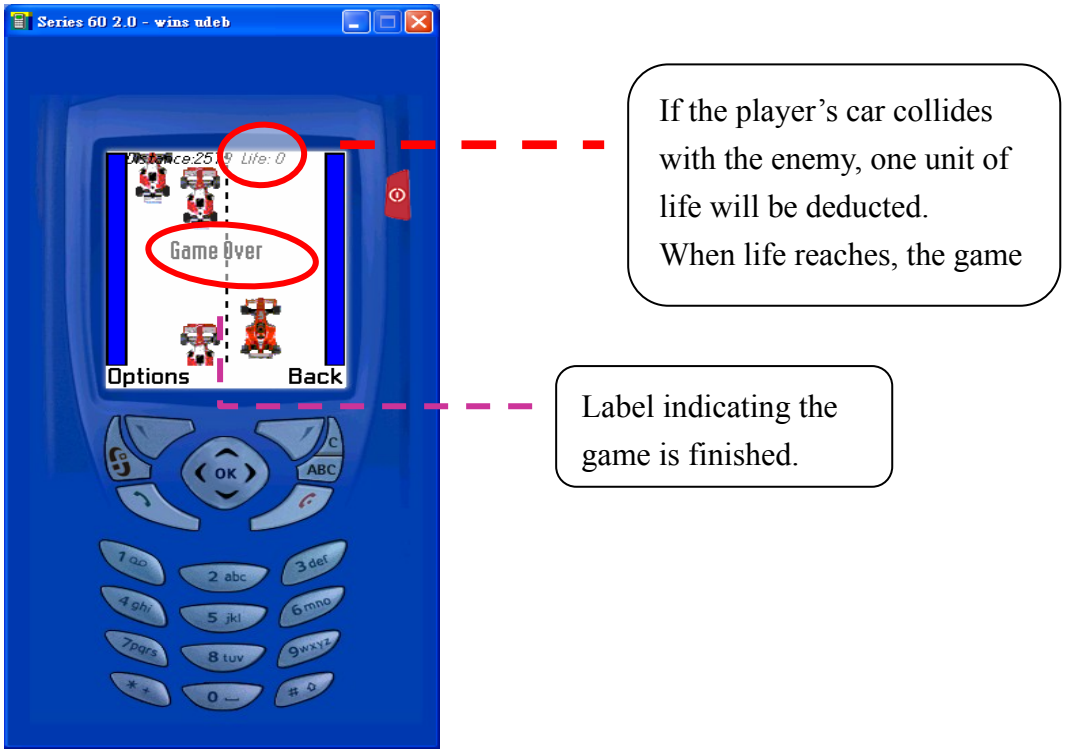


Figure 12.3

When the game is finished, the user needs to return to the main menu first. If the user wants to play again, press the play button.

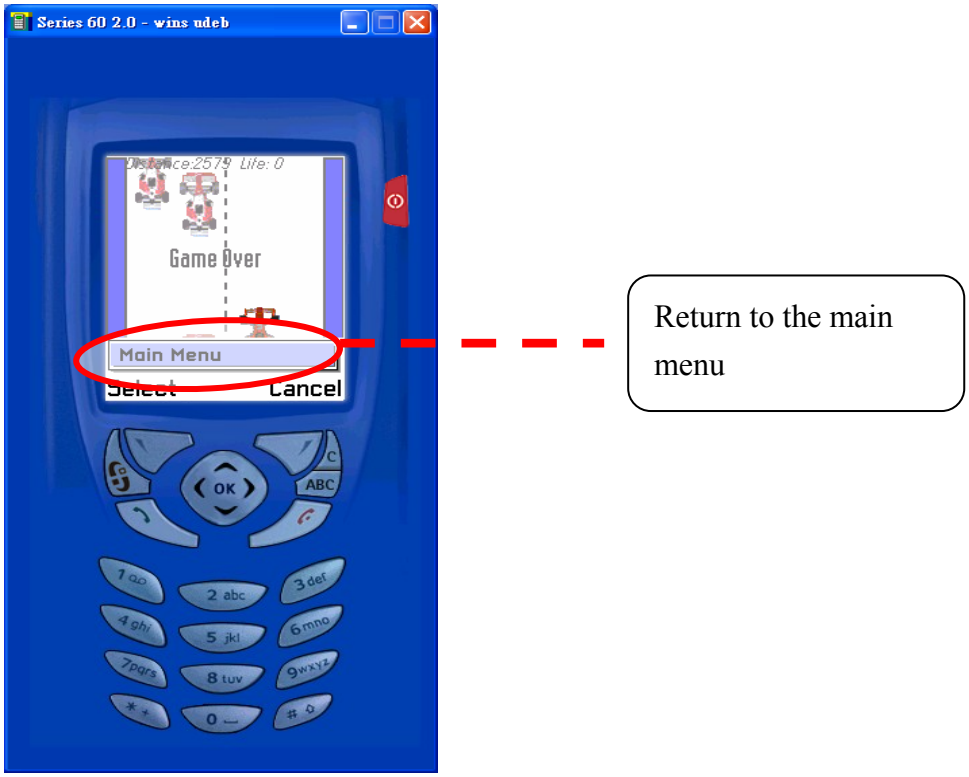


Figure 12.4

12.2 Sprite

The **Sprite** class helps to handle multiple frames, so that it can display multiple frames periodically. Thus, it creates the illusion of object's movement.

For example, a man walking might consist of three frames:

1. A man with both legs down.
2. A man with the right leg extended.
3. A man with the left leg extended.

You could then animate the man by calling the frames in sequence: 1, 2, 1,3,1,2, and so on using the Sprite class.

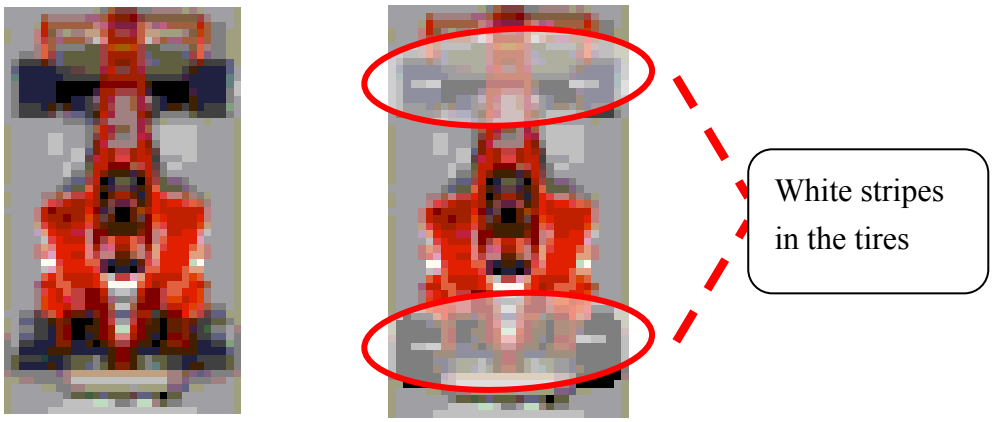


Figure 12.5 – images for sprite class

Notice that the two images in Figure 12.5 are nearly identical. The rightmost image, however, has white stripes in its tires. When these two frames are cycled quickly, it creates the illusion of speedy tire movement.

Since the use of Sprite class will consume more CPU power. In our game, only the player's car has used the Sprite class, while the enemies contain one frame only, so as to reduce the use of CPU power.

12.3 Collision Detection

Collision detection is an essential attribute of any game engine. Collision detection lets you know when two sprites are touching. Moreover, robust collision detection can make the game playing more interesting while a poor design collision detection may use a lot of computation power and thus reducing the smoothness of the game.

In our Car Racing Game, when the player's car collides with an enemy car, we will deduct one unit of energy. If the player loses all 100 energy units, the game is over. The question is, how can we implement fast but accurate collision detection on small, slow, resource-limited devices?

First, we will talk about some common collision detection techniques used in game programming. Then we will talk about our collision detection in the Car Racing Game.

12.3.1 Basic Collision Detection

The simplest form of collision detection is generally the fastest form. Each sprite and its image are treated as a rectangle. If one sprite's rectangle overlaps another sprite's rectangle, as in Figure 15.2, then we consider the sprites as having collided.

.

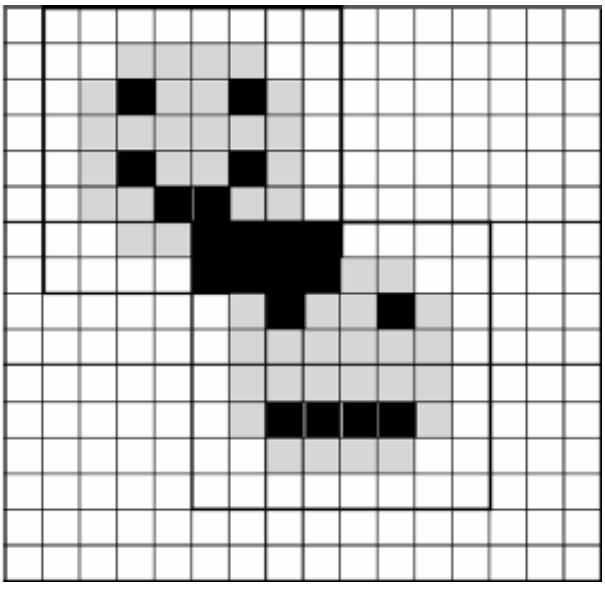


Figure 12.6 - Simple collision between two sprites

To implement this type of detection, you need to take the x position, y position, width, and height of two sprites and then do some simple math, as shown in the following.

```
public boolean collide(Sprite sprite)
{
    if ((x + width) > sprite.getX() &&
        x < sprite.getX() &&
        (y + height) > sprite.getY() &&
        y < sprite.getY())
        return true;
    return false;
}
```

However, most of the sprites are not actually rectangular. In our game, the racing car is shaped more like an "I". Using this kind of collision detection, the game might deduct energy from your car, even if the car doesn't touch any enemy.

12.3.2 Advance Collision Detection

In the previous section we talked about a way of detecting sprite collision using overlapping rectangles. This type of collision detection is very inaccurate. For instance, if the transparent corners of a ball sprite touch the corners of another ball sprite, the game will think they have collided. The player, however, will see two balls move past each other without touching. In this section, we will talk about several advanced detection techniques that can solve the above problem.

The techniques are:

1. Collision detection with multiple levels
2. Collision detection with multiple areas

Solution 1: Multiple Levels

The concept of multiple levels is that the object is separated into two

levels. For example, in shooting game, it needs to detect the collision of the bullet with the objects. The image of an object can be separated into two levels. The larger rectangle surrounds the entire object. The smaller rectangle, which is a child of the larger rectangle, denotes the center of the object. When a collision occurs, the game is told which level is hit.

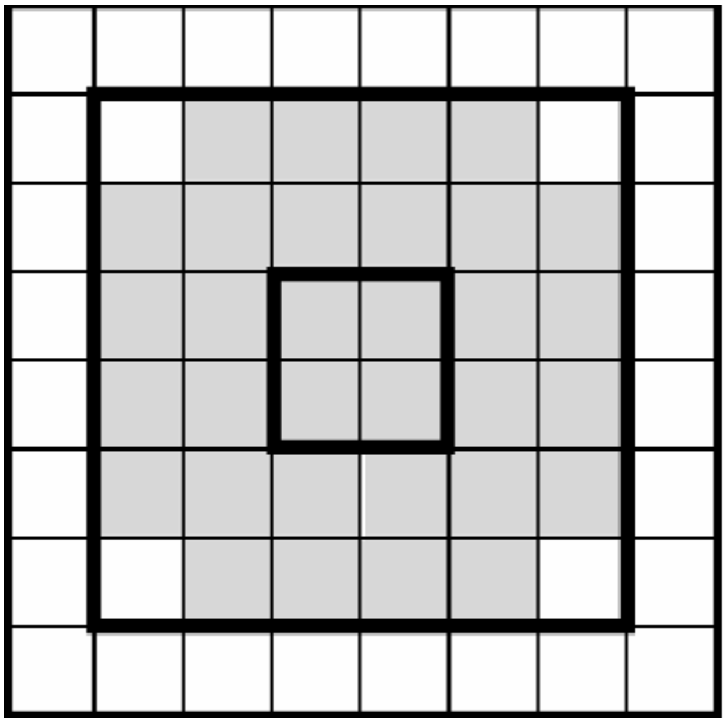


Figure 12.7 - Multiple levels of collision

Each level is represented by 4 attributes – upper-left coordinate (x, y) of the area, as well as the width and height. The following code shows how to detect a multilevel collision.

```
int areas[][] = {{0, 0, 10, 14} ,
{3, 2, 4, 11}};
public int collide(Sprite sprite)
{
    for (int i = 0; i < areas.length; i++)
    {
        if ((areas[i][0] + areas[i][2]) > sprite.getX() &&
            areas[i][0] < sprite.getX() &&
            (areas[i][1] + areas[i][3]) > sprite.getY() &&
            areas[i][1] < sprite.getY())
                return i;
```

```
        }
        return -1;
    }
```

The collide() method tests whether a given sprite has collided with a specific area. The method returns an integer value that represents the level number. The root level has a value 0. If there is no collision, -1 is returned. Thus by examining the value returned, we can know which level of the sprite is hit.

In reality, the game would need to make mxn comparisons for one collision. It is because it needs to check each area of one sprite against each area of another sprite. Therefore if one sprite has *m* areas, and the other one has *n* areas, mxn comparisons are needed.

Solution 2: Multiple Areas

A non-rectangular image can be partitioned into a finite number of rectangular parts. For example, the circle in figure xxx has been divided into three rectangles.

Any digital nonrectangular image can be partitioned into a finite number of rectangular parts.

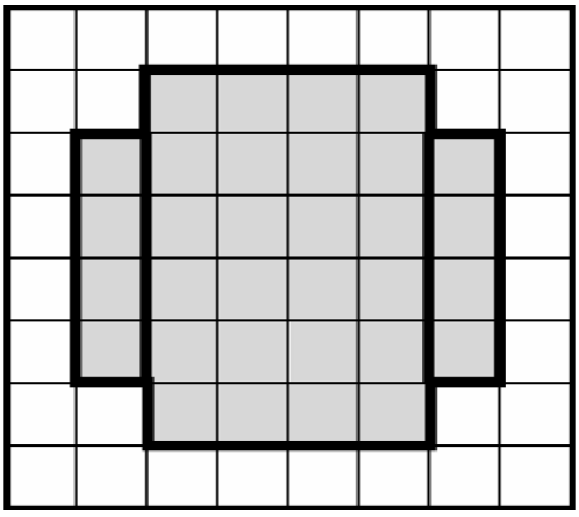


Figure 12.8 – Multiple areas of collision.

We can detect if two sprites have collided by checking every rectangle of one sprite against every rectangle of another. This type of collision detection is very accurate. However, the more rectangles your sprite is

made up of, the more checking iterations

Area collision detection can be implemented similarly to level detection. Simply create an array of a structure that contain four components (x, y, width and height).

```
int areas[][] = {{2, 1, 6, 3} , {3, 4, 4, 5} ,
{0, 9, 10, 14}};
public boolean collide(Sprite sprite)
{
    for (int i = 0; i < areas.length; i++)
    {
        if ((areas[i][0] + areas[i][2]) > sprite.getX() &&
            areas[i][0] < sprite.getX() &&
            (areas[i][1] + areas[i][3]) > sprite.getY() &&
            areas[i][1] < sprite.getY())

            return true;
    }

    return false;
}
```

The collide() method returns true if at least one of the parts collide with another sprite.

In our Car Racing Game, we have used the simplest method – treating the sprite as a rectangle (the basic collision detection) since in the mobile phone, the CPU speed is low. Moreover, in our game, we divide the screen into 4 columns. Therefore the enemies will only appear in one of the columns. This makes the collision detection in our game more accurate and simpler. The following code shows how we implement the collision detection.

```
int collision()
{
  for(x=0;x<NoOfEnemy;x++)
```

```
    {
      if(Enemy[x]->pos==iCar->centerX/columnWidth &&
           Enemy[x]->centerY+EnemyHeight >= iCar->centerY)

           return 1;
    }

    return 0;
}
```

The collision function return 1 only when the player's car is in the same column with the enemy (Enemy[x]->pos == iCar->centerX/ columnWidth) and when the rear part of the enemy hit the center of the player's car.

12.4 Conclusion

In this chapter, we have demonstrated that making use of the motion tracking engine is possible to game development. In our game, it can still play smoothly while using our motion tracking engine. It shows that the engine will not affect the smoothness of the games. Therefore, developers can use it to develop more robust and interactive games using the motion tracking engine.

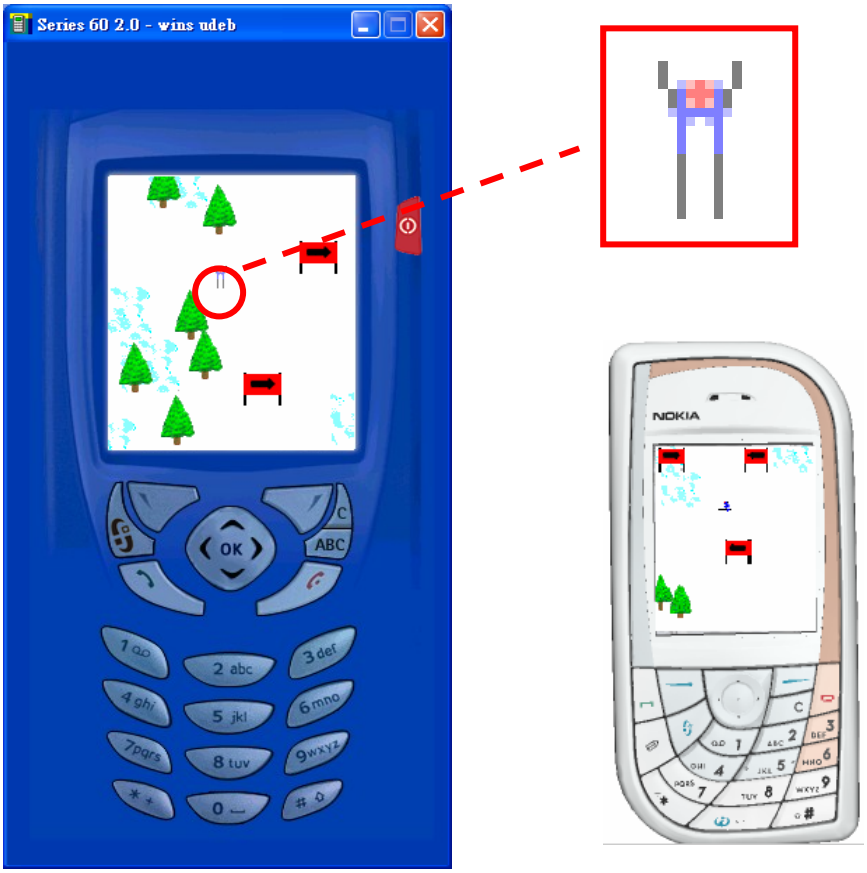
Chapter 13: Skiing Game

We have developed a rotation movement engine based on the translation movement algorithm developed. In order to test the possibilities of using the rotational engine in different applications, we have used the engine in a skiing game (The skiing game is a sample program obtained from the book "Developing Series 60 Applications: A Guide for Symbian OS C++ Developers")

13.1 Overview

The following shows how to play the skiing game with the rotation of the phone.

In this game, we define 6 levels with each level -2,-1, and 0,1,2,3. For example, level 1 means the phone has rotated right about 6 degree; level 2 means the phone has rotated right about 12 degree, etc… When the phone is upright, the skier will slide down vertically down the mountain.



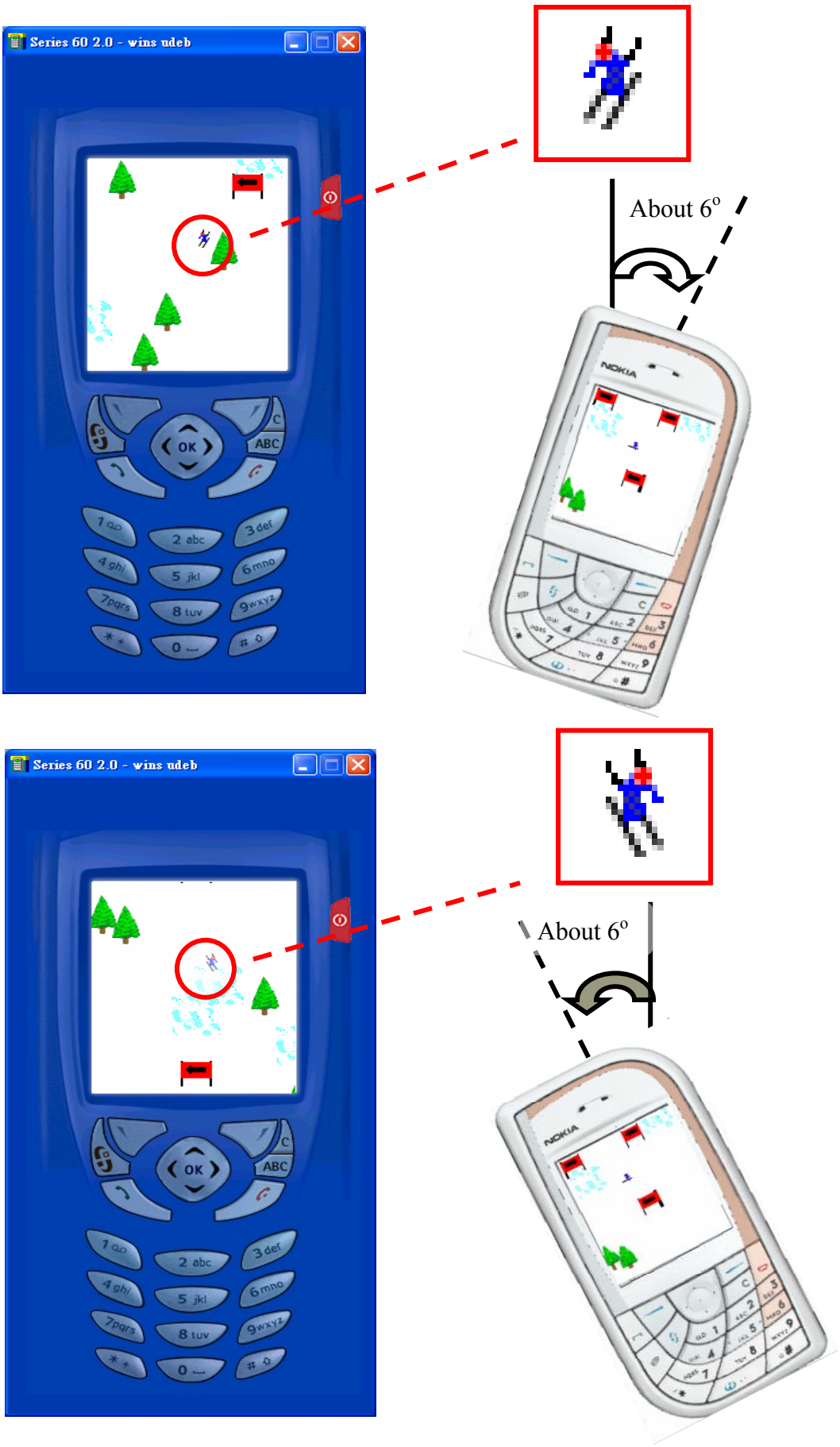


Figure 13.1 Skiing Game

13.2 Structure of the Skiing Game

In this section, we will talk about the structure of the skiing game, and how to use the rotation engine.

Common Routine

Some functionality needs to be available in multiple areas of the application, including methods to load bitmaps. This is implemented by using distinct namespaces. The file DoubleBufferArea.cpp implements many functions which help with the handling and rendering of bitmaps. The core part of the skiing game is the CSkiEngine class which is responsible for the game logic.

The Game View and Control

While the view class is responsible for handling key presses, the control handles the drawing of the user interface.

Game Engine

This class is responsible for the game logic and keeping check of the skier's status. It handles the pictures that are displayed. It also contains the timer functionality which is activated when the game starts.

Motion Tracking Engine

This class is responsible for tracking user's movement. By creating an instance of it in the Game Engine class, the engine will start to work automatically. The Game Engine can then use the tracking result to determine the status of the skier.

Chapter 14: Experimental Result

14.1 Computation load of SSD and SAD

There are two matching criteria commonly used in block matching algorithm, they are SAD and SSD. We have tested how much SAD is faster than SSD by a simple code. Recall that the equations of SAD and SSD are as follow:

$$SAD(x,y) = \sum_{i=1}^{N}\sum_{j=1}^{N} | X(i,j) - Y(i+x, j+y) | \qquad where\ |x,y| \le W$$

$$SSD(x,y) = \sum_{i=1}^{N}\sum_{j=1}^{N} [X(i,j) - Y(i+x, j+y)]^2 \qquad where\ |x,y| \le W$$

The code to test the performance of SSD is as follow:

```
for(int i=0; i<100; i++)
    for(int j=1; j<=1000000; j++){
        d = dataA[i] - dataB[i];
        sum += d*d;
    }
```

Code snippet 1

This code snippet carries out 100 million operation of SSD. The sum of squared difference is stored in "sum". This code snippet costs **922ms** to run in a 2.0GHz personal computer.

Similarly, the code to test the performance of SAD is as follow:

```
for(int i=0; i<100; i++)
    for(int j=1; j<=1000000; j++){
        sum+=abs(dataA[i] - dataB[i]);
    }
```

Code snippet 2

This code snippet carries out 100 million operation of SAD. The sum of absolute difference is stored in "sum". This code snippet costs **1297ms** to run. Surprisingly, absolute operation is much slower than multiplication operation. This is because in this code snippet, abs() function is called instead of doing simple arithmetic operation. Calling function involves procedure prolog which

produce a significantly large overhead when the function is called very frequently. In order to improve the speed of absolute operation, we handle the absolute operation by ourselves rather than use the Math class function, the code snippet become:

```
for(int i=0; i<100; i++)
    for(int j=1; j<=1000000; j++){
        sum+=dataA[k]>dataB[k]?dataA[k]-dataB[k]:dataB[k]-dataA[k];
        }
```

Code snippet 3

This code snippet costs **781ms** to run which is about 15% faster than snippet 1. This code snippet is more efficient because it doesn't involve function calling. In total, snippet 4 requires 1 comparison and jump operation (dataA[k]>dataB[k]?), 1 difference operation (dataA[k] – dataB[k] OR dataB[k] – dataA[k]), 1 summation operation and 2 for loop. This code snippet is not yet optimal, it is because dataA[] and dataB[] are image pixels arrays, accessing elements in these arrays cost a long time. To minimize the access of the image array and computation operations, we change the snippet to:

```
    for(int i=0; i<100; i++)
        for(int j=1; j<=1000000; j++){
            d = dataA[k] - dataB[k];
            if(d>=0) e+=d;
            else e-=d;
        }
```

Code snippet 4

This code snippet costs only **672ms** to run which is about 30% faster than snippet 1. This code snippet is more efficient than snippet 3 because it requires the same amount of computation operations while reduced the number of access of image arrays to two.

We concluded that computation load of SAD is smaller than that of SSD. With code snippet 4, SAD is about **30%** faster. Therefore, we would use code snippet 4 in the calculation of SAD matching criterion.

14.2 Improvement of ESA by SEA/PPNM

Testing Environment:

CPU – 2.0GHz Pentium 4

Block Matching Parameter:

Block Width	31 pixels
Block Height	31 pixels
Search Window Width	81 pixels
Search Window Height	81 pixels

Measuring Method:

In SEA and PPNM, SAD of the eliminated impossible candidate blocks needs not to be calculated. Thus we measure the performance of SEA and PPNM by counting the number of blocks involved in calculating the SAD.

Algorithm	# of blocks calculated in SAD	Speedup	Computation Time (x 5)	Speedup
ESA	6561	1.00	2140 ms	1.00
SEA+PPNM	2304	2.85	516 ms	4.15

SEA+PPNM algorithm show significant improvement in speed over ESA. It is about 4 times faster than ESA.

14.3 Enhancement of SEA/PPNM by PDE

Experiment of this part is carried out in the same testing environment using block matching parameter as before.

Measuring Method:

Since in PDE, condition “PSAD(x, y) > SAD(x, y)” is checked every time a

row of pixels' difference is added to partial sum PSAD, PDE reduces computation load in term of row (with size of 1 x 31) of pixel. Thus we measure the performance of PDE by counting the number of rows involved in calculating SAD.

Result:

Algorithm	# of rows of pixels' difference calculated	Speedup	Computation Time (x 5)	Speedup
ESA	203391	1.00	2140 ms	1.00
ESA+PDE	69024	2.95	500 ms	4.28

Since the code overhead of PDE is very small, time for checking "PSAD(x, y) > SAD(x, y)" condition is not significant and can be neglected. Speedup measured by numbers of rows of pixels involved in calculation is proportional to speedup measured by computation time.

Although PDE and SEA/PPNM improves speed of ESA in different aspect, they do affect each other. In our final algorithm, we have also used SEA and PPNM method. These two methods remove impossible candidates in a fast way and remain candidates that are quite close to the previous block. The remaining candidates enter SAD calculation stage and PDE method is used to improve the speed. Since the SAD of these candidates is close to that of the optimum block, removal rate of PDE is reduced. Below is a table showing speedup of PDE over SEA+PPNM algorithm:

Algorithm	# of rows of pixels' difference calculated	Speedup	Computation Time (x 5)	Speedup
SEA+PPNM	71734	1.00	516 ms	1.00
SEA+PPNM +PDE	64643	1.11	312 ms	1.65

From the above result, we can see that PDE still have significant speed up in computation time over the SEA+PPNM algorithm although its rate of removing impossible candidates is lower. Therefore, in our final algorithm, we included PDE method to improve the speed in calculating SAD.

Now With SEA+PPNM+PDE algorithm, the computation time for one

block is 62 ms (= 312 / 5 ms) on average. It has been fast enough to real-time track object but lagging level is still quite significant.

14.4 Enhancement by Spiral Scan Method

Comparison of Code overhead of Spiral Scan method with Raster Scan method:

Raster Scan method is very simple to implement. Here is the pseudo code:

```
for(j=TOPLEFTY; j<=TOPRIGHTY; j++){
    // For each row
    for(i=TOPLEFTX; i<=TOPRIGHTX; i++){
        // For each column
        SAD ();
    }
}
```

Spiral Scan method is a bit more complicated. The pseudo code has been optimized so that less computation is required:

```
SAD ();
for(d=1; d<=DX; d++){
    di = -d;
    dj = -d;
    for(k=0; k<(d<<3); k++){
        i = LeftTop_x_coord.  + di;
        j = LeftTop_y_coord.  + dj;
        SAD ();
        if(k<(d<<1))
            di ++;
        else if(k<(d<<2))
            dj ++;
        else if(k<((d<<2) + (d<<1)))
            di --;
        else
            dj --;
    }
}
```

Although spiral scan method has a bit higher code overhead, the overhead which is of the Big O of (DX^2) is less significant, when compared with the complexity of SAD which is of the Big O of (DX^2 BW^2).

We carried out an experiment to compare the performance of ESA and spiral ESA.

Algorithm	Computation Time (x 5)	Computation Time
ESA	2141 ms	428 ms
Spiral ESA	2156 ms	431 ms

The performance of spiral ESA is similar to ESA. However, it greatly improve the speed of algorithm when PDE/SEA/PPNM is used together assumed that most of the motion is center-biased. This assumption of center-biased motion is no longer an assumption when adaptive method is also used.

14.5 Enhancement by Adaptive Spiral Method

Performance of adaptive spiral method is evaluated by comparing the predicted motion vectors with the real motion vectors. Below is an extract of a list of blocking matching results of real-time motion tracking with an input video captured from web camera.

(Learning Rate = 1.0) i.e. Previous "Real" = Current "Expect"

Expect: 0 0 **Real: 0 0** Real dist.: 0.0 Adapt dist.: 0.0

Expect: 0 0 Real: 5 2 Real dist.: 5.4 Adapt dist.: 5.4

Expect: 5 2 Real: 7 0 Real dist.: 7.0 Adapt dist.: 2.8

Expect: 7 0 Real: 8 1 Real dist.: 8.1 Adapt dist.: 1.4

Expect: 8 1 Real: 9 0 Real dist.: 9.0 Adapt dist.: 1.4

Expect: 9 0 Real: 9 0 Real dist.: 9.0 Adapt dist.: 0.0

Expect: 9 0 Real: 12 -2 Real dist.: 12.2 Adapt dist.: 3.6

Expect: 12 -2 Real: 8 -2 Real dist.: 8.2 Adapt dist.: 4.0

Expect: 8 -2 Real: 2 -2 Real dist.: 2.8 Adapt dist.: 6.0

Expect: 2 -2 Real: -1 0 Real dist.: 1.0 Adapt dist.: 3.6

Expect: -1 0 Real: -4 0 Real dist.: 4.0 Adapt dist.: 3.0

Expect: -4 0 Real: -6 0 Real dist.: 6.0 Adapt dist.: 2.0

Expect: -6 0 Real: -16 3 Real dist.: 16.3 Adapt dist.: 10.4

Expect: -16 3 Real: -19 4 Real dist.: 19.4 Adapt dist.: 3.2

Expect: -19 4 Real: -13 2 Real dist.: 13.2 Adapt dist.: 6.3

```
Expect: -13  2  Real: -12  0    Real dist.: 12.0  Adapt dist.: 2.2
Expect: -12  0  Real: -17 -2    Real dist.: 17.1  Adapt dist.: 5.4
Expect: -17 -2  Real: -14 -1    Real dist.: 14.0  Adapt dist.: 3.2
…
Expect:   5  0  Real:   8 -1    Real dist.: 8.1   Adapt dist.: 3.2
Expect:   8 -1  Real:   6  0    Real dist.: 6.0   Adapt dist.: 2.2
Expect:   6  0  Real:   6  0    Real dist.: 6.0   Adapt dist.: 0.0
Expect:   6  0  Real:   5  0    Real dist.: 5.0   Adapt dist.: 1.0
Expect:   5  0  Real:   4  0    Real dist.: 4.0   Adapt dist.: 1.0
Expect:   4  0  Real:   4  0    Real dist.: 4.0   Adapt dist.: 0.0
Expect:   4  0  Real:   2  0    Real dist.: 2.0   Adapt dist.: 2.0
Expect:   2  0  Real:   1  0    Real dist.: 1.0   Adapt dist.: 1.0
Expect:   1  0  Real:   1  0    Real dist.: 1.0   Adapt dist.: 0.0
…
Average Real dist.: 7.5752 Average Adapt dist.: 2.7201
```

Each row of this list is printed every time the adaptive spiral algorithm is run. In this list, "Expect" is the predicted motion vector, and "Real" is the real optimum motion vector found by the algorithm. Both are represented by <x-axis movement, y-axis movement of tracking object in term of pixels >. The physical meaning of "Real dist" is the distance between non-adaptive search window's center (or say previous block position) and optimum position while "Adapt dist." is the distance between adaptive search window's center and optimum position. They are calculated by:

$$\textit{Real dist.} = \sqrt{(optimal\ \ x-axis\ \ movement)^2 + (optimal\ \ y-axis\ \ movement)^2}$$

$$\textit{Adapt dist.} = \sqrt{(predicted\ \ x-axis\ \ movement)^2 + (predicted\ \ y-axis\ \ movement)^2}$$

These distances are equivalent to the length of the corresponding motion vectors. The smaller these distances, the faster the algorithm runs. If "Real dist." is smaller than "Adapt dist." on average, non-adaptive spiral algorithm would run faster. If "Real dist." is larger than "Adapt dist." on average, adaptive spiral algorithm would run faster. For natural motion, we observed that the "Adapt dist." is much smaller than "Real dist.", which means adaptive spiral algorithm is preferred. The input video used in this experiment contains

an object moving naturally, it is observed that the "Adapt dist." is always smaller than the "Real dist.". On average, Adapt dist. is 2.7201 while real dist. is 7.5752. We can see that the average adapt dist. is smaller, thus adaptive spiral algorithm run faster.

14.6 Performance of the Translational Tracking Engine on Symbian

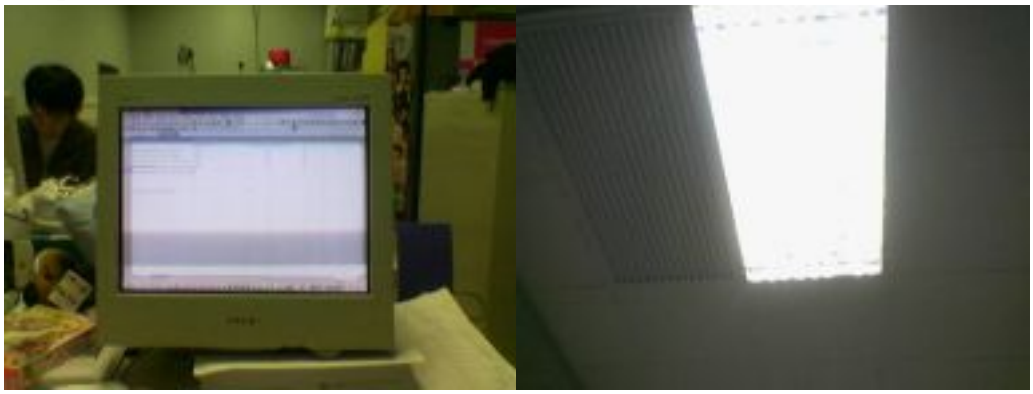
After we have developed our tracking engine, we have done some tests to evaluate the speed of the engine. The experiments are conducted as follow:

1. Define several patterns of movement
2. Apply each pattern of movement on different backgrounds, e.g. indoor, outdoor, bright and dark environment
3. Count the times of running the tracking algorithm in **t** seconds
4. Running time of the tracking algorithm is calculated by **t**/count

In this experiment, since we just want to evaluate the speed of the tracking algorithm. We need to be caution that the tracking block should not be out of the screen; otherwise feature selection will also be triggered.

Every time, a frame is ready, the tracking algorithm will be called 10 times. The frame rate in Symbian phone is 14 frames/sec. That means the interval between each frame is about 0.07s. If the tracking algorithm runs longer than 0.07s, the display will be lag. If the algorithm is fast enough, then in one second, it should have been called 14x10 = 140 times, thus the speed of the algorithm should be smaller or equal to 1/140 = 7ms.

The following figures show the results obtained by conducting the experiments in different environments.



a	B
c	D
e	f
g	h
i	

Figure 14.1 (a) monitor (b) luminous lamp (c) plasma (d) whiteboard
(e) door (f) outdoor (g) blue-white wall (h) tree (i) white wall

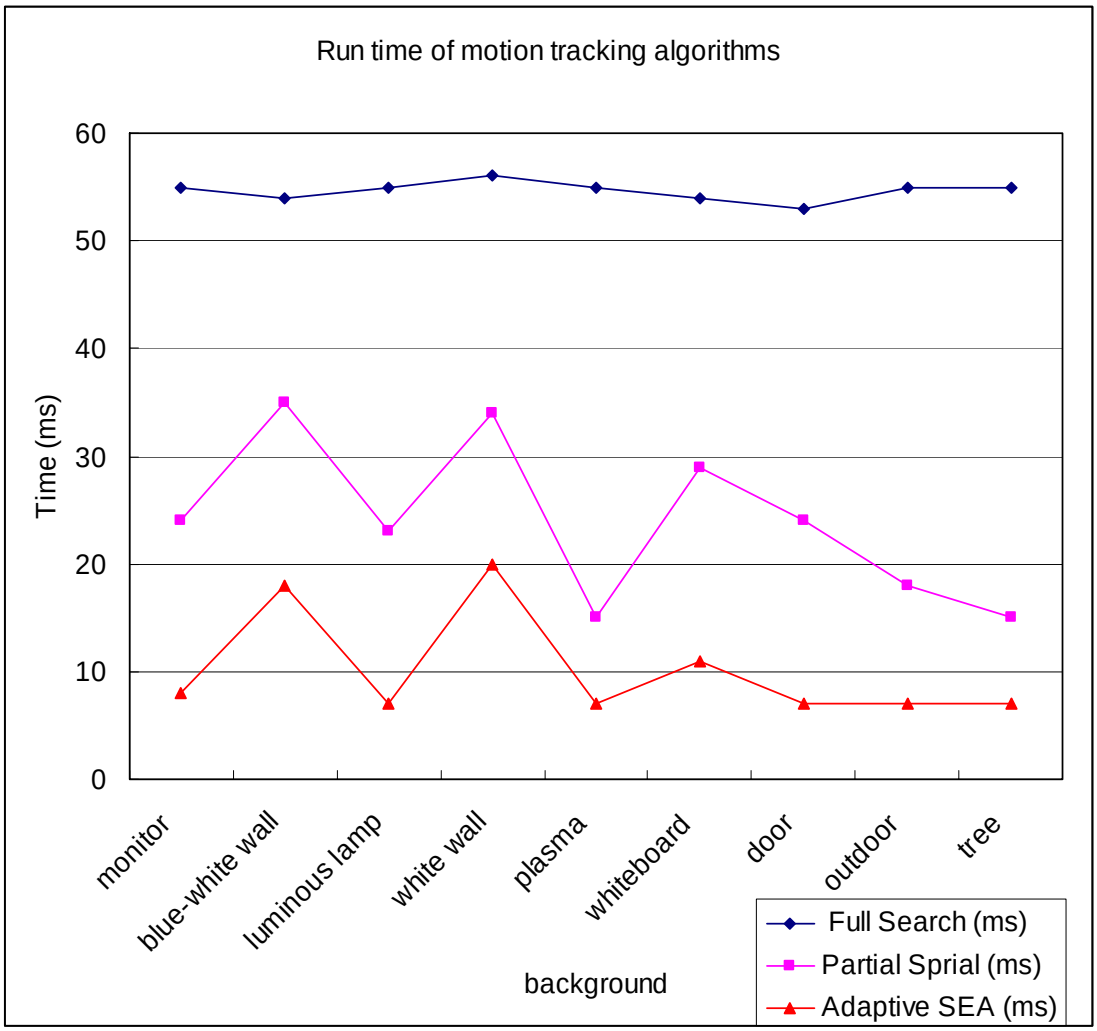


Figure 14.2 – Comparing the speed of different algorithms

14.6.1 Analysis

From the above experimental result, we can find that the run time for the Full Search is nearly constant in any kind of environment. This is true that for Full Search, all the candidate blocks are examined, regardless of the environment. Therefore, it should have constant running time. And when using the exhaustive search, the display appears to be lag as expected.

For Partial Spiral Search algorithm, we have made use of Partial Distortion Error (PDE) and Spiral Scan order. It will reject a candidate block if the error has already exceeded the error for the current best match.

Thus, with this early rejection mechanism, this algorithm runs faster than the Full Search. However, the speed of the algorithm will be affected by the background. This is because, in some background, eg flat region, all the candidate blocks have similar error with the feature block and hence cannot find a good feature block for tracking. Therefore, we cannot take advantage of PDE, and the run time varies.

For our final algorithm, the run time varies slightly in different backgrounds. The reasons are similar to the reasons in Partial Spiral Search that the performance of the algorithm will be affected if it cannot find a good feature block for tracking. Thus, it showed that finding a good feature block is very important.

Although the run time of our final algorithm varies slightly in different environment, we can see that it is capable of running at a speed of about 7ms. That means using our tracking algorithm will not make the display appear to be lag.

14.7 Performance of the Rotational Tracking Engine

After we have developed our rotational tracking engine, we have done some tests to evaluate the accuracy of the engine. The experiments are conducted as follow:

1. Rotate the phone from vertical to horizontal level
2. Record the angle measured by the rotational tracking algorithm
3. Repeat the above 2 processes in different backgrounds

The following figures show the results obtained by conducting the experiments in different environments.

1	2
3	4
5	6
7	8

Figure 14.3 (1) background 1 (b) background 2 (c) background 3 (d) background 4 (e) background 5 (f) background 6 (g)background 7l (h) background 8

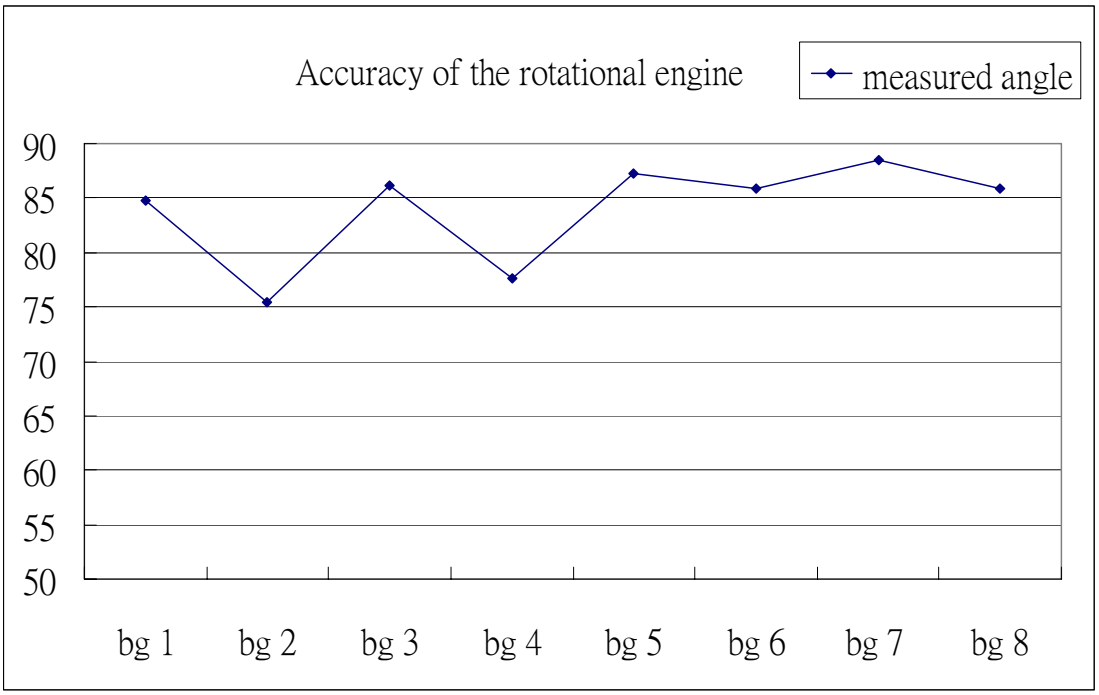


Figure 14.2 – Comparing the accuracy of the algorithm in different backgrounds

14.7.1 Analysis

From the above experiment, our rotational algorithm can give a accurate result close to the actual angle rotated. However, there are some cases that the rotational tracking engine does not perform well. It is because, in these backgrounds, the feature block is found on an edge. When the phone rotates, the best match found has the same problem as in the problem mention is Chapter 8 “Enhance Feature Selection”, Figure 8.1. Thus, if a feature block is found on an edge, this will make the accuracy of the engine to decrease.

Chapter 14: Project Schedule

The table below lists the our schedule:

Month	Task Completed
June 2004	Plan the aim and approach of our FYP project
	Learn the basic of Symbian OS Architecture
July 2004	Get familiar with the programming environment of Symbian and learn the Symbian programming Language
	Learn Bluetooth programming
August 2004	Get familiar with the programming environment of Microsoft Visual C++ and learn MFC programming
	Study motion tracking and block matching algorithm
	Learn OpenCV programming
September 2004	Implement Exhaustive Search Algorithm (ESA) on PC using MFC and OpenCV
	Implement Three Step Search (TSS) block matching algorithm
	Compare performance of SAD and SSD matching criteria
	Implement Successive Elimination Algorithm (SEA) and PPNM algorithm
October 2004	Implement Partial Distortion Elimination (PDE)
	Implement Spiral Scan method and Adaptive Search Window Method
	Finalize the algorithm used for real-time motion tracking: Adaptive Spiral SEA PPNM PDE algorithm
	Make a pong game using C# on PC using web camera as video capture device and our motion-tracking algorithm output as input method
	Construct a "MotionTrack" Symbian program that can capture video using the onboard camera
November 2004	Implement the final algorithm in the "MotionTrack"

	program
	Fine tuning the algorithm in "MotionTrack" to yield best result, e.g. the block matching parameters
	Develop a pong game on Symbian on the top of the "MotionTrack" program
	Prepare First Term presentation and demonstration
	Write First Term FYP report
December 2004	Develop rotation tracking engine
	Design adaptive window method for rotation tracking engine
January 2005	Study Bluetooth programming technique on Windows and Symbian
	Develop virtual mouse application
	Study game programming on Symbian
February 2005	Study graphical programming on Symbian
	Develop car racing game
March 2005	Develop ice skiing game
April 2005	Improve feature selection algorithm
	Prepare Second Term presentation and demonstration
	Write FYP report

Chapter 16: Contribution of Work

16.1 Introduction

Now, I am going to state my contribution of work and the knowledge gained through this project.

Our FYP project can mainly be divided into three parts; they are the testing platform part, the algorithm part and the application part. All of these parts are essential yet difficult to implement. During the summer time before this semester, my partner and I have already learnt many things that are to be used in our FYP project. This makes us well prepared to do the FYP and have enough time to do this project.

16.2 Preparation of Work

During the summer time, I have learnt the Symbian OS Architecture and have learnt how to program applications on Symbian phone. Programming on Symbian is not as easy as that on window and is a bit tedious. It requires quite a number of steps: compile, build, make install file, transfer the install file to Symbian phone, receive and install the program before I can really run and test my application on Symbian phone. The Symbian emulator on window saves me much time on developing applications, but when it comes to some applications that require Bluetooth connection and need to access camera function, I can't rely on the Symbian emulator and must be tested on real Symbian phone. However, I enjoy programming on Symbian. Part of the reason is that it is highly object-oriented. Concept of class and hierarchy are highly required during programming on Symbian because the basic structure of every Symbian application involves many classes including hierarchical classes. I have learnt a lot of object-oriented programming techniques during making the Symbian applications. When trying to make some Symbian applications during the summer time, I mainly focus on studying the image manipulation function and Bluetooth communication method on Symbian. I have made a simple application testing how to capture video and access pixels in the image frame of the video, and also an application testing how to connect two Bluetooth devices and send message between them. This experience facilitates me to build the

testing platform on Symbian and make the application using Bluetooth to communicate.

Apart from learning Symbian, I have also learnt to use Window MFC with OpenCV library. Programming MFC is not easy, but it is at least easier than programming on Symbian.

The most important thing and the most useful thing that I have learnt during the summer time is the method of tracking object's motion. I have studied many kinds of methods ranged from optical flow method to block matching method. We at last agreed and chose to use block matching method as the motion tracking algorithm for our application.

16.2 The Algorithm Part

After we have chosen to use block matching method, I have studied many papers about motion tracking using block matching algorithm. Some papers suggested some algorithms that claimed to have improvement over older methods. I have tested the performance of those algorithms and finally agreed with my partner to use some of them as part of the final algorithm we used. Apart from using the existing algorithm, I have designed a method that improve over the existing algorithm to suite the need of our applications, and that is adaptive spiral method.

After translational motion tracking algorithm was finished, we planned to develop an engine that detect rotational motion. We observed that translational motion tracking engine can track firmly when the phone is rotated, we come up an idea to make use of this property to construct the rotation tracking engine. Since adaptive window method for rotation tracking algorithm is different, I have worked out an equation to predict the position of tracking block and this equation is capable of predicting both linear and circular motion. A simple application is made to illustrate the rotational motion tracking result.

At last, feature selection algorithm is modified. Since the previously used algorithm has the deficiency of regarding edge as a good feature which is in fact not a desirable feature for motion tracking. We have developed a new feature selection algorithm that can avoid finding edge feature and make use of variance

to select complex feature block.

16.3 The Testing Platform Part

With the knowledge of programming window MFC and OpenCV, we worked together for a few days to build up a testing platform on window so that we can test and implement algorithms on it at the start of this semester. In order to facilitate the performance testing, we have continued to improve the program to facilitate us to debug and fine tune the algorithms.

After we have come up with the final algorithm, we built a testing platform on Symbian which is also capable to convert to a real application using the motion tracking result as motion input. After the overall framework of the testing platform was completed, I implemented some of block matching algorithms including our final algorithm on Symbian. Because the data types and methods in Symbian and window are not the same, those that are implemented on window can't be used directly on Symbian and must be re-implemented again.

16.4 The Application Part

After the final algorithm of the MotionTrack application has successfully been implemented, I am currently working on the virtual mouse application that uses the tracking result to control the cursor movement on desktop PC. Since this application involves Bluetooth programming on window and requires accessing window cursor, I am still studying the way to program it and implementation of this application is in progress.

After the algorithm part was finished, we developed the virtual mouse application. As this application adopts Bluetooth as the wireless communication method and we was not familiar with Bluetooth at first, we studied Bluetooth programming on Symbian and Windows.

At last, we have also implemented our rotation tracking engine into the Skiing game in order to illustrate the use of the engine.

16.5 Conclusion

In conclusion, I have learnt MFC programming, OpenCV programming, Symbian programming and many motion tracking algorithms in this semester. I have got familiar with Visual C++ and the ways to debug window program and Symbian program on it. My partner and I have worked together to implement many block matching algorithms and the two testing platform on window and on Symbian. And finally, we succeed to make a real application that makes use of the onboard camera as the motion input.

Using the final version of translational motion tracking algorithm, rotation tracking algorithm is implemented. Some methods are used to improve its reliability and its speed is improved by adaptive method. A useful application, Virtual Mouse, which fully utilizes the function of translational motion tracking engine is then made. A game, Skiing game, which fully utilizes the function of rotation tracking engine is modified to demo our engine.

Chapter 17: Conclusion

In this project, the major difficulties are the speed and accuracy of the motion tracking, because our objective is to develop a real-time motion tracking algorithm which can be used in camera-based mobile devices. We have studied a lot of motion tracking algorithms and done experiments to investigate their performance. The results show that in order to have high accuracy, we cannot use the fast-search algorithms. Hence, we decided to use the most accurate block-matching algorithm – The Exhaustive Search Algorithm and tried to improve the speed of the tracking while stilling preserving a high accuracy.

We tried many methods to increase the speed of the exhaustive search algorithm. Finally, we developed new algorithms (Adaptive Search Window, Spiral Search and Feature Selection) and combined the proposed algorithms with the exhaustive search algorithm. As a result, the accuracy and speed are improved significantly. On top of the translational motion tracking engine, we build the rotational motion tracking engine which can support detection of the rotational movement of the phone.

Besides, we studied OpenCV which is a Open Souce Computer Vision Library and MFC in the summer so that we developed a testing platform in the PC to test the performance of motion tracking algorithms. The testing platform provided a good

environment for us to develop the motion tracking algorithm in a generic way that it can be used in any devices with camera integrated and are programmable. After tested thoroughly in the PC, we test the performance of our motion tracking algorithm on the Symbian phone and fine tune the algorithm.

Finally, we have developed real-time motion tracking applications in the Symbian phone – Nokia 6600. Now, the applications can track the movement in real-time. We concluded that our algorithm would work well in other kinds of mobile device, because its performance was already good in Symbian phone which has very limited computation power and resources.

The last but not least, we can make use of the motion vectors found as an innovative input method to many applications, such as virtual mouse, car racing, skiing and other camera-based games. The motion tracking applications in the Symbian showed the possibilities of developing other interesting applications, such as the motorcycle game that we have mentioned in the introduction, by using a camera.

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Chapter 19: Reference

1. J.N. Kim, S.C. Byun, B.H. Ahn, “Fast full search motion tracking algorithm using various matching scans in video coding,” Journal of Electronic Imaging / October 2002 / Vol. 11(4)
2. J.N. Kim and T.S. Choi, ‘‘A fast three-step search algorithm with minimum checking points using unimodal error surface assumption,’’ IEEE Trans. Consum. Electron. 44(3), 638–648 (1998).
3. R. Li, B. Aeng, and M.L. Liou, ‘‘A new three-step search algorithm for block

motion tracking,'' IEEE Trans. Circuits Syst. Video Technol.4, 438–442 (1994).

4. J.U. Tham, S. Ranganath, M. Ranganath, and A.A. Kassim, ''A novel unrestricted center-biased diamond search algorithm for block motion tracking,'' IEEE Trans. Circuits Syst. Video Technol. 8, 369–377 (1998).
5. S. Zhu and K.K. Ma, ''A new diamond search algorithm for fast block-matching motion tracking,'' IEEE Trans. Image Process. 9, 287–290 (2000).
6. J. Chalidabhongse and C.-C. J. Kuo, ''Fast motion vector estimation using multiresolution-spatio-temporal correlations,'' IEEE Trans. Circuits Syst. Video Technol. 7, 477–488 (1997).
7. H.S. Oh and H.K. Lee, ''Adaptive adjustment of the search window for block-matching algorithm with variable block size,'' IEEE Trans. Consum. Electron. 44(3), 659–666 (1998).
8. K.W. Lim, B.C. Song, and J.B. Ra, ''Fast hierarchical block matching algorithm utilizing spatial motion vector correlation,'' Proc. SPIE 3024, 284–292 (1997).
9. J.C. Tsai, C.H. Hsieh, S. K.Weng, and M. F. Lai, ''Block-matching motion tracking using correlation search algorithm,'' Signal Process. Image Commun. 13, 119–133 (1998).
10. B. Liu and A. Zaccarin, ''New fast algorithms for the estimation of block motion vectors,'' IEEE Trans. Circuits Syst. Video Technol. 3, 148–157 (1991).
11. W. Li and E. Salari, ''Successive elimination algorithm for motion tracking,'' IEEE Trans. Image Process. 4, 105–107 (1995).
12. H. S. Wang and R.M. Mersereau, ''Fast algorithms for the estimation of motion vectors,'' IEEE Trans. Image Process. 8, 435–438 (1999).
13. X.Q. Gao, C.J. Duanmu, and C.R. Zou, ''A multilevel successive elimination algorithm for block matching motion tracking,'' IEEE Trans. Image Process. 9, 501–504 (2000).
14. T.M. Oh, Y.R. Kim, W.G. Hong, and S.J. Ko, ''A fast full search motion tracking algorithm using the sum of partial norms,'' Proc ICCE, pp. 236–237 (2000).
15. C. H. Cheung and L. M. Po, "Generalized Partial Distortion Search Algorithm For Fast Block Motion Estimation," 2001 IEEE International conference on Acoustics, Speech, and Signal Processing, vol. 3, pp. 1601-1604, May 2001, Salt Lake City, USA.
16. Y.C. Lin and S.C. Tai, ''Fast full-search block-matching algorithm for

motion-compensated video compression,'' IEEE Trans. Commun. 45, 527–531 (1997).

17. J.N. Kim and T.S. Choi, ''Adaptive matching scan algorithm based on gradient magnitude for fast full search in motion tracking,'' IEEE Trans. Consum. Electron. 45, 762–772 (1999).
18. F. Dufaux and F. Moscheni, "Motion tracking Techniques for Digital TV: A Review and a New Contribution", Proceedings of the IEEE, Vol 83, No.6, June 1995, pp. 123-134.
19. H. Gharavi and M. Mills, "Block-Matching Motion tracking Algorithms – New Results", IEEE Transactions on Circuits and Systems, Vol 37, No.5, May 1990, pp.649-651.
20. J.Jain and A Jain, "Displacement Measurement and its Application in Interframe Image Coding", IEEE Transactions on Communications, Vol. 29, No 12, December 1981, pp. 1799-1808.
21. J.Koga, K. Iiunuma, A. Hirani, Y. Iijima, and T.Ishiguro, "Motion Compensation Interframe Coding for Video Conferencing", Proceedings of the National Telecommunications Conference, 1981, pp. G5.3.1-5.3.5.
22. W. Lee, Y. Kim, R.J. Gove, and C.J. Read, "Media Station 5000: Integrating Video and Audio", IEEE Multimedia, Vol. 1, No. 2, 1994, pp.50-61.
23. R Shrinivasan and K Rao, "Predictive Coding Based on Efficient Motion tracking", IEEE Transaction on Communications, Vol. 33, No. 8, August 1985, pp. 888-896.
24. Netravali and B. Haskell, "Digital Pictures: Representation, Compression, and Standards", Plenum Press, New York, 1995.
25. B. K. P. Horn and B. G. Schunck, "Determining optical flow," Artif. Intell., vol. 17, pp. 185–203, 1981.
26. S. S. Beauchemin and J. L. Barron. "The Computation of Optical Flow". ACM Computing
27. J. L. Barron, D. J. Fleet and S. S. Beauchemin. "Performance of Optical Flow Techniques".
28. M. J. Black. "Robust Incremental Optical Flow". PhD thesis, Yale University, 1992
29. C.-H. Lee and L.-H. Chen, "A Fast Motion Estimation Algorithm Based on the Block Sum Pyramid," IEEE Trans. Image Processing, vol. 6, pp. 1587-1591, Nov. 1997.
30. B. Zeng, R. Li, and M. L. Liou, "Optimization of fast block motion estimation algorithms," IEEE Trans. Circuits Syst. Video Technol., vol. 7, pp. 833-844, Dec. 1997.

31. T. Koga, et. al., “Motion-compensated interframe coding for video conferencing,” in Proc. Nat. Telecommunications Conf., New Orleans, LA, Dec. 1981. pp. G5.3.1-G5.3.5
32. J. R. Jain and A. K. Jain, “Diaplacement measurement and its application in interframe image coding,” IEEE Trans. Commun., vol. COM-29, pp. 1799-1808, Dec. 1981.
33. L.-K. Liu and E. Feig, “A block-based gradient decent search algorithm for Block motion estimation in video coding,” IEEE Trans. Circuits Syst. Video Technol., vol. 6, pp. 833-844, Aug. 1996.
34. L.-M. Po and W.-C. Ma, “A novel four-step search algorithm for fast block motion estimation,” IEEE Trans. Circuits Syst. Video Technol., vol. 6, pp. 3133-316, Jun. 1996.
35. C. W. Lam, L. M. Po and C. H. Cheung, "A New Cross-Diamond Search Algorithm for Fast Block Matching Motion Estimation", Proceeding of 2003 IEEE International Conference on Neural Networks and Signal Processing, pp. 1262-1265, Dec. 2003, Nanjing, China.
36. C. Zhu and L. M. Po, "Partial distortion sensitive competitive learning algorithm for optimal codebook design," IEE Electronics Letters, vol. 32, no. 19, pp. 1757-1758, Sept. 1996.
37. C. H. Cheung and L. M. Po, "Adjustable Partial Distortion Search Algorithm for Fast Block Motion Estimation," IEEE Trans. on Circuits and Systems for Video Technology, Vol.13, No. 1, pp. 100-110, Jan. 2003.
38. C. Zhu, X. Lin, L. P. Chau, and L. M. Po, "Enhanced Hexagonal Search for Fast Block Motion Estimation," IEEE Trans. on Circuits and Systems for Video Technology, vol. 14, Issue 10, pp. 1210 - 1214, Oct. 2004.
39. C. H. Cheung and L. M. Po, "Novel Cross-diamond-hexagonal Search Algorithms for Fast Block Motion Estimation," IEEE Trans. on Multimedia, vol. 7, No. 1, pp. 16 - 22, Feb 2005.
40. E. Dubois and J. Konrad, “Estimation of 2-D motion fields from image sequences with application to motion-compensated processing,” in Motion Analysis and Image Sequence Processing, M. I. Sezan and R. L. Lagendijk, Eds. Boston, MA: Kluwer, 1993.
41. C. H. Cheung and L. M. Po, "A Fast Block Motion Estimation Using Progressive Partial Distortion Search", 2001 International Symposium on Intelligent Multimedia, Video and Speech Processing, pp. 506-509, May 2001.
42. J. K. Aggarwal and N. Nandhakumar, “On the computation of motion from sequences of images—A review,” Proc. IEEE, vol. 76, pp. 917–935, Aug.

1988.

43. D. H. Ballard and O. A. Kimball, “Rigid body motion from depth and optical flow,” Comput. Vis., Graph. Image Processing, vol. 22, pp. 95–115, 1983.
44. H. Shariat and K. E. Price, “Motion estimation with more than two frames,” IEEE Trans. Pattern Anal. Machine Intell., vol. 12, no. 5, pp. 417–433, 1990.
45. T. J. Broida and R. Chellappa, “Estimation of object motion parameters from noisy images,” IEEE Trans. Pattern Anal. Machine Intell, vol. PAMI-8, no. 1, pp. 90–99, 1986.
46. C. W. Ting, L. M. Po and C. H. Cheung, "Center-Biased Frame Selection Algorithms For Fast Multi-Frame Motion Estimation in H.264", Proceeding of 2003 IEEE International Conference on Neural Networks and Signal Processing, pp. 1258-1261, Dec. 2003, Nanjing, China.
47. H. C. Longuet-Higgins, “A computer algorithm for reconstructing a scene from two projections,” Nature, vol. 293, pp. 133–135, 1981.
48. C. H. Cheung and L. M. Po, " A Novel Block Motion Estimation Algorithm with Controllable Quality and Searching Speed", 2002 IEEE International Symposium on Circuits and Systems, vol. 2, pp. 496-499, May 2002, Scottsdale, Arizona
49. J. Bouquet and P. Perona, “Visual navigation using a single camera,” in Proc. 5th Int. Conf. Comput. Vision, 1995.
50. J.J. Francis and G. de Jager, “*A Sum Square Error based Successive Elimination Algorithm for Block Motion Estimation”,* 2002

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Appendix 1: API Documentation

Below is the API documentation written for developers:

Class CVideoEngine

This class contains the code that implements both the translational and rotational motion tracking engine. When this class is created and initialized, camera capturing and motion tracking engine functionality will be set up. Upon creation, this class requires a parameter which should be the View class. This View class is required to implement certain functions that are called every time motion tracking result is produced. Those functions can be used to display out the result. In order to increase the speed of our algorithm, many variables are set as macro variables to reduce loading of frequently used variable from main memory. These variables are shown below and are subjected for developer to change if applicable.

Macro variables

Format: <Variable name> <Default value>: Description

Feature Selection parameters

FBW 15: Feature block width

FBH 15: Feature block height

FSTEP 1: Pixel to skip after scanning 1 pixel in the feature block

FBx 3: Min. x-distance between feature blocks

FBy 3: Min. y-distance between feature blocks

FNox 26: Number of candidate feature blocks in a row

FNoy 26: Number of candidate feature blocks in a column

VARThreshold 200: Min. variance a feature block will be selected

PDEThreshold 44000: Min. SSD of a feature block with its nearby block

Rotation Tracking parameters

AngleThreshold 0.174532925199: Difference in slope between two tracking blocks in order to increment the angle level by 1

Motion Tracking parameters

BW 8: Half block width of tracking block

BH 8: Half block height of tracking block

BW2 17: BW*2+1

BH2 17: BH*2+1

BW4 289: BW2*BW2
DX 8: Half of the search window width
DY 8: Half of the search window height
STEP 1: Pixel to skip after a pixel in a block is used in block matching
STEPSIZE 160: Width of a frame

Variables

TInt iMode

iMode=0: Use Adaptive Spiral SEA PPNM PDE SSD algorithm

iMode=1: Use Spiral PDE SSD algorithm

iMode=2: Use Spiral SEA PPNM PDE SSD algorithm

iMode=3: Use Adaptive Spiral PDE SSH algorithm

TInt iDetectMode

iDetectMode=0: Use Translational Motion Tracking Engine

iDetectMode=1: Use Rotational Motion Tracking Engine

TInt iDisplayMode

When rotation tracking engine is in use,

iDisplayMode=0: do not display rotation angle result

iDisplayMode=1: display rotation angle result

TInt iLevelMode

iLevelMode=0: rotation angle result is not quantized

iLevelMode=1: rotation angle result is quantized as discrete level

TInt iPredictionMode

iPredictionMode=0: Adaptive method is not used

iPredictionMode=1: Adaptive method is used, prediction is made

TInt iLevel

Store the quantized rotation angle result

TReal iStartAngle

Store the previous angle of the two tracking blocks with reference to the horizontal line

TReal iCurAngle

Store the current angle

Functions for Developers

void ConstructL(CMotionTrackAppView* iAppView2)

Constructor of this class. Parameter required is a View class with some functions implemented.

void ViewFinderFrameReady(CFbsBitmap& aFrame)

Callback function from framework when a frame is newly captured. In this function, feature selection, motion tracking algorithms are called. Motion tracking result is available at the end of this function. By default, it will call some functions in View class to display the motion tracking result. Developers are free to modify this function to suit their needs.

void Prediction(TInt x,TInt y,TInt x2,TInt y2,TReal angle, TInt &iAdapti,TInt &iAdaptj,TInt &iAdapti2, TInt &iAdaptj2,TInt movex,TInt movey)

Function to predict user's next movement based on the two tracking blocks' positions and previous movement.

void AdaptSpiralSearch_SEAenhanced(CFbsBitmap &img1, CFbsBitmap &img2, TInt OFFSETW, TInt OFFSETH, TInt& BESTI, TInt& BESTJ, TInt& BESTSUM, TInt adapti, TInt adaptj)

Function that runs the translational motion tracking algorithm.