Department of Computer Science and Engineering

The Chinese University of Hong Kong

2004/2005 Final Year Project

First Term Report

LYU 0404

Mobile Motion Tracking using Onboard Camera

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1 December, 2004

Abstract

This report describes the motivation, background information, experiments done and problems encountered 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, in the aspects of highlighted feature on how image manipulations can be done 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 would play an important role in our project.

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 the 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.

Finally, we will describe the application that we have made and discuss what other possible applications can be developed using our motion tracking algorithm.

Content

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.

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:

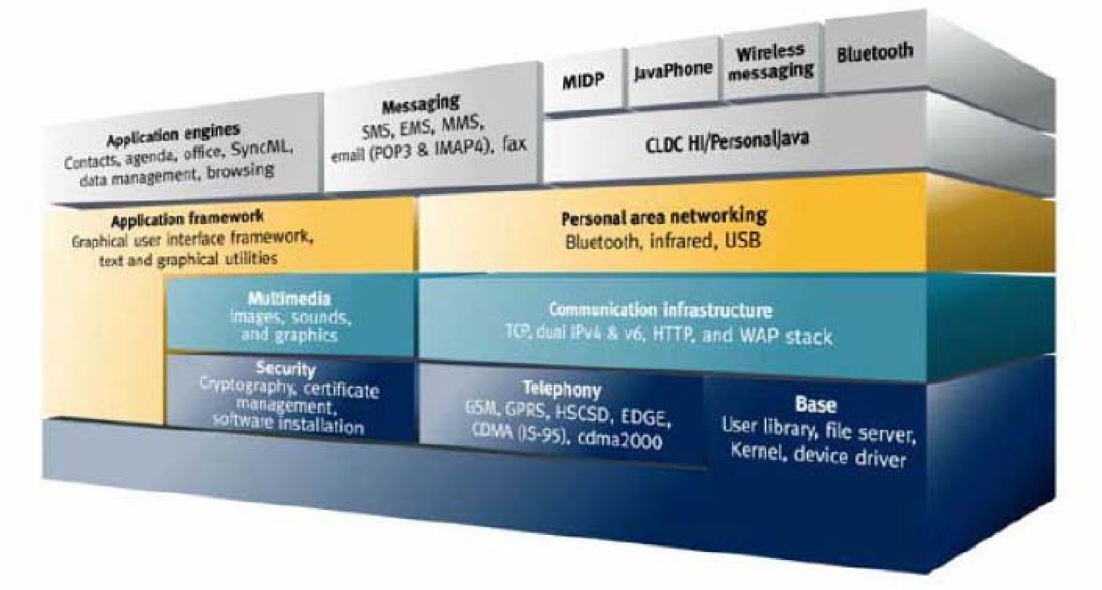


Figure 2.1 Symbian 7.0 architecture

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:

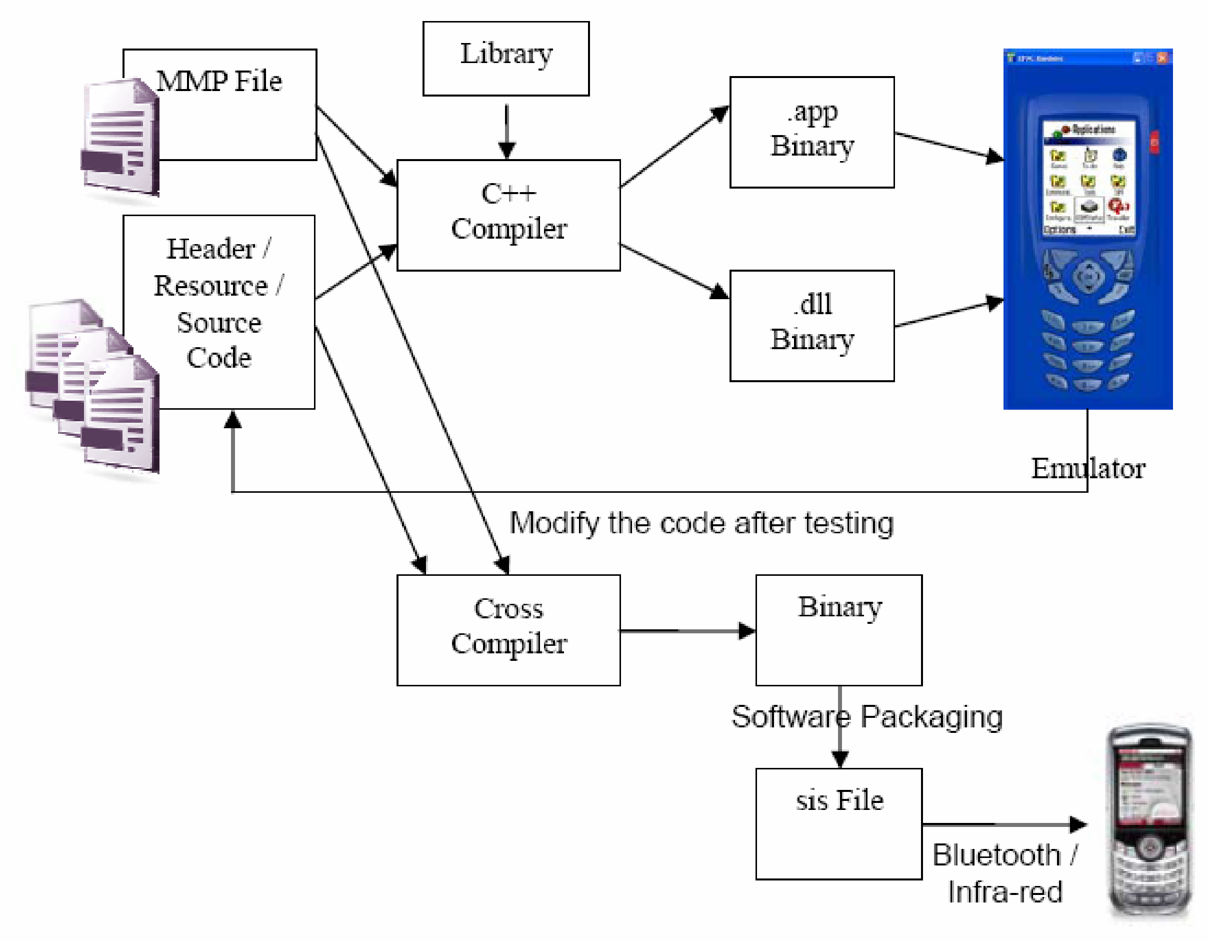


Figure 2.2 Development cycle of Symbian program

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

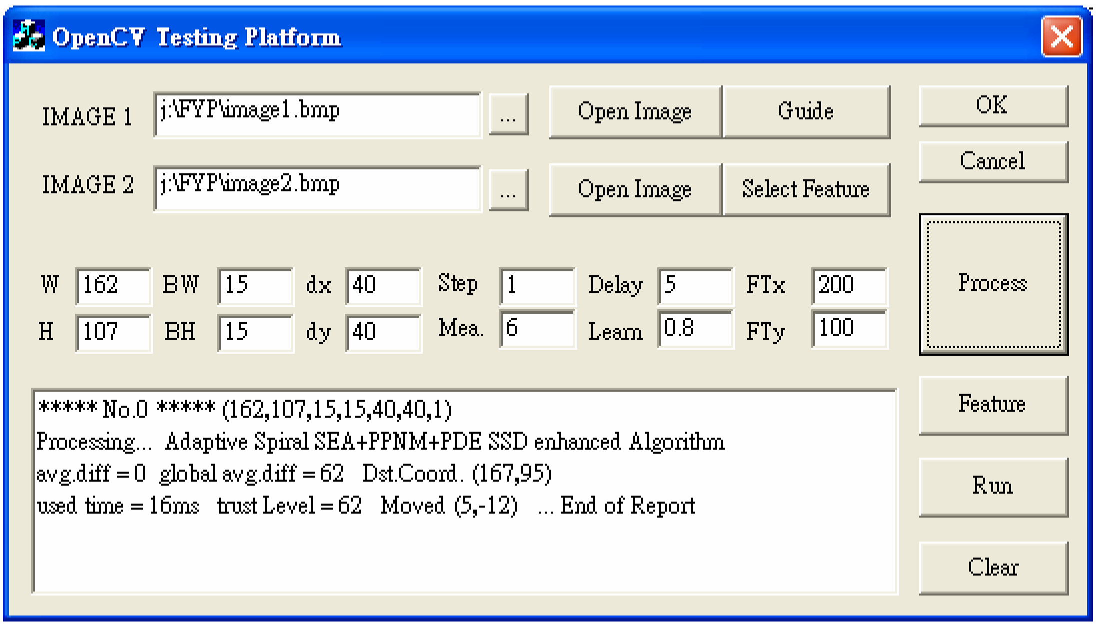


Figure 3.1 Snapshot of our OpenCV Testing Platform

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

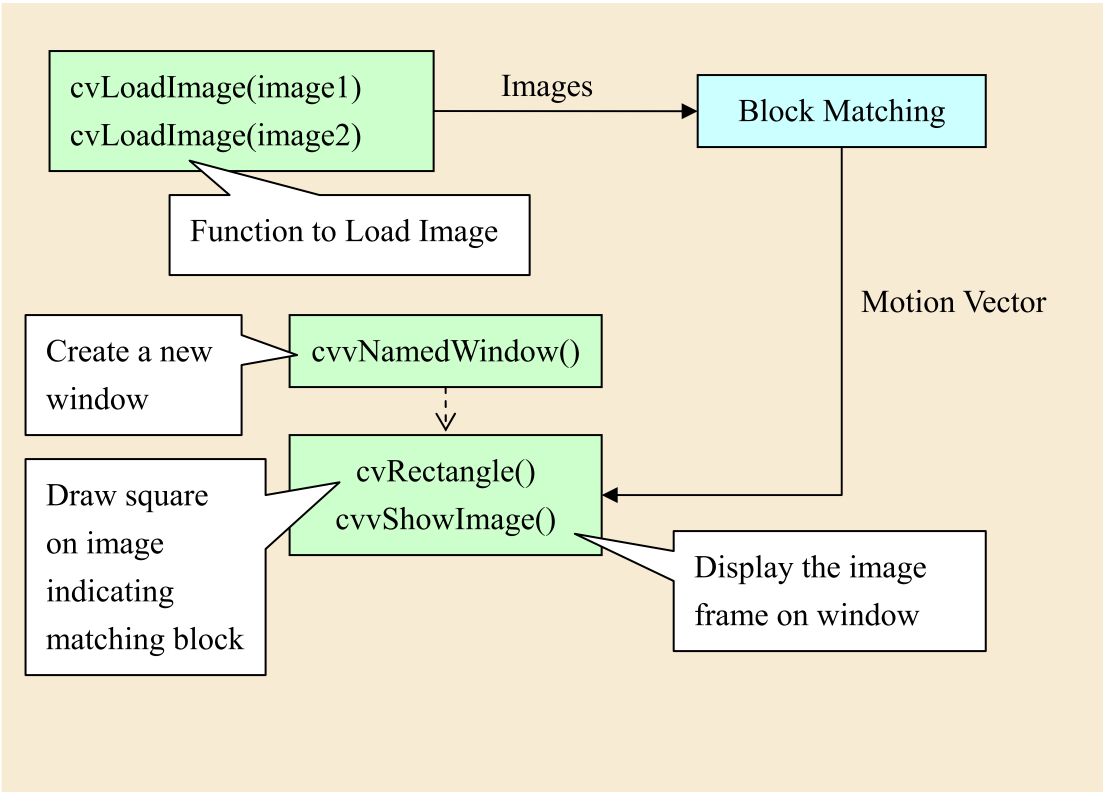
…	Open up a file explorer. Allow users to choose the image used for static frames motion tracking
Open Image	New a window and display the corresponding image on the window
Guide	Read the block matching parameters. Display a red square on image 1 denoting the previous block's location and a green square 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.

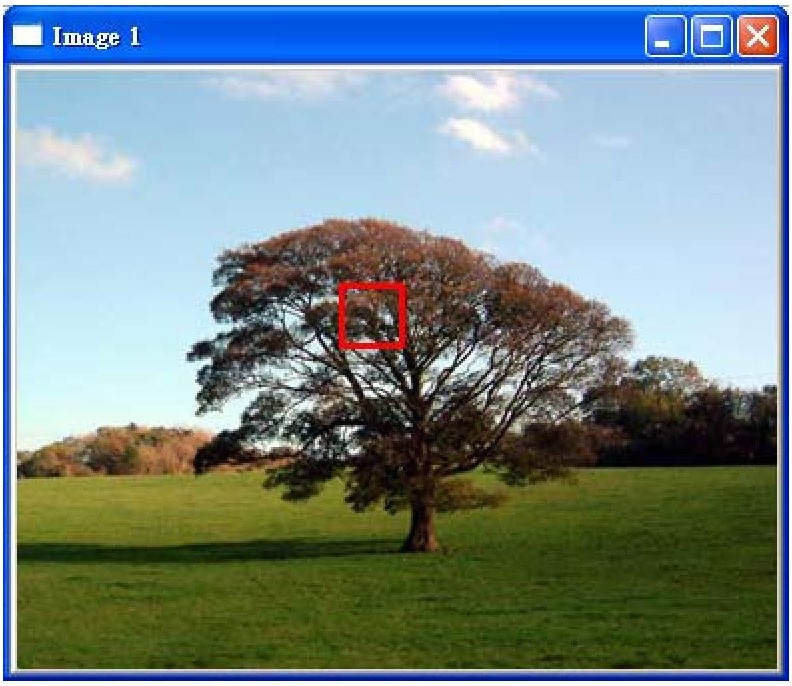


Figure 3.2 Input Image 1 and previous block marked as red square

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

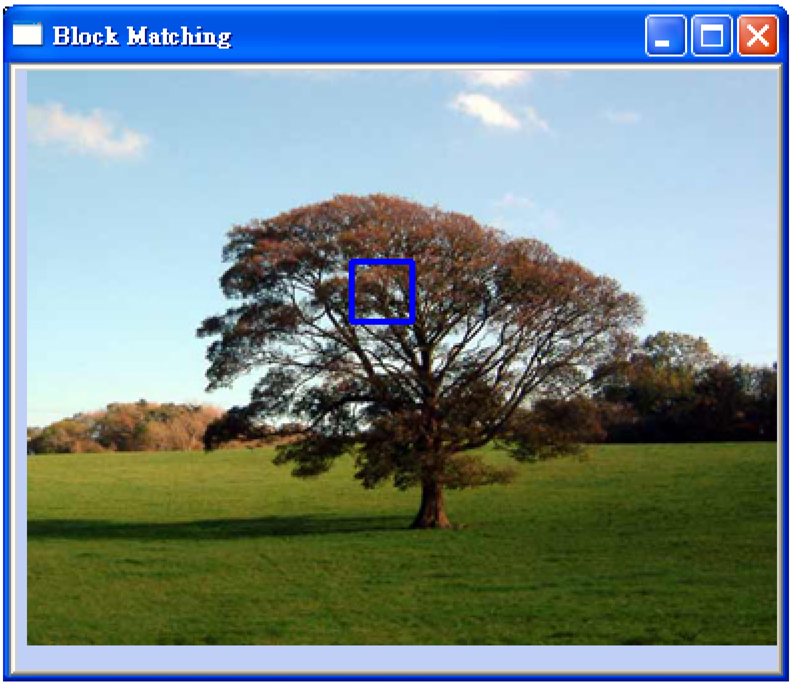


Figure 3.4 Block Matching Result, the best matched marked as blue square

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.

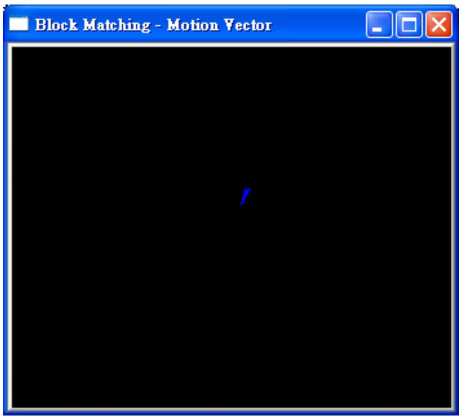
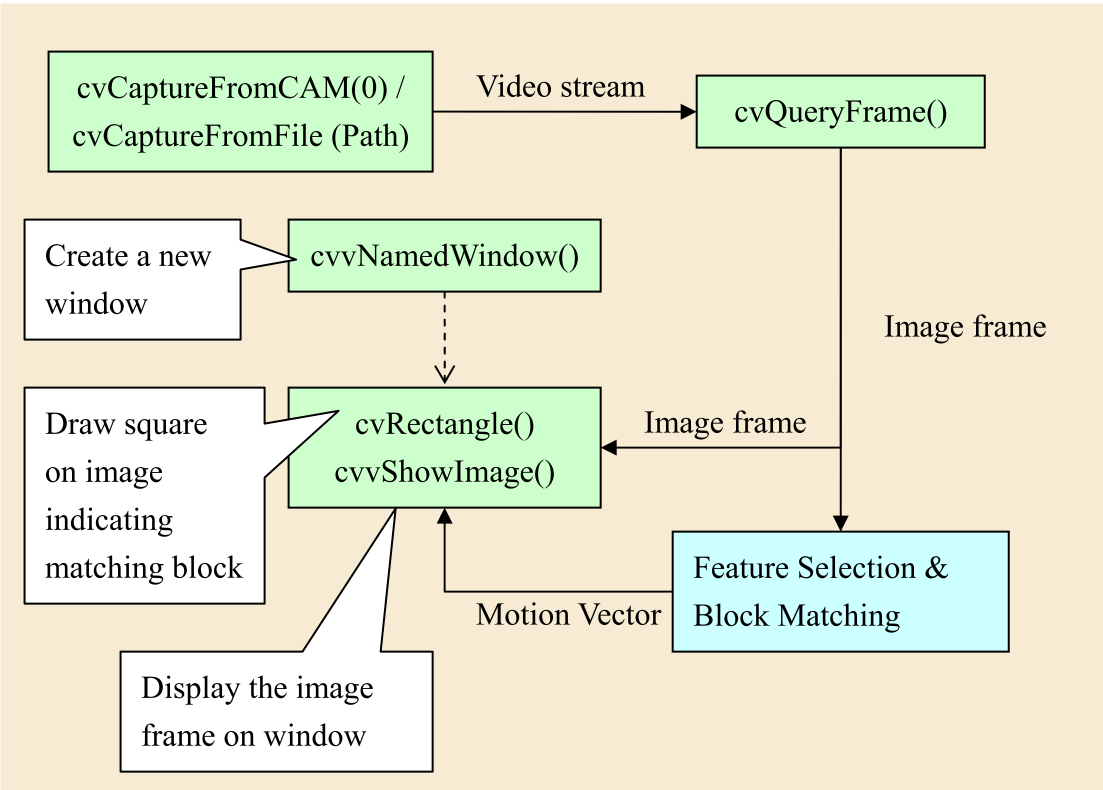


Figure 3.5 Motion Vector, pointing toward top right direction

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

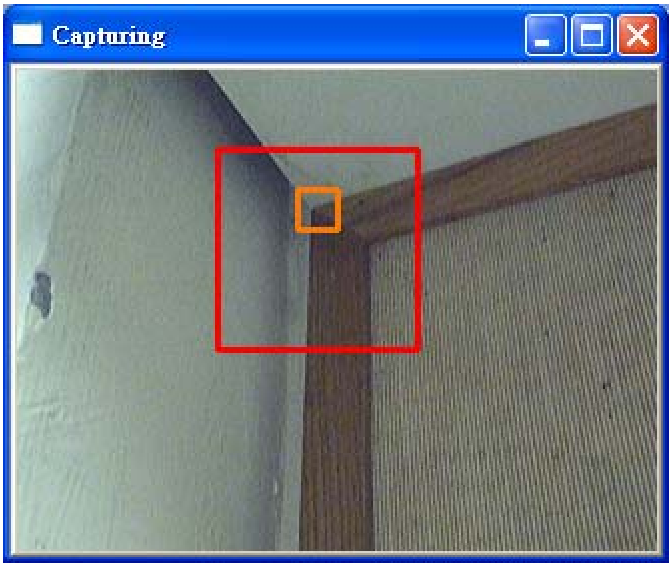


Figure 3.6 *Feature* Window

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

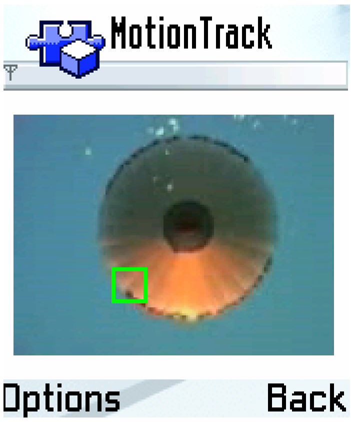
After the final algorithm was implemented and tested in window OpenCV testing platform, we finally built a platform ("MotionTrack" application) on Symbian and implemented our algorithms on it so that we can further test the performance of our algorithms on Symbian phone. Other applications can also be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

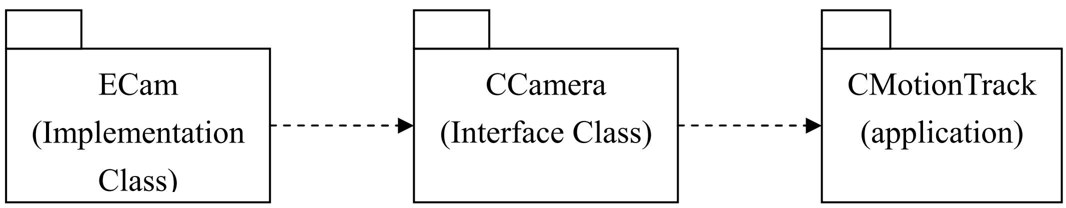
4.3 Design and Implementation

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.

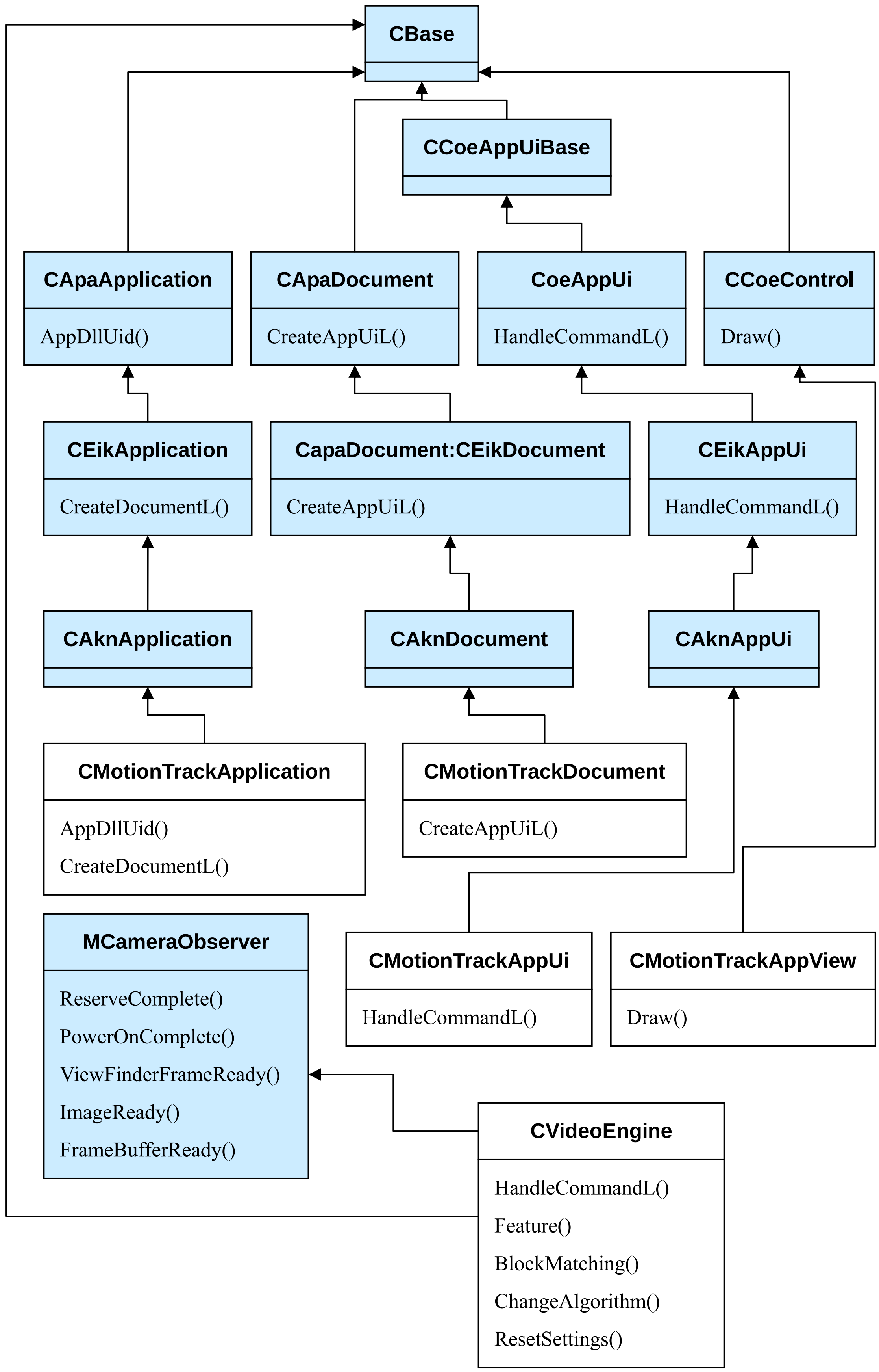
4.3.1 Class Structure

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:

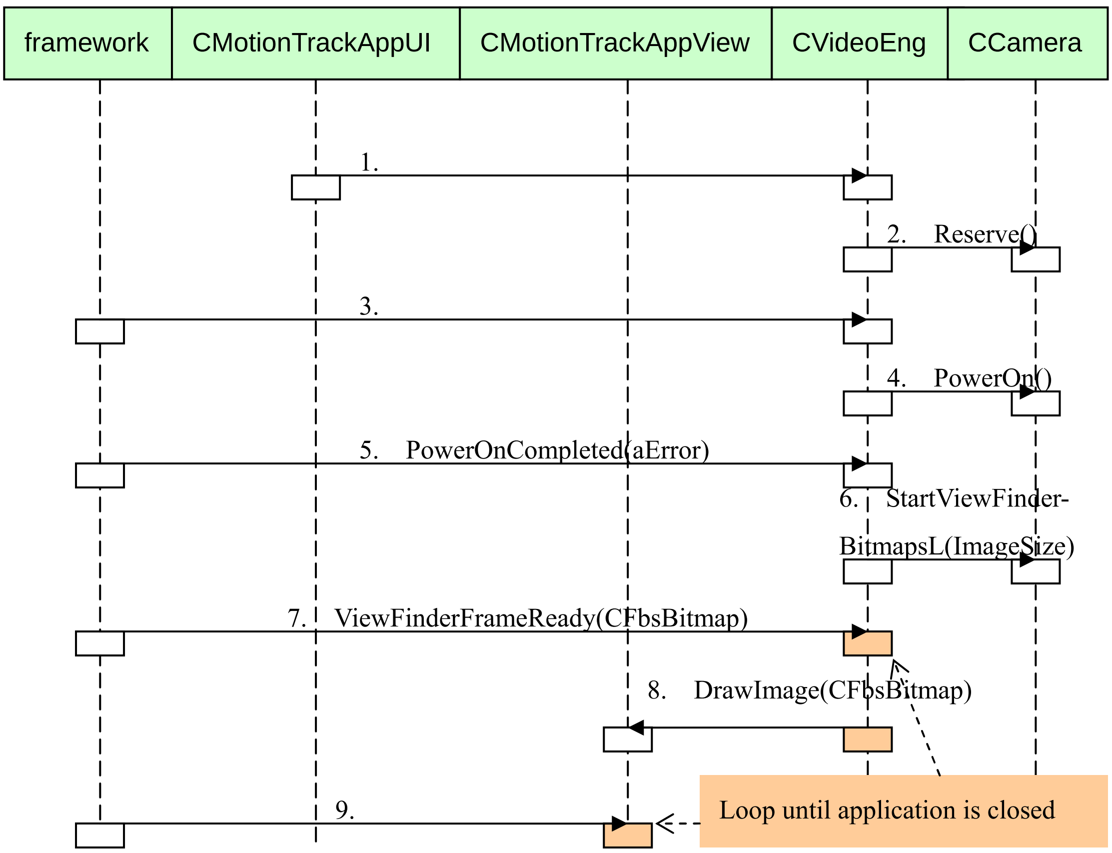


This diagram shows the classes implemented by MotionTrack application, and which files implement those classes. All the classes are derived from CBase. CBase has a number of useful features: it initialises all member data to zero, it has a virtual destructor, and it implements support for the Symbian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

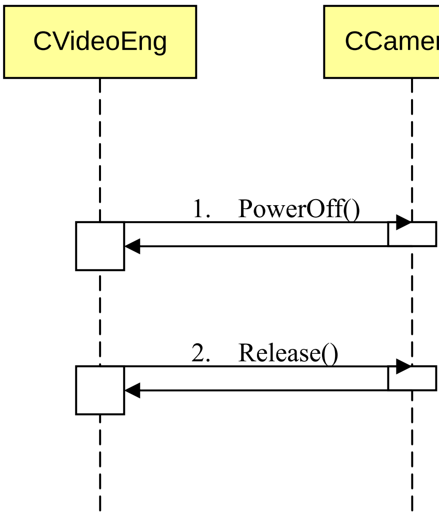


Function	Description
1	CMotionTrackAppUi calls the ConstructL method of the class CVideoEngine.
2	The CVideoEngine sends the asynchronous reserve request to the camera. If the camera is not yet reserved, the camera reserve session identification is stored.
3	The client will give the reservation answer 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.

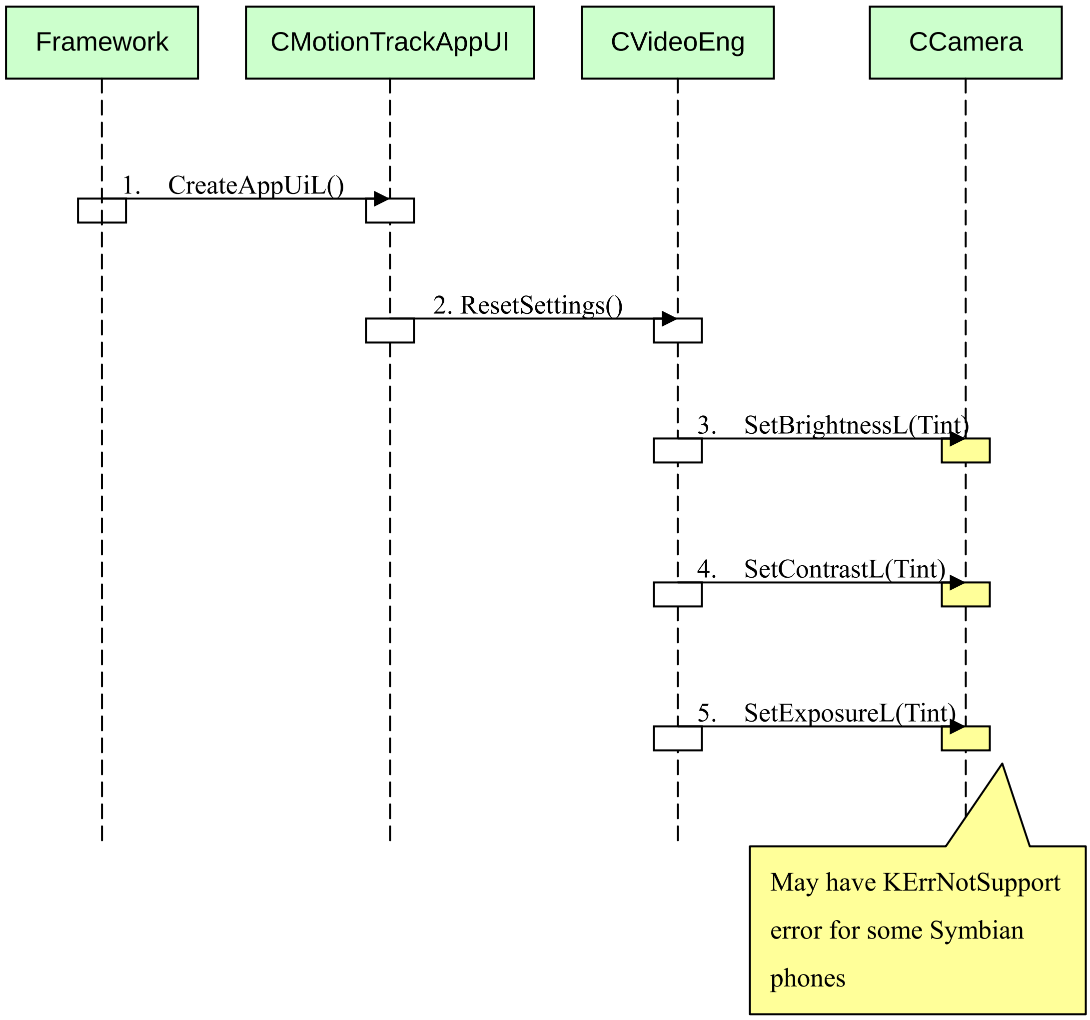
The UML sequence diagram below shows the function how the camera release is done.



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.

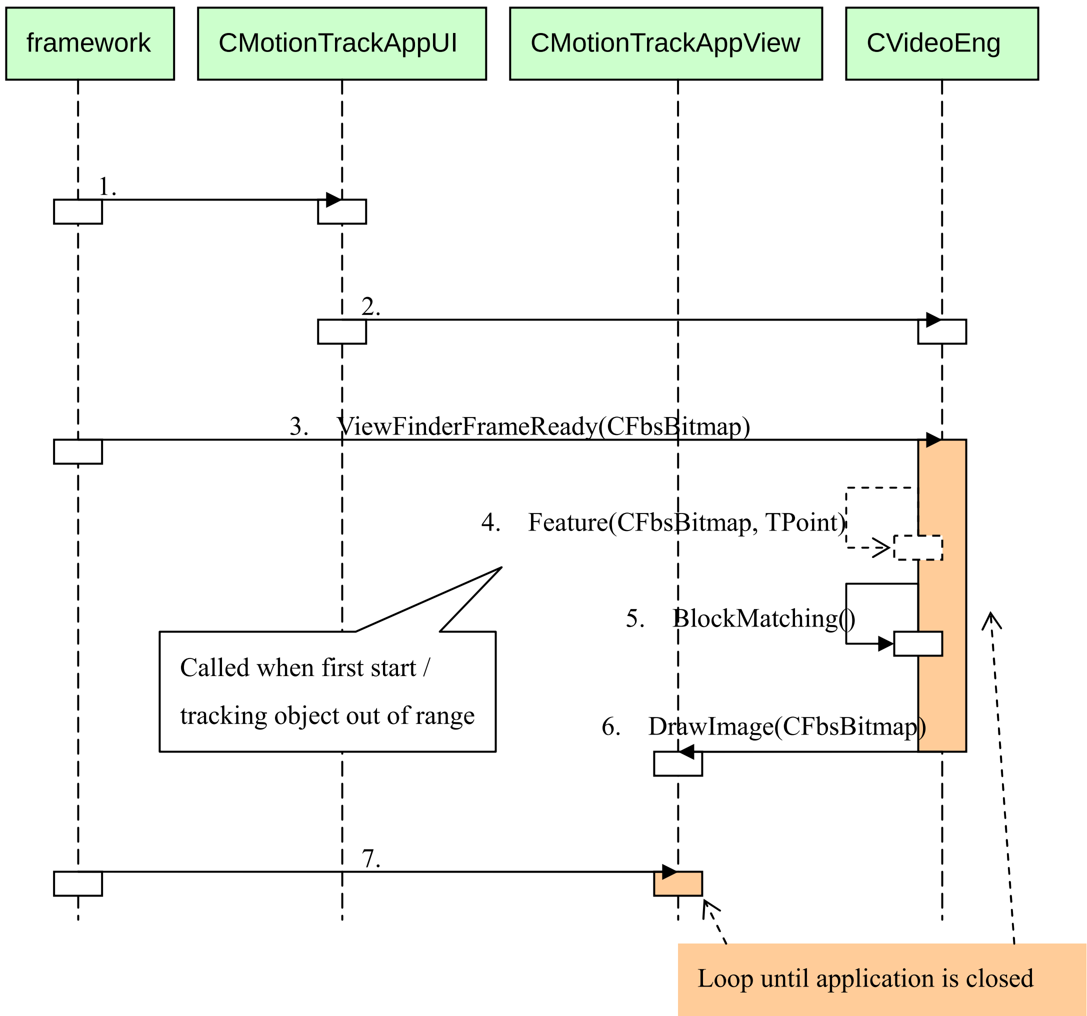
4.3.4 Reset Contrast, Brightness and Exposure Mode of camera

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: 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.

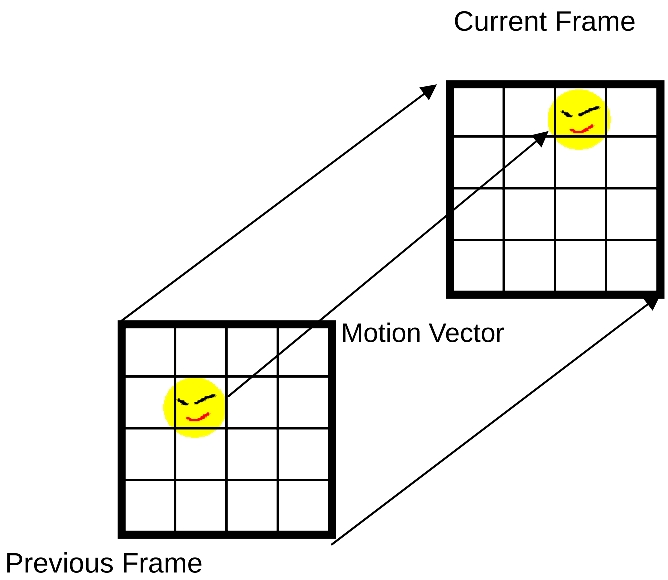


Figure 5.1 Block matching

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.

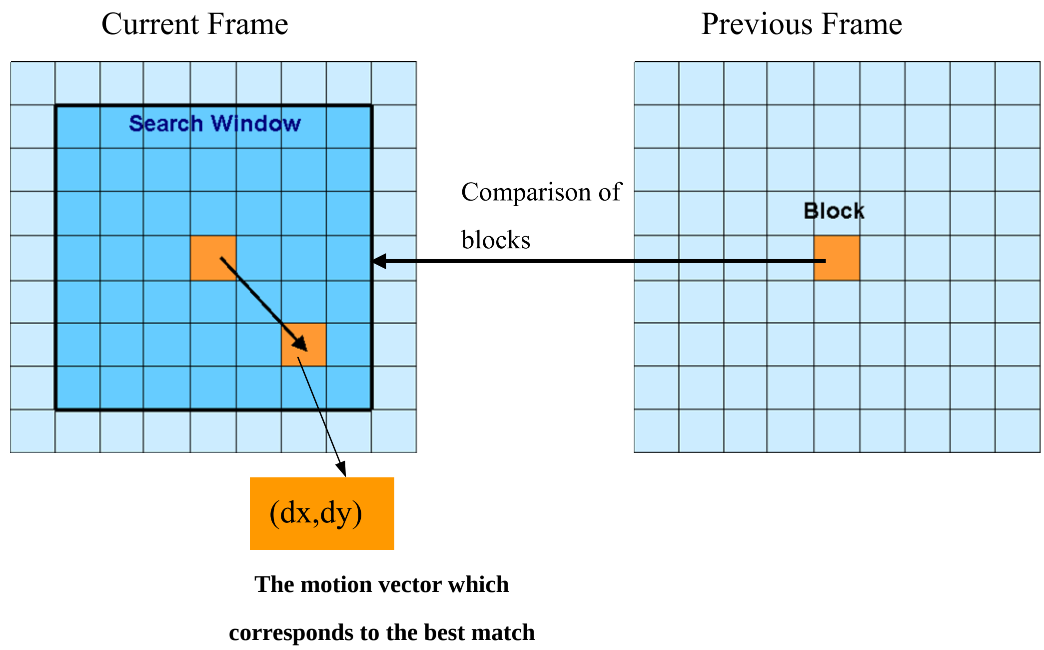


Figure 5.2 Motion tracking: a block is compared against the blocks in the search area in the current frame.
The motion vector corresponding to the best match is returned.

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

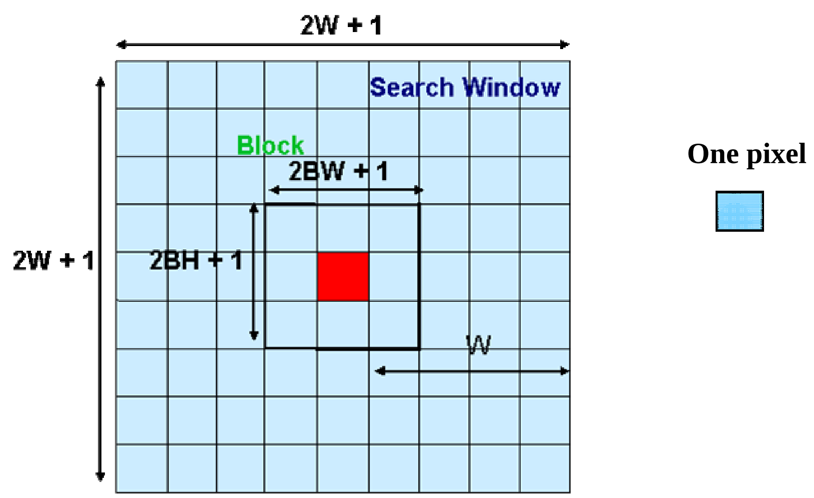


Figure 5.3 The search area in block-matching motion tracking techniques
The red grid is the center pixel of the block

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.

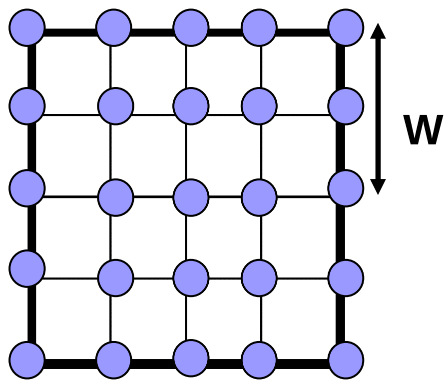


Figure 5.4 The exhaustive search evaluates the cost function in all locations in the search area

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]

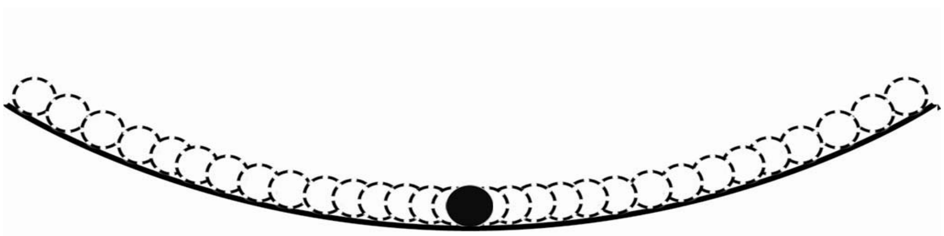


Figure 5.5 Weights generated by the cost function increase monotonically from the global minimum

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).

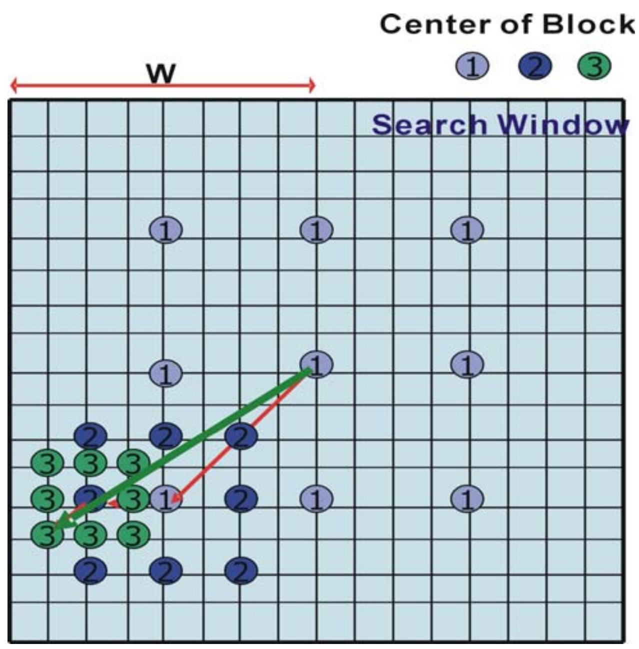


Figure 5.6 An example of the three-step search algorithm.

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.

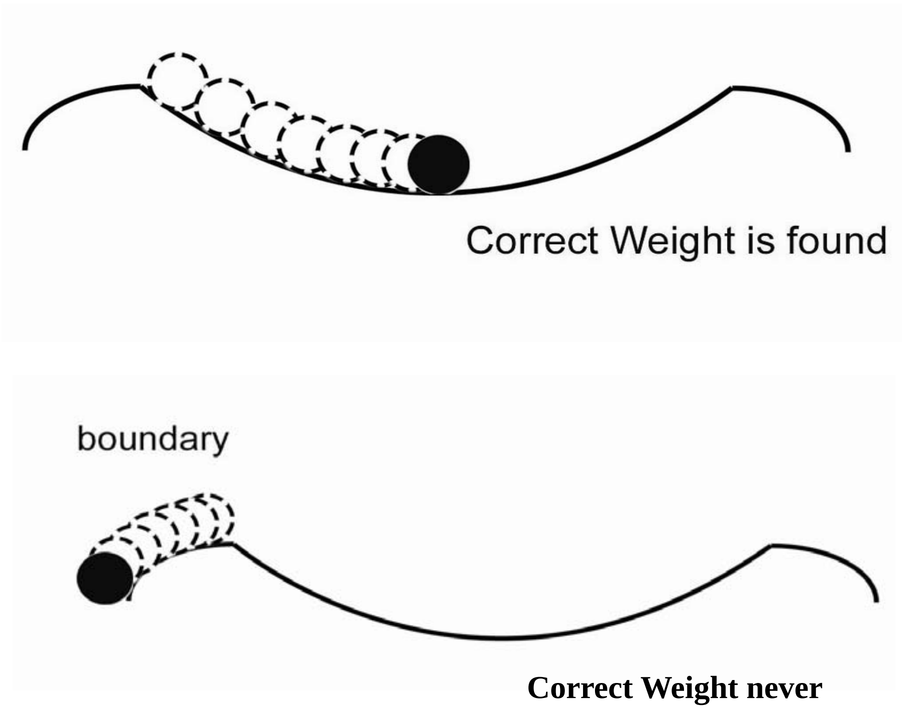
5.2.4.2 Time Complexity

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:

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

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,

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

$$\mathit{from}\ \ |A_1 + A_2| \le |A_1| + |A_2|$$

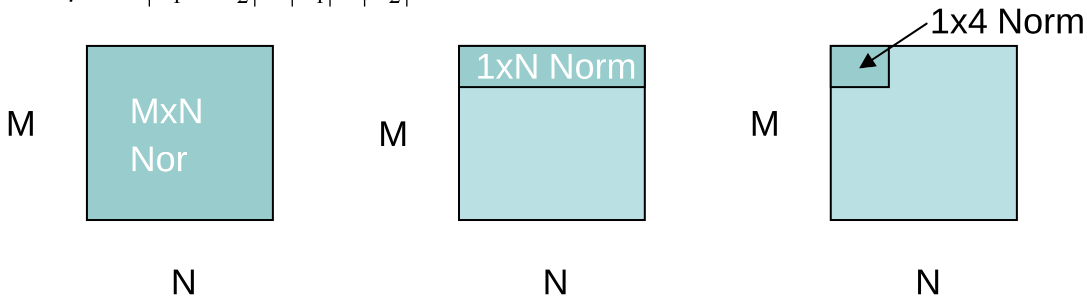


Figure 5.7 Different size of sub-blocks

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

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

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.

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

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

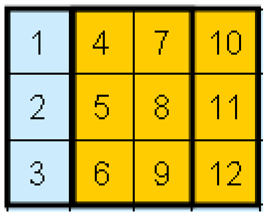


Figure 5.8

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.

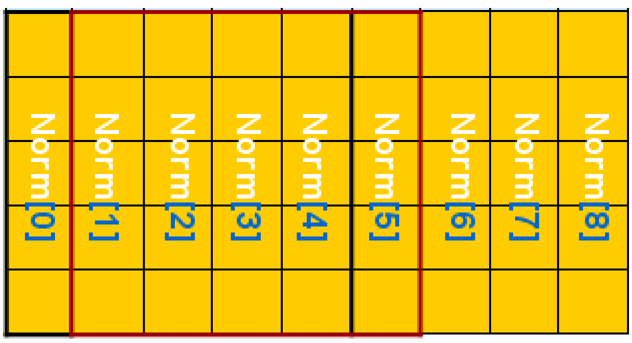


Figure 5.9

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.

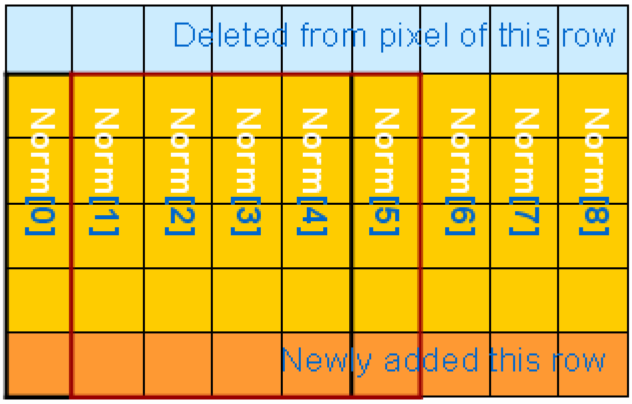


Figure 5.10

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.

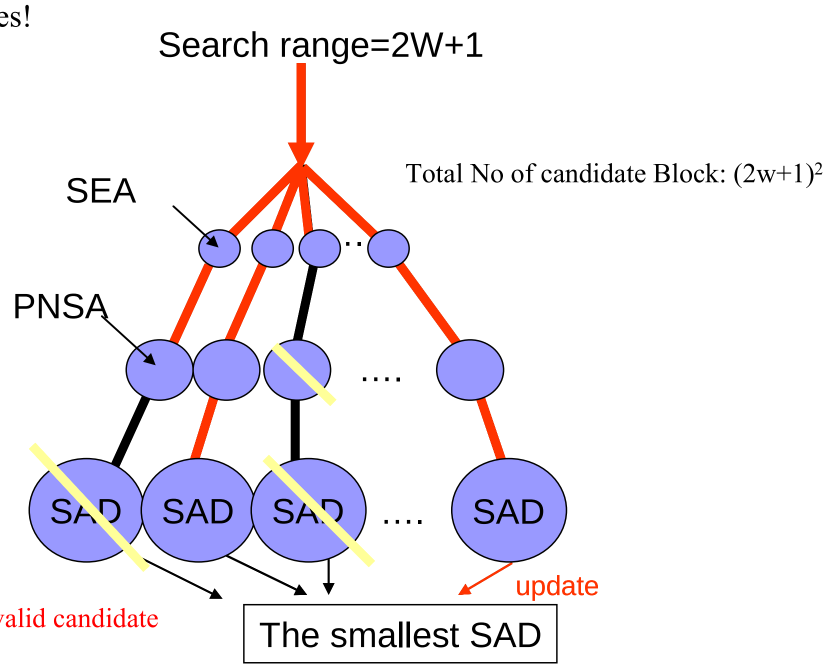
$\sum_{j=1}^{N} X(i,j)$ term is the sum of pixel values in one of the column in a block. This sum is exactly the norm of the block we calculated during the fast calculation of block sum. Therefore, if we keep the norm value in form of a 2D array, we can use that value as the $\sum_{j=1}^{N} X(i,j)$ term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



Probability of eliminating invalid candidate block:
SEA < PNSA < SAD
Computation Load:
SEA < PNSA < SAD

Tree pruning decision

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.

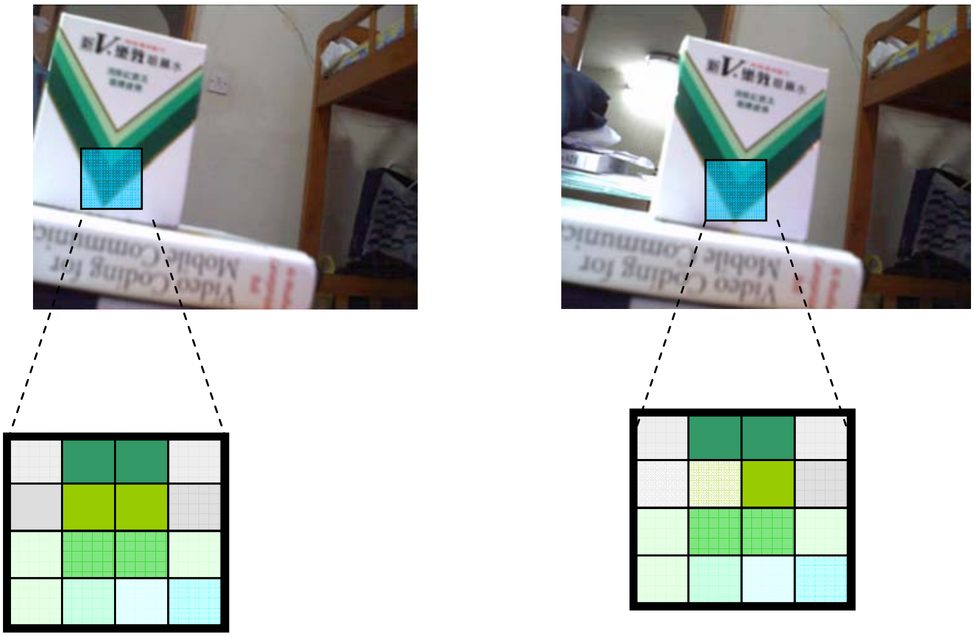


Figure 5.12 illustrating the intensity stability hypothesis.
Each region of pixels translates with little change in intensity or relative position.

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.

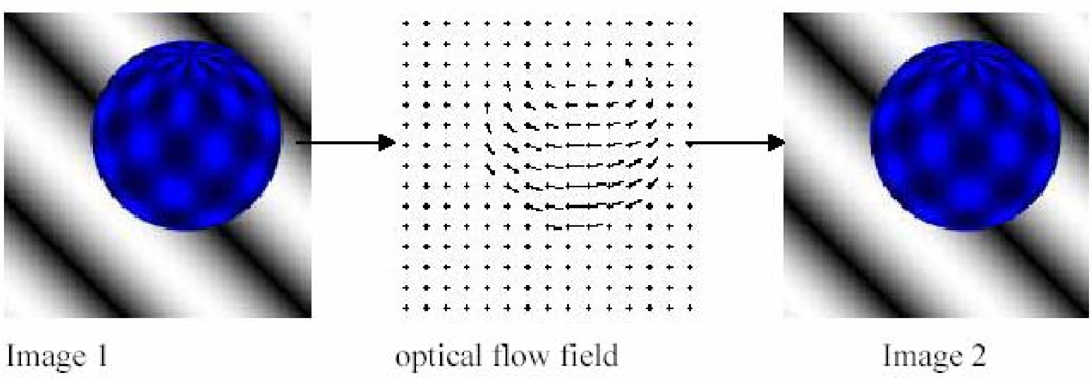


Figure 5.13 Illustration of Optical Flow

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

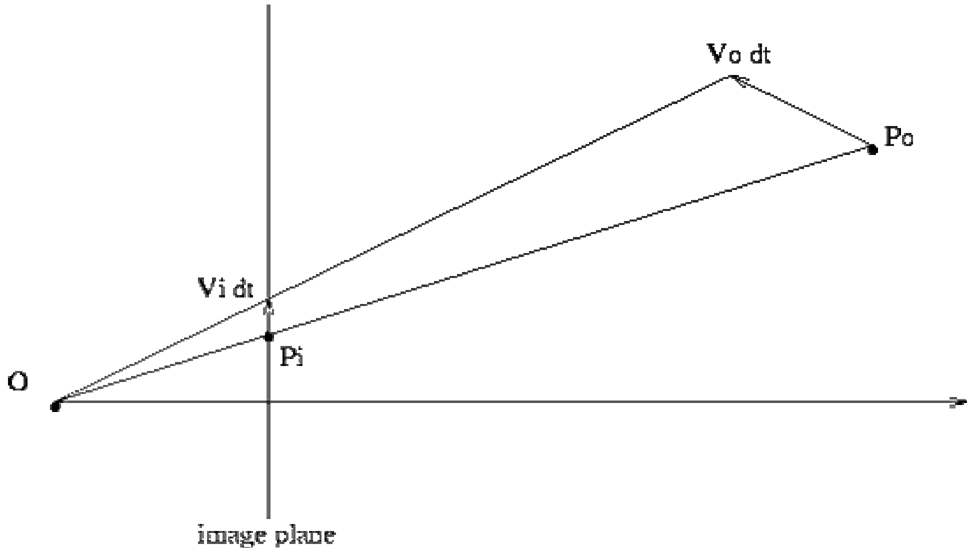
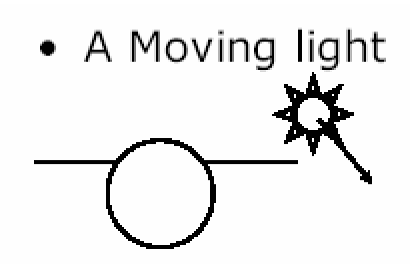


Figure 5.14 Object motion creates a motion field on the 2D image plane

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.



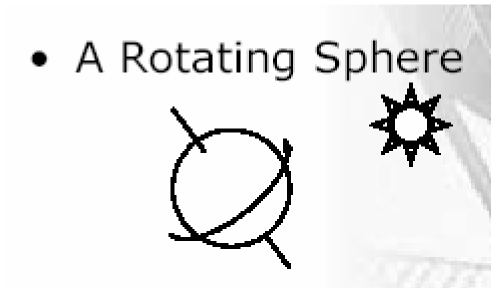


Figure 5.15 Figure 5.16

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:

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

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

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

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

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

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

where

fx = $\frac{\partial I}{\partial x}$,fy = $\frac{\partial I}{\partial y}$ and f_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.

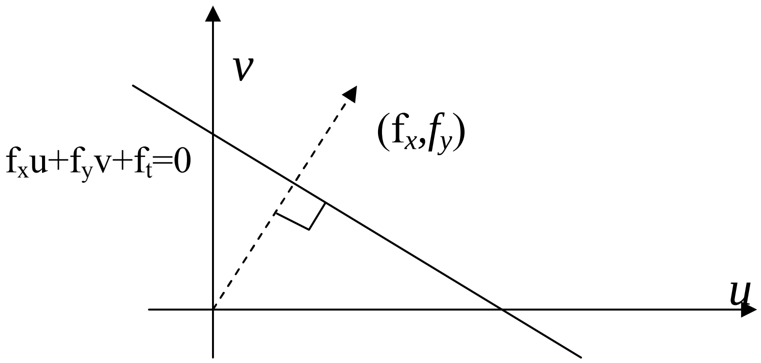


Figure 5.17 geometric explanation of equation (2)

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

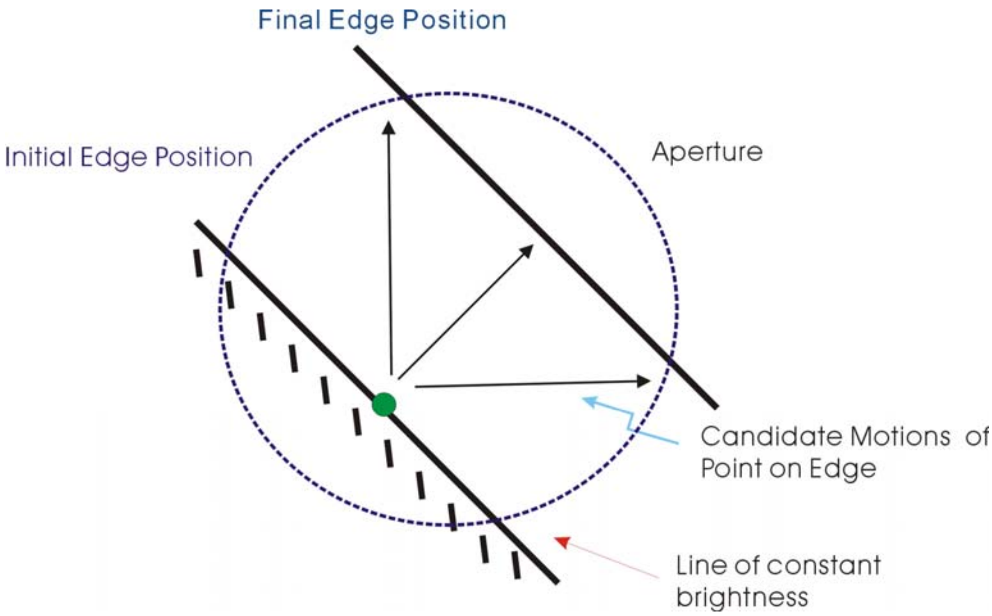


Figure 5.18 aperture problem

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

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

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

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.

Adaptive Spiral SEA PPNM **PDE** SSD Algorithm

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 can still ensure that 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:

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

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 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 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 effect on the calculation of SAD, it is compatible with other type of algorithms, such as SEA and PPNM.

5.7.2 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:

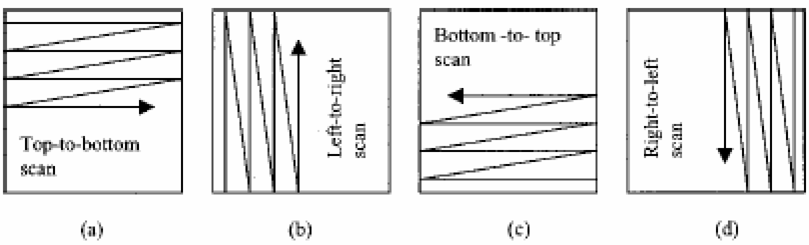


Fig. 1 Various matching scans: (a) Top-to-bottom scan, (b) left-to-right scan, (c) bottom-to-top scan, (d) right-to-left scan.

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 the implementation of video compensation and coding, each block in previous frame has fixed position and the object tracked by each one varies from frame to frame. At frame 1, a block is tracking object A; however, at frame 2, that block may be tracking object B which motion is totally different from object

A. Since each block does not track the same object, it is useless for it to carry history for the motions of its tracking objects.

In our application, on the contrary, it is very useful to carry history of the motions. In contrast with tracking objects in a frame, 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

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

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 more 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

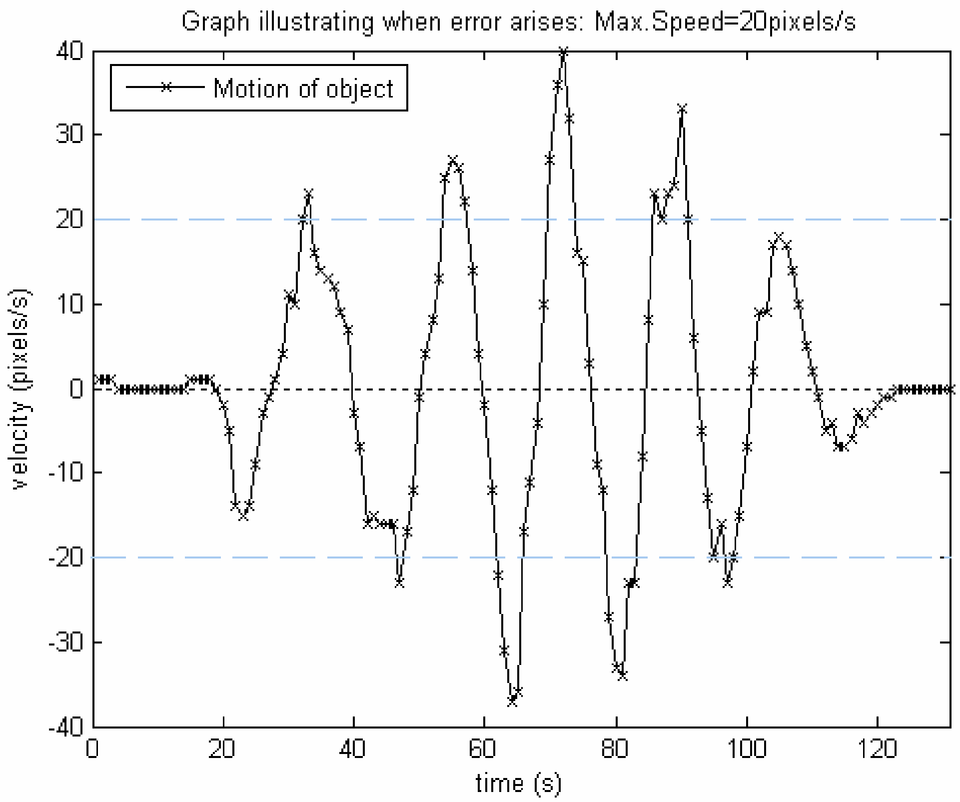


Figure 5.19

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 Adaptive Spiral SEA PPNM PDE SAD Algorithm. The velocity means how many pixels the object has moved, positive mean it is moving to the right direction, negative mean to the left. The algorithm is run every second, then the velocity is just equal 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 fall 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.

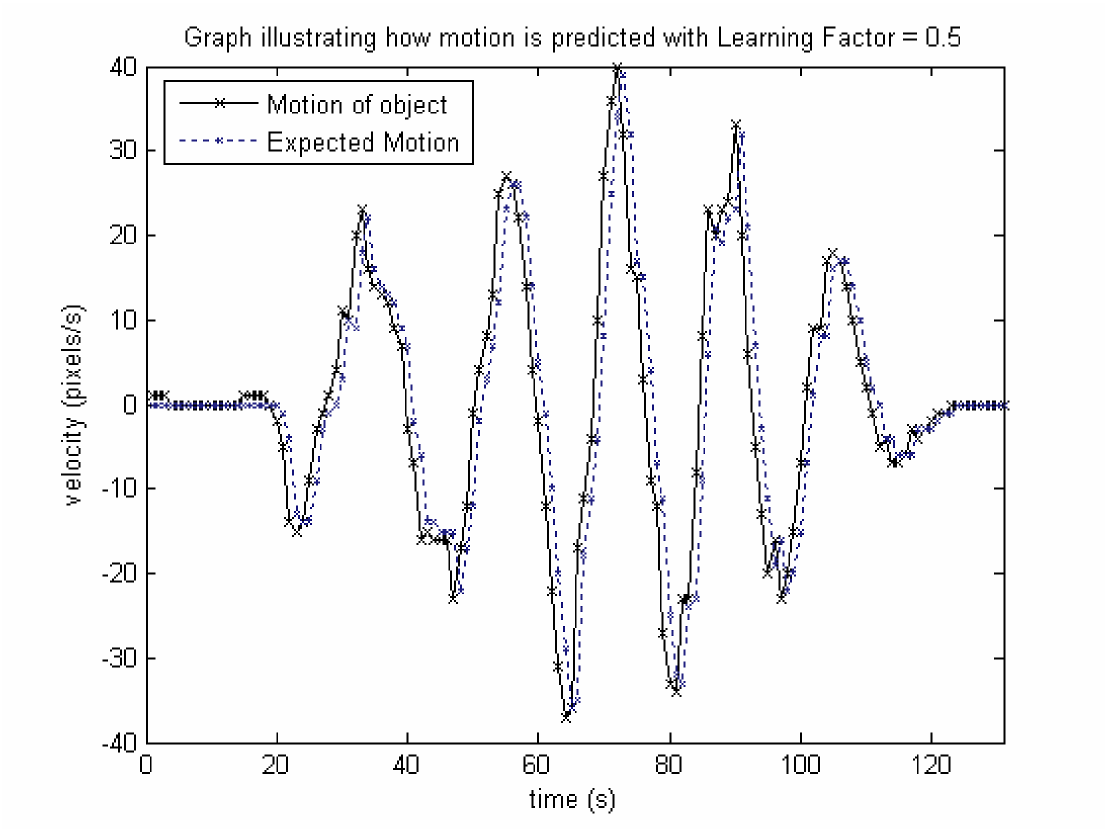


Figure 5.20

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.

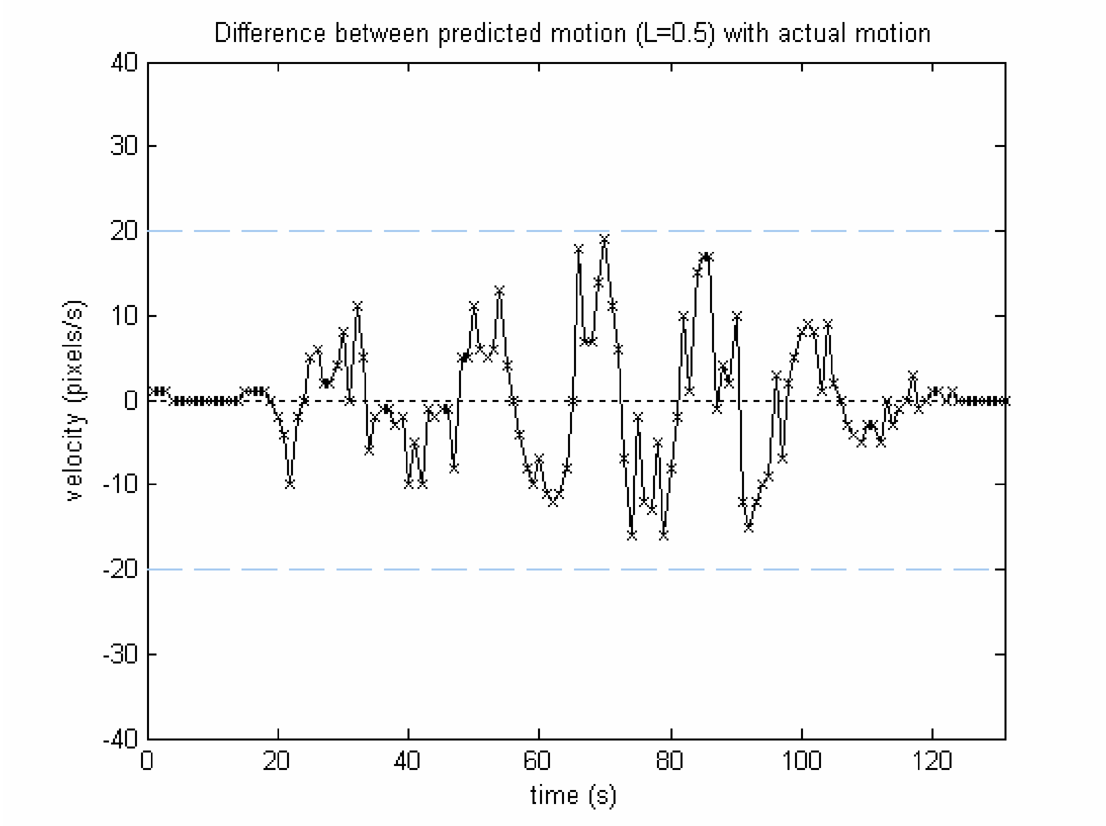


Figure 5.21

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 mean 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 give 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 environment, learning factor = 1.0 can be used, while on mobile environment, since the noise in the image captured by the camera on mobile phone is relatively higher, a bit lower learning factor can be used.

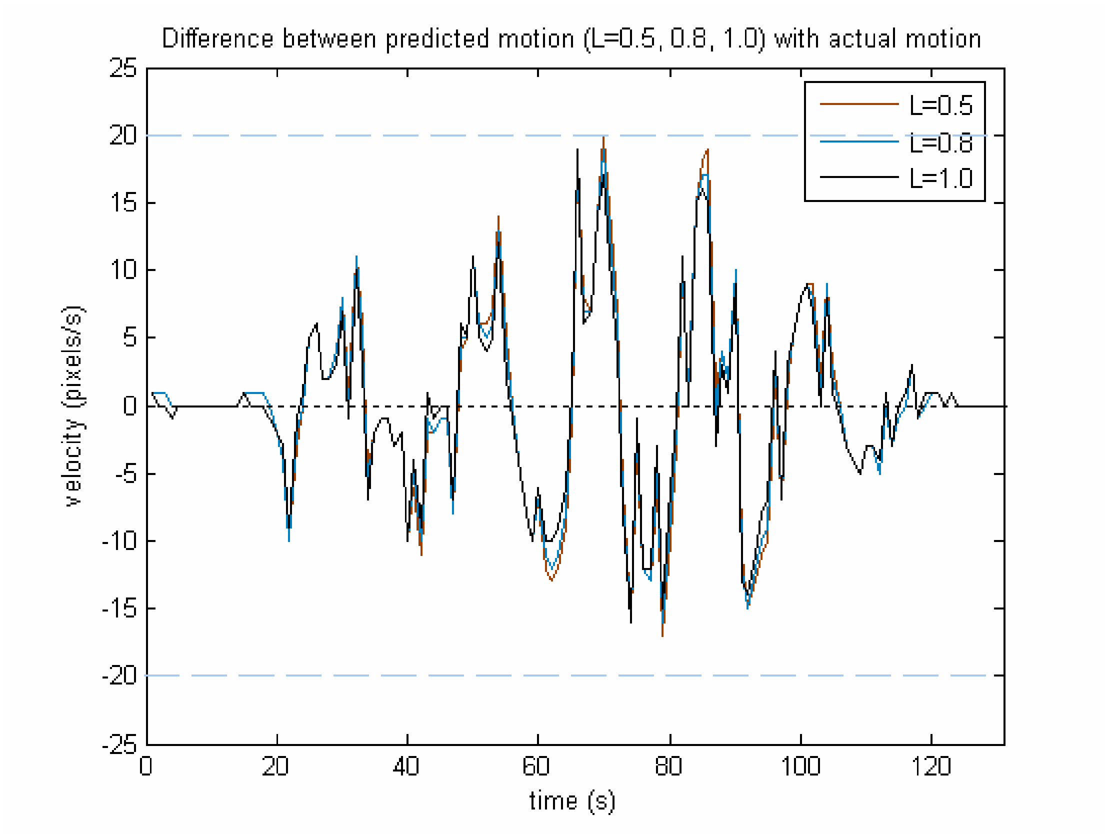


Figure 5.22

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:

$$|\,Velocity\,| < W\ pixels/s \quad \ldots\ (5.39)$$

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:

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

5.8.3 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.

5.8.4 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:

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

Thus global minimum SAD found earlier lead 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:

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

Thus global minimum SAD found earlier lead to less computation on SAD. 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 improve the speed of our algorithm. This is our motivation to use spiral scan method as the block scanning method.

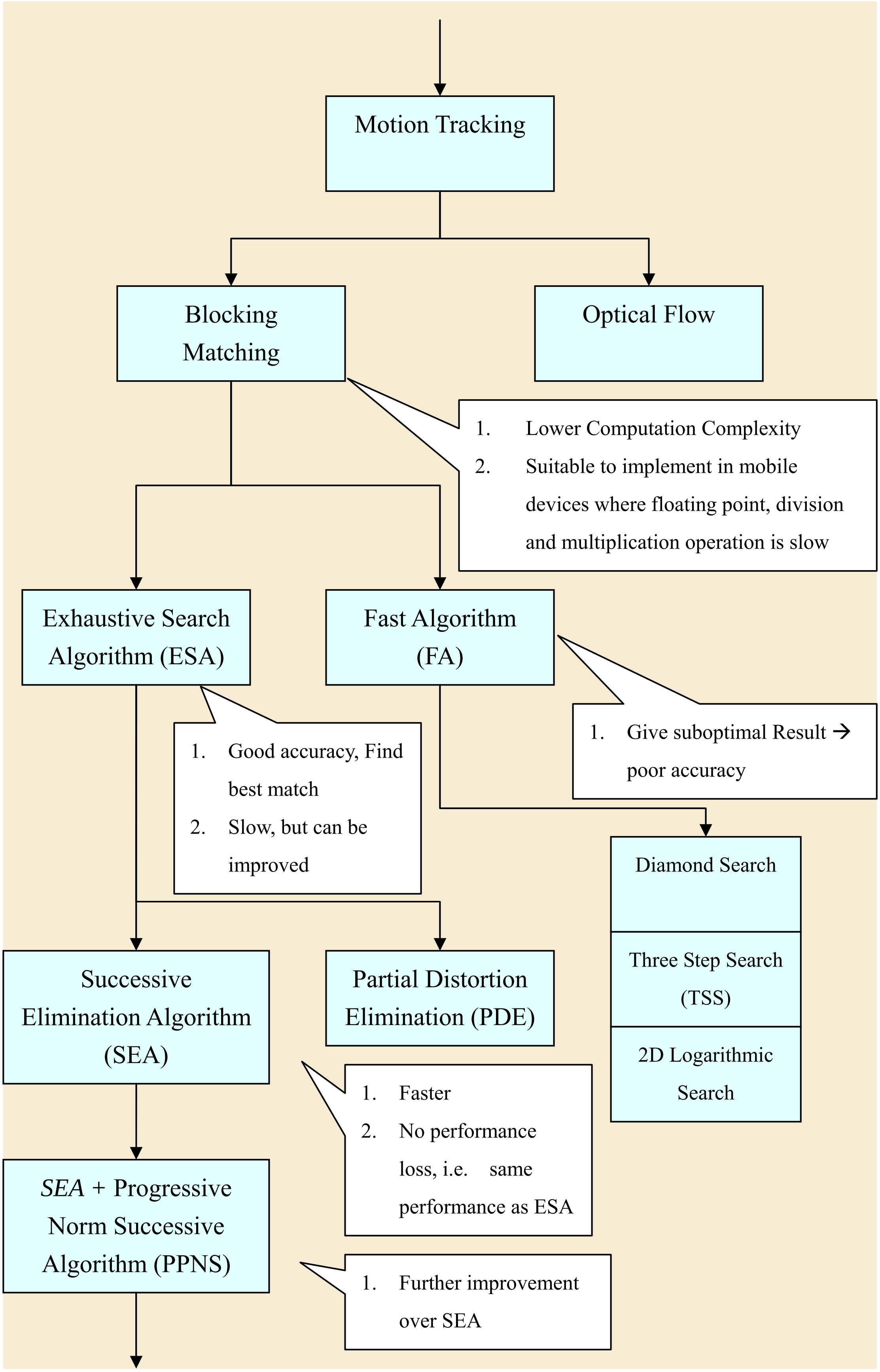
5.9.1 Spiral Scan Method

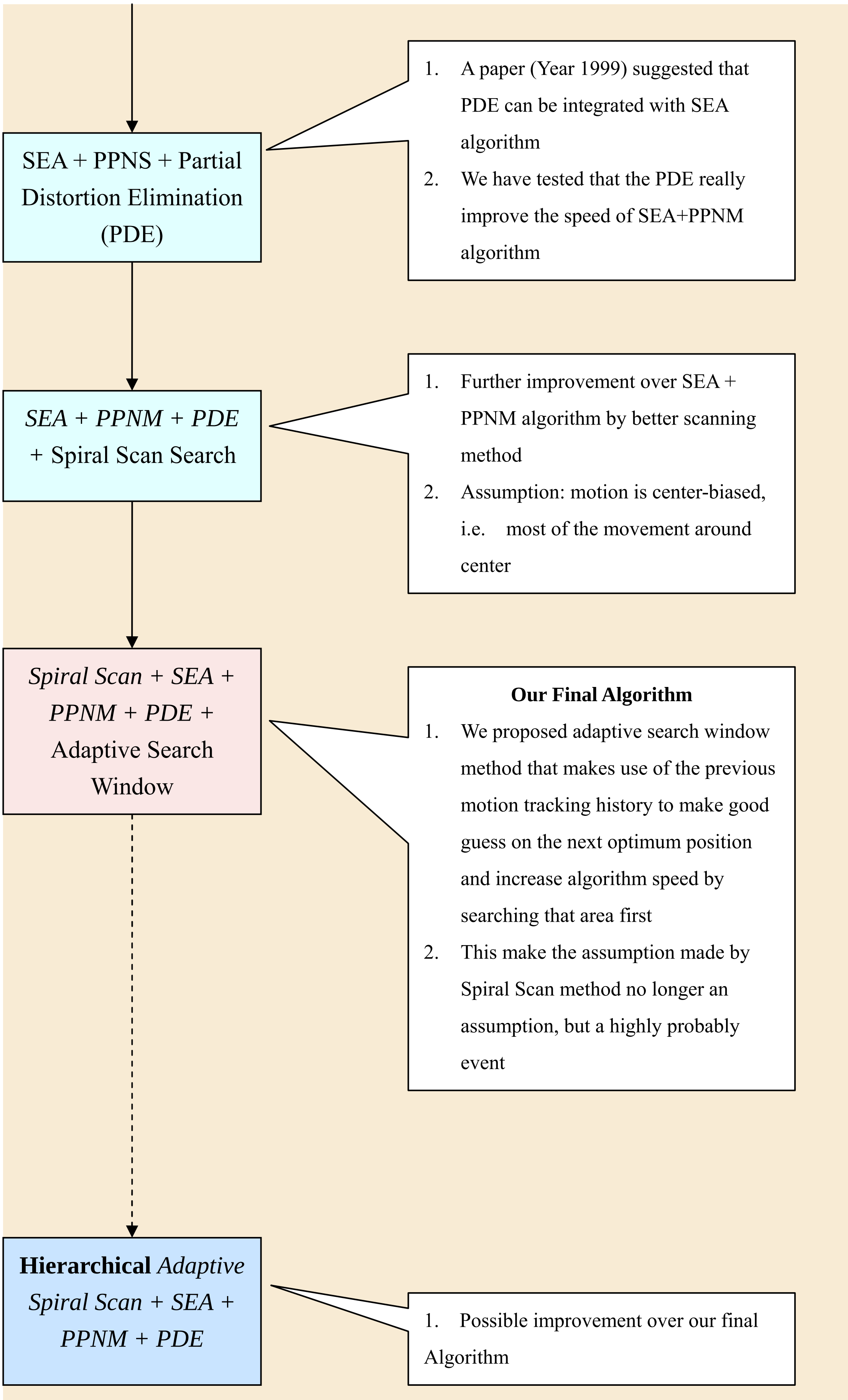
Instead of starting at the left top position, we can start find the SAD at the center of the search window first, then find the SAD at position that are 1 pixels away from the center, then 2 pixels away from the center, …etc. When adaptive search window method is used, most of the motion vectors are center biased. That is, the optimum point would have higher probability to locate at the center of the search window. Since spiral scan method scan 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 improve speed of our algorithm.

5.9.1 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

Chapter 6: 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.

6.1 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.

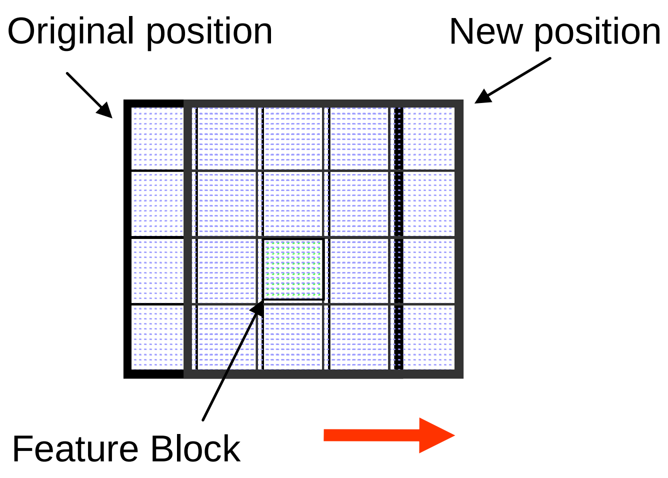


Figure 6.1 A reference block in flag region

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.

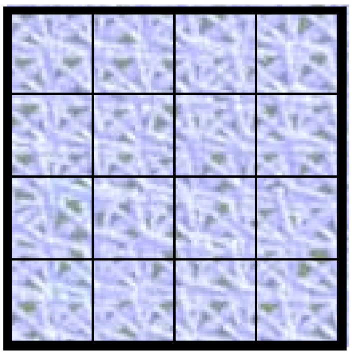


Figure 6.2 repeated pattern background

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

6.2 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.

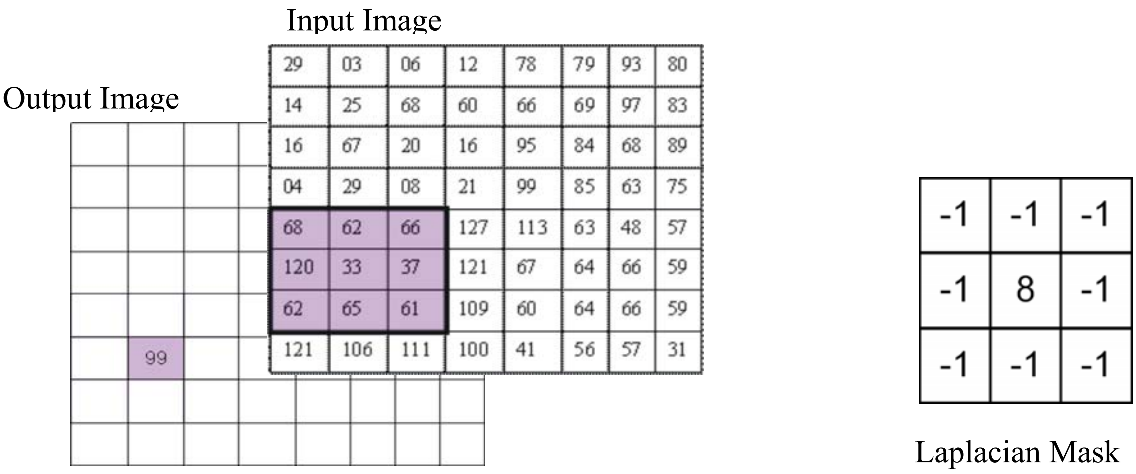


Figure 6.4

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

6.3 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.

6.4 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 7: Applications

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.

7.1 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:

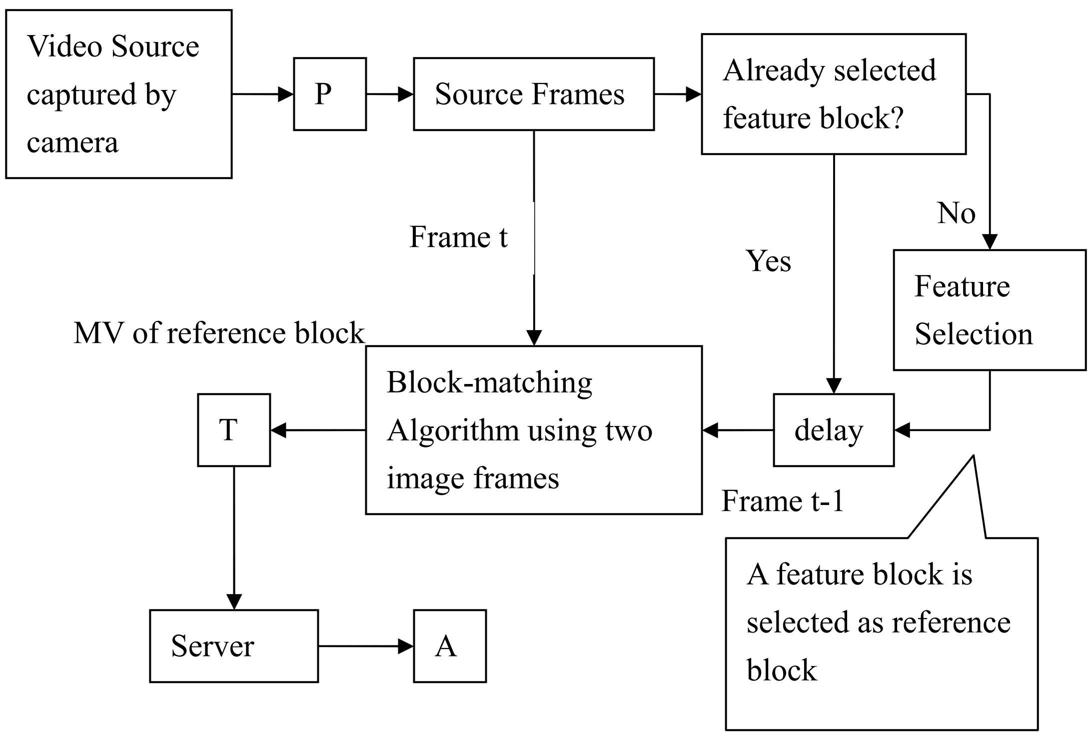


Figure 7.1 Flow Chart of developing motion tracking application

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.

7.2 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.

7.2.1 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.

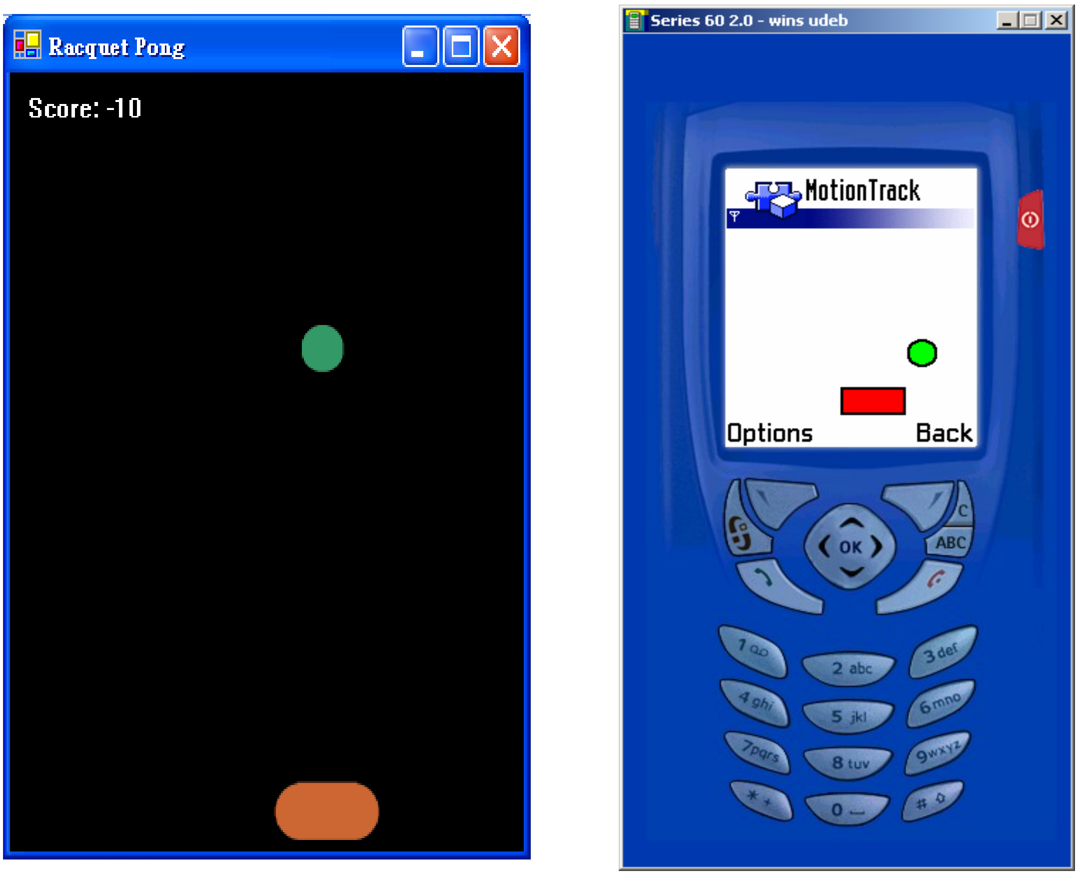


Figure 7.2 Screenshot of the pong game

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

7.2.2 Virtual Mouse

We are implementing a virtual mouse system that users can use their Symbian phone as a mouse for the desktop computers. We further developed our "MotionTrack" application. By following the flow chart in figure 5.x, we developed a server as shown in figure 6.x and the server will receive the motion vector via Bluetooth. It will instruct the cursor to move according to the motion vector.

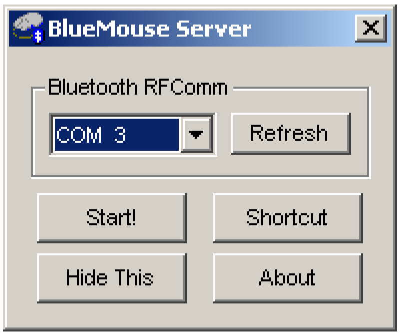


Figure 7.3 A server program for receiving motion vector

7.3 Other Possible Application

7.3.1 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 8: Experimental Result

8.1 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.

8.2 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.

8.3 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.

8.4 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.

8.5 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:

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

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

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.

Chapter 9: Project Progress

The table below lists the project progress in this semester:

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 Developing virtual mouse application on Symbian Prepare First Term presentation and demonstration Write First Term FYP report

Chapter 10: Contribution of Work

10.1 Introduction

In this session, I will state my contribution of work in this project, and what I have learned through this project.

The development of our final year projected can be divided into 4 main stages: the preparation stage, testing platform, development stage, and deployment stage. In the preparation stage, once we figured out the objective of our project, we learned the related materials in the summer, so that we could start the development of algorithm as soon as possible. Because our project involved a lot of techniques that we did not know, we needed to start studying in the summer.

10.2 Preparation Stage

Once we had decided our project objective – motion tracking on the mobile phones using onboard camera, we needed to study the motion tracking algorithms and got familiar with the Symbian programming.

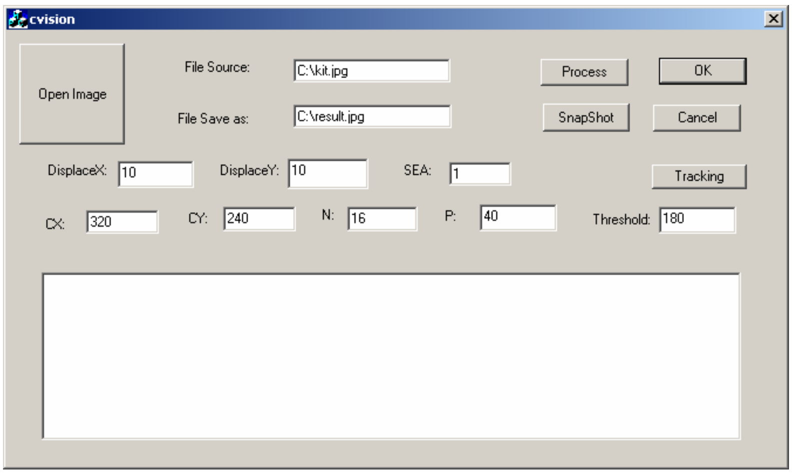
In the summer, we started to learn Symbian programming and write programs on it. I have spent one month reading the books and studying sample programs on Symbian programming. I wrote some programs on the Symbian so that I got familiar with GUI programming on Symbian and wrote a application using Bluetooth (a program that use Bluetooth to send messages to the others). Moreover, I studied how to access the camera in Symbian and use it to capture video. All of these were vital to the later development of our project. After a month of work on the Symbian, we decided that Symbian was used as the platform for our project. Then we decided to switch to the algorithm part.

Since we had not got any knowledge on motion tracking techniques, we needed to start studying from the very basic concept. I started to learn the block-matching algorithms which are commonly used in video compression while my partner started to learn the optical flow algorithm first. By discussing with each other, we learned more efficiently and I quickly picked up the concept of block-matching algorithms and optical flow. Finally we decided to focus on the block-matching algorithms.

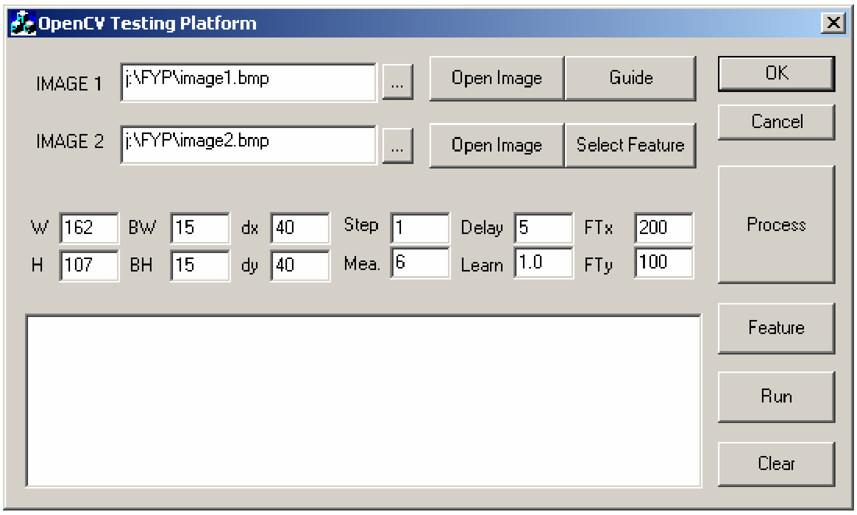
10.3 Testing platform

Since programs developing on Symbian programming is difficult to be debugged and evaluated. We tried to develop a testing platform on PC by ourselves. Finally, we decided to use the OpenCV for developing such platform.

OpenCV is an open source library for computer vision and image manipulation. I studied from the examples provided and from the Internet. Then we started to develop the testing platform using the Microsoft Foundation Classes (MFC). By using MFC, we worked together to develop a Window program quickly and by integrating with the OpenCV, the program can access the USB camera and capture video, extract frames from video source and save as bitmaps. The figure below shows the first version of our testing platform.



Afterward, we enhanced the functionality of the testing platform, so that we could test the performance of the algorithms much more easily, as shown below.



10.4 Development stage

After reading lot of papers, my partner and I started to implement the motion tracking algorithm proposed by the papers. For example, I implemented the three-step search algorithm to test its performance while my partner implemented the exhaustive search algorithm.

Both of us tried to read different papers on motion tracking techniques. I developed a feature selection algorithm to improve the performance of the motion tracking algorithm. After many discussions, we finally developed our motion tracking algorithm by combining proposed algorithm and our new algorithms.

10.5 Deployment stage

After finalized our motion tracking algorithm, we started to program on the Symbian phone. We made the basic framework in Symbian, so that we could quickly deploy the motion tracking algorithm on it. After that, I was responsible for implementing the feature selection and development of the pong game.

10.6 Conclusion

In this project, I have learned a lot of things. I am now familiar with the Symbian programming, OpenCV and MFC. Apart from this, I also learned a lot in the field of video processing, particular for motion tracking. I enjoyed the learning process and I am now able to build other Symbian applications.

Chapter 11: 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.

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 and 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.

Chapter 12: Future Work

12.1 Further Improve the Block Matching Algorithm by Hierarchical method

On top of our final algorithm, there is one more existing algorithm that may improve the speed of our algorithm. However, because the performance of our final algorithm is already quite good and the hierarchical motion tracking algorithm is complex to implement, we haven't implemented it in this semester. We may implement it in the next semester to see if it really improves the speed.

12.2 Study and implement algorithms to detect rotation angle

Currently, our motion-tracking algorithm can only detect the translational movement of the phone. Our next goal is to detect rotation of the phone in addition to the translational movement. With this property, we can develop many funny games that make use of the tilting angle of the phone such as motorcycle game.

12.3 Develop virtual mouse application

This is one of the big applications we will develop in our FYP project. We are now working on it. Right now, if the client side sends the motion vectors too fast to the server, the connection between the server and client will be broken. We will enhance the stabilities of the system and modify the codes so that the system has a higher precision in response to the movement.

12.4 Develop Multiplayer Game

We have studied the Bluetooth in the Symbian. By using Bluetooth, we can transmit game data between two devices. And we may develop an interesting game that allows the players to play interactively with each others, by using the motion tracking technique. For example, if we can develop the detection of rotational movement of the phone, we can use the phone as a table tennis racquet. By tracking the movement of the "racquet", the two players can play virtual table tennis interactively

12.5 Develop other interesting applications

We will continue to think out any interesting applications that make use of the motion-tracking engine we have developed and implement some of them. The game we have talked about mainly use the motion input to control the lateral movement or rotation of a gaming object, and the applications we have talked about mainly use the motion input to control the cursor in some operating systems. There are other types of applications and games that can make good use of the motion input. For example, a Sniper game that requires players to hold the phone stably before shooting the target can make use of our motion input to measure the shaking level of players' hand.

12.6 Build SDK

Currently, all of our applications are developed on top of the algorithm platform (The MotionTrack program). This will be troublesome when the scale of the application to be built is large. We may build a motion tracking dynamic link library (ddl) with header file so that other applications can use the motion tracking function easily.

Chapter 13: Acknowledgement

We would like to thank our final year project supervisor, Professor Michael Lyu. He gave us a lot of valuable suggestions and provided us necessary equipments for the project.

We would also like to express our thanks to Edward Yau who gave us innovative ideas and suggestions on our project.

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