

# LEGENDARY OF 18 WEAPONS - MOTION CAPTURE DATA ANALYSIS FOR WII REMOTE

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# OUTLINE

- Introduction
  - Background information
  - Motivation & Objective
- The Wii Remote
  - How to get data from Wii Remote ?
  - What can be obtained from Wii Remote ?
- Method of Classification
  - Possible Classification Methods
  - Working Principle of Dynamic Time Warping
- How do we apply Dynamic Time Warping ?
- Tuning
- Future Work
- Q & A

# INTRODUCTION

# BACKGROUND INFORMATION

## ◉ Legendary of 18 Weapons

- 18 major weapons used in traditional martial art



\* Images are extracted from <http://www.kenchan.com.hk>

# BACKGROUND INFORMATION

## ○ Motion capture

- Recording movements in a digital manner
- With the use of accelerometers

## ○ Wii Remote

- Has built-in accelerometers
- Capture movements of 1 hand
- Can be extended to both hands with the use of Nunchuk



# MOTIVATION

- **Wii is a revolutionary console**
  - A new method of playing games
  - Costly to buy a console
- **Wii Remote can pair with personal computers**
  - Capture data using Wii Remote and send to computer
  - Players can still enjoy with specially-designed games



# OBJECTIVES

- ⦿ Construct a motion classifier
- ⦿ Build an interface
  - A game, or an educational software
  - Perform motions in front of computer
  - Recognize correctly and be displayed in the computer

# THE WII REMOTE



# HOW TO GET DATA FROM WII REMOTE ?

- ◉ Bluetooth as the communication channel
- ◉ Pair up with Bluetooth USB adapter to communicate
- ◉ Use Wii Remote API get the data from Wii Remote
  - *WiiYourSelf!* as the API
  - Be integrated to our classifier



# WHAT CAN BE OBTAINED FROM WII REMOTE?

- ◎ 3D Acceleration data
  - x axis, y axis, z axis
- ◎ Infra-red data
  - Used with sensor bar
  - Determine pointing position





# METHOD OF CLASSIFICATION

# POSSIBLE CLASSIFICATION METHODS


## ◉ Tree-based & rule-based

- Compute attributes based on motion data
  - Relative Max / Min Acceleration Time
  - Initial / Average / End Acceleration
  - Rotation angle
- WEKA
  - Open source data mining software
  - Generate decision trees / rule with different tree-based / rule-based algorithms based on values of attributes
    - C4.5 decision tree learner



# POSSIBLE CLASSIFICATION METHODS

## ◎ Similarity search

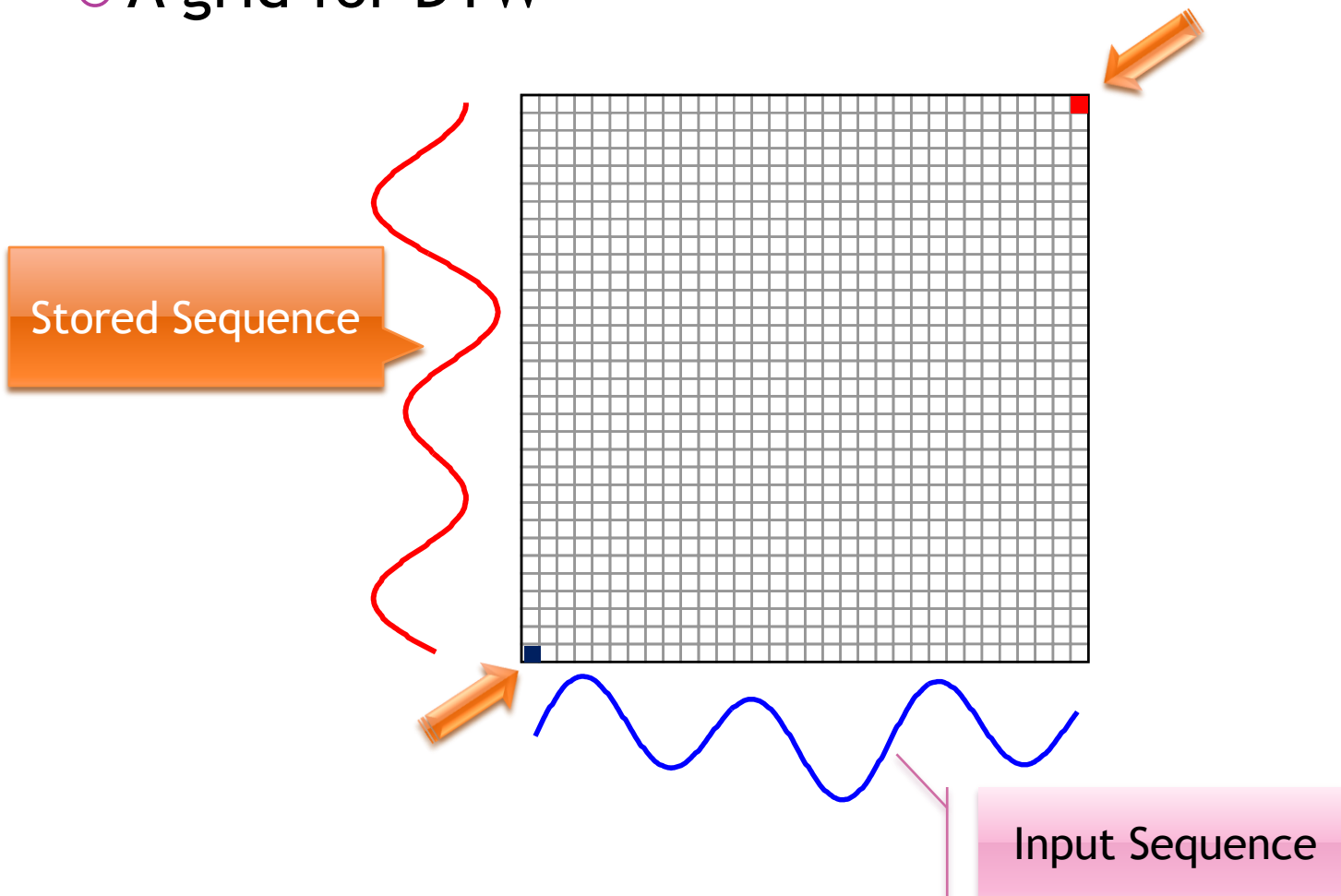
- No further computations needed
- Compare patterns of motion data
- Euclidean Distance Algorithm
- Dynamic Time Warping 

# WORKING PRINCIPLE OF DYNAMIC TIME WARPING

- Find the best match between two given sequences.
- Sequences mapped non-linearly with the time dimension.
  - To detect similarity regardless of variations in time and speed
- To produce a matching
  - First model sequences into a 2-dimensional grid

# WORKING PRINCIPLE OF DYNAMIC TIME WARPING

- A grid for DTW

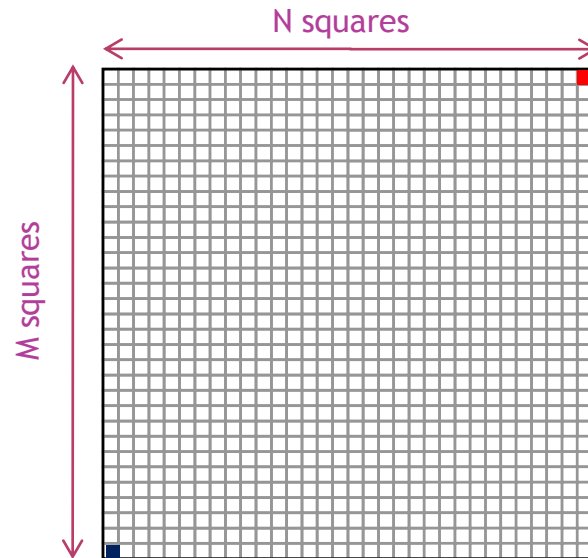




# WORKING PRINCIPLE OF DYNAMIC TIME WARPING

## ⦿ Dimension of grid

- Determined by the total number of data points of the sequence
- One data point is related with one row / column of squares



# WORKING PRINCIPLE OF DYNAMIC TIME WARPING

- The next step is to compute the values for all the squares
- Each square stores a distance ...

- Defined by sum of 2 parts

$$\gamma(i,j) = d(s_i, p_j) + \min [\gamma(i-1, j-1), \gamma(i-1, j), \gamma(i, j-1)]$$

- The Euclidean distance between the corresponding elements of the two sequences
- Minimum distances among the 3 neighboring squares

# WORKING PRINCIPLE OF DYNAMIC TIME WARPING

- Euclidean distance is defined as the ordinary distance that could be measured with a ruler
  - For two points  $P$  and  $Q$  in general  $n$ -dimension space, it is defined as:

$$\sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \dots + (p_n - q_n)^2} = \sqrt{\sum_{i=1}^n (p_i - q_i)^2}$$

- In particular for 3D space
  - For two 3D points,  $P = (p_x, p_y, p_z)$  and  $Q = (q_x, q_y, q_z)$ , the Euclidean is defined as:

$$\sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_3 - q_3)^2}$$

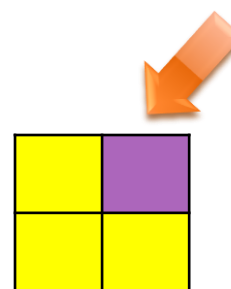
# WORKING PRINCIPLE OF DYNAMIC TIME WARPING

- The next step is to compute the values of all the squares
- Each square stores a distance ...

- Defined by sum of 2 parts

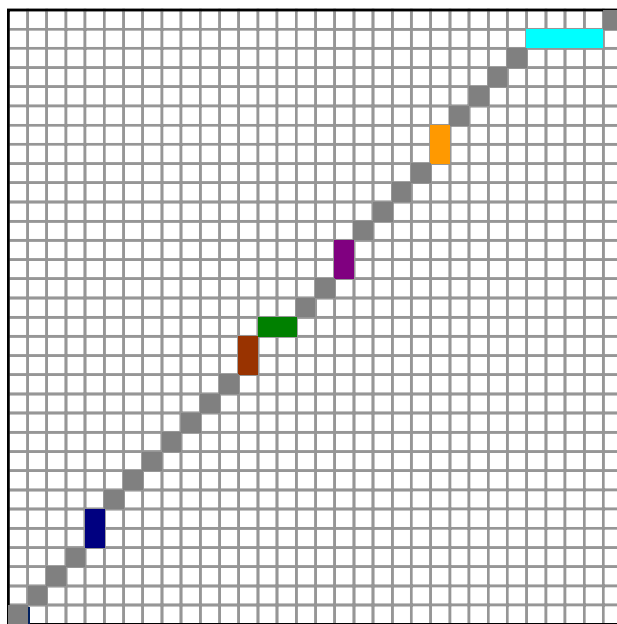
$$\gamma(i,j) = d(s_i, p_j) + \min [\gamma(i-1, j-1), \gamma(i-1, j), \gamma(i, j-1)]$$

- The Euclidean distance between the corresponding elements of the two sequences
- Minimum distances among the 3 neighboring squares
  - Values computed already



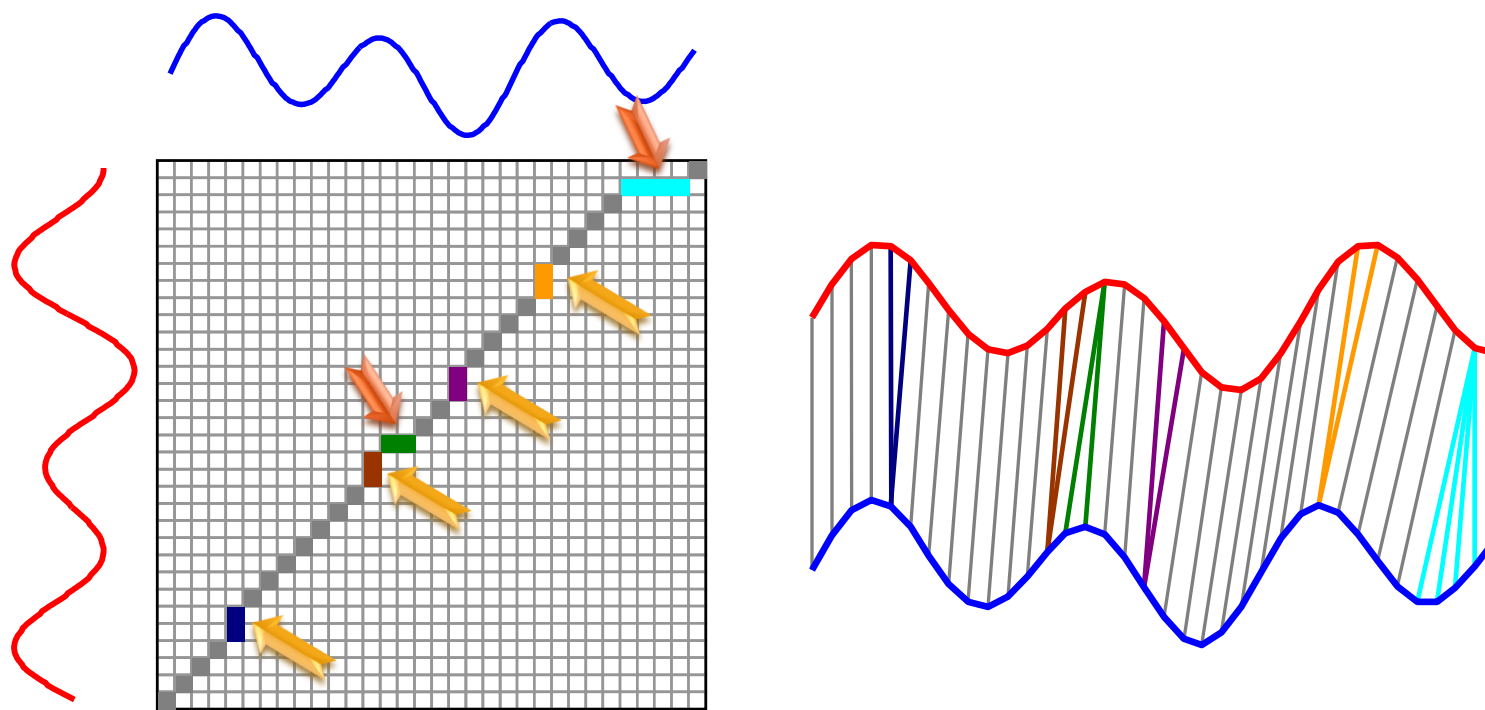
# WORKING PRINCIPLE OF DYNAMIC TIME WARPING

- Next is to find a path within the grid which minimizes the total distance from the blue square to the red square



# WORKING PRINCIPLE OF DYNAMIC TIME WARPING

- Warping path is found
  - Just the shortest path computed
- Defines the mapping between two sequences



# HOW DO WE APPLY DYNAMIC TIME WARPING?

# DATA STRUCTURE

## Motion Database

2

A

Left

Reference  
Motion  
Data

Reference  
Motion  
Data

Reference  
Motion  
Data

Reference  
Motion  
Data



# EXAMPLE

Time	X	Y	Z
0	1.000	2.519	0.480
15	0.720	2.667	0.320
30	0.120	2.963	0.240
45	-0.120	3.111	0.280
60	-0.600	3.519	0.440
75	-1.120	3.852	0.520
90	-1.280	4.000	0.640
105	-1.440	4.111	1.000
120	-1.680	4.148	1.160
135	-2.400	4.185	1.400
150	-2.880	4.185	1.440
165	-3.480	4.222	1.400
180	-3.280	4.222	1.280
195	-2.960	4.222	1.200
210	-2.480	4.222	1.000
225	-2.360	4.259	0.960
240	-2.360	4.259	0.840
255	-2.640	4.259	0.960
270	-3.400	4.259	1.000
285	-3.800	4.259	0.920
300	-3.480	4.296	0.840
315	-2.320	4.222	0.760
330	-2.040	4.259	0.920
345	-2.360	4.111	1.040
360	-2.520	3.519	0.840
375	-2.440	3.185	0.680
390	-2.000	2.630	0.400
405	-1.720	2.407	0.280

Time	X	Y	Z
0	1.400	1.963	0.760
15	1.240	2.111	0.760
30	0.880	2.593	0.720
45	0.440	2.926	0.760
60	0.240	3.074	0.760
75	-0.120	3.444	0.840
90	-0.360	3.667	0.840
105	-0.920	3.963	0.960
120	-1.320	4.074	0.920
135	-2.000	4.148	1.000
150	-2.520	4.185	1.200
165	-2.880	4.222	1.240
180	-3.240	4.222	1.240
195	-4.120	4.222	1.400
210	-4.280	4.222	1.240
225	-3.600	4.259	1.000
240	-2.840	4.259	1.000
255	-2.760	4.259	1.080
270	-3.120	4.296	1.280
285	-3.720	4.259	1.320
300	-4.600	4.296	1.000
315	-3.960	3.926	0.560
330	-3.360	3.593	0.440
345	-2.240	3.519	0.600
360	-1.960	3.593	0.760
375	-1.800	3.481	0.960
390	-1.880	3.222	1.000
405	-2.000	2.630	0.760
420	-1.920	2.370	0.600
435	-1.680	1.926	0.400
450	-1.520	1.704	0.320

Reference Motion of Same Type

Motion To Classify

# THE INPUT DATA

Time (Millisecond)	X	Y	Z
0	1.00	2.52	0.48
15	0.72	2.67	0.32
30	0.12	2.96	0.24
45	-0.12	3.11	0.28
60	-0.60	3.52	0.44
75	-1.12	3.85	0.52
90	-1.28	4.00	0.64
105	-1.44	4.11	1.00
120	-1.68	4.15	1.16
135	-2.40	4.19	1.40
150	-2.88	4.19	1.44

# APPLYING DYNAMIC TIME WARPING

Dynamic Time Warping Cost:

$$\gamma(i, j) = d(s_i, p_j) + \min [\gamma(i-1, j-1), \gamma(i-1, j), \gamma(i, j-1)]$$

Typically:

$$d(s_i, p_j) = |s[i] - p[j]|$$

In our case:

$$d(s_i, p_j) = \sqrt{(s[i].X - p[j].X)^2 + (s[i].Y - p[j].Y)^2 + (s[i].Z - p[j].Z)^2}$$



# TAKE DURATION INTO CONSIDERATION

	Duration (Millisecond)
Reference Motion of Same Type	405
Motion to Classify	450
<b>Average</b>	<b>427.5</b>

7.2 19.1 21.0 24.2  
7.1 18.9 21.3 23.9  
5.3 17.6 19.5 21.6  
5.0 16.9 18.4 20.2  
5.1 16.3 17.1 18.1  
5.7 16.5 16.8 17.5

$$\text{DTW Error(Similarity)} = 17.534 \div 427.5 = 0.041$$

# DTW ERROR RESULT

Motion Name	Error
Left	0.041
TopRightCircle	0.245
LeftCircle	0.196
Dash	0.273
CircleUp	0.162

Classified As: Left

TUNING

# REASONS FOR LOW ACCURACY?

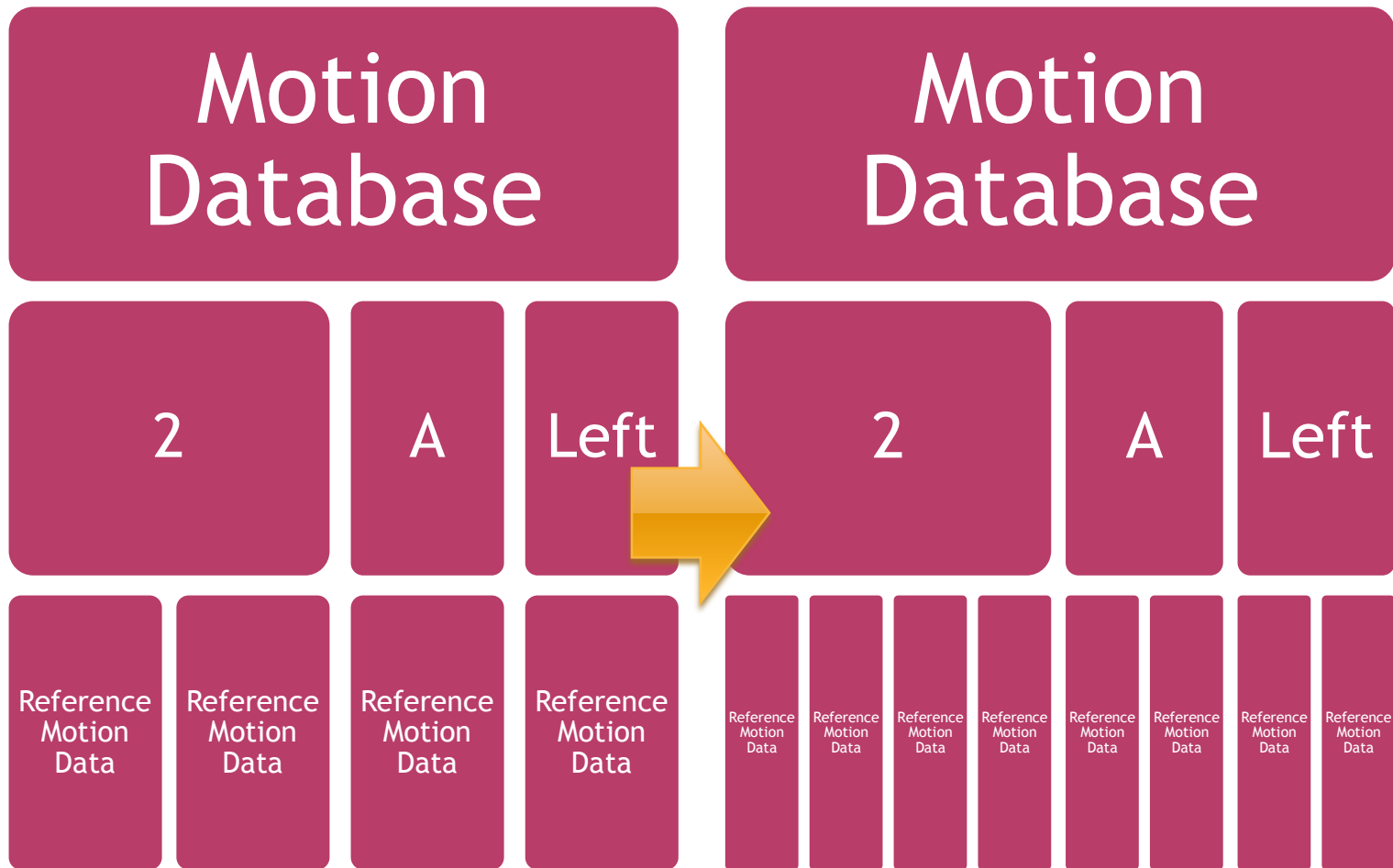
- ⦿ Performed not in the same way
- ⦿ Button pressed in wrong moment
- ⦿ Similar motions
- ⦿ Bad quality of reference motion



# ANALYZED METHODS OF TUNING

- ⦿ Number of Reference Motion
- ⦿ Error Compensation
- ⦿ Average of Motion Data as Reference Motion

# NUMBER OF REFERENCE MOTION

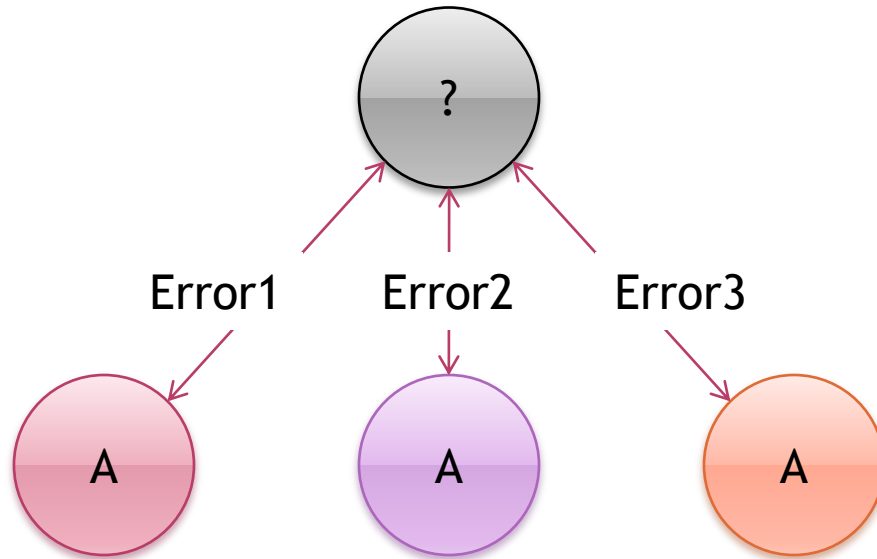


# NUMBER OF REFERENCE MOTION

- ⦿ Increase number of reference motions of the same type of motion
- ⦿ Run Dynamic Time Warping on more reference motions

# NUMBER OF REFERENCE MOTION

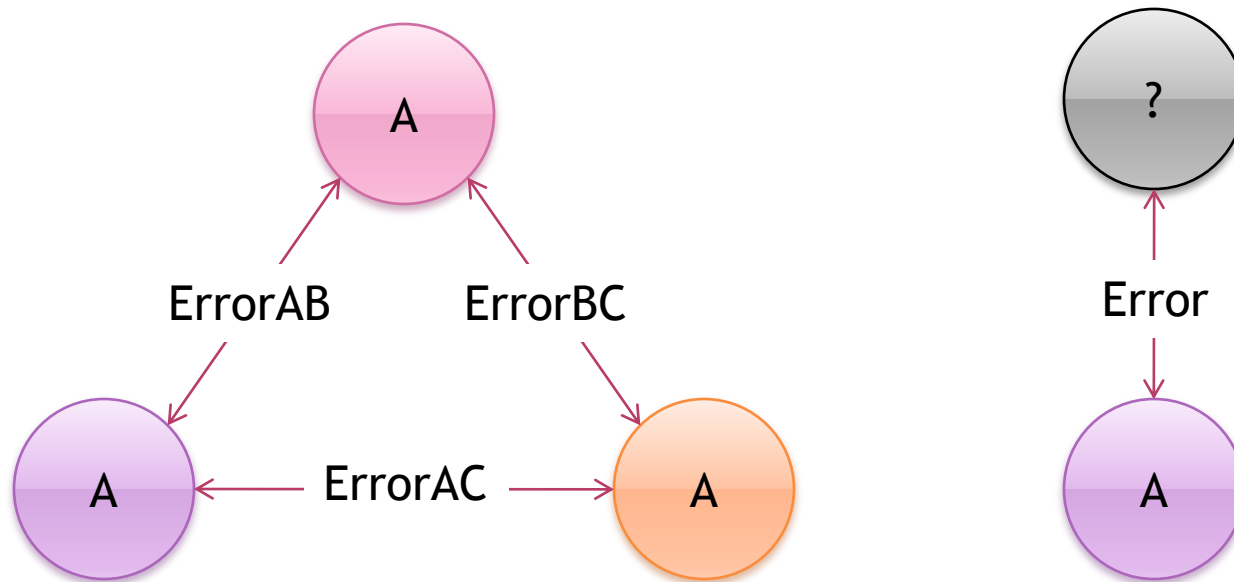
⦿ float dtwError(Motion A, Motion B);



⦿ Similarity = (Error1+Error2+Error3) ÷ 3

# ERROR COMPENSATION

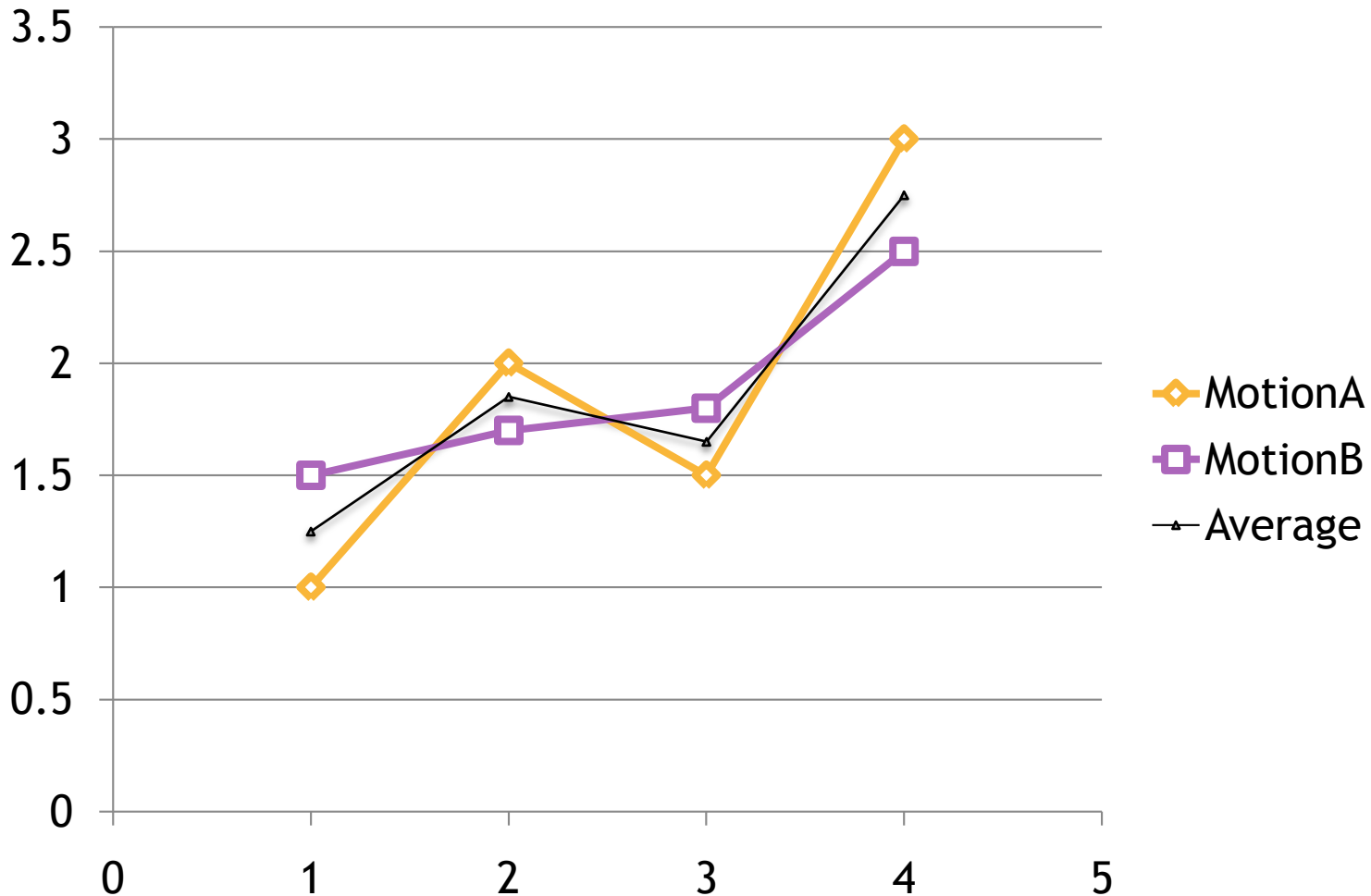
⦿ float dtwError(Motion A, Motion B);



⦿ AllowedError = (ErrorAB+ErrorBC+ErrorAC)÷3

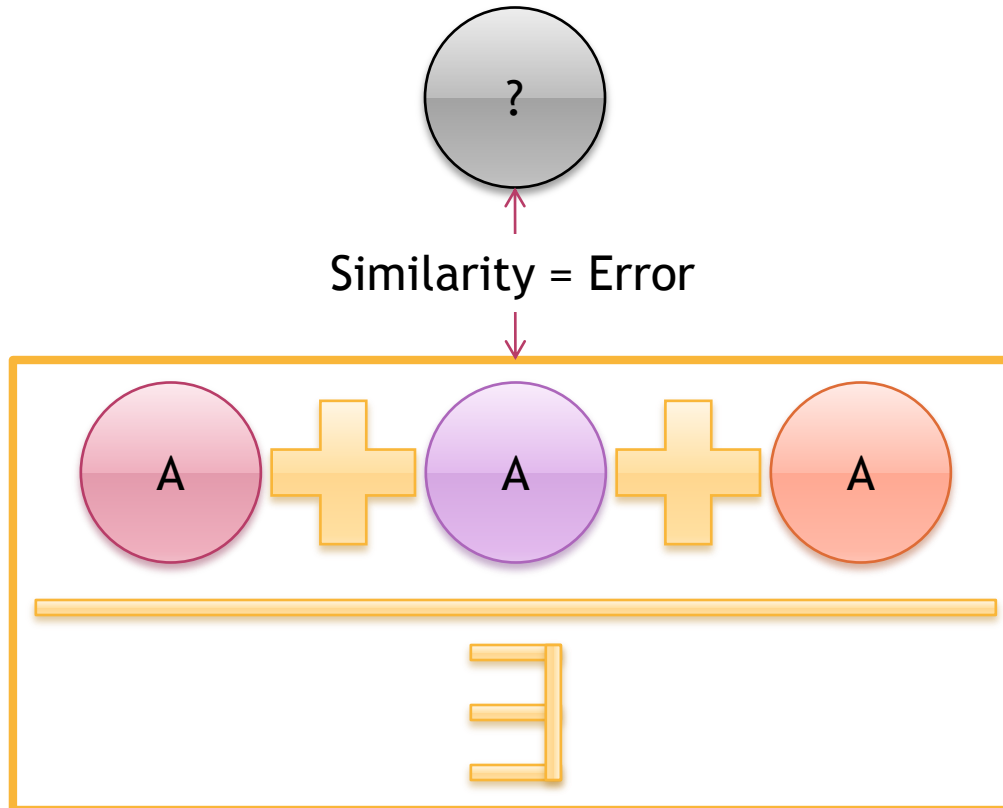
⦿ Similarity = Error - AllowedError

# AVERAGE OF MOTION DATA AS REFERENCE MOTION



# AVERAGE OF MOTION DATA AS REFERENCE MOTION

⦿ float dtwError(Motion A, Motion B);



# MOTIONS USED

- ◉ Five Directions
- ◉ Cursive Writing Letters
- ◉ Discrete Motions
- ◉ Numbers
- ◉ Dao Motions



# CONFIGURATIONS USED

	Reference Motion (R)	Error Compensation (E)	Average Motion (A)
Configuration 1	1		
Configuration 2	1	3	
Configuration 3	3		
Configuration 4	3	3	
Configuration 5	5		
Configuration 6	5	3	
Configuration 7			3
Configuration 8		3	3

# CLASSIFICATION ACCURACY

Configuration	Five Directions (By 3 People)	Letter	Discrete	Dao Motions	Number (By 3 People)	Average
R=1	92.57%	100%	99.51%	100%	85.69%	95.55%
R=1,E=3	95.59%	100%	98.52%	100%	90.41%	96.90%
R=3	91.06%	100%	99.50%	100%	95.47%	97.21%
R=3,E=3	91.92%	100%	99.50%	100%	98.13%	97.91%
R=5	94.18%	100%	99.50%	100%	97.07%	98.15%
R=5,E=5	94.90%	100%	99.50%	100%	98%	98.48%
A=3	91.52%	100%	99.50%	100%	97.47%	97.70%
E=3,A=3	92.66%	100%	99.50%	99.29%	90.41%	96.37%

# EFFECT OF DIFFERENT TUNING

	Preparation?	Time?	Space?
Reference Motion	No	Largely	Largely
Error Compensation	Yes	Slightly	Slightly
Average Motion	Yes	No Effect	No Effect

# CONCLUSION

- ◉ Depend on requirement in choosing
- ◉ Hybrid can be considered

# FUTURE WORK

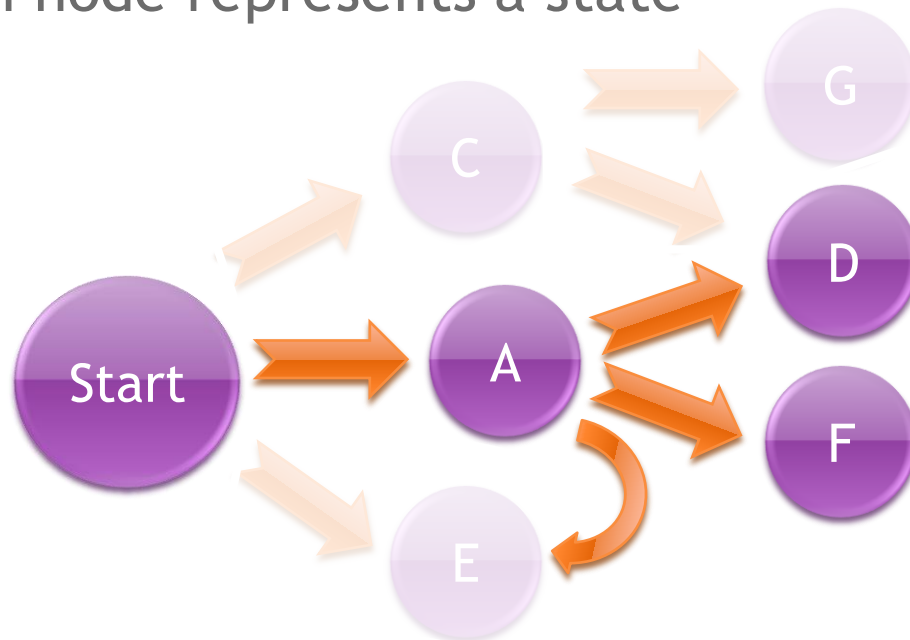
# FUTURE WORK

- ⦿ A game demo
- ⦿ Educational software of Chinese Martial Art
- ⦿ Motion Finite State Machine
  - Making use of game rules to minimize the amount of possible candidates in classification
    - Limit the type of motions that can be followed

# FUTURE WORK

## ◉ Motion Finite State Machine

- Each node represents a state



- Allow players to perform motions in any sequence but still maintain high accuracy

# FUTURE WORK

- A game demo
- Educational software of Chinese Martial Art
- Motion Finite State Machine
- **Early Recognition**
- **Two hand weapons using Nunchuk**
- **“Button-less”**



Q & A