Upper Limb Motion Recognition Based on Mobile IMU Signal

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Abstract

The tradition screen based interaction method is based on eyes and hand. A hand-free and eye free interaction method can improve the usage of the mobile. In this project, I purposed a framework to identify human upper limb motion only based on mobile in order to enhance the study of the mobile motion interaction. The FFT features are applied in deep neural network. The output of the neural network forward into a classifier to do classification. The result is evaluated by a confusion matrix. The project also figure out the challenge of the problem by study the real usage context.

Content

1 Introduction

Background: The most general human mobile interaction method is based on a touch screen. Users have to stop and visually attending to the screen when they want to interact with mobile in any situation. People have to stop and look at the screen which limits the ability for mobile to server people [1]. For example, derivers cannot make a call because the eyes are not free when driving. The concern of traffic accident which caused by mobile is increased [2]. Considering to fulfilling the rich situations, it is very important to design an invisible interaction method.

Motivation: The new approaches to do mobile interaction can be based on cameras [3], Electromyography (EMG) [4, 5] or Inertial Measurement Units (IMUs) [6, 7]. This project presents a motion identification framework, which only based on IMU signal, to improve the study about IMU based mobile interaction approach.
Actually, some experts believe that gesture interaction is the most promised way to interact [10, 11, 12].There are several advantages of the IMU based motion interaction approach. For one thing, the mobile has become more and more portable, ubiquitous and smart nowadays. Most of mobile is embedded with IMUs. It is convenient because it does not need extra devices [8, 9]. The second advantage is that, the IMU Sensor is suitable for many complex environments. The camera is strongly influenced by the light level and EMG is also very easy influenced by the noise [10, 11]. The IMU sensor is more suitable for the complex context in real world. However, IMU based approach does not measures the trace directly. A robust method is necessary to identify the motion command [7]. In this case, improving IMU based motion identification ability is helpful to improve the mobile interaction.

Method: IMU is the electronic devices which used to detect body movement information. Accelerator and gyroscope are IMU. Until now, a triaxial accelerator and a triaxial gyroscope are embedded in the most of smart devices. The accelerator is applied to collection accelerated velocity and gyroscope is applied to collect an-

gular velocity in this project.
For now, the general method to do motion identification is based on feature extraction and classification. The features includes wavelet transform, Fast Fourier Transform, some parameters of the data like mean, power, entropy and correlation [14, 15, 16]. For classification, the methods include decision tree, byes algorithm, KNN, Support Vector Machine (SVM) and deep neural network [14, 15, 16, 17].

Research Aims: In this project, a framework about upper arm motion identification is proposed to enhance the mobile interaction. I attempt to recognize human upper arm motion only based on mobile IMU signal. This includes two part of works. The first one is to do feature extraction and the second one is to do classification. Some algorithms, like Dynamic Time warping (DTW), Fast Fourier Transform (FFT), are applied on feature extraction and there are some tips to get a better classification result. The challenge part will also detailed in this project. For example, the gap between the model and the real world context is a big challenge of this work. The signal is based on IMU coordinates and gravity have strong influence on the data of signal. This project will purposed new methods rely on the real world environment.

Research Question The project is mainly aimed to answer the following questions. The first one is why identify the human motion only based on mobile is difficult. The second question is how to select the parameters to be the feature. As mentioned before, there are many methods are applied to be the feature in many studies [14, 15, 16]. However, not all the parameters is valuable in this problem. Selecting bad parameter is not effective and even make negative influence on the result. In this case, parameter selection is also important in this problem. The last question is about neural network. RNN is applied in this project. The node selection, the parameter toning should also be considered.

Solution: In this project, I mainly aimed to offer a framework to do upper limb motion identification. IMUs which embedded in mobile are the only equipment which used to do sensing because I do not want extra devices reduce the user experience when doing interaction [7]. Aimed to offer a robust result, I choose FFT algorithm to do feature extraction and deep neural network to do classification. The reason will be explained in the following section.
The row data from the mobile is stored in a text file. The row data is processed in order to generate the structured data which applied in the framework. Then the feature is extracted and forward into Long Short Term Memory (LSTM) neural network.

Contribution: The contribution of the project can be summarized as shown below. First of all, a new framework is purposed to do upper limb motion identification. The upper limb mobility is studied and the challenge part of the motion identification problem is detailed. Secondly, there is a gap between the equipment and the real use algorithm. Some efforts are applied in order to fix the gap to improve the performance of the work. The next contribution is that a new auto separation method is purposed to help people separate time sequence data. It is a great helpful to expand the input data scale and saved lots of effort on data annotation. The last contribution is that more and more people wear mobile in everyday life. Improving hand and eye free system is help to improve the ability of the phone to serve people.

2 Literature Review

In this section, the relevant literature is reviewed.

2.1 Mobile Interaction

The most popular interaction system is stop and interaction. It is designed only for users who stopping and visually focus on the touch screen of the mobile. A good interaction system which go beyond visually attention and hand-screen interaction can greatly expand the usability of the phone [1]. Now, the mobile is increasingly portable and smart so more and more people like to wear the mobile in everyday life such as doing exercise. The exercise like running, bicycling or walking is highly intensive and have benefits on human health [18]. People tend to wear mobile during doing exercise to get some support. Another obvious example is use phone in cars. It is very easy to cause accident when deriver use phone and lost attention about the road [3].Some experts believe that, new interaction method is need in order to increase the usability of the mobile in real world context [1].

The most popular interaction system is stop and interaction. It is designed only for users who stopping and visually focus on the touch screen of the mobile. A good interaction system which go beyond visually attention and hand-screen interaction can greatly expand the usability of the phone [1]. Now, the mobile is increasingly portable and smart so more and more people like to wear the mobile in everyday life such as doing exercise. The exercise like running, bicycling or walking is highly intensive and have benefits on human health [18]. People tend to wear mobile during doing exercise to get some extra support. Another obvious example about shortage of eye-hand based interaction is use phone in cars. It is very easy to cause accident when deriver use phone and lost attention about the road [3].Some experts believe that, new interaction method is need in order to increase the usability of the mobile in real world context [1]. There are many methods can be applied to do upper arm motion recognition. Motions can be identified by a camera. However, the vision techniques is not suitable in this problem because the clutter and complex lighting level in real world [19]. And it is obvious, the camera limits the coverage area of the most promised method is sensor based identification. There are many sensors are utilized in motion recognition such as title, IMUs, surface electromyography (EMG), capacitance and conductivity. For example, some experts offer a motion identification framework which utilize the accelerator and capacitance [20]. Another example is about an IMU and EMG fusion method. The IMU signal and EMG signal are fusion by a Kalman Filter to improve the accuracy of the predication [21]. Considering the user experience, I do not want users to wear extra equipment. Adding extra sensors is also a budget if the system applied in real use. In this case, only the sensors which embedded in mobile will be applied in this project. Accelerator and gyroscope are sensors which embedded in most of smart phones. So, only accelerator and gyroscope are used in this project. Solely depend on IMU signal is proved problematic on accuracy and some small motion [21]. In this case, a more robust methods should be put up to improve the purely IMU based method.

2.2 Modelling

Time sequence modelling can be considered as a dynamic system. It can be described as a state and an external variable [25]. Hidden Markov Model, statistic algorithm and deep neural network are methods which applied in modelling [26, 27]. Hidden Markov Model determined the state parameters in many stages but not one stage which makes it not popular as before [28, 29]. Recursive Neural Network is a promised method to modelling dynamic system. RNN node have a state parameter to represent current state and another input parameter represents the external variable [25]. The usability of the deep neural network model increases [29].

There two main part to achieve IMU based upper arm motion identification with DNN method. The first one this feature extraction and the other one is classification [6, 7, 14]. The feature includes some parameters of the signal like mean, power, correlation, entropy [14, 15, 16]. Some algorithms can also applied the in feature extraction like Fast Four Transform (FFT), Discrete Cosine Transformation (DCT), Discrete Wavelet Transformation (DWT) [21, 23, 24,]. There also many methods to do classification. It includes KNN, Bayes Algorithm, Decision Dree and Support Vector Machine (SVM) [14, 15, 17]. Deep Learning method can be applied both feature extraction and classification and some man made feature can benefit the deep neural network to do feature extraction [14].

2.3 Mobility of Upper Limb

The upper limb is connected to the shoulder. Shoulder is a joint which provide great flexibility of motion. The shoulder can flexion, extension, abduction and adduction. It makes the upper limb can be lift forward and backword. And it makes upper arm can rotate by shoulder. And it makes upper arem can lift right or left which depend on the side of the arm [30, 31].

3 Data Collection

3.1 Environment

The data is collected in google Nexus 5X. As the table shown below. There are 10 types of sensors supported in android.

Sensor	Sensor event data	Description	Units of measure
TYPE_ACCELEROMETER	SensorEvent.values[0]	Acceleration force along the x axis (including gravity).	m/s^2
	SensorEvent.values[1]	Acceleration force along the y axis (including gravity).	
	SensorEvent.values[2]	Acceleration force along the z axis (including gravity).	
TYPE_ACCELEROMETER_UNCALIBRATED	SensorEvent.values[0]	Measured acceleration along the X axis without any bias compensation.	m/s^2
	SensorEvent.values[1]	Measured acceleration along the Y axis without any bias compensation.	
	SensorEvent.values[2]	Measured acceleration along the Z axis without any bias compensation.	
	SensorEvent.values[3]	Measured acceleration along the X axis with estimated bias compensation.	
	SensorEvent.values[4]	Measured acceleration along the Y axis with estimated bias compensation.	
	SensorEvent.values[5]	Measured acceleration along the Z axis with estimated bias compensation.	
TYPE_GRAVITY	SensorEvent.values[0]	Force of gravity along the x axis.	m/s^2
	SensorEvent.values[1]	Force of gravity along the y axis.	
	SensorEvent.values[2]	Force of gravity along the z axis.	
TYPE_GYROSCOPE	SensorEvent.values[0]	Rate of rotation around the x axis.	rad/s
	SensorEvent.values[1]	Rate of rotation around the y axis.	
	SensorEvent.values[2]	Rate of rotation around the z axis.	
TYPE_GYROSCOPE_UNCALIBRATED	SensorEvent.values[0]	Rate of rotation (without drift compensation) around the x axis.	rad/s
	SensorEvent.values[1]	Rate of rotation (without drift compensation) around the y axis.	
	SensorEvent.values[2]	Rate of rotation (without drift compensation) around the z axis.	
	SensorEvent.values[3]	Estimated drift around the x axis.	
	SensorEvent.values[4]	Estimated drift around the y axis.	
	SensorEvent.values[5]	Estimated drift around the z axis.	
TYPE_LINEAR_ACCELERATION	SensorEvent.values[0]	Acceleration force along the x axis (excluding gravity).	m/s^2
	SensorEvent.values[1]	Acceleration force along the y axis (excluding gravity).	
	SensorEvent.values[2]	Acceleration force along the z axis (excluding gravity).	
TYPE_ROTATION_VECTOR	SensorEvent.values[0]	Rotation vector component along the x axis ($x * \sin(\theta/2)$).	Unitless
	SensorEvent.values[1]	Rotation vector component along the y axis ($y * \sin(\theta/2)$).	
	SensorEvent.values[2]	Rotation vector component along the z axis ($z * \sin(\theta/2)$).	
	SensorEvent.values[3]	Scalar component of the rotation vector (($\cos(\theta/2)$)).[1]	
TYPE_SIGNIFICANT_MOTION	N/A	N/A	N/A
TYPE_STEP_COUNTER	SensorEvent.values[0]	Number of steps taken by the user since the last reboot while the sensor was activated.	Steps
TYPE_STEP_DETECTOR	N/A	N/A	N/A

[32]

The accelerator and gyroscope are the IMUs which applied in this project. Android operating system support 5 IMU data collection modes with frequency 100 Hz, 250 Hz, 500 Hz, 500 Hz, or 1000 Hz. In this project, the data is collected with frequency 100HZ. 100 HZ is selected in the work. From the table, it is easily get that accelerator and gyroscope are all triaxial sensor. The receiving time and a label to separate two kind of sensor are also necessary record in this project. So, there are 8 attributes of the row data. The row data is stored in a .txt file. The format is as figure shown below.

```
1:   3.178191  10.205178  2.191443 1568103089462
1:   3.171006  10.023157  2.4908204 1568103089540
1:   3.278782  9.929751  2.5171657 1568103089620
1:   3.3937428  9.85311  2.5459058 1568103089700
1:   3.408113  9.857901  2.3974147 1568103089781
1:   3.412903  9.965676  2.2561085 1568103089858
1:   3.5063088  10.054293  2.2249732 1568103089939
1:   3.551814  9.996812  2.2489235 1568103090019
1:   3.6212697  9.953702  2.1531227 1568103090097
2:   3.06  9.07  2.1399999 1568103090109
1:   3.671565  10.003997  2.076482 1568103090176
2:   3.07  9.08  2.08 1568103090189
1:   3.6859353  9.958491  2.071692 1568103090256
2:   3.08  9.08  2.07 1568103090270
1:   3.6883302  9.881851  2.074087 1568103090336
2:   3.12  9.07  2.06 1568103090347
1:   3.68354  9.8866415  2.0046315 1568103090414
2:   3.1499999  9.059999  2.05 1568103090434
1:   3.6859353  9.965676  1.9447559 1568103090493
2:   3.1399999  9.059999  2.04 1568103090510
1:   3.7601807  10.027947  1.9974464 1568103090576
2:   3.12  9.07  2.03 1568103090590
1:   3.7098854  9.968072  2.0357666 1568103090655
```

Data Storage

The time is recorded by UNIX timestamp. UNIX timestamp is a data sequence to represent the number of seconds past since 1st January 1970 in order to provide high accurate data recording. It can reduce the influence of leap time for recording. The accuracy of timestamp in this project is nanosecond. The comparison form is as shown below.

Time	Second
One Minute	60
One Hour	3600
One day	86400
One Week	604800
One Month	2629743
One Year	31556736

In this case, it is clear that a 13-bit data sequence timestamp is applied to record the time.

3.2 Introduction of Motion

As the mobility of upper limb mentioned before, the arm connection to the shoulder. Shoulder is a joint with good flexibility. As figures shown below the mobile is stabled. People can lift the arm forward or backward (state1 to state2), lift the arm to left/right (state1 to state3 depend on the left/right arm), people can rotate the arm (state3 to state4) and people can also rotate the arm and make the elbow draw a circle. It is obvious, there four motions will be study in this project.

State1

State2

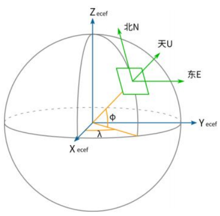
State3

State4

3.3 IMU Coordinate and World Coordinate

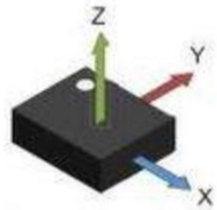
Two primary coordinates should be considered in this project. The first one is world coordinate and the second one is IMU coordinate.

The world coordinate is a rectangular coordinate which applied to descript position in specific space. In generally use, the world coordinate refers to the inertial Cartesian coordinate system relevant to the earth. The advantage of world coordinate is clear. The movement of the object can be described very obviously. The disadvantage of the world coordinate is that one position can be achieved by infinity number of combination of positions. This especially concerns the robots which multiple joints.



World Coordinate

The IMU coordinate is as figure shown below. The coordinate is build up based on the position and gesture of the sensor. In this case, the base of the coordinate is not still relevant to the world. It is not a non-inertial Cartesian coordinate.



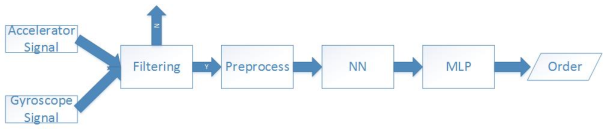
IMU Coordinate

The camera can get information based on world coordinate and the IMU sensor get the information based on IMU coordinate.

4 Methods and Algorithm Design

4.1 Overview

The overview of the model is as figure shown below.



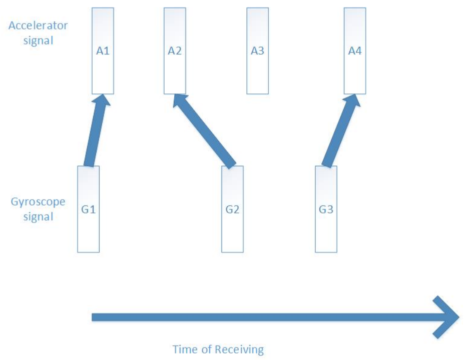
Overview

There are 4 main components of the whole framework. The row date sequence are forward into the filter to do filtering. A structured data set will be generated and forward into the preprocess component. In preprocess component, the time sequence is separated and labelled. The parameter or FFT features is also extracted in this component. Then, features can be applied in Neural Network to do training or testing. The detail of each component will introduced in the following paragraph.

4.2 Filter and Filtering

This component is mainly aimed to generate structured data. As the data storage figure shown before. The gap between two signals is not uniformed. And two kinds of signal are stored in one txt file. The filter separate the two different signal based on label and uniform the gap between signals based on linear predication.

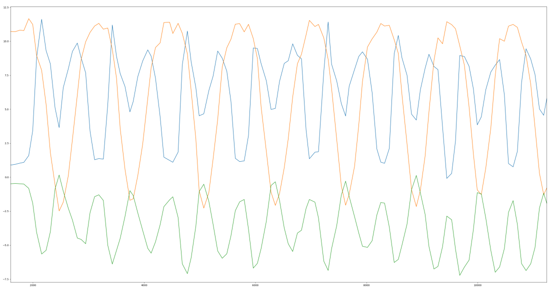
The signal from accelerator and from gyroscope are processed on same sampling time. In this case, the two signals are aligned in time domain.



Uniform and Aligment

4.3 Preprocessing

The preprocessing stage include two process. They are segment separation and feature extraction.



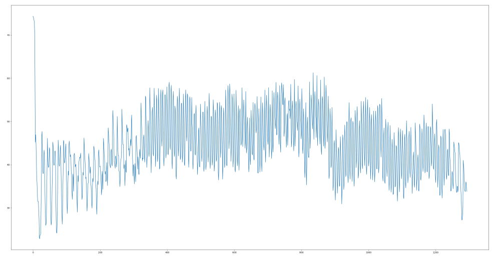
Data after Filtering

4.3.1 Separate

The structured data sequence which input to the data preprocess component is as shown above. It is lots of reputations of same motion. The sequence have to be segmented and annotated before using. Manual segmentation and annotation is time consuming and not very effective. It is impossible to deal with large amount of data manually. In this case, an auto separation and annotation method is needed.
The separate method is inspired by the segmentation method of image [13]. There is a distance calculation algorithm to evaluate the similarities of different sequence. The data is first going through a window with stable size. The low distance part is tend to be the interested point. Then the window with different is applied to detect the real length of the segment.
Dynamic Time Warping algorithm: The equation of DTW is as shown below.

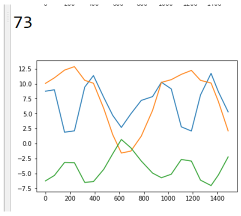
$$D = min \frac{\sum_{n=1}^{N} [d(x_{i(n)}, y_{i(n)})W_n]}{\sum_{n=1}^{N} W_n} \quad (1)$$

DTW is an algorithm to calculate the distance of sequence with different length and scale [13]. It applies dynamic programing method to accumulate all the minimum distance in order to compare the similarities of two sequence with different length, size and phase on time domine.
Principle Component Analysis (PCA): The PCA algorithm projects the data into principle base to centralize the information. The principle axis is the axis (base) with biggest variance after projection. In this project, the data sequence after PCA on principle axis is the most significant plot. Another advantage to applied PCA is that, the variance ratio can be applied as the weight for different axis to do marking.
Procedure: Firstly, the data will forward into a stable window to do marking. Then, a data sequence about marks is generated. It is as shown below.

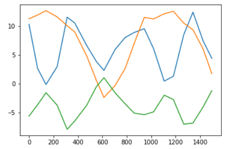


Distance Sequence

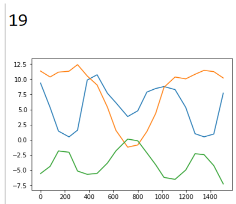
As the figure shown, the distance may be high in some local minimum point because the target have different length. The absolute length between window and target is large which tends to high distance. But the tendency can also represent the position. As experiment, if a point is local minimum point, and it is also the smallest distance in a small range. The point is the position of a target.
After finding the positon, windows with different size will be applied in order to find the accurate size of the target.



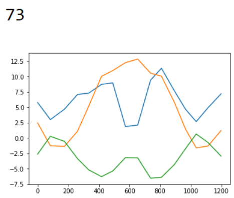
Stable Window Segmentation1



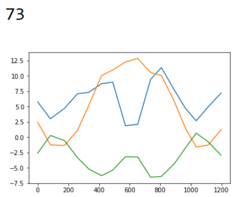
Stable Window Segmentation2



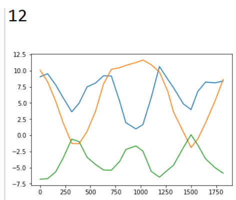
Stable Window Segmentation3



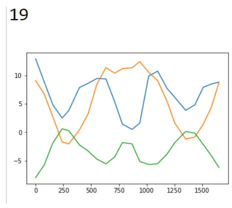
Bounding Window Segmentation1



Bounding Window Segmentation1

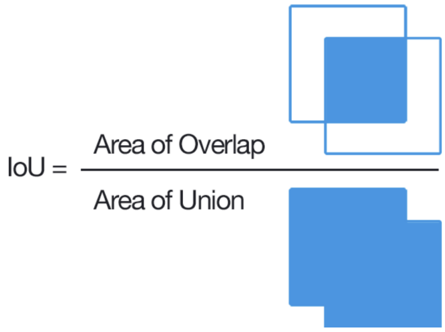


Bounding Window Segmentation2



Bounding Window Segmentation3

Intersection over Union (IOU) Evaluation: The function of Intersection over Union (IOU) is as shown. It is used to evaluate segmentation result.

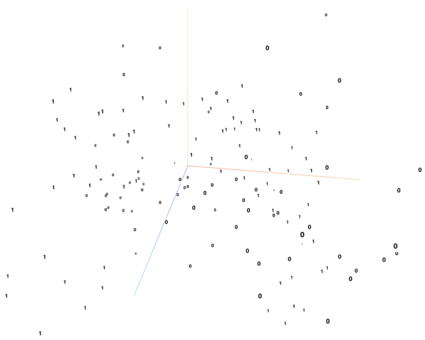


IOU Evaluation

IOU algorithm calculates the ratio between the overlap and union of prediction and real target. The IOU more than 0.67. In this case, the result is good and the auto segmentation and annotation algorithm can be applied in the project.

4.3.2 Feature extraction

There are many features can be applied in this project. Selection feature is important to get a good result. The parameters like mean, power entropy is not suitable in this project. The following figure represent the confusion coordinate of parameter features. The result is decomposed into 3 axis by PCA algorithm to illustrate. It is quite clear, the motion cannot classify by these features and the model learned nothing.

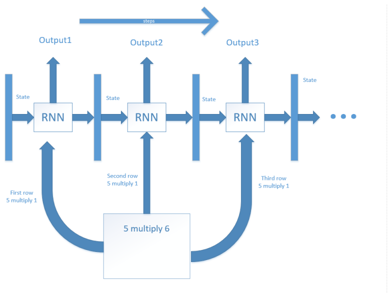


Confusion Matrix

The FFT algorithm is applied to do feature extraction in this project. The accurate of FFT in this work is 8. The FFT features are Hermitian-symmetric. So, only 5 impose is needed to represent an axis of signal. The accelerator signal and gyroscope signal are 3-D signal. In this case, output features is a 5 multiply 6 matrix.

4.4 NN Architecture

The features are forward into Deep Neural Network model to do another feature extraction and classification. The Recursive Neural Network is applied in there. The finial classification method is take advantage of a Multiple Layer Perception (MLP). LSTM node is a kind of RNN which adopted in this work. It is better to avoid information vanishment in many steps. LSTM node improve the performance of the architecture.



RNN Architecture

There are 6 channels of input, in this case, the input length is set which is important when applying RNN architecture. Figures above shows the training procedure of the model. A sequence of code will finally generated after six steps which hold the information of target. Then the output is forward into a MLP architecture to determine the final result.

5 Result and Analyses

5.1 Result

The confusion table is shown below. Rotation1 is draw circle with elbow and Rotation2 is state2 to state3

real predication	R1	L Forward	L Right	R2
Rotation1	93	3	4	0
Lift Forward	3	87	10	0
Lift Right/Left	3	19	78	0
Rotation2	0	0	0	100

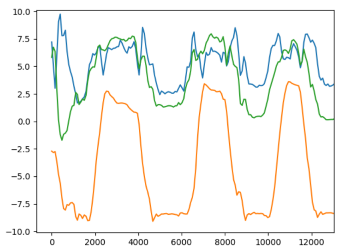
The table shows the confusion matrix of the four motions which studied in this project. The rotation2 is recognized very well. The motion trace is very different from the other three motions. It is almost still only gesture is changing. However, the accuracy to recognize two lift motions in different direction is low. This two motions have similar motion patterns. The misclassification of rotation1 is small. The percentage of misclassify rotaion1 to two lift motions is similar. And motion1 is the motion with big complexity. The training result is good compare with lift movement.

5.2 Feature Selection Analyse

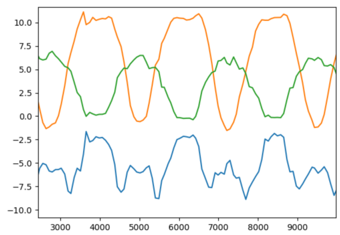
As mentioned before, there is a pilot study about parameter features. It is improved that the parameter feature is not suitable for this shot period low intensive motion recognition problem. It is more suitable to be applied in activity identification like identify walk, stand still or bicycling. For one thing, the Gravitational acceleration is much more dominant compared with the acceleration generated by motion. For another thing, the parameter features, like mean, is not so obvious for the motions.

5.3 Lift motions Analyse

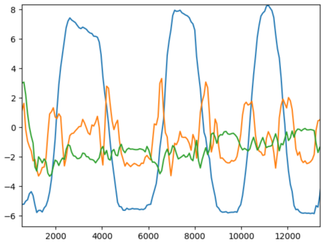
The lift the arm forward and lift to the left/right have the same motion pattern. This may cause the misclassification. As the figures shown below.



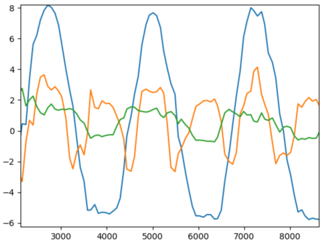
Lift Motion1



Lift Motion2



Lift1 PCA



Lift2 PCA

From the figure signal of the two motions is similar. The algorithm of the PCA function is illustrated.

$$X = \begin{pmatrix} a_1 & a_2 & \dots & a_m \\ b_1 & b_2 & \dots & b_m \\ c_1 & c_2 & \dots & c_m \end{pmatrix} \tag{2}$$

X is the data set.

$$C = \frac{1}{m} X X^T = \begin{pmatrix} \frac{1}{m}\sum_{i=1}^{m} a_i^2 & \frac{1}{m}\sum_{i=1}^{m} a_i \times b_i & \dots \; \frac{1}{m}\sum_{i=1}^{m} a_i \times c_i \\ \frac{1}{m}\sum_{i=1}^{m} b_i \times a_i & \frac{1}{m}\sum_{i=1}^{m} b_i^2 & \dots \; \frac{1}{m}\sum_{i=1}^{m} b_i \times c_i \\ \frac{1}{m}\sum_{i=1}^{m} c_i \times a_i & \frac{1}{m}\sum_{i=1}^{m} c_i \times b_i & \dots \; \frac{1}{m}\sum_{i=1}^{m} c_i^2 \end{pmatrix} \tag{3}$$

C is the covariance matrix. The dialogue element of C is variance and the other elements are covariance.

$$Y = PX \tag{4}$$

$$\begin{aligned} D &= \frac{1}{m} Y Y^T \\ &= (PX)(PX)^T \\ &= PCP^T \end{aligned} \tag{5}$$

$$P = E^T \tag{6}$$

$$Y = PX \tag{7}$$

The eigen matrix is aimed to get the diagonal matrix and the eigen vector is the direction with biggest variance. In this case, matrix P multiply data set matrix is the matrix based on the component base.
By the figure of the sequence, the signal after PCA is similar. The two motions on the principle base is similar. It proves that the two lift motion have the same movement pattern.

5.4 Gravity Analyse

In spite of noise, there two accelerations influenced when moving. The first one is the gravity and the second one is the acceleration of the motion. The direction of the gravity is no change in world coordinate. The movement acceleration is vertical to the movement trace.
Any movement can be decomposed into a translation and a rotation. It can be described as a Lie Group SE(3). Changing coordinate or doing movement both can described as a left or right product of Lie Group. So changing coordinate is relevant to do a movement in original coordinate.
As mentioned before, the direction of gravity is no change in world coordinate. And as discussed, changing coordinate or object use same equation. So, the motion of IMU coordinate can be describe the gravity which decomposed into the IMU coordinate. However, the accelerator generated by people does not. The direction is change on world coordinate. So the motion of IMU (coordinate) cannot describe the decomposition on IMU coordinate.
It is improved, the PCA algorithm is like transfer the gravitational acceleration from IMU coordinate to principle base coordinate and two motion signals after PCA is similar. So, the gravitational acceleration compare with the acceleration generated by arm is dominant in this problem. The result of previous section and the learning outcome support this point of view.

6 Evaluation and Conclusion

In this project, I present a framework to recognize four upper limb motion in order to contribute the study of motion interaction. A memory based learning and bounding window method is put up to do auto segmentation and annotation on time sequence data. The accuracy is fine and the auto annotated data is successfully applied in the project.

Deep learning method is unexplainable but the specialist can also contribute to the feature extraction phase. In this project, I improved that the gravity decomposed on IMU coordinate is the significant information which should be considered. The gravity on IMU coordinate is dominant so accuracy of quick motion easy to be misclassification. And the gravity information should be applied as much as possible when doing motion identification.
This report also purposed an architecture to do human upper limb motion detection. The total accuracy is around 90 percent. The motion for high intensive or low intensive is high. The motion with same motion pattern is easy to misclassification.

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