An Online Segmentation Method using Dynamic Time Warping

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Abstract

THE Segmentation plays an important role in the analysis of human rehabilitation movements. This paper proposes an online approach to segment time serial data using the fastDTW and ZVC. The proposed method first applies ZVC algorithm to select the segment candidate points, then uses fastDTW to identify the segments along the candidate points. The evaluation of this proposed method was carried out, based on two rehabilitation datasets with 7 exercises and 120 subjects. The results shows that the proposed algorithm achived segmentation accuracy 90.67% on average.

Index Terms: segementation, fast DTW, pattern mining

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Chapter 1

Introduction

For the recovery of patients who are after surgeries, the exercise therapy has long been a recommended efficient method in the treatment. A typical approach is that a patient will perform some exercises under the instruction and supervising of a physiotherapist, who will be responsible for determining the patient's progress and providing advices. So the studies on an automatic and quick-response tool for the assessment to measure the movements is a hot topic.

Motion capture systems [1] can be used to get access to human body movement data based on time series, or with the help of sensors such as Inertial Measurement Units(IMU) [2]. The segmentation is required to apply on the data, providing the start and end points automatically. After that, with further classification works on those recognized movements, a feedback can be generated that if the movements on the exercise is correct.

A difficulty could be the large variability on movements,with the existance of degrees-of-freedom(DoF). It brings great chanllenges on the scalability of segmentation algorithms. Another difficulty is that online system requires very quick feedback, so the designed algorithm should be more efficient.

The proposed approach is a template-based segmentation algorithm, by using Fast DTW as the recognition algorithm. An important DoF is selected first, then the canditate points are selected by zero-velocity-crossing (ZVC). The novelty is focusing on the feature extraction when applying Fast DTW. The algorithm applied on seven exercises performed by 120 individuals, reaching the segmentation average accuracy of 90.67%.

Chapter 2

Related Works

The segmentation and identification on the time-series data is a hot topic since it can be applied on many fields, like speech recognition, price prediction and human movement recognition. A method to perform is that first seeking for templates (the patterns), then the comparison algorithm would be applied on the time-series data, and eventually figure out if a segment matches any one of the templates. In this chapter, first the introduction of main idea of a method in selecting candidate points will be given, following by a comparison algorithm.

2.1 ZVC

ZVCs(zero-velocity crossing) was proposed by Pomplun and Mataric [3]. ZVCs can identify the points where the joint segments changed directions, which have the possibility of a movement changing. ZVC algorithm is not a motion identification method, and it can cause over-segment for the reason of noisy data. Since it is not template-based, it could be hard to identify and remove the points that are not important. But ZVC is an approach that can provide candidate points with carefully-selected thresholds. And the segments that are separated by the candidate points will be ready for the recognition algorithm.

2.2 DTW

Dynamic Time Warping (DTW)[4] is a comparison method applied to recognition of the movement templates.

It is often used to calculate the similarity of two time series, by measuring the distance between them. Another way of the distance measurement method is *Euclidean distance*. But when it comes to time series, the distance would be the sum up of the squared distances from each nth point in both of the time series. One situation is that if the shapes of the two series are similar but one is shifted slightly then the Euclidean distance would be large and the two series might be considered as not similar. Dynamic Time Warping is aimed at warping the time axis by stretching or shrinking, to find an optimal alignment for both of the two series.

It has widely used in many fields, like speech recognition [5], other disciplines including gesture recognition and data mining. In movement segmentation, Fast DTW, as an extented algorithm, is used as an approach of comparison and recognition.

An approach is that when starts doing recognition, a front pointer points to the start point, and a rear pointer is moving to the following points. Each time the rear pointer moves, the segment within the two pointers would be compared with the templates by using Fast DTW, until it has been recognized as a template. This approach requires expensive cost and does not perform well when it applies to online segmentation.

Chapter 3

Proposed Approaches

The proposed algorithm first detects the significant DoF, then extracts ZVC points. Next the algorithm classifies observation segment along the ZVC points, and finally combines them into the complete movements. The selection of significant DoF, extraction of ZVC points, segment classification and movement combination are described in the following sections.

3.1 Selection of Significant DoF

The velocity data contains three sets of data: X,Y and Z. The set with low degree of noise and a high recognizability should be selected as the segmentation object, which can help to improve accuracy and speed. For each set in velocity calculate the global height: sort the velocity values, and then get the average of the maximum 10% as Avg_{max}, and the average of the minimum 10% as Avg_{min}. The global height **H** should be Avg_{max} - Avg_{min}. Choose the one with the maximum global height.

3.2 Extraction of ZVC Points

ZVC is used to select candidate points by a threshold (θ_{th}) on observation data. We choose the data points whose θ is within a very small range. Because the θ value of each point is only approximate to zero, it is distributed near the baseline (θ_{bs}). Actually,

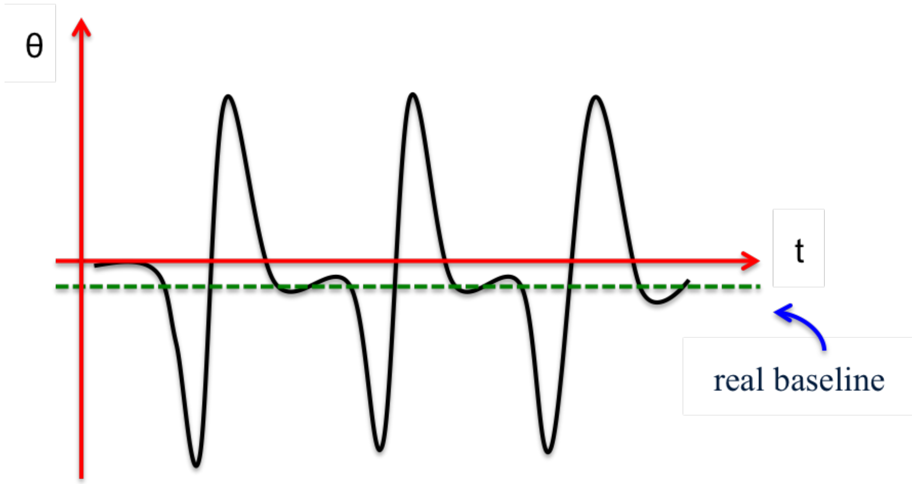

Fig. 1 Baseline offset: real baseline is not the zero points.

the θ values of the candidates should be:

$$\theta_{bs} - \theta_{th} \leq \theta candidate \leq \theta_{bs} + \theta_{th} \tag{3.1}$$

The baseline is not always when θ equals to zero, although it should be. In the real operations, there might exist operational errors or device faults. A situation is shown in **Fig.1: baseline offset**, the dash line indicates the real baseline, which is lower than when θ equals to zero . If still keep the wrong one, lots of candidate points would be missed, thus leading to a lower accuracy.

In order to calculate the real baseline, to calculate the trimmed mean on the velocity values is a method. First scan the movement velocity values, and then sort them, ignore outliers (the maximum 10% and the minimum 10%). Calculate the average value of the rest as the real baseline.

After the candidate points are selected, a sliding window in **Fig. 2** is set to move from a candidate point to the next one, and there is no overlap when it is moving. All the points within the sliding window will be a segment and compared with the templates.

3.3 Segment Classification

This section includes two parts: feature extraction and FastDTW.

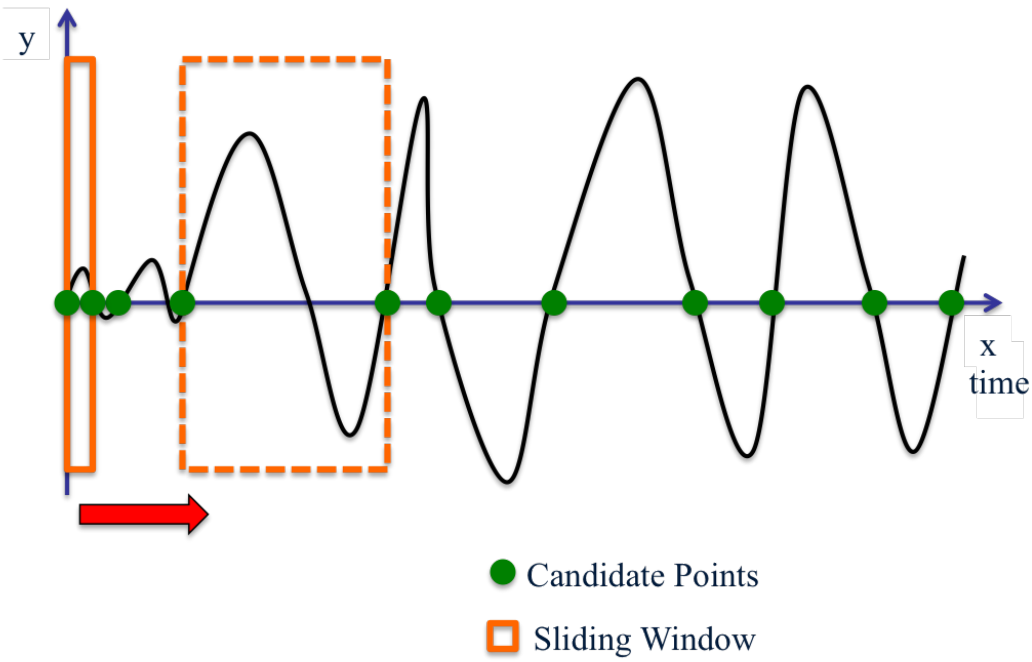

Fig. 2 Sliding Window: moves from a candidate points to another.

3.3.1 Feature Extraction

To speed up identifying, feature searching is an essential approach. Good features can make improvements in accuracy; while at the same time raise up the efficiency with fewer data. The extraction of the features are described in the followings:

1. Calculate Global Height

The proposed approach first gets the global height (H). Scan over the observation data, sorting the velocities in descending order. Get the average of the maximum 10 percent as Avg_{max}, and the average of the minimum 10 persent as Avg_{min}. The global height H should be $Avg_{max} - Avg_{min}$.

2. Sorting

For each segment in the sliding window, when scanned over, sorting every point by velocity in descending order. Sorting can help selecting features.

3. Select Feature Points

After sorting, there are five points should be selected: first point, last point, max-velocity point (peak), min-velocity point(dip) and the middle point. Middle point is in the

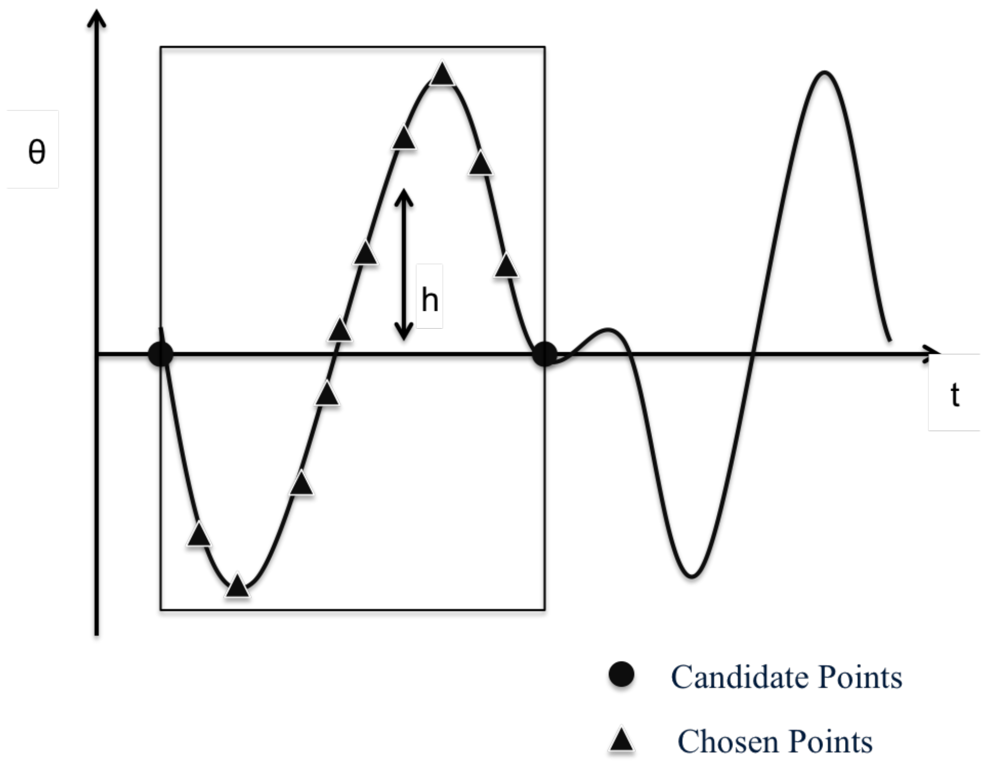

Fig. 3 Select feature points

middle *position* of max and min. The other points can be selected randomly, shown in **Fig.3**. Then get the height (the absolute value of velocity) of every point as $\{h_1, h_2, h_3, h_4, \ldots, h_n\}$, divide the heights by the global height H as the features. This will not change the order of them, because for each sliding window, the global height keeps constant.

3.3.2 FastDTW

DTW has an O(N^2) of time and space complexity which still can be improved. The Fast Dynamic Time Warping, proceeded by Stan Salvador and Philip Chan [4] ,used a multilevel approach that gives a linear complexity in both time and space, and can find a warp path that is nearly optimal. Compared with other two existing approximate DTW algorithms: Sakoe-Chuba Bands and Data Abstraction, the result of their algorithm gives a higher accuracy. The method has three key operations: *Coarsening*, by shrinking a time series that represents the same curve with fewer data points; *Projection*, get a warp path through a lower resolution, then use it as initial guess for a higher one, the standard

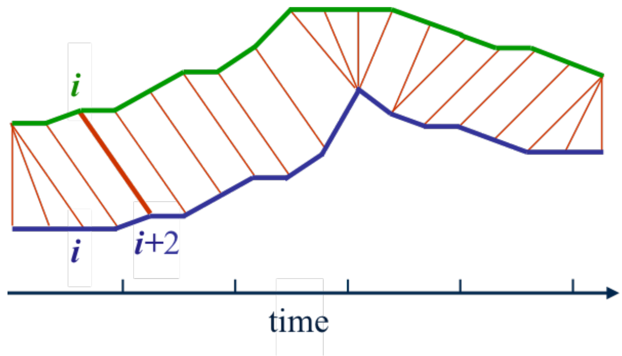

Fig. 4 Fast DTW finds a distance between two time series

DTW would be run; *Refinement*, local adjustments would be used to refine the warp path. Although Fast DTW has no guarantees for finding the optimal solution, it can provide an approximate path, which is somehow enough for doing our comparison and recognition in the human movements data with errors in the acceptable range. FastDTW aligns two time series by warping the time dimension, which makes it a more intuitive similarity measure. That is the way to give how similar the two shapes are.

Fig. 4 demonstrates how the algorithm finds the distance between two time series. The position i in green line would be assigned to position $i+2$ in blue line, instead of the same position i. The reason is, Fast DTW warps the time and it reckons that the trends near the two positions are more similar, which lead to smaller distance.

3.4 Movement Combination

The Fast Dynamic Time Warping is used as the comparison algorithm. The segment in the sliding window (between two candidate points) would be passed in and compared with all the templates, and the distances are sorted with the smallest one will be chosen as the most similar template. Then the segment will be marked as the same *primitive* (will be introduced in the next chapter) with the recognized template. The candidate points will be considered as a start point and an end point, and it will move on to the next segment until the end of the series.

Chapter 4

Evaluation

This chapter contains the evaluation of the approaches, first the dataset introduction is give, and then the procedures is included. Last part is the experimental results and discussion.

4.1 Dataset

120 healthy volunteers were selected to participate in the experiment. Inertial measurement units have been used to this experiment of recognizing movements. They are small, unobtrusive and relatively inexpensive, which make them easy to use and not restricted to only a harsh laboratory environment.

The performed exercises and details are shown in Table 1(Exercise Studied). These simple but frequently performed exercises were adapted from the Total Hip Replacement Exercise Guide of American Academy of Orthopaedic Surgeons [7],including heel slide exercise, straight leg raise exercise, inner range quadriceps exercise, knee extension in sitting exercise, hip abduction in standing exercise, hip flexion in standing exercise and hip extension in standing exercise.The algorithm on the study was applied to the seven exercises on two datasets.

Each participant wore a pair of shorts and a light T-shirt dsuring the testing which impaired the impact of environment. The IMUs were secured to the leg that was being exercised for data collection; one on the thigh (T), one on the shin (S), and one on

Table 1: Exercises Studied

Exercise	Description of Exercise	Deviation (s)
Heel Slide	In supine lying, the exercise is performed by flexing the hip and knee to slide the foot closer to the ipsi-lateral hip.	-Excessive external rotation at the hip during the exercise (ER)
Straight Leg Raise	In supine lying, the exercise is performed by flexing the hip lifting the leg off the supporting surface while keeping the knee in full extension.	- Excessive knee flexion (Knee Flx) - Excessive ankle plantarflexion (Pflx)
Inner Range Quadriceps Extension	A roll/wedge is placed under the knee to be exercised. The exercise is performed by contracting the quadriceps femoris muscle to bring the knee from a position of slight flexion into full extension.	- Excessive ankle plantarflexion (Pflx) - Lifting whole leg off supporting surface (Thigh Lifts)
Knee Extension in Sitting	In sitting, with upper thigh supported on the chair, the exercise is performed by contracting the quadriceps femoris muscle to bring the knee from a position of flexion into full extension.	- Reduced knee extension range of motion during exercise (Red ROM)
Hip Abduction	In standing, the exercise is performed by lifting the leg out to the side.	- Excessive lateral flexion of trunk (Lat Flx Trunk) - Excessive hip flexion (Hip Flx)
Hip Flexion	In standing, the exercise is performed by lifting the leg forwards out in front of the body.	- Excessive trunk flexion (Trunk Flx)
Hip Extension	In standing, the exercise is performed by lifting the leg backwards out behind the body.	- Excessive trunk flexion (Trunk Flx) - Excessive knee flexion (Knee Flx)

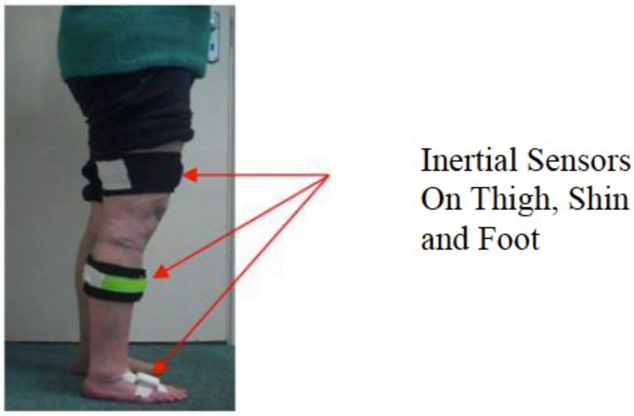

Figure 5: IMU sensor placements

the foot (F) (in Fig 5 sensor placements) [6]. The IMU is 5.3 cm 3.2cm 1.5cm, weights 15 grams, which cannot lead to extra or hindering movements, and it contains a tri-axial accelerometer and a tri-axial gyroscope.

Along with the IMUs, the Cartesian Optoelectronic Dynamic Anthropometer (CODA) motion capture system (Charnwood Dynamics, Leicestershire, UK) was used to collect real-time movement data at a sampling rate of 100 Hz.With the demonstration and instructions of a physiotherapist, participants could gave correct performance on each of the exercise ten times as a record.

4.2 Procedures

This section contains the procedures of data analysis, including candidate points selection, introduction of templates and primitives, follwing by recognition and combination.

4.2.1 Candidate Points

For each exercise, the following parameters were obtained from the IMU: acceleration in X,Y,Z, velocity in X,Y,Z and strength in X,Y,Z. **Fig 6** shows the an example of plotting data when doing heal slide (HS) in the position of thigh, with the horizontal axis being time stamp and vertical axis being the velocities.

Different thresholds were set according to the differences of the exercises and the

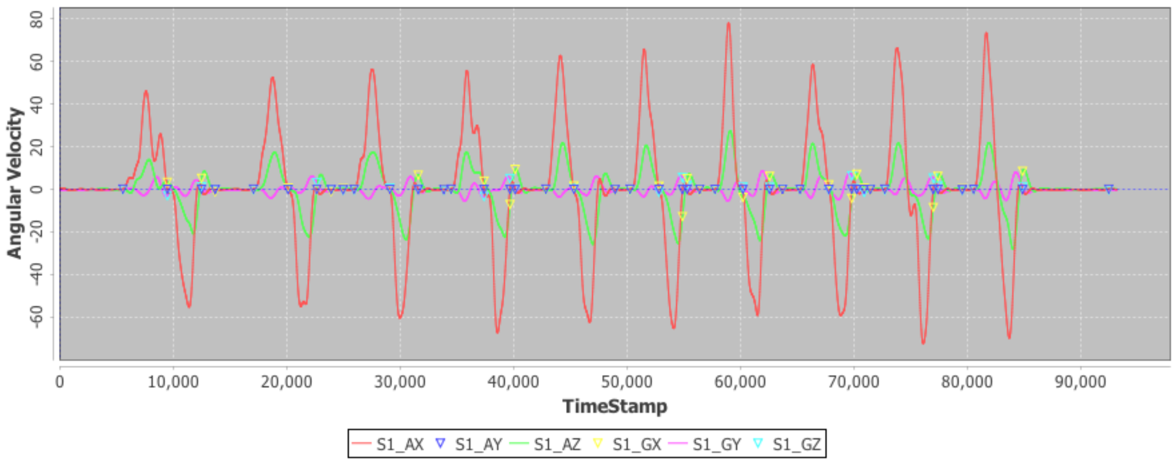

Figure 6: An example of velocity and candidate points in IRQ of thigh, where threshold is 0.1.

placements. The threshold should eliminate the outliers and keep stable with the majority of the values. In this experiment, the threshold was around 0.02 to 0.1.

According to the ZVC algorithm, different thresholds were chosen to match the experimental object. For the reason of DoF, in **Fig 6**,the velocity data of X were chosen (red line) with blue triangle points as candidate points, under the threshold of 0.1.

4.2.2 Templates Selection

The templates were selected visually from the plots. After the observation of velocity plots, 3 *primitives* (marked as the type of the templates) were set to be the templates shown in **Fig 7**: templates with two waves (a peak and a dip), templates with one wave (a peak or a dip) and templates with no obvious waves. The first two primitives were considered to be movements while the last was considered as silence between the movements. During the experiment, 5 templates were selected for each primitive of every axis in each exercise.

Among all the templates, there are three different primitives: -1 (the shape with approximate constant), 1 (the shape with one peak), 0 (the shape with a peak and a dip). For primitive 0 and 1, shown in the **Fig. 7**, each of which has two original shapes.

After feature selection, all of them can be seen as the extraction shapes. Primitive 0 gives a shape of two connected triangles, because it has two peaks; primitive 1 gives a

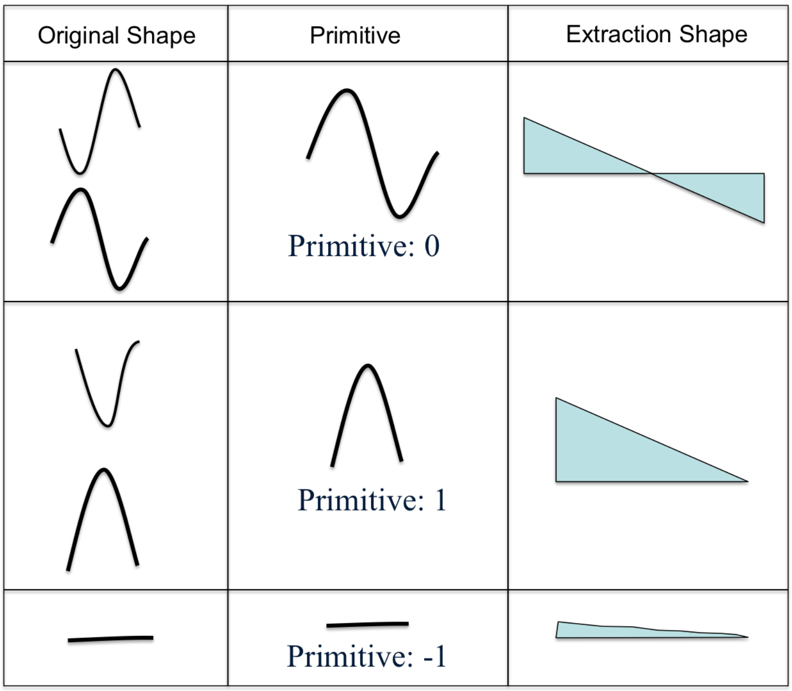

Figure 7. Templates, primitives and extraction.

shape of one triangle, and it can be seen as a half of primitive 0; primitive -1 gives a shape of a very thin line, for the θ value being low around zero. One advantage for sorting in feature selection is that, it can get rid of different original shapes. After sorting, all the shapes that belong to the same primitive would show the same extraction shape.

4.2.3 Recognition and Combination

After pre-processing and candidates selection, feature extraction was performed. Fast DTW was used to compare the templates and the values in the sliding window. Five templates were compared respectively, which would output five distances. The template with the minimum distance was reckoned as the most similar one, and the primitive value (0, 1 or -1) would be the result of recognition.

The series of the primitives was generated after comparison, which contains 0,-1 and 1. In the experiment, a complete movement might be recognized as more than one single primitives. Primitive 0 was a combination of two primitive 1: (Fig 6, the blue point at 10,000 and 20,000 in TimeStamp) the pattern was separated as a peak and a dip; (Fig 6, the blue points at 22,000 to 25,000 in TimeStamp) or a primitive -1 might be recognized

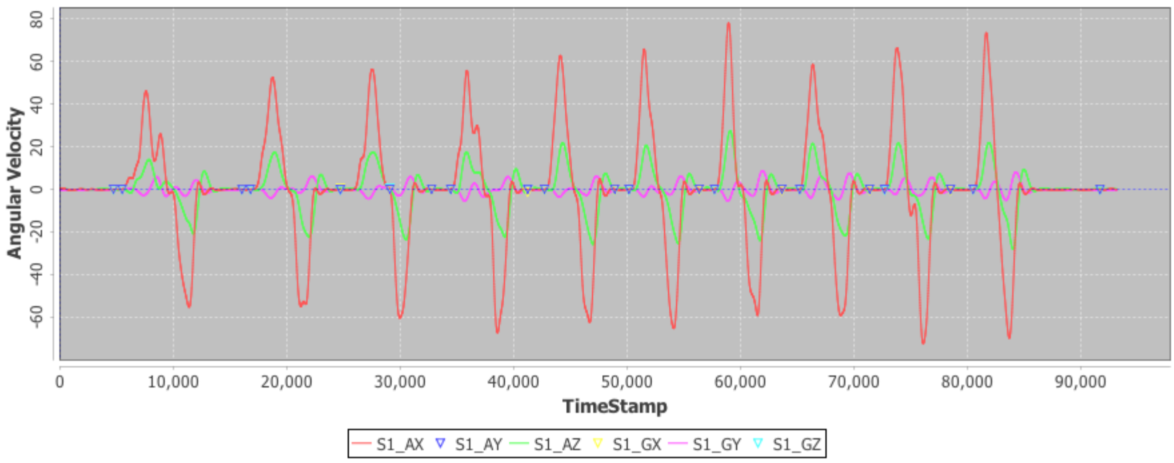

Figure 8. Result after combination.

as more than one primitive -1: the long silence was separated as some short ones.

In order to solve the problem, a combination function was needed: when meet a primitive 1 following another primitive 1, combine them to a primitive 0; when meet more than one primitive -1 that are continuous, keep the first and last two, which makes sure that the important points are kept. After combination, shown in **Fig 8**, the redundant candidate points were removed.

4.3 Experimental Results and Discussion

Table 2, 3 illustrate the results of two datasets. The critera of segmmentation accracy includes *overlapped-movement, missed-movement, false-movement, missed-silence.* Other evaluations are based on computation time and memory used. The average segmentation accuracies of dataset 1 and 2 are 94.48% and 86.86%.

When a movement is recognized, if there are other points on the segment besides the start and end points, then the movement is considered as an *overlapped* movement. If more than one movements are connected and should separated by breaking points but the algorithm fails to mark any points, then all the movements are marked as *missed-movements*. *False-movement* is the situation that a silence is uncorrectly recognized as a movement. *Missed-silence* is a silence that missed because of the lack of breaking points. In Table 2 and 3, the *Memory Avg.* refers to the average memory of each ten movements

Table 2: Dataset 1 Result

Recognition accuracy, memory and time for each exercise.

heel slide					Memory Avg.	Templates Memory	Time Avg.
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	24	16
thigh	91.82%	98.91%	100.00%	96.91%			
shin	90.55%	98.55%	100.00%	98.00%			
foot	91.45%	98.00%	100.00%	96.18%			
hip abduction					Memory Avg.	Temp Memory	Time Avg.
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	24	20
thigh	96.96%	96.79%	100.00%	98.75%			
shin	96.79%	96.07%	100.00%	98.04%			
foot	96.07%	97.50%	99.82%	98.57%			
hip extension					Memory Avg.	Temp Memory	Time Avg.
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	24	24
thigh	95.09%	98.73%	100.00%	98.36%			
shin	96.18%	98.00%	100.00%	98.55%			
foot	96.91%	96.91%	100.00%	97.45%			
knee extension					Memory Avg.	Temp Memory	Time Avg.
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	24	24
thigh	96.30%	97.22%	100.00%	98.33%			
shin	94.44%	95.00%	100.00%	98.70%			
foot	95.93%	96.11%	100.00%	96.67%			
hip flexion					Memory Avg.	Temp Memory	Time Avg.
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	24	24
thigh	97.22%	95.00%	100.00%	97.22%			
shin	96.30%	86.48%	100.00%	91.48%			
foot	95.56%	91.30%	100.00%	93.89%			
IRQ					Memory Avg.	Temp Memory	Time Avg.
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	24	22
thigh	7.74%	99.25%	100.00%	99.62%			
shin	48.30%	100.00%	100.00%	100.00%			
foot	71.51%	87.36%	100.00%	92.08%			
SLR					Memory Avg.	Temp Memory	Time Avg.
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	24	15
thigh	76.92%	100.00%	100.00%	100.00%			
shin	66.92%	98.46%	100.00%	99.04%			
foot	68.46%	97.12%	100.00%	98.27%			

cost and *Temp. Memory* refers to the memory of all the templates cost in that exercise. The *Time Avg.* is the average recognition time for a single movement in the exercise.

Threshold Selection

The threshold for candidate points in ZVC have impacts on the computation time and accuracy. Small thresholds will raise the probability of missing candidate points, which results in more miss-silences and miss-movements, and a lower accuracy in recognition, to some extend. High threshold values will capture more candidate points which make sure that all the important points are included, but at the same time the computation time is increased, with more possible for false-movements and overlapped movements.

Data Quality

The proposed algorithm was not tested on the data with more complicated patterns, so there is no guarantee that it will reach the same level of accuracy. Meanwhile, the approach is very sensitive to noises and requires high quality datasets, thus requiring some efforts on data cleaning when searching for an important DoF.

Table 3: Dataset 2 Result

Recognition accuracy, memory and time for each exercise.

					Memory Avg.	Time Avg.	Temp Memory
SAKE							
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	14	24
thigh	58.61%	99.12%	100.00%	99.49%			
shin	80.66%	97.59%	100.00%	98.47%			
foot	85.04%	98.25%	100.00%	98.98%			
IRQ					Memory Avg.	Time Avg.	Temp Memory
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	14	24
thigh	65.54%	98.22%	100.00%	98.86%			
shin	72.13%	97.23%	100.00%	98.56%			
foot	74.26%	98.66%	100.00%	99.06%			
HS					Memory Avg.	Time Avg.	Temp Memory
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	11	24
thigh	65.41%	88.12%	100.00%	92.82%			
shin	58.82%	96.12%	100.00%	97.76%			
foot	53.06%	92.82%	100.00%	95.29%			
SHF					Memory Avg.	Time Avg.	Temp Memory
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	13	24
thigh	87.63%	92.44%	100.00%	95.78%			
shin	87.78%	91.56%	100.00%	95.33%			
foot	82.96%	94.22%	100.00%	97.04%			
SHE					Memory Avg.	Time Avg.	Temp Memory
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	15	24
thigh	86.59%	95.18%	100.00%	97.18%			
shin	92.12%	96.12%	100.00%	96.35%			
foot	88.35%	96.82%	100.00%	93.29%			
SHA					Memory Avg.	Time Avg.	Temp Memory
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	9	24
thigh	82.55%	97.06%	100.00%	98.43%			
shin	88.43%	60.78%	100.00%	68.24%			
foot	86.86%	68.04%	100.00%	71.96%			
SLR					Memory Avg.	Time Avg.	Temp Memory
location	Overlapped-Movements	Missed-Movements	False-Movements	Missed-Silence	32	27	24
thigh	81.16%	89.65%	100.00%	93.95%			
shin	75.81%	96.05%	100.00%	97.91%			
foot	69.65%	95.12%	100.00%	97.33%			

Chapter 5

Conclusion and Future Works

The study is to propose a segmentation algorithm on the sensor-collected data in some exercises, which intends to provide a high accuracy and a quick feedback. The exercises will be performed by patients who need to do certain movements to recovery, which calls for a supervising exercise feedback system that allows them to correct the movements in real-time.

According to the evaluation, the recognition accuracy and efficiency are acceptable which makes the algorithm a potential one to achive online segmentation on human movements.In this evaluation, the accuracy depends on the quality of data, selected features and templates, and all of them require more efforts to be improved. For pattern mining, new algorithms can be developed to improve accuracy and can be applied to not only sensor-collected data, but also any time series data such as voice recognition and gesture recognition.

Variability in human movements is a big difficulty in online segmentation. The performance in one single exercise shows the variability in the movements of the people with different ages, genders, weights and other body conditions. As for the same person, variability also occurs in different sensor placements and exercises. Template-based comparison demands standard and representative templates, and variability leads to difficulties in sampling on making standards. The future works will be on how to select qualified templates effectively from diverse movements datasets.

A potential extention on the feedback system could be an instruction system. That is when a movement is recognized as a not correct one, the system will be able to give suggestions and instructions on why the movement is not correct and how to perform well. The future works could also be on the more intelligent and interactive surpervising system.

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