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Template-Matching-Based Detection of Freezing of Gait Using Wearable Sensors

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Abstract

Parkinson's disease (PD) lead to lots of injuries associated with fall incidences every year, causing lots of human suffering and assets loss for patients. Freezing of Gait (FOG), which is one of the most common symptoms of PD, is quite responsible for most incidents. Although lots of research have been done on characterize analysis and detection methods of FOG, large room for improvement still exists in the high accuracy and high efficiency examination of FOG. In view of the above requirements, this paper presents a template-matching-based improved subsequence Dynamic Time Warping (IsDTW) method, and experimental tests were carried out on typical open source datasets. Results show that proposed IsDTW not only embodies higher experimental accuracy (92%), but also has a significant runtime efficiency.

Keywords: Parkinson's disease; freezing of gait (FOG); template matching; Dynamic Time Warping (DTW); wearable sensors.

1. Introduction

Parkinson's disease (PD) is a kind of common neurological disorder caused by dopamine and gradually loss function of other subcortical neurons. PD usually causes the patients' movement function disorder, starting from tremors of one side body or activity clumsy, and further involves the contralateral limb [1, 2]. Clinical manifestations

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of Parkinson's disease are mainly for static tremor, bradykinesia, myotonia and freezing of gait (FOG). Among them, FOG is a kind of typical symptom. The patient is not easy to maintain the balance of the body, and is likely to fall on the road surface with even a bit uneven. Its typical symptoms are loss of ability to walk in a sudden, feet stuck on the ground and disable to move in a few minutes or no longer to move again. FOG seems to be common in the start period of walking, turning, moving close to the target or when one is worried whether he is able to get through the known obstacles, e.g., getting through the revolving door. Every year, fall incidence rates range from 50% to 70%, and it's one of the main reasons for being disability to PD patients [1-8].

For both drug and non-drug therapy methods, the detection and forewarning of FOG are significantly important. Wearable sensors are widely used to realize the real-time detection and alarming of FOG for PD patients. Previous studies usually focus on the fusion of sensors like baroceptor, IMU, etc. They capture the sensor signals when PD patients in activity and do deep analysis of the wavelets, give out alarms before FOG occurs. The research topics about forewarning of FOG based on wearable sensors mainly concentrate on the selection of sensors [5], locations [9] and high effective algorithms [10].

Different from the traditional statistical methods, template matching is a high effective recognition method with both high recognition accuracy and efficiency, which has been applied for physical activity. Muscillo et al. [11] proposed user-dependent templates to target recognition of arm-specific tasks. Likewise, Chen and Shen [12] focused on recognizing activities performed with the right upper limb using a classification framework based on template matching. Stifefmeier et al. [13] proposed an innovative approach consisting of encoding motion data into sequence of finite symbols and performing activity recognition by using string-matching algorithms. However, to the best of our known, no effort has been paid in the real-time detection of FOG.

To summarize, traditional statistical methods for FOG detection have low accuracy and efficiency, and it can hardly meet the requirements for practice real-time applications. Template-matching methods is of high performance advantages, however, it is seldom used in FOG detection. The purpose of this paper was to investigate the use of template matching for the detection of FOG.

2. Template-Matching Methods

Template matching algorithm is an approach for comparing two time sequences in term of both their state and dynamics. Time series can be used for classifying primitive physical activities from data provided by wearable sensors, such as accelerometers. Template Matching is a high-level machine learning technique that identifies the parts on one sample that match a predefined template. Template Matching techniques are flexible and relatively straightforward to use, which makes them one of the most popular methods of subsequence detection.

2.1. Euclidean Distance

Euclidean metric, namely Euclidean distance, is a common adopted definition of distance. It refers to the actual distance between two points in Multidimensional space, or the natural length of vector (namely the distance between this point and the origin point). Respectively, denote $X = [x_1, x_2, ..., x_i, ..., x_m]$and $Y = [y_1, y_2, ..., y_i, ..., y_n]$ as two temporal sequences. Thus, the distance d_i ($i = 0, ..., n-m-1, n < m$) could be calculated from vector X and Y. For the ith sample, the regularized Euclidean distance could be represented as $d_i = \sqrt{\sum_{k=1}^{m}(Y(i+k) - X(k))^2}$.

2.2. Dynamic Time Wrapping (DTW)

In daily life, there is no doubt that Euclidean distance is the most frequently used distance measuring method. However, for some special applications, Euclidean distance is of obvious defects, especially temporal sequence with different length. DTW could be used to measure the similarity or distance of these two sequences. The core of DTW is based on the idea of dynamic programming, automatically searching for the optimal path with local optimization method. Taking the minimum accumulation of distortion between two vectors as the objective, could avoid errors caused by different time length.

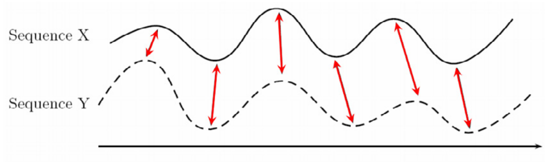


Figure 1. A typical pair of sequences for DTW comparison.

A typical pair of sequences for DTW comparison is shown in Fig. 1. Define sequence X as template signal and Y as recorded signal, whose length are respectively n and m, namely

$$\begin{aligned} X &= (t_1, x_1), (t_2, x_2), \ldots, (t_i, x_i), \ldots, (t_n, x_n) \\ Y &= (t_1, y_1), (t_2, y_2), \ldots, (t_j, y_j), \ldots, (t_m, y_m)' \end{aligned} \tag{1}$$

In order to align these two sequences, a $n \times m$ matrix is needed, while element (i, j) represent the DTW distance $d(x_i, y_j)$ (generally 1st normal form $||d(x_i, y_j)||_1$) between x_i and y_j. Namely, each element in the matrix stands for the similarity between two points in X and Y, and the smaller the distance is, the greater the similarity. DP is applied to find optimal path crossing a number of grids in the matrix and calculation is conducted among the points crossed by the path.

The paths that satisfy all above conditions could be as many as exponential, but the minimum cost path is the one we are interested in. Thus, the following equation could be achieved:

$$Dist(X, Y) = d(x_i, y_j) + \min \begin{cases} Dist(i-1, j-1) \\ Dist(i-1, j) \\ Dist(i, j-1) \end{cases}, \tag{2}$$

2.3. *Subsequence Dynamic Time Wrapping (sDTW)*

DTW is mainly suitable for comparing sequences that are independent from each other. However, in general situations, it is more common that search repeated “child segments” from a long sequence. Thus, results obtained from DTW is meaningless. sDTW is designed for this kind of applications.

The core idea of sDTW is that divide distance matrix D into subbands, and use traditional DTW to search the optimal path in subbands. Firstly, divide D into several inclined strip-like regions with the same width. Considering the actual situation, there are 50% overlap between adjacent regions. Among them, s1 and s2 are respectively the starting point of the two subbands. Assume the displacement from s1 to s2 is R, and the width of inclined region is $2R+1$. Thus, for a $m \times n$ matrix, the number of its contained regions is $\lfloor (n-1)/R + (m-1)/R \rfloor$.

Afterwards, find the optimal path in each strip-like region using DTW. In each optimal path, only a small segment is corresponding to the similar parts of these two consecutive sequences. So we need to cut out the specific subpaths, which should meet these requirements: 1) the points contained in subpath, namely the length of subpath is smaller than L; 2) the average of all points in the subpath, namely the average of subpath is smaller than θ. Given a subpath with N points, whose the length of subpath is L and the average of subpath is θ, work out the LCMA (length-constrained minimum average) is as follows:

$$f = \min_{1 \le s \le t \le N} \frac{1}{t-s+1} \sum_{k=s}^{t} Dist(i_k, j_k), t-s+1 \ge L \tag{3}$$

2.4. Cross Correlation

In signal processing, it's often to study the similarity of two signals, in order to implement signal detection, recognition and extraction. The method that could be used to analyze the similarity of signals is called Cross Correlation. Given two temporal sequences X and Y, whose length are respectively n and m, its cross-correlation function is defined as:

$$C_{YX}(\tau)=\frac{1}{n-1}\sum_{i=0}^{n-1}[Y(i+\tau)][X(i)], \tag{4}$$

Generally speaking, cross-correlation index could be used to normalize the standard deviation of two signals, and the cross correlation coefficient is defined as:

$$\gamma_{YX}(\tau)=\frac{C_{YX}(\tau)}{\sigma_{YY}\sigma_{XX}}, \tag{5}$$

where σ_{XX} and σ_{YY} are respectively the standard deviation of X and Y, and the value of $\gamma_{YX}(\tau)$ is between -1 and +1. If $\gamma_{YX}(\tau)$=-1, it illustrates that X and Y have the same shape but opposite phase; If $\gamma_{YX}(\tau)$=0, it illustrates that X and Y have no similarities; If $\gamma_{YX}(\tau)$=-1, it illustrates that X and Y are totally the same. When the signal is compared with itself, it's called self-correlation, defined as follows:

$$\hat{R}_{YY}(\tau)=\frac{1}{m-1}\sum_{i=0}^{m-\tau-1}[Y(i+\tau)][Y(i)], \tag{6}$$

This function is often used to identify periodic signals from white noise in order to recognize signal cycle and repetitive patterns.

3. System Overview and Algorithm Design

Former researchers have studied the detection method for FOG with time and frequency domain features extracted by FFT [14]. These studies have already achieved a good accuracy but poor real-time characteristic. In this chapter, basing on the point of template matching, we proposed an improved subsequence Dynamic Time Wrapping (IsDTW) method, to realize the real-time and high precision FOG detection and alarm. IsDTW gives out a good real-time performance as well as high accuracy.

The whole process could be divided into two stages: data pre-processing and subsequence searching.

Notations: the original signal is denoted as $X=\{(t_1,x_1),(t_2,x_2),\ldots,(t_i,x_i),\ldots,(t_n,x_n)\}$, the query subsequence is denoted as $Y=\{(t_1,y_1),(t_2,y_2),\ldots,(t_j,y_j),\ldots,(t_m,y_m)\}$. $X_{i,j}$ stands for the subsequence from time i to time j in sequence X. The Framework of the whole system is presented in Fig. 2.

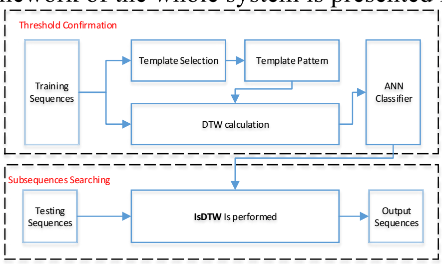
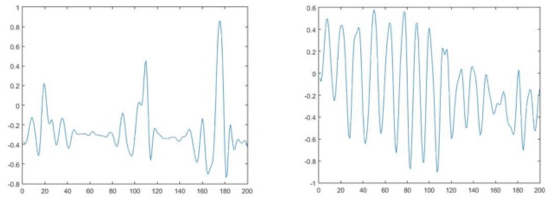


Figure 2. System Framework Diagram.

3.1. Template Generation

The template sequence is $Y=\{(t_1,y_1),(t_2,y_2),\ldots,(t_j,y_j),\ldots,(t_m,y_m)\}$, its length m is the predefined window length. The sequence contains several sensor data subsequences, such as accelerometer data A_x, A_y, A_z. The sample data contains lots of labeled FOG and non-FOG data. Divide these data into subsequences with length of m, and average them with method of "interp1" integrated in Matlab. Apply this operation to each axis of the subsequences, and finally the template of FOG gaits is achieved, shown in Fig 3.



(a) (b)

Figure 3. Gait template: (a) Regular gaits; (b) FOG gaits template.

3.2. Threshold Confirmation

The most urgent issue to be solved in proposed algorithm is how to determine the threshold value of loss function. In common sense, due to the differences of various subjects and noise, the expected threshold value could vary from person to person. For the above reasons, in this paper, we proposed a dynamic threshold estimation method based on former statistical model. In data pre-processing stage, we construct an Artificial Neural Network (ANN) classifier to obtain the optimal threshold value ε, which is suitable for each subject, using labelled training data. This method depends on machine learning technique, running on a large amount of actual data, which makes it has higher running speed and credibility.

3.3. Similarity Computation: Improved Subsequence DTW: IsDTW

Similar with DTW, we proposed this improved sDTW method to compute the similarity of two sequences by updating distance matrix. In each loop of the algorithm processing, two variables are stored, $D(t,k)$ and $X(t,k)$. $D(t,k)$ denotes the minimum DTW value of sequence Y and subsequence $S_{i,t}$. $X(t,k)$ denotes the start time of sequence $X_{i,t}$, namely $i = X(t,k)$. $D(t,k)$ could be obtained by following methods:

$$D(t,k) = \left\| x_t - y_k \right\| + D_{best}, \tag{7}$$

$$D_{best} = \min \begin{cases} Dist(t, k-1) \\ Dist(t-1, k) \\ Dist(t-1, k-1) \end{cases}, \tag{8}$$

where $D(t,0)=0$, $D(0,0) = D(0,k) = +\infty, (t = 1,2,\ldots, n \text{ and } k=1,2,\ldots,m)$. Similarly, $X(t,k)$ could be obtained by following methods:

$$X(t,k) = \begin{cases} X(t, k\text{-}1), & If\ D_{best} = D(t,k-1) \\ X(t-1,k), & If\ D_{best} = D(t-1,k) \\ X(t-1,k-1), & If\ D_{best} = D(t-1,k-1) \end{cases}, \tag{9}$$

where $X(t,0) = t$.

IsDTW is targeted for searching all possible subsequences $X_{i,j}$ that the similarity satisfies the given threshold ε between sequence X and template Y, namely $Dist(X_{i,j}, Y) \le \varepsilon$, where $j = i + m - 1,\ and\ i = 1,2,\ldots, n\text{-m+1}$. The whole algorithm could be described as follows:

Input: x_t at time t

Output: similar subsequences: $s_{i,t}$

For k=1 to m **do**
  Calculate $D(t,k)$ and $X(t,k)$

End

IF $D_{\min} \le \varepsilon$ **then**
  IF $\forall D(t,k) > D_{\min} \vee X(t,k) > t_e$ **then**
    Return $D_{\min}, t_s, t_e$
    $D_{\min} = +\infty$
    For k=1 to m **do**
      IF $X(t,k) \le t_e$ **then**
        $D(t,k) = +\infty$
      End
    End
  End
End
If $D(t,m) \le \varepsilon \wedge D(t,m) \le D_{\min}$ **then**
  $D_{\min} = D(t,m)$
  $t_s = X(t,m)$
  $t_e = t$
End
For k=0 to m **do**
  $D(t-1,k) = D(t,k)$
  $X(t-1,k) = D(t,k)$
End

4. Results and Analysis

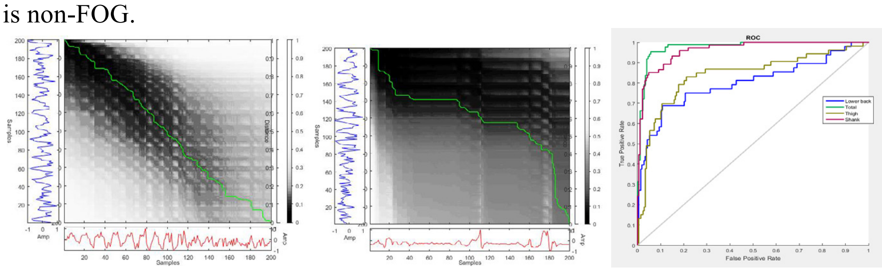
This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation as well as the experimental conclusions that can be drawn.

4.1. Datasets

The method proposed in this paper is verified on open source dataset [29]. Bachlin et al. recruited 10 PD patients as experimental subject, among which there are 7 male and 3 female; whose ages satisfy 66.5±4.8 years and disease duration is 13.7±9.67 years. All subjects are with the history of FOG and could walk freely in the condition of "off-medicine" without external assistance. All data is collected and analyzed in the condition of "off-medicine".

4.2. Results Discussion

Fig. 5 shows the template matching results with using IsDTW to detect FOG gaits and regular gatis. It could be clearly seen that when FOG template compares with pathological data, shown in Fig.4-(a), the DTW path tends to be more straight and the cumulative distance (namely D) is smaller. It indicates that the more the compared two subsequences have higher similarity, and in other words, the detection result is FOG. When FOG template compares with disease-free data, shown in Fig. 4-(b), the DTW path is more winding and the cumulative distance is bigger, and the detection result is non-FOG.



(a) (b) (c)

Figure 4. IsDTW matching diagram: (a) with FOG gaits; (b) with regular gaits; (c) ROC Diagram.

The effect of FOG detection and sensor locations has been analyzed separately by ROC curve as following. IsDTW is applied to the dataset and ROC curves of each subset is drawn in Fig. 4-(c), namely lower back mounted sensor (blue curve), thigh mounted sensor (brown curve), shank mounted sensor (red curve) and all three sensors (green curve). Since the detection method has a better performance when the ROC curve is closer to upper left corner, we conclude from visual inspection that it's with better performance when all sensor data is used. When only shank data is adopted, the result shows less better performance. This may be because the shank part can more reflect the characteristics of FOG gaits.

5. Conclusions

In this paper, we discuss the detection of FOG with utilizing of template-matching methods. Contrast experiments are carried out on open source dataset OPPORTUNITY. Template-matching methods are compared with Euclidean, DTW, sDTW and Cross Correlation. Experimental results show that template-matching methods have certain advantages, and our proposed IsDTW apparently have higher accuracy, making it more applicable in practice applications.

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