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Feature Recognition of Body Dance Motion in Sports Dancing

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Abstract
The motion capture of body dance in sports dancing is a process requiring much time and effort, and its recognition cannot be timely achieved, wherein the motion patterns with different types and lengths are connected. Compared with the segmented motion pattern recognition, it faces with another challenge: to detect their boundaries (starting and ending frames) when recognizing each pattern. For this purpose, this paper puts forward two different solutions. One is to use OE-DTW with open ending to find out optimum matching features in complete and incomplete patterns, wherein each input motion sequence is considered as a complete pattern, while each prototype pattern is considered as an incomplete pattern. In this way, the segmentation and recognition of each embedded motion pattern are successively conducted. The other method is to put forward a layered matching method based on punishment by taking advantage of SVD time series relationship obtained sub fragments in SegSVD. As a result, the ending of each embedded pattern can be detected by the top matching situation of the prototype patterns.
Key words: BODY DANCE MOTION, DYNAMIC TIME WARPING, INTEGRATED PATTERN, OPTIMUM MATCHING

1. Introduction

For greater natural and realistic captured body dance motion in sports dancing, motion capture data are usually collected continuously by the capture object. Each original data may contain several continuous motion patterns (i.e. basic motions), so capture data requires plenty of post processing. In other words, a large amount of time and labors are required to find out starting and ending frames of motion patterns in these data and label their types. Consequently, this paper concentrates on the segmentation and recognition method of automatic continuous motion patterns.

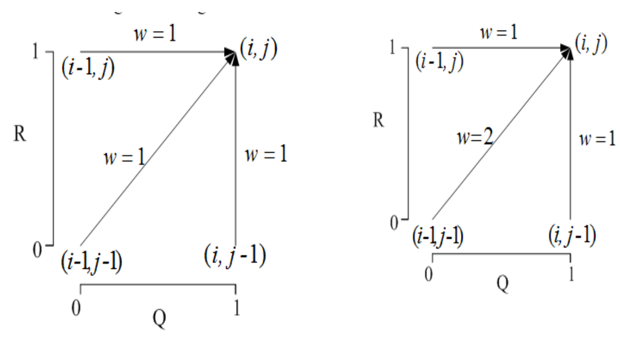
We assume that, the data to be recognized are connected continuously by legal (i.e. predefined) motion patterns, without any (i.e. unpredefined) motions. The recognition of continuous motion patterns faces three challenges as stated below. Startlingly, the type and boundary (i.e. starting and ending frames) of each motion pattern in input data are both previously unknown. Secondly, the differences between different samples with same type may be significant, reflecting not only on the difference in sample length caused by different capture speeds, and different motion styles. Thirdly, there are also some different motions with certain similarities, posing it more difficult to distinguish these samples. In the recognition process, these challenges may bring about two recognition mistakes: mis-classification of continuous motion patterns, mis-detection of motion pattern boundaries.

For segmentation of input motion data in our work, because all motion patterns are artificially predefined basic motions, the method proposed in literatures [1-2], i.e. to use the changes in local features (such as cumulative reconstruction error or low-level kinematics feature) of data to segment input data into sub patterns, is not applicable. It is because the definition of these motion patterns is random, so they may be extremely complex or simple, and specific features cannot be used to determine the boundaries. Therefore, this paper uses the indirect segmentation method, i.e. to match input data with training data, determine boundaries of motion patterns, and do the segmentation. Dynamic programming methods similar to DTW are often applied to the recognition of continuous motion patterns for their validity in time series patterns with various lengths. Continuous dynamic programming (CDP) and OE-DTW are two most typical methods, and both of them are variations of DTW. CDP [3] exempts from restriction that their starting frames must be matched when matching the foregoing two patterns. In this way, character strings of optimum matching can be farthest found out to segment and recognize each motion pattern. Contrary to C-DP, OE-DTW exempts from the restriction that their ending frames must be matched when matching the foregoing two patterns in DTW. Thus, motions to be processed can be recognized before being fully input and incomplete pattern problem can be effectively solved by OE-DTW [4]. This paper puts forward a segmentation and recognition method based on OE-DTW for continuous motion patterns. On one hand, for greater performance of this method, a new global restriction solution K-Repetition and a series of detection conditions for elastic ending are introduced. On the other hand, we use the layered structure of SegSVD introduced in the previous chapter to extend to the recognition of continuous motion patterns. Because SegSVD can retain the time series information of frames in initial data and represent original samples into a multilayered structure. In this way, we are able to achieve a continuous form of SegSVD, and design a new similarity algorithm based on ten-layered matching. As a result, the ending frames of each motion pattern in the input data could be judged by the top matching situation of prototype pattern, and it type also can be determined by similarity values calculated.

2. Recognition of Continuous Pattern Based on OE-DTW

2.1 Global Restriction K-Repetition

As shown in Figure 1, the existing global restrictions all rely on the diagonal of T distance matrix, in other words, they are established under the prerequisite condition that the length of two patterns are known. As a result, these methods can be applied to OE-DTW. The ending of optimum matching road bridge in OE-DTW is unknown in advance, so it does not rely on the leading diagonal.



(a) (b)

Figure 1. Two Different Weighting Methods

Through the observation and analysis of non-ideal matching cases in DTW, we have found out that most of inadvisable matchings are provided with a joint phenomenon that some frames in one pattern may be matched to many frames in another pattern, manifesting as many horizontal and vertical lines in path matching figure (as shown in Figure 1(a)). As a result, we introduce K-Repetition, a new global restriction.

The basic idea of K-Repetition is to avoid the generation of non-ideal matching paths by restricting the matching number of frames. To be specific, each frame in a pattern shall not be matched to frames in another pattern for more than k times. Figure 2 has shown a DTW matching example based on K-Repetition, wherein solid lines contain lawful paths, while imaginary lines contain unlawful paths.

It is because the frame q_i is matched by frames in R for 4 times, which exceeds the regulated k times and the frame Υ_j are matched by frames in Q for 5 times (also exceeds the regulated k times).

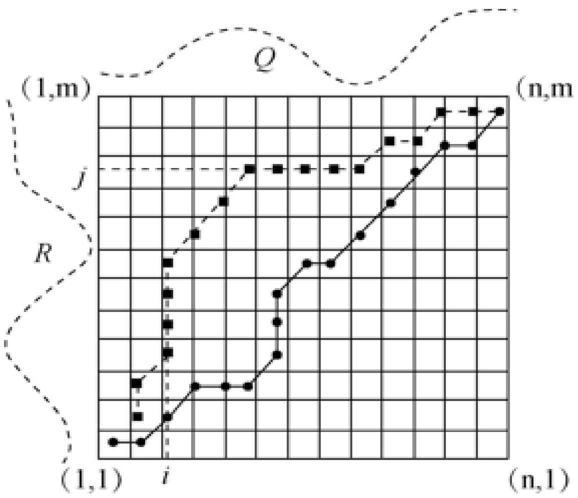


Figure 2. Pattern Matching Based on K-Repetition (k = 3)

K-Repetition restricts the matching number of frames in the pattern. As a result, if a frame in a pattern has been matched for k times, then it cannot be matched to other frames. K-Repetition has no need to rely on the leading diagonal of distance matrix, so it can be applied to OE-DTW.

2.2 Elastic Ending Detection

OE-DTAW determines optimum matching prefix of input pattern in reference pattern by the minimum distance value. However, due to the difference among patterns, this rigid method cannot always return to the optimum matching. Figure 3 has shown an example for this, wherein part of solid lines is the result of OE-DTW. From the shape of pattern, we can learn that the part of imaginary lines acting as optimum matching of Q and R is more convincing.

Therefore, we propose a solution for elastic ending detection. The basic idea of this solution is to extend the OE-DTW matching path between two patterns as long as we can, and thus to avoid the local optimum situation as shown in Figure 3. According to the result of equation $D_{OE}(\mathrm{Q},\mathrm{R})$ and obtained ending, this solution for elastic ending detection may be achieved by the following conditions: $J'=J$; While $J'<m\,\&\&\,D_{OE}(\mathrm{Q},\mathrm{R})\times(1+\varepsilon)>\mathrm{D}(n,J'+1)$ $\quad J'=J'+1$

2.3 Recognition Algorithm

We adopt the concrete procedures of OE-DTW recognition based on K-Repetition and elastic ending detection to recognize the continuous motion patterns. Literature [5] has initially put forward to use OE-DTW to solve the incomplete pattern recognition (i.e. the prefix of complete pattern), i.e. to match the input incomplete pattern with the complete pattern, and thus to determine its corresponding type and optimum matching prefix in the pattern.

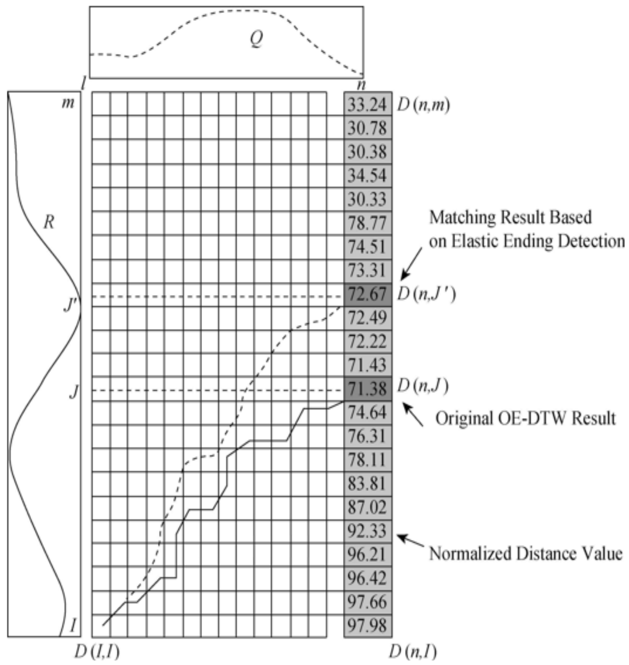


Figure 3. An Example of OE-DTW

In relation to the recognition of continuous patterns, each input motion data is connected by several motion patterns. As a result, if we deem an input continuous pattern as a complete pattern, while other continuous patterns respectively as incomplete patterns, then the continuous pattern recognition also can be transferred into the problem of incomplete pattern recognition. For instance, as shown in Figure 4, prototype patterns corresponding to the unknown input motion data are incomplete patterns.

By using OE-DTW, we match prototype patterns centralized by data with the input motions one by one, and thus to determine its optimum matching. Assume that Ra is the optimum matching of input data (i.e. the smallest OE-DTW distance value), then the concrete prefix part in the input data and type of it as A can be determined. After that, we segment the prefix part from input data, and use the same method to segment and recognize the subsequent data successively, until all frames are recognized.

In addition, the lengths of motion patterns usually have ceiling values (for example, the ceiling value of our experimental data is 300). For saving time in calculation, the input data cannot be considered as integrity to input OE-DTW in the process of recognition. For instance, as in Figure 4, when recognizing the first pattern, the result matching front section of input data (such as first 300 frames) with Ra is same with the result matching all the input data with Ra. However, the former input method can save a large number of calculation amounts. As a result, we define len as the length ceiling value of motion patterns, and only front len frame of data to be recognized can be matched with prototypes in each process of recognition.

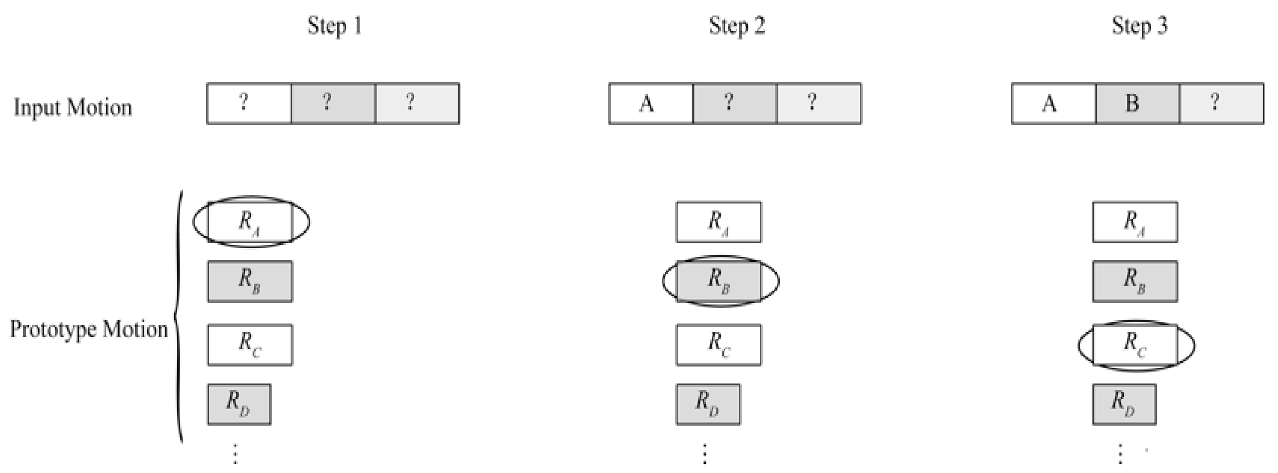


Figure 4. Recognition of Continuous Motion Patterns

According to the analysis stated above, the recognition of continuous motion patterns based on OE-DTW could be achieved by the following four steps, wherein parameter start is used for the indexing in the input motion data. Before recognizing, start shall be initialized as the starting frame, i.e. start = 1,

1). To successively input the len frame from start, and represent it by matrix M;

2). To use OE-DTW to match M with each prototype pattern $R_i(i=1,2,\dots,C)$ (wherein C is the number of prototype pattern), and record the corresponding results, i.e. the returned OE-DTW distance value and ending position J(z) based on conditions of elastic ending detection.

3). If $D_{OE}(R_e, M)$ $(1 \le c \le C)$

is the minimum value in the OE-DTW distance result set $D_{OE}(R_i, M)$ $(i=1,2,\dots C)$
then frame $J(c)$ can be judged as the ending frame of the current input motion pattern, and the motion pattern from frame start to $J(c)$ can be recognized within Rc. The fragment from frame start to $J(c)$ can be segmented from I and update start= $J(c)+1$.

4). If all frames in I can be dealt, then the recognition process may be terminated, if not, return to Step 1.

By using the above-mentioned method, the continuous patterns in the input motion data can be segmented and recognized in succession. The computation complexity for the recognition of each motion pattern is $O(C \times L \times len)$, , wherein L is average length of the prototype pattern.

3. Continuous Pattern Recognition Based on SegSVD

3.1 Continuous SegSVD

SegSVD is proved of great affectivity in the feature extraction and MTS classification [6]. The layered structure of SegSVD makes for recording the time series information between frames, and larger layer serial number indicates closer distance from frame to the sample ending. Inspired by the foregoing facts, we extend SegSVD to the problem of continuous motion pattern recognition. By introducing a new similarity calculation method, we take advantage of the medium and top matching situation of SegSVD to judge the ending of input data and achieve the recognition purpose. Assume that the length of continuous SegSVD pattern to be processed is known, we can process all the patterns into feature space with same number and size of layered structures and for the classification. However, this issue has conflict with recognition of continuous motion pattern, so the length of continuous motion pattern to be processed is known and the starting and ending position are to be determined. As a result, we achieve continuous form of SegSVD, i.e. continuous SegSVD. Each motion is to be processed with fixed layer structure. However, the layers are dynamically increased by the input of frames, wherein the concrete method is to increase one layer based on the obtained result at frames of certain number (such as W) are input, until all the frames are processed. As a result, the pattern length is not necessary in continuous SegSVD, and patterns with different lengths can generate SegSVD structure with different layers.

The algorithm 1 elaborates the realization process of continuous SegSVD. Along with the input of data frames, the continuous SegSVD constructs SegSVD structure and its extraction features in succession. In this way, the application in the recognition of continuous motion becomes possible.

Algorithm input: pattern A and ω (slide window size)

Algorithm output: RA (continues SegSVD result of A) and initialization of L (layers of the claimed structure),

$$M = null, L = 0$$

While A still has frames not to be processed
Input ω frame and represent them as matrix B
(i) $M = M + BTB$
(ii)Conduct SVD processing to M, $M = V_L \sum_L V_L^T$
end while
Return result

$$RA = \left\{ Level(\mathrm{i}) \middle| Level(i) = \{\Sigma_i, V_i\}, 1 \le i \le L \right\}$$

Algorithm 1: Realization of Continuous SegSVD

3.2 Similarity Calculation Based on Punishment

The continuous SegSVD achieves the input and processing of motion data at the same time. For continuous motion recognition, we need a relevant similarity calculation method to obtain the matching result of continuous calculation input data. SegSVD is processed as unlit-layered motion data structure, so we also are required to consider the similarity calculation from the perspective of layer-layer.

To determine the matching layer of $T.Level(i)$ in these two recognition ways of continuous motion patterns, one intuitionistic method is to calculate similarity of all layers, and choose the layer with maximum similarity as the optimum matching. This method can achieve the local optimum, but may lead to three problems, as shown below. The time series is not consistent, such as, $T.Level(i)$ is matched to $R.Level(i+1)$, while $T.Level(i)$ is matched to $R.Level(i+1)$, it is obviously contradictory to the time series of frames in the data. Too many layers in T are matched to a layer in R. the distance between two continuous layers in T and two corresponding matching layers in R is too large. These three phenomena may lead to negative effects on layers of these two patterns, and thus to achieve the global optimum. In order to solve these problems, we introduce the layer matching method based on punishment.

Step 1 :
For k=j to lr
$P_{i+1,k} = (1 - IS(k, j) + \alpha \times t) \times |k - j - 1| \times \gamma$
(ii) $S_{i+1}{}^{(k)} = \Psi(\mathrm{T.Level}(i+1), R.\mathrm{Level}(k)) - P_{i+1,k}$;
End for
Step 2
(i) $j' = \arg\max_k (S_{i+1}{}^{(k)})(j \le k \le l_r)$

(ii) $S_{i+1} = S_{i+1}^{(j')}$ $i.e., \max_k \left(S_{i+1}^{(k)}\right)$

The foregoing two steps explain the concrete procedure of the layer matching method based on punishment. For the inconformity problem in time series, this method exerts some restrictions. Once $R.Level(j)$ is matched to $T.Level(i)$, all layers lower than J may be calculated with $T.Level(i+1)$ any longer, so we only consider the matching of j and above layers in $T.Level(i+1)$.

4. Experimental Results and Analysis

In order to test the performance of continuous motion recognition method proposed above, we conduct a large number of experiments.

4.1 Experimental Data

The motion data are all provided by Motion Capture Laboratory in City University of Hong Kong [7]. By using optical motion capture system (as shown in Figure 1.2), we collect 19 basic motions (i.e. motion patterns) of A-go-go dancing and provide with the particulars of these motion patterns [8]. Each type of motions is collected by 5 captured person with different dancing skills, each captured person implements each type of motions for 3 times. As a result, each type of motions has 15 samples and 285 motion pattern samples are captured in total. As can be seen from each motion in the Table, these motions with certain similarity (such as the starting part of iMove 8 and Move 12) have relatively large difference in N. In addition, these 5 captured person also collect 4 continuous motion data sets for testing, and testing data in these sets have motion patterns with various number. These data are saved in the form of BVH (i.e. site angle), but for convenient comparison of motions captured by the different captured person or various directions, we eliminate root feature in dancing motions. Furthermore, in order to reduce the difference between data, features of five end sites and foot sites are also not taken into consideration in the experiment. Finally, each motion data is comprised of feature information of the remaining 17 sites.

4.2 Experimental Results

We adopts the nearest neighboring rule (1NN) to make motion recognition, wherein the concrete practice is to select n motion pattern samples as prototypes for each type of motions, thus the recognition of testing motions could be depended by maximum similarity value or minimum distance obtained from these prototypes. Referring to the practice in literature [9], by choosing the sample of minimum average DTW distance from 15 motion samples as the pro-to-type, and thus to obtain 19 prototype patterns in total.

In addition, since the task in this chapter is to segment and recognize continuous motion patterns, we introduce the recognition degree of accuracy for the continuous motion patterns as the evaluation standard for this recognition method. The accurate recognition of motion patterns in input data flow should consider correct classification and accurate detection of pattern boundaries, so the error within 30 frames are set to be acceptable (i.e. correct) in the experiment.

Figure 5 shows the manifestation in the given motion testing data set of these three methods. The experimental result has proved the availability of these two proposed methods, whose recognition degrees of accuracy on these four testing sets are higher than CDP. The results of these three methods have a common ground, i.e. the average recognition degree of accuracy reduces with the increase of motion pattern number in the testing sample. It is because there are too many motion patterns in the input data, then pro-babilities of wrong recognition and wrong detection of ending these methods have in the recognition process would be higher, and these errors will be continuously affect the subsequent motion patterns. We can see from the result that the performance of DCP is more stable than our methods, i.e. its amplitude reduction in the recognition degree of accuracy is not that large of our proposed methods. It can be explained from CDP features: by removing restrictions from the starting and ending frame matching based on DTW, the unsound matching of the current pattern have smaller influence on the matching of subsequent patterns and smaller volatility in its performance.

Figure 3.9(a) has shown that DTW based on K-Repetition has less recognition errors than original DTW, while 3.9(b) has shown that DTW based on K-Repetition has better performance on incompletepattern recognition than original DTW.

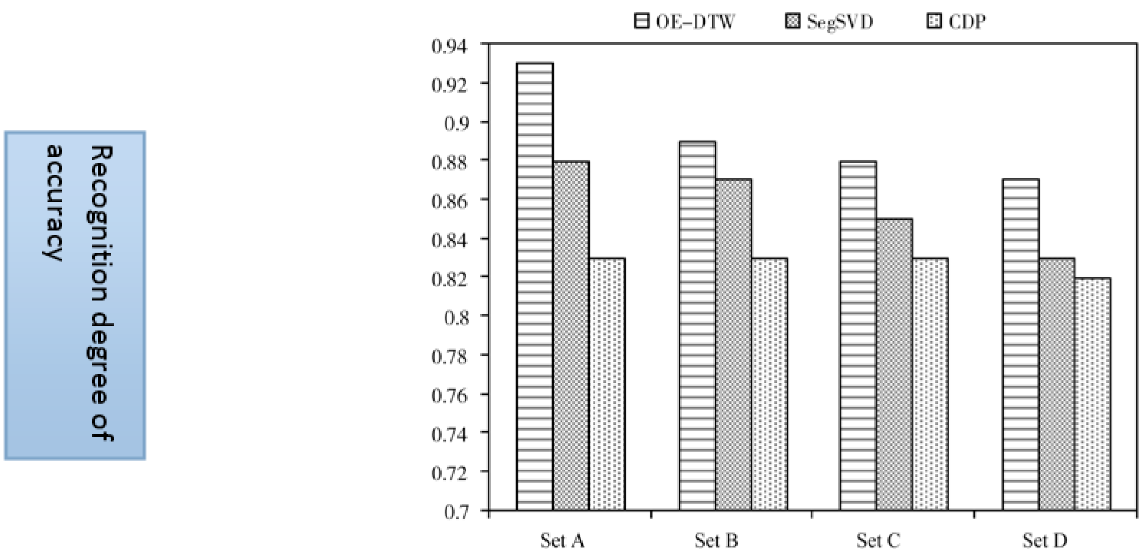


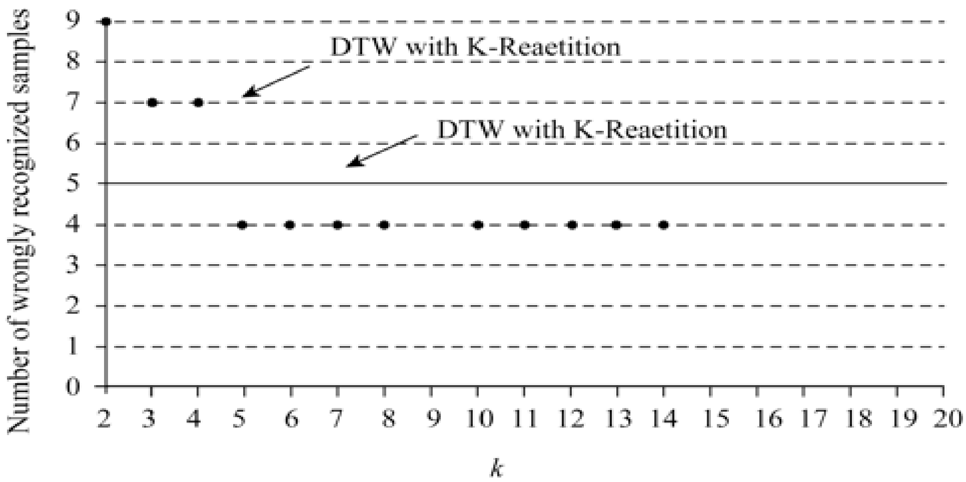
Figure 5. Recognition degree of accuracy in four continuous motion testing sets

These two experiments have both convincingly demonstrated that K-Repetition can improve the recognition performance of DTW/OE-DTW. In addition, from the experimental result, when k = 5, both DTW and OE-DTW can obtain relatively good recognition results.

Firstly, we randomly choose a motion sample as the prototype in each type of motions, while remaining samples are used for testing for 7 times (i.e. 7 groups), wherein Table 1 has shown the recognition results of each experiment. By these results, continuous Seg+SVD has better cognition performance in these 7 experiments than SVD+kWAS in which the prototype pattern is comprised of the sample with minimum average DTW distance. The recognition degree of accuracy of continuous SegSVD outclasses the result of SVD+kWAS, which is shown in Table 1.

Table 1. (continued) Recognition degree of accuracy of SegSVD and SVD+kWAS in 7 random experiments

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Average value
Continuous SegSVD	0.824	0.832	0.929	0.833	0.930	0.810	0.908	0.867
SVD+kWAS[22]	0.745	0.797	0.850	0.762	0.837	0.797	0.789	0.797



(a) Segmented motion pattern recognition

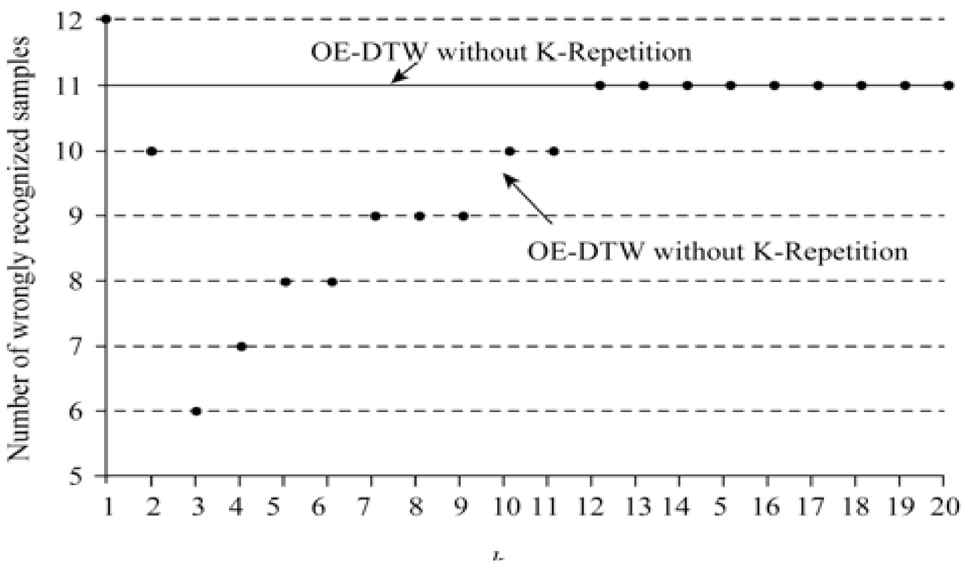


Figure 6. Test the performance of K-Repetition and determine the value of k

Table 2. (continued) Recognition degree of accuracy of SegSVD and SVD+kWAS in specific prototype sets

	Average recognition degree obtained from 7 random experiments	Recognition degree in the prototype set comprised by the minimum average DTW distance
Continuous SegSVD	0.867	0.991
SVD+kWAS[22]	0.797	0.890

5. Conclusion

For features of sports dancing, this paper puts forward two recognition methods for continuous motion patterns. For one method, we extend OE-DTW to the recognition of continuous motions, improve its performance, and propose a new global restriction K-Repetition and elastic ending detection mechanism for use. For the other method, based on SegSVD introduced in the previous chapter, we achieve continuous SegSVD and apply it to the continuous motion recognition by using the weighting similarity calculation method based on punishment. Both of these two methods are proved of effectiveness through experiments, and their recognition degrees of accuracy are better than the results of other methods.

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