Cooperative Warp of Two Discriminative Features for Skeleton Based Action Recognition

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ABSTRACT The study of human motion recognition has attracted many attentions in recent years. In this paper, a simple but effective feature combination is proposed by us for human action recognition based on skeletal points. The two features that make up this combination are the preprocessed 3D joint positions and the velocities of these 3D joints respectively. Then we use a combination of DTW [1], Fourier transform and SVM to model these actions and classify them. Because in the process of DTW, we use these two features to cooperate with each other to warp action samples, we call it the cooperative warp of two discriminative features (CWTDF). We also considered another scenario that we use these two features to warp their action samples respectively and then combine them before the classification process. We call it the separate warp of two discriminative features (SWTDF). But in this case, the classification performance is not as good as the cooperative warp situation. Although our feature representation is relatively simple, it is so sufficiently discriminative that our classification performance outperforms many state-of-the-art strategies based on skeletal points.

1. INTRODUCTION

Human motion recognition is an ancient research field. It has many applications such as human-computer interaction, security monitoring, elderly care, and entertainment. Because early action recognition methods process the action sequences extracted from RGB cameras [2][3][4][5], it was largely influenced by changes in illumination and subject texture variations. Moreover, the calculation amount of processing RGB image sequences is much larger than that of processing 3D joint position sequences from the depth images. Fortunately, with the invention of Microsoft Kinect and the introduction of a new skeleton tracking algorithm [6] which can extract 3D joint positions in real time, all the problems were solved. Many researchers then built their own action models using these 3D joint positions [7][8]. Vemulapalli et al. [8] used the method of lie group and lie algebra to build the skeletal model.

Inspired but different from [8], We combined two discriminative features which are preprocessed 3D joint position values and 3D joint velocity values on each frame of the action sequence. In the subsequent DTW process, these two features synergized to make the warped features more discriminative. Although the two features are relatively simple, our classification performance
outperforms Vemulapalli et al. [8] on the dataset of MSR-Action3D. The duration of our program is much less than theirs. The main contributions of this paper are as follows.

1) A simple but effective feature combination for action recognition is proposed in this paper.
2) We experimentally verified that the cooperative warp of the two discriminative features has higher classification accuracy than the separate warp of these two discriminative features.

Organization: Section 2 is a brief review of action recognition methods based on depth data. Section 3 shows the method of data preprocessing and describes the proposed skeletal representation. Section 4 introduces the method of temporal modeling and classification of the action sequences. Section 5 gives the experimental results. Section 6 concludes the paper.

2. RELATED WORK

Human action recognition approaches based on depth information are divided into three types, which are based on skeletal points, original depth data, and the combination of these two features.

Skeleton-based methods: [9] proposed a feature representation which was called EigenJoints. The feature included static joint positions, the motion between two adjacent frames in an action sequence, and the motion between the initial frame and the current frame. Then the NBNN classifier was employed to classify the actions. Another skeletal joint feature was called HOJ3D [10]. They divided the whole 3d space into n bins and used the Gaussian weight function to associate the skeletal joints with these bins in the 3d space. Then they used a clustering algorithm to get the key postures and modelled the postures using a discrete Hidden Markov Model (HMM). A human action representation which was called SMIJ was proposed by [11]. They calculated the variances or the velocities of the human joint angles over a period to determine which a few angles were the most informative during that period. Then they combined the most informative joint angles of each time period of the entire temporal action sequence as the final action representation. A motion representation using 3d geometric relationships between body parts in each frame of an action sequence was proposed by [8]. Because the geometric relationships of rotation and translation between two body parts are members of the Lie group, they used curves in the Lie group to model the human actions. [22] proposed a descriptor which was called 3DMTG, which combined the 3D Moving Trend feature that captured the dynamic characteristics of the skeletal joints and Geometry feature that captured the offset of the initial frame and the current frame. We used skeleton feature only in this paper.

Original depth data based methods: [12] proposed a depth data based method which was called a bag of 3D points. A static gesture was characterized by some 3D points which were obtained from the original depth data of each frame. And then these static poses made up the whole movement. [13] proposed a method which was called HON4D. The depth sequences were described by a histogram which was obtained by calculating the distribution of the 4D surface normal.

Methods of a combination of these two features: [14] combined the local occupancy pattern feature and the relative 3D positions of skeletal joints. In order to model the action sequences, the method of three levels Fourier time pyramid was employed to represent the two features. [15] proposed an approach to fuse the spatiotemporal features and skeleton joint features. The spatiotemporal features were collected by performing the interest points detection and local feature description. The skeletal joint features were collected by computing the pairwise differences of skeleton joints and the frame difference. Then the random forests method was performed to combine these two features.

3. METHOD OF DATA PREPROCESSING AND THE PROPOSED SKELETAL REPRESENTATION

In this section, we first introduce how to preprocess the original skeletal data from the three datasets, and then introduce how to calculate the action descriptor proposed in this paper.

3.1 Method of Data Preprocessing

All datasets were processed in the following three steps.
First, in order to make the skeletal position data invariant when a person stands in different locations of the scene, we placed the joint position of hip center at the origin of the coordinate system by using every joint position to subtract the hip center position.

Second, to make the skeletal positions invariant to different subject scales, we used the algorithm which was proposed in [16] to process the original data. According to the principle of the algorithm, we took the skeleton of one subject as the reference, and calculated the body part lengths of this skeleton, and normalized all the other skeletons to the reference ensuring that the body parts of all the other skeletons had the same length with the corresponding body parts of the reference skeleton without changing the joint angles of other skeletons. For all the other samples in the datasets, in each frame, we used the breadth-first search (BFS) algorithm, starting from the root joint (hip center joint), moving to the joints associated with this body joint, and successively modified the joint positions without changing the angles of these joints.

Third, when a person is performing an action, different views to the camera will result in different skeletal coordinates. In order to normalize these spatial coordinates, we rotated the x-axis of the original coordinate system to make sure it was parallel to the horizontal plane projection of the left hip to right hip vector, and then we computed the coordinates of the skeletal points in the new coordinate system using the method proposed in [10].

3.2 The Proposed Skeletal Representation

3.2.1 The 3D joint positions feature
Let's define the skeleton joint positions from the action sequences as $P_{ij} = (p_{ijx}, p_{ijy}, p_{ijz})$, where $i \in \{1, \ldots, M\}$ and $j \in \{1, \ldots, N\}$, with $M$ the total number of human body joints and $N$ the total number of frames in an action sequence. $P_{ij}$ is a column vector with length 3. The identifier $p_{ijx}$, $p_{ijy}$, and $p_{ijz}$ respectively represent the three-dimensional coordinate value on the x-axis, y-axis, and z-axis of the $i$th body joint in frame $j$ of an action sequence. So the whole action can be represented as a matrix $A = [P_{ij}]$, where $i \in \{1, \ldots, M\}$ and $j \in \{1, \ldots, N\}$.

Since the length of each action in a dataset is different, for the convenience of later calculation, we interpolate all actions in each dataset into $N$ frames by using the method of cubic spline interpolation [8], where $N$ is the maximum length of the action sequence in each dataset. We denote $A'$ as the action representation after interpolation.

3.2.2 The velocity of 3D joints feature
Let's define the $V_{ij} = (p_{ij+1}x - p_{ij-1}x, p_{ij+1}y - p_{ij-1}y, p_{ij+1}z - p_{ij-1}z)$, where $i \in \{1, \ldots, M\}$ and $j \in \{2, \ldots, N-1\}$, with $M$ the total number of human body joints and $N$ the total number of frames of the action sequences (after interpolation). So the velocity feature of the whole action can be represented as a matrix $B = [V_{ij}]$, where $i \in \{1, \ldots, M\}$ and $j \in \{2, \ldots, N-1\}$.

3.2.3 The combination of two features
Let's take the second column to the $N-1$ column of $A'$ to form a new matrix which we call it $A''$. So $A''$ has the same number of columns as $B$. And then we splice each column of $A''$ and each column of $B$ into a new column to form a new matrix $C$. We denote $C = \begin{bmatrix} A'' \\ B \end{bmatrix}$ as the final feature.

4. TEMPORAL MODELING AND CLASSIFICATION APPROACH
When you use a depth camera to collect human movements, the three problems you often face are that different people do the same movements for different durations, different movements have different durations, and some frames in the action sequence will be very noisy, which we call them subject rate variations, action duration variations, and sensor noise.

To handle the subject rate variations, a general idea is to make the actions of the same category as similar as well. The DTW algorithm can resample the action sequence to minimize the sum of the
distance between the action sequence and the reference action sequence. So we calculate a nominal action sample as the reference for every action category using the algorithm proposed in [8] and warp the training action samples and test action samples to this nominal sample using DTW. In the MSR-Action3D dataset, for example, the number of action categories is 20. For every category, we calculate a nominal action sample, and then use the nominal sample to warp the training samples and test samples for the entire dataset, so we can warp out altogether 20 sets of data, then after the Fourier temporal pyramid representation of these warped actions which is described in the next paragraph, for each set of data, we use the training data to train out a binary linear SVM classifier, then we can train out altogether 20 linear SVM classifiers.

To handle the action duration variations and sensor noise problems, the warped samples are represented by the representation of Fourier time pyramid which is proposed in [14]. It is robust to noise because it discards the high-frequency Fourier coefficients. It is insensitive to action duration variations because two time series with different durations have the same Fourier coefficient magnitudes. In order to capture more information about the actions, we partitioned the time series in three different ways, which is called the three-layer Fourier temporal pyramid model. The first way is to divide the whole sequence as a partition, the second way is to partition the sequence equally into two parts, and the third way is to partition the sequence equally into four parts, so we get a total of seven time series. For each time series, we apply the Short Fourier Transform [20] and then concatenate these transformed Fourier coefficients as the final features.

Then we use multiple trained one-vs-rest linear SVM classifiers to classify the actions in the test set. The whole process of our approach is shown in Figure 1.

Figure 1. The whole process of our approach. The left half of the figure shows the training process and the right half shows the test process. L represents the number of action categories in a dataset.
5. EXPERIMENTAL RESULTS
In this section, three benchmark datasets are employed to evaluate our skeletal representation. In order to illustrate our proposed feature representation is more discriminative, we did another experiment: we warped the two features separately and represented them by the Fourier temporal pyramid respectively. Finally, we combined them before the classification process.

For all the datasets, we use the same evaluated method with [14] [15], which half subjects are used for training and other half are used for test. We provided 10 different combinations of training data and test data and then averaged their test results to get the final results.

5.1 Comparison with World Famous Methods
We compare our experimental results to many state-of-the-art approaches. The comparison results are shown in Table 1, Table 2 and Table 3 respectively.

Table 1. Comparison on MSR-Action3D dataset [12]

| Approach                         | Accuracy (%) |
|----------------------------------|--------------|
| Proposed approach                | 90.90        |
| Histogram of 3D joints [10]      | 78.90        |
| EigenJoints [25]                 | 81.40        |
| Actionlet Ensemble [14]          | 88.20        |
| HON4D [13]                       | 88.36        |
| Lie group [8]                    | 89.48        |
| Skeletal shape trajectories [21] | 90.0         |

Table 2. Comparison on Florence3D-Action dataset [17]

| Approach                           | Accuracy (%) |
|------------------------------------|--------------|
| Proposed approach                  | 88.38        |
| Multi-part bag-of-poses [17]       | 82.0         |
| Motion Trajectories [19]           | 87.0         |

Table 3. Comparison on UTKinect-Action dataset [10]

| Approach                           | Accuracy (%) |
|------------------------------------|--------------|
| Proposed approach                  | 95.38        |
| Random forests [15]                 | 87.90        |
| Grassmann manifold [18]             | 88.50        |
| Histogram of 3D joints [10]         | 90.90        |
| Motion Trajectories [19]            | 91.50        |

In the three tables above, we can clearly see that the classification accuracy of our method is higher than that of many famous methods in all the three datasets. Especially, our approach outperforms Lie group [8] 1.4 percentage points on MSR-Action3D dataset while we use the same classification method as [8]. This further indicates that although our method is only a combination of two simple features, it is more discriminative than [8] using complex spatial rigid body geometry. The running time of our method is also much less than [8] because our feature dimension is much less than [8].

Figure 2 provides the classification confusion matrix of 20 actions in the MSR-Action3D dataset. In figure 2, we can clearly see that the classification accuracy of only 4 actions is lower than 88% while the classification accuracy of 12 actions is higher than 97%. The classification accuracy of a few actions is low because they are too similar to some movements, such as hammer and forward punch, high arm wave and hand catch, hand catch and side boxing, draw a circle and draw X.
Figure 3 provides the classification confusion matrix of 9 actions in Florence3D-Action dataset. In figure 3, we can see that the more similar two actions are, the more confusing they would be. For example, to answer a phone is likely to be confused with to drink, and to answer a phone is likely to be confused with to read watch.

Figure 4 shows the classification confusion matrix of 10 actions in UTKinect-Action dataset. In figure 4, we can see that the classification accuracy of all movements is higher than 94% except the action throw. The reason is that the action throw is too similar to push.
5.2 Comparison of The Two Methods Proposed in This Paper

Table 4, Table 5, and Table 6 show the comparison result between the two methods proposed in this paper in three datasets respectively. One way is to combine the two features (proposed in 3.2) and then go through the DTW and the Fourier transform. Another way is the two features go through the DTW and the Fourier transform respectively and then being combined. As shown in the following three
tables, our experiment proved that the first method is superior to the second one in all three datasets. We analyze the reasons for this result is that two kinds of discriminative information work together to warp more accurate and discriminative information than they work separately.

Table 4. Comparison of the two methods proposed in this paper (MSR-Action3D dataset)

| Approach             | Accuracy (%) |
|----------------------|--------------|
| Cooperative Warp (CWTDF) | 90.90        |
| Separate Warp (SWTDF)  | 90.24        |

Table 5. Comparison of the two methods proposed in this paper (Florence3D-Action dataset)

| Approach             | Accuracy (%) |
|----------------------|--------------|
| Cooperative Warp (CWTDF) | 88.38        |
| Separate Warp (SWTDF)  | 87.29        |

Table 6. Comparison of the two methods proposed in this paper (UTKinect-Action dataset)

| Approach             | Accuracy (%) |
|----------------------|--------------|
| Cooperative Warp (CWTDF) | 95.38        |
| Separate Warp (SWTDF)  | 95.18        |

6. CONCLUSION
A simple but effective feature combination for human motion recognition is proposed in this paper. The performance of our approach outperforms that of many state-of-the-art methods in three benchmark datasets. We also used experiments to prove that cooperative warp is more powerful than separate warp in action recognition.

The limitation of our method is that we need to complete the whole movement to classify it. In the following work, we will study how to classify the movement before it is completed, in order to make it easier for real-time human motion recognition.

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