Dynamic gesture retrieval: searching videos by human pose sequence

Cheng Zhang*

*Faculty of Information Technology, Beijing University of Technology, Beijing 100124, China

Abstract
The number of static human poses is limited, it is hard to retrieve the exact videos using one single pose as the clue. However, with a pose sequence or a dynamic gesture as the keyword, retrieving specific videos becomes more feasible. We propose a novel method for querying videos containing a designated sequence of human poses, whereas previous works only designate a single static pose. The proposed method takes continuous 3d human poses from keyword gesture video and video candidates, then converts each pose in individual frames into bone direction descriptors, which describe the direction of each natural connection in articulated pose. A temporal pyramid sliding window is then applied to find matches between designated gesture and video candidates, which ensures that same gestures with different durations can be matched.

Keywords:
Dynamic Gesture Retrieval, Pose Sequence, Gesture Recognition, Gesture Search, Articulated Pose

1. Introduction
The proposed method focuses on matching video clips with human pose sequence. The human pose estimation methods are considerably advanced during last few years leveraging the development of deep learning, which makes estimating human poses from an unconstrained video possible. Based on these works, our method is constructed to accept a sequence of poses as the keyword, and retrieves video clips with similar pose sequences.

Being able to search through human videos by pose sequence enables the possibility of locating a specific dynamic gesture from large amount of videos without the needs of knowing the name of the gestures and adding proper descriptions to all candidate videos. Comparing with existing methods e.g. retrieving by image [1] or retrieving by pose [2] [3] [4], the proposed method takes temporally dynamic gesture as the keyword, and search through a video with arbitrary duration.

To compare the similarity of two dynamic gestures, the distance between two pose sequences (namely PS distance) must be measured. To achieve that, there are two main challenges: Firstly, the raw 3d pose features is not suitable for measuring the PS distance. This is because that pose features is formed by 3d coordinates representing the absolute human limb positions, which are sensitive to camera movements, but a desired pose descriptor should only reflects human gestures which is invariant to camera translations.
Secondly, the dynamic gestures are temporally scalable. That is, to make a gesture, different people tend to move with different speeds, so as to finish the same gesture with variable durations. Retrieving process should focusing on the gesture but not the speed, so the method has to be temporally flexible to match gestures made with different speeds. To address the first challenge, we propose a descriptor called bone direction descriptor (BD descriptor) which describes the 3d direction of each natural connection in 3d articulated pose model. To address the second problem, we apply a temporal pyramid sliding window on video candidates to match gestures with different durations.

2. Pose sequence distance

This section finds the numerical distance between two pose sequences, so as to measure their similarity. To this end, the BD descriptor is introduced to remove camera translation information from poses. The 3d pose features are denoted as $v_{p,t}$, $p \in \{1, ..., P\}$, $t \in \{1, ..., T\}$ where $P$ is the number of parts predicted by 3d pose estimation method and $T$ is the total number of interested frames. $v_{p,t} \in R^3$ where each $v_{p,t}$ represents an $(x, y, z)$ location in 3d space. Although different pose estimation methods give different number of parts $T$, in most methods, these parts can be connected following the natural structure of human skeleton [5]. Use the set $H$ to denote the set of number of connected pairs, where each pair of connection is formed by two pair numbers $(i, j)$, then the connection set $C_t$ for frame $t$ can be described by equation (1):

$$C_t = \{ v_{i,t}v_{j,t} | (i, j) \in H \}$$ (1)

The BD descriptor is inspired by the spatial features mentioned in [6]. This paper upgrades the angle spatial features into 3d space. Essentially, all the connections in $C_t$ are used as vectors (namely bone vectors) with the direction of top-down suppose the person was standing on the ground with two arms naturally hanging on both sides. This vector set $S$ is denoted as equation (2):

$$s_{b,t} = v_{j,t} - v_{i,t}, (i, j) \in H$$

$$S_t = \{s_{b,t} | b \in (1, ..., B)\}$$ (2)
In equation 2, $B$ is the total number of connections, which is different than total number of parts $P$ because one part can have multiple connections. Then, the gravity unit vector $g$ is introduced as an unit vector pointing at the direction of gravity. For conventional 3D coordinate system where $(x, y, z)$ values represent (width, height, depth), $g$ has a value of $(0, 1, 0)$. Using $g$ as a reference, the angle between bone vector $s$ and gravity vector $g$ can be measured by degree and this value is not affected by the absolute position of a person. However, it is tricky to choose the range of degree. Intuitively, some parts like arms can do 360 degree rotation, so setting the range from 0 to 360 seems feasible. But this setting leads to the problem of having large value jumps between small movements around the boundary, therefore not suitable for measuring the similarity of two poses. Meanwhile, setting the range from 0 to 180 leads to another problem of two different limb positions share a same feature value. To address this, the cos and sin values are used to describe each angle. The final BD descriptor $d_{b,t}$ for bone $b$ and frame $t$ is denoted by equation 3 to 5:

$$d_{b,t} = \{\phi_{b,t}^{\sin}, \phi_{b,t}^{\cos}\}$$ (3)

$$\phi_{b,t}^{\sin} = \frac{s_{b,t} \times g}{\|s_{b,t}\|\|g\|}$$ (4)

$$\phi_{b,t}^{\cos} = \frac{s_{b,t} \cdot g}{\|s_{b,t}\|\|g\|}$$ (5)

Equation 3 shows that a BD descriptor is a vector containing 2 values, they are the sin and cos angle values between gravity unit vector $g$ and bone vector $s$. Equation 4 and 5 show the details of sine and cosine value computations.

The PS distance $k$ is defined using $d_{b,t}$ as equation 6 where $d^1$ and $d^2$ represents BD descriptors of the pose sequence 1 and 2 accordingly.

$$k = \frac{1}{T} \frac{1}{B} \sum_{t=1}^{T} \sum_{b=1}^{B} |d_{b,t}^1 - d_{b,t}^2|$$ (6)

In equation 6, $B$ denotes the total number of connections, $T$ denotes the total number of keyword frames. This equation computes the difference of each frames between two sequences.

3. Temporal pyramid sliding window

The PS distance is able to measure the similarity between two sequences of same length. However, different people can make an identity dynamic gesture with different speeds, the duration of the same gesture in videos can be varied. It is desired for the method to match two gestures with same limb movements and different durations $T^1$ and $T^2$. Our proposed method provides temporal pyramid sliding window to address this problem. A normal sliding window slides through the entire candidate video with a fixed window length, producing a sequence of PS distances. That is, to match the start point of a pose sequence with exact gesture and duration, the time point with smallest PS distance value is searched, as shown in equation 7.
\[T_{\text{match}} = \arg \min_t f_{\text{slide}}(d^{\text{key}}, d^{\text{cand}})\]  

(7)

Where \(T_{\text{match}}\) indicates the starting point of matched result. Sliding window \(f_{\text{slide}}\) computes PS distance at each sliding position:

\[f_{\text{slide}}(d^{\text{key}}, d^{\text{cand}}) = \{k(d^{\text{key}}, f_{\text{subseq}}(d^{\text{cand}}, t, T^{\text{key}})) | t \in (1, ..., T^{\text{cand}} - T^{\text{key}})\}\]  

(8)

In equation \(8\), \(d^{\text{key}}\) denotes the set of BD descriptor used as searching keyword, \(d^{\text{key}} = d_{b,t} | b \in (1, ..., B), t \in (1, ..., T^{\text{key}})\) where \(T^{\text{key}}\) denotes the length of keyword pose sequence. \(d^{\text{cand}}\) denotes the set of BD descriptor used as candidates. Function \(f_{\text{subseq}}\) cuts a sequence, which takes three arguments: the sequence, starting point and duration. \(k(\cdot)\) computes the PS distance given two sequences of same length. The sliding window \(f_{\text{slide}}\) produces one PS distance value at each sliding location, forming a collection of PS distances at each time point. Finally, as described in \(7\) the time point with smallest PS distance value is considered the best match. The \(\arg \min\) can be changed to a threshold to match multiple results.

As mentioned, the normal sliding window matches videos of exact gestures and durations, where the time duration of keyword window and candidate window are same. The temporal pyramid sliding window is proposed to extend or reduce the temporal receptive field of candidate window, and resamples the BD descriptor sequence to have the same length with keyword BD descriptor sequence, so as to compute the PS distance. After the resampling, extended window plays the video clip faster with a larger temporal receptive field, reduced window plays the video clip slower with a smaller temporal receptive field. Formally, given a set of pyramid parameters \(L\), the frame rate \(r\) of resampled window is denoted by equation \(9\) where \(r^{\text{original}}\) denotes the frame rate when \(\lambda = 1\).

\[r_\lambda = \frac{r^{\text{original}}}{\lambda}, \lambda \in L\]  

(9)
4. Experiments

We conduct experiments on UTKinect-Action dataset \cite{7} to evaluate our method. This dataset provides videos of single person actions with human part positions computed from RGB images and depth maps. Different episodes in this dataset record different person. We use video clips from episode 1 as the searching keyword which contains a gesture, and search for similar gestures from other episodes.

Figure 1 uses 20 frames of walking gesture as the keyword and retrieves similar gestures from other episodes. In the figure, left images show the pose sequence used as the searching keyword, right images show the retrieved best matches from another video. It can be seen that the desired gesture is correctly retrieved. Figure 2 shows the PS distance at each sliding window location on episode 2, where smaller value means better match.

Figure 3 includes 30 frames of waving gesture as the keyword, the proposed method correctly retrieved similar gesture.

5. Conclusion

We have developed a novel searching method that takes a dynamic gesture (a sequence of human poses) as input, and matches videos containing similar gestures with various durations. As far as we know, previous methods only retrieve video frames by a single pose. The proposed method enables the possibilities of searching a video of sports, behaviors, commanding gestures etc. without knowing its name by imitating the representative gesture as the searching keyword. The experiment result shows that the proposed method is capable of searching a dynamic gesture from a video by using pose sequence as input.

In future work, this method needs further improvements to be able to run in practical situations, e.g. dealing with partially occluded people, handling multiple people in same frame which relates to pedestrian tracking, dealing with variable speeds for different stages of same gesture etc.

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