Large-scale Continuous Gesture Recognition Using Convolutional Neural Networks

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Abstract—This paper addresses the problem of continuous gesture recognition from sequences of depth maps using convolutional neural networks (ConvNets). The proposed method first segments individual gestures from a depth sequence based on quantity of movement (QOM). For each segmented gesture, an Improved Depth Motion Map (IDMM), which converts the depth sequence into one image, is constructed and fed to a ConvNet for recognition. The IDMM effectively encodes both spatial and temporal information and allows the fine-tuning with existing ConvNet models for classification without introducing millions of parameters to learn. The proposed method on the Large-scale Continuous Gesture Recognition of the ChaLearn Looking at People (LAP) challenge 2016. It achieved the performance of 0.2655 (Mean Jaccard Index) and ranked 3rd place in this challenge.

Index Terms—gesture recognition; depth map sequence; convolutional neural network, depth motion map

I. INTRODUCTION

Gesture and human action recognition from visual information is an active research topic in Computer Vision and Machine Learning. It has many potential applications including human-computer interactions and robotics. Since first work [2] on action recognition from depth data captured by commodity depth sensors (e.g., Kinect) in 2010, many methods [3], [4], [5], [6], [7], [8], [9] for action recognition have been proposed based on specific hand-crafted feature descriptors extracted from depth or skeleton data. With the recent development of deep learning, a few methods have also been developed based on Convolutional Neural Networks (ConvNets) [10], [11], [12] and Recurrent Neural Networks (RNNs) [13], [14], [15], [16]. However, most of the works on gesture/action recognition reported to date focus on the classification of individual gestures or actions by assuming that instances of individual gestures and actions have been isolated or segmented from a video or a stream of depth maps/skeletons before the classification. In the cases of continuous recognition, the input stream usually contains unknown numbers, unknown orders and unknown boundaries of gestures or actions and both segmentation and recognition have to be solved at the same time.

There are three common approaches to continuous recognition. The first approach is to tackle the segmentation and classification of the gestures or actions separately and sequentially. The key advantages of this approach are that different features can be used for segmentation and classification and existing classification methods can be leveraged. The disadvantages are that both segmentation and classification could be the bottleneck of the systems and they can not be optimized together. The second approach is to apply classification to a sliding temporal window and aggregate the window based classification to achieve final segmentation and classification. One of the key challenges in this approach is the difficulty of setting the size of sliding window because durations of different gestures or actions can vary significantly. The third approach is to perform the segmentation and classification simultaneously.

This paper adopts the first approach and focuses on robust classification using ConvNets that are insensitive to inaccurate segmentation of gestures. Specifically, individual gestures are first segmented based on quantity of movement (QOM) [1] from a stream of depth maps. For each segmented gesture, an Improved Depth Motion Map (IDMM) is constructed from its sequence of depth maps. ConvNets are used to learn the dynamic features from the IDMM for effective classification. Fig. 1 shows the framework of the proposed method.

The rest of this paper is organized as follows. Section II briefly reviews the related works on video segmentation and gesture/action recognition based on depth and deep learning. Details of the proposed method are presented in Section III. Experimental results on the dataset provided by the challenge are reported in Section IV, and Section V concludes the paper.

II. RELATED WORK

A. Video Segmentation

There are many methods proposed for segmenting individual gestures from a video. The popular and widely used method employs dynamic time warping (DTW) to decide the delimitation frames of individual gestures [17], [18], [19]. Difference images are first obtained by subtracting two consecutive grey-scale images and each difference image is partitioned into a grid of $3 \times 3$ cells. Each cell is then represented by the average value of pixels within this cell. The matrix of the cells in a difference image is flattened as a vector called motion feature and calculated for each frame in
the video excluding the final frame. This results in a $9 \times (K - 1)$ matrix of motion features for a video with $K$ frames. The motion feature matrix is extracted from both test video and training video which consists of multiple gestures. The two matrices are treated as two temporal sequences with each motion feature as a feature vector at an instant of time. The distance between two feature vectors is defined as the negative Euclidean distance and a matrix containing DTW distances between the two sequences is then calculated and analysed by Viterbi algorithm [20] to segment the gestures.

Another category of gesture segmentation methods from a multi-gesture video is based on appearance. Upon the general assumption that the start and end frames of adjacent gestures are similar, correlation coefficients [21] and K-nearest neighbour algorithm with histogram of oriented gradient (HOG) [22] are used to identify the start and end frames of gestures. Jiang et al. [1] proposed a method based on quantity of movement (QOM) by assuming the same start pose among different gestures. Candidate delimitation frames are chosen based on the global QOM. After a refining stage which employs a sliding window to keep the frame with minimum QOM in each windowing session, the start and end frames are assumed to be the remained frames. This paper adopts the QOM based method and its details will be presented in Section III-A.

B. Depth Based Action Recognition

With Microsoft Kinect Sensors researchers have developed methods for depth map-based action recognition. Li et al. [2] sampled points from a depth map to obtain a bag of 3D points to encode spatial information and employ an expandable graphical model to encode temporal information [23]. Yang et al. [4] stacked differences between projected depth maps as a depth motion map (DMM) and then used HOG to extract relevant features from the DMM. This method transforms the problem of action recognition from spatio-temporal space to spatial space. In [5], a feature called Histogram of Oriented 4D Normals (HON4D) was proposed; surface normal is extended to 4D space and quantized by regular polychorons. Following this method, Yang and Tian [6] cluster hypersurface normals and form the polynormal which can be used to jointly capture the local motion and geometry information. Super Normal Vector (SNV) is generated by aggregating the low-level polynormals. In [8], a fast binary range-sample feature was proposed based on a test statistic by carefully designing the sampling scheme to exclude most pixels that fall into the background and to incorporate spatio-temporal cues.

C. Deep Learning Based Recognition

Existing deep learning approach can be generally divided into four categories based on how the video is represented and fed to a deep neural network. The first category views a video either as a set of still images [24] or as a short and smooth transition between similar frames [25], each color channel of the images is fed to one channel of a ConvNet. Although obviously suboptimal, considering the video as a bag of static frames performs reasonably well. The second category represents a video as a volume and extends ConvNets to a third, temporal dimension [26], [27] replacing 2D filters with 3D equivalents. So far, this approach has produced little benefits, probably due to the lack of annotated training data. The third category treats a video as a sequence of images and feeds the sequence to an RNN [28], [13], [14], [15], [16]. An RNN is typically considered as memory cells, which are sensitive to both short as well as long term patterns. It parses the video frames sequentially and encodes the frame-level information in their memory. However, using RNNs did not give an improvement over temporal pooling of convolutional features [24] or over hand-crafted features. The last category represents a video as one or multiple compact images and adopts available trained ConvNet architectures for fine-tuning [10], [11], [12], [29]. This category has achieved state-of-the-art results of action recognition on many RGB and depth/skeleton datasets. The proposed gesture classification in this paper falls into the last category.
III. PROPOSED METHOD

The proposed method consists of two major components, as illustrated in Fig. 1: video segmentation and construction of Improved Depth Motion Map (IDMM) from a sequence of depth maps as the input to ConvNets. Given a sequence of depth maps consisting of multiple gestures, the start and end frames of each gesture are identified based on quantity of movement (QOM) [1]. Then, one IDMM is constructed by accumulating the absolute depth difference between current frame and the start frame for each gesture segment. The IDMM goes through a pseudo-color coding process to become a pseudo-RGB image as an input to a ConvNet for classification. The main objective of pseudo-color coding is to enhance the motion pattern captured by the IDMM. In the rest of this section, video segmentation, construction of IDMM, pseudo-color coding of IDMM, and training of the ConvNets are explained in detail.

A. Video Segmentation

Given a sequence of depth maps that contains multiple gestures, the start and end frames of each gesture is detected based on quantity of movement (QOM) [1] by assuming that all gestures starts from a similar pose, referred to as neutral pose. QOM between two frames is a binary image obtained by applying the step function from 0 to 1 at the ad hoc threshold of 60. The global QOM of a frame at time $t$ is defined as QOM between Frame $t$ and the very first frame of the whole video sequence. A set of frame indices of candidate delimitation frames was initialised by choosing frames with lower global QOMs than a threshold. The threshold was calculated by adding the mean to twice the standard deviation of global QOMs extracted from first and last 12.5% of the averaged gesture sequence length $L$ which was calculated from the training gestures. A sliding window with a size of $\frac{L}{2}$ was then used to refine the candidate set and in each windowing session only the index of frame with a minimum global QOM is retained. After the refinement, the remaining frames are expected to be the delimiting frames of gestures.

B. Construction Of IDMM

Unlike the Depth Motion Map (DMM) [4] which is calculated by accumulating the thresholded difference between consecutive frames, two extensions are proposed to construct an IDMM. First, the motion energy is calculated by accumulating the absolute difference between the current frame and the neutral pose frame. This would better measure the slow motion than original DMM. Second, to preserve subtle motion information, the motion energy is calculated without thresholding. Calculation of IDMM can be expressed as:

$$IDMM = \sum_{i=1}^{N} |(\text{depth of frame})^i - \text{depth of neutral frame}|$$

(1)

where $i$ denotes the index of the frame and $N$ represents the total number of frames in the segmented gesture. For simplicity, the first frame of each segment is considered as the neutral frame.

C. Pseudocoloring

In their work Abidi et al. [30] used color-coding to harness the perceptual capabilities of the human visual system and extracted more information from gray images. The detailed texture patterns in the image are significantly enhanced. Using this as a motivation, it is proposed in this paper to code an IDMM into a pseudo-color image and effectively exploit/enhance the texture in the IDMM that corresponds to the motion patterns of actions. In this work, a power rainbow transform is adopted. For a given intensity $I$, the power rainbow transform encodes it into a normalized color $(R^*, G^*, B^*)$ as follows:

$$R^* = \{(1 + \cos(\frac{4\pi}{3\times255}I))/2\}^2$$

(2)

$$G^* = \{(1 + \cos(\frac{4\pi}{3\times255}(I - \frac{2\pi}{3}))/2\}^2$$

$$B^* = \{(1 + \cos(\frac{4\pi}{3\times255}(I - \frac{4\pi}{3}))/2\}^2,$$

where $R^*$, $G^*$ and $B^*$ are the normalized RGB values through the power rainbow transform. To code an IDMM, linear mapping is used to convert IDMM values to $I \in [0, 255].$

The resulting IDMMs are illustrated as in Fig. 2.

D. Network Training & Classification

One ConvNet is trained on the pseudo-color coded IDMM. The layer configuration of the ConvNets follows that in [31]. The ConvNet contains eight layers, the first five are convolutional layers and the remaining three are fully-connected layers. The implementation is derived from the publicly available Caffe toolbox [32] based on one NVIDIA Tesla K40 GPU card.

The training procedure is similar to that in [31]. The network weights are learned using the mini-batch stochastic gradient descent with the momentum set to 0.9 and weight decay set to 0.0005. All hidden weight layers use the rectification (RELU) activation function. At each iteration, a mini-batch of 256 samples is constructed by sampling 256 shuffled training color-coded IDMMs. All color-coded IDMMs are resized to $256 \times 256$. The learning rate for fine-tuning is set to $10^{-3}$ with pre-trained models on ILSVRC-2012, and then it is decreased according to a fixed schedule, which is kept the same for all training sets. For the ConvNet the training undergoes 20K iterations and the learning rate decreases every 5K iterations. For all experiments, the dropout regularisation ratio was set to 0.5 in order to reduce complex co-adaptations of neurons in nets.

Given a test depth sequence, a pseudo-colored IDMM is constructed for each segmented gesture and the trained ConvNet is used to predict the gesture label of the segment.
TABLE I: Information of the ChaLearn LAP ConGD Dataset.

| Sets    | # of labels | # of gestures | # of RGB videos | # of depth videos | # of subjects | label provided | temporal segment provided |
|---------|-------------|---------------|-----------------|-------------------|---------------|-----------------|--------------------------|
| Training| 249         | 30442         | 14134           | 14134             | 17            | Yes             | Yes                      |
| Validation| 249       | 8889          | 4179            | 4179              | 2             | No              | No                       |
| Testing | 249         | 8602          | 4042            | 4042              | 2             | No              | No                       |
| All     | 249         | 47933         | 22535           | 22535             | 21            | -               | -                        |

Fig. 2: The samples of IDMMs for six different gestures. The labels from top left to bottom right are: Mudra1/Ardhachandra; Mudra1/Ardhapataka; Mudra1/Chandrakala; Mudra1/Chatura; Mudra1/Kartarimukha; Mudra1/Pataka.

IV. EXPERIMENTS

In this section, the Large-scale Continuous Gesture Recognition Dataset of the ChaLearn LAP challenge 2016 (ChaLearn LAP ConGD Dataset) and evaluation protocol are described. The experimental results of the proposed method on this dataset are reported and compared with the baselines recommended by the challenge organisers.

A. Dataset

The ChaLearn LAP ConGD Dataset is derived from the ChaLearn Gesture Dataset (CGD). It has 47933 RGB-D gesture instances in 22535 RGB-D gesture videos. Each RGB-D video may contain one or more gestures. There are 249 gestures performed by 21 different individuals. The detailed information of this dataset is shown in Table I. In this paper, only depth data was used in the proposed method. Some samples of depth maps are shown in Fig. 3.

B. Evaluation Protocol

The dataset was divided into training, validation and test sets by the challenge organizers. All three sets include data from different subjects and the gestures of one subject in validation and test sets do not appear in the training set.

Jaccard index (the higher the better) is adopted to measure the performance. The Jaccard index measures the average relative overlap between true and predicted sequences of gestures. For a sequence $s$, let $G_{s,i}$ and $P_{s,i}$ be binary indicator vectors for which 1-values correspond to frames in which the $i^{th}$ gesture label is being performed. The Jaccard Index for the $i^{th}$ class is defined for the sequence $s$ as:

$$J_{s,i} = \frac{G_{s,i} \cap P_{s,i}}{G_{s,i} \cup P_{s,i}}$$

where $G_{s,i}$ is the ground truth of the $i^{th}$ gesture label in sequence $s$, and $P_{s,i}$ is the prediction for the $i^{th}$ label in sequence $s$. When $G_{s,i}$ and $P_{s,i}$ are empty, $J_{s,i}$ is defined to be 0.

Then for the sequence $s$ with $l_s$ true labels, the Jaccard Index $J_s$ is calculated as:

$$J_s = \frac{1}{l_s} \sum_{i=1}^{L} J_{s,i}$$

For all testing sequences $S = s_1, \ldots, s_n$ with $n$ gestures, the mean Jaccard Index $\overline{J_S}$ is used as the evaluation criteria and calculated as:

$$\overline{J_S} = \frac{1}{n} \sum_{j=1}^{n} J_{s_j}$$
C. Experimental Results

The results of the proposed method on the validation and test sets and their comparisons to the results of the baseline methods \[33\] (MFSK and MFSK+DeepID) are shown in Table II. The codes and models can be downloaded at the author’s homepage: https://sites.google.com/site/pichaossites/.

TABLE II: Accuracies of the proposed method and baseline methods on the ChaLearn LAP ConGD Dataset.

| Method          | Set    | Mean Jaccard Index $J_S$ |
|-----------------|--------|--------------------------|
| MFSK            | Validation | 0.0918                   |
| MFSK+DeepID     | Validation | 0.0902                   |
| Proposed Method | Validation | 0.2403                   |
| MFSK            | Testing  | 0.1464                   |
| MFSK+DeepID     | Testing  | 0.1435                   |
| Proposed        | Testing  | 0.2655                   |

The results showed that the proposed method significantly outperformed the baseline methods, even though only single modality, i.e. depth data, was used while the baseline method used both RGB and depth videos.

The first three winners’ results are summarized in Table III. We can see that our method is among the top performers and our recognition rate is very close to the best performance of this challenge (0.265506 vs. 0.269235 & 0.286915), even though we only used depth data for proposed method. Regarding computational cost, our implementation is based on CUDA 7.5 and Matlab 2015b, and it takes about 0.8s to process one depth sequence for testing in our workstation equipped with 8 cores CPU, 64G RAM, and Tesla K40 GPU.

TABLE III: Comparison the performances of the first three winners in this challenge. Our team ranks the third place in the ICPR ChaLearn LAP challenge 2016.

| Rank | Team          | Mean Jaccard Index $J_S$ |
|------|---------------|--------------------------|
| 1    | ICT-NHCT      | 0.286915              |
| 2    | TARDIS        | 0.269235              |
| 3    | AMRL (ours)   | 0.265506              |

V. Conclusions

This paper presents an effective yet simple method for continuous gesture recognition using only depth map sequences. Depth sequences are first segmented so that each segmentation contains only one gesture and a ConvNet is used for feature extraction and classification. The proposed construction of IDMM enables the use of available pre-trained models for fine-tuning without learning afresh. Experimental results on ChaLearn LAP ConGD Dataset verified the effectiveness of the proposed method.
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