1. Introduction

Recognition of human actions from videos has gained much interest in recent years due to its wide ranges of potential applications, such as video surveillance, video retrieving, and human-computer interaction. Although much progress has been made, it still remains a challenging problem due to cluttered background, camera motion, occlusions, viewpoint changes, and large variations in the same class.

Recently, it has become more and more popular to employ sparse representation-based methods for various computer vision tasks, such as image classification [1], face recognition [2], [3], and human action recognition [4]–[8]. Sparse representation-based methods for human action recognition first compute the sparse feature representation with learned dictionary and then pool over the entire video to form the final representation, where average pooling and max pooling are usually used. However, pooling over the entire video neglects any spatio-temporal information of features, resulting in non-discriminative representation.

A common way to overcome this drawback is to use spatio-temporal pyramids [9]. However, this provides a representation too coarse to capture the rich relationship between features. Moreover, it needs shot boundary detection which is not robust enough for complex video contents.

To robustly capture the spatio-temporal information of features, we propose a novel method based on statistics on changes of sparse coding coefficients. We first represent features using the sparse coding method. Then we count the number of changes of sparse coding coefficients frame by frame to robustly capture the temporal information of features in spatial pyramids. Finally, the statistics histograms are fed into a support vector machine with a spatial pyramid matching kernel [10] for final classification. Our method needs no additional steps, such as shot boundary detection, and therefore is more robust. Moreover, our method is easy to compute. We test our method on KTH dataset [11] and UCF Sports dataset [12], and experiment results show its effectiveness in human action recognition.

The remainder of the letter is organized as follows. In Sect. 2, we first present the sparse coding method and then introduce our proposed method in detail. In Sect. 3, we conduct experiments on two benchmark datasets to demonstrate the effectiveness of our method. Finally, in Sect. 4, we conclude the letter.

2. Proposed Approach

In this section, we first introduce the sparse coding method and then present how to count the changes of sparse coding coefficients. At last, we show how to use our method for human action recognition.

2.1 Sparse Coding

There are many methods can generate sparse representation for features of a video. Although our method is independent on sparse coding methods, considering the coding efficiency, we employ LLC [1] as our feature coding method.

Let $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N] \in \mathbb{R}^{P \times N}$ be a set of $N$ features and $\mathbf{D} = [\mathbf{d}_1, \mathbf{d}_2, \ldots, \mathbf{d}_K] \in \mathbb{R}^{P \times K}$ the learned dictionary with $K$ atoms. Let $\mathbf{A} = [\alpha_1, \alpha_2, \ldots, \alpha_N] \in \mathbb{R}^{K \times N}$ be the coding coefficient matrix. LLC coding method computes coding coefficients as follows:

$$\alpha_j = \underset{\alpha_j}{\text{argmin}} \| \mathbf{x}_j - \mathbf{D} \alpha_j \|^2 + \lambda \| \mathbf{e}_j \odot \alpha_j \|^2$$

s.t. $\mathbf{1}^T \alpha_j = 1$ \hspace{1cm} (1)

where $\mathbf{e}_j = \exp(\text{dist}(\mathbf{x}_j, \mathbf{D})/\sigma)$ and $\text{dist}(\mathbf{x}_j, \mathbf{D})$ denotes the Euclidean distance between $\mathbf{x}_j$ and atoms of dictionary $\mathbf{D}$. $\sigma$ is a parameter controlling the weight vector $\mathbf{e}_j$. $\odot$ denotes the element-wise multiplication. In our experiments, we employ the approximated LLC for fast encoding, i.e., each feature is encoded by the nearest $k$ dictionary atoms.
2.2 Statistics on Temporal Changes of Coding Coefficients

Traditional methods pool over the entire video, neglecting any spatio-temporal information. For human action recognition, the temporal information of features is very important. We propose to employ the temporal changes of coding coefficients to capture the temporal information between features.

Given a video, we divide it into 3D grids only in spatial space at $L$ different levels of resolution, and a spatial pyramid is constructed. As illustrated in Fig. 1, we take $L = 2$ for example. The $l$-th level will have $4^l$ cells. In a cell with $V$ frames, the representation $f_i = [f_i(1), \ldots, f_i(K)]^T$ for frame $v_i$ is obtained by pooling over the sparse coding coefficients of features located in frame $v_i$. Then temporal information for frame $v_i$ can be described by changes of coding coefficients between $v_i$ and its next frame $v_{i+1}$. The changes can be captured by a matrix $M_l$ of size $2$-by-$K$:

$$M_l = \begin{bmatrix} m_{l}(1, 1) & \ldots & m_{l}(1, K) \\ m_{l}(2, 1) & \ldots & m_{l}(2, K) \end{bmatrix}$$

(2)

Each row of $M_l$ consists of 0 and 1. The non-zero elements of its first row denote the coding coefficients of $v_i$ is larger than that of $v_{i+1}$, and the non-zero elements of second row denote the coding coefficients of $v_i$ is smaller than that of $v_{i+1}$, i.e.,

$$m_{l}(1, j) = \begin{cases} 1, & \text{if } f_i(j) > f_{i+1}(j) \\ 0, & \text{otherwise} \end{cases}$$

(3)

and

$$m_{l}(2, j) = \begin{cases} 1, & \text{if } f_i(j) < f_{i+1}(j) \\ 0, & \text{otherwise} \end{cases}$$

(4)

Then matrix $M_l$ is reshaped to a vector $b_l$ as the histogram representation for frame $v_i$. The histogram representation $g$ of the cell is computed as:

$$g = \sum_i b_i / V^*$$

(5)

where $V^*$ is the number of frames taken into consideration\(^1\).

The concatenated histogram of cells at level $l$ forms the final representation for the corresponding grid.

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\(^1\)A frame is considered only if it and its next frame have non-zero and different coding coefficients.

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2.3 Action Classification

After histogram representation of all grids is computed, we employ a support vector machine with a spatial pyramid matching kernel for action classification. Suppose we have $C$ channel features, the spatial pyramid matching kernel between videos $Y$ and $Z$ is computed as:

$$\kappa(Y, Z) = \sum_{l=0}^{L} w_l \sum_{c=1}^{C} \kappa(h_{Y}^{lc}, h_{Z}^{lc})$$

(6)

where $w_l$ is the weight for the $l$-th level grid and computed as:

$$w_l = \begin{cases} 1/2^{L-l}, & \text{if } l = 0 \\ 1/2^{L-l-1}, & \text{if } 1 \leq l \leq L \end{cases}$$

(7)

$h_{Y}^{lc} = [h_{Y}^{lc}(1), \ldots, h_{Y}^{lc}(j), \ldots]^T$ and $h_{Z}^{lc} = [h_{Z}^{lc}(1), \ldots, h_{Z}^{lc}(j), \ldots]^T$ are the histogram representations of the $c$-th channel features in the $l$-th level grid for videos $Y$ and $Z$ respectively, and $\kappa(h_{Y}^{lc}, h_{Z}^{lc})$ is the histogram intersection kernel:

$$\kappa(h_{Y}^{lc}, h_{Z}^{lc}) = \sum_j \min(h_{Y}^{lc}(j), h_{Z}^{lc}(j))$$

(8)

where $j$ is the index of histogram components.

3. Experiments

In this section, to demonstrate the effectiveness of our method, we conduct experiments and compare it with other excellent methods on two benchmarks: KTH dataset and UCF Sports dataset.

3.1 Parameter Settings

For video representation, we use the code provided by the author of [13] with the default parameter settings to locate spatio-temporal interest points which are further described by histogram of gradient (HOG) and histogram of flow (HOF) [14]. The HOG/HOF features are further pre-processed by principal component analysis and whitening into features with dimensions of 100 ($C = 1$). We construct a three-level spatial pyramid ($L=2$), and max pooling is employed as the pooling function. The dictionary $D$ is computed using $k$-means algorithm and its size is empirically set to 1000 for KTH and UCF Sports datasets.

3.2 Experiment Results on KTH Dataset

The KTH dataset is a standard and popular benchmark for human action recognition. It has six action classes in total (e.g., clapping, running, walking), each of which is performed in four different scenarios by 25 subjects, resulting in a total of 599 videos. We follow recent evaluations on KTH dataset using the LOOCV strategy for classification,
In order to demonstrate the superiority, we compare the performance of our method with that of spatial pyramid method and spatio-temporal pyramid method. As illustrated in Fig. 2, with different $k$ in LLC, our method always performs better. When $k = 5$, we achieve the best accuracy of 96.99%. Table 1 compares our result with previous works, and we achieve the highest accuracy using the same classification strategy. Figure 3 shows the confusion matrix for KTH dataset with $k = 5$. From it, we can observe that wrong classifications usually occur between “jogging” and “running”, which are very similar and hard to classify.

### Table 1: Recognition results of different methods on KTH dataset

| Method                      | Year | Accuracy(%) |
|-----------------------------|------|-------------|
| Wang et al. [15]            | 2009 | 92.1        |
| Zhang et al. [5]            | 2012 | 95.06       |
| Wang et al. [8]             | 2012 | 94.17       |
| Wang et al. [16]            | 2013 | 94.2        |
| Peng et al. [7]             | 2014 | 94.4        |
| Spatial pyramid + LLC       |      | 96.16       |
| Spatio-temporal pyramid + LLC |    | 96.16       |
| Proposed method + LLC       |      | 96.99       |

### Table 2: Recognition results of different methods on UCF Sports dataset

| Method                      | Year | Accuracy(%) |
|-----------------------------|------|-------------|
| Wang et al. [15]            | 2009 | 85.6        |
| Zhang et al. [5]            | 2012 | 87.33       |
| Wang et al. [8]             | 2012 | 86.6        |
| Wang et al. [16]            | 2013 | 88.0        |
| Zhang et al. [6]            | 2014 | 86.7        |
| Spatial pyramid + LLC       |      | 88.0        |
| Spatio-temporal pyramid + LLC |    | 86.67       |
| Proposed method + LLC       |      | 90.0        |

In the UCF Sports dataset, the dataset consists of 150 video clips belonging to 10 action classes: diving (Dive), golf swinging (Golf), kicking (Kick), lifting (Lift), horse-riding (Ride), running (Run), skateboarding (Skate), swinging at the bench (BSwing), swinging at the high bar (HSwing), and walking (Walk). We increase the amount of samples and use a leave-one-sample out cross-validation setting as suggested in [15]. Figure 4 compares the performance of spatial pyramid method, spatio-temporal method, and our method with

### Fig. 5: Confusion matrix for UCF Sports dataset
different $k$ in LLC. When $k = 1$ or $k = 11$, we achieve the best accuracy of 90.0%. Table 2 compares our result with other excellent methods, and we achieve the highest accuracy using the same classification strategy. Figure 5 shows the confusion matrix for UCF Sports dataset with $k = 11$. From it, we can observe that wrong classifications usually occur between “skateboarding” and “walking”.

4. Conclusion

In this letter, we propose a novel histogram representation to overcome the drawback of traditional sparse representation-based methods for human action recognition. Our method counts the temporal changes of sparse coding coefficients of features in the spatial pyramids to incorporate spatio-temporal information of features. It needs no additional steps and is easy to compute. Experiment results on two benchmarks show the robustness of our method and its superiority in human action recognition.

Acknowledgements

This work was supported by the Fundamental Research Funds for the Central Universities of China under Grant 10611201312014 and Scientific and Technological Research Program of Chongqing Municipal Education Commission of China under Grant KJ1401207.

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