

Human Action Attribute Learning Using Low-Rank Representations

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Abstract—This paper studies the problem of learning human action attributes based on union-of-subspaces model. It puts forth an extension of the low-rank representation (LRR) model, termed the hierarchical clustering-aware structure-constrained low-rank representation (HCS-LRR) model, for unsupervised learning of human action attributes from video data. The effectiveness of the proposed model is demonstrated through experiments on five human action datasets for action recognition.

I. INTRODUCTION

Human activities comprising a sequence of actions can be represented hierarchically [1]. The bottom level of this hierarchy contains multiple action attributes, which describe an action at the finest resolution [2]. In this paper, we propose to represent human action attributes based on the *union-of-subspaces* (UoS) model [3], where each action attribute corresponds to one of the subspaces. A human action or activity can then be uniquely represented as a sequence of transitions from one action attribute to another, which in turn can be used for human action recognition. We propose a *hierarchical clustering-aware structure-constrained LRR* (HCS-LRR) model for unsupervised learning of action attributes from video data without the need to specify the number of attributes a priori. Our results confirm the superiority of HCS-LRR over the state-of-the-art subspace clustering approaches for human action recognition.

II. HIERARCHICAL CLUSTERING-AWARE

STRUCTURE-CONSTRAINED LOW-RANK REPRESENTATION

In this work, we learn action attributes using two local visual descriptors: HOG (histograms of oriented gradients) [4] and MBH (motion boundary histogram) [5]. The extracted features are represented by a matrix $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N] \in \mathbb{R}^{m \times N}$. Each column \mathbf{x}_i has unit ℓ_2 norm and corresponds to the feature vector of a frame and n_τ adjacent optical flow fields for HOG and MBH features, respectively. Suppose these N feature vectors are drawn from a union of L low-dimensional subspaces $\{\mathcal{S}_\ell\}_{\ell=1}^L$ of dimensions $\{d_\ell\}_{\ell=1}^L$. The *clustering-aware structure-constrained LRR* (CS-LRR) model amounts to solving the following optimization problem [6]:

$$\begin{aligned} \min_{\mathbf{Z}, \mathbf{F}, \mathbf{E}} \|\mathbf{Z}\|_* + \alpha \|\mathbf{B} \odot \mathbf{Z}\|_1 + \beta \text{tr}(\mathbf{F}^T (\mathbf{V} - \frac{|\mathbf{Z}| + |\mathbf{Z}^T|}{2}) \mathbf{F}) + \lambda \|\mathbf{E}\|_1 \\ \text{s.t. } \mathbf{X} = \mathbf{XZ} + \mathbf{E}, \mathbf{F}^T \mathbf{F} = \mathbf{I}, \end{aligned} \quad (1)$$

where \odot denotes the Hadamard product and $\|\cdot\|_l$ indicates a certain regularization strategy involving \mathbf{E} . Similar to [7], the (i, j) -th entry of \mathbf{B} is defined as $b_{i,j} = 1 - \exp(-\frac{1 - |\mathbf{x}_i^T \mathbf{x}_j|}{\sigma})$, where σ is the mean of all $1 - |\mathbf{x}_i^T \mathbf{x}_j|$'s. The binary matrix $\mathbf{F} \in \mathbb{R}^{N \times L}$ indicates the cluster membership of the data points, i.e., $\forall i, f_{i,\ell} = 1$ if \mathbf{x}_i lies in subspace \mathcal{S}_ℓ and $f_{i,\ell} = 0$ otherwise. Defining an affinity matrix \mathbf{W} as $\mathbf{W} = \frac{|\mathbf{Z}| + |\mathbf{Z}^T|}{2}$, the matrix $\mathbf{V} \in \mathbb{R}^{N \times N}$ is a diagonal matrix

whose diagonal elements are defined as $v_{i,i} = \sum_j w_{i,j}$. Problem (1) can be solved by using linearized alternating direction method [8].

In order to estimate the number of attributes L within data, we introduce a hierarchical subspace clustering algorithm based on CS-LRR model. Once we have obtained the optimal representation matrix $\hat{\mathbf{Z}}$ by solving Problem (1), we set the coefficients in $\hat{\mathbf{Z}}$ below a given threshold to zeros and denote the resulting matrix by $\tilde{\mathbf{Z}}$. We then define the affinity matrix as $\mathbf{W} = \frac{|\tilde{\mathbf{Z}}| + |\tilde{\mathbf{Z}}^T|}{2}$. Let $\mathbf{X}_{p|\ell}$ be the collection of samples belonging to the ℓ -th cluster at the p -th level ($p \geq 0$) and $\pi_{p|\ell}$ denote the set containing the indices of all \mathbf{x}_i 's that are assigned to $\mathbf{X}_{p|\ell}$. We start at the top with all data points in one cluster, i.e., $\mathbf{X}_{0|1} = \mathbf{X}$ and $\pi_{0|1} = \{1, 2, \dots, N\}$. Then at each level $p \geq 0$, we split $\mathbf{X}_{p|\ell}$ into two sub-clusters by applying spectral clustering [9] on $[\mathbf{W}]_{\pi_{p|\ell}, \pi_{p|\ell}}$ (the submatrix of \mathbf{W} whose rows and columns are indexed by $\pi_{p|\ell}$). Note that when $p \geq 2$, we have an additional step which decides whether or not to further divide each single cluster (i.e., subspace) at the p -th level into two clusters (subspaces) at the $(p+1)$ -th level. The cluster $\mathbf{X}_{p|\ell}$ is divisible if and only if (i) the relative representation errors of the data samples using the child subspace are less than the errors calculated using the parent subspace by a certain threshold, and (ii) the dimensions of the two child subspaces meet a minimum requirement. Otherwise the cluster $\mathbf{X}_{p|\ell}$ is a leaf cluster and will not be divided any further. This process is repeated until we reach a predefined maximum level P in the hierarchy. We term our hierarchical subspace clustering algorithm based on CS-LRR model as HCS-LRR. Note that the maximum number of leaf clusters is $L_{\max} = 2^P$ in this setting, which we set as a key input parameter in (1). We omit further details here and refer the reader to [10] for a full explanation of the algorithm.

III. EXPERIMENTS

We evaluate the performance of our proposed method for human action recognition on five datasets: Weizmann [11], Ballet [12], UIUC [13], Keck [14] and UCF Sports [15]. We compare the performance of HCS-LRR with LRR [3], SSC [16], SC-LRR [7], and LSR [17]. The number of clusters L for these algorithms is set (i) to be the same number of leaf subspaces generated by HCS-LRR (denoted by $\langle \text{Algorithm} \rangle\text{-}L_P$) and (ii) to be the same as the number of actions in the training data (denoted by $\langle \text{Algorithm} \rangle\text{-}Q$). For classification we use a non-linear SVM [18] with a Gaussian Dynamic Time Warping (DTW) kernel [19], where the distance between two video sequences is computed by applying DTW [20] on the Grassmann manifold. This computation only involves using subspace transition vectors of the videos. We use both *one-vs.-all* and *one-vs.-one* approach for classification, denoted by “SVM/ova” and “SVM/ovo” in Table I, respectively. The classification results are listed in Table I, from which we make the conclusion that by representing the human actions using the attributes learned by HCS-LRR, we are always able to recognize the actions at a higher rate compared to other methods.

TABLE I
ACTION RECOGNITION RESULTS (%)

Dataset	Feature	Classifier	Subspace clustering method								
			HCS-LRR	LRR- L_P	LRR- Q	SSC- L_P	SSC- Q	SC-LRR- L_P	SC-LRR- Q	LSR- L_P	LSR- Q
Weizmann	HOG	SVM/ova	92.22	65.56	52.22	58.89	48.89	64.44	63.33	58.89	65.56
		SVM/ovo	95.56	82.22	66.67	64.44	51.11	68.89	68.89	71.11	72.22
	MBH	SVM/ova	87.78	85.56	64.44	85.56	64.44	81.11	68.89	86.67	71.11
		SVM/ovo	85.56	87.78	66.67	84.44	61.11	81.11	66.67	85.56	71.11
Ballet	HOG	SVM/ova	67.80	59.32	30.51	67.80	38.98	66.10	42.37	54.24	61.02
		SVM/ovo	62.71	62.71	52.54	64.41	42.37	64.41	57.63	54.24	61.02
	MBH	SVM/ova	71.19	69.49	61.02	54.24	20.34	61.02	62.71	67.80	67.80
		SVM/ovo	69.49	67.80	61.02	45.76	44.07	67.80	61.02	62.71	67.80
UIUC	HOG	SVM/ova	100	77.14	91.43	98.57	81.43	100	90.00	100	91.43
		SVM/ovo	100	92.86	98.57	100	78.57	100	91.43	100	85.71
	MBH	SVM/ova	100	100	95.71	100	100	100	78.57	100	100
		SVM/ovo	100	100	95.71	100	100	100	77.14	100	100
Keck	MBH	SVM/ova	87.30	76.98	66.67	74.60	71.43	79.37	80.16	57.14	61.11
		SVM/ovo	90.48	76.98	74.60	78.57	73.81	84.92	84.13	70.63	69.05
UCF	MBH	SVM/ova	66.13	67.74	60.48	66.13	54.84	64.52	50.81	64.52	54.03
		SVM/ovo	75.81	75.00	57.26	75.81	53.23	73.39	45.16	68.55	50.00

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