DYNAMIC TEXTURE RECOGNITION USING ENHANCED LBP FEATURES

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ABSTRACT

This paper addresses the challenge of recognizing dynamic textures based on spatial-temporal descriptors. Dynamic textures are composed of both spatial and temporal features. The histogram of local binary pattern (LBP) has been used in dynamic texture recognition. However, its performance is limited by the reliability issues of the LBP histograms. In this paper, two learning-based approaches are proposed to remove the unreliable information in LBP features by utilizing Principal Histogram Analysis. Furthermore, a super histogram is proposed to improve the reliability of the LBP histograms. The temporal information is partially transferred to the super histogram. The proposed approaches are evaluated on two widely used benchmark databases: UCLA and Dyntex++ databases. Superior performance is demonstrated compared with the state of the arts.

Index Terms— Local Binary Pattern, Dynamic Texture Recognition, Super Histogram, Principal Histogram Analysis

1. INTRODUCTION

Dynamic textures (DT) are sequences of images of moving scenes that exhibit certain stationarity properties in time [1, 2]. The dynamics of texture elements are statistically similar and temporally stationary. The recognition of DT is challenging as it involves the analysis of both the spatial appearance of static texture patterns and temporal variations in appearance.

In many approaches [1, 2, 3, 4, 5], the global spatial-temporal variations of a DT were modeled as a dynamic system. In [5], Ravichandran et al. proposed to use a bag of LDSs to represent DTs for view-invariant DT recognition. Most recently, Xu et al. proposed to model DTs as dynamic systems with self-similarities and to utilize dynamic fractal analysis for DT recognition [2]. All those approaches emphasize on the temporal variations of DTs, but may not be able to capture the local spatial appearance of DTs.

local binary patterns (LBP) [1] is a simple yet powerful local feature descriptor because of its robustness to illumination variation and alignment error. Zhao et al. proposed volume local binary patterns (VLBP) and LBP-TOP for DT recognition [6]. In [7], LBP and a Pyramid of Histogram of Oriented Gradients (PHOG) were used to represent the spatial texture information. However, the performance of LBP is limited by the reliability issues. The problem mainly arises from insufficient elements to construct the LBP histograms. Firstly, patch-based LBP leads to fewer elements in the histogram of each patch. Secondly, the image is smooth in nature, and hence some LBP patterns rarely appear in the histogram. The occurrence probabilities of those rare patterns can not be reliably estimated. Lastly, the image noise may cause reliability issue as well.

The reliability issues of the LBP histograms have been addressed in literature. For Uniform-LBP (ULBP) [8], non-uniform patterns are considered as rare and noisy patterns, and hence grouped into one bin. The reliability issues of those non-uniform patterns are partially solved. As LBP is sensitive to quantization noise, a tri-state local ternary pattern (LTP) was proposed in [9]. However, the reliability issues of the LBP histograms remain unsolved.

In this paper, two learning-based approaches are proposed to tackle the reliability issues. As pointed out in [10, 11], PCA can be used not only for dimension reduction, but more importantly to remove the dimensions that are harmful to reliable classification. In the proposed approaches, Principal Histogram Analysis (PHA) is applied on the covariance matrix of the LBP histograms of each patch to remove the unreliable information residing in the LBP histograms. The proposed approaches are different from [12, 13], in which PCA is applied on the concatenated LBP feature vector. The dimension of covariance matrix of the concatenated feature vector is so high that it can not be reliably estimated. In contrast, for the proposed approaches, the covariance matrix is calculated on a patch-wise basis and of much smaller size. Thus, it can be better estimated.

DT recognition largely relies on spatial information [7]. In addition, each frame of DTs is in general similar. Inspired by these, a super histogram is constructed by averaging over all the frames along temporal direction. The temporal information is partially transferred to the super histogram. Compared with the approaches that the histograms are compared on a frame-to-frame basis [7], the proposed super histogram can better handle spatial-temporal variations in DTs.

The main contributions of this work are in two-fold. Firstly, we identify the reliability issues of LBP features, and two approaches based on Principal Histogram Analysis are proposed to remove unreliable information residing in LBP features. Secondly, the super histogram is proposed to further improve the reliability of the LBP histograms. The proposed approaches demonstrate superior performance on UCLA and DynTex++ databases for DT recognition.

2. THE PROPOSED LEARNING-BASED LBP

For patch-based LBP, a LBP histogram is extracted from each patch and all the histograms are concatenated to form the final feature vector. Due to the limited number of elements to construct the histograms, those histograms cannot be reliably estimated. We utilize Principal Histogram Analysis on the covariance matrix of the LBP histograms to remove the unreliable information. The proposed

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[1]Unless otherwise states, LBP refers to $LBP_{8,2}$.

learning-based LBP can be derived in a patch-independent manner or a patch-dependent manner.

2.1. The Proposed Patch-Independent Learning-Based LBP

The block diagram for patch-independent learning-based LBP (PI-LBP) is shown in Fig. 1. For the tightly cropped DTs, e.g. the UCLA database [3, 4] and the DynTex++ database [7], the histogram of each patch is similar to each other, and hence the patch locality is not critical. The covariance matrices of different patches can be summed up and the unreliable information in the LBP histograms can be removed.

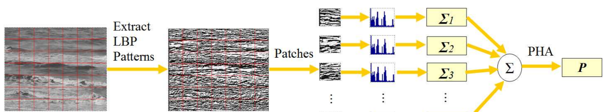


Fig. 1: Block diagram of PI-LBP. One unified projection matrix $\mathbf{P}$ is obtained for all patches.

The proposed PI-LBP is derived by applying principal component analysis on the LBP histograms. Let $\mathbf{h}_{i,j,k} \in \mathbb{R}^{256}$ denote the histogram of i-th patch of j-th image of k-th class. The total scatter matrix is obtained as:

$$\mathbf{\Sigma}_t = \sum_i \sum_{j,k} (\mathbf{h}_{i,j,k} - \mu_i)(\mathbf{h}_{i,j,k} - \mu_i)^T, \quad (1)$$

where $\mu_i = \frac{1}{N}\sum_{j,k} \mathbf{h}_{i,j,k}$ is the mean histogram of i-th patch and N is the total number of training samples. PCA is then applied on $\mathbf{\Sigma}_t$, e.g. $\mathbf{\Sigma_t} = \mathbf{\Phi}\mathbf{\Lambda}\mathbf{\Phi}^T$. Eigenvectors $\mathbf{\Phi}_m$ corresponding to m largest eigenvalues are selected, and $\mathbf{h}_{i,j,k}$ is projected to the feature space as $\mathbf{f}_{i,j,k} = \mathbf{\Phi}_m^T(\mathbf{h}_{i,j,k} - \mu_i)$.

Mahanalobis distance is shown to perform well on classification. Thus, we normalize the feature vector by the inverse of the within-class scatter matrix $\mathbf{\Sigma}_w^f$. $\mathbf{\Sigma}_w^f$ is defined as:

$$\mathbf{\Sigma}_w^f = \sum_i \sum_k \sum_j (\mathbf{f}_{i,j,k} - \mu_{i,k}^f)(\mathbf{f}_{i,j,k} - \mu_{i,k}^f)^T, \quad (2)$$

where $\mu_{i,k}^f = \frac{1}{N_k}\sum_j \mathbf{f}_{i,j,k}$ is the mean feature vector of i-th patch of k-th class in the feature space and N_k is the number of samples for k-th class. After performing PCA on $\mathbf{\Sigma}_w^f$, e.g. $\mathbf{\Sigma}_w^f = \mathbf{\Phi}_w\mathbf{\Lambda}_w\mathbf{\Phi}_w^T$, the normalized feature vector for PI-LBP is obtained as:

$$\mathbf{g}_{i,j,k} = (\mathbf{\Phi}_m\mathbf{\Phi}_w\mathbf{\Lambda}_w^{-0.5})^T(\mathbf{h}_{i,j,k} - \mu_i). \quad (3)$$

Discriminant analysis can be applied to further reduce the dimensions. The between-class scatter matrix is calculated as:

$$\mathbf{\Sigma}_b^g = \sum_i \sum_k (\mu_{i,k}^g - \mu_i^g)(\mu_{i,k}^g - \mu_i^g)^T, \quad (4)$$

where $\mu_{i,k}^g = \frac{1}{N_k}\sum_j \mathbf{g}_{i,j,k}$, and $\mu_i^g = \frac{1}{c}\sum_k \mu_{i,k}^g$; c is the number of class. Then, we apply PCA on $\mathbf{\Sigma}_b^g$, e.g. $\mathbf{\Sigma}_b^g = \mathbf{\Phi}_b\mathbf{\Lambda}_b\mathbf{\Phi}_b^T$. The first t eigenvectors $\mathbf{\Phi}_{b,t}$ corresponding to t leading eigenvalues are selected and the feature vector by applying discriminant analysis is obtained as:

$$\hat{\mathbf{g}}_{i,j,k} = (\mathbf{\Phi}_m\mathbf{\Phi}_w\mathbf{\Lambda}_w^{-0.5}\mathbf{\Phi}_{b,t})^T(\mathbf{h}_{i,j,k} - \mu_i). \quad (5)$$

Unless otherwise stated, 1-NN classifier with Chi-square distance measure is used for classification. Since $\mathbf{g}_{i,j,k}$ or $\hat{\mathbf{g}}_{i,j,k}$ may be negative, Chi-square distance is modified slightly as:

$$\chi_w^2(\mathbf{x}, \mathbf{y}) = \sum_{i,l} \frac{(x_{i,l} - y_{i,l})^2}{|x_{i,l}| + |y_{i,l}|}, \quad (6)$$

where $\mathbf{x}, \mathbf{y}$ are the concatenated LBP feature vectors of two samples; $x_{i,l}$ and $y_{i,l}$ are l-th dimension of i-th patch.

2.2. The Proposed Patch-dependent Learning-Based LBP

For PI-LBP, patch locality is suppressed since a common projection matrix is obtained for all the patches. However, for those non-cropped DTs, e.g. DynTex database [14], the histogram of one patch may be significantly different from the other. In such a scenario, a patch-dependent learning-based LBP (PD-LBP) can be derived to extract the intrinsic property of each patch. The block diagram for PD-LBP is shown in Fig. 2.

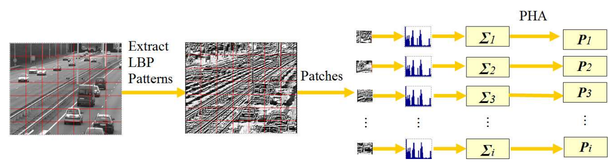


Fig. 2: Block diagram of patch-dependent learning-based LBP. In order to capture the intrinsic property of different patches, one projection matrix $\mathbf{P}_i$ is built for each patch.

For PD-LBP, the total scatter matrix for i-th patch is defined as:

$$\tilde{\mathbf{\Sigma}}_i = \sum_{j,k} (\mathbf{h}_{i,j,k} - \mu_i)(\mathbf{h}_{i,j,k} - \mu_i)^T. \quad (7)$$

PCA is then applied on $\tilde{\mathbf{\Sigma}}_i$, e.g. $\tilde{\mathbf{\Sigma}}_i = \tilde{\mathbf{\Phi}}_i\tilde{\mathbf{\Lambda}}_i\tilde{\mathbf{\Phi}}_i^T$. We select $\tilde{m}$ eigenvectors $\tilde{\mathbf{\Phi}}_{i,\tilde{m}}$ corresponding to $\tilde{m}$ largest eigenvalues and project the histogram of i-th patch $\mathbf{h}_{i,j,k}$ to the feature space as $\tilde{\mathbf{f}}_{i,j,k} = \tilde{\mathbf{\Phi}}_{i,\tilde{m}}^T(\mathbf{h}_{i,j,k} - \mu_i)$. The rest procedures are similar to those of PI-LBP. Finally, one projection matrix is built for each patch.

2.3. Comparisons with Other Approaches

Both the proposed PI-LBP/PD-LBP and Uniform-LBP [8] aim to reduce the feature dimensions. In ULBP, unreliable non-uniform patterns are grouped into one bin, but discriminative information may be lost during grouping. In addition, some non-uniform patterns may have higher occurrence frequency than the uniform patterns, and hence may carry more information than the uniform patterns. By learning a projection matrix for dimension reduction based on a large amount of training samples, the proposed approaches can better remove the unreliable information in the LBP histograms.

Compared with PCA on the concatenated LBP features (PCA-cLBP) [12, 13], for the proposed approaches the covariance matrices of the LBP histograms can be better estimated. If the image is divided into I patches, we have in total NI samples to estimate the covariance matrix of 256×256 dimensions for PI-LBP, whereas for

PCA-cLBP we have only N samples to estimate the covariance matrix of $256I \times 256I$ dimensions. Much more samples are available to estimate the covariance matrix of much smaller size for PI-LBP, and hence its covariance matrix can be better estimated. For PD-LBP, we have N samples to estimate the covariance matrix of 256×256 dimensions for each patch. The reliability of its covariance matrix is between PCA-cLBP and PI-LBP. However, compared with PI-LBP, the patch locality is preserved for PD-LBP and the projection matrix can better capture the intrinsic property of each patch.

3. THE PROPOSED SUPER HISTOGRAM

DT recognition largely relies on the spatial information [7]. For example, on UCLA 50-class classification problem, a recognition rate of 90% is achieved by utilizing spatial LBP alone. It is consistent with the human perception on DTs. Given only one frame per DT, human can easily differentiate DTs. The temporal information serves as further verification. In general, each frame of DT is spatially similar. Inspired by these, a super histogram is proposed.

Let $\mathbf{h}_{i,p} \in \mathbb{R}^{256}$ denote the histogram of i-th patch of p-th frame. The super histogram $\mathbf{h}_i^s$ for i-th patch of this sequence is:

$$\mathbf{h}_i^s = \frac{1}{P} \sum_p \mathbf{h}_{i,p}, \tag{8}$$

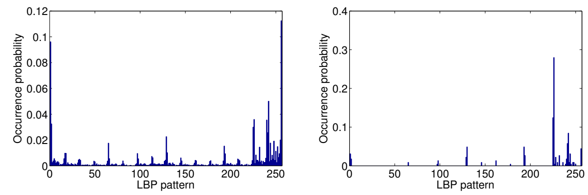
where P is the number of frames in this sequence. The proposed super histogram of LBP mainly captures the local spatial appearance of DTs. The temporal information is partially transferred into the super histogram, as the super histogram is obtained by averaging the histograms over all frames.

The proposed super histogram can better handle the spatial-temporal variations in DTs compared with the approach that the histograms are compared on a frame-to-frame basis [7]. The histogram based on each frame is less reliable as it has fewer elements than the super histogram. In addition, due to the temporal variations, it is difficult to match two DTs on a frame-to-frame basis.

The proposed super histogram is also superior to the approach that a LBP histogram is extracted on the super image obtained by averaging over all the frames. For the super image, we end up with only one frame. The histogram built upon the super image has a limited number of elements only, and hence it is still not reliably estimated. In the proposed approach, the image local structures are extracted in each frame, and those structure patterns are used to construct the super histogram. In contrast, those image local structures are lost when constructing the LBP histogram of super image. To illustrate the difference between those two approaches, we plot them for the first patch of the first DT in the UCLA database as shown in Fig. 3. Each frame is divided into $3 \times 3 = 9$ patches. For the super histogram, the occurrence probabilities of all the LBP patterns are well estimated. However, for the histogram of super image, the occurrence probabilities of many patterns are zero as shown in Fig. 3(b).

4. EXPERIMENTS

The proposed PI-LBP and PD-LBP are compared with LBP, ULBP [8], PCA-cLBP [12, 13] as well as the state of the arts [2, 5, 7] on the UCLA database [3, 4] and the DynTex++ database [7]. Unless otherwise stated, the LBP histograms of all the frames are averaged along the temporal direction to produce the super histogram. LBP, ULBP, PCA-cLBP, PI-LBP and PD-LBP are all based on the super histogram. The optimal dimensions for PI-LBP/PD-LBP are determined in a pretrial.



(a) Super histogram (b) Histogram of supper image

Fig. 3: The super histogram and the histogram of super image.

4.1. Recognition on the UCLA Database

The UCLA DT database [3, 4] has been widely used as a benchmark dataset [2, 5, 7]. It consists of 50 classes of DTs, each with 4 sequences. Each sequence contains 75 frames of 48×48 pixels. Those 50 classes can be further grouped into 9 classes as they contain the same DT at different viewpoints. 9-class classification on the UCLA database is more challenging [5, 7]. Our initial experiment shows that on the UCLA database, the recognition rates are insensitive to the choice of the number of patches. Here, each frame is divided into $3 \times 3 = 9$ patches.

For 50-class classification, we gradually increase the number of frames of the testing sequences, e.g. first frame, first two frames, and etc. The LBP histograms of those frames are averaged along temporal direction. For the training sequences, the histograms are averaged over all the frames. We perform 4-fold cross validation as in [2, 5, 7], and the average recognition rates are shown in Table 1.

Table 1: The recognition rates vs. the number of frames in the test sequence.

Num of Frame	LBP	ULBP	PCA-cLBP	PI-LBP	PD-LBP
1	97.5%	95.0%	92.0%	**97.5%**	**97.0%**
2	97.5%	94.5%	93.5%	98.0%	98.0%
5	96.5%	95.5%	95.0%	98.0%	97.0%
10	97.0%	96.5%	95.0%	98.0%	98.0%
20	98.0%	97.0%	97.5%	99.5%	97.5%
40	98.0%	98.0%	99.0%	99.0%	99.0%
75	99.5%	99.5%	99.5%	**100.0%**	**100.0%**

It is interesting to note that by utilizing the first frame only, a high recognition rate is achieved, e.g. 97.5% for PI-LBP and 97.0% for PD-LBP. It is consistent with the human perception on DTs that DT recognition largely relies on the spatial information. Furthermore, it enables fast searching or indexing of DTs as one frame per DT only is required. When all the frames are utilized, a recognition rate of 100% is achieved for the proposed PI-LBP and PD-LBP.

For 9-class classification, we adopt the same experimental setup as in [2, 7]. The experiment is repeated 20 times. In each trial, each class is randomly bisected. Half are used as the training and gallery set, and the other half are used as the testing set.

The results are summarized in Table 2. A slightly higher recognition rate is achieved for the proposed PI-LBP and PD-LBP compared with LBP, ULBP and PCA-cLBP. The current best recognition rate is 100.0% for 50-class classification and 97.5% for 9-class classification [2]. The proposed PI-LBP and PD-LBP on super histogram achieve the same recognition rate of 100.0% for 50-class classification and the better recognition rate of 98.2% and 98.1% for 9-class classification.

Table 2: The average recognition rates on the UCLA DT database for 50-class and 9-class classification problems.

Method	50-Class	9-Class
Bag of dynamical systems [5]	-	80.0%
DL-PEGASOS algorithm [7]	99.0%	95.6%
Dynamic Fractal Analysis [2]	100.0%	97.5%
LBP + super histogram	99.5%	97.9%
ULBP + super histogram	99.5%	97.8%
PCA-cLBP + super histogram	99.5%	97.7%
PI-LBP + super histogram	**100.0%**	**98.2%**
PD-LBP + super histogram	**100.0%**	**98.1%**

4.2. Recognition on the DynTex++ Database

In order to provide a richer benchmark for DT recognition, the DynTex database [14] is re-organized as the DynTex++ database in [7]. It consists of 36 classes of DTs. Each class contains 100 sequences of size $50 \times 50 \times 50$. We use the same experimental setting as in [2, 7]. For each trial, 50 sequences are randomly selected from each class as the training and gallery set, and the other 50 sequences are used in testing. The experiment is repeated 20 times. Our initial experiment shows that $LBP_{8,1}$ offers better performance, and hence it is used on this dataset.

The average recognition rates vs. N_p are shown in Fig. 4. The recognition rates decrease as N_p increases. The DynTex++ database is built from tightly cropped sequences, and only one DT is present in each sequence. The image patches are similar to each other, and hence the patch locality is less important. By dividing the image into patches, the histogram will has less element, and hence less reliable. The highest recognition rates are achieved when $N_p = 1$ for the DynTex++ dataset. When $N_p = 1$, PCA-cLBP is identical to PI-LBP and PD-LBP.

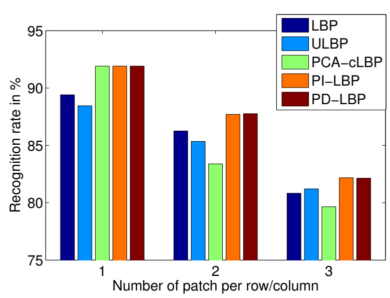


Fig. 4: The average recognition rates of LBP, ULBP, PCA-cLBP, PI-LBP and PD-LBP vs. N_p on the DynTex++ database.

The proposed PI-LBP and PD-LBP are further compared with the state of the arts. The current best recognition rate is 89.9% for DFS [2]. Before that, the recognition rate is 63.7% for DL-PEGASOS [7]. As shown in Table 3, the proposed PI-LBP/PD-LBP on super histogram significantly improve the recognition rate from 89.9% to 91.9%. If RBF SVM is used for classification, the recognition rate further increases to 92.4%.

Table 3: The average recognition rates on the DynTex++ DT database.

Method	Recognition Rate
DL-PEGASOS [7]	63.7%
Dynamic fractal analysis (DFS) [2]	89.9%
LBP + super histogram + 1-NN	89.4%
ULBP + super histogram + 1-NN	88.5%
PCA-cLBP/PI-LBP/PD-LBP + super histogram + 1-NN	**91.9%**
PCA-cLBP/PI-LBP/PD-LBP + super histogram + RBF SVM	**92.4%**

The recognition rates of each class for the proposed approaches and DFS approach [2] are shown in Fig. 5. In [2], mainly the temporal variations are exploited, whereas in the proposed approach, mainly the spatial variations are exploited. Comparing those two, the recognition rate of each class is significantly different, which indicates that those two approaches are capable to handle different DTs. It will be advantageous to fuse those two approaches.

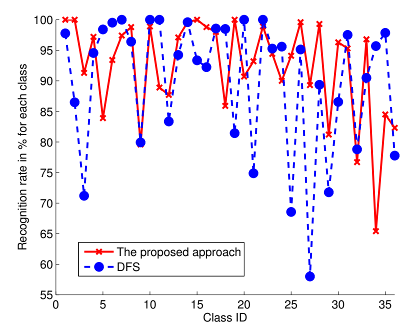


Fig. 5: The recognition rates of the proposed approach and DFS [2] for each class of the DynTex++ database.

5. CONCLUSION

This paper addresses the challenge of recognizing dynamic textures based on LBP features. We identify the reliability issues of LBP features. Two learning-based approaches, i.e. PI-LBP and PD-LBP, are proposed to tackle the problem by utilizing Principal Histogram Analysis. The super histogram is proposed to further improve the reliability. The temporal information is partially transferred into the super histogram. The proposed learning approaches on the super histogram outperform LBP, ULBP and PCA-cLBP on UCLA and Dyntex++ databases. Compared with the state of the arts, on 9-class classification of the UCLA database, the proposed PI-LBP/PD-LBP increase the recognition rate from 97.5% to 98.2% and 98.1%, respectively. On the DynTex++ database, the proposed PI-LBP/PD-LBP increase the recognition rate from 89.9% to 92.4%.

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