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Sparse Variation Pattern for Texture Classification

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Abstract—We present Sparse Variation Pattern (SVP) to extract image features for texture classification. Using the directional derivatives in a local circular neighborhood, SVP captures texture transition patterns in the spatial domain. Unlike conventional feature extraction methods, SVP characterizes the image points taking the co-occurrence of two derivatives in the same direction into account without encoding to binary patterns. Using the directional derivatives, SVP defines a dictionary to solve the classification problem with sparse representation. The proposed texture descriptor was evaluated on the FERET and the LFW face databases, and the PolyU palmprint database. Comparisons with the existing state-of-the-art methods demonstrate that the SVP achieves the overall best performance on all three databases.

I. INTRODUCTION

Texture classification is a fundamental problem in computer vision and plays a significant role in a wide range of applications including medical image analysis [1], remote sensing [2], object recognition [3], and content-based image retrieval [4]. Texture analysis is important in many applications of computer image analysis for classification or segmentation of images based on local spatial variations of intensity or color. The extraction of features that describe texture structure with high discriminant ability and low redundancy is a significant factor in texture representation. These features, which can be scalar numbers or discrete histograms or empirical distributions, characterize the textural properties of the images such as spatial structure, contrast, roughness, and orientation. In texture classification, unlike other forms of classifications where the objects being categorized have a definite structure, most textures have stochastic variations which make them difficult to model. Therefore, extracting features which are invariant with respect to the undesirable geometrical and/or photometric variations such as illumination variation, viewpoint changes, non-rigid surface deformation, and noise is still a challenging problem. A good texture classification algorithm not only capture should highly discriminative information, but also should be robust to environmental changes.

Existing feature extraction methods are performed in either the spatial or the frequency domain. In the spatial domain, texture descriptors are based on the statistical measures of the texture patterns. Liu et al. [5] proposed Radon Representation-Based Feature Descriptor (RRFD) for texture classification. RRFD extracts Radon features which are invariant under geometric affine transformations by projecting points into Radon-points using the Radon transform [6]. The effectiveness of local descriptors has been proved in texture representation [3], [7]. The Local Binary Pattern (LBP) [8] is a non-parametric

method that extracts the structure of local regions based on the intensity differences between the central point and the neighboring points. Research shows that the LBP with a sign operator captures more discriminative information than the LBP with the magnitude operator [9]. A Completed Local Binary Pattern (CLBP) [9] was proposed based on these operators and the center point's texture value. Local Derivative Pattern (LDP) [3] was proposed to capture more detailed information by introducing high-order derivatives. However, if the order of the derivatives increases, LDP becomes very sensitive to noise. Local Ternary Pattern (LTP) [10] was proposed to decrease the noise sensitivity of LBP, especially near uniform intensity regions. LTP provides three values for encoding (-1, 0, and 1) using a pre-defined threshold instead of the two values (0 and 1) used in LBP and LDP.

Frequency domain methods consider the texture image in the frequency domain using frequency transforms such as the Discrete Cosine Transform (DCT) [11], and the Fourier Transform [12]. Hoang et al. [13] proposed a pattern descriptor based on Radon [6], Fourier [12], and Mellin [12] (RFM) transforms. The descriptor was obtained by applying 1-D Fourier-Mellin and Fourier transforms on the radial and the angular coordinates of the patterns' Radon image, respectively. Gomez et al. [14] proposed a texture image descriptor based on the Curvelet transform [15] and a statistical model of the frequency distribution of the curvelet coefficients in images. By applying curvelet transform and adjusting the levels of energy for sub-bands to a generalized Gaussian model, an image representation which captured the edge distribution at different orientation and scales was obtained.

To use information in both frequency and spatial domains, wavelet-based representations have been proposed by many researchers for texture analysis. Celik et al. [16] proposed a texture classifier which uses both the magnitude and the phase of the Dual-Tree Complex Wavelet Transform (DT-CWT) sub-bands. For each texture image, a multi-scale texture feature vector is extracted from the magnitude and the phase of DT-CWT sub-bands in different scales. In [17], a texture descriptor was introduced based on Multi-Fractal Spectrum (MFS). A wavelet pyramid was proposed to encode multi-scale and multi-orientation information of texture images. MFS is estimated for each individual component in the wavelet pyramid (low-frequency component, high-frequency component, and wavelet leaders [18]).

We present a novel texture classification method called Sparse Variation Pattern (SVP). SVP represents an image by the sparse directional derivatives in local neighborhoods. In

this representation, a dictionary is built based on the directional derivative patterns of the image. The directional derivatives capture the pattern transitions in the spatial domain. Existing descriptors such as LBP [8] and LDP [3] extract features from a given image by encoding the texture points into binary codes. Using these features, they rely on conventional classifiers such as k-nearest neighbor to classify a given image. Combining the feature extraction and the classification steps, SVP performs the classification task without encoding the texture point and just using the signed magnitude pattern transitions. Comprehensive experiments are conducted on the FERET [19], Labeled Faces in the Wild (LFW) [20], and PolyU [21] datasets. Comparisons with existing state-of-the-art approaches show the proposed method consistently achieves better results.

II. SPARSE VARIATION PATTERN

Unlike conventional texture analysis algorithms such as LBP [8] and LDP [3] which encode the texture regions to a binary code, Sparse Variation Pattern (SVP) describes the texture image by representing the texture transition patterns in the sparse domain without encoding resulted in more detailed discriminative information. Different from learning-based approaches which build a texture model for each class in the training data, SVP features are directly extracted from texture images without any training procedures.

Given an image $f(x, y)$, we define a local neighborhood for each image point to calculate directional derivatives. Let (x_0, y_0) be a point in $f(x, y)$, we define a circular neighborhood around it with radius r (bold circle in Figure 1). This circle specifies $8r$ neighbors for each point on its circumference. We call this circle the "Neighboring Circle". Each point on the neighboring circle is the center of another circle, called the "Secondary Circle" (dashed circle in Figure 1). The secondary circle specifies a circular neighborhood with the same radius r for the neighboring circle's point. Due to this structure, we calculate the texture transitions within the circular neighborhoods using directional derivatives.

Let $f(x_0, y_0)$ be a texture point in the given image $f(x, y)$, where x_0 and y_0 are the spatial coordinates of the texture point.

Fig. 1: Defining the neighboring and the secondary circles.

Considering $f(x_0, y_0)$ as the center point of the structure, the texture points on the neighboring circle are defined as

$$f_i^{NC}(x_i, y_i) = f(x_0 + r \cos(\theta_i), y_0 + r \sin(\theta_i)); \quad (1)$$

$$i = 1, \dots, 8r$$

where r is the radius of the neighboring circle and $\theta_i = 2\pi(i-1)/8r$ is the angle of the i -th neighboring circle's texture point with respect to the x axis. x_i and y_i are the coordinates of the i -th texture point on the neighboring circle.

As mentioned, each texture point on the neighboring circle is surrounded by $8r$ neighbors specified by the secondary circle. The j -th neighboring texture points of the i -th neighboring point, $f_{ji}^{SC}(x_j, y_j)$, is defined as

$$f_{ji}^{SC}(x_j, y_j) = f(x_i + r \cos(\varphi_{ji}), y_i + r \sin(\varphi_{ji})); \quad (2)$$

$$i = 1, \dots, 8r \quad \& \quad j = 1, \dots, 8r$$

where $\varphi_{ji} = 2\pi(j-1)/8r$ is the angle of the j -th neighboring texture point of the i -th neighboring point with respect to the x axis. x_j and y_j are the spatial coordinates of each secondary circle's point.

SVD takes the spatial directional variations into account to capture the texture transition pattern of the given image. Here, we use directional derivatives to obtain the spatial variation of the texture. Using the texture points of both the neighboring circle and the secondary circle, the first-order directional derivatives along θ direction, $\partial f_a(x, y)/\partial \theta$, and along φ direction, $\partial f_{bc}(x, y)/\partial \varphi$, are defined as

$$\partial f_a(x, y)/\partial \theta = f_a^{NC}(x_a, y_a) - f(x_0, y_0); \quad (3)$$

$$a = 1, \dots, 4r$$

$$\partial f_{bc}(x, y)/\partial \theta = f_{bc}^{SC}(x_b, y_b) - f_c^{NC}(x_c, y_c); \quad (4)$$

$$b = 1, \dots, 4r \quad \& \quad c = 1, \dots, 8r$$

where a denotes the a -th neighbor of the center point and b is the b -th neighbor on the secondary circle of the c -th neighboring circle's point.

In order to compute the directional derivatives, we only consider the first $4r$ directions ($a = 1, \dots, 4r$ and $b = 1, \dots, 4r$). Because the remaining neighboring points are considered in the derivative calculation by changing the spatial coordinates of the neighboring circle's center point.

Generally, the n^{th} -order directional derivatives are computed from the $(n-1)^{th}$ -order directional derivatives along θ and φ direction using the following recursive equations

$$\partial^n f_a(x, y)/\partial \theta^n = \partial^{n-1} f_a^{NC}(x_a, y_a)/\partial \theta^{n-1} - \partial^{n-1} f(x_0, y_0)/\partial \theta^{n-1}; \quad (5)$$

$$a = 1, \dots, 4r$$

$$\partial^n f_{bc}(x, y)/\partial \varphi^n = \partial^{n-1} f_{bc}^{SC}(x_b, y_b)/\partial \varphi^{n-1} - \partial^{n-1} f_c^{NC}(x_c, y_c)/\partial \varphi^{n-1}; \quad (6)$$

$$b = 1, \dots, 4r \quad \& \quad c = 1, \dots, 8r$$

where $\partial^{n-1} f(x_0, y_0)/\partial \theta^{n-1}$ and $\partial^{n-1} f_a^{NC}(x_a, y_a)/\partial \theta^{n-1}$ are the $(n-1)^{th}$ -order directional derivatives along θ direction in the center of the neighboring circle and between neighboring circle and its specified neighbors, respectively.

$\partial^{n-1} f_{bc}^{SC}(x_b, y_b) / \partial \varphi^{n-1}$ denotes the $(n-1)^{th}$ -order directional derivative of the b -th neighbor of the c -th neighboring circle's texture points along φ direction. These derivatives are computed as

$$\partial^{n-1} f(x_0, y_0) / \partial \theta^{n-1} = \partial^{n-2} f(x_0, y_0) / \partial \theta^{n-2} - \partial^{n-2} f(x_0 + r \cos(\theta), y_0 + r \sin(\theta)) / \partial \theta^{n-2}; \quad (7)$$

$$\partial^{n-1} f_a^{NC}(x_a, y_a) / \partial \theta^{n-1} = \partial^{n-2} f_a^{NC}(x_a, y_a) / \partial \theta^{n-2} - \partial^{n-2} f(x_a + r \cos(\theta), y_a + r \sin(\theta)) / \partial \theta^{n-2}; \quad (8)$$

$$\partial^{n-1} f_{bc}^{SC}(x_b, y_b) / \partial \varphi^{n-1} = \partial^{n-2} f_{bc}^{SC}(x_b, y_b) / \partial \varphi^{n-2} - \partial^{n-2} f(x_b + r \cos(\varphi), y_b + r \sin(\varphi)) / \partial \varphi^{n-2}; \quad (9)$$

where $\partial^{n-2} f(x_0, y_0) / \partial \theta^{n-2}$ and $\partial^{n-2} f_a^{NC}(x_a, y_a) / \partial \theta^{n-2}$ are the $(n-2)^{th}$ -order directional derivatives along θ direction within the neighboring circle and between the neighboring circle and its specified neighbors, respectively. $\partial^{n-2} f_{bc}^{SC}(x_b, y_b) / \partial \varphi^{n-2}$ is the $(n-2)^{th}$ -order directional derivative of the b -th neighbor of the c -th neighboring circle's texture points along φ direction. $\partial^{n-2} f(x_0 + r \cos(\theta), y_0 + r \sin(\theta)) / \partial \theta^{n-2}$ and $\partial^{n-2} f(x_a + r \cos(\theta), y_a + r \sin(\theta)) / \partial \theta^{n-2}$ denote the $(n-2)^{th}$ -order directional derivatives along θ direction in neighboring of the central point and neighboring of the neighboring circles' points, respectively. $\partial^{n-2} f(x_b + r \cos(\varphi), y_b + r \sin(\varphi)) / \partial \varphi^{n-2}$ is the $(n-2)^{th}$ -order directional derivatives along φ direction in neighboring of the secondary circle.

Once the n^{th} -order directional derivatives are computed, we define Directional Derivative Pattern (DDP) for all $4r$ directions which represent the co-occurrence of two directional derivatives in a same direction for all the texture image's points i.e. the texture transition pattern. The n^{th} -order directional derivative pattern represents the texture transition pattern for each texture point along $\alpha_b = 2\pi(b-1)/8r$ direction. In order to calculate the n^{th} -order derivative pattern for the k -th point of the given image $f(x, y)$ along direction α_b , we consider the co-occurrence of two directional derivatives in a same direction by defining each element of the n^{th} -order derivative pattern vector as the product of two direction derivatives within the neighboring circle and the secondary circle as

$$DDP_{k, \alpha_b}^{(n)}(f(x, y)) = \left[\frac{\partial^n f_b(x, y)}{\partial \alpha_b^n} \times \frac{\partial^n f_{b1}(x, y)}{\partial \alpha_b^n} \dots \frac{\partial^n f_b(x, y)}{\partial \alpha_b^n} \times \frac{\partial^n f_{b8r}(x, y)}{\partial \alpha_b^n} \dots \right]^T; \quad (10)$$

$b = 1, \dots, 4r \quad \& \quad k = 1, \dots, (M \times N)$

where the superscript T denotes the transpose operation.

Using the n^{th} -order directional derivative pattern, we compute the sparse representation of each object. Here, we define a dictionary matrix which models each texture image. Suppose there are P texture images per object. To make the dictionary matrix, we concatenate the column vectors of the n^{th} -order directional derivative patterns along α_b direction such that each column of the dictionary is normalized to the unit magnitude. Therefore, a column of the dictionary matrix for the s -th image

of the given object along α_b direction, d_{s, α_b} , is defined as

$$d_{s, \alpha_b} = [DDP_{1, \alpha_b}^{(n)}(f(x, y))^T \quad DDP_{2, \alpha_b}^{(n)}(f(x, y))^T \dots DDP_{(M \times N), \alpha_b}^{(n)}(f(x, y))^T]^T; \quad (11)$$

$b = 1, \dots, 4r$

Using all the $4r$ directional derivative patterns for each image, $4r$ columns for each object are obtained. Repeating this process for all images of each object, we obtain the desired dictionary matrix for sparse representation of each object. In this way, the dictionary matrix for each object contains $P \times 4r$ columns in which each column called signal-atom in the literature.

$$D = [d_{1, \alpha_1} \quad \dots \quad d_{1, \alpha_{4r}} \quad \dots \quad d_{P, \alpha_1} \quad \dots \quad d_{P, \alpha_{4r}}]; \quad (12)$$

Once the dictionary matrix D , $(M \times N \times 8r) \times (P \times 4r)$, with $4r$ atoms per gallery object is obtained, we can calculate the sparse representation of each object. Since the dictionary is overcomplete, we can represent each object as a sparse linear combination of the dictionary atoms, i.e. $Z = Dw$, where w is a sparse vector. Given a signal Z and a dictionary D , the sparse decomposition problem aims to find the sparsest representation for Z . A solution for this problem is to minimize the objective function, $\min \|w\|_0$, with respect to the constraint $\|Z - Dw\|_2 \leq \varepsilon$, where ε is a positive constant which stands for the permissible deviation of the representation Dw from the original signal Z . One solution to this problem is the Basis Matching Pursuit algorithm [22]. A matching pursuit is a greedy algorithm which rather than solving the optimal approximation problem, refines the signal approximation with an iterative procedure. Using the basis matching pursuit algorithm, we compute a linear expansion of Z over a set of column vectors of D . This is done by a successive approximation of Z with orthogonal projections on the atoms of D . Assuming $d_0 \in D$, the vector Z can be decomposed into

$$Z = \langle Z, d_0 \rangle d_0 + R_Z; \quad (13)$$

where $\langle \cdot, \cdot \rangle$ denotes the inner product procedure and R_Z is the residual vector after approximating Z in direction of d_0 . Clearly d_0 is orthogonal to R_z , hence

$$\|Z\|^2 = |\langle Z, d_0 \rangle|^2 + \|R_Z\|^2; \quad (14)$$

In order to minimize $\|R_Z\|$, we must choose d_0 such that $|\langle Z, d_0 \rangle|$ is the maximum. The matching pursuit is an iterative algorithm that further decomposes the residue R_Z by projecting it on a column vector of D that matches R_Z the best, as it was done for Z . This procedure is repeated until the residue becomes smaller than a threshold. For each query image, matching is performed by considering the minimum Euclidean distance between its sparse code and that of the gallery images. The model in the gallery with the minimum distance is considered as the correct match.

$$M = \min_{i, j} \|q_i - g_j\|; \quad (15)$$

where M denotes the minimum distance between sparse codes of the i -th query image, q_i , and the j -th gallery image, g_j .

III. EXPERIMENTAL RESULTS

We evaluate the performance of the proposed method using the FERET database [19], and the Labeled Faces in the Wild (LFW) database [20], and the PolyU palmprint database [21]. Note that we chose the same radius value for both circles, i.e. the neighboring and the secondary circle. Therefore, the value of this radius r is the only free parameter and is determined experimentally using the FERET database. Once its optimal value is determined, we use the same value for all experiments. The sample images of each database is shown in Figure 2. As can be seen, the LFW database contains face images taken in uncontrolled condition and covers a wide range of variations. The PolyU palmprint database comprises the texture image of different palms. The FERET database covers a wide range of varieties such as illumination, expression, and aging.

The FERET database is widely used to evaluate face recognition algorithms. It consists of a total of 14,051 gray-scale images representing 1,199 individuals. The images contain variation in lighting, facial expressions, pose angle, etc. We used the gallery and the probe sets specified in the FERET evaluation protocol [19]. The facial images are divided into five sets. **Fa** set containing 1,196 frontal images of 1,196 subjects was used as the gallery set, while **Fb** set (1,195 images with expression variations), **Fc** set (194 images taken under different illumination conditions), **Dup I** set (722 images taken later in time between one minute to 1,031 days), and **Dup II** (234 images, a subset of Dup I taken at least after 18 months) were used as the probe sets. All the frontal face images were normalized by aligning the location of the eyes and cropped to 160×160 points.

The rank-1 recognition rate of the proposed algorithm is computed using SVPs with different radii of the neighboring circle and the secondary circle, r , versus the SVP's order (see Figure 3). As can be seen, the recognition rate is significantly improved when the order of local pattern is increased from the first-order SVP to the second-order SVP for all radii. Then, the performance drops as the SVP's order increases. On the other hand, as the radius of the neighboring circle and the secondary circle increase the accuracy of the SVP drops. This means that SVP captures more detailed information in small local regions. The results prove the effectiveness of the second-order SVP in classifying the given texture images. Moreover, the best value for the radius of the neighboring circle and the secondary circle

Fig. 2: Sample images from **Top row**: the LFW face database [20], **Middle row**: the PolyU palmprint database [21], **Bottom row**: the FERET face database [19].

Fig. 3: Rank-1 recognition rate versus SVP's order and the radius.

is $r = 1$. Therefore, we used the second-order SVP with radius $r = 1$ in all the remaining experiments.

A. Results on the FERET database

The rank-1 recognition rates of SVP using different probe sets of the FERET face database are compared to the state-of-the-art approaches in Table 1. As can be seen, SVP achieves 8.24%, 9.24%, 1.94%, and 0.24% improvement over Local Binary Pattern (LBP) [8], Local Derivative Pattern (LDP) [3], Extended Sparse Representation-Based Classifier (ESRC) [23], and the fusion of Local Gabor Binary Pattern and Local Gabor XOR Pattern (LGBP+LGXP) [24] on the **Fb** probe set, respectively. These results mean that the proposed SVP is more robust with respect to variations of facial expressions. Also, the recognition accuracy on the **Fc** probe set proves that the proposed method is invariant under illumination changes. The SVP significantly improves the recognition rate on both the **Dup I** and **Dup II** probe sets.

TABLE I: Comparison of the rank-1 recognition rates (%) on the FERET face database.

Method	Fb	Fc	Dup I	Dup II
*LBP [8]	91.00	65.00	53.50	36.00
*LDP [3]	90.00	88.00	63.00	55.00
ESRC [23]	97.30	95.40	93.80	92.80
LGBP+LGXP [24]	99.00	99.00	94.00	93.00
SVP	99.24	98.51	99.42	98.75

*The results are from [3].

B. Results on the LFW database

The LFW database [20] contains 13,233 face images of 5,749 subjects with large variations in pose, illumination, and expressions. A total of 1,680 subjects have two or more images, among which 158 subjects have at least 10 images. Two configurations for this database, called image-restricted training and unrestricted training, are followed. In the case of image-restricted configuration, the training dataset has no information about the subject identity, only interpersonal and intrapersonal image pair labels are available. Thus, according to this configuration, the face recognition system is solving a binary classification problem. In contrast, the unrestricted training configuration allows the experimenter to use the image

set labeled with individual's name for model learning. We experiment with the unrestricted configuration, as our algorithm is designed to deal with the problem of texture classification. The configuration organizes the data into two views, View 1 is for algorithm development and View 2 is for performance evaluation. In View 2, the configuration divides the database into 10 subsets. The subjects in each subset are distinct. In our experiment, we divided the database into 10 equal sized sets. The benchmark test is repeated 10 times, each time one set is used for testing and 9 others are used for training as in [20].

The rank-1 recognition rate and the standard deviation of the SVP and the benchmark approaches on LFW database are summarized in Table 2. The results demonstrate that the proposed method consistently achieves the highest recognition rate compared to the benchmarks. SVP improves the recognition accuracy by 10.66%, 8.50%, 5.83%, 4.13%, and 3.25% over Local Binary Pattern Multishot (LBP Multishot) [25], Local Binary Pattern Probabilistic Linear Discriminant Analysis (LBP PLDA) [26], Soft Local Binary Pattern (SLBP) [27], Covariance Matrix Descriptor (CMD) [28], and CMD+SLBP [29].

TABLE II: Comparison of the rank-1 recognition rate (%) $\pm$ standard deviation on the LFW face database.

Method	Recognition Rate $\pm$ Standard Deviation (%)
LBP Multishot [25]	85.17 $\pm$ 0.61
LBP PLDA [26]	87.33 $\pm$ 0.55
SLBP [29]	90.00 $\pm$ 1.33
*CMD [28]	91.70 $\pm$ 1.10
CMD+SLBP [29]	92.58 $\pm$ 1.36
SVP	95.83 $\pm$ 1.25

*The result is from [29].

C. Results on the PolyU palmprint database

The PolyU palmprint database [21] contains 7,752 gray-scale images corresponding to 386 different palms in bitmap image format. Around twenty samples from each of these palms were collected in two sessions where around ten samples were captured in the first session and the second session, respectively. The average interval between the first and the second collection was two months. In our experiments, the central part of each original image was automatically cropped using the algorithm in [30]. The cropped images were resized to 128×128 regions of interest.

In Table 3, the rank-1 recognition rate of SVP and other benchmark palmprint recognition approaches are summarized. Here, SVP achieves 99.41% identification rate compared to 84.67%, 93.33%, 95.70%, 95.71%, and 98.30% identification rate for 2D Locality Preserving Projection (2DLPP) [31], 2D Local Graph Embedding Discriminant Analysis (2DLGEDA) [32], Linear Discriminant Analysis (LDA) [33], Discriminant Projection Embedding (DPE) [34], and Laplacianface [35], respectively. Hence, SVP outperforms current benchmark approaches for palmprint identification.

TABLE III: Comparison of the rank-1 recognition rate (%) of SVP and the benchmarks on the PolyU palmprint database.

Method	Recognition Rate (%)
2DLPP [31]	84.67
2DLGEDA [32]	93.33
LDA [36]	95.70
DPE [34]	95.71
Laplacianface [26]	98.30
SVP	99.41

D. Performance evaluation

The performance statistics are illustrated by computing cumulative match scores for the FERET (see Figure 4) and the LFW and PolyU (see Figure 5) test datasets, respectively. The horizontal axis gives the rank, and the vertical axis is the percentage of correct classification results. In the FERET face dataset, the experiments are performed for all four test subsets (*Fb*, *Fc*, *Dup I*, and *Dup II*), individually. In Figure 4, it can be seen that the rank-1 recognition rates are 99.24%, 98.51%, 99.42%, and 98.75% of *Fb*, *Fc*, *Dup I*, and *Dup II* respectively, and 100% of the images are correctly classified in the rank 9. In Figure 5, one can see that the rank-1 recognition rate is 95.83% and 99.41% for the LFW face dataset and the PolyU palmprint dataset, respectively. 100% of the images are correctly classified in the rank 8 and 15 for the PolyU and the LFW datasets, respectively.

Fig. 4: Cumulative match score for the FERET dataset.

Fig. 5: Cumulative match score for the LFW and the PolyU datasets.

IV. CONCLUSION

In this paper, a novel method for texture classification called Sparse Variation Pattern (SVP) is proposed. SVP captures the spatial variations of the texture image using the directional derivatives in a local circular neighborhood. Different from the traditional feature extraction methods which encode the image point into a binary code, SVP's features are extracted directly from gray-level images without any binary encoding process. It considers the co-occurrence of two directional derivatives with the same direction to make the dictionary matrix for each object. Using this dictionary matrix and the matching pursuit algorithm, we obtain a sparse representation of the image. The proposed SVP was tested on three standard datasets: the FERET and the LFW face databases and the PolyU palmprint database. In all experiments, the algorithm was compared with state-of-the-art benchmarks. Our results show that the proposed SVP outperforms existing state of the art methods on three benchmark databases

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