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FACE RECOGNITION USING *SCAN*-BASED LOCAL FACE DESCRIPTOR

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ABSTRACT

This paper describes *SCAN* descriptor as a local face descriptor to represent a face image. *SCAN* techniques that originally for image compression and data hiding were used to locally extract face image features to represent the face image. Simulations were conducted on the subset of cropped Yale Face Database B by either varying uniformly the face image pixels (intensities) or lowering their resolutions in the database subset. The simulation results show that *SCAN* descriptor has recognition rate that outperforms for both either two global face descriptors, i.e. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), or two local face descriptors, i.e. Local Binary Pattern (LBP) and Multi-Scale Local Binary Pattern (MLBP).

Keywords: *SCAN*, local face descriptor, global face descriptor, recognition rate.

INTRODUCTION

The rise of terrorist acts as criminal conduct or acts of bombing protesters / motorcycle gang that often act anarchist or theft at a supermarket / bank / parking area requires two approaches, namely prevention through a more rigorous examination of persons suspected of (preventive) and search for people who are suspected of having committed a crime (curative). To facilitate this search, one needs a system that can assess the similarity among subjects that are monitored against the existing database.

Face, as one of biometrics, is a prominent and easiest information that needed this matching process. This is because face is a form of personal identification based on biometric person who found in him, not what he owns (e.g. ID card) or what he remembers (password) [1]. Therefore, as a human being, anywhere, anytime, under any conditions, someone automatically always bring their identity information in the form of face.

Face recognition accuracy is determined by a description / representation of face images and the design of classifiers. The purpose of representation is to obtain a set of facial feature (characteristic) of a face image which minimizes the intra-class variations (e.g. between different facial image but from the same individual), while maximizing the inter-class variation (e.g. between image different individual faces). Meanwhile, essentially a classifier is a function that discriminates a set of novel facial features to determine its identity. It is important to note that in representing a face, if the representation of the face is not robust enough, even the most sophisticated classifiers will fail to perform the role for face recognition. Therefore, it is important to carefully define the representation of the face that will be taken when designing a face recognition system [2].

Generally, face recognition problem can be formulated as : given static (still) or video images of a scene as a novel pattern, identify or verify it by comparing with patterns stored in a database [3]. As mentioned in [4], typical practical face recognition problem is a set of unconstrained conditions, where lighting, image resolution, pose, and occlusions, are among factors that deteriorate recognition rate. This situation exacerbated generally only a single face image that available for training phase [3, 5].

Face descriptor can be divided into two categories, namely global face descriptor and local face descriptor. Global face descriptor is obtained by processing the entire face (integral/whole face image) directly to obtain important information from a face. Two famous global face descriptors are PCA and LDA [6, 7].

In contrast, local face descriptor typically obtained by feature extraction from specific components/regions of a face. In the development, along with the need for a face recognition system that is real (typical practical), then the local facial image descriptors received attention from researchers and attempt to develop a local facial descriptor that is more robust against to variations in lighting, occlusions, and the blurred facial images (low-resolution)[8]. LBP and its successor, MLBP, can be named as the famous corner stone among local face descriptors [9, 10].

SCAN METHODOLOGY

A scanning of a two dimensional array P_{mxn} = $\{p(i,j) : 1 \leq i \leq m, 1 \leq j \leq n \}$ can be considered as a *bijective* function that maps every element of P_{mxn} into a set of distinctive one dimensional array $Q = \{1,2, ..., mn - -1, mn\}$[11]. In other words, a scanning of a two dimensional array is an order in which each element of the array is accessed exactly once.

Basically, *SCAN* is a family of formal languages-based two-dimensional spatial as a generic methodology for accessing a large number of of wide variety of scanning paths easily [11]. It has several versions, such as Simple *SCAN*, Extended *SCAN*, and Generalized *SCAN*, each of which can represent and generate a specific set of scanning paths. It also has a set of basic scan patterns, a set of transformations, and a set of rules to compose simple scan patterns to obtain complex scan patterns [11]. These basic scan patterns are shown in Figure-1.

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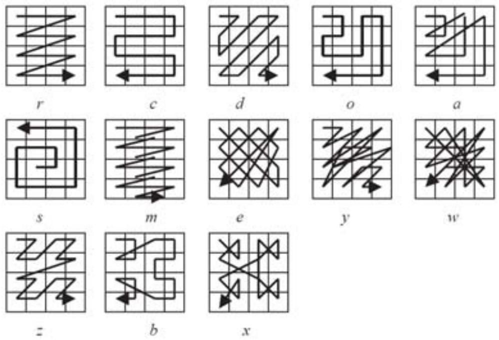
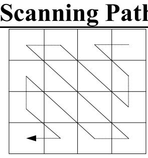
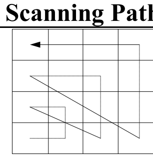
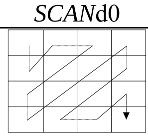
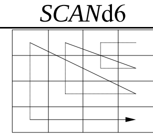
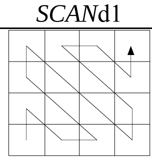
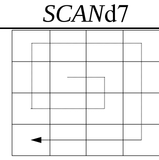
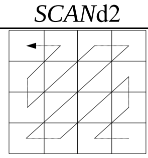
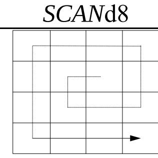
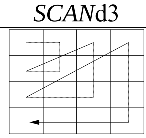
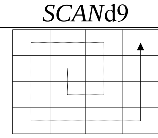
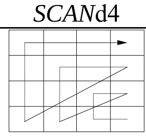
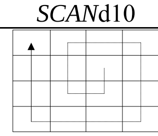


Figure-1. Basic *SCAN* patterns [11].

SCAN-BASED LOCAL FACE DESCRIPTOR

This paper uses twelve scanning paths, each working along whole non-overlapping face image blocks, where each block has 4 by 4 pixels. The reason for choosing these SCAN patterns is due to they generate robust discriminative local-features which is characterized by the resulting minimum cumulative absolute difference (error). Table-1 depicts all scanning paths that used to extract features from each face image.

Table-1. The twelve scanning paths.

No	Type and Name of Scanning Path	No	Type and Name of Scanning Path
1	 *SCAN*d0	7	 *SCAN*d6
2	 *SCAN*d1	8	 *SCAN*d7
3	 *SCAN*d2	9	 *SCAN*d8
4	 *SCAN*d3	10	 *SCAN*d9
5	 *SCAN*d4	11	 *SCAN*d10
6	 *SCAN*d5	12	 *SCAN*d11

There are four steps for face image representation by using *SCAN* descriptor. The first three steps works on each block of a face image. These steps can be summarized as follows.

First, for each scan path, do scanning and calculate the cumulative absolute difference according to the scanning path that is working. Second, choose the scan path that produces the minimum cumulative absolute difference as the best scan path. Third, encode the best scan path as a feature using binary code. This binary code represents each block of a face image. Table-2 shows the pair of each scan path and its binary code. Ultimately, to represent the whole face image, concatenate all the best scan path codes as a sequence of binary code feature vector. These steps were run both for training phase to extract information from each image in the database and for testing (classifying) phase, where finally a novel sequence of binary code was compared with the stored best scan path codes and the face recognition system will identify it as one in the database that has the maximum number of binary code that matches for each corresponding block face image.

Table-2. Binary code for each scanning path.

No	Name of Scanning Path	Binary Code
1	*SCAN*d0	0000
2	*SCAN*d1	0001
3	*SCAN*d2	0010
4	*SCAN*d3	0011
5	*SCAN*d4	0100
6	*SCAN*d5	0101
7	*SCAN*d6	0110
8	*SCAN*d7	0111
9	*SCAN*d8	1000
10	*SCAN*d9	1001
11	*SCAN*d10	1010
12	*SCAN*d11	1011

We illustrate this error pattern coding scheme as follows. Let $I(x,y)$ is a face image with dimension mxn, where m ($m = 2^k$) and n ($n = 2^l$) are the width and the height of the face image, respectively, and k does not need to be equal with l (k, l = 2, 3, 4,...). To extract the local features, first, we divide the face image into several non-overlapping blocks, where each block has 4 by 4 pixels, which results in L blocks ($L = (m\mathrm{x}n)/16$). Subsequently, we evaluate each block by using all scan paths. Figure-2(a), Figure-2(b), and Figure-2(c) depict the block face image before scanned, scan path type that is working (e.g. *SCAN*d0), and the block face image after scanned, respectively.

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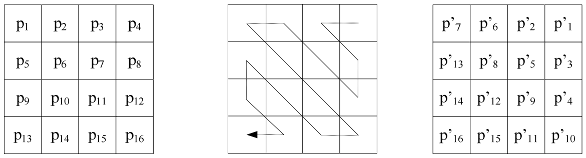

(a) Face image block before scanned (b) Scan path that is working (e.g. *SCAN*d0) (c) Face image block after scanned

Figure-2. Block face image before and after scanned.

For j = 1, 2,..., 12, to calculate the cumulative absolute difference for the resulting face image block after scanned can be expressed as:

$$e_j = \sum_{k=1}^{15} \left| p'_{k+1} - p'_k \right| \quad (1)$$

Eventually, the scanning path j that resulting the minimum cumulative absolute difference (e_j) was decoded as listed in Table-2.

SIMULATION PROCEDURES

Yale Face Database B is one of standard database to evaluate any face recognition algorithm (method), especially for studying illumination effects on face recognition [12]. Subset of this database that we used for simulations contains cropped grayscale face images that consists of 38 subjects, each has 60 face images. Each cropped face image has dimension 168 by 192 pixels. For every subject, we consider only one pose (frontal) among nine poses. We pick only one face image for each subject in the training phase to get its face descriptor. Figure-3 shows the samples of cropped face images used to evaluate our method.

Figure-3. Samples of cropped face images [13].

We evaluate the descriptor performance (recognition rate and time needed for testing), either for global (PCA and LDA) or local (LBP, MLBP and *SCAN*) descriptor. The first simulation was conducted to evaluate the descriptor performance against pixel intensity changes. For the first simulation, in the testing phase, we duplicate all the face images in the database subset and also reduce uniformly all their pixel intensities with different intensity scales for each face image.

In the second simulation, we evaluate the performance descriptor against blurred face images. In contrast with the first one, we only reduce the resolution of each face image with scale 0.2 (the resulting face image is only one-fifth the original one) in the database subset without duplicating all the face images for the second simulation. Figure-4 and Figure-5 display the sample face images for these, respectively.

Figure-4. Samples of the intensity-reduced face image.

Figure-5. Samples of the lower-resolution face image.

SIMULATION RESULTS AND DISCUSSIONS

Table-3 and Table-4 show the results for the first and second simulation, respectively. Instead of using recall-precision as in [8], the recognition rate was calculated by dividing the number of true match-identity with the number of face images in database subset that used for each simulation, i.e. 4560 (2x38x60) for the first one and 2280 (38x60) for the second one.

Table-3. The first simulation results.

Descriptor type	Descriptor name	Recognition rate (%)	Testing time (seconds)
Global Descriptor	PCA	4.74	9.95
	LDA	17.48	10.14
Local Descriptor	LBP	12.37	17.50
	MLBP	45.33	4397.08
	SCAN	59.56	325.56

Table-4. The second simulation results.

Descriptor type	Descriptor name	Recognition rate (%)	Testing time (seconds)
Global Descriptor	PCA	20.44	3.75
	LDA	35.39	3.49
Local Descriptor	LBP	3.68	6.42
	MLBP	44.08	1210.32
	SCAN	44.34	163.29

For both simulations, it is obvious that every global face descriptor has testing time that faster than every local face descriptor. This is plausible because as described earlier that a global face descriptor works

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directly on the whole face image rather than local face descriptor that works on block-by-block for a face image.

As stated earlier, the first simulation was conducted by reducing uniformly all pixel intensities with different intensity scales for each face image in the testing phase. Due to all the face descriptors are appearance-based [6, 7, 9, 10], it is obvious that in general the local face descriptor is better than the global descriptor. It means that in general the local descriptor may adapt the pixel intensity changes rather the global descriptor. Among local descriptors, SCAN descriptor as a local face descriptor is more robust against pixel intensity changes compared to the other descriptors.

The second simulation was conducted to evaluate each face descriptor against blurred face images. It might happen whether the camera may be out of focus or the distance between the camera and the subject being observed is not close enough. It seems *not* all local face descriptor have better performance in term of recognition rate than global face descriptor. As described in [9], LBP as a local face descriptor has good performance only for monotonic intensity changes, not for a noisy (blurred) one. It is also suprisingly that both PCA and LDA get higher recognition rate than the first simulation. Their methods that based on preserving the most significant eigenvalues might give a more discriminating power that leads in better recognition rate. But overall, as in first simulation, *SCAN* descriptor as a local face descriptor is more *robust* against low resolution (blurred) face image compared to the other descriptors.

For both simulations, we use four radii for the local decriptor MLBP. We choose these to accomodate the multi-scale of the face image in order to gain more discriminative power. Although in the second simulation its performance is rather similar with *SCAN* descriptor, but MLBP is more time consuming than *SCAN*.

CONCLUSIONS

We have conducted two kinds of simulations for each face descriptor, either global (PCA and LDA) or local (LBP, MLBP and *SCAN*). From both simulations, it is obvious that *SCAN* as a local face descriptor has the best performance in term of recognition rate among face descriptors.

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