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Face recognition using selected topographical features

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ABSTRACT

This paper represents a new features selection method to improve an existed feature type. Topographical (TGH) features provide large set of features by assigning each image pixel to the related feature depending on image gradient and Hessian matrix. Such type of features was handled by a proposed features selection method. A face recognition feature selector (FRFS) method is presented to inspect TGH features. FRFS depends in its main concept on linear discriminant analysis (LDA) technique, which is used in evaluating features efficiency. FRFS studies feature behavior over a dataset of images to determine the level of its performance. At the end, each feature is assigned to its related level of performance with different levels of performance over the whole image. Depending on a chosen threshold, the highest set of features is selected to be classified by SVM classifier.

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1. INTRODUCTION

Face recognition was deeply studied through the last decades [1]. Several types of features were presented with different levels of recognition accuracy [2]. Each type of feature represent an amount of information extracted from the image, and more represented information in chosen feature provides more accuracy in recognition results [3]. Spatial filtering was adopted to extract points of interest, which are grouped to form candidate features. A probability-based statistical model is built to select the most powerful features for face recognition [4]. In another approach, the authors used RGB-D images based on the extracting and the concatenating of the scale invariant feature transform (SIFT) descriptors from these data sources for face recognition [5]. Jie Chen et al turned transformation feature by adopting specific version of local binary patterns (LBP) as a face descriptor. Such features provided encouraging classification accuracy, but with unacceptable error rate sometimes [6]. Face descriptor is also adopted for extracting face feature in order to provide face recognition. The authors adopted enhanced local binary pattern (EnLBP) as an adaption of LBP and they divided studied image into 3×3 blocks. For each block, the EnLBP features provided mean values of each block instead of the ordinary number of LBP [7].

In this paper, since TGH provide more information than traditional edges [8], they are adopted by combining them with the proposed feature selection method to choose the best set among them. The rest of this of this paper contains brief explanation of TGH then the selection method; then face recognition results and their analysis. Final section contains the conclusions extracted from this work.

2. TOPOGRAPHICAL FEATURES TGH

Although TGH were previously used in recognition researches [9, 10], their accuracy results were relatively low regarding other types of features. One of the potential reasons of the lack in their usage is the huge amount of produce features. Recently, it was used in object recognition researches but with the same problem of huge number of features [11]. Since TGH assigns each image pixel to the corresponding feature. On the other side, TGH provides more information than traditional image edges and lines, see Figure 1(a). Yet, and choosing only image lines and edges may ignore significant information.

Such problem can be solved by choosing efficient ones among produced features overall image, which was a noticeable obstacle [12]. After manipulating the image with set of masks to find the orthogonal polynomial of the image [13], image gradient and Hessian matrix of second derivatives are computed to extract TGH (Peak, Pit, Saddle, Ridge, Ravine, Zero crossing, Flat, Increasing area and Decreasing area) [14], see Figure 1(b). According to definitions, each literature defines some kinds of TGH to be image edges and lines. As a result, dealing with TGH provides more information, and the next section explains the proposed feature selection method to overcome high number of provided feature. Since TGH is an existed feature type, this paper focuses on explaining feature selection, and aforementioned literatures discuss TGH in details.

(a) (b) (c)

Figure 1. Traditional image edges ignore significant information, while TGH study all available features: (a) original image, (b) image edges, and (c) TGH fFeatures

3. FACE RECOGNITION FEATURE SELECTOR (FRFS)

This method seeks for features using similar rules used in LDA to evaluate feature significance [15]. According to non-parametric feature test in LDA, efficient features must yield high differences over inter-class images against low differences over intra-class images [16]. This technique adopt testing single feature in each round by measuring yielded differences over inter and intra-class to record its level of efficiency. Then proposed technique moves to the second feature and so on till the last feature. Different levels of efficiency are filtered by controlled threshold that determines selected set of features with highest efficiency. Locations of selected features from learning dataset are allocated to choose recognition features from test dataset in test stage.

To illustrate proposed FRFS, assume that learning dataset contains n×m images contain n persons and m image for each of them. Each the image $Im_{ij}$is of h×k size, which is used to produce TGH features as:

$$im_{ij} = \begin{bmatrix} f_{11} & f_{12} & f_{13} & \cdots & f_{1k} \\ f_{21} & f_{22} & f_{23} & \cdots & f_{2k} \\ f_{h1} & f_{h2} & f_{h3} & \cdots & f_{hk} \end{bmatrix} \tag{1}$$

The first feature from each image in learning dataset is transferred to the inspection matrix:

$$\mathrm{I}_{11} = \begin{bmatrix} \mathrm{f11}_{11} & \cdots & \mathrm{f11}_{1j} & \cdots & \mathrm{f11}_{1m} \\ \mathrm{f11}_{i1} & \cdots & \mathrm{f11}_{ij} & \cdots & \mathrm{f11}_{im} \\ \mathrm{f11}_{n1} & \cdots & \mathrm{f11}_{nj} & \cdots & \mathrm{f11}_{nm} \end{bmatrix} \tag{2}$$

where I_{11}: is the inspection matrix of the feature f_{11} over learning dataset

$f11_{ij}$: the first feature f11 taken from the image in the row *i* and column *j* of the learning dataset

Statistical laws dispersion are used to measure the changes within values over inter-class and intra-class, which are standard deviation SD and roughness coefficient *rc* [17]. Values dispersion is measuring using SD by computing their deviation from the average, and it is usedin this paper to measure two types of changes. Firstly, SD over each row is used to evaluate the changes over different images for the same person, which represents interior differences (intra-changes). Secondly, SD over each column is used to evaluate changes over different person in each line of images (inter-changes). The μ and SD of each row are computed as:

$$\mu_{\mathrm{i}} = \frac{\sum_{\mathrm{j}=1}^{\mathrm{m}} \mathrm{f11}_{\mathrm{ij}}}{\mathrm{m}} \tag{3}$$

$$SD_{ri} = \frac{\sum_{j=1}^{m}(f11_{ij} - \mu_i)^2}{m} \quad (4)$$

Accordingly, μ and SD of each column are computed as:

$$\mu_j = \frac{\sum_{i=1}^{n} f11_{ij}}{n} \quad (5)$$

$$SD_{cj} = \frac{\sum_{i=1}^{n}(f11_{ij} - \mu_j)^2}{n} \quad (6)$$

This produces the next matrix:

$$I_{11} = \begin{bmatrix} f11_{11} & \dots & f11_{1j} & \dots & f11_{1m} & SD_{r1} \\ f11_{i1} & \dots & f11_{ij} & \dots & f11_{im} & SD_{ri} \\ f11_{n1} & \dots & f11_{nj} & \dots & f11_{nm} & SD_{rn} \\ SD_{c1} & \dots & SD_{cj} & \dots & SD_{cm} & \end{bmatrix} \quad (7)$$

SD for each row is called SD_{ri} to distinguish them from SD for each column (SD_{ci}). Several values of SD are produced over intra-changes one for each person.To get one SD value over all intra-class, SD_{intra} is computed using next average rule:

$$SD_{intra} = \frac{\sum_{i=1}^{n} SD_{ri}}{n} \quad (8)$$

Accordingly, SD_{inter} is computed as:

$$SD_{inter} = \frac{\sum_{j=1}^{m} SD_{cj}}{m} \quad (9)$$

The final value of efficiency$E_{final}$for the feature $f_{11}$is computed by dividing SD_{inter} over SD_{intra} as:

$$E_{final} = \frac{SD_{inter}}{SD_{intra}} \quad (10)$$

The second measure of dispersion is roughness coefficient which divides the differences between the successive values over their differences from the mean. Such measure reduces or eliminates the effect of big differences between successive values [17].

$$rc = \frac{\sum_{i=2}^{n}(x_i - x_{i-1})^2}{\sum_{i=2}^{n}(x_i - \mu)^2} \quad (11)$$

In some cases, successive images yield significant differences due to different styles, face hair, face expression or other factors, which can be handled using *rc.*Accordingly, the matrix in (7) will be:

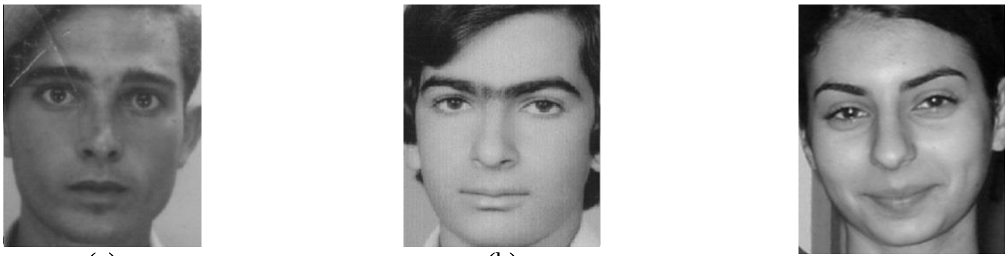
$$I_{11} = \begin{bmatrix} f11_{11} & \dots & f11_{1j} & \dots & f11_{1m} & rc_{r1} \\ f11_{i1} & \dots & f11_{ij} & \dots & f11_{im} & rc_{ri} \\ f11_{n1} & \dots & f11_{nj} & \dots & f11_{nm} & rc_{rn} \\ rc_{c1} & \dots & rc_{cj} & \dots & rc_{cm} & \end{bmatrix} \quad (12)$$

The best value of E_{final} is the biggest one since it refers SD_{inter} has highest level regarding SD_{intra}. E_{final} is transferred to the corresponding location in a matrix for Efficiency of Features *EFF*, thus, E_{final} for the feature f_{11} is transferred to *EFF* (1,1). Equations (2) to (10) are re-applied on the next feature and so on until covering all features in the image matrix im_{ij}. As result, *EFF* matrix will contain different values for different levels of efficiency of features, and choosing features with highest efficiency provide best set of candidate features. To control the number of chosen features, a threshold is proposed, and values of E_{final} lower than the threshold is ignored. Depending on chosen set of features, images are classified using the standard support vector machine SVM [18, 19].

4. RESULTS AND DISCUSSION

Experiments of this work used fairly distorted and good images of standard FG-NET which contains (912 of 1002) face-images, which are captured for males and females in different occasions. Highly distorted images are excluded from the study due to their affection on yielded results. All studied images are manipulated to be gray-scale and with size of (512×512). Comparison used in this paper is mean absolute error (MAE).

Although building 2D polynomial for the image uses set of enhancing masks, image quality affects recognition rate (RR). Low image quality may cause blurry or add lines and undesirable details to the image, which may cause non-real details. Where TGH depends on differences between values [20], undesirable effects may create non-real features as shown in Figure 2.



(a) (b) (c)

Figure 2. Image quality affects the classification accuracy and causes error rate in recognition results: (a) fairly distorted MAE=92.78, (b) acceptable MAE=93.93, and (c) high quality MAE=94.12

As face recognition feature selector (FRFS) measures the performance of each feature and chooses the highest set of them using a threshold, controlling the threshold value affects RR value. Increasing the threshold value provides features with highest level of performance, yet it may ignore significant set of features, and big number of chosen features requires longer processing time. On the other side, decreasing threshold value ensures choosing all significant features, but they be combined by low level-performance features, which affects recognitions accuracy. Experiments yielded best results when threshold value chooses the highest 27% of the features performance. Only low percentage of features is chosen, though such percentage provides significant number of features due to the huge number of produced features. See Figure 3.

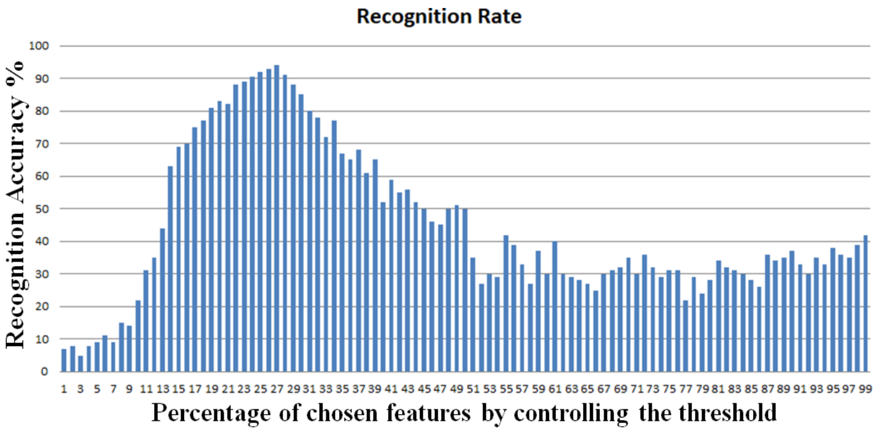


Figure 3. Recognition rate due to the value of chosen threshold

FG-Net face dataset is collected from number of ordinary images, which are not prepared for scientific purposes [21]. Faces in such images may contain glasses, hair style and face hair as shown in Figure 4. Such undesirable conditions affects recognition accuracy, yet experiments yielded encouraging results as shown in Table 1. Faces in some of images are rotated in two directions, first one is the rotation around the vertical axis when some persons are leaning his head to the left or right, while some others turns their faces to left or right direction around the horizontal axis as shown in Figure 5.

Figure 4. Glasses, hair style and face hair affect the recognition by hiding some features or creating new ones

Table 1. Recognition rate under the effects of glasses, hair style and face hair

Condition	RR
Hair Style	93.41
Face Hair	93.03
Glasses	92.81

Figure 5. Some faces are rotated around the horizontal or vertical axis

Experimental results showed that TGH features have more robustness against rotation around the vertical axis, which is justified by two points. As TGH features are produced using differences between values rather than the values themselves, they have lower level of effects against rotation and illumination [9]. Secondly, this type of rotation changes features positions only, while the second type of rotation hides or creates features due to the illumination and the view angle. Rotation around the horizontal axis yielded lower rate in recognition accuracy.

For benchmarking with state of art, proposed collection between TGH features and FRFS method yielded encouraging results. Comparing with highest yielded RR, proposed technique yielded noticeable improvement considering all types of tested images by reaching (93.95%) for recognition accuracy, while best results are yielded by applying proposed technique on images with best condition when TGH and FRFS reach (94.12) for recognition accuracy as shown in Table 2.

Table 2. Comparing proposed technique with state of art

Techniques	RR
Affine transformation due to viewing angle and distance variations. Therefore, affine invariant feature extraction [22]	92.50
Local and Holistic features with Neural Networks [23]	93.46
Signal Reconstruction with Neural Networks[24]	93.89
HAAR-like features and eigenfaces [25]	93.91
Proposed Technique (Average)	**93.95**
Proposed Technique (Best)	**94.12**

5. CONCLUSION

In this paper, a collection of topographical features which are extracted from face images after finding the 2D polynomial of the image. They are extracted by computing image gradient and Hessian matrix of second order derivatives of image. Due the huge number of produced features, the proposed technique of face recognition feature selection FRFS is applied to choose the best set of produced features. Selected features recorded robustness against rotation with insignificant level of effects for glasses, hair style and face hair. The entire performance of the proposed technique recorded encouraging results against state of art. For future works, we propose studying the effects of facial expression on TGH features extracted by FRFS.

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