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Re-expression of Face Images with Help of Samples from Other Face Datasets

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Abstract. *A novel algorithm for classification of possibly occluded face images is proposed in this paper. And the algorithm first constructs a normalized face dataset and then uses it to re-express face images to be classified. The proposed algorithm enables face images to be partially standardized, so difference between occluded and non-occluded face images of the same person can be partly eliminated and better accuracy can be attained. The performance of the proposed algorithm is demonstrated by extensive experiments.*
Keywords: Face recognition, Occluded face image, Classification

1. **Introduction.** Though face recognition has a long time of research history and the face recognition technology has been applied in suitable fields, this technology is still faced with difficulties in the real world. For example, recognition of occluded face images is one challenging task [1]. Occlusion enlarges the error rate of recognition of faces. As we know, humans are also difficult in identifying known people by observing their occluded faces. Thus, it is easy to understand that automatic recognition of occluded faces is challenging. Compared with recognition of conventional face images, recognition of severely occluded faces usually obtains much lower accuracy. The main reason why it is hard to classify occluded face images is that occluded and non-occluded face images of the same person are very different, so more erroneous classification decisions may be caused. If occlusion appears with other issues e.g. facial expression variation, and there will be more difficulties [2, 3]. Under occlusion and pose variation, there are also severe difficulties in face recognition [4, 5].

Special algorithms may be designed for classification of occluded face images. Thus, it seems that if a face image is occluded, then a special algorithm can be applied; otherwise, an ordinary face recognition algorithm is used. However, it is unknown which group the face image belongs to. As a result, it is necessary that a feasible recognition algorithm should be appropriate for all cases.

A couple of methods are exploited for processing occluded face images. For example, the subspace methods with the goal to obtain best reconstruction of samples are proposed [6]. Sparse representation and its improvements are proved to be effective for robust recognition of occluded face images [7]. Learning an occlusion dictionary is also a feasible means [8, 9]. Yang et al not only attained a Gabor occlusion dictionary but also regularized the coding coefficients on dictionary by l_2-norm. L_2-norm based regularization has shown good performance in classification of high-dimensional data [10, 11]. Special means such as Markov random fields are also able to deal with occluded face images [12]. From the viewpoint of features, most of methods for recognition of occluded face images can be categorized into two groups, holistic methods and local methods. For instance, subspace methods and Gabor features based methods are typical examples of holistic and local methods, respectively.

Various ideas are also proposed to tackle other difficulties in face recognition. For example, because a face usually has only a few original training samples, enlarging the number of available training samples is a feasible means [13]. Producing virtual face images is a good idea and corresponding schemes have attained promising results [14, 15, 16]. Virtual face images may be derived from original training samples by using simple or relative complex algorithms [17, 18, 19, 20]. For these algorithms, the symmetry nature of a face can play a good role in enhancing variety of training samples [19]. In particular, the use of the symmetry nature allows us to attain more virtual training samples than original training samples [17]. The symmetry nature of the face is also beneficial to face detection [21, 22, 23]. Because of the fact that most real face images are not strict symmetrical images, mirror images of original face images can also be viewed as virtual face samples, which usually results in good performance for face recognition [24]. The symmetry nature is also useful for study of psychophysiology [25]. Score fusion is a good way to integrate original training samples and derived training samples [26]. A superimposed sparse parameter (SSP) classifier for face recognition can reduce the computation cost [27]. And a method with neighborhood feature line segment for image classification can be used for face recognition [28].

In this paper, it is proposed to construct a normalized face dataset and to use it to re-express face images to deal with. The advantage of the proposed algorithm is that face images to deal with can be partially standardized. As a result, much difference between test samples and training samples including occluded and non-occluded face images of the same person can be alleviated and better accuracy can be attained. Experiments show that this interesting idea does bring accuracy improvement.

2. **The proposed algorithm.**

2.1. **Construction of the normalized face dataset.**

A number of face images are selected from existing datasets and are used to produce normalized face samples. Let n_i stand for the i-th normalized face sample in the form of column vector. Suppose that there are M normalized face samples and they are defined as $N = [n_1 \dots n_M]$.

2.2. **Re-expression of current face images.**

In this subsection, how to get re-expression of current face images is discussed. Let tr_j be the current j-th training sample in the form of column vector. Let t be the current test sample in the form of column vector. And t is assumed to be approximately denoted by $t \approx N\delta$. The solution of $\delta$is attained using $\tilde{\delta} = (N^T N + \mu I)^{-1} N^T t$. Let $\tilde{t} = N\tilde{\delta}$ be re-expression of current test sample t. Hereafter $\tilde{t}$is viewed as the current test sample. $\tilde{\theta} = (N^T N + \mu I)^{-1} N^T tr_j$ is calculated and the current j-th training sample is denoted by $\tilde{g}_j = (N^T N + \mu I)^{-1} N^T tr_j$. Actually, $\tilde{g}_j$ is re-expression of tr_j.

Based on $\tilde{g}_j$ and $\tilde{t}$, a classification algorithm is used to perform decision-making for $\tilde{t}$.

3. **Insight into the algorithm.**

In this section, the intuitive reasonability of the proposed algorithm is analyzed and its visual results are presented. Figure 1 provides original face images from the AR dataset and the corresponding re-expressions. From this figure, the same person re-expressions have less difference than the original face images. Besides the difference caused by occlusion is weakened, the difference associated with illuminations and facial expression can be partially eliminated. As a result, better recognition can be achieved.

Superficially, the algorithm proposed in this paper is somewhat similar with a subspace method. Both of them can be regarded procedures to exploit transform axes to obtain features of samples. Specifically, the subspace method e.g. principal component analysis and linear discriminant analysis uses eigenvectors of an eigen-equation as transform axes and exploit them to produce features of samples. However, the proposed algorithm exploits normalized faces as transform axes and processes the attained results as features. In some sense, the normalized faces act as a group of basis that not only allows all samples to be standardized but also makes data uncertainty in image samples to be decreased.

The procedure used in this paper can be thought as a generalized two-step representation procedure of test samples. In the first step representation of a test sample is obtained using the normalized face dataset. In the second step representation of a test sample is obtained using the current training samples. Previous research has indicated that two-step representation is beneficial to correct classification of test samples [17].

The quantized analysis of samples are provide, too. The between-class average distance of original “unit” samples is 0.4189. However, the between-class average distance of “unit” re-expressions of original

Figure 1. Original face images (the first row) and the corresponding re-expressions (the second row).

samples is 0.3956. This shows that the proposed algorithm is able to enhance similarity of samples of the same person. A "unit" sample is attained by converting a sample in the form of vector into a unit vector with a norm of 1. The between-class average distance is the mean of the distances between all "unit" samples of the same person.

4. **Experiments.** The GT dataset with 750 face images is used to produce the normalized face dataset. As a result, the normalized dataset includes 750 vectors. The proposed algorithm chooses collaborative representation classification (CRC) as the classification algorithm, so it just needs to be compared with CRC.

4.1. **Experiment on the AR dataset.** The AR dataset is first used to reveal performance of the proposed algorithm. This dataset contains 3120 images of faces and every face has 26 images. These images contain normal images and occlusion images occluded by scarfs and glasses. The number of faces is 120. Table 1 shows error rates of the algorithms on the AR dataset. In this table, the first row presents how many images of a face are used as training samples to conduct experiments. For example, "10" means that the first 10 images of each face are exploited as training samples and the other images are regarded as test samples. It is too easy to see that the proposed algorithm brings very good results, i.e. lower error rates.

Table 1. Error rates of the algorithms on the AR dataset.

	10	11	12	13
The proposed algorithm	32.50	23.22	24.23	25.38
Original CRC	33.18	25.72	26.96	28.97

4.2. **Experiment on the occluded ORL dataset.** The original gray face images in the ORL dataset are resized into 56 by 46 matrices. Then the sixth to tenth face images of every subject are partially occluded by a fixed image block. The region to be occluded is randomly selected. The other face images are not changed. All these images are used to constitute a new dataset whose first part is the non-occluded images and the second part is the occluded images. Figure 2 shows some images from this dataset. The first 3,5 and 7 face images of every subject in the new dataset are respectively used as training samples and the other images are regarded as test samples. Table 2 also tells us that the proposed algorithm on this dataset is better.

Table 2. Error rates of the algorithms on the occluded ORL dataset.

	3	5	7
The proposed algorithm	23.21	20.50	10.00
Original CRC	23.93	21.00	10.83

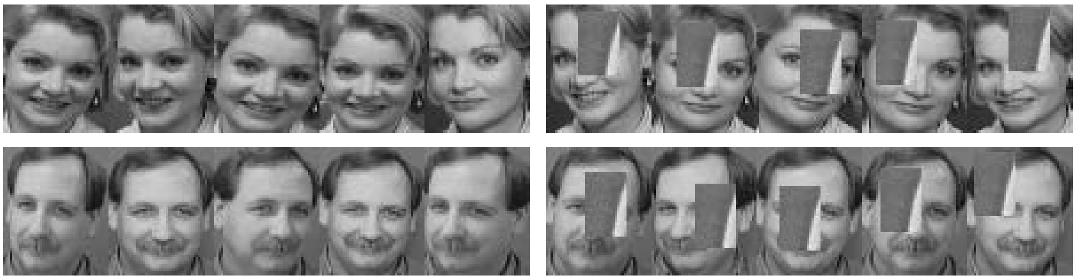

Figure 2. Some images from the occluded ORL dataset attained in the paper.

5. **Conclusions.** The proposed normalized face dataset and the algorithm shows that other face datasets are useful for obtaining more proper representation of face images and for better classification results. The main reason is that the use of the normalized face dataset allows current face images to be partially standardized. As a result, difference between all face images including occluded and non-occluded face images of the same person can be decreased. The experiments demonstrate good performance of the proposed algorithm.

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