Robust Minimum Squared Error Classification Algorithm with Applications to Face Recognition

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Abstract

Although the face almost always has an axisymmetric structure, it is generally not symmetrical image for the face image. However, the mirror image of the face image can reflect possible variation of the poses and illumination opposite to that of the original face image. A robust minimum squared error classification (RMSEC) algorithm is proposed in this paper. Concretely speaking, the original training samples and the mirror images of the original samples are taken to form a new training set, and the generated training set is used to perform the modified minimum sqreared error classification(MMSEC) algorithm. The extensive experiments show that the accuracy rate of the proposed RMSEC is greatly increased, and the the proposed RMSEC is not sensitive to the variations of the parameters.

Keywords: Mirror image, robust minimum squared error classification (RMSEC), modified minimum sqreared error classification(MMSEC), pattern recognition

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1. Introduction

As one of the most active branches in the field of biometrics recognition, face recognition is attracting more attention [1–6]. Classifier designing is one of the most important technologies in pattern recognition. Various classification approaches have been proposed over more than ten years [7-12]. Among them, the Nearest-Neighbor (NN) classifier [9] , the minimum squared error classification (MSEC) classifier and the Nearest-Mean (NM) classifier are most widely used because of their simplicity and availability. In the NN classifier, the test sample is assigned to the category of its nearest neighbor from the labeled training set. In NM classifier, the test sample is assigned to the category of its nearest class mean instead of searching the nearest training sample. In MSEC,the training samples and the responding class label are respectively used to act as the input and output, and MSEC tries to find the mapping that may best convert the input into the corresponding output. In other words, MSEC first gets the mapping that may well transforms the training sample into the responding class label and then uses the obtained mapping to produce the class label of the test sample.

The minimum squared error classification (MSEC) achieves good performance in many classification problems. It has been proven that MSEC can be applied to two-class Classification. When the number of training samples is infinity, MSEC is identical to linear discriminant analysis (LDA)[13]. In addition, MSEC has been extended to multi-class calssification, such as, kernel MSE[14,15], “lasso” based MSE [16, 17], and so on. Although the minimum squared error classification (MSEC) can reach high accuracy under most circumstances, it still cannot perform well in the case where there are a number outliers or severe noise. Real-world face recognition is a typical example in which the appearance of the face image for testing might be very different from that of the face image for training of the same subject. This is caused by varying facial expressions, poses and illuminations [8-20]. As a consequence, many classification errors may appear. The modified minimum squared error classification (MMSEC) [10] differs from the minimum squared error classification (MSEC) , and it simultaneously predicts the class labels of the test sample and the training samples nearest to it and the test sample is classified according to the predicted results. The MMSEC algorithm has a strong robustness and gets much higher classification accuracy than the MSEC algorithm.

It has been proved that the variations between images of the same face due to poses illuminations, and expressions might be greater than image difference between different faces [21]. In order to deal with these challenges, people have made a lot of efforts. For example, the quotient image method [22, 23], the illumination compensation method [24-26],the illumination cones method [27] and the pose invariant virtual classifiers method [28, 29] have been proposed. In addition, if a face has sufficient available training samples, which can fully convey possible variations of the poses, facial expressions and illuminations, good recognition result of the face images may be obtained. However, in a real-world face recognition system, a limited number of training samples are usually available. Consequently, they cannot express many variations of the appearance of the face [30]. In order to remedy this problem, the literatures have proposed to synthesize new samples from the true face images or to produce reasonable virtual samples [31-35].

It is known that a normal face almost has a symmetrical structure [11]. Many studies of symmetry and associated techniques have been motivated. For example, it is very useful to quickly locate the candidate faces in face detection for the symmetry property of the human face [36]. Xu et al. [31] proposed a mehod that used the symmetry of the face to generate new training samples and simultaneously use the original and new generated“symmetrical” training samples to perform face recognition.

We assumes that the “symmetrical” face image is an axisymmetric image. However, it usually suffers from the misalignment problem of the face image for a real-world face recognition system. This problem does lead to the asymmetry of face image. Therefore, the generated “symmetrical” face images seem to not be a natural face image and even be strange. Though many methods have been proposed to generate synthesized or virtual face images which can reflect the possible variation of the face. It should be noted that few literature generated synthesized or virtual face images by means of the structure symmetry. This motivates us to use the face symmetric structure to improve previous face recognition methods.

In this paper, a robust minimum squared error classification algorithm (RMSEC) is proposed. The mirror images of training samples are firstly generated. The generated mirror images can reflect some possible appearance of the face. For example, for the two face images of a same object, one has a left shadow illumination and the other has a right shadow illumination, as shown in Figure 1. The difference between them will be obviously great according to the Euclidean distance metric. This may lead to misclassification when one image is training image and the other image is test image. Therefore, it will be difficult to get satisfactory recognition performance for the face recognition method using only the original face images. However, it might be very samll according to Euclidean distance metric for the difference between either of the two face images and the mirror image of the other original face image. So it will be very useful to correct classification recognition for the use of the face mirror image. A new training set are composed of the original training images and its mirror images. The new training set is used to perform modified minimum squared error classification (MMSEC) algorithm. We can obtain higher classification accuracy by using the proposed RMSEC algorithm.

The remainder of this paper is organized as follows.: Section 2 briefly reviews the minimum squared error classification method (MSEC). We describe the modified minimum squared error classification algorithm (MMSEC) in Section 3. The proposed robust minimum squared error classification algorithm (RMSEC) is presented in Section 4. Section 5 conducts extensive experiments on face databases. The final section concludes the paper.

2. The Minimum Squared Error Classification (MSEC)

In this section we provide specific description of the main steps of the MSEC method. We assume that there are C classes and each class has n training samples and all the samples has been converted into one-dimensional column vectors. Let $x_1, x_2, \cdots, x_N$ be all the N training samples (N = Cn). A C-dimensional vector is used to represent the class label. We assume that any sample belongs to the k-th class, then the kth element value of its class label is one and the other element values are all zeroes, namely, $g_k = [\underbrace{0\ \ 0 \cdots 0}_{k-1}\ 1\ 0 \cdots 0]$. Let $X = [x_1, x_2, \cdots, x_N]^T$ and $G = [g_1^T, g_2^T, \cdots, g_N^T]^T$. MSEC has the following equation:

$$XA = G \tag{1}$$

where A is a transform matrix.

We can get A by using $\tilde{A} = (X^T X + \lambda I)^{-1} X^T G$. λ is a small positive constant and I is the identity matrix.

A test sample y can be classified using equation as follows:

$$g_y = y\tilde{A} \tag{2}$$

The following equation is used to respectively calculate the Euclidean distances between g_y and the each class label of all the C classes.

$$dt_i = \left\| g_y - g_i \right\|_2, \; i = 1, 2, \cdots, C \tag{3}$$

If $k = \arg\min_i dt_i$, then test sample y is eventually assigned to the k-th class.

3. The Modified Minimum Squared Error Classification (MMSEC)

In the modified minimum squared error classification (MMSEC) algorithm, the class labels of the test sample and the training samples nearest to it are firstly predicted, and then the test sample is ultimately classified by means of the the predicted results [10]. The algorithm of MMSEC includes the following steps.

1. Solve the equation (1).

2. Predict the class label of test sample y using equation (2). The Euclidean distance between g_y and the class label g_i of the i-th class is calculated using equation (3).

3. The K training samples that are nearest to the test sample according to the Euclidean distance are chosen and denoted by $p_1, \cdots p_K (1 \le K \le N)$, which are called the K nearest neighbor training samples of the test sample. Let $g_{p_1}, g_{p_2}, \cdots, g_{p_K}$ be the predicted class labels of the K nearest neighbor training samples $p_1, p_2, \cdots, p_K$. The contribution between the p_i and the n-th class can be evaluted by $dis_i^n = \left\| g_{p_i} - g_n \right\|_2$. g_n is the class label of the n-th class. The following equation is used to evaluate the contribution between these K training samples and the n-th class.

$$dis_y^n = \sum_{i=1}^{K} \gamma_i dis_i^n \tag{4}$$

where γ_i is a coefficient and set to $\gamma_i = 1 - (dis\tan ce_i / \sum_{j=1}^{K} dis\tan ce_j), \; j = 1, \cdots, K$, $dis\tan ce_i$ is the Euclidean distance between p_i and the test sample.

4. Compute the "distance" between the i-th class and the test sample y.

$$con_i = w_1 dt_i + w_2 dis_y^i \tag{5}$$

where w_1 and w_2 are the weight coefficients, and $w_1 + w_2 = 1$. A smaller deviation con_i means a greater contribution to representing the test sample. If $h = \arg\min_i con_i$, we will assign test sample y into the h th class.

4. The Robust Minimum Squared Error Classification (RMSEC)

In the practical application, each object has only a limited number of training sample. It can obtain more training samples to furtherly improve the recognition performance for the proposed method. Although the mirror imgae is generated from the original face image, it does reflect possible variation of the original face image in pose and illumination. Therefore, the use of the mirror image indeed makes the face recognition methods to use more available informatin of the face.

The proposed method has two advantages. Firstly, The different between the predicting class labels of the training samples and the true value of the training samples is smaller than the MMSEC during the training phase. the proposed mehtod can substantially increase rate. Secondly, The difference between the predicting class labels of the test samples and the true value of the test samples is smaller than the MMSEC during the test phase. The proposed method is robust. The main idea of the proposed method is generally described as three steps. The first step generates the corresponding mirror image for each training sample. The new training set is generated in the second step, which is composed of the original training samples and the new generated mirror images. The third step use the new training samples to perform modified minimum squared error classification (MMSEC). The proposed RMSEC algorithm is summarized as follows.

Step 1. The corresponding mirror image of each training sample is generated. We assume that there are C classes and each class has n training samples. Assume $z_1, z_2, \cdots, z_N$ ($z_i \in R^{p\times q}$ is 2D image matrix) be all the N training samples (N = Cn). For any z_i, the corresponding mirror face image of the original training sample $z_i^{'}$ can be generated using the following equation.

$$z_i^{'}(:,(1:q)) = z_i(:, q+1-(1:q)) \tag{6}$$

Step 2. The original N training samples and the generated new N mirror images are respectively converted into one-dimensional column vectors, denoted by $Z_1, Z_2, \cdots, Z_N$ and $Z_1^{'}, Z_2^{'}, \cdots, Z_N^{'}$. The new training set Z has 2N training samples.

$$Z = [Z_1, Z_1^{'}, Z_2, Z_2^{'}, \cdots, Z_N, Z_N^{'}] \tag{7}$$

Step 3. The generated new training set Z is used to perform the modified minimum squared error classification (MMSEC) algorithm.

5. Experiments and Results

The Yale, CMU PIE, FERET and AR face databases are respectively used to do experiments. To make the comparison, we also test MSEC method, and the modified minimum squared error classification (MMSEC) [10]. For simplicity, we will show only the experimental results of our method with $w_1 = 0.75, w_2 = 0.25$ and $w_1 = 0.8, w_2 = 0.2$, respectively.

5.1 The Approximate Face Image

In order to illuminate that the mirror image generated by the proposed method does reflect some possible appearance of the face, which are not shown by the original training samples.

Some original training face images and the corresponding mirror images are selected to be shown in **Fig. 1**.

Fig. 1. The original training images and the corresponding mirror images. L1) The original training images from the YaleB database. L2) The test images from the YaleB database. L3) The corresponding mirror images. L4) The original images from ORL face database. L5) The corresponding mirror images.

5.2 Experiments on Yale Face Database

The Yale face database contains 165 images of 15 individuals, and each person has 11 images under various facial expressions and lighting conditions. In our experiments, each image is manually cropped and resized to 100×80 pixels. **Fig. 2** shows sample images of one person.

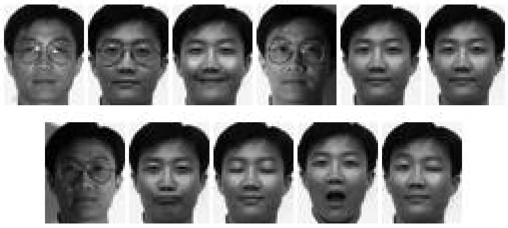

Fig. 2. Sample face images from the Yale database.

In the experiment, we respectively took the first one, two, three face images of each subject as the original training samples and treated the remaining face images as the test set. **Table 1** gives the recognition results. From **Table 1**, it can be seen that the proposed RMSEC method obtains a far higher recognition rate than MSEC and MMSEC. Moreover, the proposed method is insensitive to the parameter values. When the first face image of each subject is used as the training set and the rest for testing, the maximal recognition rate of MSEC, MMSEC and RMSEC is respectively 88%, 90% and 96%.

Table 1. Recognition rate of different methods on the Yale database (%)

Methods	**Number of the original training samples per class**		
	1	2	3
MSEC	88	92.59	95.83
MMSEC (w1=0.75, K=1)	90.00	94.81	95.83
MMSEC (w1=0.75, K=2)	88.67	92.59	95
MMSEC (w1=0.75, K=3)	89.33	92.59	95
MMSEC (w1=0.8, K=1)	89.33	95.56	95.83
MMSEC (w1=0.8, K=2)	88.67	92.59	95.83
MMSEC (w1=0.8, K=3)	89.33	92.59	95.83
RMSEC (w1=0.75, K=1)	94.67	98.52	97.50
RMSEC (w1=0.75, K=2)	94.67	98.52	97.50
RMSEC (w1=0.75, K=3)	96.00	97.78	97.5
RMSEC (w1=0.8, K=1)	96.00	97.78	97.5
RMSEC (w1=0.8, K=2)	96.00	97.78	97.50
RMSEC (w1=0.8, K=3)	96.00	97.04	97.50

The K indicates that K training samples that are nearest to the test sample,and w1 is the weight coefficient.

5.3 Experiments on CMU PIE Face Database

The CMU PIE face database [37] contains 68 subjects with 41 368 face images as a whole. The face images were captured by 13 synchronized cameras and 21 flashes, under variations in pose, illumination, and expression. In this paper, We fixed the pose and expression,and we got 21 images under different lighting conditions for each subject. Each image in CMU PIE was manually cropped and resized to 32×32 pixels. **Fig. 3** shows some sample images of one person.

Fig. 3. Sample face images from the CMU PIE database.

In this experiment, the number of the training samples per subject is the first one or the first two. The rest of the database is used for testing. **Table 2** shows the recognition performance of the MSEC, MMSEC and RMSEC. It can be also seen from **Table 2** that the recognition accuracy of the suggested RMSEC is higher than that of the other methods. When one image of each subject is used as the training set and the rest for testing, the maximal recognition rate of MSEC, MMSEC and RMSEC is respectively 85.22%, 89.41% and 96.25%.

Table 2. Recognition rate of different methods on the CMU PIE database (%)

Methods	**Number of the original training samples per class**	
	1	2
MSEC	85.22	92.41
MMSEC (w1=0.75, K=1)	86.47	91.95
MMSEC (w1=0.75, K=2)	89.19	94.66
MMSEC (w1=0.75, K=3)	89.12	96.21
MMSEC (w1=0.8, K=1)	86.69	93.50
MMSEC (w1=0.8, K=2)	89.34	95.12
MMSEC (w1=0.8, K=3)	89.41	96.36
RMSEC (w1=0.75, K=1)	93.38	98.45
RMSEC (w1=0.75, K=2)	93.01	98.30
RMSEC (w1=0.75, K=3)	93.68	98.37
RMSEC (w1=0.8, K=1)	96.25	98.92
RMSEC (w1=0.8, K=2)	95.88	98.68
RMSEC (w1=0.8, K=3)	96.10	98.84

The K indicates that K training samples that are nearest to the test sample,and w1 is the weight coefficient.

5.4 Experiment on FERET Face Database

The FERET database [38] contains a total of 13,539 face images of 1,565 subjects. The images vary in size, pose, illumination, facial expression, and age. We selected 1400 images of 200 individuals (each one has 7 images). Each image was cropped to 80×80 pixels. **Fig. 4** shows images of one individual.

Fig. 4. Sample face images from the FERET database

In this experiment, We respectively select the first one, two and three images of each object to act as training set, and the remaining face images are used to testing set. **Table 3** shows the classification accuracies. From **Table 3**, we can see that the proposed RMSEC classifies much more accurately than other two methods. We can also see that the recognition rates of MMSEC and RMSEC are close when the training sample size is one. Especially, when the training sample size of each subject is three, the proposed RMSEC improves the recognition rate by about 13%.

Table 3. Recognition rate of different methods on the FERET database(%)

Methods	**Number of the original training samples per class**		
	1	2	3
MSEC	43.67	57.60	45.12
MMSEC (w1=0.75, K=1)	47.92	63.4	56
MMSEC (w1=0.75, K=2)	49.25	64.6	56.63
MMSEC (w1=0.75, K=3)	48.67	64.3	56.63
MMSEC (w1=0.8, K=1)	48.5	63.1	55.63
MMSEC (w1=0.8, K=2)	48.83	64.4	55.87
MMSEC (w1=0.8, K=3)	48.08	64	55.5
RMSEC (w1=0.75, K=1)	48.67	71	71
RMSEC (w1=0.75, K=2)	49.33	71.83	71.50
RMSEC (w1=0.75, K=3)	48.67	71.80	70.63
RMSEC (w1=0.8, K=1)	47.25	70.80	68.63
RMSEC (w1=0.8, K=2)	48.5	71.4	69.25
RMSEC (w1=0.8, K=3)	48.42	70.70	68.75

The K indicates that K training samples that are nearest to the test sample,and w1 is the weight coefficient.

5.5 Experiment on AR Face Database

The AR face database [39] contains over 4000 color face images of 126 people, including 26 frontal views of faces with different facial expressions, lighting conditions, and occlusions for each people. The pictures of 120 individuals were taken in two sessions (14 days apart) and each session contains 13 color images. Fourteen face images (each session containing 7) of these 120 individuals are selected in our experiment. The images are converted to grayscale. **Fig. 5** shows sample images of one person.

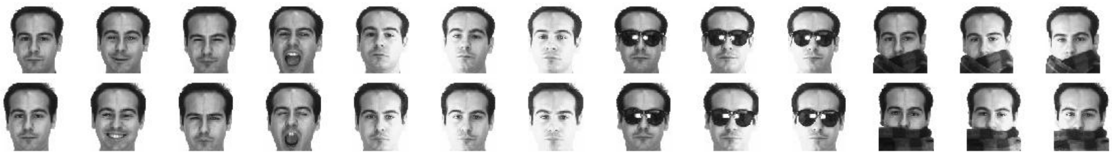

Fig. 5. Sample face images from AR database.

In our experiment, we respectively select the first one and two images of each object to act as training set, and the remaining face images are used to testing set. The classficatin results are shown in **Table 4**. It can be seen from **Table 4** that the recognition performance of the proposed RMSEC and MMSEC is close.

Table 4. Recognition rate of different methods on the AR database(%)

Methods	**Number of the original training samples per class**	
	1	2
MSEC	68.37	67.36
MMSEC (w1=0.75, K=1)	68.5367	67.4675
MMSEC (w1=0.75, K=2)	69.2667	67.5028
MMSEC (w1=0.75, K=3)	69.7	67.6381
MMSEC (w1=0.8, K=1)	69.2333	68.1975
MMSEC (w1=0.8, K=2)	69.7967	68.1928
MMSEC (w1=0.8, K=3)	69.93	68.3381
RMSEC (w1=0.75, K=1)	68.87	67.78
RMSEC (w1=0.75, K=2)	69.70	67.85
RMSEC (w1=0.75, K=3)	70.2	68.02
RMSEC (w1=0.8, K=1)	69.60	68.51
RMSEC (w1=0.8, K=2)	70.23	68.54
RMSEC (w1=0.8, K=3)	70.43	68.72

The K indicates that K training samples that are nearest to the test sample,and w1 is the weight coefficient.

6. Conclusion

In this paper, We proposed a robust minimum squared error classification (RMSEC) algorithm which simultaneously uses the original training samples and the corresponding mirror images of the original training samples to perform the modified minimum squared error algorithm. The mirror image is able to be used to simulate possible variation of the face image and it can reduce the side-effect of the pose and illumination difference between the training and test samples of the same face. The proposed RMSEC is able to get higher recognition accuracy than MMSEC. A large number of face recognition experiments show a good performance of our method.

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