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Maximum–minimum–median average MSD-based approach for face recognition

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ABSTRACT

A new and efficient improved maximum scatter difference (MSD) model is introduced in this paper. The main weakness of the MSD model is that the class mean vector is constructed via class sample average when the within-class and between-class scatter matrices are formed. For a few of given samples with non-ideal conditions (e.g., variations of expression, pose and noisy environment), the assessment result is very weak by using the class sample average. That is because there will be some outliers in these samples. Therefore, the recognition performance of maximum scatter difference criterion will decline significantly. To solve the problem, in the traditional MSD model, we use within-class maximum–minimum–median average vector to construct within-class scatter matrix (S_w) and between-class scatter matrix (S_b) instead of within-class mean vector. The experimental results show that an improvement of the MSD model is possible with the proposed technique in ORL and Yale face database recognition problems.

1. Introduction

In recent years, face recognition approach plays an important role in most of the real world applications such as access control, security surveillance and card identification. In controlled conditions, face recognition technique has made much progress such as [1–5]. As we all know, in the face recognition field, two popular methods are Eigenfaces approach [6] and linear discriminant analysis (LDA) approach [7]. The main idea of the Eigenfaces approach is to generate a set of orthonormal projections by maximizing the covariance over all the samples. So, it is an effective method to represent each face image. However, this approach cannot work well due to the fact that the classification information cannot be fully used in the classification process. The main idea of LDA is trying to find optimal projection vectors via maximizing the ratio between S_b and S_w (see the Eq. (5)). We all know the fact that LDA is better than Eigenfaces in face recognition performance. But, LDA cannot be used directly in most of the world face recognition task when the S_w is singular. Therefore, many researchers have made great efforts in developing advanced techniques for solving the problem [8–12]. However, the biggest shortcoming of all these approaches is that we must calculate the inverse matrix of S_w.

For the above mentioned weakness, a maximum scatter difference (MSD) criterion was proposed by Song et al. [13]. The main idea and advantage of MSD are that the difference of both S_b and S_w as discriminant criterion and the inverse matrix of S_w need not be calculated, respectively. However, in the traditional MSD model, the class mean vector is estimated in terms of the class average. In face recognition, for a few of given samples, the assessment result is very weak by using the class sample average, especially when there are outliers in the sample set with noise and corrosion [14]. For this problem, many researchers proposed corresponding methods [15,16,18]. Li proposed a median MSD-based (MMSD) method [15], which adopts the within-class median vector to estimate the class mean vector in the MSD model for face recognition problem. A more effective null subspace discriminant (MN(Sw)) method [16] by Gao proposed to handle the face recognition problem. MN(Sw) is a two stage linear discriminant analysis learning approach, which first transforms the original space by employing a basis of S_w null space, and then in the transformed space the maximum of S_b is pursued, where in the second stage, within-class median vector is used in the LDA model.

Actually, face recognition is a complex pattern classification task in that face images involve many variations (e.g., facial expression, pose and the affection of illumination is most serious in the real world). The variations between the images of the same face due to illumination and viewing direction are almost larger than the image variations due to a change in face identity [16].

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Therefore, all these non-ideal conditions will produce some outliers in the training set. However, for a practical face recognition task, only a few of the image samples are available for training each class, so it is difficult to give an accurate estimate of the class mean vector in terms of the class sample average. The inaccurate estimate of the class mean vector must have a negative effect on the robustness of the MSD model under the non-ideal conditions. To solve the disadvantage, the within-class maximum–minimum–median average vector is used to estimate the class mean vector in the MSD model. So, the experimental results will show the proposed MSD model is more robust than the existing MSD model.

The rest of this paper is organized as follows. The existing MSD model is briefly introduced in Section 2. Section 3 introduces the concept of maximum–minimum–median average. Our proposed approach is introduced in Section 4. Finally, the experiment results and conclusions are drawn in Sections 5 and 6, respectively.

2. Maximum scatter difference (MSD) criterion

In this section, we first introduce some important notations used in this paper. Suppose there are c known pattern classes, the S_b and S_w can be described as Eqs. (1) and (2), respectively.

$$S_b = \frac{1}{N}\sum_{i=1}^{c} N_i(\mathbf{m}_i - \mathbf{m}_0)(\mathbf{m}_i - \mathbf{m}_0)^T, \quad (1)$$

$$S_w = \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N_i}(\mathbf{x}_i^j - \mathbf{m}_i)(\mathbf{x}_i^j - \mathbf{m}_i)^T, \quad (2)$$

where N_i is the number of training samples in the ith class and N is the total number of training samples and $N = \sum_{i=1}^{c} N_i \cdot \mathbf{x}_i^j$ denotes the jth training sample in class i, the mean vector of training samples in class i is denoted by $\mathbf{m}_i$ and the mean vector of all training samples is $\mathbf{m}_0 = (1/N)\sum_{i=1}^{N}\mathbf{x}_i$. From the classical LDA method, the samples can be separated easily if the ratio of the between-class scatter and the within-class scatter is maximized.

In this paper, a maximum scatter difference based discriminant criterion [13] is defined as follows:

$$J(\mathbf{g}) = \mathbf{g}^T S_b \mathbf{g} - \beta \cdot \mathbf{g}^T S_w \mathbf{g} = \mathbf{g}^T(S_b - \beta \cdot S_w)\mathbf{g}, \quad (3)$$

where β is a non-negative constant to balance S_b and S_w. In order to contract the value field of β to a small area, Li proposed a modified version of MSD model as follows [17]:

$$J(\mathbf{g}) = \mathbf{g}^T(\alpha S_b - (1-\alpha)S_w)\mathbf{g}, \quad (4)$$

where $0 < \alpha < 1$. From the Eq. (4), we can see that it is more convenient to be used than original MSD.

By the property of the extreme value of generalized Rayleigh quotient, the optimal solution set maximizing (4) are the eigenvectors $g_1, g_2, \ldots g_k$ corresponding to the first k largest eigenvalues $\lambda_1, \lambda_2, \ldots \lambda_k$, where $\lambda_1 \geqslant \lambda_2 \geqslant \cdots \geqslant \lambda_k$. So the optimal projection matrix is formed by $G = [g_1, g_2, \ldots, g_k]$. According to the analysis above, for a given sample $\mathbf{x}$, its features can be obtained by transformation $\mathbf{y} = \mathbf{G}^T\mathbf{x}$.

When comparing the maximum scatter difference criterion with the classical LDA criterion (viz. Fisher discriminant criterion, Eq. (5)), we can easily find that the former avoids calculation of the inverse within-class scatter, as $S_w^{-1}S_b$ is substituted by $S_b - \beta \cdot S_w$, this cannot only be made computationally more efficient but also avoids the singular problem of the within-class scatter [15].

$$J(\mathbf{g}) = \frac{\mathbf{g}^T S_b \mathbf{g}}{\mathbf{g}^T S_w \mathbf{g}}. \quad (5)$$

3. Concept of maximum–minimum–median average

In this section, firstly, we briefly review the concept of median by [14] proposed to handle face feature recognition problems. Median is the middle value in a distribution for a finite list of numbers, above and below which lie an equal number of values. In mathematics, median refers to the number that is located at the middle of a set of numbers that have been arranged in a descending order. In addition, in cases where there are two values in the middle then the mean of these two values is picked as the median. However, maximum–minimum–median average (A3M) is the mean value of sum of maximum, minimum and median in a distribution for a finite list of numbers, except for these outliers. For the choice of A3M, we give two simple examples as follows:

Case 1. The number of input data values is odd, for Example 9, we have:

♯1 = {4.36, 4.05, 12, 4.15, 2, 4.24, 4.47, 4.68, 4.55}.

Ordered ♯1 = {2, 4.05, 4.15, 4.24, 4.36, 4.47, 4.55, 4.68, 12}.

A3M-operated ♯1 = {4.05, 4.15, 4.24, 4.36, 4.47, 4.55, 4.68}.

Median Ordered $\sharp 1 = 4.36$, **Average** Ordered $\sharp 1 = 4.944$,

A3M A3M-operated $\sharp 1 = \frac{max(A3M-operated\sharp 1)+min(A3M-operated\sharp 1)+median(A3M-operated\sharp 1)}{3} \approx 4.363$.

Case 2. The number of input data values is even, for Example 10, we have:

♯2 = {4.36, 4.05, 12, 4.15, 2, 4.24, 4.47, 4.68, 4.55, 4.75}.

Ordered ♯2 = {2, 4.05, 4.15, 4.24, 4.36, 4.47, 4.55, 4.68, 4.75, 12}.

A3M-operated ♯2 = {4.05, 4.15, 4.24, 4.36, 4.47, 4.55, 4.68, 4.75}.

Median Ordered $\sharp 2 = \frac{4.36+4.47}{2} = 4.415$, **Average** Ordered ♯2 = 4.925,

A3M A3M-operated $\sharp 2 = \frac{max(A3M-operated\sharp 2)+min(A3M-operated\sharp 2)+median(A3M-operated\sharp 2)}{3} \approx 4.405$.

Like the sample average and sample median, the maximum–minimum–median average (A3M) can also be used as an estimator of the central tendency such as the population mean. And, it is generally considered that the A3M is a more robust estimator of the central tendency than the sample average and sample median for data with outliers. From the above examples, we can also see that the A3M does work better than the average and median when the outliers "2" and "12" exist in the data sets.

For the calculation problem of median vector, we can adopt the following procedure [14–16]. Given a random sequence of n-dimensional volume vectors $W_1, W_2, \ldots, W_q$, the following data matrix can be obtained.

$$W = (W_1, W_2, \ldots, W_q) = \begin{pmatrix} w_{11} & \cdots & w_{1q} \\ \vdots & \vdots & \vdots \\ w_{n1} & \cdots & w_{nq} \end{pmatrix}. \quad (6)$$

Therefore, the median vector of $W_1, W_2, \ldots, W_q$ can be defined as $M = (M_1, M_2, \ldots, M_n)^T$, where M_i is the median of elements on the ith row of the input data matrix W. Specifically, the symbol $\mathrm{Median}(\cdot)$ denotes the median operator of a set numbers, that is $M_i = \mathrm{Median}(\{w_{i1}, w_{i2}, \ldots, w_{iq}\})$.

In addition, we can adopt the following procedure to calculate the maximum–minimum–median average (A3M) vector. Block diagram of A3M calculation is shown in Fig. 1. First a 3×3 window is run across the noisy or corroded images from left to right and top to bottom. The detection of corrupted or uncorrupted pixel is governed by checking whether the central pixel value of the selected