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CURSE OF MIS-ALIGNMENT IN FACE RECOGNITION: PROBLEM AND A NOVEL MIS-ALIGNMENT LEARNING SOLUTION

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ABSTRACT

In this paper, we present the rarely concerned curse of mis-alignment problem in face recognition, and propose a novel mis-alignment learning solution. Mis-alignment problem is firstly empirically investigated through systematically evaluating Fisherface's sensitivity to mis-alignment on the FERET face database by perturbing the eye coordinates, which reveals that the imprecise localization of the facial landmarks abruptly degenerates the Fisherface system. We explicitly define this problem as ***curse of mis-alignment*** for highlighting its graveness. We then analyze the sources of curse of mis-alignment and group the possible solutions into three categories: invariant features, mis-alignment modeling, and alignment retuning. And then we propose a set of measurement combining the recognition rate with the alignment error distribution to evaluate the overall performance of specific face recognition approach with its robustness against the mis-alignment considered. Finally, a novel mis-alignment learning method, named E-Fisherface, is proposed to reinforce the recognizer to model the mis-alignment variations. Experimental results have impressively indicated the effectiveness of the proposed E-Fisherface to tackle the curse of mis-alignment problem.

1. INTRODUCTION

Face recognition (FR) researches have been motivated by both its scientific values and its wide potential applications in public security, law enforcement and commerce. Related research activities have significantly increased and much progress has been achieved during the past few years [1]. However, most of the current systems work only under constrained conditions, even requiring the subjects highly cooperative. Therefore, the general problems in FR remain unsolved, especially under the practical unconstrained conditions. Clearly, challenges lie in not only the academic level but also the application system designing level.

For a practical fully automatic FR system, face detection, feature alignment and classification are three indispensable steps. Indeed, much work has been done on face detection, feature alignment and face recognition respectively. However, we surprisingly noticed that little attention has been paid to the seamless integration of these steps into a complete system. To better concentrate on the recognition problem, it has been an implied convention that researchers in FR community always assume that the facial features (generally the two eyes) in the input images have been ***accurately*** localized, which is commonly manually labeled in their experiments.

Herein comes out one problem: has the facial feature alignment been solved so perfectly? Evidently, the answer is ***no***, especially under the unconstrained imaging conditions with uncooperative subjects. To our knowledge, for a general size face image (e.g. 92 by 112 pixels), the alignment error for one landmark may be up to more than 5 pixels. On the other hand, researchers who work on feature alignment may commonly admit this error "correct". Even more serious situation is that, the accurate alignment of some landmarks is essentially ambiguous. Figure 1 shows the eye-center case. This clearly suggests that, at least to date, the accurate alignment should not be expected and trusted reliably.

(a) (b) (c)

Fig.1. Accurate alignment for some landmarks is essentially ambiguous: taking the eye-center alignment for example. It is heavily subject to the subjective feeling, but widely used as the anchor points for normalization.

Therefore, to compensate for the possibly inevitable mis-alignment, the face modeling and/or the back-end classifying procedure must be robust enough to the abhorrent mis-alignment. Regarding the problem, some previous articles did have mentioned more or less. Dynamic Link Architecture (DLA) [3] processes the problem by modeling faces as graphs comprised of the local characteristics and relationship of different facial components. More recently, Martinez has addressed the imprecise localization problem by finding the subspace that represents this error for each of the training images [4]. Note that, perturbation method [5] and global affine transformation correlation [6] has also been proposed to address the similar problem in the OCR field. Yet, these solutions are far from being systematical and deep. This paper attempts to investigate the problem systematically and quantitatively.

2.CURSE OF MIS-ALIGNMENT: PROBLEM, EMPIRICAL INVESTIGATION, AND CATEGORY OF POSSIBLE SOLUTIONS

Fisherface [2] has been recognized as one of the most successful FR methods. Our static tests of Fisherface on many databases also show its excellent performance provided that the faces have been manually aligned accurately. However, it is totally not the same case for our practical system based on Fisherface, which has puzzled us a lot. To investigate this strange phenomenon, we collected many face images that have been incorrectly recognized. The results showed that for most of them, the centers of the eyes have been inaccurately localized with a possible deviation of up to 5 pixels from their real position. Namely, the performance degradation mostly resulted from the incorrect alignment. This suggests that, to solve this problem, one should further develop more accurate face alignment method; on the other hand, the robustness of the face modeling and classification method to mis-alignment must be greatly improved. To go deep into the problem, we begin from evaluating the Fisherface systematically.

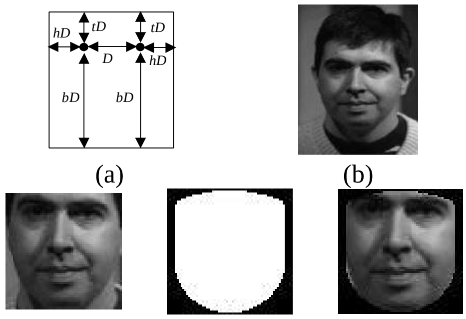
2.1 Evaluating Fisherface's Robustness to Mis-alignment

Fisherface [2] is one of the most successful FR technologies, which conducts Fisher Discriminant Analysis (FDA) after PCA. To evaluate its robustness to mis-alignment, we test it on the FB probe set from the FERET face database. Fig.1 shows the structure of the FERET standard face database we use to evaluate Fisherface's robustness to mis-alignment. Note that the FERET face database has strictly distinguished the testing set (comprised of Gallery and Probe sets) from the training set.

In the FERET face database, the coordinates of the eyes in all the face images have been provided, which can be used as the ground-truth alignment. In our face recognition system, faces are normalized as shown in Fig.2. Faces are firstly cropped out, as Fig.2 (c), by placing the two eyes at fixed locations specified in Fig.2 (a). A mask, as shown in Fig.2 (d), is then covered over the face region to eliminate the background and hairstyle. Eventually, all faces are warped to the size of 64x64 as shown in Fig.2 (e) from its original form as in Fig.2 (b).

Table.1 Structure of the FERET face database we use to evaluate Fisherface's robustness to mis-alignment

Database		#Persons	#Images	Description
Training set (*L*)		429	1002	Near-frontal faces
Testing Set	Gallery (*G*)	1196	1196	Near-frontal faces under normal lighting
	Probe Set--FB	1195	1195	Near-frontal faces under Normal lighting with different expressions.



(a) (b)
(c) (d) (e)

Fig.2 Face normalization method used in our experiments

To evaluate the Fisherface's robustness to mis-alignment systematically and quantitatively, we test the variance of its recognition rate with the deliberated perturbation of the eye coordinates of the ***probes*** in order to observe the relationship between the recognition rate and the mis-alignment degree. It is not difficult to understand that the mis-alignment of the eyes is equivalent to the variation of the affine parameters such as translation, rotation and scale. Concisely, experiments are conducted to investigate the influence of the variation of translation, rotation and scale separately rather than their combination. Figure 3 illustrates some examples with normalization error due to mis-alignment of translation, rotation and scale, from which much appearance variation can be observed. Note that, nevertheless, in our experiments, the alignment of the images from the training set and the gallery is kept precise, that is, the PCA and LDA are both trained normally without any perturbation.

The evaluation results are shown in Figure 4 with (a) (b) and (c) representing the translation, rotation and scale cases respectively. Note that, in figure 4 (b), each graduation (about 4.2 degrees) of the horizontal axis is caused by one pixel deviation of the two eyes from their ground-truth position along the opposing vertical direction (that is, one up, the other down). Similarly, in figure 4 (c), each graduation (about 0.07 scale change) comes from one pixel deviation of the two eyes from their ground-truth position along the opposing horizontal direction (that is, one left, the other right).

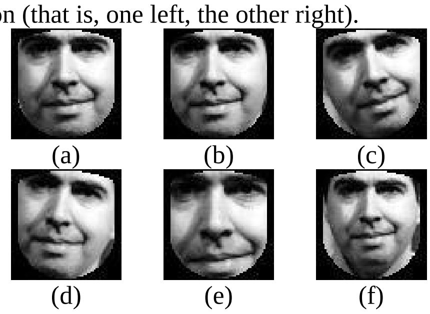
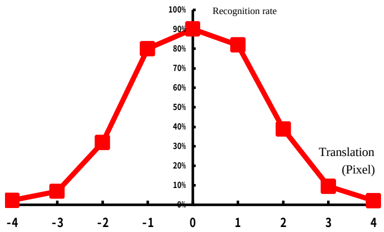
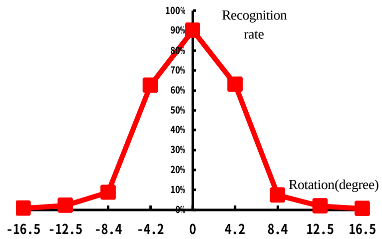


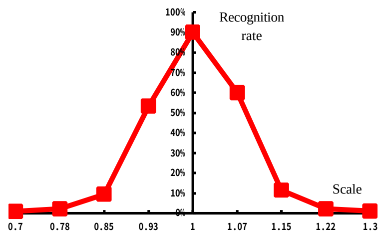
Fig. 3 Normalization error due to mis-alignment



(a)Translation



(b) Rotation



(c) Scale

Fig. 4. Relationship between the rank-1 recognition rate of the Fisherface and the mis-alignment of translation, rotation and scale

From Figure 4, one can see clearly that the rank-1 recognition rate of the Fisherface method degrades abruptly with the increase of the mis-alignment. For example, 10 percents decrease are observed for a pixel translation, while 20 percents for 4.2 degrees of rotation, and almost 30 percents for 0.07 scale changing also caused by a pixel deviation. Such abrupt degradation of the performance is hardly acceptable for a practical face recognition system, in which one or two pixels of mis-alignment are almost unavoidable. Therefore, it is really a problem that must be paid more attention to seriously.

2.2 Problem Analysis and Possible Solutions

To address the mis-alignment problem clearly and highlight the significance of the problem, in this paper, we explicitly define the "curse of mis-alignment" problem as following. We then discuss the sources of curse of mis-alignment, as well as its possible solutions.

Definition 1: Curse Of Mis-Alignment (Hereinafter abbreviated as COMA)

Curse of mis-alignment is defined as the abrupt degradation of the recognition performance when small mis-alignment occurs which is caused by the inaccurate localization of the facial landmarks.

The purpose of alignment is to build the semantic correspondence between the pixels in different images, and eventually to classify by matching the pixels with the same semantic meanings. Therefore, mis-alignment implies that the classification may base on totally meaningless matching. Figure 5 (a) through (c) illustrate this point clearly in an extreme but intuitive way, in which one attempts to match two uniform single-pixel rectangle with one (red and dashed line) be the shifted, rotated, and scaled version of the other (blue and real line). Evidently, the matching would be meaningless even with only one pixel of mis-alignment. Figure 5 (d) through (g) show the similar case for face images, in which (e) is a scaled version of (d), (f) is their blend and (g) is the result of absolute subtracting (e) from (d). Much unexpected difference appears which may leads to mis-classification eventually.

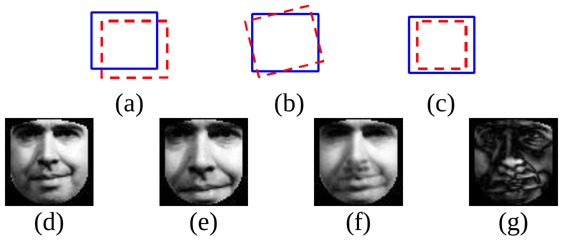


Fig. 5 Meaningless matching caused by mis-alignment

Possible solutions to COMA can be divided into three categories: invariant features, mis-alignment modeling, and alignment retuning.

For invariant feature methods, one attempts to model face images using mis-alignment invariant features to achieve robust recognition. Elastic graph [3] have been proposed as such kind of feature.

The second approach would not rely on invariant feature, but try to learn the mis-alignment into the face modeling or classification. The method proposed by Martinez belongs to this category, in which the gallery is augmented by perturbation and modeled by Gaussian Mixture Models (GMM) [4]. We have also worked on this method previously [7].

Since COMA comes up from alignment error, the third method naturally further retunes the alignment. A typical method is the Global Affine Transform method [6]. However, it should be different from pure alignment algorithms in that the retune should rationally make use of the feedback information from the matching or classification procedure.

In addition, it is a natural choice to integrate these three strategies for more robust algorithms.

3.PERFORMANCE EVALUATION WHEN CONSIDERING MIS-ALIGNMENT

Distinct algorithms would have different robustness to mis-alignment. Hence, the pure rank-1 recognition rate, when no mis-alignment occurs, would no longer be appropriate for evaluating and comparison. Considering two different algorithms A and B, how their recognition rates vary with the degree of mis-alignment has been drawn (tested using the method in section 2.1) in Figure 6. As can be seen, under well-alignment situation, B's recognition rate is as high as 100%, while that of A's is only 92%. Traditionally, we would safely conclude that B outperforms A. However, is it the fact? Our answer is "***NO***". This may seem somewhat anti-intuitive, but we would soon demonstrate its correctness.

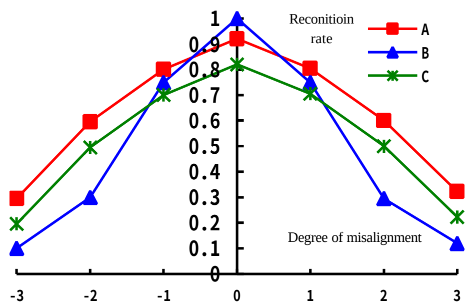


Fig.6 Relationship between the mis-alignment and the recognition rates of three FR methods A, B, and C

Let us consider how it would be if we integrate A and B into a practical face recognition system. We further assume A and B adopt the same frontal-end feature alignment method, which is unavoidably non-perfect, but with a Gaussian distributed mis-alignment from the ground truth, that is, the alignment error satisfies:

$$p(\partial) \sim N(m, s^2). \tag{1}$$

where $\partial = d(P, P^*)$ is the deviation, with P the localized position and P^* the ground truth. We then evaluate the performance of different algorithms as follows:

Definition 2. Overall recognition rate considering mis-alignment robustness is defined as:

$$r^* = \int_{\Omega} P(\partial) r(\partial) d\partial \tag{2}$$

where ∂ is the degree of mis-alignment; Ω restricts the range of possible mis-alignment; $P(\partial)$ is the pdf of the mis-alignment; and $r(\partial)$ represents the recognition rate when mis-alignment ∂ occurs.

*R** is in fact the weighted average of the recognition rate with its corresponding mis-alignment probability. Therefore, it is more appropriate than the pure single recognition rate to evaluate the performance of a practical system integrated by the feature alignment procedure and the recognition procedure.

Nevertheless, it is also necessary to evaluate the robustness of an algorithm to the mis-alignment independent of its recognition rate. For example, consider the algorithm C, whose recognition rates are 10% lower than A's, as shown in Figure 6. Intuitively, C should have the same robustness to mis-alignment as A. To process this case, we further define the following robustness measurement:

Definition 3. Robustness to mis-alignment is defined as:

$$R = \int_{\Omega} P(\partial) \frac{r(\partial)}{r_0} d\partial = \frac{r^*}{r_0}. \tag{3}$$

where r_0 is the recognition rate with perfect alignment.

R, ranging in (0, 1), measures the degradation degree of a recognition method against the mis-alignment. A larger *R* implies the recognition method be more robust (i.e. less sensitive) to the mis-alignment.

The definition of the r^* and *R* greatly facilitates the evaluation of different algorithms when considering the mis-alignment. Take the A, B, and C in figure.6 for example, assuming $p(\partial) \sim N(0,1)$, their r^* and *R* are shown in table.2, from which we can evidently conclude that ***A outperforms B*** when mis-alignment is considered. In addition, one can see that C has the same robustness as A, that is, $R_C = R_A$, though its r^* is 10% lower than A's, which completely coincides with the intuition.

Table.2 Performance comparison between A, B, and C with the proposed evaluation measurements

Algorithms	r_0 (%)	r^*(%)	*R*
A	92	82.3	0.895
B	100	79.5	0.795
C	82	72.3	0.895

4. PROPOSED E-FISHERFACE: A MIS-ALIGNMENT LEARNING SOLUTION

Mis-alignment leads to the divergence of the samples from the same class, that is, it enlarges the within-class scatter and reduces the between-class scatter to some degree. That is why the Fisherface has degraded abruptly when mis-alignment occurs even with very small deviations. Accordingly, we propose a natural way to solve the curse of mis-alignment problem by learning the appearance variations due to mis-alignment, which we call "Enhanced Fisherface" (hereinafter abbreviated as *E-Fisherface*), which is essentially a training-reinforced version of the original Fisherface method.

4.1 Design of the E-Fisherface method

Simply speaking, E-Fisherface firstly generates multiple "virtual" samples from each sample in the training set by perturbing the positions of the landmarks, such as the centers of the two eyes. These "virtual" samples are then fed into the training stage to compute the FDA, thus, the mis-alignment can be modeled into the FDA to converge the within-class samples and diverge the between-class ones. The procedure is described in detail as follows:

4.1.1 Compute PCA from the original training set.
Gray-level image is commonly too high dimensional for performing effective FDA, therefore, PCA is used prior to the FDA. As to the training set for learning PCA, there are two alternatives: one is the original training set; the other is the augmented training set. Considering the computing complexity, we choose to use the original training set. For the FERET case, all the 1002 face images in the training set are normalized (as described in section 2.1) and used to compute PCA. The leading 400 eigenfaces are reserved to form the W_{pca} for FDA.

4.1.2 Compute FDA from the augmented training set
For each face image in the training set, we then derive multiple normalized face samples by perturbing its eye coordinates from their ground-truth positions in a mode of eight-neighbors deviation. As shown in Figure 7, each eye has 9 positions to move. Therefore, totally $9x9=81$ virtual samples can be derived from one input example. Figure 8 illustrates some examples of the derived virtual samples.

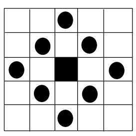


Figure.7 The eight-neighbors for the eye center perturbation

Thus, for the FERET training set with 1002 images, $1002x81=81,162$ examples are obtained. These face images are then projected to the W_{pca} to reduce dimension from 4096 to 400. And then the reduced PCA features are used to compute the FDA matrix W_{fda}, which is expected to have modeled the appearance variations, caused by the mis-alignment, as within-class variations.

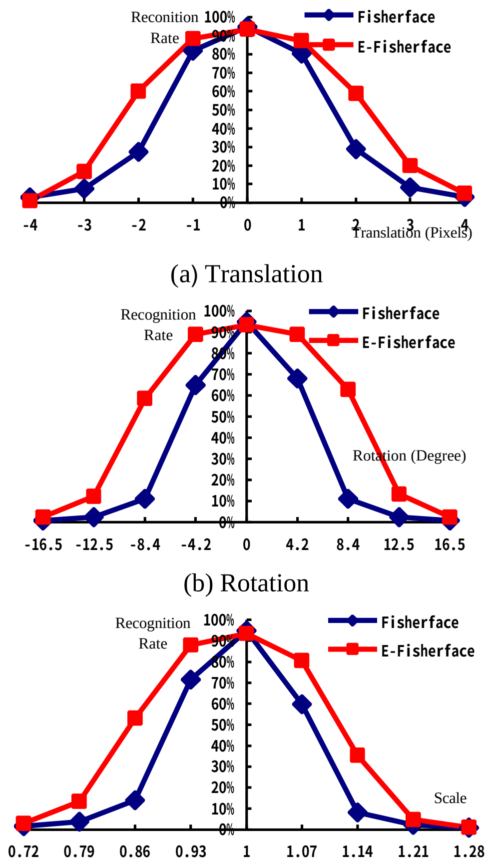
Figure.8 Examples of virtual face images derived from one training sample by 8-neighbors perturbation

4.1.3 Recognize using the enhanced FDA
After the W_{pca} and W_{fda} have been computed, the recognition process becomes a simple one, which is totally the same as in Fisherface. Namely, all the images in the gallery are normalized, projected to PCA, and converted to FDA feature eventually. For each probe in the FB, it is processed in the same way to get its FDA feature, and then the resulting FDA feature is matched through all the FDA features in the gallery to determine the maximal similarity as the final recognition results.

Note that the proposed method in this paper is greatly different from the method proposed by Martinez in that, 1) In our method, perturbation occurs in the training stage to augment the training set rather than the gallery in the testing stage as in Martinez's method; 2) In our method, FDA is computed to learn the mis-alignment for all the face images to be processed in the training stage, while in Martinez's method, Gaussian mixture models have to be learned for each face image in the gallery. Therefore, our method does not increase the spatial and temporal complexity that much as Martinez's method, except for the extra time for training the FDA from the augmented training set.

We then test the proposed E-Fisherface method and compare it with the Fisherface from their robustness to the mis-alignment viewpoint. Figure 9 and table 3 illustrate the comparison.

The comparison has evidently indicated that the proposed E-Fisherface has much better overall performance than the original Fisherface, except for a bit decrease when the alignment is perfect enough. It is more robust against the mis-alignment especially for the rotation and scale cases.



(a) Translation

(b) Rotation

(c) Scale

Fig.9 Comparison between the Fisherface and the proposed E-Fisherface from the angle of robustness to mis-alignment

Table.3. Performance comparison of the Fisherface and the proposed E-Fisherface using the proposed evaluation measurement assuming $p(\partial) \sim N(0,1)$

Mis-alignment	Methods	r_0 (%)	r^*(%)	R
Translation	Fisherface	94.8	80.2	0.846
	E-Fisherface	93.4	86.4	0.925
Rotation	Fisherface	94.8	71.2	0.751
	E-Fisherface	93.4	87.0	0.931
Scale	Fisherface	94.8	70.8	0.747
	E-Fisherface	93.4	82.9	0.887

5. CONCLUSIONS AND FUTURE WORK

In this paper, the rarely concerned curse of mis-alignment problem in face recognition is investigated, and a novel mis-alignment learning solution is proposed as well. The main contributions of this paper include:

(1) Curse of mis-alignment problem is explicitly defined to highlight its graveness through systematical empirical investigation of the Fisherface's sensitivity to mis-alignment on the FERET face database by perturbing the eye coordinates, which reveals that the imprecise localization of the facial landmarks abruptly degenerates the Fisherface system.

(2) We then analyze the sources of curse of mis-alignment and categorize the possible solutions into three categories: invariant features, mis-alignment modeling, and alignment retuning.

(3) A set of measurement combining the recognition rate with the alignment error distribution is proposed to evaluate the overall performance of specific face recognition method when its robustness against the mis-alignment is considered and specific mis-alignment distribution is given.

(4) Finally, a novel mis-alignment learning method, named E-Fisherface, is proposed to reinforce the Fisherface to model the mis-alignment variations. Experimental results have impressively indicated the effectiveness of the proposed E-Fisherface to tackle the curse of mis-alignment problem.

Our future work would focus on other solutions to COMA problems, such as searching mis-alignment invariant features, or retune the alignment based on the feedback of the matching confidence. The combination of these methods should also be considered.

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