A Survey on Face Recognition based on Linear Regression Model

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Abstract*-A linear regression based method is a hot topic inface recognition community. Recently, sparse representation andcollaborative representation based classifiers for face recognitionhave been proposed and attracted great attention. We present a novel approach of face identification by formulating the pattern recognition problem in terms of linear regression. Many classic and contemporary face recognition algorithms work well on public data sets, but degrade sharply when they are used in a real recognition system. This is mostly due to the difficulty of simultaneously handling variations in illumination, image misalignment, and occlusion in the test image. We consider a scenario where the training images are well controlled and test images are only loosely controlled. This model can efficiently and effectively recognize faces under a variety of realistic conditions, using only frontal images under the proposed illuminations as training

***Keywords*- Face recognition, linear regression, occlusion, image misalignment, illumination.**

I. INTRODUCTION

Face recognition is a classical topic in computer vision and pattern recognition community for its great needs in many areas. Although great progress has been made by many researchers, it is still a challenging problem because of the large variations existed in the face images, e.g., variations in illumination conditions, misalignment, poses, facial expressions and various noises (i.e. occlusion, corruption and disguise). Recently, linear regression analysis based methods have become a hot topic in face recognition community. Wright et al. [1] proposed a new face recognition framework called sparse representation based classification (SRC), which casts the recognition problem as seeking a sparse linear representation of the query image over the training images.

Furthermore, Naseem et al. [2] developed a linear model representing a probe image as a linear combination of class specific galleries and proposed the linear regression classification (LRC) algorithm. Zhang et al. [3] proposed a new classification scheme, namely collaborative representation based classifier (CRC), which emphasizes the role of collaborative representation in the classification task. More recently, Yang et al. [4] proposed a two-dimensional (2D) image matrix based model and employed nuclear norm constraint as a criterion to make full use of the low-rankstructural information caused by some occlusion andillumination changes. These popular classifiers have achieved some interesting results. However, they are very sensitive when the images are with misalignment (2D deformation) or pose variations (3D deformation).

A number of approaches have been reported in the literature, such as Principle Component Analysis (PCA) [4], [5], Linear Discriminant Analysis (LDA) [6], and Independent Component Analysis (ICA) [7], [8]. Primarily, these approaches are classified in two categories, i.e., reconstructive and discriminative methods. Reconstructive approaches (such as PCA and ICA) are reported to be robust for the problem of contaminated pixels [9], whereas discriminative approaches (such as LDA) are known to yield better results in clean conditions [10]. Apart from these traditional approaches, it has been shown recently that unorthodox features, such as down sampled images and random projections, can serve equally well. In fact, the choice of the feature space may no longer be so critical [11]. What really matters is the dimensionality of feature space and the design of the classifier.

Further, for the problem of severe contiguous occlusion, amodular representation of images is expected to solve the problem [12]. Based on this concept, we propose an efficient Modular LRC Approach. The proposed approach segments a given occluded image and reaches individual decisions for each block. These intermediate decisions are combined using a novel Distance-based Evidence Fusion (DEF) algorithm to reach the final decision.

The proposed DEF algorithm uses the distance metrics of the intermediate decisions to decide about the “goodness” of a partition. There are two major advantages of using the DEF approach. First, the nonface partitions are rejected dynamically; therefore, they do not take part in the final decision making. Second, the overall recognition performance is better than the best individual result of the combining partitions due to the efficient decision fusion of the face segments.

We will motivate and study this new approach to classification within the context of automatic face recognition. Human faces are arguably the most extensively studied object in image-based recognition. . Conversely, the theory of sparse representation and compressed sensing yields new insights into two crucial issues in automatic face recognition: the role of feature extraction and the difficulty due to occlusion.

II. LINEAR REGRESSION FOR FACE RECOGNITON

The problem of identifying partially occluded faces could beefficiently dealt with using the modular representation approach [13]. Contiguous occlusion can safely be assumed local in nature ina sense that it corrupts only a portion of conterminous pixels ofthe image, the amount of contamination being unknown. In themodular approach, we utilize the neighborhood property of thecontaminated pixels by dividing the face image into a number ofsub images. Each sub image is now processed individually and a final decision is made by fusing information from all of thesub images. A commonly reported technique for decision fusion is majority voting [13].

However, a major pitfall with majority votingis that it treats noisy and clean partitions equally. For instance, ifthree out of four partitions of an image are corrupted, majorityvoting is likely to be erroneous no matter how significant the cleanpartition may be in the context of facial features. The task becomeseven more complicated by the fact that the distribution of occlusion over a face image is never known a priori and therefore, along withface and nonface sub images, we are likely to have face portions corrupted with occlusion.

Some sophisticated approaches have been developed to filter out the potentially contaminated image pixels (for example, [14]). In this section, we make use of the specificnature of distance classification to develop a fairly simple butefficient fusion strategy which implicitly deemphasizes corruptedsub images, significantly improving the overall classification accuracy.We propose using the distance metric as evidence of our beliefin the “goodness” of intermediate decisions taken on the sub images;the approach is called “Distance-based Evidence Fusion.”

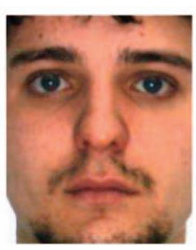

Fig. 1 Samples of cropped and aligned face.

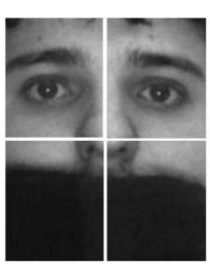

Fig. 2 The Linear Regression Method approach

III. CONCLUSIONS

In this paper we have presented an extensivesurvey of machine recognition ofhuman faces and a brief review of relatedpsychological studies. We have considered from still images. In additionto a detailed review of representative work. In the paradigm of view-based face recognition, the choice of features for a given case study has been a debatable topic. Recentresearch has, however, shown the competency of unorthodoxfeatures such as downsampled images and random projections, indicating a divergence from the conventional ideology.

The Linear Regression approach in fact conforms to this emerging belief. Ithas been shown that with an appropriate choice of classifier, the down sampled images can produce good results compared to the traditional approaches. The simple architecture of the proposed approach makes it computationally efficient, therefore suggesting a strong candidacy for realistic video-based face recognition applications.Other future directions include the robustness issues relatedto illumination, random pixel corruption, and pose variations. In this, the face identification task as a problem of linear regression is considered. The Linear Regression method extensively evaluated. Specifically, the challenges of varying facial expressions and contiguous occlusion are addressed. Apart from the Modular LRC approach forface identification in the presence of disguise, the LRC approachyields high recognition accuracies without requiring any preprocessingsteps of face localization and/or normalization. We arguethat in the presence of non ideal conditions such as occlusion, illumination, and severe gestures, a cropped and aligned face is generally not available.

Therefore, a consistent reliable performancewith unprocessed standard databases makes the Linear Regression method appropriate for real scenarios. For the case of varying gestures, the Linear Regression approach has been shown to cope well with themost severe screaming expression where the state-of-the-art techniques lag behind, indicating consistency for mild and severe changes. For the problem of face recognition in the presence of disguise, the Linear Regression method using an efficient evidentialfusion strategy yields the best reported results in the literature.

The impressive face recognition capability of the human perception system has one limitation: the number and types offaces that can be easily distinguished. Machines, on the other hand, canstore and potentially recognize as many

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To conclude our paper, we present a conjecture about face recognition based onpsychological studies and lessons learnedfrom designing algorithms. We conjecture that different mechanisms are involved inhuman recognition of familiar and unfamiliarfaces. For example, it is possiblethat 3D head models are constructed, byextensive training for familiar faces, butfor unfamiliar faces, multiview 2D imagesare stored. This implies that we have fullprobability

density functions for familiarfaces, while for unfamiliar faces we onlyhave discriminant functions.

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