RECOGNIZING FACE WITH CONSECUTIVE OCCLUSION USING MARKOV CHAIN

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Abstract- Face Recognition (FR) technology is software that can identify human face from any digital image/ video. In the real world, faces with occlusion such as sunglasses, scarf, mask etc., are quite common, especially in uncooperative scenario. The facial occlusion is one critical factor that affects the performance of face recognition. One cannot predict human face, when the face has been occluded. In recent years, Markov chain model a hotspot of dealing with face recognition under different illuminations and facial occlusions. The basic idea of Markov chain model is to recover clean images from degraded images or occluded images by using the clean training samples. Then the reconstructed images are used for face recognition. Note that the residual image which is a difference between the raw and reconstructed image containing most of the occluded information. In this paper two contributions are created for occlusion detection: i) a new occlusion detection method is presented by combining the information of both raw image and residual image; ii) the non-occluded part for face recognition has a better result than using reconstructed image is empirically displayed. The main objective of this paper is to get information.

Keywords: Face recognition with occlusion, Markov Chain, residual image.

1. INTRODUCTION

Face recognition technology is playing a more and more important role in our daily lives, such as access control, credit card verification, video surveillance etc. Many researchers developed many techniques and algorithms in FR. Even though, there comes a problem when the face is occluded. Nevertheless, the acquisition facial images might be occluded by other objects (sunglasses, scarf, mask etc.) which have a harmful effect on face recognition systems. In recent years, Markov Chain model were proposed to solve the occluded face recognition problem by recovering the clean image from one occluded image. These methods like linear regression classifier (LRC), sparse representation based classification (SRC) and collaborative representation based classification (CRC) all achieved expected results. And the nuclear norm based matrix regression (NMR) method proposed by Yang et al. significantly outperforms the other methods in recovering the clean image . All these method used the reconstructed images for classification. We consider the fact that the reconstructed images might remove some useful information and introduce some incidental information. Therefore, whether the reconstructed images are suitable for occluded face recognition needs study. During face recognition, the occluded face image may generate error. In this paper, the main goal is to know information about error in advance in sequential occlusion to get free from occlusion.

(a) (b)

Fig.1: Example Training Data
a) Occluded face image b) Normal face image

2. LITERATURE SURVEY

In the literature of face recognition, traditional holistic feature based approaches are sensitive to outlier pixels, performing poorly against occlusion. Local feature based approaches are roughly divided into two categories in terms of patch-dependent or data-dependent. Combined with partial matching methods, the local features are more robust because they are not extracted from the entire image. Nonetheless, they are still inevitably affected by invalid pixels and far from being robust enough in practical classification tasks. An alternative solution addresses occlusion via a two-stage approach. It first identifies and discards the occluded pixels, and then performs the classification on the rest [1]. As one can imagine, its classification performance is greatly determined by the occlusion identification accuracy. If too much discriminative information is abandoned, the following classification becomes difficult. To enhance the accuracy of occlusion identification, [2] adopts the prior that the occlusion is spatially continuous and consequently achieves excellent performance. However, such unsupervised approach might cause misestimate when occlusion is severe. For instance, a scarf larger than half of the testing face may be considered as a useful signal, and therefore face pixels may be discarded in each iteration. We call it a degenerate solution. Besides, the algorithm in [3] has to be carried out subject-by-subject and exhaustively search the class with the minimum normalized error, which is time-consuming and detrimental to real-time applications

Recently, several occlusion dictionary based approaches [4] for robust face recognition have been attached more and more importance. This kind of method is capable of efficiently handling various occlusions. They exploit characteristics of non-occluded and occluded region, assuming that both of them can be coded over the corresponding part of dictionary [5]. These methods act in the similar way with each other. Concretely, an occlusion dictionary is concatenated to the original dictionary to perform occlusion coding. The goal is to jointly represent the occluded image. Fig. 1 illustrates how occlusion dictionary methods work. By seeking a sparse solution, the occluded image successfully decomposes into face and occlusion. The classification is carried out via the corresponding coefficients. Hence, they cast the recognition problem with occlusion as the one without occlusion, since occlusion is regarded as an extra and special class in training samples. On the other hand, these occlusion dictionary based approaches choose different occlusion dictionary, leading to very different performance. More specifically, sparse representation-based classification (SRC) [6] employs an identity matrix as the occlusion dictionary, showing promising robustness to random pixel corruption and small contiguous occlusion. exploits the local characteristics of Gabor feature, and proposes Gabor feature based sparse representation classification (GSRC). The Gabor feature of identity matrix exists high redundancy, so it can be compressed to a compact form for efficiency. Extended SRC (ESRC) [7] points out that intra-class variant dictionary contains useful information. By exploiting the difference images between two samples in the same class, ESRC can handle certain occlusion. The recent improvement is made by [8], namely structured sparse representation based classification (SSRC). They obtain common occlusion samples from occluded images with projection residuals, and utilize K-SVD to train occlusion dictionary, making appended occlusion atoms to be more representative. SSRC achieves higher accuracy in both recovery and recognition. Texture Features can be extracted using local binary pattern (LBP).

Markov chains have many applications as statistical models of real-world processes, such as studying cruise control systems in motor vehicles, queues or lines of customers arriving at an airport, exchange rates of currencies, storage systems such as dams, and population growths of certain animal species.[9] The algorithm known as PageRank, which was originally proposed for the internet search engine Google, is based on a Markov process. Furthermore, Markov processes are the basis for general stochastic simulation methods known as Gibbs sampling and Markov chain Monte Carlo, are used for simulating random objects with specific probability distributions, and have found extensive application in Bayesian statistics

Hence, this work Markov chain model is proposed to recover clean images from degraded images or occluded images by using the clean training samples. Then the reconstructed images are used for face recognition. Note that the residual image which is a difference between the raw and reconstructed image containing most of the occluded information. In this paper two contributions are created for occlusion detection: i) a new occlusion detection method is presented by combining the information of both raw image and residual image; ii) the non-occluded part for face recognition has a better result than using reconstructed image is empirically displayed. The main objective of this paper is to get information about the error distribution in advance.

3. PROPOSED WORK

Formally, a Markov chain is a probabilistic automaton. The probability distribution of state transitions is typically represented as the Markov chain's transition matrix. If the Markov chain has N possible states, the matrix will be an N x N matrix, such that entry (I, J) is the probability of transitioning from state I to state J. Additionally, the transition matrix must be a stochastic matrix, a matrix whose entries in each row must add up to exactly 1. This makes complete sense, since each row represents its own probability distribution.

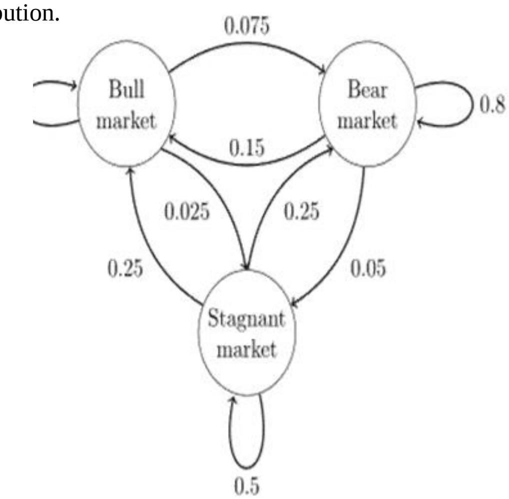

Fig.2: Sample Markov Chain, With States as Circles and Edges as Transitions

As discussed above, face recognition can be cast as a problem of recovering an input signal x 2 Rn from corrupted measurements y = Ax + e, where A 2 Rm_n with m > n. Let F be a matrix whose rows span the left null space of A2. Applying F to both sides of the measurement equation gives

~y := Fy = F(Ax + e) = Fe:

So the recovery problem is reduced to the problem of reconstructing a sparse error vector e from the observation Fe. While this problem is very hard in general, in many situations solving the convex relaxation min kvk1 s.t. Fv = ~y= Fe exactly recovers e.

Candes et. al. [6] have characterized the recoverability of the sparse solution to the above problem in terms of the restricted isometry property (RIP) of the matrix F. The k-restricted isometry constant _k 2 R is defined as the smallest quantity such that for any k-sparse typical result states 1-minimization is guaranteed to recover any k-sparse x whenever the matrix F satisfies _2k < 1. Notice that this argument treats every possible k-sparse supports equally. However, in many applications, we have prior information about the distribution of the supports. To extend the theory to such structured sparsity, [8] introduced the (k; _)-probabilistic RIP (PRIP). A matrix F is said to satisfy the PRIP if there exists a constant _k > 0 such that for a k-sparse signal x whose support is a considered as a random variable, (2) holds with probability f1.

Based on results from Compressed Sensing theory, for a randomly chosen matrix to have RIP of order k requires at least m = O(k log(n=k)) measurements [6]. However, it has been shown that a matrix can have PRIP of order k with only m = O(k + log(D)) measurements, where D is the cardinality of the smallest set of supports of size k for which the probability that the support of a k-sparse signal x does not belong to the set is less than _ [8]. Then for distributions that allow a small D, the required number of measurements essentially grows linearly in k, much less than the general case. The distribution of contiguous supports precisely falls into this category3. Thus, we should expect to recover sparse errors with such supports from much fewer measurements. Or equivalently, from a fixed number measurements, we should expect to correct a larger fraction of errors from `1-minimization if we know how to properly harness information about the distribution.

4. CONCLUSION

In this paper, we propose a Markov model, which simultaneously separates the occlusion and classifies the test image by coding over the occlusion sample. In future Comprehensive experimental results show that Markov chain can better deal with face recognition with occlusion than most existing well-performing algorithms.

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