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Fast Face Identification System with Occlusions

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ABSTRACT

In this paper, we propose an iterative method to address the face identification problem with block occlusions. Our approach utilizes a robust representation based on two characteristics in order to model contiguous errors (e.g., block occlusion) effectively. The first fits to the errors a distribution described by a tailored loss function. The second describes the error image as having a specific structure (resulting in low-rank in comparison with image size). We will show that this joint characterization is effective for describing errors with spatial continuity. Our approach is computationally efficient due to the utilization of the alternating direction method of multipliers. A special case of our fast iterative algorithm leads to the robust representation method, which is normally used to handle non contiguous errors (e.g., pixel corruption). Extensive results on representative face databases (in constrained and unconstrained environments) document the effectiveness of our method over existing robust representation methods with respect to both identification rates and computational time.

Key words: Face identification, robust representation, low-rank estimation, iterative reweighted coding.

1. INTRODUCTION

FACE Identification (FI) focuses on deducing a subject's identity through a provided test image and is one of the most popular problems in computer vision. Typically, test images exhibit large variations, such as occlusions. Ideally, if the training set contains the same type of occlusion as the test image then identification becomes a rather straightforward task. In practice, however, there is no guarantee that the collected data would cover all different occlusions for all identities of interest. The image database consists of non-occluded faces of subjects with intra-class illumination differences while the query face exhibits a 70% random block occlusion that covers most of the informative features of the face. In applications where prior knowledge such as the region and the object of occlusion is not provided, an appropriate modelling of the error between the test image and the training samples is necessary.

In this work, we propose an iterative method to solve the FI problem with occlusions. We consider the same scenario as according to which we are given "clean" frontal aligned views with a block occlusion which appear in any position on the test image but is "unseen" to the training data. When corrupted training data are provided that are not frontally aligned (e.g., scenarios in an unconstrained environment) a tool such as RPCA and SLR is employed to separate outlier pixels and corruptions from the training samples as a pre-processing step. Then, the "clean" frontal aligned faces are used for training data to perform face identification with occluded test images.

As already mentioned with the robust methods, high computational cost is exhibited and identification results significantly degrade with over 50% random block occlusion. Our approach is based on a new iterative method which is efficient in terms of computational cost and robust to block occlusions up to 70%.

2. LITERATURE SURVEY

During 1964 and 1965, Bledsoe, along with Helen Chan and Charles Bisson, worked on using the computer to recognize human faces (Bledsoe 1966a, 1966b; Bledsoe and Chan 1965). He was proud of this work, but because the funding was provided by an unnamed intelligence agency that did not allow much publicity, little of the work was published. Given a large database of images (in effect, a book of mug shots) and a photograph, the problem was to select from the database a small set of records such that one of the image records matched the photograph. The success of the method could be measured in terms of the ratio of the answer list to the number of records in the database. Bledsoe (1966a) described the following difficulties.

This project was labeled man-machine because the human extracted the coordinates of a set of features from the photographs, which were then used by the computer for recognition. Using a graphics tablet(GRAFACON or RAND TABLET), the operator would extract the coordinates of features such as the center of pupils, the inside corner of eyes, the outside corner of eyes, point of widows peak, and so on. From these coordinates, a list of 20 distances, such as width of mouth and width of eyes, pupil to pupil, were computed. These operators could process about 40 pictures an hour. When building the database, the name of the person in the photograph was associated with the list of computed distances and stored in the computer. In the recognition phase, the set of distances was compared with the corresponding distance for each photograph, yielding a distance between the photograph and the database record. The closest records are returned.

Because it is unlikely that any two pictures would match in head rotation, lean, tilt, and scale (distance from the camera), each set of distances is normalized to represent the face in a frontal orientation. To accomplish this normalization, the program first tries to determine the tilt, the lean, and the rotation. Then, using these angles, the computer undoes the effect of these transformations on the computed distances. To compute these angles, the computer must know the three-dimensional geometry of the head. Because the actual heads were unavailable, Bledsoe (1964) used a standard head derived from measurements on seven heads.

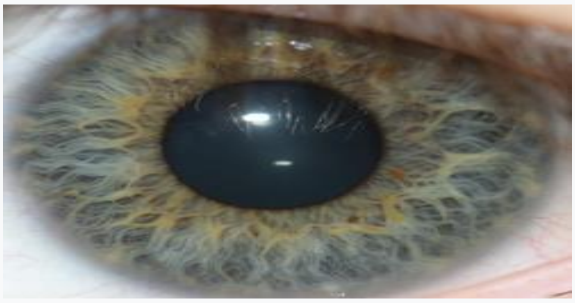
After Bledsoe left PRI in 1966, this work was continued at the Stanford Research Institute, primarily by Peter Hart. In experiments performed on a database of over 2000 photographs, the computer consistently outperformed humans when presented with the same recognition tasks (Bledsoe 1968). Peter Hart (1996) enthusiastically recalled the project with the exclamation, "It really worked!"

By about 1997, the system developed by Christoph vonderMalsburg and graduate students of the University of Bochum in Germany and the University of Southern California in the United States outperformed most systems with those of Massachusetts Institute of Technology and the University of Maryland rated next. The Bochum system was developed through funding by the United States Army Research Laboratory. The software was sold as ZN-Face and used by customers such as Deutsche Bank and operators of airports and other busy locations. The software was "robust enough to make identifications from less-than-perfect face views.

3. EXISTING METHOD

3.1 IRIS TECHNOLOGY

Iris recognition biometric systems apply mathematical pattern-recognition techniques to images of the irises of an individual's eyes.



Iris recognition is an automated method of biometric identification that uses mathematical pattern-recognition techniques on video images of one or both of the irises of an individual's eyes, whose complex patterns are unique, stable, and can be seen from some distance.

Retinal scanning is a different, ocular-based biometric technology that uses the unique patterns on a person's retina blood vessels and is often confused with iris recognition. Iris recognition uses video camera technology with subtle near infrared illumination to acquire images of the detail-rich, intricate structures of the iris which are visible externally. Digital templates encoded from these patterns by mathematical and statistical algorithms allow the identification of an individual or someone pretending to be that individual. Databases of enrolled templates are searched by matcher engines at speeds measured in the millions of templates per second per (single-core) CPU, and with remarkably low false match rates.

Several hundred million persons in several countries around the world have been enrolled in iris recognition systems for convenience purposes such as passport-free automated border-crossings and some national ID programs. A key advantage of iris recognition, besides its speed of matching and its extreme resistance to false matches is the stability of the iris as an internal and protected, yet externally visible organ of the eye.

3.2 BIOMETRIC

Biometrics is the technical term for body measurements and calculations. It refers to metrics related to human characteristics. Biometrics authentication (or realistic authentication) is used in computer science as a form of identification and access control. It is also used to identify individuals in groups that are under surveillance.

Biometric identifiers are the distinctive, measurable characteristics used to label and describe individuals. Biometric identifiers are often categorized as physiological versus behavioral characteristics. Physiological characteristics are related to the shape of the body. Examples include, but are not limited to fingerprint, palm veins, face recognition, DNA, palm print, hand geometry, iris recognition, retina and odour/scent. Behavioral characteristics are related to the pattern of behavior of a person, including but not limited to typing rhythm, gait, and voice. Some researchers have coined the term behaviometrics to describe the latter class of biometrics.

More traditional means of access control include token-based identification systems, such as a driver's license or passport, and knowledge-based identification systems, such as a password or personal identification number. Since biometric identifiers are unique to individuals, they are more reliable in verifying identity than token and knowledge-based methods; however, the collection of biometric identifiers raises privacy concerns about the ultimate use of this information.

4. PROPOSED METHOD

In this section we propose an iterative method to address the FI problem with block occlusions. Our approach utilizes the robust representation with two characteristics and uses a tailored loss function based on M-estimators. The Method handles contiguous errors that are considered low-rank in comparison to the size of the image and is efficient in terms of computational cost. A special case of our method is also utilized to solve efficiently the robust representation problem for non-contiguous errors.

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We can represent the test sample with occlusion as the superposition of training samples and a representation error **e**, thus, the degradation model is,

$$\mathbf{y} = \mathbf{Ta} + \mathbf{e},$$

Thus, the test sample can be represented as a linear combination of the samples in **T**. The face identity is chosen based on the minimum class residual provided by the estimated coefficients **a** as in. The residual image **e** in our model has two characteristics:

1) It includes mainly the occluded object, and therefore it is considered low-rank in comparison to image size since many of its rows or columns are zero.

2) It follows a distribution that can be effectively described by a tailored potential loss function

We expect that the calculation of **e** based on the two characteristics mentioned above will lead to an accurate estimation of the **a** coefficients and provide the correct identity. Although the first characteristic has been employed in and the second in robust representation methods, both of them are necessary to adequately describe the residual image and are used together for the first time in our work. In particular, enforcing only the second characteristic will not necessarily lead to an error image that is structured and low-rank.

5. CONCLUSION

In this work we proposed a method to describe contiguous errors effectively based on two characteristics. The first fits to the errors a distribution described by a tailored loss function. The second describes the error image as structural (low-rank).

Our approach is computationally efficient due to the utilization of ADMM. The extensive experimental results support the claim that the proposed modelling of the error term can be beneficial and more robust than previous state-of-the-art methods to handle occlusions across a multitude of databases and in different scenarios. A special case of our algorithm leads to the robust representation problem which is used to solve cases with non-contiguous errors. We showed that our fast iterative algorithm was in some cases faster by an order of magnitude than the existing approaches.

6. FUTURE SCOPE

The use of spherical canonical images allows us to perform matching in the spherical harmonic transform domain, which does not require preliminary alignment of the images. The errors introduced by embedding into an expressional space with some predefined geometry are avoided. In this facial expression recognition setup, end-to-end processing comprises the face surface acquisition and reconstruction, smoothening, sub sampling to approximately 2500 points. Facial surface cropping measurement of large positions of distances between all the points using a parallelized parametric version is utilized. The general experimental evaluation of the face expressional system guarantees better face recognition rates. Having examined techniques to cope with expression variation, in future it may be investigated in more depth about the face classification problem and optimal fusion of colour and depth information. Further study can be laid down in the direction of allele of gene matching to the geometric factors of the facial expressions. The genetic property evolution framework for facial expressional system can be studied to suit the requirement of different security models such as criminal detection, governmental confidential security breaches etc.

REFERENCES

[1] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, “Face recognition: A literature survey,” ACM Comput. Surv., vol. 35, no. 4, pp. 399–458, Dec. 2003.

[2] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, “Web-scale training for face identification,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2015, pp. 2746–2754.

[3] M. Turk and A. Pentland, “Eigenfaces for recognition, J. Cognit. Neurosci., vol. 3, no. 1, pp. 71–86, Jan. 1991.

[4] P. N. Belhumeur, J.P.Hespanha, and D.Kriegman, “Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 7, pp. 711–720, Jul. 1997.

[5].L. Zhang, M. Yang, and X. Feng, “Sparse representation or collaborative representation: Which helps face recognition?” in Proc. IEEE Int. Conf. Comput. Vis., Barcelona, Spain, Nov. 2011, pp. 471–478.

[6] Q. Shi, A. Eriksson, A. van den Hengel, and C. Shen, “Is face recognition really a compressive sensing problem?” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2011, pp. 553–560.

[7] J. Lai and X. Jiang, “Classwise sparse and collaborative patch representation for face recognition,” IEEE Trans. Image Process., vol. 25, no. 7, pp. 3261–3272, Jul. 2016.

[8] J. Lai and X. Jiang, “Modular weighted global sparse representation for robust face recognition,” IEEE Signal Process. Lett., vol. 19, no. 9.