Volume 5, Issue 4, 2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Regularized Robust Coding for Biometricand Face Recognition Techniques

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Abstract: Recently the sparse representation based classification (SRC) has been proposed for robust face recognition (FR). In SRC, the testing image is coded as a sparse linear combination of the training samples, and the representation fidelity is measured by the l2-norm or l1-norm of the coding residual. Such a sparse coding model assumes that the coding residual follows Gaussian or Laplacian distribution, which may not be effective enough to describe the coding residual in practical FR systems. Meanwhile, the scarcity constraint on the coding coefficients makes SRC's computational cost very high. In this paper, we propose a new face coding model, namely regularized robust coding (RRC), which could robustly regress a given signal with regularized regression coefficients. By assuming that the coding residual and the coding coefficient are respectively independent and identically distributed, the RRC seeks for a maximum a posterior solution of the coding problem. An iteratively reweighted regularized robust coding (IR3C) algorithm is proposed to solve the RRC model efficiently. Extensive experiments on representative face databases demonstrate that the RRC is much more effective and efficient than state-of-the-art sparse representation based methods in dealing with face occlusion, corruption, lighting and expression changes, etc.

Key Terms: Face recognition, regularization, robust coding, sparse representation.

I. INTRODUCTION

As one of the most visible and challenging problems in computer vision and pattern recognition, face recognition (FR) has been extensively studied in the past two decades, and many representative methods, such as Eigen face , Fisher face and SVM , have been proposed. Moreover, to deal with the challenges in practical FR system, active shape model and active appearance model were developed for face alignment; LBP and its variants were used to deal with illumination changes; and Eigen images and probabilistic local approach [9] were proposed for FR with occlusion. Although much progress have been made, robust FR to occlusion/corruption is still a challenging issue because of the variations of occlusion, such as disguise, continuous or pixel-wise occlusion, randomness of occlusion position and the intensity of occluded pixels. The recognition of a query face image is usually accomplished by classifying the features extracted from this image. The most popular classifier for FR may be the nearest neighbor (NN) classifier due to its simplicity and efficiency. In order to overcome NN's limitation that only one training sample is used to represent the query face image, Li and Lu proposed the nearest feature line (NFL) classifier, which uses two training samples for each class to represent the query face. The proposed the nearest feature plane (NSP) classifier, which uses three, samples to represent the test image. Later on, classifiers using more training samples for face representation were proposed, such as the local subspace classifier (LSC) and the nearest subspace (NS) classifiers, which represent the query sample by all the training samples of each class. Though NFL, NSP, LSC and NS achieve better performance than NN, all these methods with holistic face features are not robust to face occlusion. Generally speaking, these nearest classifiers, including NN, NFL, NFP, LSC and NS, aim to find a suitable representation of the query face image, and classify it by checking which class can give a better representation than other classes. Nonetheless, how to formulate the representation model for classification tasks such as FR is still a challenging problem. In recent years, sparse representation has been attracting a lot of attention due to its great success in image processing, and it has also been used for FR and texture classification. Based on the findings that natural images can be generally coded by structural primitives (e.g., edges and line segments) that are qualitatively similar in form to simple cell receptive fields, sparse coding represents a signal using a small number of atoms parsimoniously chosen 3out of an over-complete dictionary. The scarcity of the coding coefficient can be measured, which counts the number of nonzero entries in a vector. Since the combinatorial l0-norm minimization is an NP-hard problem, the l1-norm minimization, as the closest convex function to l0-norm minimization, is widely employed in sparse coding, and it has been shown that l0-norm and l1-norm minimizations are equivalent if the solution is sufficiently sparse.

II. RELATED WORK

Proposed Method:

Regularized Robust Coding (RRC)

The conventional sparse coding model is equivalent to the so-called LASSO problem. The face recognition problem can be formulated as follows: Given an input face image and a database of face images of known individuals, how can we verify or determine the identity of the person in the input image?

Use the Face for Recognition:

Biometric-based techniques have emerged as the most promising option for recognizing individuals in recent years since, instead of authenticating people and granting
them access to physical and virtual domains based on passwords, PINs, smart cards, plastic cards, tokens, keys and so forth, these method s examine an individual's physiological and/or behavioural characteristics in order to determine and/or ascertain his identity. Passwords and
PINs are hard to remember and can be stolen or guessed; cards, tokens, keys and the like can be misplaced, forgotten, purloined or duplicated; magnetic cards can become corrupted and unreadable. However, an individual's biological traits cannot be misplaced, forgotten, stolen or forged. Biometric-based technologies include identification based on physiological characteristics (such as face, fingerprints, finger geometry, hand geometry, hand veins, palm, iris, retina, ear and voice) and behavioral traits (such as gait, signature and keystroke dynamics) [1]. Face recognition appears to offer several advantages over other biometric methods, a few of which are outlined here: Almost all these technologies require some voluntary action by the user, i.e., the user needs to place his hand on a hand-rest for fingerprinting or hand geometry detection and has to stand in a fixed position in front of a camera for iris or retina identification. However, face recognition can be done passively without any explicit action or participation on the part of the user since face images can be acquired from a distance by a camera. This is particularly beneficial for security and surveillance purposes. Furthermore, data acquisition in general is fraught with problems for other biometrics: techniques that rely on hands and fingers can be rendered useless if the epidermis tissue is damaged in some way (i.e., bruised or cracked). Iris and retina identification require expensive equipment and are much too sensitive to any body motion. Voice recognition is susceptible to background noises in public places and auditory fluctuations on a phone line or tape recording. Signatures can be modified or forged. However, facial images can be easily obtained with a couple of inexpensive fixed cameras. Good face recognition algorithms and appropriate pre-processing of the images can compensate for noise and slight variations in orientation, scale and illumination. Finally, technologies that require multiple individuals to use the same equipment to capture their biological characteristics potentially expose the user to the transmission of germs and impurities from other users. However, face recognition is totally non-intrusive and does not carry any such health risks.

Applications

Face recognition is used for two primary tasks:

1. Verification (one-to-one matching): When presented with a face image of an unknown individual along with a claim of identity, ascertaining whether the individual is who he/she claims to be.
2. Identification (one-to-many matching): Given an image of an unknown individual, determining that person's identity by comparing (possibly after encoding) that image with a database of (possibly encoded) images of known individuals.

There are numerous application areas in which face recognition can be exploited for these two purposes, a few of which are outlined below.

- Security (access control to buildings, airports/seaports, ATM machines and border checkpoints; computer/network security; email authentication on multimedia workstations).
- Surveillance (a large number of CCTVs can be monitored to look for known criminals, drug offenders, etc. and authorities can be notified when one is located. For example, this procedure was used at the Super Bowl 2 in another instance, according to a CNN report, two cameras linked to state and national databases of sex offenders, missing children and alleged abductors have been installed recently.
- Image database investigations (searching image databases of licensed drivers, benefit recipients, missing children, immigrants and police bookings).
- Witnesses face reconstruction.

Face Recognition Techniques:

The method for acquiring face images depends upon the underlying application. For instance, surveillance applications may best be served by capturing face images by means of a video camera while image database investigations may require static intensity images taken by a standard camera. Some other applications, such as access to top security domains, may even necessitate the forgoing of the non-intrusive quality of face recognition by requiring the user to stand in front of a 3D scanner or an infra-red sensor. Therefore, depending on the face data acquisition methodology, face recognition techniques can be broadly divided into three categories: methods that operate on intensity images, those that deal with video sequences, and those that require other sensory data such as 3D information or infra-red imagery

Face Recognition from Intensity Images using Featured-based:

Feature-based approaches first process the input image to identify and extract (and measure) distinctive facial features such as the eyes, mouth, nose, etc., as well as other fiducially marks, and then compute the geometric relationships among those facial points, thus reducing the input facial image to a vector of geometric features. Standard statistical pattern recognition techniques are then employed to match faces using these measurements. Early work carried out on automated face recognition was mostly based on these techniques. One of the earliest such attempts was by Kanade, who employed simple image processing methods to extract a vector of 16 facial parameters - which were ratios of distances, areas and angles (to compensate for the varying size of the pictures) and used a simple Euclidean distance measure for matching to achieve a peak performance of 75% on a database of 20 different people using 2 images per person (one for reference and one for testing).

III. IMPLEMENTATION

Multi Biometric System:

Multi Biometric system is use more than one biometric system for one multi biometric system for more security. Uni-biometric system is easy to hack but multi biometric system is not easy to hack because one person does not obtain two traits of the same individual. This is the reason that multi biometric system is more secure than unibiometric system. How to work the multi biometric system? It contains the two steps (1) Enrollment on that Multi biometric first create the data base of users. And (2) verification on that when user try to gate access on the system then at that time first system captures the characteristic of the person then system match the input data to the data base sample. And then person gate authentication or conclude as a fake user. An introduction of application of biometric system used in this paper are face recognition system, fingerprint recognition system, iris recognition system.

Face recognition and attack on system:

The most acceptable biometrics is Face reorganization, because it is one of the most universal methods of identification that humans use in their visual interactions and acquisition of faces. The face recognition systems make different between the background and the face. It is most important when the system has to identify a face within a throng. The system then makes use of a person's facial features – its valleys and peaks and landmarks and treats these as nodes that can be compared and measured against those which are stored in the system's database. There are approximately 80 nodes comprising the face print that makes use of the system and this includes the eye socket depth, jaw line length, distance between the eyes, cheekbone shape, and the width of the nose. It is very challenging to develop this recognition technique which can accept the effects of facial expressions, age, slight variations in the imaging environment. Attack on the face recognition system is that figure fake and genuine image are shown and that images are find out due to different method of face recognition. In face recognition system fake users attack on system by capturing the picture to the mobile devices or camera. And try to authenticate.

Fingerprint recognition and attacks on system:

Every fingerprint of each person is considered to be unique, Even the Twins also contain different fingerprint. Fingerprint recognition is the most accepted biometric recognition method. Fingerprints have been used from long time for identifying individuals. Fingerprints consist of ridges and furrows on the surface of a fingertip. Now fingerprint recognition system is used in iphone, there are many areas where the fingerprint recognition system used. But attackers attack on fingerprint recognition system. Attackers first capture real fingerprint then they make fake fingerprint by using silicon, playdoh and gelatin and try to access the system.

Iris Recognition attacks on system

Iris recognition is a computerized method of biometric identification which uses mathematical Model recognition techniques on video images of the irises of an individual's eyes, whose Complex random patterns are single and can be seen from some distance. Iris cameras perform detection of a person's identity. The iris scans process start to get something on film. It combines computer vision, statistical inference, pattern recognition and optics. The iris is the colored ring around the pupil of every human being and like a snowflake; no two are the same. Each one is unique. An attack on the iris is not so easy but how to attack on the system is as shown below. To create a fake iris is of tree step

1) Original images are capture for a better quality.
2) They are printed on a paper using a commercial printer.
3) Printed images are presented at the iris sensor.

Advantages of Multi-biometric Systems over a unibiometric system

- Better Security: - The multi-biometric system increases the security level. Unibiometric system is easy to attack but the multi-biometric system is not so easy because attacker cannot obtain two traits of the same individual.
- More secure than other system
- Multiple Fingerprint scanner support
- Multiple IRIS Scanner support

Applications:

- Multi-biometric system is used in India for making Aadhar card this multi-biometric system is used face recognition, iris recognition, and fingerprint recognition.
- Multi-biometric system used in Airport.
- Multi-biometric system is used in banking.

Face Recognition from Video Sequences:

Since one of the major applications of face recognition is surveillance for security purposes, which involves real-time recognition of faces from an image sequence captured by a video camera, a significant amount of research has been directed towards this area in recent years. A video-based face recognition system typically consists of three modules: one for detecting the face; a second one for tracking it; and a third one for recognizing it. Most of these systems choose a few good frames and then apply one of the recognition techniques for intensity images to those frames in order to identify the individual. A few of these approaches are briefly described below. Howell and Buxton employed a two-layer RBF network for learning/training and used Difference of Gaussian (DoG) filtering and Gabor wavelet analysis for the feature representation, while the scheme from was utilized for face detection and tracking. Training and testing were done using two types of image sequences: 8 primary sequences taken in a relatively constrained environment, and a secondary sequence recorded in a much more unconstrained atmosphere. The image sequences consisted of 62 to 94 frames. The use of Gabor wavelet analysis for feature representation, as opposed to DoG filtering, seemed to yield better recognition results.

IV. CONCLUSION

This paper presented a novel robust regularized coding (RRC) model and an associated effective iteratively reweighted regularized robust coding (IR3C) algorithm for robust face recognition (FR). One important advantage of RRC is its robustness to various types of outliers (e.g., occlusion, corruption, expression, etc.) by seeking for an approximate MAP (maximum a posterior estimation) solution of the coding problem. By 28 assigning adaptively and iteratively the weights to the pixels according to their coding residuals, the IR3C algorithm could robustly identify the outliers and reduce their effects on the coding process. Meanwhile, we showed that the l2-norm regularization is as powerful as l1-norm regularization in RRC but the former has much lower computational cost. The proposed RRC methods were extensively evaluated on FR with different conditions, including variations of illumination, expression, occlusion, corruption, and face validation. The experimental results clearly demonstrated that RRC outperforms significantly previous state-of-the-art methods, such as SRC, CESR and GSRC. In particular, RRC with l2-norm regularization could achieve very high recognition rate but with low computational cost, which makes it a very good candidate scheme for practical robust FR systems.

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