Volume 5, Issue 10, October-2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Robust Multimodal Biometrics Recognition: A Review

Suvarnsing G. Bhable
Department of Computer Science & IT
Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, Maharashtra, India

Sangramsing Kayte
Department of Computer Science & IT
Dr. Babasaheb Ambedkar Marathwada University, Aurangabad
Maharashtra, India

Jaypalsing N. Kayte
Department of Computer Science & IT
Dr. Babasaheb Ambedkar Marathwada University, Aurangabad
Maharashtra, India

Dr. Charansing Kayte
Assistant Professor
Department of Digital and Cyber Forensic, Aurangabad, Maharashtra
India

Abstract— Biometric recognition systems rely on a single biometric signature for authentication. While the advantage of using multiple sources of information for establishing the identity has been widely recognized, computational models for multimodal biometrics recognition have only recently received attention. We propose a multimodal sparse representation method, which represents the test data by a sparse linear combination of training data, while constraining the observations from different modalities of the test subject to share their sparse representations. Thus, we simultaneously take into account correlations as well as coupling information among biometric modalities. A multimodal quality measure is also proposed to weigh each modality as it gets fused. Furthermore, we also kernelize the algorithm to handle nonlinearity in data. The optimization problem is solved using an efficient alternative direction method. Various experiments show that the proposed method compares favorably with competing

Keywords—Biometrics, Multimodal biometrics, feature fusion, Quality-Based Fusion, sparse representation

I. INTRODUCTION

Biometric systems rely on a single source of information such as a single iris or fingerprint or face for authentication [1]. Unfortunately, these systems have to deal with some of the following inevitable problems [2]:

a. Noisy data. Poor lighting on a user’s face or occlusion are examples of noisy data.
b. Nonuniversality. The biometric system based on a single source of evidence may not be able to capture meaningful data from some users. For instance, an iris biometric system may extract incorrect texture patterns from the iris of certain users due to the presence of contact lenses.
c. Intraclass variations. In the case of fingerprint recognition, the presence of wrinkles due to wetness [3] can cause these variations. These types of variations often occur when a user incorrectly interacts with the sensor.
d. Spoof attack. Hand signature forgery is an example ofthis type of attack.

It has been observed that some of the limitations of unimodal biometric systems can be addressed by deploying multimodal biometric systems that essentially integrate the evidence presented by multiple sources of information such as iris, fingerprints, and face. Such systems are less vulnerable to spoof attacks, as it would be difficult for an imposter to simultaneously spoof multiple biometric traits of a genuine user. Due to sufficient population coverage, these systems are able to address the problem of nouniversality. Classification in multibiometric systems is done by fusing information from different biometric modalities. Information fusion can be done at different levels, broadly divided into feature-level, score-level, and rank-/decisionlevel fusion. Due to preservation of raw information, feature-level fusion can be more discriminative than scoreor decision-level fusion [4]. But, feature-level fusion methods have been explored in the biometric community only recently. This is because of the differences in features extracted from different sensors in terms of types and dimensions. Often features have large dimensions, and fusion becomes difficult at the feature level. The prevalent method is feature concatenation, which has been used for different multibiometric settings [5]. However, for high-dimensional feature vectors, simple feature concatenation may be inefficient and nonrobust. A related work in the machine learning literature is multiple kernel learning (MKL), which aims to integrate information from different features by learning a weighted combination of respective kernels. A detailed survey of MKL-based methods can be found in [6]. However, for multimodal systems, weight determination during testing is important, based on the quality of modalities. Also, a corrupted test sample from a modality must be rejected by the algorithm. Such a framework is not yet feasible in the MKL settings. Methods like those given in [7] try to exploit information from data from a different view to improve classifier performance. However, [9] being an unsupervised technique, is not suited for classification tasks, and [10] reduces to the MKL framework in a supervised setting. Similarly, SVM-2k [10] jointly learns SVM for two views, while maximizing the agreement between the projections of data from the two views . It is, however, not clear how this can be extended to multiple views, which is common in multimodal biometrics. A Fisher-discriminant-analysis-based method has also been proposed for integrating multiple views in but it is also similar to MKL with kernel Fisher Discriminant analysis as the base learner.

In recent years, theories of sparse representation (SR) and compressed sensing (CS) have emerged as powerful tools for efficient processing of data in nontraditional ways [10]. This has led to a resurgence in interest in the principles of SR and CS for biometrics recognition . Wright et al. [11] proposed the seminal sparse representation-based classification (SRC) algorithm for face recognition. It was shown that by exploiting the inherent sparsity of data, one can obtain improved recognition performance over traditional methods especially when data are contaminated by various artifacts such as illumination variations, disguise, occlusion, and random pixel corruption. Pillai et al. [10] extended this work for robust cancelable iris recognition. Nagesh and Li [11] presented an expression-invariant face recognition method using distributed CS and joint sparsity models. Patel et al. [12] proposed a dictionary-based method for face recognition under varying pose and illumination. A discriminative dictionary learning method for face recognition was also proposed by Zhang and Li [12]. For a survey of applications of SR and CS algorithms to biometric recognition, see [14], [15] and the references therein.

Motivated by the success of SR in unimodal biometric recognition, we propose a joint sparsity-based algorithm for multimodal biometrics recognition. It is based on the well-known regularized regression method, multitask multivariate Lasso.The proposed method imposes common sparsities both within each biometric modality and across different modalities. The idea of joint sparsity has been explored recently for image classification and segmentation . However, our method is different from these previously proposed algorithms based on joint sparse representation for classification. For example, Yuan and Yan proposed a multitask sparse linear regression model for image classification. This method uses group sparsity to combine different features of an object for classification. Zhang et al. [16] proposed a joint dynamic sparse representation model for object recognition. Their essential goal was to recognize the same object viewed from multiple observations, i.e., different poses. Our method is more general in that it can deal with both multimodal as well as multivariate sparse representations.

This paper makes the following contributions:

- We present a robust feature level fusion algorithm for multibiometric recognition. Through the proposed joint sparse framework, we can easily handle unequal dimensions from different modalities by forcing the different features to interact through their sparse coefficients. Furthermore, the proposed algorithm can efficiently handle large dimensional feature vectors.
- We make the classification robust to occlusion and noise by introducing an error term in the optimization framework.
- The algorithm is easily generalizable to handle multiple test inputs from a modality.
- We introduce a quality measure for multimodal fusion based on the joint sparse representation.
- We kernelize the algorithm to handle nonlinearity in the data samples.

A preliminary version of this work appeared in [15], which describes just the linear version of the algorithm, robust to noise and occlusion. Furthermore, extensive experimental evaluations are presented here.

A. Paper Organization

The paper is organized as follows: In Section 2, we describe the proposed sparsity-based multimodal recognition algorithm, which is kernelized in Section 4. The quality measure is described in Section 3. Experimental evaluations on a comprehensive multimodal data set and a face database are described in Section 5. Finally, in Section 6, we discuss the computational complexity of the method. Concluding remarks are presented in Section 7.

II. JOINT SPARSITY-BASED MULTIMODAL BIOMETRICS RECOGNITION

Consider a multimodal C-class classification problem with D different biometric traits. We propose to exploit the joint sparsity of coefficients from different biometric modalities to make a joint decision. To simplify this model, let us consider a bimodal classification problem In this section, we consider a more general problem where the data are contaminated by noise. In this case, the observation model can be modelled. The optimization problem (5) is convex but difficult to solve due to the joint sparsity constraint. In this section, we present an approach based on the classical alternating direction method of multipliers (ADMM) [13], [14] to solve (5). Note that the optimization problem (1) can be solved by setting _2 equal to infinity.

III. QUALITY-BASED FUSION

Biometric quality assessment is an active field of research [13], with many quality assessment algorithms proposed such as [14]–[16]. Recent efforts have also been focused on the standardization of biometric quality information and its incorporation to biometric data structures [14]. In biometric systems working in verification mode, several steps are typically performed once a signal has been acquired:

1) preprocessing, in which the input signal is enhanced to simplify subsequent steps;

2) feature extraction, in which we further process the signal to generate a discriminative and compact representation;

3) matching, where the feature representation of the input biometric signal is compared against the template corresponding to the claimed identity that is stored in the system database, resulting in a similarity or matching score; and

4) decision, where the score is compared to a decision threshold in order to accept or reject the input identity claim. In multibiometric systems working at the matching score level, the output score is further combined with scores from other systems in a fusion stage to generate a new matching score that is then used for recognition. Prior to the fusion, the scores can be transformed to a common domain through a normalization step [12].

There are several roles regarding a quality measure in the context of biometric systems: 1) monitoring tool in order to accumulate statistics of the system (e.g., to identify sources experiencing problems); 2) to recapture a sample not having enough quality; and 3) to switch between different processing blocks of the system (qualitybased conditional processing. Since the work presented here falls in the last category, only related work in this domain will be covered next.
In this paper, we propose a score fusion approach that presents advantages over other methods when signals originate from heterogeneous biometric sources. We adopt a probabilistic Bayesian framework, presenting two stages. First, the similarity scores of each modality are mapped to a probabilistic loglikelihood-ratio via a procedure known as calibration. Second, the calibrated scores, interpretable as log-likelihoodratios, are summed. The whole process is represented in Fig. 2, and both steps are described below. Quality-based conditional processing is performed in: 1) the normalization stage using different calibration functions depending on the device used for query acquisition, which is estimated from quality signals; and 2) the fusion stage, discarding scores which come from lowquality sources.

IV. KERNEL SPACE MULTIMODAL BIOMETRICS RECOGNITION

The class identities in the multibiometric data set may not be linearly separable. Hence, we also extend the sparse multimodal fusion framework to kernel space. The kernel function is the inner product is an implicit mapping projecting the vector x into a higher dimensional space. We evaluated our algorithm on two publicly available data sets—the WVU multimodal data set and the AR face data set [14]. In the first experiment, we tested on the WVU data set, which is one of the few publicly available data sets that allows fusion at the image level. It is a challenging data set consisting of samples from different biometric modalities for each subject.
we show the applicability of the proposed approach to fusing information from weak biometrics extracted from face images. In particular, the periocular region has been shown to be a useful biometric [17]. Similarly, the nose region has also been explored as a biometric . Sinha et al. [16] have demonstrated that eyebrows are important for face recognition. However, each of these subregions may not be as discriminative as the whole face. The challenge for fusion algorithms is to be able to combine these weak modalities with a strong modality based on the whole face. We demonstrate how our framework can be extended to address this problem. Furthermore, we also show the effects of noise and occlusion on the performance of different algorithms. In all the experiments, Bi was set to be identity for convenience, i.e., we assume background noise to be sparse in the image domain.

V. CONCLUSIONS

As biometric technology is increasingly deployed, it will be a common situation to replace parts of operational systems with newer designs and/or to operate with information from different sources. a novel joint sparsity-based feature level fusion algorithm for multimodal biometrics recognition. The algorithm is robust as it explicitly includes both noise and occlusion terms. An efficient algorithm based on the alternative direction was proposed for solving the optimization problem. We also proposed a multimodal quality measure based on sparse representation. Furthermore, the algorithm was kernelized to handle nonlinear variations. Various experiments have shown that the method is robust and significantly improves the overall recognition accuracy. However, it has not been addressed yet for the general multimodal setting. This is a challenging problem, and can be investigated as a future direction to this paper.

REFERENCES

[1] A. Ross, K. Nandakumar, and A.K. Jain, Handbook of Multibiometrics. Springer, 2006.
[2] A. Ross and A.K. Jain, "Multimodal Biometrics: An Overview," Proc. European Signal Processing Conf., pp. 1221-1224, Sept. 2004.
[3] P. Krishnasamy, S. Belongie, and D. Kriegman, "Wet Fingerprint Recognition: Challenges and Opportunities," Proc. Int'l Joint Conf. Biometrics, pp. 1-7, Oct. 2011.
[4] A. Klausner, A. Tengg, and B. Rinner, "Vehicle Classification on Multi-Sensor Smart Cameras Using Feature- and Decision-Fusion," Proc. IEEE Conf. Distributed Smart Cameras, pp. 67-74, Sept. 2007.
[5] A. Rattani, D. Kisku, M. Bicego, and M. Tistarelli, "Feature Level Fusion of Face and Fingerprint Biometrics," Proc. IEEE Int'l Conf. Biometrics: Theory, Applications, and Systems, pp. 1-6, Sept. 2007.
[6] Sangramsing Kayte, Suvarnsing G.Bhable and Jaypalsing Kayte, "A Review Paper on Multimodal Biometrics System using Fingerprint and Signature". IJCA Volume 128 – No.15, October 2015.
[7] V.M. Patel and R. Chellappa, "Sparse Representations, Compressive Sensing and Dictionaries for Pattern Recognition," Proc. Asian Conf. Pattern Recognition, pp. 325-329, Nov. 2011.
[8] J.K. Pillai, V.M. Patel, R. Chellappa, and N.K. Ratha, "Secure and Robust Iris Recognition Using Random Projections and Sparse Representations," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 33, no 9, pp. 1877-1893, Sept. 2011.
[9] X.-T. Yuan and S. Yan, "Visual Classification with Multi-Task Joint Sparse Representation," Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 3493-3500, June 2010.
[10] S.S.S. Crihalmeanu, A. Ross, and L. Hornak, "A Protocol for Multibiometric Data Acquisition, Storage and Dissemination," technical report, Lane Dept. of Computer Science and Electrical Eng., West Virginia Univ., 2007.
[11] A. Martnez and R. Benavente, "The AR Face Database," CVC technical report, June 1998.
[12] A. Moorhouse, A. Evans, G. Atkinson, J. Sun, and M. Smith, "The Nose on Your Face May Not Be So Plain: Using the Nose as a Biometric," Proc. Int'l Conf. Crime Detection and Prevention, pp. 1-6, Dec. 2009.

[13] C.J. Burges, “A Tutorial on Support Vector Machines for Pattern Recognition,” Data Mining and Knowledge Discovery, vol. 2, pp. 121- 167, June 1998.

[14] A. Rakotomamonjy, F. Bach, S. Canu, and Y. Grandvalet, “SimpleMKL,” J. Machine Learning Research, vol. 9, pp. 2491-2521, 2008.

[15] R. Bolle, J. Connell, S. Pankanti, N. Ratha, and A. Senior, “The Relation between the ROC Curve and the CMC,” Proc. Fourth IEEE Workshop Automatic Identification Advanced Technologies, pp. 15-20, 2005.

[16] K. Nandakumar, Y. Chen, S. Dass, and A. Jain, “Likelihood Ratio- Based Biometric Score Fusion,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 30, no. 2, pp. 342-347, Feb. 2008.

[17] M. Elad, Sparse and Redundant Representations. Springer, 2010.

© 2015, IJARCSSE All Rights Reserved