International Journal of Innovative Research in Advanced Engineering (IJIRAE) ISSN: 2349-2163
Issue 4, Volume 2 (April 2015) www.ijirae.com

A Review of Robust Multimodal Biometric Recognition using Joint Sparse Representation

Kalyan K. Pattekar*
PG Scholar, Dept. of CSE, GCOE, Aurangabad.

Urmila M. Sawant
PG Scholar, Dept. of CSE, GCOE, Aurangabad.

Prof. S. D. Sapkal
Asst. Professor, Dept. of CSE, GCOE, Aurangabad.

Dr. R. R. Deshmukh
Professor, Dept. of CSIT, Dr. BAMU, Aurangabad.

Abstract*— Conventional biometric recognition frameworks depend on a solitary biometric signature for validation. While the playing point of utilizing various wellsprings of data for making the identity has been generally perceived, computational models for multimodal biometrics recognition have just recently got consideration. So we review here a multimodal inadequate representation system, which speaks to the test information by a scanty straight mixture of preparing information, while obliging the perceptions from distinctive modalities of the test subject to impart their meager representations. Concurrently, we consider relationships and additionally coupling data among biometric modalities. We also review a multimodal quality measure for weighing every modality as it gets combined. An algorithm based on alternative direction technique is used to solve the optimization issue. Different investigations demonstrate that this technique contrasts positively and contending combination based techniques.

***Keywords*— Multimodal biometrics, feature fusion, sparse representation.**

I. INTRODUCTION

Biometric recognition refers to the use of distinctive physiological (e.g. fingerprints, face, retina, iris) and behavioral (e.g. gait, signature) characteristics, called biometric identifiers (or simply biometrics) for automatically recognizing individuals. The biometric system which uses a single biometric trait for identifying an individual based on his physiological or behavioral characteristic is called as unimodal biometric system. It depends on a single source of biometric trait for authentication purpose [2]. In some situations, these systems are not able to provide the ideal performance and have to deal with some limitations like noise in sensed data, distinctiveness, nonuniversality, intraclass variations, spoof attacks [3]. These limitations can be overcome by forming multimodal biometric system which combines the information from multiple biometric traits like iris, fingerprints, and face. In multimodal biometric system, it is difficult for an imposter to simultaneously spoof multiple biometric traits of a genuine user and therefore such systems are less vulnerable to spoof attacks.

Information fusion from multiple biometric traits can be done at three different levels, feature level fusion, score level fusion, rank/decision level fusion. The feature level fusion strategy preserves maximum information of multiple biometric traits and therefore it can be more discriminative than score or decision level fusion. Many times the features extracted from multiple biometric traits have large dimensions, therefore fusion at feature level becomes hard. A feature concatenation technique has been used for different multibiometric settings [4], [5], [6]. It may not be efficient and robust for high-dimensional feature vectors. Theories of sparse representation (SR) are used for efficient processing of data in non-traditional manner [7]. This method uses the sparse representation for the fusion of extracted biometric features [1].

II. LITERATURE REVIEW

The seminal sparse representation based classification (SRC) algorithm for face recognition was proposed by Wright et al. [8]. With the use of inherent sparity of data, the recognition performance of this system is more than traditional methods especially when data are contaminated by various artifacts such as illumination variations, occlusion, disguise, and random pixel corruption. This work was extended by Pillai et al. [9] for robust cancelable iris recognition. Nagesh and Li [10] proposed an expression invariant face recognition technique using distributed CS and joint sparity models. A dictionary based method for face recognition under changing pose and illumination was proposed by Patel et al. [11]. Zhang and Li [12] proposed a discriminative dictionary learning technique.

The sparse representation can be viewed as a linear combination of a few related training samples to represent and classify test samples. The linear combination is a weighted sum of all training samples, in which some training samples have zero coefficients and only small fraction of entries are nonzero. This representation is discriminative naturally, as it could select the subset of base vectors which express the most concentrated input signal and automatically reject other less concentrated representations. Therefore, we can exploit sparse representation to perform classification task.

The theory of joint sparity has been analyzed recently for image classification. Zhang et al. [13] presented a joint dynamic sparse representation technique for object recognition. Yuan and Yan [14] presented a multitask sparse linear regression technique for image classification. In this technique, various features of an object are combined by using group sparity for classification. It has proved that the joint representation of multi-features is very helpful for classification. These techniques were used to recognize the same object viewed from multiple perceptions, i.e., different poses.

III. THE JOINT SPARITY BASED MULTIMODAL BIOMETRICS RECOGNITION

In this paper, we present an overview of joint sparity based multimodal biometric recognition as shown in fig. 1. This technique deals with multimodal and multivariate sparse representations.

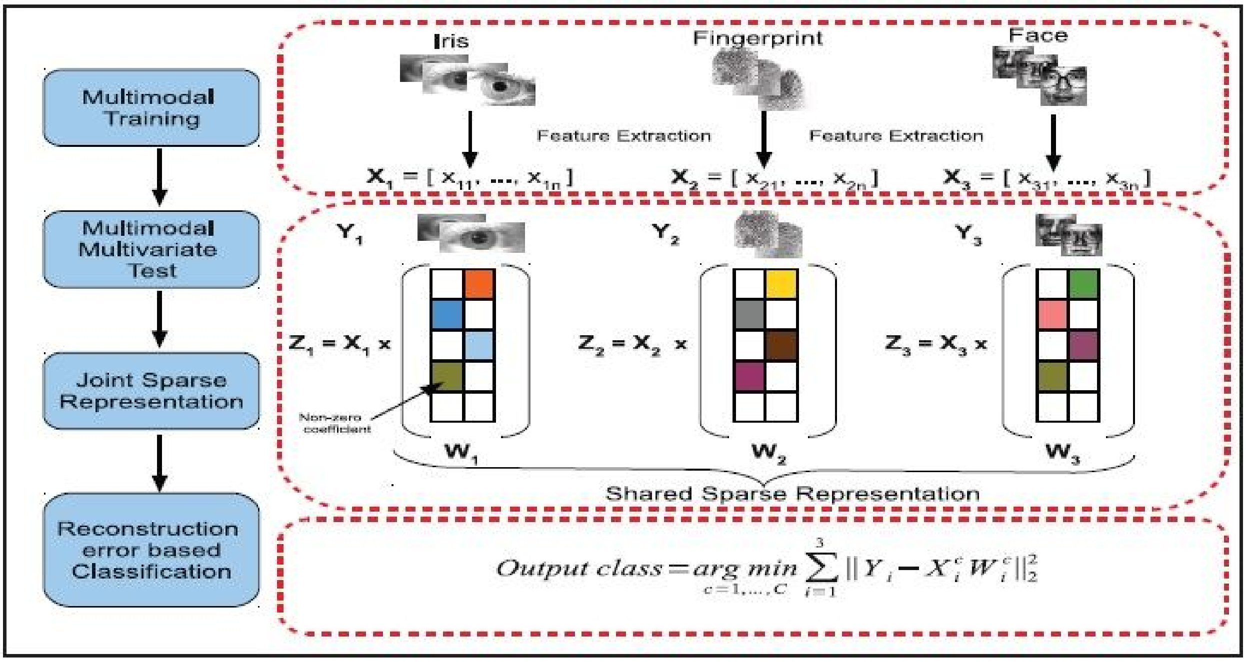

Fig. 1. Overview of Joint Sparity Based Multimodal Biometric Recognition.

This technique describes the test information by a scanty straight mixture of preparing information, while obliging the perceptions from distinctive modalities of the test subject to impart their sparse representations.

This technique describes the feature level fusion of multimodal biometric traits e.g. iris, fingerprint, and face. By using this joint sparse technique, the unequal dimensions from these three modalities are handled by forcing the different features to interact through their sparse coefficients. It also handles the large dimensional feature vectors.

In multimodal biometrics recognition problem, given test samples Y, which consists of D distinct modalities $\{Y^1, Y^2 \dots, Y^D\}$, where each sample Y^i consists of d_i perceptions $Y_j^i = [Y^i{}_1\, Y^i{}_2 \dots, Y^i{}_{d_i}] \in IR^{n_i \times d_i}$, here the objective is to identify the class to which a test sample Y belongs to.

A. Multimodal Multivariate Sparse Representation

It is not constrained that the number of samples per modality to be the same, as it is considered in forming training matrix. This problem is addressed by a multimodal multivariate sparse representation based algorithm [15], [16], [17].

B. Robust Multimodal Multivariate Sparse Representation

The robustness of the system needs to be measured when data contains noise. By introducing an error term in the optimization framework, the classification will be robust to occlusion and noise.

C. Optimization Algorithm

It is not easy to make the system fully effective due to the joint sparity constraint. The alternating direction method of multipliers (ADMM) [18], [19] is used to solve the optimization problem. The sparse multimodal biometrics recognition technique (SMBR) is used which takes into account the sparse error.

IV. QUALITY-BASED FUSION

In multimodal biometric fusion, more importance should give to the more reliable modalities. Therefore the quality measure of biometric trait is important in multimodal biometric fusion. A quality measure based on sparse representation was presented in [8]. To check the quality of biometric traits which are being combined, a sparse concentration index (SCI) is calculated. The value of SCI decides whether a given test sample is of good quality. The test samples with SCI close to 1 are of high quality and with SCI close to 0 are of poor quality.

V. CONCLUSION AND FUTURE SCOPE

In this paper, we reviewed robust multimodal biometric recognition based on the joint sparse representation. The method is robust as it incorporates both noise and occlusion terms. The optimization problem can be solved by using efficient algorithm based on alternative direction. A multimodal quality measure can be used to measure the quality of biometric traits which are being combined. This method is robust and significantly improves the overall recognition accuracy.

Biometrics is a promising field for providing the security for confidential data. Among all biometrics, retina is one of the most popular biometric trait. If retina is cumulatively combined with the modalities, the system can have a better robustness and performance.

REFERENCES

[1] Sumit Shekhar, Vishal M. Patel, Nasser M. Nasrabadi, and Rama Chellappa, “Joint Sparse Representation for Robust Multimodal Biometrics Recognition”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 36, no. 1, pp. 113-126, January 2014.
[2] A. Ross, K. Nandakumar, and A.K. Jain, “Handbook of Multibiometrics”, Springer, 2006.
[3] A. Ross and A.K. Jain, “Multimodal Biometrics: An Overview,” Proc. European Signal Processing Conf., pp. 1221-1224, Sept. 2004.
[4] 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.
[5] X. Zhou and B. Bhanu, “Feature Fusion of Face and Gait for Human Recognition at a Distance in Video,” Proc. Int’l Conf. Pattern Recognition, vol. 4, pp. 529-532, Aug. 2006.
[6] A.A. Ross and R. Govindarajan, “Feature Level Fusion of Hand and Face Biometrics,” Proc. SPIE, vol. 5779, pp. 196-204, Mar. 2005.
[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. Wright, A.Y. Yang, A. Ganesh, S.S. Sastry, and Y. Ma, “Robust Face Recognition via Sparse Representation,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 31, no. 2, pp. 210-227, Feb. 2009.
[9] 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.
[10]P. Nagesh and B. Li, “A Compressive Sensing Approach for Expression-Invariant Face Recognition,” Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 1518-1525, June 2009.
[11]V.M. Patel, T. Wu, S. Biswas, P. Phillips, and R. Chellappa, “Dictionary-Based Face Recognition under Variable Lighting and Pose,” IEEE Trans. Information Forensics and Security, vol. 7, no. 3, pp. 954-965, June 2012.
[12]Q. Zhang and B. Li, “Discriminative K-SVD for Dictionary Learning in Face Recognition,” Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 2691-2698, June 2010.
[13]H. Zhang, N.M. Nasrabadi, Y. Zhang, and T.S. Huang, “Multi-Observation Visual Recognition via Joint Dynamic Sparse Representation,” Proc.IEEE Int’l Conf. Computer Vision, pp. 595-602, Nov. 2011.
[14]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.
[15]M. Yuan and Y. Lin, “Model Selection and Estimation in Regression with Grouped Variables,” J. Royal Statistical Soc.: Series B, vol. 68, pp. 49- 67, Feb. 2006.
[16] L. Meier, S.V.D. Geer, and P. Bhlmann, “The Group Lasso for Logistic Regression,” J. Royal Statistical Soc.: Series B, vol. 70, pp. 53-71, Feb. 2008.

[17]N.H. Nguyen, N.M. Nasrabadi, and T.D. Tran, "Robust Multi-Sensor Classification via Joint Sparse Representation," Proc. Int'l Conf. Information Fusion, pp. 1-8, July 2011.
[18]J. Yang and Y. Zhang, "Alternating Direction Algorithms for l1 Problems in Compressive Sensing," SIAM J. Scientific Computing, vol. 33, pp.250-278, 2011.
[19]M. Afonso, J. Bioucas-Dias, and M. Figueiredo, "An Augmented Lagrangian Approach to the Constrained Optimization Formulation of Imaging Inverse Problems," IEEE Trans. Image Processing, vol. 20, no. 3, pp. 681-695, Mar. 2011.