International Journal of Ethics in Engineering & Management Education
Website: www.ijeee.in (ISSN: 2348-4748, Volume 2, Issue 6, June 2015)

Ordinal Feature Selection for IRIS and Palm print Recognition

Shaik Touseef Ahmad
Dept. of Electronics and Communication Engineering
SJB Institute of Technology, Bangalore
Touseef094@gmail.com

Sandesh Kumar B. V
Assistant professor
Dept. of Electronics and Communication Engineering
SJB Institute of Technology, Bangalore
sandeshkbv@sjbit.edu.in

***Abstract*— Ordinal measures have been demonstrated as an effective feature representation model for iris and palmprint recognition. However, ordinal measures are a general concept of image analysis and numerous variants with different parameter settings, such as location, scale, orientation, and so on, can be derived to construct a huge feature space. This paper proposes a novel optimization formulation for ordinal feature selection with successful applications to both iris and palmprint recognition. The objective function of the proposed feature selection method has two parts, i.e., misclassification error of intra and interclass matching samples and weighted sparsity of ordinal feature descriptors. Therefore, the feature selection aims to achieve an accurate and sparse representation of ordinal measures. And, the optimization subjects to a number of linear inequality constraints, which require that all intra and interclass matching pairs are well separated with a large margin. Ordinal feature selection is formulated as a linear programming (LP) problem so that a solution can be efficiently obtained even on a large-scale feature pool and training database. Extensive experimental results demonstrate that the proposed LP formulation is advantageous over existing feature selection methods, such as mRMR, ReliefF, Boosting, and Lasso for biometric recognition, reporting stateof-the-art accuracy on CASIA and PolyU databases.**

***Index Terms*—Iris, palmprint, ordinal measures, feature selection,linear programming**

I. INTRODUCTION

IRIS and palmprint texture patterns are accurate biometric modalities with successful applications for personal identification.The success of a texture biometric recognition system heavily depends on its feature analysis model, against which biometric images are encoded, compared and recognized by a computer. It is desirable to develop a feature analysis method which is ideally both discriminating and robust for iris and palmprint biometrics. On one hand, the biometric features of should have enough discriminating power to distinguish interclass samples. On the other hand, intra-class variations biometric patterns in uncontrolled conditions such as illumination changes, deformation, occlusions, pose/view changes, etc. should be minimized via robust feature analysis. Therefore it is a challenging problem to achieve a good balance between inter-class distinctiveness and intra-class robustness. Generally the problem of feature analysis can be divided into two sub-problems, i.e. feature representation and feature selection. Feature representation aims to computationally characterize the visual features of biometric images. Local image descriptors such as Gabor filters, Local Binary Patterns and ordinal measures are popular methods for feature representation of texture biometrics

II. RELATED WORK

Feature selection is a key problem in pattern recognition and has been extensively studied. However, finding an optimal feature subset is usually intractable and in most cases there are only solutions to suboptimal feature selection [6]. Since no generic feature selection methods are applicable to all problems, a number of feature selection methods have been proposed [7]–[13]. These methods employ different optimization functions and searching strategies for feature selection. For example, the criteria of Max-Dependency, Max-Relevance is used to formulate an optimization based feature selection method mRMR [11]. ReliefF is a simple yet efficient feature selection method suitable for problems with strong dependencies between features[12]. ReliefF has been regarded as one of the most successful strategies in feature selection because the key idea of the ReliefF is to estimate the quality of features according to how well their values distinguish between instances that are near to each other [12].

Most research works on feature selection mainly focus on generic pattern classification applications rather than specific applications in biometrics. This paper mainly addresses the efficient feature selection methods applicable to biometric authentication. Boosting [14] and Lasso have been proved as the well performed feature selection methods in face recognition. Boosting has become a popular approach used for both feature selection and classifier design in biometrics. Boosting algorithm aims to select a complementary ensemble of weak classifiers in a greedy manner. A reweighting strategy is applied for training samples to make sure that every selected weak classifier should have a good performance on the “hard” samples which cannot be well classified by the previously selected classifiers. Boosting has achieved good performance in visual biometrics, including both face detection and face recognition . However, boosting can not guarantee a globally optimal feature set and an overfitting result may be obtained if the training data is not well designed. Destrero et al. proposed a regularized machine learning method enforcing sparsity for feature selection of face biometrics based on Lasso regression The Lasso feature selection aims to solve the following penalized least-squares problem.

III. FEATURE SELECTION BASED ON LINEAR PROGRAMMING

The objective of feature selection for biometric recognition is to select a limited number of feature units from the candidate feature set (Fig. 2). In this paper, a feature unit is defined as the regional ordinal encoding result using a specific ordinal filter on a specific biometric region. We aim to use a machine learning technique to find the weights of all ordinal feature units. So that feature selection can also be regarded as a sparse representation method, i.e. most weight values are zero and only a compact set of feature units have the weighted Contribution to biometric recognition. The basic idea of the proposed feature selection method is to find a sparse representation of ordinal features on the condition of large margin principle. On one hand, the intra and inter-class biometric matching results are expected to be well separated with a large margin. On the other hand, the number of selected ordinal features should be much smaller than the large number of candidates. These two seemingly contradictory requirements are well integrated in our feature selection method.

IV. ORDINAL FEATURE SELECTION FOR IRIS RECOGNITION

Iris texture varies from region to region in terms of scale, orientation, shape of texture primitives, etc. So it is needed to use region specific ordinal filters to achieve the best performance. Therefore iris images are divided into multiple blocks and different types of ordinal filters with different parameter settings are applied on each image block. So that feature selection methods can be used to find the most effective set of image blocks with the most appropriate setting of parameters. In this paper, the preprocessed and normalized iris image is divided into multiple regions and a number of di-lobe and tri-lobe ordinal filters with variable scale, orientation and inter-lobe distance are performed on each region to generate 47,042 regional ordinal feature units.

Each feature unit, which is jointly determined by the spatial location of iris region and the corresponding ordinal filter, is constituted by 256 ordinal measures or 32 Bytes in feature encoding. The objective of feature selection is to select a limited number of OM feature units from the candidate feature set.

The experimental part of this paper aims to test and compare the proposed Linear Programming (LP) method with four feature selection methods for ordinal iris feature analysis,

All these feature selection methods used for selecting the effective set of ordinal measures are simply named as LP-OM, Boost-OM, Lasso-OM, mRMR-OM and ReliefF-OM respectively. There exist a number of variants of boosting, so we tried Adaboost and Gentleboost in experiments and found that Gentleboost performs slightly better than Adaboost. So Gentleboost is used in this paper to represent a typical category of feature selection methods based on Boosting. In this paper, three iris image datasets in CASIA Iris Image Database Version 4.0 (CASIA-IrisV4), namely CASIA-Iris-Thousand, CASIA-Iris-Lamp and CASIA Iris Interval, are used in the experiments.

To demonstrate the advantage of feature selection methods for visual biometrics, a randomly selected ordinal feature set with the same number of feature units is employed as the baseline algorithm. Such an ordinal feature representation method without feature selection is denoted as Random-OM. To demonstrate the benefit of feature selection in iris recognition, A number of hand-crafted parameter settings are tried for these two methods and the best results are reported in this paper. The idea of sparse representation of iris features has been recently proposed by Kumar, using L1 regularization. So the main feature selection method can be represented by Lasso-OM.

V. ORDINAL FEATURE SELECTION FOR PALMPRINT RECOGNITION

Palmprint provides a reliable source of information for automatic personal identification and has wide and important applications. This paper mainly focuses on feature analysis of palmprint biometrics. And the details of palmprint image preprocessing can be found in the existing publications. For palm print images, the gaps between neighboring fingers can be used as the landmark points for correction of the rotation and scale changes of palmprint images and then the central region can be cropped as the input of feaure analysis. In this paper, all palmprint images are normalized into a central ROI region with resolution 128×128. And then each ordinal filter is performed on the ROI to generate 32×32=1024 Bits (128 Bytes) ordinal code following the feature extraction routine of most state-of-the-art palmprint recognition algorithms [4], So if we select N ordinal filters for palmprint image analysis, the template size for each palmprint image is 128 N Bytes. Because of the difference between the texture primitives in iris and palmprint biometric patterns, we need to provide biometric modality specific ordinal filters as the input of feature selection.

VI. CONCLUSION

A number of conclusions can be drawn from the study.

• The identity information of visual biometric patterns comes from the unique structure of ordinal measures. The optimal setting of parameters in local ordinal descriptors varies from biometric modality to modality, subject to subject and even region to region. So it is impossible to develop a common set of ordinal filters to achieve the best performance for all visual

International Journal of Ethics in Engineering & Management Education
Website: www.ijeee.in (ISSN: 2348-4748, Volume 2, Issue 6, June 2015)

biometric patterns. Ideally it is better to select the optimal ordinal filters to encode individually specific ordinal measures via machine learning. However, such a personalized solution is inefficient in large-scale personal identification applications. So the task of this paper turns to a suboptimal solution, learning a common ordinal feature set for each biometric modality, which is expected to work well for most subjects.

• A main contribution of this paper is a novel optimization formulation for feature selection based on linear programming (LP). Our expectations on the feature selection results, i.e. an accurate and sparse ordinal feature set, can be described as a linear objective function. Such a linear learning model has three advantages. Firstly, it is simple to build, understand, learn and explain the feature selection model. Secondly, linear penalty term is robust against outliers. Thirdly, linear model only needs a small number of training samples to achieve a global optimization result with great generalization ability.

• Weighted sparsity is proposed in this paper and the results show that it performs better than traditional sparse representation methods. So it is better to incorporate prior information of candidate features into the optimization model in sparse learning.

REFERENCES

[1]. A. K. Jain, A. A. Ross, and K. Nandakumar, Introduction to Biometrics. New York, NY, USA: Springer-Verlag, 2011.
[2]. T. Tan and Z. Sun, “Ordinal representations for biometrics recognition,” in Proc. 15th Eur. Signal Process. Conf., 2007, pp. 35–39.
[3]. Z. Sun and T. Tan, “Ordinal measures for iris recognition,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 31, no. 12, pp. 2211–2226, Dec. 2009.
[4]. Z. Sun, T. Tan, Y. Wang, and S. Z. Li, “Ordinal palmprint representation for personal identification,” in Proc. Conf. Comput. Vis. Pattern Recognit. (CVPR), vol. 1. 2005, pp. 279–284.
[5]. Z. Chai, Z. Sun, H. Mendez-Vazquez, R. He, and T. Tan, “Gabor ordinal measures for face recognition,” IEEE Trans. Inf. Forensics Security, vol. 9, no. 1, pp. 14–26, Jan. 2014.
[6]. H. Liu and L. Yu, “Toward integrating feature selection algorithms for classification and clustering,” IEEE Trans. Knowl. Data Eng., vol. 17, no. 4, pp. 491–502, Apr. 2005.
[7]. L. Yu and H. Liu, “Efficient feature selection via analysis of relevance and redundancy,” J. Mach. Learn. Res., vol. 5, pp. 1205–1224, Oct. 2004.
[8]. M. A. Hall, “Correlation-based feature selection for discrete and numeric class machine learning,” in Proc. 17th Int. Conf. Mach. Learn., 2000, pp. 359–366.
[9]. S. Das, “Filters, wrappers and a boosting-based hybrid for feature selection,” in Proc. 18th Int. Conf. Mach. Learn., 2001, pp. 74–81.
[10]. Q. Song, J. Ni, and G. Wang, “A fast clustering-based feature subset selection algorithm for high-dimensional data,” IEEE Trans. Knowl. Data Eng., vol. 25, no. 1, pp. 1–14, Jan. 2013.
[11]. H. Peng, F. Long, and C. Ding, “Feature selection based on mutual information criteria of max-dependency, max-relevance, and minredundancy,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 8, pp. 1226–1238, Aug. 2005.
[12]. R.-S. Marko and K. Igor, “Theoretical and empirical analysis of ReliefF and RReliefF,” Mach. Learn. J., vol. 53, nos. 1–2, pp. 23–69, 2003.
[13]. G. Guo and C. R. Dyer, “Simultaneous feature selection and classifier training via linear programming: a case study for face expression recognition,” in Proc. Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2003, pp. 346–352.
[14]. P. Viola and M. Jones, “Robust real-time face detection,” Int. J. Comput. Vis., vol. 57, no. 2, pp. 137–154, May 2004.