

Analysis on Real-Time Multimodal Biometric Recognition Using Surf Feature

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ABSTRACT: Fusion of information plays an effective role in multimodal recognition systems. Fusion of image or information can occur at different levels. In this paper feature level image fusion is used. Fusion at the feature level involves the integration of feature sets corresponding to multiple modalities. Since the feature set contains richer information about the raw biometric data than the match score or the final decision, integration at this level is expected to provide better recognition results. Feature extraction can be performed by using SURF which is a local feature detector and descriptor that can be used for tasks such as object recognition. Here, two different combinations of multimodal biometrics systems are performed. One very important area of image processing, in which algorithms are used to detect and isolate various desired portions or shapes (features). This paper explores a comparison of two most popular algorithms. The algorithms are Joint Sparse Representation code (JSRC) and Multiple kernel learning (MKL). Feature fusion algorithms are applied to each multimodal biometric system individually and the performance of the system is analyzed. In this paper, a feature fusion technique is proposed that considers the class associations in feature sets, and the method was called as Discriminant correlation Technique (DCT), eliminates the between class correlation and restricts the correlations to be within classes.

KEYWORDS: *DCT, MKL, JSRC, Feature Extration*

I. INTRODUCTION

Biometrics is an automated method of identifying a person or verifying the identity of a person based on a physiological or behavioral characteristic. Examples of physiological characteristics include hand or finger images, facial characteristics. Biometric authentication requires comparing a registered or enrolled biometric sample (biometric template or identifier) against a newly captured biometric sample (for example, captured image during a login). During Enrolment a sample of the biometric trait is captured, processed by a computer, and stored for later comparison. Biometric recognition can be used in Identification mode, where the biometric system identifies a person from the entire enrolled population by searching a database for a match based solely on the biometric. Sometime identification is called "one-to-many" matching. A system can also be used in Verification mode, where the biometric system authenticates a person's claimed identity from their previously enrolled pattern. This is also called "one-to-one" matching. In most computer access or network access environments, verification mode would be used. Most of the real-world biometric systems, so-called unimodal, rely on the evidence of a single source of biometric information. Multimodal biometric systems, on the other hand, fuse multiple sources of biometrics information to make a more reliable recognition. Fusion of the biometrics information can occur at different stages of a recognition system. In case of Matching-score level fusion consolidates the scores generated by multiple classifiers pertaining to different modalities. In case of decision level fusion the final results of multiple classifiers are combined via techniques such as majority voting. Finally, Fusion at the feature level involves the integration of feature sets corresponding to multiple modalities. Since the feature set contains richer information about the raw biometric data than the match score or the final decision, integration at this level is expected to provide better recognition results.

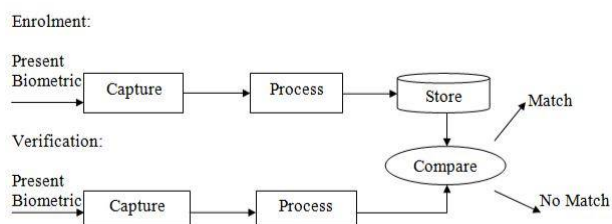


Figure1.1 Biometric Authentication Systems

II. FEATURE EXTRACTION & FEATURE FUSION

A. Feature extraction techniques

In pattern recognition and in image processing, feature extraction is a special form of dimensionality reduction. The main goal of feature extraction is to obtain the most relevant information from the original data and represent that information in a lower dimensionality space. Common feature extraction techniques include Histogram of oriented Gradients (HOG), Speeded Up robust features (SURF), Local Binary Patterns (LBP), Haar Wavelets and color histograms.

In computer Vision Speeded Up robust features (SURF) is a patented local feature detector and descriptor. It can be used for tasks such as object recognition, image registration, classification or 3D reconstruction. It is partly inspired by the scale-invariant feature transform (SIFT) descriptor. The standard version of SURF is several times faster than SIFT and more robust against different image transformations than SIFT. To detect interest points SURF uses an integer approximation of the determinant of Hessian blob detector, which can be computed with 3 integer operations using a precomputed integral image. This algorithm has three main parts: interest point detection, local neighborhood description and matching.

B. Feature level fusion using DCT(Discriminant Correlation Technique)

In case of feature level fusion, the data itself or the features extracted from multiple biometrics are fused. Matching-score level fusion consolidates the scores generated by multiple classifiers pertaining to different modalities. Finally, in case of decision level fusion the final results of multiple classifiers are combined via techniques such as majority voting.

Feature level fusion is believed to be more effective than the other levels of fusion because the feature set contains richer information about the input biometric data than the matching score or the output decision of a classifier. Therefore, fusion at the feature level is expected to provide better recognition results. However, matching-score level fusion and decision level fusion are more popular in the literature and there is not much research on feature level fusion. The reason is the difficulty of feature level fusion in cases where the features are not compatible, e.g., eigen-coefficients of faces and minutiae set of fingerprints, or when commercial biometric systems do not provide access to the feature sets (nor the raw data), which they use in their products. The goal of the feature fusion for recognition is to combine relevant information from two or more feature vectors into a single one, which is expected to be more discriminative than any of the input feature vectors.

In this paper, a feature fusion method that considers the class associations in feature sets is proposed and the method, called Discriminant Correlation Technique (DCT), eliminates the between-class correlations and restricts the correlations to be within classes. DCT has the characteristics of the CCA based methods in maximizing the correlation of corresponding features across the two feature sets and in addition de-correlates features that belong to different classes within each feature set.

III. EXPERIMENTAL RESULTS AND ANALYSIS

A. Recognition Algorithms(MKL and JSRC)

Multiple kernel learning refers to a set of machine

learning methods that use a predefined set of kernels and learn an optimal linear or non-linear combination of kernels as part of the algorithm. Reasons to use multiple kernel learning include a) the ability to select for an optimal kernel and parameters from a larger set of kernels, reducing bias due to kernel selection while allowing for more automated machine learning methods, and b) combining data from different sources (e.g. sound and images from a video) that have different notions of similarity and thus require different kernels. Instead of creating a new kernel, multiple kernel algorithms can be used to combine kernels already established for each individual data source.

Multiple kernel learning algorithms have been developed for supervised, semi-supervised, as well as unsupervised learning. Most work has been done on the supervised learning case with linear combinations of kernels, however, many algorithms have been developed. The basic idea behind multiple kernel learning algorithms is to add an extra parameter to the minimization problem of the learning algorithm. As an example, consider the case of supervised learning of a linear combination of a set of n kernels K . We introduce a new kernel, where β is a vector of coefficients for each kernel.

Algorithm

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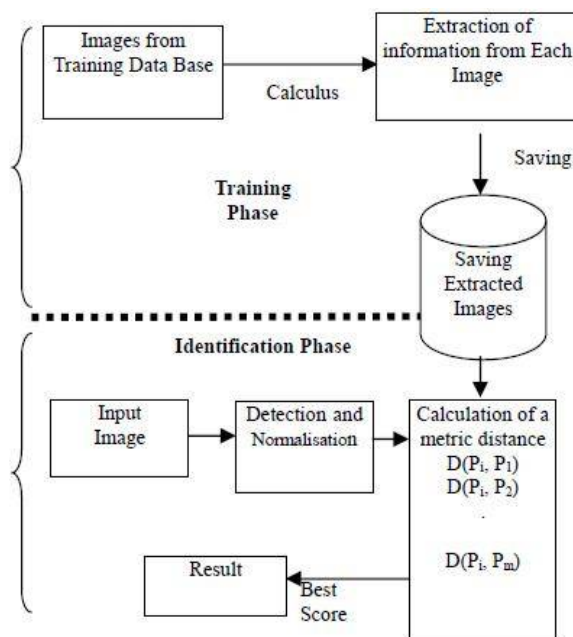


Fig. 2. Recognition Algorithm Stages.

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CLASSIFICATION BASED ON SPARSE REPRESENTATION

In recent years, theories of sparse representation (SR) and compressed sensing (CS) have emerged as powerful tools for efficient processing of data in non-traditional ways. This has led to resurgence in interest in the principles of SR and CS for biometrics recognition. Wright et al. 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. extended this work for robust cancelable iris recognition. Nagesh and Li presented an expression-invariant face recognition method using distributed CS and joint sparsity models. Patel et al. 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. For a survey of applications of SR and CS algorithms to biometric recognition, Motivated by the success of SR in unimodal biometric recognition, we propose a joint sparsity-based algorithm for multimodal biometrics recognition. Our work is based on the well-known regularized regression method. 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. 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. 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. Last, we kernelize the algorithm to handle nonlinearity in the data samples.

We evaluated our algorithm on two publicly available data sets—the WVU multimodal data set [35] and the AR face data set. 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.

WVU Dataset

The WVU multimodal data set is a comprehensive collection of different biometric modalities such as fingerprint, iris, palmprint, hand geometry, and voice from subjects of different age, gender, and ethnicity. It is a challenging data set, as many of these samples are corrupted with blur, occlusion, and sensor noise.

AR Face Dataset

The AR face dataset consists of faces with varying illumination, expression and occlusion conditions, captured in two sessions. We evaluated our algorithms on a set of 10 users. Images from the first session, 7 for each subject were used as training and the images from the second session, again 7 per subject, were used for testing. For testing the fusion algorithms, four weak modalities were extracted from the face images: left and right periocular, mouth and nose regions. This was done by applying rectangular masks as shown in Figure 9, and cropping out the respective regions. These, along with the whole face, were taken for fusion.

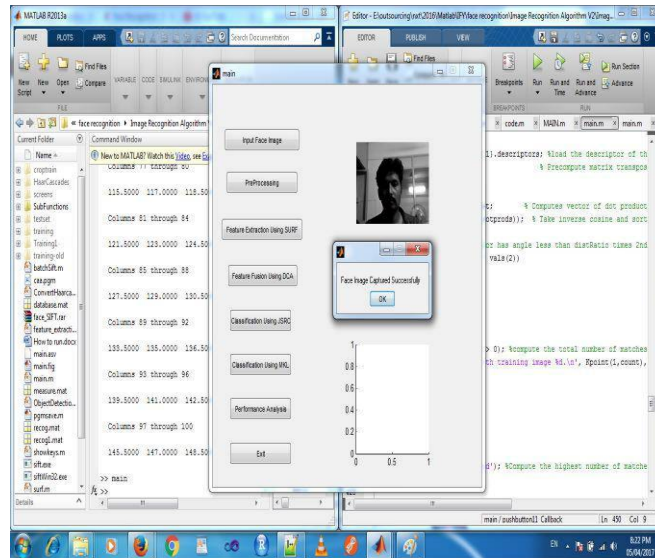


Fig 3: Capturing Face

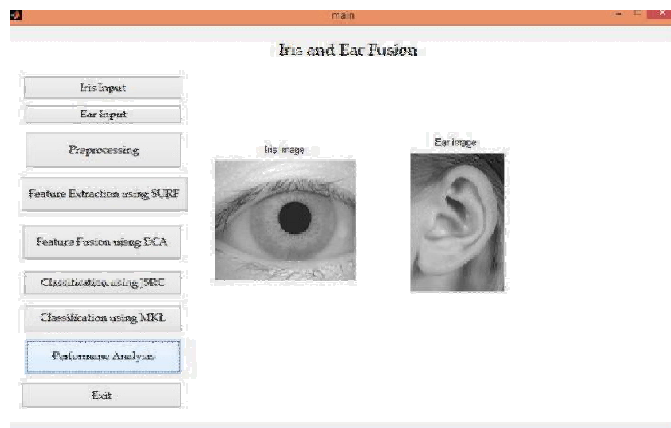
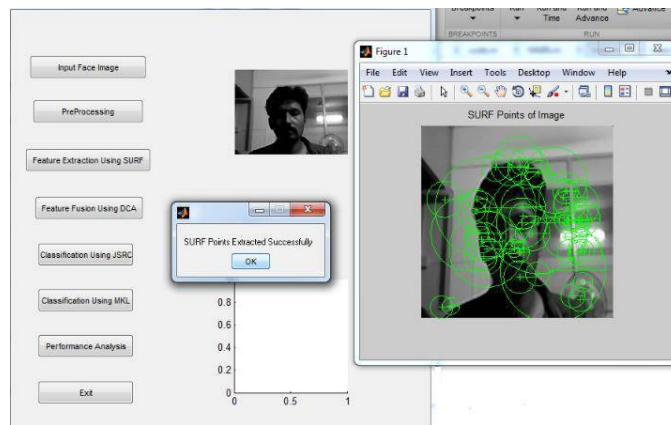


Fig 4: SURF Feature Extraction

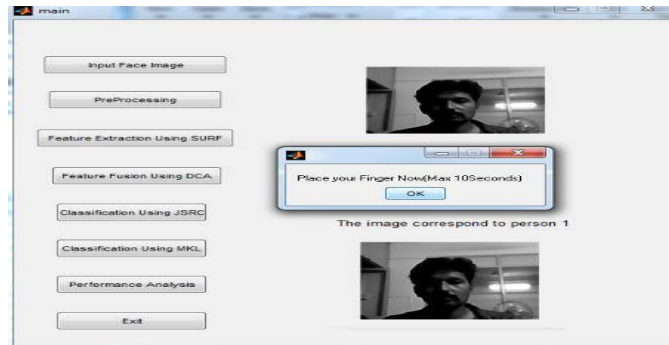


Fig 5: Combination of ear and iris

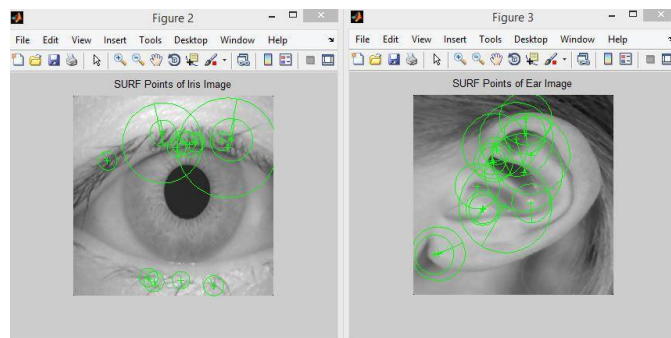


Fig 6: SURF Feature Extraction

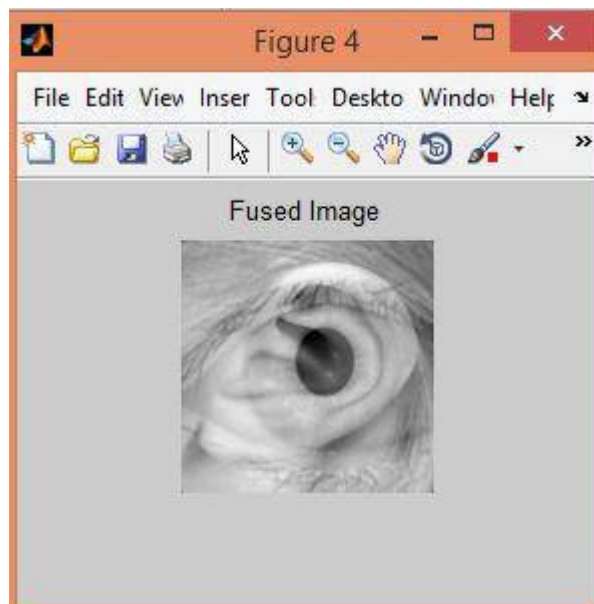


Fig 7: Fusion using DCT

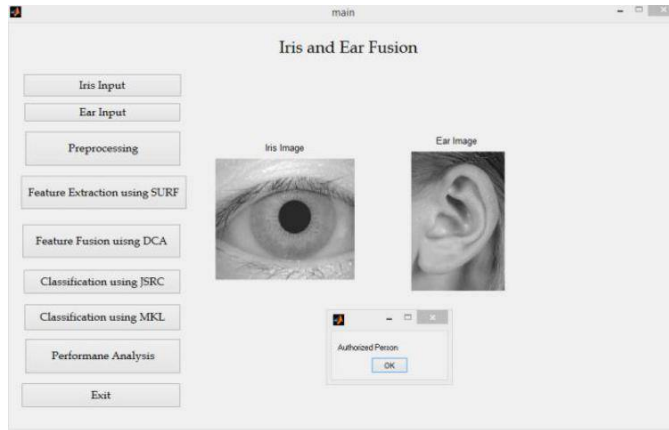


Fig 8: Result After matching Iris and Ear

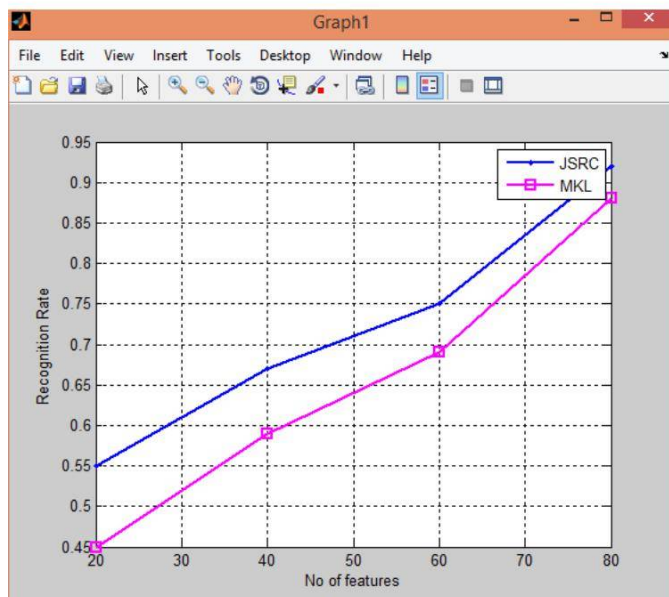


Fig 9: Analysis of JSRC and MKL

IV. CONCLUSION

In this paper, we presented a feature fusion technique based on correlation analysis of the feature sets. Our proposed method, called Discriminant Correlation Technique, contemplates the class associations of the samples in its analysis. It aims to find transformations that maximize the pair-wise correlations across the two feature sets and at the same time separate the classes within each set. These characteristics make DCT an effective feature fusion tool for pattern recognition applications. Experimental results demonstrated the efficacy of our proposed approach in fusion of multimodal feature sets or different feature sets extracted from a single modality. In addition, the DCT method is computationally efficient and can be employed in real-time applications.

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