Use of histogram distances in Iris Authentication

Seung-Seok Choi, Sungsoo Yoon, Sung-Hyuk Cha and Charles C. Tappert
Computer Science Department, Pace University
861 Bedford Road, Pleasantville, New York, 10570 USA
{scha, ctappert}@pace.edu

Abstract

Quantitatively establishing the discriminative power of iris biometric data is considered. Multi-level 2D wavelet transform has been widely used for iris verification system. While previous approaches compute only means and variances, we propose using a histogram distance. We also use a methodology to establish a measure of discrimination that is statistically inferable. To establish the inherent distinctness of the classes, i.e., validate individuality, we transform the many class problem into a dichotomy by using a "distance" between two samples of the same person and between those of two different peoples. We demonstrate that using histogram matching results better performances than using only means and variances.

Key Words: *Iris recognition, Dichotomy model, Histogram, Distance measure, Biometrics*

1. Introduction

In this paper, we present a dichotomy method to authenticate a person based on iris biometric, i.e., establishing a measure of discriminative power of iris that is statistically inferable. It is a method for measuring the reliability of classification of all classes based on information obtained from a small sample of classes drawn from the class population. In Dr. Cha' s dissertation work [2], supported by NIJ, he showed the individuality of handwriting using the distance statistics [3]. We extend the method used in [2-3] to the iris verification. Recently, Pankanti et al. employed the same model to establish the individuality of fingerprints [4].

Several methods for iris recognition have been proposed. However, most of them focused on using statistical features such as mean and variance as feature vectors. L. Ma et al. tried to extract more distinctive statistical features by using filtering process [14]. G.Kee et al. presented tree-structured wavelet transform in order to obtain mean and standard deviation, which are used as iris feature sets [15]. Mallat suggested that statistics obtained from wavelet decomposition be sufficient for presenting texture difference [16].

In this paper, we claim that they are not enough and take a different approach using histograms and distance measures. Histograms of three level of 2D wavelet transform are used as feature sets, which are transformed into histogram distance domain using distance computation [1] in order to utilize the dichotomy model [2,3]. Experiment results show that ordinal histogram distance measures are well fit as feature sets especially in biometric data such as iris images.

In the dichotomy model, we transform the many-class-problem into a dichotomy by using a "histogram distance" between two samples of the same class and between samples of two different classes. In this model, two patterns are categorized into one of only two classes; they are either from the same class or from the two different classes. Given two iris data samples, the feature distance between two samples is first computed. This feature distance value is used as data to be classified as positive (intra-variation, within person or identity) or negative (inter-variation, between different people or non-identity). We use the terms, intra-person distance and inter-person distances and the ⊕ and ∅ notations throughout the rest of this paper.

The rest of the paper is organized as follows. Section 2 introduces a statistically inferable approach to establish the individuality using the *dichotomy* model, showing the dichotomy transformation process. Section 3 shows wavelet transform as a method of feature extraction. Section 4 applies the new model to the problem of establishing the individuality of iris data using the histogram distances. Finally, section 5 draws some conclusion.

2. Dichotomy Model and Dichotomy Transformation

Consider the multiple class problem where the number of classes is small and one can observe many instances of each class. To show the individuality of the classes statistically, one can cluster the instances into classes and infer the separation to the entire population. It is an easy and valid method to establish the individuality as long as a substantial number of instances for each class are observable. However, consider the *many class problem* where the number of classes is too large to be observed, such as the population of a country. Many pattern identification problems and most of the forensic science applications mentioned above fall under the aegis of the many class problems. Although classification techniques that assume a fixed number of classes are not useful for establishing individuality in many class problems, most of the existing studies use the *identification* model of measuring the confusion matrix [5-11]. As the number of classes is enormously large and almost infinite, we shall demonstrate that this problem is seemingly insurmountable. To this end, we propose a *dichotomy model* that can handle the *many class problem*. In this section, we show how to transform a large *polychotomy* problem into a simple *dichotomy* problem, a classification problem that places a pattern in one of only two categories.

In the *dichotomy* model, we formally state the problem as follows: given two randomly selected biometric samples, the problem is to determine whether the two exemplars belong to the same person with two types of confusion error probabilities. Figure 1 depicts the whole process using the *dichotomy transformation*.

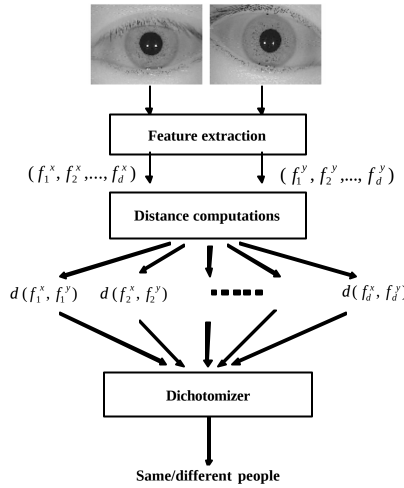
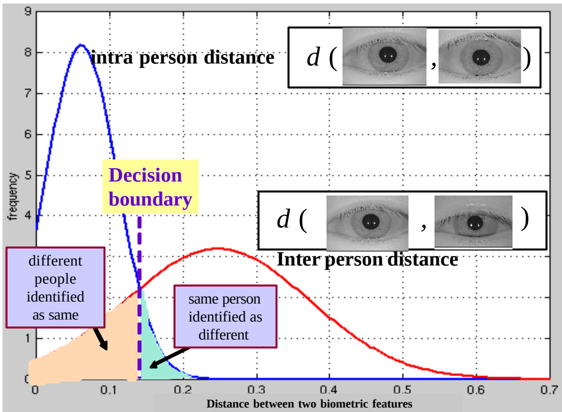


Figure 1. Iris verification process and dichotomy

Let f_i^j be the i^{th} feature of j^{th} biometric data. First, features are extracted from both biometric data *x* and *y*: $\{f_1^x, f_2^x, \cdots, f_d^x\}$ and $\{f_1^y, f_2^y, \cdots, f_d^y\}$. And then, each feature distance is computed, that is, feature domain transform into feature distance domain: $\{d(f_1^x, f_1^y), d(f_2^x, f_2^y) \cdots, d(f_d^x, f_d^y)\}$. d is absolute difference between two real values. The *dichotomizer* takes this feature distance vector as an input and outputs the decision, same or different people.

Figure 2 illustrates the two output distributions to represent the relationship between two classes. *Type I error*, a , occurs when the same person's biometric data are identified as coming from different people and *type II error*, b , occurs when the biometric data provided by two different people are identified as coming from the same person. *Type I error* is the probability of error that one classifies two biometric data as different people even though they belong to a same person. *Type II error* is the left-side area of the negative distributions, i.e., the probability of error that one classifies two biometric data as coming from the same person even though they belong to two different people.



(a)

Figure 2. Type I and II errors

In this model, the objective is to validate the individuality of biometric data statistically but not to detect the difference of particular instances. We are attempting to infer the individuality of the entire population based on the individuality of the sample of *n* people, where *n* is much less than the population. We claim that the *dichotomy* model is a sound and valid *inferential statistics* approach.

3. Feature extraction and distance computation

The proposed dichotomy transformation model requires first the extraction of features and then the application of suitable distance measures. 2D multiresolution wavelet transform is used to extract histogram features from a given modality. The hierarchical wavelet transform decompose the original iris image into a set of frequency windows that have narrower bandwidths in the lower frequency region [17].

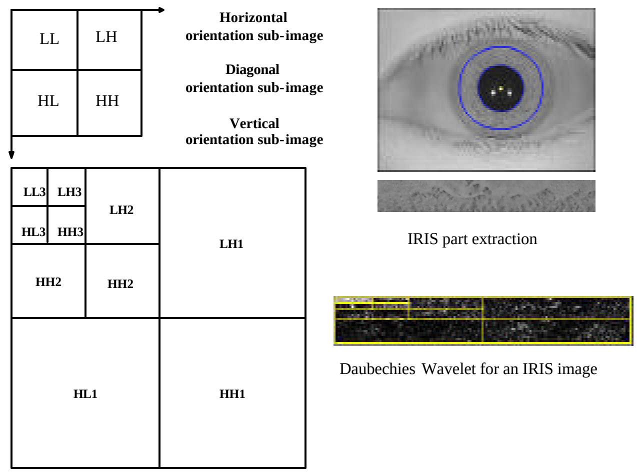


Figure 3 Three-level wavelet transform.

Decomposed images by using wavelet transform represent multiresolution from detailed images to approximation images in each level. As shown in Figure 3, LH, HL, HH represent detailed images for horizontal, vertical, and diagonal orientation respectively in one-level. Sub image LL corresponds to approximation image and is further decomposed, which results in two-level wavelet decomposition. The result of three-level decomposition is shown in below of Figure 3. The linear type of histogram is obtained as a feature vector from each decomposed sub image.

4. Experiments

In this section, we describe the specification of the IRS database consisting of subject demographic data and features obtained from an IRIS sample. From around 60 subjects, 800 IRIS images are taken. Each subject provided 6~24 exemplars. Thus, the IRIS database consists of two entities: subject data and IRIS feature data. Figure x. shows a few exemplars from the IRIS database. Age range is from 19 to 36. Iris images distinguish left or right eyes and whether the subject wears glasses or lens.

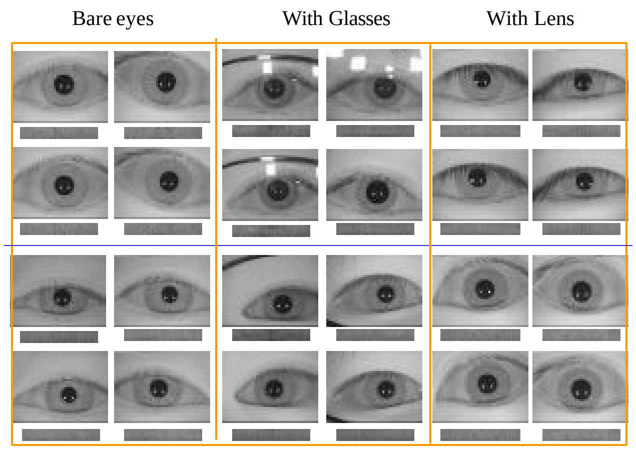


Figure 4 Samples from the IRIS database.

The 2D Daubechies wavelet transform technique is used to extract features from an IRIS image. Each iris image is decomposed into 3 levels and each sub-image is divided into 2x2 windows, which results in 12 different sub images and 12 linear type of histogram as feature sets. For each window, histogram distance is computed to convert feature domain into feature distance domain. Absolute vector difference is taken in order to build the within and between class distance vector. For the purpose of performance comparison, statistical features such as mean and variance of each wavelet image are also computed.

We use the ANN for a dichotomizer because it is equivalent to multivariate statistical analysis. There is a wealth of literature regarding a close relationship between neural networks and the techniques of statistical analysis, especially multivariate statistical analysis, which involves many variables [12, 13]. Samples of both classes are divided into 6 groups of 500 in size. One pair set is used as a training set and the other set is used as a validation set. The rest of them are used as testing sets. On average, 97% accuracy performance is achieved using the histogram distance as feature sets and the artificial neural network as a dichotomizer.

5. Conclusion

Although biometrics, e.g., such as face, voice, iris, etc, are widely used to identify a person, statistically inferable study, i.e., validating the individuality of each modality has not been done.

The *dichotomy* model is a sound and valid *inferential statistics* approach in which the multiple category identification problem is transformed into a two-category problem by defining a distance between two samples and taking those values as intra- and inter-person distance data. Therefore, dichotomy model with feature distance domain can be used to establish the discriminative power of a given set of features for any biometric domain. The 97% of performance shows that using histogram as a feature vector rather than statistical features such as mean and variance and its distance measurement are well suitable for biometric data such as iris data.

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