Biometrics Verification: a Literature Survey

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ABSTRACT
Biometric verification refers to an automatic verification of a person based on some specific biometric features derived from his/her physiological and/or behavioral characteristics. A biometric verification system has more capability to reliably distinguish between an authorized person and an imposter than the traditional systems that use a card or a password. In biometrics, a person could be recognized based on who he/she is rather than what he/she has (ID card) or what he/she knows (password). Currently, biometrics finds use in ATMs, computers, security installations, mobile phones, credit cards, health and social services. The future in biometrics seems to belong to the multimodal biometrics (a biometric system using more than one biometric feature) as a unimodal biometric system (biometric system using single biometric feature) has to contend with a number of problems. In this paper, a survey of some of the unimodal biometrics will be presented that are either currently in use across a range of environments or those still in limited use or under development, or still in the research realm.

Keywords: Biometrics, Unimodal Biometrics, Multimodal Biometrics, Verification, Identification, Recognition.

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1. INTRODUCTION

Human verification has traditionally been carried out by using a password and/or ID cards. These methods can be easily breached, for password can be guessed and ID card can be stolen, thus rendering them unreliable [Jain et al. 2006]. Biometrics refers to identifying a person based on his or her physiological or behavioral characteristics; it has the capability to reliably distinguish between an authorized person and an imposter. A biometrics system is a recognition system which operates by acquiring biometric data from an individual, extracting feature sets and comparing it with the template set in the database. Depending upon the application context, the identity of a person can be resolved in two ways: verification and identification. In the former, a person to be identified submits a claim; which is

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either accepted or rejected. In the latter, a person is identified without a person claiming to be identified. In literature, however, verification and identification are interchangeably used for biometrics recognition [Jain et al. 1997].

2. BIOMETRICS

There are many biometrics in use today and a range of biometrics that are still in the early stages of development. Biometrics can, therefore, be divided into two categories: those that are currently in use across a range of environments and those still in limited use or under development, or still in the research realm. Here we present literature survey for some of the biometrics of the two categories.

2.1. Biometrics Currently in Use across a Range of Environments

2.1.1. Fingerprint

Fingerprint is the pattern of ridges and valleys on the tip of a finger and is used for personal verification of people. Fingerprint based recognition method because of its relatively outstanding features of universality, permanence, uniqueness, accuracy and low cost has made it most popular and a reliable technique and is currently the leading biometric technology [Jain et al. 2004]. There is archaeological evidence that Assyrians and Chinese ancient civilizations have used fingerprints as a form of identification since 7000 to 6000 BC [Maltoni et al. 2003]. Henry Fauld in 1880 laid the scientific foundation of the modern fingerprint recognition by introducing minutiae feature for fingerprint matching [Maltoni et al. 2003]. Current fingerprint recognition techniques can be broadly classified as Minutiae-based, Ridge feature-based, Correlation-based [Jain and Prabhkar, 2001] and Gradient based [Aggarwal et al. 2008].

Most automatic fingerprint identification systems employ techniques based on minutiae points [Jain and Prabhkar, 2001]. Although the minutiae pattern of each finger is quite unique, noise and distortion during the acquisition of the fingerprint and errors in the minutiae extraction process result in a number of missing and spurious minutiae [Chikkerur et al. 2006]. To overcome the difficulty of reliably obtaining minutiae points from a poor quality fingerprint image, ridge feature-based method is used. A ridge is a pattern of lines on a finger tip. This method uses ridge features like the orientation and the frequency of ridges, ridge shape and texture information for fingerprint matching. However, the ridge feature-based methods suffer from their low discrimination capability [Maltoni et al. 2003]. The correlation-based techniques make two fingerprint images superimposed and do correlation (at the intensity level) between the corresponding pixels for different alignments. These techniques are highly sensitive to non-linear distortion, skin condition, different finger pressure and alignment [Yousiff et al. 2007]. Most of these techniques use minutiae for alignment first.

The smooth flow pattern of ridges and valleys in a fingerprint can be also viewed as an oriented texture [Jain and Prabhkar, 2001]. [Jain et al. 2000] describe a global texture descriptor called 'Finger Code' that utilizes both global and local ridge descriptions for an oriented texture such as fingerprints. A variation to this method is used by [Chikkerur et al. 2006] that use localized texture features of minutiae and another one by [Zhengu et al. 2006] that uses texture correlation matching. Further, [Aggarwal et al. 2008] proposed gradient based approach to capture textural information by dividing each minutiae neighbourhood locations into several local regions of which histograms of oriented gradients are then computed to characterize textural information around each minutiae location. Recently, [Jhat et al. 2011] proposed that Texture feature of Energy of a fingerprint can be used for effecting fingerprint verification.

Face

Face recognition for its easy use and non intrusion has made it one of the popular biometric [Chellappa, 1995]. A summary of the existing techniques for human face recognition can be found in [Chellappa et al. 1995; Zhao et al. 2003]. Further, a survey of existing face recognition technologies and challenges is given [Abate et al. 2007]. A number of algorithms have been proposed for face recognition. Such algorithms can be divided into two categories: geometric feature-based and appearance-based. Appearance-based methods include: Eigenfaces [Turk and Pentland, 1991], Fisherfaces [Belhumeur et al. 1997], Independent Component Analysis (ICA) [Bartlett et al. 2002], Kernel Principal Component Analysis (KPCA) [Scholkopf et al. 1999, Kim et al. 2002], Kernel Fisher Discriminant Analysis (KFDA) [Liu 2004, Yang 2002], General Discriminant Analysis (GDA) [Baudat and Anouar, 2000], Neural Networks [Lawrence et al. 1998], and Support Vector Machine (SVM) [Phillips, 1999; Jonsson et al. 2002].

An inherent drawback of appearance-based methods is that the recognition of a face under a particular lighting and pose can be performed reliably when the face has been previously seen under similar circumstances. Further, in appearance-based methods the captured features are global features of the face images and facial occlusion is often difficult to handle in these approaches. Geometric feature-based methods are robust against variations in illumination and viewpoints but very sensitive to feature extraction process. The geometry feature-based methods analyze explicit local facial features, and their geometric relationships. The geometry feature-based methods include: Active Shape Mode [Cootes et al. 1995; Yuille, 1991], Elastic Bunch Graph matching [Wiskott et al. 1997] and Local Feature Analysis (LFA) [Penev and Atick 1996].

Recognition of faces from still images or 2D images is a difficult problem, because the illumination, pose and expression changes in the images create great statistical differences and the identity of the face itself becomes shadowed by these factors. To overcome this problem 3D face recognition has been proposed which has the potential to overcome feature localization, pose and illumination problems, and it can be used in conjunction with 2D systems. Research using 3D face data to identify humans was first published by [Cartoux et al. 1989]. The 3D face data encodes the structure of the face and so is inherently robust to pose and illumination variations. Applying HMMs to 3D face verification was first attempted by [Achermann et al. 1997]. A recent advance for 3D face verification has been to show the applicability of the Gaussian Mixture Model (GMM) parts-based approach [Mccool et al. 2008]. The drawbacks of 3D face recognition include high cost and decreased ease-of-use for laser sensors, low accuracy for other acquisiton types, and the lack of sufficiently powerful algorithms.

Iris

The iris is a thin circular diaphragm, which lies between the cornea and the lens of the human eye. A survey on the current iris recognition technologies is available in [Bowyer et al. 2008]. [Flom and Ara, 1987] first proposed the concept of automated iris recognition. It was John Daugman who implemented a working automated iris recognition system [Daugman, 1993; Daugman, 2003]. Though Daugman's system is the most successful and most well known, many other systems have also been developed. An automatic segmentation algorithm based on the circular Hough transform is employed by [Wildes, 1997]. [Boles and Boashash, 1998] extracted iris features using a 1-D wavelet transform. [Sanchez-Avila and Sanchez-Reillo, 2002], further developed the iris representation method proposed by Boles et al. [Lim et al. 2001] extracted the iris feature using 2-D Haar wavelet transform and [Park et al. 2003] utilized directional filter banks to extract the normalized directional energy as a feature. [Kumar et al. 2003] employed correlation filters. Recently Ma et al. proposed two iris recognition methods, one using multi-channel Gabor filters [Ma et al. 2002] and the other using circular symmetric filters [Ma et al. 2002]. Later, they proposed an improved method based on characterizing key local variations with a particular class of wavelets, recording a position sequence of local sharp variation points in these signals as features [Ma et al. 2004]. Several other methods have also been developed for iris recognition. [Chen et al. 2006] proposed using Daugman's 2-D Gabor filter with quality measure enhancement. [Du et al. 2006] proposed using 1-D local texture patterns and [Sun et al. 2005] proposed using moment- based iris blob matching.

Hand geometry

Hand geometry refers to the geometric structure of the hand that is composed of the lengths of fingers, the widths of fingers, and the width of a palm, etc. The advantages of a hand geometry system are that it is a relatively simple method that can use low resolution images and provides high efficiency with great users' acceptance [Golfarelli et al. 1997, Jain et al. 1999]. A brief survey of reported systems for hand-geometry verification can be found in [Golfarelli et al. 1997;Jain et al. 1999; Sanchez-Reillo et al. 2000; Pavesic et al.]. An elaborate survey on hand geometry verification is given in [Dutan, 2009]. Geometrical features of the hand constitute the bulk of the hand features adopted in most of the hand recognition systems. One advantage is that geometrical features are more or less invariant to the global positioning of the hand and to the individual planar orientations of the fingers. Among numerous geometrical measures include lengths, widths, areas, and perimeters of the hand, fingers and the palm. [Jain et al. 1999], have shown that hand geometrical features solely are not sufficiently discriminative. Therefore, for more demanding applications one must revert to alternative features such as hand global shape, appearance and/or texture. [Jain et al. 1999] thus use 16 axes predetermined with the aid of five pegs. [Sanchez-Reillo et al. 2000] use a similar set of geometric features, containing the widths of the four fingers measured at different latitude, the lengths of the three fingers and the palm. [Wong and Shi, 2002], in addition to finger widths, lengths and interfinger baselines, employ the fingertip regions. [Bulatov et al. 2002] describe a peg-free system where 30 geometrical measures are extracted from the hand images. In addition to widths, perimeters and areas of the fingers, they also incorporate the radii of inscribing circles of the fingers.

The other approach in hand geometry verification is contour-based [Jain and Duta, 1999]. The contour is completely determined by the black-and-white image of the hand and can be derived from it by means of simple image-processing techniques. It can be modelled by features that capture more details of the shape of the hand than the standard geometrical features do. Accordingly, various techniques have been proposed to obtain and mathematically represent these hand features [Sanchez-Reillo, 2000; Alexandra et al. 2002]. Recently, [Yoruk et al. 2006] introduced a more accurate and detailed representation of the hand using the Hausdorff distance of the hand contour, and Independent Component Analysis (ICA).

Palmprint

Palmprint is the region between the wrist and fingers. Palmprint features like ridges, singular points, minutia points, principal lines, wrinkles and texture can used for personal verification [Shu and Zhang, 1998]. There are two types of palmprint verification systems: high resolution and low resolution. High resolution system employs high resolution images, while low resolution system employs low resolution images. In high resolution images, ridges, singular points and minutia points are used as features. In low resolution images, it is principal lines, wrinkles and texture that are used as features. Palmprint verification techniques can be mainly divided into four categories: (1) line based [Zhang and Zhang, 2004;Han et al. 2003;Lin et al. 2005;Wu et al. 2004;Wu et al. 2006;Liu and Zhang, 2005;Liu et al. 2007]; (2) texture based [Zhan et al. 2003, Kong et al. 2006]; (3) orientation based [Kong and Zhang, 2006, Kong et al. 2006]; and (4) appearance based [Wu et al. 2005; Connie et al. 2005;Lu et al. 2003;Wu et al. 2003; Ribaric and Fratric 2005;HU et al. 2007;Yang et al. 2007].

A line in a palmprint is its basic feature. Line based approaches, therefore, play an important role in palmprint verification. Zhang et al. used overcomplete wavelet expansion and directional context modeling technique to extract principal lines-like features [Zhang and Zhang, 2004]. Han et al. proposed using Sobel and morphological operations to extract the line like features from palmprint images [Han et al. 2003]. Lin et al. applied the hierarchical decomposition mechanism to extract principal palmprint features, which includes directional and multi-resolution decompositions [Lin et al. 2005]. Additionally, Wu et al. and Liu et al. proposed two different approaches based on palm lines in which the palm lines were regarded as a kind of roof edge, and extracted according to the zero-cross points of lines' first-order derivative and the magnitude of second derivative [Wu et al. 2004; Wu et al. 2006;Liu and Zhang, 2005;Liu et al. 2007]. The main approaches based on texture extract exploit 2-D Gabor filter [Zhang et al. 2003, Kong et al. 2006]. Zhang and Kong et al. proposed an approach based on texture called as PalmCode for palmprint verification, which exploit zero-crossing information on a palmprint image by using Gabor filter [Zhang et al. 2003]. Subsequently, Kong et al. used fusion rule at feature layer to further improve PalmCode, named as FusionCode [Kong et al. 2006].

Recently, orientation codes have been found to be most promising methods, since the orientation feature contains more discriminative power than other features, and is more robust for the change of illumination. Kong and Zhang were the first who investigated the orientation information of the palm lines for palmprint verification and their approach was defined as Competitive Code [Kong and Zhang, 2004, Kong et al. 2006]. Wu et al. proposed another approach based on orientation named as palmprint orientation code (POC) [Wu et al. 2005]. Moreover, some important appearance based approaches [Connie et al. 2005;Lu et al. 2003;Wu et al. 2003; Ribaric and Fratric 2005;Hu et al. 2007;Yang et al. 2007] include such methods as principal component analysis (PCA), independent component analysis (ICA), locality preserving projections (LPP), linear discriminant analysis (LDA), etc., have also been exploited for palmprint verification.

Speaker /voice

Speaker/voice verification combines physiological and behavioral factors to produce speech patterns that can be captured by speech processing technology. Inherent properties of the speaker like fundamental frequency, nasal tone, cadence, inflection etc. are used for speech authentication. Speaker recognition systems are classified as text-dependent (fixed-text) and text- independent (free-text). The text-dependent systems generally perform better than text-independent systems because of the foreknowledge of what is said can be exploited to align speech signals into more discriminant classes. The text-dependent systems, however, require a user to repronounce some specified utterances, usually containing the same text as the training data. A survey of text-dependent verification techniques is given in [H´ebert, 2008].

Text-dependent systems are also called Fixed Phrase Verification Systems, where a fixed phrase is used both during the training and the verification time and thus the Dynamic Time Wrapping (DTW) [Furui, 1981] approach has been mostly used for such systems. Nowadays, Text-dependent systems based on Hidden Markov Model (HMM) using Gaussian or multi-Gaussian distributions [BenZeghiba and Bourland, 2006] are more popular. In text independent speaker verification, the users are not restricted to any fixed or prompted phrases. They have the freedom to say whatever they want. To account for the expected freedom of utterances different methods have been proposed such as: Long-term statistics and multidimensional autoregressive [Montacie et al. 1992]; Vector quantization [Soong et al. 1997]; HMMs [Naik et al. 1989]; Artificial Neural Networks(ANN) [Farrell et al. 1994]; Gaussian Mixture Models (GMMs) [Reynolds and Rose 1995; Reynolds et al. 2000]; and SVM [Campbell et al. 2006]. The GMMs are the basis in most of the Speaker verification systems today. Recently, the combined GMM-SVM method [Djemili et al. 2007] has been shown to give gave slightly better results than the GMM method alone.

Signature

Handwritten signature is one of the first accepted civilian and forensic biometric verification technique in our society [Abuhaiba, 2007]. Human verification is normally very accurate in identifying genuine signatures. Signature verification systems use the distinctive behavioural features of a signature (such as speed, pressure and stroke order) to verify the identity of the user, as opposed to a simple physical crosscheck of one signature and another. The signature verification problem can be classified into two categories: offline and online. Off-line method identifies signatures using an image processing procedure whereby the user is supposed to have written down completely the signature onto a template that is later captured by a CCD camera or scanner to be processed. On-line signature verification involves the capturing of dynamic signature signals such as pressure of pen tips, time duration of whole signature and velocity along signature path. On-line systems use special input devices such as tablets, while off-line approaches are much more difficult because the only available information is a static two-dimensional image obtained by scanning pre-written signatures on a paper; the dynamic information of the pen-tip (stylus) movement such as pen-tip coordinates, pressure, velocity, acceleration, and pen-up and pen- down can be captured by a tablet in real time but not by an image scanner. The off-line method, therefore, needs to apply complex image processing techniques to segments and analyse signature shape for feature extraction. Hence, on-line signature verification is potentially more successful. Nevertheless, off-line systems have a significant advantage in that they do not require access to special processing devices when the signatures are produced. Types of signature verification, methods and performance evaluation can be found in [Plamondon and Lorette, 1989; Leclerc and Plamondon, 1994; Plamondon and Srihari, 2000]. Among the many offline signature verification techniques, HMM-based [Camino et al 1999;Fang et al. 2002], Fuzzy Logic [Hanmandlu et al. 2005; Ismail and Gad, 2000; Simon et al. 1997], Neural Networks (NNs) [Vélez et al. 2003], Neuro-fuzzy [Franke et al. 2002], Genetic Algorithms (GAs) [Ramesh AND Narasimha, 1999], Elastic Graph Matching [Fang et al. 2002], Dynamic Time Warping [Shanker and Tajagopalan, 2007], Optimal Displacements Functions [Muzukami et al. 2002] and Fuzzy Snake Model [Vélez José et al. 2009] are worth noting. Similarly for online signature verification, so far there have been many widely employed methods, for example, Artificial Neural Networks [Martens and Claesen 1996;Wu et al. 1997; KATONA et al. 1995], Dynamic Time Warping [Mautner et al. 2002;Rhee et al. 2001; Quan and Ji, 2005.], and the Hidden Markov Models [Nelson et al. 1994; Bourlard and Morgan, 1998].

2.2. Biometrics in Limited Use or Underdevelopment, or Still in the Research Realm

2.2.1. Earshape

It is known that the shape of the ear and the structure of the cartilegenous tissue of the pinna are distinctive. Although a newcomer in the biometrics field, ears have long been used as a means of human identification in the forensic field. A small literature on ear biometrics is given in [Pun and Moon, 2004; Yan and Bowyer, 2005]. A recent survey on ear biometrics has been provided by [Hurley et al. 2008]. Although ear recognition is a relatively new topic, researchers have already come up with various approaches which drastically differ from each other in terms of acquisition, raw data interpretation and feature extraction. Some of them hve been widely used in human verification, e.g. Principal Component Analysis PCA [Victor et al. 2002], Neural Networks [Carreira-Perpinan, 1995] and Force field transformation [Hurley et al. 2005].

Most ear biometric approaches have exploited the ear's planar shape. One of the first ear biometric works utilizing machine vision was introduced by [Burge and Burger, 1998] based on adjacency graph which was calculated from a Voronoi diagram of the ear curves. [Hurley et al. 2005] used force field feature extraction to map the ear to an energy field. The geometrical properties of ear curves have also been used for recognition [Choras, 2005; Iannarelli, 1989]. The most prominent example of these has been proposed by [Iannarelll, 1989], was based on measurements between a numbers of landmark points, determined manually. [Naseem et al. 2008] have proposed the use of sparse representation, following its successful application in face recognition. The 3D structure of the ear has also been exploited, and good results have been obtained [Yan and Bowyer 2007; Chen and Bhanu, 2007]. [Yan et al. 2007] captured 3D ear images using a range scanner and having segmented the ear, they used Iterative Closest Point (ICP) registration for recognition. [Chen et al. 2007] proposed a 3D ear detection and recognition system using a model ear for detection, and using a local surface descriptor and ICP for recognition. Though using 3D can improve the performance, using 2D images is consistent with deployment in surveillance or other planar image scenarios. In related studies [Akkermans et al. 2005] developed an ear biometric system based on the acoustic properties of the outer and middle ear.

2.2.2. Knuckle crease

The image pattern formation from the finger-knuckle bending is highly unique and makes this surface a distinctive biometric identifier [Woodard and Flynn, 2005]. [Woodard and Flynn, 2005] were the first to exploit the use of finger knuckle surface in biometric systems. However, their work did not provide a practical solution in establishing an efficient system using the outer fingers. Later, [Kumar and Ravikanth, 2007; Kumar and Ravikanth, 2009] proposed another approach to personal authentication using 2D finger-back surface imaging features. In Kumar's later work [Kumar and Zhou, 2009; Kumar and Zhou, 2009] used the robust line orientation code proposed in Jia et al. 2008 to extract the orientation of the finger-back surface images. Few works have also studied use of knuckle print texture on the fingers as a biometric characteristic for recognition. Li et al. 2003 used a hierarchical classification method to study knuckle print based on location and line features [LI et al. 2004]. In Ribaric and Fratric, 2005, principal Component Analysis was employed to project finger images into lower dimensional subspace. Apart from that, [Loris and Alessandra, 2009] also investigated knuckle features by fusing the knuckle print pattern from the middle and ring fingers. Recently, Kumar and Ravikanth, 200] has detailed the usage of finger knuckle surface for online user identification using combination of sub-space features.

2.2.3. Brain/EEG

Using elctroencephalogram (EEG) as a biometric is a new approach. Poulos et al, 1999 have proposed to model the EEG signal using autoregressive (AR) models and then using Kohonen's Vector Quantizer (VQ) for the classification. Paranjape et al, 2001 also proposed to represent the EEG signal using AR models, however, discriminant analysis is employed to perform the classification. Palaniappan and Ravi, 2003 further investigated features based on the spectral power of the signal together with a fuzzy Neural Network for the classification. More recently Gaussian Mixture Models and Maximum a Posteriori model adaptation has been proposed in S´ebastien, 2007.

2.2.4. Heart sound/ECG

The use the electrocardiogram (ECG) as a biometric has been found to give relatively high result for human recognition [Biel et al. 2001; Israel et al. 2005]. Israel et al, 2005 investigated the effect of the state of anxiety of an individual on its ECG features through a series of high and low stress tasks. Test results show that the features extracted from the ECG signal are unique to an individual and invariant to the individual state of anxiety. Israel et al, 2005 also found that the identification performance is independent of the electrode placements. However, ECG for identification is generally cumbersome due to the many electrodes required [Biel et al. 2001].

3. MULTIMODAL BIOMETRICS VERFICATION

Most of the biometric systems that are in use in practical application use a single piece of information for recognition and are as such called unimodal biometric systems. The unimodal biometric recognition systems, however, have to contend with a variety of problems like non-universality, susceptibility to spoofing, noise in sensed data, intra –class variations, inter-class similarities. Some limitations of the unimodal biometric systems can be alleviated by using multimodal system [Brunelli and Falavigna, 1995]. A biometric system that combines more than one sources of information for establishing human identity is called a multimodal biometric system. Combining the information cues from different biometric sources using an effective fusion scheme can significantly improve accuracy [Hong et al, 1999] of a biometric system.

The information fusion in multibiometrics can be done in different ways: fusion at the sensor level, feature extraction level, matching score level and decision level. Sensor level fusion is rarely used as fusion at this level requires that the data obtained from the different biometric sensors must be compatible, which is seldom the case. Fusion at the feature extraction level is not always possible as the feature sets used by different biometric modalities may either be inaccessible or incompatible. Fusion at the decision level is too rigid as only a limited amount of information is available. Fusion at the matching score level is , therefore, preferred due to presence of sufficient information content and the ease in accessing and combining match scores [Ross, 2007].

A number of works showing advantages of multimodal biometric verification systems have been reported in literature. Brunelli and Falavigna, 1995 have proposed personal identification system based on acoustic and visual features, where they use a HyperBF network as the best performing fusion module. Duc et al, 1997 proposed a simple averaging technique combining face and speech information. Kittler et al, 1998 have experimented with several fusion techniques using face and voice biometrics, including sum, product, minimum, median, and maximum rules and they have found that the best combination results are obtained for a simple sum rule. Hong and Jain, 1998 proposed a multimodal personal identification system which integrates face and fingerprints that complement each other. The fusion algorithm combines the scores from the different experts under statistically independence hypothesis. Ben-Yacoub et al, 1999 proposed several fusion approaches, such as Support Vector Machines (SVM), tree classifiers and multi-layer perceptrons, combining face and voice biometrics. Pigeon and Vandendorpe, 1998 proposed a multimodal person authentication approach based on simple fusion algorithms to combine the results coming from face and voice biometrics. Choudhury et al, 1999 proposed a multimodal person recognition using unconstrained audio and video and the combination of the two features is performed using a Bayes net. Ross and Jain, combine face, fingerprint and hand geometry biometrics combining them under sum, decision tree and linear discriminant- based method. The sum rule is reported to outperform others. Various other biometric combinations have been proposed [Jain et al. 2004; Chen and Chu, 2005; Nageshkumar et al. 2009] that report that combining more than one biometric modalities together result in improved performance than using them alone.

4. CONCLUSION

Biometrics refers to an automatic authentication of a person based on his physiological and/or behavioral characteristics. The usage of biometrics as a reliable means of authentication is currently gaining momentum, thou the industry is still evolving and emerging. The unimodal biometric recognition systems have to contend with a variety of problems and thus presently the amount of applications employing unimodal biometric systems is quite limited. Some limitations of the unimodal biometric systems can be alleviated by using multimodal biometric systems, which integrate information at various levels to improve performance. The future of biometrics can thus be envisaged to perhaps belong to multimodal biometric systems.

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