A Survey on Soft Biometric Techniques

D. Evangeline and A. Parkavi

Abstract It is well known that biometrics can be employed for person identification and is widely adopted in workplaces for attendance monitoring. In recent days, it is applied for criminal and victim identification through soft biometrics which does not possess universality and permanence factors like hard biometrics. This domain of soft biometrics is still in its infancy and needs lot of research directions as researchers are focusing on discovery of certain soft biometric traits, whose accuracy needs to be improved by application of relevant pre-processing techniques. In this paper, survey on such works has been done. Soft biometric traits like wrist, blood vessel patterns, vein patterns, androgenic hair, ear, periocular traits, skin texture, shape of body and certain skin marks are studied elaborately.

Keywords Soft biometrics · Ear · Periocular biometrics · Shape of body · Skin marks

1 Introduction

Biometrics is a means of identification of individuals through their behavior or features [1]. Biometrics is primarily used for authentication. There are many human biometric features like iris, face, palm-print, fingerprint, etc., To improve the accuracy of person identification, many such physiological biometric features can be combined and multi-modal biometric system can be adopted. Behavioral biometrics like gait, speech, etc., has caught the attention of researchers today. All such biometric information from an individual are captured by biometric systems and features are extracted from the biometric image and those features are compared against the templates stored in database [2]. Eventually, the results of comparison can establish

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the identity of individual. Apart from person recognition, deductions of attributes like age, gender, height, weight, BMI, etc., are also possible. The biometric factors are defined by the following characteristics: universality, uniqueness, permanence, collectability, performance, acceptability and circumvention [3]. These characteristics are considered when opting for any biometric system. The other challenge that any traditional biometric trait faces is dealing with occlusions. Mask, scarf, hat, makeup, etc., are some of the occlusions to be dealt in face recognition [4]. When it comes to retina or iris, the occlusions may occur with glasses and lenses. In case of palm-print or fingerprint, it may be some cuts or bruises.

2 Taxonomy

In general, the broad field of biometrics is classified into hard and soft biometrics. Hard biometrics is based on those features which adhere to the seven characteristics of biometrics. On the contrary, soft biometrics lacks uniqueness and permanence. Yet, they can be employed to identify an individual [5]. Soft biometrics can be formally defined as estimation or use of personal characteristics describable by humans that can be used to aid or effect person recognition [6]. Hence, it is evident that while hard biometric features in general can uniquely identify a person and is applicable for authentication, soft biometrics can be applied for victim and criminal identification. Recent studies have proved soft biometrics to be a successful technique to identify criminals in the mob, terrorists in the videos published by them and criminals and victims involved in pornography. But person identification from soft biometrics is very challenging since biometric images are captured in a controlled environment for hard biometric image acquisition, contrary to soft biometric images captured in ill-illuminated environments and the subjects also try to conceal their identity by covering up their faces with mask.

Taxonomy of biometrics is illustrated in Fig. 1. There are many biometric attributes based on which the traits are chosen. Physiological attributes are characteristic of the body. Fingerprint, palm-print, iris, retina and face are some biometric traits chosen on basis of physiological features [18]. Geometric attributes also play a role in biometrics. Hand geometry [19] and finger geometry [20] have also been experimented in biometrics. Considering the auditory attributes, speech recognition is also taken as a valid biometric trait [21]. Even, DNA samples of human can be employed in biometric systems [22]. When it comes to soft biometrics, wrist and ear can be taken as visual attributes, body and face geometry can be taken as anthropometric attributes.

Table 1 shows soft biometric traits related to hard biometrics. With respect to biometrics, demographic attributes refer to attributes like age, gender, race, etc., that is widely observed in population statistics. Attributes like Body Mass Index (BMI), height, weight, skin lesions, wrinkles, etc., can be considered as medical attributes. Mostly, face occluding characteristics like hats, glasses, scarf, hat, etc., are some material characteristics in soft biometrics [2]. While facial expressions, gait, keystroke dynamics and accent in speech are valuable behavioral traits, it is also

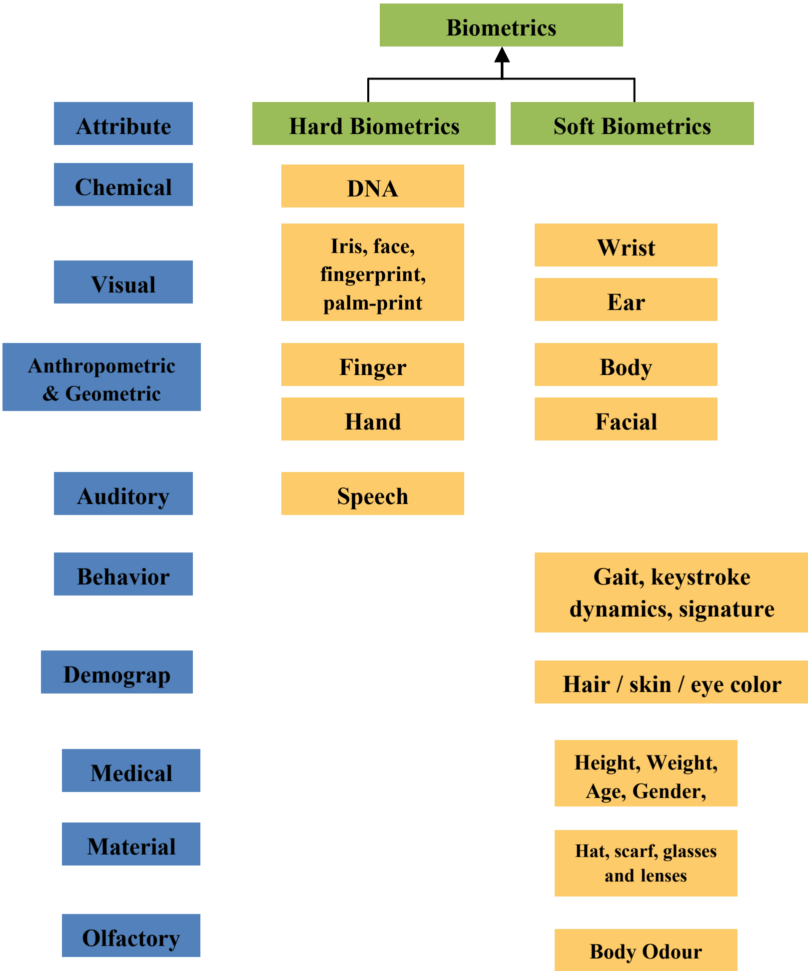

Fig. 1 Taxonomy of biometrics

surprising that attributes like body odor [23], an olfactory attribute could contribute in person identification.

3 Related Work

There are many soft biometrics which have been studied extensively and there are a plenty of new ones under research. Androgenic hairs grow in the follicle and remain there for a year in legs. When it falls out also, it grows at the same place and has a long cycle [24]. As lower legs of criminals are visible in images captured in

Table 1 Examples of soft biometric traits related to hard biometrics

Physiological traits	
Hard biometrics	Soft biometrics
Eye (Retina, Iris)	Periocular [7]
Face	Glass [8], lens, hat, accessories
	Eye/skin/hair color [9]
	Beard/mustache [10]
	Ear shape [11]
Body parts	Blood vessels [12] Vein patterns [13]
	Skin texture [14]
	Body geometry, Silhouette [15]
	Scars, marks and tattoos [16]
Palmprint	Wrist [17]

riots, androgenic hair visible is studied. However, images captured by surveillance cameras were not considered but high quality images captured by reporters using DSLR cameras were regarded within the scope of the paper. External ear is chosen as a soft biometric trait in Purkait [11]. Uniform color distribution, less impact of age, unaffected by change of facial expression or facial makeup, imaging of ear feasible at a long distance are some of the significant reasons that makes it a valid biometric trait. But, it should be noted that elongation of lobule may increase ear length for people over 60 years of age. During imaging of ear itself, ten anatomical landmarks like Superaurale, Subaurale, Intertragica Inferior, Protragion, Antitragus Superior, Incisura Anterior Auris Posterior, Concha Superior, Posterior Most Point on the Antihelical Curvature, Postaurale and Lobule Posterior were identified. Also, seventeen distances were also computed from these landmarks. Since wrists are visible when terrorists hold weapons, when criminals touch victims in sex offences, it was studied extensively [17].

Since non-facial body sites are imaged using high quality cameras in sexual offences, blood vessel patterns between skin and muscle were chosen as soft biometric traits [12]. On basis of the principles of optics and skin biophysics, veins can be uncovered from any part of the body and the same can be used in forensic applications [13]. The upper torso of human body shows less temporal variance with arm and leg motions providing stable features and the silhouette is subject to experimentation as a suitable biometric trait [15]. Features like shoulder length, biacromial breadth, bideltoid breadth, head width, head circumference, head length, chest breadth, neck bustpoint length, neck circumference, shoulder circumference, and shoulder elbow length are some of the traits considered in silhouette. Images captured with surveillance cameras were experimented. As skin is a largest body organ and the same is visible in low-resolution images, skin texture can be developed from the images and the same can be checked for biometric validation for forensic applications [14]. Periocular region is the region around eyes and includes eyelashes, eyebrows, eyelids, eye shape, etc., Because imaging periocular region does not require user cooperation, it can be employed in person identification for images captured in surveillance cameras also. It can be observed that skin marks [25], tattoos and scars [16] can also be employed in person identification if the images are of high quality. But, focus on person identification from digital videos in crime has brought Relatively Permanent Pigmented or Vascular Skin Marks (RPPVSM) (composed of four types of skin marks—nevi, lentigines, cherry hemangiomas and seborrheic keratoses) to the notice of the researchers [26].

4 Comparative Study and Analysis

The related works are all studied and analyzed in depth with respect to various operations like Image enhancement, Feature Extraction and performance.

4.1 Skin Pixel Identification

Image enhancement is the process of improving image quality and information content of original data after processing. Since superpixels adhere to boundaries and enhance segmentation results, SLIC (Simple Linear Integrative Clustering) is employed to group pixels into meaningful patches while employing wrist as a valid soft biometric [17]. There are 200 superpixels per image. Using the mean and standard deviation statistics from RGB, HSV, LAB, YCbCr, YIQ, normalized RGB colour spaces and seven gradient maps (Sobel in two directions, Prewitt in two directions, Laplacian, Difference of Gaussians, Laplacian of Gaussians), 450 dimensional feature vector can be extracted. EoDT (Ensemble of Decision Trees) is trained with bagging method and classification as skin and non-skin pixels helps in determining the wrist part. While trying to recognize legs in the image, segmentation of skin pixels from non-skin pixels is done by filtering the input RGB image using a 3 * 3 median filter [12]. Taking R_M, G_M and B_M as the filtered R, G and B channels of the image, pixels can be identified as skin if $I_R > \overline{I_R}$ and $I_G < \overline{I_G} + \mathrm{std}(I_G)$. Here, $\overline{x}$ and $\mathrm{std}(x)$ must be regarded as mean and standard deviation of x respectively. Morphological operators can be applied on image for noise removal. While performing blood vessel extraction using directional groups, Contrast Limited Adaptive Histogram Equalization (CLAHE) helps in normalizing the contrast of input images [12].

4.2 Positive Sample Generation

In training phase, images from the same body site of the model image are called positive sample whereas the other images are called negative sample [14]. Since the number of negative samples outnumbers positive samples, more positive samples can be generated using affine transformation on the current positive samples. Model image and other images of same leg are considered as positive samples and other images of the dataset are negative samples. For treating androgenic hair patterns as soft biometrics, since the number of images in the dataset may be less and the algorithm to be robust against pose variations, positive sample generation scheme is adopted [24].

4.3 Low Resolution Alignment

Image alignment is significant since it enriches the features from images captured. For alignment of leg images, edge sampling and image registration is done [24]. The leg boundaries are extracted and the angular samples are given by center line and center point. Uniform sampling on basis of angular distance is done on leg boundaries. Now, pruning and normalization processes are applied to the two point sets which are again aligned using affine Coherent Point Drift method. The transformation matrix, thus generated and bicubic interpolation can help project all the color channels of one image onto another image. While processing skin texture, CPD was employed for image alignment of positive and negative samples and testing images to model images [14].

4.4 ROI Extraction

The Region of Interest (ROI) in WMFA (Wrist Matcher for Forensic Applications) focuses on finding the boundaries around the wrist and the two wrinkles. This is accomplished using a two stage process [17]. A heat map is constructed from these four key points from the training images and using the same, template from heap map is constructed for ROI extraction. Coherent Point Drift (CPD) method is used for finding the correspondence between key points in input image and template key point using affine transformation. After alignment, ROI can be extracted by dropping left and right parts of the input image. For extracting legs in the image captured, Region of interest is defined using six points—two points above knees, two points right below the knees, and two points on the ankles [24]. For periocular biometrics, the reference point for ROI extraction can be considered as center of iris [27], or corner of the eye [28].

4.5 Optical Models

According to Kulbeka-Munk (K-M) model [29], volume fraction of epidermis occupied by melanosomes, volume fraction of dermis occupied by blood and depth of dermis are some bio-physical parameters of the skin that account for skin color formation and even vein patterns in the skin can be unraveled by the inverse process of skin color formation [13]. Since KM model is very sensitive to KM coefficients and hence, the complex skin structure cannot be accurately measured, using another optical model [12], reflectance and transmittance can be computed using Reichman's equations. But both the models are based on the assumption of optical properties of human skin determined by three layers—stratum corneum, epidermis, and blood vessels in dermis. As some blood vessels may be present even below the dermis, hypodermis may be included for determining the blood vessel patterns.

4.6 Feature Extraction, Gridding and Information Fusion

Gabor and LBP features are extracted through dynamic and directional grid systems. But since the dynamic grid system is sensitive to viewpoint variations, blocks are rotated through different angle in directional grid system [14, 24]. The major blood vessels are given by all the optical models and the point sets can be fused to avoid noise. This is feature-level fusion. Similarly, score-level fusion can also be done [12] wherein weighted sum can be employed to combine the dissimilarity values from the optical models. All the above discussed techniques are given in Table 2.

5 Conclusion and Future Works

Androgenic hair patterns in their earlier study and analysis did not employ any gridding systems and the database used is also a relatively smaller one [30]. An extensive study on the same [24] which employed positive sample generation scheme, alignment of leg geometry, gridding and feature extraction yielded promising results compared to the previous study. Images captured using surveillance cameras are not considered in this study. In case of ear biometrics, ears with all anatomical features are considered and genetically deformed ones are not considered in this study [11]. And also, the study was limited to the Indian population. Periocular biometrics has a relatively rich literature wherein faces can be recognized irrespective of age, surgical operations on face [31], cataract surgery on periocular region [32], and gender transformation (Punam Kumari, In Press)@@. Further research on combination of handcrafted and non-handcrafted features for periocular identification, focus on critical components in that region, defining the optimal ROI, integrating semantic information with basic features, addressing the problem of overfitting owing to training with

Table 2 Techniques used in various works

Work	Pre-processing	Feature extraction	Matching
Vascular skin marks [26]	Not available	Quadrant counts and distance method	Global mapping and local mapping model
Silhouette [15]	Sampling at discrete points and uniform binning	Shape context descriptors	Cost matching technique (Hungarian)
Vein patterns [13]	Not available	Kulbeka Munk model to uncover vein patterns from distribution maps of melanin, haemoglobin and depth of dermis	Manual matching
Blood vessel patterns [12]	Automatic adjustment scheme for illumination intensity variation CLAHE for contrast adjustment	Gabor filter; Otsu's binarization and skeletonization Feature level and score level fusion	Coherent point drift (CPD)
Androgenic hair [24]	Positive sample generation and low resolution alignment	LBP and Gabor filters (Dynamic and directional grid systems)	PLS regression
Wrist [17]	SLIC and EoDT for skin identification Two stage scheme for wrist identification	LBP, Gabor filters SIFT,	PLS regression
Skin texture [14]	Positive sample generation and alignment with body boundaries	LBP and Gabor filters (dynamic and directional grid systems)	PLS regression
Ear [11]	Not available	Ten ear landmarks and the distances between them	Euclidean distances

small datasets, handling of medically altered images, and image acquisition from different spectrum [7].

Wrist identification was done for small dataset and low resolution images used here faced the same challenges like any other soft biometric [17]. In case of vein patterns also, small image dataset was used and it is anticipated that local context of vein pixels can improve person identification [13]. It was also observed that the accuracy of person identification through blood vessel patterns was comparatively less than other biometrics like iris, fingerprint, face, etc., Since usually evidence images and videos are compressed using JPEG and MPEG, restoring skin and other features from the same may be very demanding [12]. Skin texture like skin marks can be considered as soft biometric trait when many skin marks on large skin surface is considered.

Skin texture can outperform blood vessel patterns from NIR and color images [14]. When RPPVSM was employed as soft biometric, Complete Spatial Randomness (CSR) Test was laid as the assumption [26]. Only full back torsos were used for the study and the statistical model used here does not assume prior knowledge of the skin of torso. It does not focus on narrow body location. To deal with pose variations and camera viewpoint variations in evidence images, a 3D model can be used for transformation of images to standard pose and viewpoint for direct application of the method in the paper. Though low quality images are sufficient to identify individuals using this technique, emphasis on removal of JPEG blocking artifacts, motion blur in videos, compression problems can help in improving the accuracy. To handle the effect of make-up applied on the skin marks, image tampering method can be applied to pre-process the evidence images and video. RPPVSM identification technique used here is manual and time-consuming. Automated identification can help speed up the entire process.

The use of Shape Context for person identification through soft biometrics can be improved by extrapolating feature extraction over the entire body and exploit large set of soft biometrics [15]. Using other soft biometric traits like color, texture, face and gait along with Shape Context using multi-modal fusion techniques can improve the accuracy of person identification.

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