Intelligent Multimedia Analysis for Emerging Biometrics

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Summary. Various anthropometric studies have been conducted in the last decade in order to investigate how different physiological or behavioral human characteristics can be used as identity evidence to prove the individuality of each person. Some of these characteristics are: face, eyes, ears, teeth, fingers, hands, feet, veins, voice, signature, typing style and gait. Since the first biometric security systems appeared in the market, an increasing demand for novel techniques that will cover all different scenarios, has been observed. Every new method appears to outmatch some of its competitors but, at the same time, presents disadvantages compared to others. However, there is still no method that consists a single panacea to all different scenarios and demands for security. This is the reason for which researchers are on a continuous effort for more efficient and generic biometric modalities that can be used in various applications. In this chapter, emerging biometric modalities that appeared in the last years in order to improve the performance of biometric recognition systems, are presented. The presented methods are divided in two major categories, intrusive and non-intrusive ones, according to the level of user nuisance that each system sets off.

1 Introduction

Biometric recognition is a well-known research area that aims to provide more efficient solutions to everyday growing human need for security. Biometrics refers to methods that can be used for uniquely recognizing humans based upon one or more intrinsic physical or behavioral characteristics. In information technology, in particular, biometrics are used as a tool for efficient and reliable identity management and access control. Biometrics are also used in surveillance applications in order to identify individuals. The last decade, a large number of novel biometric modalities, such as palm, gait and veins, as well as new methods for well-known biometric modalities, such as face, voice and finger have been proposed in the literature.

Probably the most interesting problem to researchers working on the specific field, is the problem of automatic recognition/verification for security applications. On the one hand, person recognition refers to the problem of recognizing the identity of a test person (using one or more of its biometric characteristics) by selecting the most similar (best match) or the N most similar persons from a given database [14], [12]. In many recognition systems, the final decision is taken by a human expert. On the other hand, the automatic rejection or acceptance of an individual's claim for a specific identity is referred as verification. More specifically, a verification system must take the right decision when a person claims an identity that is included in the internal database. Several studies focus on the verification problem as it appears to concern many researchers working on different modalities [13]. Biometric verification is mostly used for access control whereas biometric recognition is used for surveillance applications and forensics. Although recognition and verification are different in principle the majority of the proposed biometric technologies in the literature can be easily used both for recognition and verification applications.

By many researchers working on biometrics, face recognition/verification is considered as one of the most attractive modalities, especially due to the "nature" of the body part that it concerns (face is usually exposed and an image of it can be easily obtained). For this reason it has received significant attention [14], [6], [16]. Automatic recognition of subjects based on their faces attracts the interest of researchers coming from different fields such as pattern recognition, neural networks, computer vision, computer graphics and psychology. As mentioned above, there is a large number of studies and proposed methods for a variety of applications. However, face recognition/verification and its efficiency, depends on many factors such as illumination, general environmental and recording conditions and for this reason it still remains an open issue [17], [18].

Another modality that has been under extensive research, is voice recognition [83], [19]. Voice recognition analyzes the audio signal produced by speech and uses the features extracted from it to perform identification. Noise cancellation techniques and high quality microphones can positively affect the efficiency while other conditions like background and channel noise, variable and inferior microphones and telephones , extreme hoarseness, fatigue or vocal stress can dramatically affect the result[20].

Probably the first biometric used for many years as a proof of a person's identity and consequently the most common known is fingerprints. It remains the most commonly used forensic evidence worldwide and thus engrosses many researchers. The technology is mostly based on analysis of two-dimensional data maps obtained from different types of sensors. When a finger touches or rolls onto a surface, the elastic skin deforms. The quantity and direction of the pressure applied by the user, the skin conditions and the projection of an irregular 3D object (the finger) onto a 2D flat plane introduce distortions, noise and inconsistencies in the captured fingerprint image. These problems result in inconsistent, irreproducible and non-uniform contacts and during each acquisition, their effects on the same fingerprint results are different and uncontrollable. Although fingerprint techniques are easy to implement, their performance is easily affected by factors as dryness, dirt or ageing [22], [23].

As biometrics spread, many review articles have been published reporting the advantages and disadvantages of each of the well-known methods. However, it is important to note that even though current machine recognition systems have reached a certain level of maturity, their success is limited by the conditions imposed by many real applications [6]. Besides effectiveness, the availability and the affordability of biometric technologies appear to be important requirements for biometric systems.

There is no doubt that security has been always one of the main concerns of the human species. In our days though, the need for security seems to be essential. Since there is still no method able to guarantee ultimate efficiency while the variety of possible applications is so wide, new biometric modalities emerge trying to provide solutions to the existent complicated problems. In this chapter, emerging technologies on biometrics are introduced. There is a variety of categories that biometric systems could fall into (e.g. image or non-image based, 2D or 3D based etc). We could also classify them according to principal attributes that make a biometric system practical, like universality, uniqueness, permanence, collectability and acceptability. However, for simplicity we shall separate them to intrusive and non-intrusive, according to the level of nuisance that each system sets off to the user. The separation of the modalities to intrusive and non-intrusive ones, is indeed a difficult demarcation problem which may causes different arguments. However in this chapter, a modality is characterized as intrusive only if the cooperation of the subject is indispensable during biometric testing and as non-intrusive if it is not.

It should also be mentioned that the aim of the specific chapter is not to provide analytical investigation and comparisons of the already commonly known modalities such as iris, fingerprint, face, voice, gait, retina and signature, but only to focus on emerging biometric technologies. Another thing that should be noted, is that the authors of this chapter do not allege that the emerging modalities should have better performance than any of the well known modalities. All of the presented methods have just emerged and it is obvious that time is required until these methods are actually evaluated.

2 NON INTRUSIVE SYSTEMS

The number of non-intrusive biometric systems so far is very small. Most of the developed techniques require the imminent cooperation of the person that is to be recognized. Although this voluntary cooperation is accordant with the idea of protection of the personal data, intrusive methods cannot be applied in all circumstances.

The most known method in this category is face recognition. Face recognition can be applied, in most cases, without the subject's cooperation. It usually requires only a camera pointing to the subject's direction (a face detector is used to locate the face). However, there are many face recognition algorithms that require certain position of the person in front of the camera, as well as absence of facial expressions.

Over the last twenty years, numerous algorithms have been proposed for face recognition. The latest achievements on non-intrusive biometrics present new technologies that promise to change the way of thinking in this direction. Thermogram, lip recognition, smile identification and hyperspectral analysis seem to be used in the most important and promising techniques.

2.1 Thermogram

Recognition based only on the visual spectrum has shown deficiencies in performing well under uncontrolled operating conditions. Face recognition accuracy degrades quickly when the lighting conditions are deficient or when face is not uniformly illuminated. Light reaching the sensor after it has been reflected from human faces may vary as it depends on the skin color which may also vary from person to person. Thermal IR sensors measure heat energy emitted, not reflected, from the objects. Hence thermal imaging has an important advantage in face recognition in low illumination conditions or even in total darkness, where visual face recognition techniques fail. Researchers have found that the facial heat distribution patterns obtained by infrared sensors are unique to every person. The means used for measuring the heat coming from the body is called thermography. Equinox, is an example of a database containing facial thermal images [24]. Equinox database is a collection of face imagery, in the following modalities: coregistered broadband-visible/longwave infrared (8-12 microns), midwave infrared (3-5 microns), shortwave infrared (0.9-1.7 microns). A sample taken from the database is shown in Figure 1.

Researchers in [93] examine the performance of Long-Wave Infrared (LWIR) imagery tested on different illuminations. For the evaluation, two face recognition algorithms are applied (eigenfaces [26] and Arena [27]) on LWIR and visual images respectively. For the experiments, prerecorded infrared videos of 91 subjects were used. The best performance of Arena algorithm on LWIR imagery reported to be 99% while the worst was 97%. Cases with facial expressions and glasses, proved to affect dramatically the results, as in such cases the performance is reduced. The experiment was repeated for eigenfaces applied on the same datasets used for Arena, giving 96% and 87% respectively. In a newer study, researchers in [25] indicated that thermal images perform better or similar to visible light images in many cases using Monte Carlo analysis of performance measures. Recognition performance increases further, when algorithms applied to visible and thermal infrared images are fused.

In [28], the authors propose a two stage method based on infrared images and statistical modelling of visible images. Bessel modelling is applied exclusively to the facial region by pipelining a classification algorithm to produce a unique solution. Matching is performed using a Bayesian classifier. The experiments indicated that segmentation of the facial regions, results in a better classification performance.

Fig. 1. Sample image from Equinox database [24].

Eyeglasses is one of the major problems in thermal image based approaches as they are opaque to IR radiation. Attempting to reduce the error caused, researchers in [29], fuse visual and thermal imagery exploiting the fact that visible-based recognition is less sensitive to the presence of eyeglasses. The fusion performed was pixel-based and operated in the wavelet domain. To decide how to combine thermal with visible information, genetic algorithms were employed. Although the approach managed to improve the performance presented by the single thermal IR methods, it was not able to fully eliminate illumination effects present in the visible (not IR) images. The experimental results though, according to the authors, show substantial improvements in the overall recognition performance.

The most recent advance in thermal IR is outlined in [89] where the novelty of the approach is the use of characteristic and time-invariant physiological information to construct the feature space. The motivation behind this effort is to concentrate on the permanency of innate characteristics that are under the skin. The researchers support that although thermal facial maps shift over time, the contrast between the superficial vasculature and surrounding tissue remains invariant. This physiological feature has permanence and is very difficult to be altered as it is found under the skin. Therefore, it gives a potent advantage to any face recognition method that may use it. The method uses a novel Bayesian segmentation algorithm to separate the facial tissue from the background. Additionally, it extracts the vascular contour network from the surface of the skin by using white top hat segmentation preceded by anisotropic diffusion. Thermal Minutia Points (TMPs) are localized in order to create a feature vector. Finally, recognition is performed by matching TMPbased feature vectors. Tests with 500 thermal face images from 50 subjects show an Equal Error Rate of $\simeq 6\%$.

The great advantage of thermograms as opposed to visible light images for face recognition, is their independence of ambient illumination which makes them ideal for covert surveillance. However, researchers working on this modality still need to solve several challenging problems. Thermal signatures are subject to changes according to body temperature caused by physical exercise or ambient temperature. As mentioned above, eyeglasses may result in loss of useful information around the eyes in thermal face images since glass material blocks a large portion of thermal energy. Finally, the cost of thermal cameras is much higher compared to the cost for a conventional camera which may explain the lack of new papers on the specific modality the very last years.

2.2 Hyperspectral Images

Hyperspectral cameras may provide information beyond the normal visible range which provide useful discriminant information not obtained by any other imaging methods [30], [31]. According to authors of the above papers, subsurface tissue structure is significantly different from person to person. Features obtained from hyperspectral images are relatively invariant to illumination, although they cannot be obtained in complete darkness. The experimental results of the above works, show that spectral properties of human tissue are not considerably affected by face orientation and expressions. This observation is quite important as it reveals a great advantage of hyperspectral information for face recognition, as it can be used over a large range of poses and expressions.

In the specific work, the database used consists of near-infrared hyperspectral images of 200 subjects. The face recognition algorithm proposed, exploits the spectral measurements for multiple facial tissue types. A CCD camera equipped with a liquid crystal tunable filter, collected the hyperspectral images provided 31 bands over the near-infrared (0.7μm-1.0μm) as shown in Figure 2. Each face image was represented using spectral reflectance vectors that are extracted from small facial regions (e.g. forehead, lefft/right cheek, hair, lips). Evaluation was performed by square of Mahalanobis distance. The above technique proved to be robust against facial expressions and facial pose presence. Authors report significant improvements over current face recognition systems on rotated faces. Moreover, they argue that by modelling the spectral reflectance changes due to the face orientation changes, performance can be further improved.

As an extension of their previous work researchers in [90], present results on recognizing 200 human subjects under unknown outdoor illumination in hyperspectral face images. For each subject, several near IR (NIR) images with different facial expressions and face orientations were acquired on different days under various natural illumination conditions. A set of 7258 global

Fig. 2. Thirty-one bands of hyperspectral images of one subject [31] (©2003 IEEE)
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spectral irradiance functions were used to synthesize reflected radiance images of each subject. A low-dimensional linear model for each tissue type for each subject was used to model illumination variation in radiance images. Authors advocate their system claiming that the algorithm provides accurate recognition performance for front-view probes, with or without facial expression changes. They also add that the results are promising for face recognition under unknown outdoor illumination and with various face orientations.

Another biometric solution that uses NIR imaging hardware, algorithms, and system design, has been proposed in [92]. The system is presented as another solution to illumination variation problems in face recognition modalities. An illumination invariant face representation is obtained by extracting local binary pattern (LBP) features of NIR images to compensate for the monotonic transform, thus deriving an illumination invariant face representation. Using statistical learning algorithms the most discriminative features are extracted from a large pool of invariant LBP features and construct a highly accurate face matching engine. For the dimensionality reduction and classification, LBP+LDA and LBP+AdaBoost methods have been developed. For the experiments 10000 face images of about 1000 people, all Chinese, were used for training the system. The testing dataset contained 3,237 images from a total of 35 persons and the accuracy reported by authors was 94.4%.

In [94] the novelty compared to other NIR systems, is the use of constant illumination for face recognition. Authors argue that active NIR illumination provides a constant invisible illumination condition and facilitates the automatic eye detection by introducing bright pupils. The results provided, indicate that the actively illuminated faces show better separability for all classifiers than faces under varying ambient illumination. More specifically, radial basis function (RBF), Adaboost and support vector machines (SVM) classifiers where applied on 2360 face images from 295 subjects where SVM, achieved the best results with 0% error rate.

Another study that examines the effectiveness of NIR images for face recognition [95], ascribes the success of the system presented, firstly to NIR images that facilitate the classification process and secondly, to the learning based methods with local features, proposed in the paper. Evaluation of the system on 1470 persons indicated an equal error rate of 0.3%.

The main advantage of the hyperspectral image based techniques as already mentioned, is that it overcomes problems due to illumination. As illumination is almost eliminated, the use of NIR images is also supposed to provide advantages over other methods on rotated faces, expressions and robustness over time. However, this specific modality does not seem yet to be suitable for uncooperative user applications such as face recognition in video surveillance [92]. Although many methods present impressive performance on both indoor and outdoor conditions, hyperspectral technology so far, is mainly suggested for indoor biometric applications.

2.3 Smile Recognition

Researchers in [32], proposed a system that was equipped with a high speed camera with strong zoom lens. This system was able to produce smile maps that could be used as features for identification, under the claim that they are unique for each person. The system examines the way the skin around the mouth moves over in the video frames, by tracking the tiny wrinkles in the skin and analyzing their motion. That is, the system probes the characteristic pattern of muscle deformations beneath the skin of the face. The extracted data is used to produce a motion vector containing the information about the deformation of the facial region. The deformation is insusceptible to the influence of facial make-up or smile size and is only controlled by the pattern of muscles under the skin. According to the authors, the feature map can be created, even if the smile movement is not full, as system's sensitivity is high. They also argue that smile maps can be produced without the cooperation of the person tested and this is the reason why they describe the technique as "invisible". An alternative application of the proposed method could be its use for medical reasons indicating distinctive asymmetries in movement of facial muscles caused by nerve disorders.

The method has been tested so far on samples of 4 lab members while smiling. Further experiments on a larger dataset of 30 persons have been announced. No results have been published though.

2.4 Lip Deformation Recognition

In [33], the shape similarity of lips when vowels are uttered is examined. More specifically, a person recognition method is proposed based on a mathematical morphology analysis of the lip area using three different structuring elements. The proposed structuring elements are the square, the vertical and the horizontal line and they are used for deriving a pattern spectrum of the lip images. The shape vector is compared with the reference vector to recognize an individual from its lip shape as shown in Figure 3.

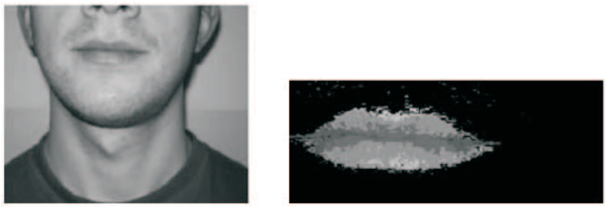


Fig. 3. Example of lower face and extracted corresponding lips area in [87].

Experiments on eight Japanese persons (classified with 100% accuracy by their lips) indicated that the shape vector obtained, contains enough information for recognition. Beyond doubt, the dataset used for the experimental procedure is very small and authors state clearly that results may be biased. As authors state, classification accuracy should be improved by a more sophisticated system. Proposed improvements refer to consideration of other structuring elements (for instance, rectangle, ellipse or asymmetric shape). A larger database is strongly required in order to evaluate better the efficiency of this method.

Another approach considers lips' shape and color features in order to determine human identity [87]. More specifically, the method calculates color features of the masked out lips and merges them with shape features of the binarized lips. Color statistics and moments as well as a set of standard geometrical parameters and the moments of Hu and Zernike are used for feature extraction. The feature vector that finally describes the lips area, consists of a selection of the most discriminant information of: Hu and Zernike moments, central moments, standard geometrical parameters, statistical color features in RGB, YUV and HSV color spaces. Experiments on a database of 38 subjects showed that the method was able to recognize successfully the 76% of the test set.

Although the results are promising for such an emerging technology, it is obvious that further improvement is strongly required for a stand alone application. It is also mentioned that reliable lip detection, acquired using surveillance cameras, consists a major drawback of the system.

2.5 Gait

Gait is one of the modalities that has been under research for more than a decade [9], [10]. However, the biometric research community still pays attention on gait, since on one hand it seems to have great potentials while on the other hand, there is still no commercial product available based on gait so far. Many psychological studies have shown that a person is possible to be recognized by the way it walks. It has been recently examined how machine vision systems could benefit from gait's individuality. Many studies have proposed gait as suitable modality for biometric applications. Here, the most representative methods will be presented.

Boyd and Little in [8] define gait to be "the coordinated cyclic combination of movements that result in human locomotion". The movements are coordinated in the sense that they must occur with a specific temporal pattern for the gait to occur. The set of movements that consist a full gait cycle repeat in every cycle. The periodicity of these movements as well as the coordinated and cyclic motion of gait makes it a unique modality. The basic techniques used in gait and motion analysis systems are: background substraction, silhouette detection, optical flow and motion energy/ history images. There is a variety of methods that are used for gait recognition and according to [8], they can be categorized by the data type that they use: shape, joint trajectory, self similarity, and pixels.

An a example of a system using joint trajectories is given in [4]. The method extracts a hip joint trajectory from a sequence of images. The trajectory for the hip hop closest to the camera is acquired. Subsequently, recognition is performed based on the Fourier components of the trajectory. The method was tested on a dataset of 10 individuals (ten repetitions each). The classification analysis showed that the phase-weighted Fourier magnitude offered a classification rate of (100%) while for just the Fourier magnitude the classification rate was (80%). A self similarity based method in [3], suggests that the image self-similarity plots of a moving person encodes much information about gait motion patterns providing discriminant information of gait sequences that is useful for gait recognition. Researchers construct a self-similarity image from the image sequence, in which pixel intensities indicate the extent to which two images in the sequence are alike, i.e., pixel (i, j) in the self-similarity image indicates the similarity of the images at times t_i and t_j.

A system based on pixel oscillation [2], demonstrates how the frequency of the gait and the timing of the component movements, determine the frequency and phase of the pixel oscillations. More specifically, authors demonstrated that an array of phase-locked loops (PLL), one per pixel, can synchronize internal oscillators to the frequency and phase of pixel oscillations. This synchronization process inherently performs frequency entrainment and phase locking. Boyd [2] uses a phasor, a complex number that represents a rotating vector, to represent the magnitude and phase of the oscillations at each pixel. Thus, once the PLL synchronization occurs, one can construct a complex image of phasors in which each pixel indicates the extent to which there are oscillations and the relative timing of the oscillations.

A more recent method [5], is based on the anthropometric proportions of human limps and the characteristics of the gait task. The system uses a single camera, does not require camera calibration and works with a wide range of directions of walking. The proposed gait analysis is based on two consecutive steps: a motion estimation method which extracts the limbs orientations with respect to the image reference system and a view-point independent gait reconstruction algorithm that normalizes and corrects the limbs inclinations in the lateral reference system. For the experiments 200 video sequences of 3 subjects, viewed at 6 different camera inclinations have been used. The authors report that the specific method has been proved to be viewpoint invariant thus, more efficient than others for real scenarios. However, discriminability reduces as the camera moves to capture a subject walking in frontal view.

Another recent study in gait identification [7], examines the effects of covariation on the recognition process. Authors show how these factors can separately affect the walking pattern. Further, they assess the contribution and discriminatory significance of the gait dynamics used for recognition. On a database of 440 samples, a recognition rate of 73.4% was achieved using a k-nearest neighbor (KNN) classifier. Authors argue, that the results confirm that person identification using dynamic gait features is still achievable with better recognition rate.

Gait presents advantages compared to other biometric modalities such as iris or fingerprints. Its main advantage is that it is effective from a distance or where only low resolution images/ video is available (e.g CCTV cameras). However, there are many factors that can negatively influence the accuracy of a gait recognition system. The speed at which someone walks or runs has little effect on the biometric, but wearing a trench coat can mask the feet, and using flip-flops can also affect the results. With respect to gait security, studies also indicated that gait biometric is robust against minimal effort impersonation attacks. However, impostors who know their closest person in the database or the gender of the users in the database can be a threat to a gait authentication system. Although gait is a subject of research for many years, it is still not suggested as a stand alone application and it is usually proposed for multimodal biometrics where it is supposed to increase the overall performance of the system.

3 Intrusive Systems

The majority of the recently developed biometric systems belong in the category of intrusive systems. These systems require the cooperation of the subject to be recognized. The level of intrusiveness is determined by the level of cooperation that they demand from the subject. Many well-known biometric modalities like iris, retina, fingerprints, keystroke dynamics and dental analysis are representative examples. In the following, the latest developments within this class of biometric recognition/verification techniques are presented.

3.1 Finger-vein Patterns

A method based on finger vein patterns is proposed in [37], [38]. Finger vein patterns found to be distinctive between twins and even between a person's left and right hand. For this reason the specific biological information has judged to be ideal for person authentication. The way vein maps are produced is illustrated in Figure 4. Authors believe, that the images obtained are very rich in information content. Irregular shading produced by various thicknesses of the finger bones and muscles, contribute to the final feature map extracted by an infrared image of a finger. The technology uses near-infrared light to detect vein vessel patterns. Thus, fluctuations in brightness due to variations in the light power or the thickness of the finger occur. The extraction of the patterns from an original image (line-tracking operations) with randomly chosen start points is repeatedly carried out. Two commonly known methods for line-shaped patterns, structural matching [39] and template matching [40] for line-shaped patterns, are used for matching. The method was tested on 678 subjects and the evaluation results showed an equal error rate (EER) of 0.145%. The proposed scheme proved to be robust against brightness fluctuations compared to conventional feature extraction techniques.

The authors in [84] based in their previous papers ([37], [38]), proposed a scheme based on finger vein patterns for biometric identification utilizing biological information. They proposed a scheme for extracting global finger vein patterns by iteratively tracking local lines from various positions to robustly extract finger vein patterns from such misty images. The proposed method extracts the centerlines of the veins from the unclear image by calculating the curvature of the cross-sectional profile of the image. To obtain the vein pattern spreading in an entire image, all the profiles in a direction are analyzed. All the profiles in four directions are also analyzed in order the vein pattern spreading in all directions to be obtained. Matching, was performed using a commonly known method for line-shaped patterns (template matching) proposed in authors' previous works.

The proposed scheme appears to be robust against brightness fluctuations, compared with the conventional feature extraction schemes. The method was tested on 678 subjects and the evaluation results showed an equal error rate (EER) of 0.0009%.

The researchers report that cold weather affects the result as mismatch ratio appears to be higher in cold conditions as the veins become less visible. It is clear that for the stability of the performance of such a technology, more efficient capture devices are needed while a more sophisticated algorithm which will be robust against these fluctuations should be designed. There are also other directions that authors consider to drive their research to. Rotation of fingers degrades identification accuracy. So, redesigning their application in such a way that would make user to place his finger in the same position every time, would improve the results. An advantage of the method is that by

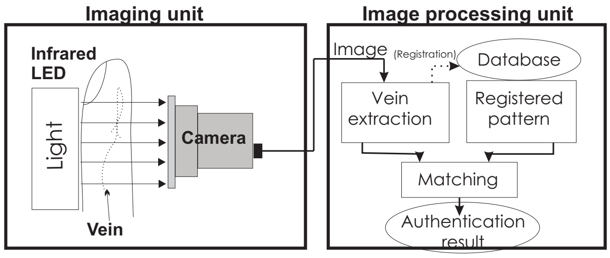


Fig. 4. Flow of finger-vein person identification [84].

its nature, can be easily combined with other biometrics, such as fingerprints and finger/hand geometry.

A commercial product based on finger vein imaging called "SecuaVeinAttestor", has already been released. Characteristics and full specification of this product can be found in [41].

3.2 Skin Spectroscopy

The measure of the intensity of light taken as a function of wavelength of energy, is called spectrum (hyperspectral is part of spectral imaging class and more specifically is a set of contiguous bands usually received from one sensor). Human skin contains unique spectral properties. A new commercial product based on these properties is presented in [43]. Skin is a tissue formed in a layered structure and has complex interaction with light. The way multiple layers and biochemical substances (collagen fibres hair follicles etc.) are set in the skin, differ from person to person. Cell size and density within the skin layers, as well as in the chemical makeup of these layers, also vary from person to person. The depth of the emitted to the skin light penetration, depends on one hand on the wavelength of light and on the other hand depends on the natural color of the skin. The reflectance spectrum of skin provides useful information about the location and concentration of various substances that appear and is highly person dependant. Thus, spectroscopic measurements can be successfully used as a biometric.

The specific product claims to recognize the individuality of each person's skin by measuring the optical effects they produce. The developed sensor illuminates a small (0.4 inch diameter) patch of skin at multiple wavelengths ("colors") of visible and near infrared light. The light that is diffusely reflected back, after being scattered in the skin, is then measured for each of the wavelengths (Figure 5). As light changes passing through the skin, is analyzed and processed to extract a characteristic optical pattern. Afterwards, this pattern is compared to the database of patterns stored in the device in order to authenticate an individual.

The optical differences caused by changes to properties of the human skin, also provide the advantage of sensitive and easy aliveness detection. The op-

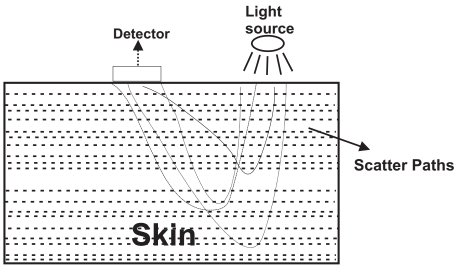


Fig. 5. Illustration showing light undergoing optical scatter as it passes through skin, resulting in a portion of light that is diffusely reflected. Different wavelengths provide different information about the skin [43].

tical signal received by non-human tissue or synthetic materials has different optical properties than the human skin. The sensor used to perform these measurements comprises several LEDs that send light at different wavelenghts into the skin, and photodiodes that read the scattered light, which is analyzed to perform the authentication. They all are embedded in an alumina ceramic housing shown in Figure 6 [44].

The sensing system has been designed to fulfill the demanding requirements of incorporating a biometric sensor in a personal portable electronic device such as a cellular telephone, laptop or PDA.

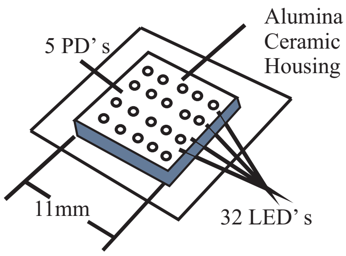


Fig. 6. Solid-state biometric sensor [44].

Inventors of the solid-state spectral biometric sensor [44] conducted experiments for a 4 months period, in several sessions, on 113 volunteers (11,000 samples total). 59 males and 54 females of different nationalities participated in the experiments. The age of the participants varied from 20 to 71 years. The equal error rate (EER) obtained for single-try data was 2.7%. However, researchers found that familiarization of the user with the system, increases remarkably the overall performance. After each person successfully used the sensor 20 times the overall EER obtained was decreased to 1.7%.

The spectroscopic approach offers a great advantage over other conventional technologies. Since skin is such a complex organ, it cannot be copied or replaced by synthetic materials, offering in the same time liveness detection. Such an approach that examines spectroscopy as liveness detection solution for biometric systems, is presented in [82].

3.3 Thermal Palm Recognition

Palm as a biometric modality is used for more than a decade [86]. Person verification using the thermal images of palm-dorsa vein patterns (instead of conventional visual images) captured by an infrared camera, is presented in [34] (Figure 7). The region of interest on the thermal images, is defined by capturing automatically two of the finger webs as the datum points. Extraction of the feature points of the vein patterns (FPVPs) is achieved by a watershed transform modified according to the properties of thermal images. The watershed transform calculates the locations of region basin minima (or maxima) [35]. The region maximum method in this case, is used to extract the FPVPs. The region maximum method selects pixels with a high gray value within a region as candidates for watershed points. Two extra restrictions have been added. The first restriction is, that the pixel with a high regional maximum value is also the central point of the region. The other is that its gray value must be larger than the mean of the pixel value inside the region.

Multiple multi-resolution filters (MRFs) are used to create multi-resolution representations of images with FPVPs. MRFs extract the dominant points by filtering miscellaneous features for each FPVP. Three different MRFs, retain the properties of multiple features of the FPVPs at the next level resolution. The first MRF is used to construct multi-scale feature point images (FPIs) and is called moment filter. The second is called mean filter and computes the means of the x and y coordinates as representation for the next level resolution, while the third is called count filter and counts the N feature points inside local square windows for a representation of the next level resolution. In order the former to be integrated, an inter-to-intra personal variation ratio (weights) is proposed, while a positive Boolean function is used to integrate the latter.

Experiments on the specific technology indicated a decent performance (false rejection rate: 2.3% and false acceptance rate: 2.3%)[34]. However, the method is still immature and a number of problems still remain unsolved. The degree of venous engorgement, ambient temperature, the condition of the vein walls and the contiguity of the vein to he surface, are some of the factors that have undesirable influence to the recognition performance. Environmental temperature may dramatically affect the results as it leads to unstable distribution patterns. Hence, it is obvious that a stand alone product based only on the vein-pattern features in palm-dorsum thermal images, could be easily proved unreliable.

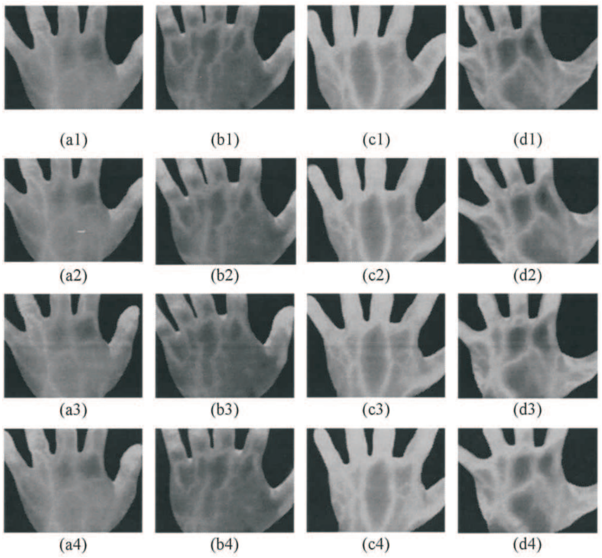
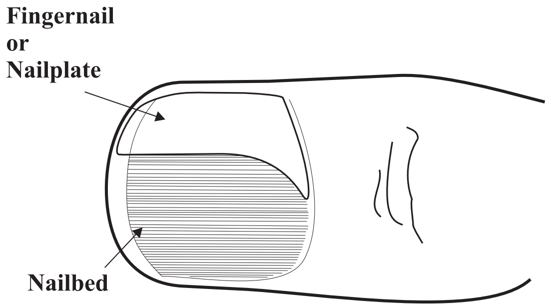


Fig. 7. Thermal images captured from four different palm-dorsa: (a1-a4), (b1-b4), (c1-c4), and (d1-d4) [34] (©2004 IEEE).

3.4 Nail ID

Researchers in [42] suggested a truly novel modality capable of identifying a person from his nailbed. More specifically, the specific commercial product reads the information hidden in the finger nail (nail and nailbed are illustrated in Figure 8). The nailbed is the vascular epidermis upon which most of the fingernail or toenail rests that has a longitudinally-ridged surface often visible through the nail. Blue thin lines observed under nail after small nail injuries is actually blood from a damaged blood vessel from inside the nailbed. The epidermal network beneath the nail is mimicked on the outer-surface of the nail. Rotating one's fingernail under a light reveals parallel lines spaced at intervals. As the nail is produced by the root, it streams down along the nailbed, which adds material to the undersurface of the nail making it thicker. It is important for normal nail growth that the nailbed is smooth.

Keratin microfibrils within the nailbed are located at the interface of the nailbed and the nailplate, or fingernail. A broadband interferometer technique detects polarized phase changes in back-scattered light introduced through the nailplate and into the birefringent cell layer. By measuring the phase of the maximum amplitude polarized optical signal, one can reconstruct the nailbed dimensions using a pattern recognition algorithm on the interferometric data. According to inventors, a numerical string (one-dimensional map) much like a "barcode" unique to each person, is generated during the identification



(a)

Fig. 8. Schematic representation of nail [42].

process. The use of the specific "barcode" results in an inexpensive commercial product.

Nailbed presents a number of advantages compared to other relevant modalities such as fingerprints and hand geometry. Since nailbed is beneath the nailplate, is extremely difficult to be copied or duplicated. The producers of this product allege that the system is able to read the hidden barcode even in the case where user is wearing surgical gloves. However, since this is a commercial product, there are no published results showing the exact performance of the system.

3.5 Ear Prints

Biometrics based on ear shape is still a subject of discussion. Indeed there is still an open discussion between researchers whether ear is unique enough to constitute a proof of individuality. However, it is an interesting topic and still attracts researchers' attention. In [45] authors argue that ear biometrics is a "viable and promising new passive approach to automated human identification". According to a possible scenario, a mugger listens at a door that he is about to break, leaves a print crated by oils and waxes on the ear. This print can be easily obtained by techniques similar to the ones used when lifting fingerprints. An attempt to correlate such an ear print to a person, was part of a research project with the collaboration of several European institutes. The study was presented in [46].

Earprints, photographs and video are some of the ways ear data can be acquired. However, all methods require the ear to be pressed against a firmed transparent material such as a glass. A sample of ear print geometry is shown in Figure 9. The polar axis shown in the figure, is a common tangent to inner edge of the impression of the (onset of the) *crus* of *helix* and the tip of *tragus*. The ear print geometry is based on the following metrical characteristics ('cues'):

- (A) Intersection of the 290$^{\o}$ line from *tragus* tip O with the median line of the *anthelix* impression
- (B) tangent point on the tip of the *antitragus* of a perpendicular from the polar axis
- (C) tangent point of tip of polar axis with the median line of the (onset of the) *crus* of *helix* impression
- (D) intersection point of the line extending OA with the median line of the outer *helix* impression
- (E) intersection point of the 345$^{\o}$ line from *tragus* tip O with the median line of the upper *helix* impression
- (O) tangent point of polar axis with the tip of *tragus*

Few researchers report advantages of the ear against face based approaches [47]. Working on ear and face recognition, using standard principal component analysis, they found recognition performance to be almost equal between face an ear. For the experiments they involved 197 subjects. Face and ear images were taken under the same conditions and same image acquisition session. The dataset was tested under pose and lighting variation. The results indicated that the performance is not significantly different between the two biometric modalities. The published results report a recognition rate of 70.5% and 71.6% with 29.5% and 28.6% false recognition rate for the face and the ear respectively.

A number of articles [48] suggest ear based solutions but the performance is not sufficient yet. The main disadvantage that appears to all ear based applications is that the subject has to turn its head perpendicularly to the camera axis or, even worse, to stick its ear in a board in order the ear sample to be taken. Therefore, such a security system would be considerably intrusive.

3.6 Mouse Dynamics

It is known that most of the currently available biometric technologies typically require special and often expensive equipment that hinders their widespread use. An advantageous solution is based on mouse dynamics [51].

It employs a similar idea to keystroke dynamics. Keystroke dynamics is a common and widely known technique since the beginning of the past decade [52]. The keystroke dynamics method measures two distinct variables: "dwell time", which is the amount of time one holds down a particular key and the "flight time", which is the amount of time it takes a person to search and press the next appropriate key.

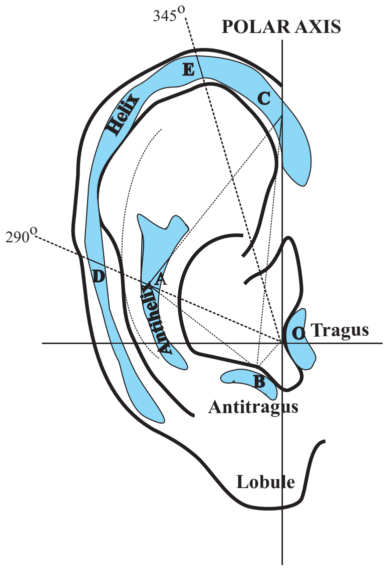


Fig. 9. Reference points for metrical characteristics ('cues') of an earprint [50].

According to the researchers, the proposed method uses state of the art pattern recognition algorithms combined with artificial intelligence to provide a biometric layer over traditional password based security. The system learns an optimum set of mouse-movement characteristics unique to the user's mouse-written signature and uses them to authenticate later signatures. It can also learn over time to include changes of the user's mouse signature characteristics. The main idea of this method is illustrated in Figure 10. First the user's mouse dynamics data are collected through an application that monitors the mouse movement for the specified duration. Certain signature characteristics are extracted in the mouse dynamics patterns, such as double-clicking speed, movement velocity and acceleration per direction.

In order to increase the performance of the system, researchers combined the conventional keystroke dynamics method with mouse dynamics. This way, a user must pass two distinct tests to gain access to restricted content. The first examines the typing style of the password and the second the dynamics of the mouse based signature. The additional level of security can vary according to application needs. In trials with 41 participants, a false acceptance rate of 4.4% and a false rejection rate of 1% where obtained respectively. In these trials, it was assumed that the password was known, whereas in reality it would not be.

In [81], the behavior characteristics from the captured data is modelled using artificial neural networks. A graphical based application involving general mouse movement, silence, drag and drop behavior, point and click behavior, is used to measure several attributes with respect to the users exertion. The

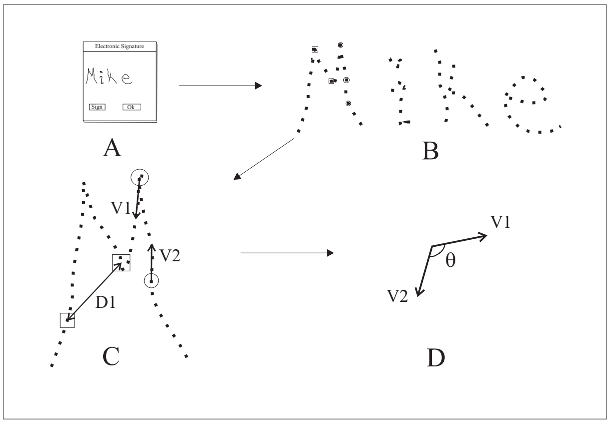


Fig. 10. Main idea of the mouse dynamics recognition system [51].

authors develop a mouse dynamic signature (MDS) for each user using a variety of machine learning techniques. The data collected for the experiments comprises of 22 participants and was used in an off-line approach to evaluate their detection system. The subjects were separated into two categories (clients and impostors) and the features obtained were used to train a neural network which finally, used for classification. The EER obtained for this study was 2.46%. The specific approach according to the authors, could also be applied for continuous user authentication.

A number of advantages are given for this method: The system builds on already familiar user skills, like mouse movements and users can reliably reproduce complex mouse based signatures. The system based on neural networks, can learn over time to incorporate changes of the users typing and mouse signature characteristics. The specific modality, is mostly proposed as an online biometric verification solution. On-line banking, shopping, or accessing web based e-mail could be a few of the possible applications. In addition, the technique can be used to validate computer-controlled access to rooms or buildings, confirming identity at security checkpoints without expensive special equipment.

3.7 Electrocardiogram (ECG)

The usual technique for the investigation of heart diseases is the electrocardiogram (ECG). The rate and the regularity of heartbeats as well as the size and the position of the chambers, the presence of any damage to the heart, are all measured by ECG. Recent studies, indicated that ECG is unique to each person [53], [54], [55]. In [56] ECG with quantifiable metrics is proposed for biometric security purposes. Data filters have been designed based on the observed noise signals. The filtered data were used for the digital extraction of the fiducial points. Stable features computed on the fiducial points characterize the individuality of a subject according to its ECG. The fiducial points are marks on the ECG signal used for measurements. The locations of the fiducial positions, noted by an apostrophe ('), are illustrated in Figure 11. Physically, the L' and P' fiducials indicate the start and end of the atrial depolarization. The corresponding S' and T' positions indicate the start and end of ventricular repolarization. The extracted features are based upon cardiac physiology and have fixed positions relative to the heartbeat.

Tests performed using the specific cardiac signal, show that results are not dependent on the location of the sensor and they are not dependent on the psychologic situation of the subject. 29 subjects participated in the experiments (males and females) between 22 and 48 years old. Every session contained a set of recordings during 7 two-minute tasks. The tests were designed in such a way that different states of anxiety to be stimulated. The hardware used for the collection of the required data was using high temporal resolution of 1000Hz unlike conventional ECG data. The measures were taken from neck and chest at the same time. For the two different measure points, a heartbeat classification of 82% and 72% was achieved respectively, while the person classification was found to be 100%.

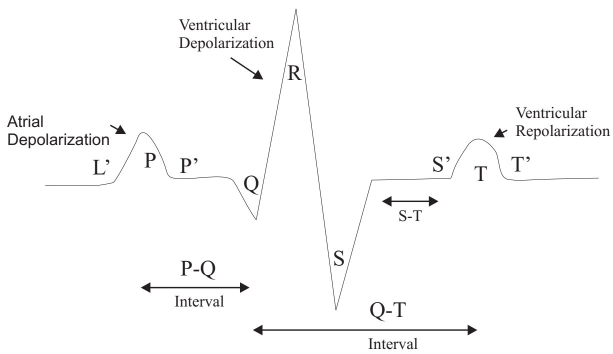


Fig. 11. ECG data for one subject across three sessions [79].

Further data collection is attempted in order to obtain more features, in order to prove stability over time and scalability of the features on large population. At the moment, the technique is highly intrusive as it requires placement of several electrodes on subject's body while the enrolment procedure is time consuming. An evaluation on how easy an ECG biometric system can be fooled by the morphology of the electrocardiogram can be found in [78].

3.8 Cognitive Biometrics

A recent work in [75] presents an alternative biometric based on cognitive abilities. The study was motivated by independent studies in cognitive neuroscience and psychiatry, reporting that the generation of random rhythms or numbers is a demanding cognitive task that carries enough information to discriminate between different clinical populations. The authors of the paper, believe that if a person generates random numbers (e.g via a keyboard) there is a cognitive load implied. This is due to the close interaction between short-term memory and internalized decision making mechanisms. Another related task, is the generation of the random tapping rhythms. Finger tapping, for instance, requires sensorimotor interaction and specific cortical networks. Interestingly, it has been demonstrated that everyone has his own eigen-rhythms regulating spontaneous finger tapping.

While many modalities have been suggested, according to authors, this is the first approach where human-generated time-series of random latencies are tested as biometric. For the generation of RTI signal a simple approach was used. A computer based exercise requires of the user to press the space key by the index finger as irregularly as possible, until an "end" message is displayed on the screen. For this purpose a square 4x4 cm, appears and disappears at random frequency while synchronized beep sounds are emitted. Authors state, that the exact reproduction of the given frequency is not the objective of this particular task. The specific example is indicative of the sort of time series one has to create.

When realization from different subjects were contrasted, the dynamics indicated a prominent idiosyncratic character. To experimentally verify that it is feasible to identify a person from Random Time-Intervals (RTI) signals and systemize such comparisons, researchers established an appropriate similarity measure. Incorporating this measure in a support vector machine (SVM) based verification system, an equal error rate of $\simeq 5\%$ was achieved. For the experiments a database of 40 person was used. Although the above approach shows potentials for future research, at the moment has a main drawback for commercial use. The enrolment procedure takes almost two minutes and of course it requires full user cooperation. Further investigation of the extracted features as well as more efficient ways for their extraction is highly required.

3.9 Eye Movement

The characteristics of the eye movement (the reaction of the eye to visual stimulation) is examined as a biometric solution in [66]. The user interface of the system, requires the subject to follow a point on a computer's monitor. All the necessary information is related to the eye movement performed during the test. To collect this information, an accurate eye tracker based on infrared reflection is used. The dataset collected consists of probes. The main challenge of this method was the extraction of a set of features suitable for identification. Each probe was collected after an eight seconds stimulus of the eye and consisted of 2048 single measurements. Each measurement consists of six values which describe the position of the point on the screen and the position of the points the right and the left eye are following respectively. Cepstrum coefficients [67] were used as discriminant features.

Every subject in the database (9 in total) was enrolled more than 30 times. 270 probes were used for training the system and 30 for testing. The average false acceptance rate for the proposed method performing person identification, found to be 2% while a high average false rejection rate of 25% was obtained.

The continuous movement of the eye for biometric purposes is also suggested in [98]. The authors, have conducted a case study to investigate the potential of the eye-tracking signal as biometric. They argue that the distance between the eyes proved to be the most discriminant feature (90% identification rate). The best dynamic feature was received from the delta pupil size which corresponds to the variation of the pupil size in time (60% identification success). The information obtained by measuring the size of the pupil itself proved to be weak giving 40% identification. Combination of different features does not seem to offer any considerable improvement. For the experiments 12 subjects participated with normal or corrected to normal vision.

In order to investigate whether there were any individual differences in eye-movement dynamics, researchers had to remove the static properties from the signal. By taking the time averages for each subject, the authors created a static user template. As long-term statistics, these were expected to carry the information about the physiological properties of the subject's eyes. By considering as feature vector the time signal, the dynamic user templates were formed. In summary, eye movement seems to provide discriminatory information. Considering that both the training and test signals had a duration of 1 second, the recognition accuracy of 40-90% can be considered according to authors of the method as high, especially taking into account the low sampling rate (50 Hz).

Eye movement as a biometric combines both behavioral and physiological characteristics compared to others like fingerprints or face which use exclusively physiological characteristics. Thus, aliveness detection is embedded in the system providing a major advantage to it. On the other hand, this technique is highly depended on the physical situation of the subject. It requires conscious effort on behalf of the subject and it would fail in cases such as drunkenness.

3.10 Dental Biometrics

Dental radiographs provide dentists with useful information concerning the condition of teeth, their roots, jaw placement and the overall composition of the facial bones. The radiographs acquired after a person's death are called postmortem (PM) and the radiographs acquired while the person is alive are called antemortem (AM). Such images, are commonly used for human identification in crime investigations. An automated method for identification based on the digital information provided by radiographs is proposed in [68]. The paper proposes an automatic technique for matching dental radiographs for identification in forensics. Feature extraction is achieved using anisotropic diffusion to enhance the images and a Gaussian mixture model to segment any dental work that may appear. In case of dental work presence, an area-based metric is used for matching it.

Matching consists of three steps. At first, a shape registration method aligns the teeth contours and computes the between distance. In the presence of dental work, matching is performed using an area-based metric. The two matching distances are then combined using posterior probabilities. Afterwards, the correspondence established for PM and AM images is used to compute the similarity between them. Finally, the distances calculated between individuals, are used for identification. Some examples of extracted teeth shapes are presented in Figure 12. For the identification task, 11 PM subjects were matched against 25 AM subjects. The results produced show an accuracy of 72%, 91% and 100% according to the number of top retrievals that have been used (1, 4 and 7, respectively).

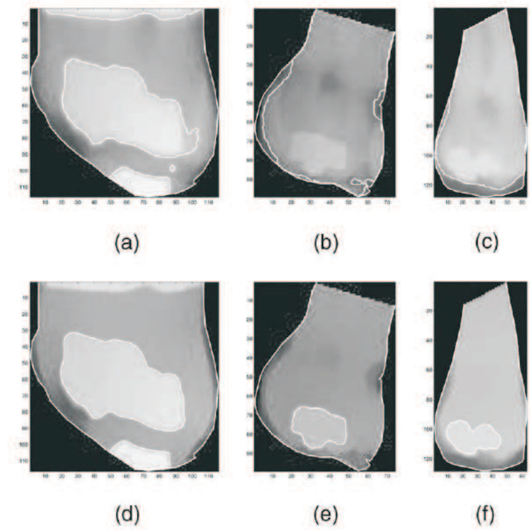


Fig. 12. The original images and the extracted contours of dental work (a), (b) and (c). The corresponding smoothed images and the extracted contours (d), (e), and (f) [68] (©2005 IEEE).

In a more recent work, researchers use exclusively dental work (DW) to perform identification [97]. The technique is based on three main processing steps: a) the dental radiographs are pre-processed to segment the dental work. The information obtained contains details about the DW (position on both jaws, size, distance between vicinal DW), b) All the collected features form a "dental code" (DC), c) This code is finally used for matching with the corresponding DC in the database.

To segment the DW from the rest of the denture, the authors use active contours (snakes). A separate snake is used for each of the DW found. The process is hastened by computing all the DWs from a binary mask. Matching is performed using Levenshtein distance. For the evaluation of the method 46 subjects participated (68 radiographs collected). The equal error rate obtained for the proposed method performing identification using the above dataset, was 11%.

Although experimental results show that dental based approaches are promising, there is still a number of challenges to overcome according to the authors [68]. First of all, for both techniques, the experiments should run on a larger database. Shape extraction is a problem for dental radiographs. For subjects with missing teeth, other features for identification must be explored. The method, as it is presented, examines the identification of individuals in the forensic domain but it can be also applied to living persons. However, a radiographic test procedure would be extremely intrusive and undesirable due to X-ray radiation hazards to human health. Another image acquisition device not based on radio-activity should be applied. Such a devise is not available nowadays.

4 Conclusion

A large number of human physiology characteristics such as iris, retina, fingerprints, face, palm, and personal behavior characteristics such as smile or gait, and different imaging methods have been suggested as biometric recognition/verification solutions. None of these modalities though, is able to provide acceptable performance in order to satisfy every market demand so far. The need for more robust and reliable security systems is continually increasing, leading to the discovery of new human personal characteristics, able to provide sufficient individuality and more efficient biometric methods.

Recent studies propose advanced techniques and sophisticated electronic devices while various human features have been suggested. Thermogram, hyperspectral images, finger veins, ECG, mouth, teeth, are some of the proposed modalities. All emerging techniques provide a number of advantages, compared to others, according to specific market requirements. However, most of the systems have only been tested on very small datasets, require expensive equipment of high technology while others, require time consuming enrolment procedures. Mulimodality and intrusiveness are only two of the issues that must be extensively investigated in the years to come.

The methods presented here have been separated for simplicity, into two main categories (intrusive and non-intrusive) according to the level of vexation that they induce to the user. Both categories contain techniques that have rather high accuracy rates and are based on very promising ideas. Although, as mentioned, none of them can guarantee satisfying performance, the intrusive methods seem to have the precedence in terms of performance results. However, the impressive number and the variety of the proposed developments clearly indicate the thirsty market demands, as well as the impressive forthcoming biometric achievements that society will encounter.

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