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ARTICLE

Emerging biometric modalities: a survey

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Abstract Many body parts, personal characteristics and signaling methods have recently been suggested and used for biometrics systems: fingers, hands, feet, faces, eyes, ears, teeth, veins, voices, signatures, typing styles and gaits. A continuously increasing number of biometric techniques have risen in order to fulfill the different kinds of demands in the market. Every method presents a number of advantages compared to the others as each technique has been created to subserve different kinds of requirements. However, there is still no method able to completely satisfy the current security needs. This is the reason why researchers continuously drive their efforts to newer methods that will provide a higher security stage. In this paper, the emerging biometric modalities are presented.

Keywords Biometrics · Emerging biometrics · Human recognition/verification

1 Introduction

Biometric recognition of people is a pioneering and evolving research area that aims to fulfil the human need for security. The term biometrics recognition of people refers to automatic security systems that rely on physical or behavioural human characteristics. In the beginning of the last decade, biometrics were considered as the most confident solution for the development of future security systems. Many body parts, personal characteristics and imaging methods have been suggested and used for biometrics systems: fingers, hands, feet, faces, eyes, ears, voices, signatures, typing styles and gaits.

The problem of automatic person recognition/verification for security applications is eventually the one that attracted the interest of the research community. 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 [1, 2]. Usually, these systems are supported by a human expert that takes the final decision for the identity of the test person. On the other hand, person verification refers to the automatic acceptance or rejection of an identity claim. That is, a test person claims the identity of a person that is included in the system database and the system has to decide either to accept the claim or not. The problem of person verification is the one that has attracted the interest of many research groups and companies in the last years and stimulated the development of many verification techniques and biometric systems using several modalities [3].

Face recognition/verification is considered as one of the most attractive biometric applications and has received significant attention [4–6]. The problem of machine recognition of human faces continues to attract researchers from disciplines such as image processing, pattern recognition, neural networks, computer vision, computer graphics, and psychology. Although a large number of algorithms and different applications have been proposed, face recognition/verification remains an active subject of research. Its ultimate efficiency is still an unsolved issue which depends on many factors like the recording conditions, the method and the image database used [7, 8].

Speaker recognition is another modality that has been under research for many years, [9]. Voice biometrics use the information contained in the speech stream to perform

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identification. They usually benefit from using good microphones and noise cancellation techniques but are vulnerable to conditions that affect the performance of these systems: background and channel noise, variable and inferior microphones and telephones, extreme hoarseness, fatigue, or vocal stress [10]. However, there are several levels of information in speech that are not affected by these conditions such as "word usage" [11].

Probably the most common known biometric is fingerprints. Fingerprint technologies are mostly based on the analysis of two-dimensional maps of fingerprints produced by a number of different sensor types. During the processing stage, the ridge patterns on the fingertip are often reduced to a digital representation for efficient storage. These technologies are practical and easy to implement but performance measures vary widely and are affected by many factors as dryness, dirt or ageing [12, 13].

As already mentioned, the number of the proposed biometrics is large and many review articles have been published, analyzing the advantages and disadvantages of each of these 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 [5]. Besides effectiveness, the availability and the affordability of biometric technologies appear to be important requirements for biometric systems.

The need for security in every day life is continuously increasing and the various possible demands require different approaches. Since the classical biometric modalities are not able to supply the needs of every possible security requirement, numerous emerging biometric modalities are presented, trying to fill the gap. In this paper we will introduce the emerging technologies on biometrics.

At this point we should mention, that the scope of this paper is not to provide an extensive review of the typical biometric solutions such as iris, fingerprint, face, voice, gait, retina and signature, but only to concentrate to emerging biometric modalities. Moreover, we should note that nowhere in this paper is claimed that any of the emerging should have better performance than any of the well studied modalities. All of the presented methods have just emerged and it is obvious that time is required until these methods are truly evaluated. The rest of the paper is organized as follows. In Sect. 2, we briefly describe the emerging biometric techniques. Conclusions are drawn in Sect. 3, summarizing the presented developments.

2 Emerging biometric modalities

2.1 Gait

Although gait has been proposed as a biometric solution over a decade ago, it is still seen as a future biometric [14, 15]. Psychological studies have demonstrated that it is possible to recognize people by the way they walk. Recently, great attention has been given on how machine vision systems are able to take advantage of gait's individuality and support biometric applications. Gait as a biometric is examined for many years and many methods have been proposed. Since the number of publications concerning the specific modality is quite large, the most representative and recent advances are presented here.

Boyd and Little in [16] 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 foul gait cycle repeat in every cycle. The periodicity of the these movements as well as the coordinated and cyclic motion of gait makes it a unique phenomenon. The basic data types used in gait and motion analysis systems are: background substraction, silhouettes, optical flow and motion energy/history images. There is a variety of methods that are used for gait recognition and according to [16], they categorized by their source of oscillations: shape, joint trajectory, self similarity, and pixel.

An example of a system using joint trajectories is given in [17]. The method extracts a hip joint trajectory from a sequence of images. Subsequently, recognition is performed based on the Fourier components of the trajectory. The method is tested on a database of 10 yields recognition rates of 80% and 100% for Fourier features, and phase-weighted Fourier features respectively. Accordingly, a self similarity based method in [18], exploits this self similarity to create a representation 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 two images at times t_i and tj_j.

A system based on pixel oscillation in [19], demonstrates how the frequency of the gait and the timing of the component motions, 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 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 technology [20], uses markerless gait analysis. the method 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 properties of the method give advantages to it, as according to authors it overcomes marker technology and makes a possible commercial product unobtrusive. The proposed gait analysis is based on two consecutive steps: a motion estimation method which extracts the limb's 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 3 subjects viewed at 6 different camera inclinations have been used. The results as illustrated, indicate that are comparable to the results obtained by reflective marker based techniques encouraging for real application scenarios.

Another recent study in gait identification [21], 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 perceivable with better recognition rate even under the different covariate factors.

Gait presents advantages compared to other biometric modalities such as iris or fingerprints. Its main advantage is that it is effective at 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 multi-modal biometrics where it is supposed that increases the overall performance of the system.

2.2 Thermogram

Conventional video cameras sensors reflect light, so that image intensities depend on both intrinsic skin reflectivity and external incident illumination, thus obfuscating the intrinsic reflectivity of skin. Thermal emission from the skin, on the other hand, is an intrinsic measurement that can be isolated from external illumination, under normal conditions.

Fig. 1 Sample mages from Equinox database [22]

Researchers have found that a unique heat distribution pattern can be obtained from the human face. This pattern can be seen by acquiring still images using infrared cameras. The different densities of bone, skin, fat and blood vessels all contribute to an individual's personal "heat signature". Example of a database containing thermal images is the Equinox database [22]. 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 few samples taken from the database are shown in Fig. 1 [22].

Nine different comparative thermogram parameters are used excluding the nose and ears, which are prone to wide variations in temperature [23]. Once an image of a face is taken, its thermal image can be matched with accuracy against a database of pre-recorded thermographs. The algorithm is based on Monte Carlo analysis of performance measures. This analysis reveals that under many circumstances, using thermal infrared imagery yields higher performance, while in other cases performance in both modalities is equivalent. Performance increases further when algorithms on visible and thermal infrared imagery are fused.

A study in [23] examines the invariance of Long-Wave Infrared (LWIR) imagery with respect to different illumination conditions from the viewpoint of performance comparisons of two face recognition algorithms (eigenfaces [24] and Arena [25], respectively) applied to LWIR and visible imagery. A rigorous data collection protocol has been developed that formalizes the meaning of thermal IR in face recognition analysis. The experimental procedure performed on a database of prerecorded infrared videos of 91 subjects. The classification performance for ARENA on LWIR imagery reported to be up to 99% while the minimum score achieved was 97%. The minimum score reported for the case where the training set comprised by frames representing different expressions and faces with glasses. The performance of eigenfaces on LWIR imagery, was 96% and 87% for the same training sets used for Arena algorithm respectively.

A comprehensive performance study of multiple appearance-based face recognition methodologies, on visible and thermal images is presented in [26]. This analysis (based on Monte Carlo analysis) reveals that, under many circumstances, the use of thermal infrared images yields better performance, while in other cases, performance in both modalities is similar. Recognition performance increases further, when algorithms applied to visible and thermal infrared images are combined. The matching is achieved by the use of a Bayesian classifier. The experiments where performed on Equinox database while the higher matching rate produced reported to be equal to 89,6%.

In [27, 28], a two stage face recognition method based on infrared images and statistical modelling of visible images is presented, aiming to decrease the error caused by the presence of eyeglasses. An enhanced approach is proposed by applying Bessel modelling on the facial region only, rather than on the entire image and by pipelining a classification algorithm to produce a unique solution. Although both approaches managed to improve the performance presented by the single IR methods, they were not able to fully discount 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 on thermal IR is outlined in [29] 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. In following, 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 TMP-based feature vectors. Tests with 500 thermal faces from 50 subjects show an eer of $\simeq$6.

One of the obvious advantages of systems using thermal images is the ability to operate in complete darkness, which makes them ideal for covert surveillance. Thermograms also offer robustness over certain kinds of disguises. The structures that are imaged are beneath the skin and this makes their alteration almost impossible. They are also robust to aging and unaffected by traumatic epidermic accidents. However, they have other limitations, including the fact that glasses are opaque to IR radiation. The presence of glasses and thick facial hair, as well as substantial perspiration, which may be the result of exertion of heat are major problems that considerably affect the results [30].

2.3 Near infrared images

Near-infrared (NIR) images obtained from hyperspectral cameras provide useful discriminant information for human face recognition that cannot be obtained by other imaging methods [31, 32]. The use of near-infrared hyperspectral images for face recognition, over a database of 200 subjects, is examined in the above referenced works. More specifically, a face recognition algorithm is described that exploits the spectral measurements for multiple facial tissue types. The images were collected using a CCD camera equipped with a liquid crystal tunable filter to provide 31 bands over the near-infrared (0.7–1.0 μm) as shown in Fig. 2.

Spectral measurements over the near-infrared spectrum allow the sensing of subsurface tissue structure which is significantly different from person to person, but relatively stable over time while the provided facial features are somewhat illumination invariant. The experimental results show that the local spectral properties of human tissue are nearly invariant to face orientation and expression which allows hyperspectral information to be used for recognition over a large range of poses and expressions.

In [31], it is experimentally demonstrated that this algorithm can be used to recognize faces over time in the presence of changes in facial pose and expression. The authors claim, that the algorithm performs significantly better than the current face recognition systems for identifying rotated faces. Performance might be further improved by modelling the spectral reflectance changes due to face orientation changes. As an extension of their previous work researchers in [33], present results on recognizing 200 human subjects under unknown outdoor illumination in hyperspectral face images. For each subject, several NIR images with different facial expressions and face orientations were acquired on different days under various natural illumination conditions. A set of 7258 global spectral irradiance functions were used to synthesize reflected radiance images of each subject. A low-dimensional linear model for each tissue type

Fig. 2 Thirty-one bands of NIR images of one subject [31]

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 various face orientations.

Another solution, including active NIR imaging hardware, algorithms, and system design, is presented in [34]. The system is presented as another solution to problems created due to illumination variation in face recognition modalities. An illumination invariant face representation is obtained by extracting local binary pattern (LBP) features 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. Testing dataset contained 3,237 images from a total of 35 persons and the accuracy reported by authors was 94.4%.

In [35] the novelty compared to other NIR systems, is the use of constant illumination for face recognition. Authors advocate that active NIR illumination provides a constant invisible illumination condition and facilitates the automatic eye detection by introducing bright pupils. The result 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 [36], ascribe the success of the system presented, firstly to NIR images that, as advocate, 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 if 0.3%.

The main advantage of the NIR image based techniques as already mentioned, is that it overcomes problems due to illumination. The use of NIR images is also supposed to provide advantages over rotated faces, expressions and robustness over time. However, the specific modality does not seem yet to be suitable for uncooperative user applications such as face recognition in video surveillance [34]. Although many methods present impressive performance on both indoor and outdoor conditions, near infrared technology so far, is mainly suggested for indoor cooperative user applications.

2.4 Smile recognition

Another method for person recognition is suggested in [37]. A high speed camera with a strong zoom lens allows smile maps to be produced. This map is claimed to be unique for each person. This new method compares images of a person, taken fractions of a second apart, while the person is smiling. The system probes the characteristic pattern of muscle deformations beneath the skin of the face. The way the skin around the mouth is moved over the video frames, is analyzed by tracking the change position and direction of tiny wrinkles in the skin. The data is used in order to produce motion vectors describing the deformations of the facial region. This deformation is controlled by the pattern of muscles under the skin and is not affected by the size of the smile or the presence of make-up. It is noted that a full smile is not required as the system is sensitive enough to produce a map of features-even when people are trying to keep an unchanged expression. The proposed technique is “invisible”, because smile maps can be produced without the suspects knowing that they are tracked. Further application of this method is hoped to be found in medicine. Some nerve disorders cause distinctive asymmetries in movement of facial muscles.

The system has been successfully tested so far only on a very small database consisted of samples of 4 lab members while smiling. The system is currently tested on a larger group of 30 smiling faces but no results have been reported so far.

2.5 Lip recognition

A lip deformation recognition method that uses shape similarity when vowels are uttered is proposed in [38]. In this method, a mathematical morphology analysis is applied on the lip area using three different structuring elements. The proposed structuring elements are the square, vertical and 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 Fig 3.

Experimental results show that the shape vector contains enough information to perform recognition. In particular, eight Japanese persons could be classified with 100.0% accuracy by their lips. Of course the test set is very small, the results may be biased and authors make this clear. They note that the system is not sophisticated yet and classification accuracy has to be improved by considering other structuring elements (for instance, rectangle, ellipse or an asymmetric shape). The test on a significantly larger database is incontestably required to assess the performance of this method.

Another approach [39] considers lips' shape and color features in order to determine human identity. 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. The feature vector that finally describes lips, consists of a selection of the most discriminant information of: Hu moments, central moments, of Zernike, standard geometrical parameters, statistical color features in RGB, YUV and HSV color spaces. Experiments on a database of 38 subjects show that the method was able to recognize successfully the 76% of the under test samples.

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 lip detection, especially acquired from surveillance cameras, consist a major drawback of the system.

2.6 Thermal palm recognition

Palm print recognition has been investigated for more than 10 years [40]. A large number of methods has been proposed

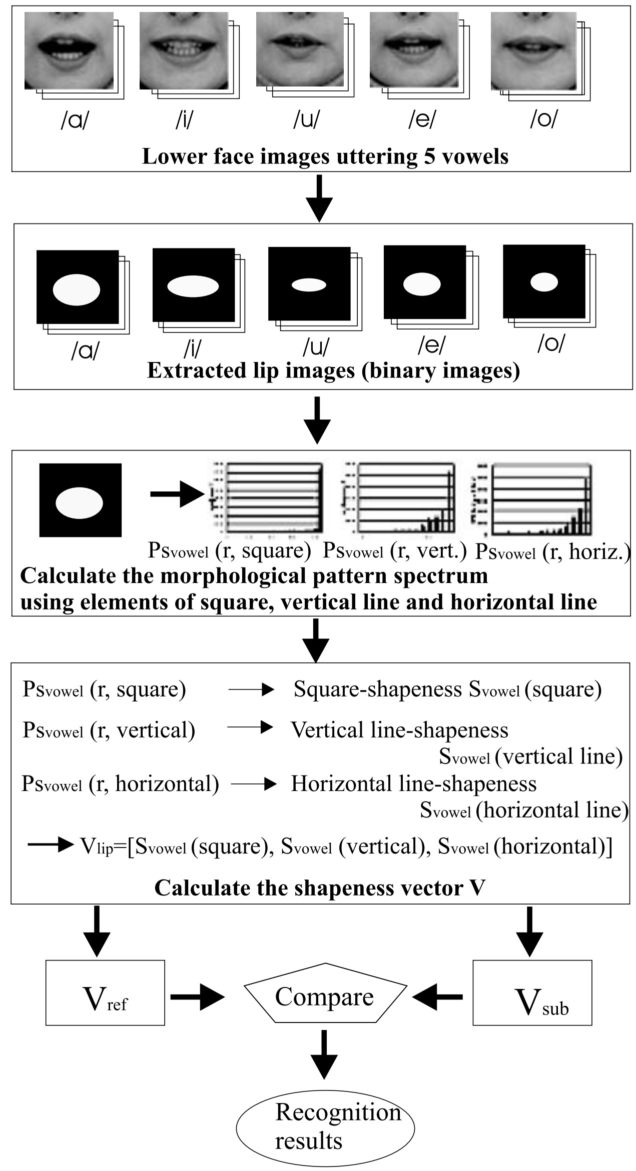


Fig. 3 Overview of the Lip recognition system in [38]

and many different problems have been addressed. A novel approach for personal verification using the thermal images of palm-dorsa vein patterns captured by an infrared camera is presented in [41] (Fig. 4). Two of the finger webs are automatically selected as the datum points to define the region of interest on the thermal images. Feature points of the vein patterns (FPVPs) are extracted by a watershed transform modified according to the properties of thermal images. The watershed transform calculates the locations of region basin minimal (or maxima) [42]. In this case, the region maximum method is used to extract the FPVPs, while 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. According to the heat conduction law (Fourier Law), multiple features can be extracted from each FPVP for verification.

Multiresolution representations of images with FPVPs are obtained using multiple multiresolution filters (MRFs) that extract the dominant points by filtering miscellaneous features for each FPVP. More specifically, three different MRFs are used to retain the properties of multiple features of the FPVPs at the next level resolution. The first MRF is called moment filter and is used to construct multiscale feature point images (FPIs). 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. A hierarchical integrating function is then applied to integrate multiple features and multiresolution representations. The former is integrated by an inter-to-intra personal variation ratio (weights) and the latter is integrated by a positive Boolean function.

The experimental results show rather satisfactory performance (false rejection rate: 2.3% and false acceptance rate: 2.3%) [41]. However, there is still need for further investigations to confirm performance in adverse conditions. The effects caused by the ambient temperature, the thickness of the skin, the degree of venous engorgement, the condition of the vein walls and the nearness of the vein to the surface, are some of the conditions that affect the recognition rate. Finally, any variation in the surrounding temperature may lead to unstable distribution patterns. This is one of the main problems for this method and it is difficult to be resolved by relying only on the vein-pattern features in palm-dorsum thermal images. Some issues in using palm prints for personal identification have not been well addressed. For instance, we know that ridges in palm prints are stable for a person's whole life but the stability of principal lines and wrinkles has not been systemically investigated.

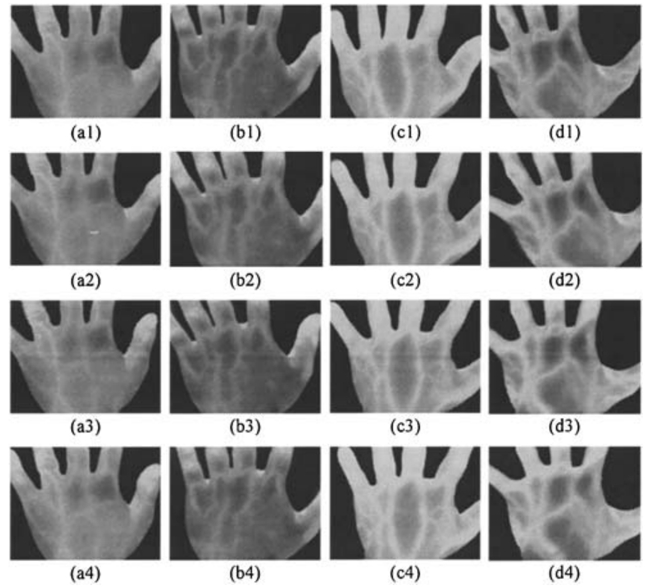


Fig. 4 Thermal images captured from four different palm-dorsa: (**a1–a4**), (**b1–b4**), (**c1–c4**), and (**d1–d4**) [41]

2.7 Hand/finger knuckle

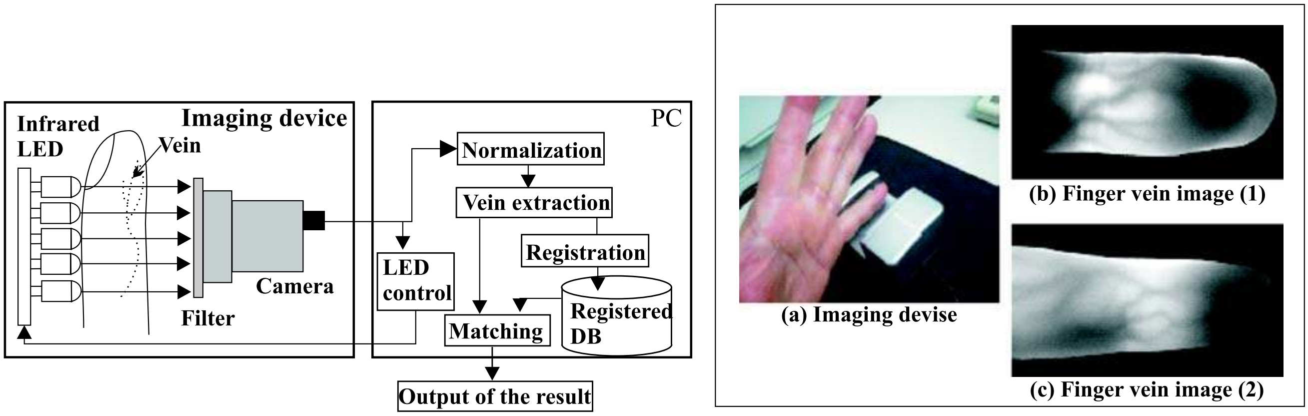
In [43], a first approach of another novel biometric verification system based on the texture of the hand knuckles is presented. This method uses knuckle images isolated from the hand. The wrinkle of the knuckle images are extracted to a black and white image which is used as biometric feature. The different repetitions of the hands are aligned according to a reference image called "training image". As verifiers, the authors use a hidden Markov model and a Support Vector Machine. The feature for hidden Markov model is the sequence of image columns, while the feature for support vector machine is a vector with the concatenate columns of the image.

The training samples have been chosen randomly from the database set and the tests have been performed using different samples. In order to enhance the experimental results, the proposers of this method, repeated the training and testing procedure ten times with different randomly chosen training and testing sets. The testing results indicate a similar equal error rate of 0.094 for both classifiers with a database consisting of 8 samples of 20 people hand. The authors note that this is a preliminary database but they argue that the results are encouraging for further research on the specific modality.

A more particular area of the hand is investigated in [44]. Finger knuckles are claimed to be also unique and their surface can be used as a distinctive identifier. The finger geometry in conjunction with the knuckle texture obtained from a single finger image improve the overall performance of the system. The method analyzes the texture of the normalized knuckle regions in spatial and frequency domain using two dimensional Gabor filters. The proposers of the specific technique tested their system on 105 users and report accuracy comparable to or better than other hand-based biometrics systems. However, it is also reported that the performance of finger-knuckle identification depends sensitively on the accuracy of knuckle segmentation from the fingers or hands being measured. Traditional texture-phase information using knuckle lines and creases are not yet satisfactory and further efforts are required.

2.8 Finger-vein patterns

Another method for personal identification is proposed in [45], based on finger-vein patterns. The authors proposed a scheme based on finger vein patterns as a scheme of biometric identification utilizing biological information. A brief



(a) (b)

Fig. 5 (**a**) Principle of personal identification using finger-vein patterns, (**b**) Prototype of finger-vein imaging device and examples of infrared images of a finger [45]

idea about how the finger images are produced is illustrated in Fig. 5. Since the finger vein images taken to obtain finger vein patterns are obtained by irradiating the fingers with infrared rays, fluctuations in brightness due to variations in the light power or the thickness of the finger occur.

This paper proposes a scheme for extracting global finger vein patterns by iteratively tracking local lines from various positions to robustly extract finger vein patterns from such unclear images. Researchers argue that an image of a finger captured under infrared light contains not only the vein pattern, but also irregular shading produced by the various thicknesses of the finger bones and muscles. 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 work [46, 47].

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%.

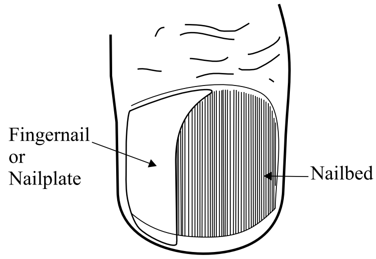
It is also reported, that the mismatch ratio is slightly higher during cold weather, because the veins of the finger can become less visible. Therefore, a device that can capture the vein pattern more clearly and a feature extraction algorithm that is robust against these fluctuations should be investigated. The authors consider improving their system in another direction as well. They believe that three dimensional rotation of the finger degrades the identification accuracy. So, they consider modifying their application in such a way that it will force the user to place a finger in the same position every time. This method can be easily combined with other biometric techniques based on parts of the hand like fingerprints, finger/hand geometry. Another main disadvantage of this technology, is that it cannot be easily fitted in small devices (mobiles, cards etc.) like fingerprints. Thicker fingers present difficulties as light penetration may be insufficient in many cases.

It is worth noting that a commercial product called "SecuaVeinAttestor" is based on finger vein imaging. Full specification and characteristics of this product are given in [48].

2.9 Nail ID

A really novel biometric modality is presented in [49]. It describes a commercial product that is supposed to identify a person by reading the information that is hidden in the finger nail, more specifically in the nailbed. The nail and nailbed are shown in Fig. 6. The nailbed is an essentially parallel epidermal structure located directly beneath the fingernail. Anyone who has suffered a mashed fingernail may have seen one or more thin blue lines appear under the nail. The line is 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. The human nailbed is a unique longitudinal, tongue-in-groove spatial arrangement of papillae and skin folds arranged in parallel rows. During normal growth, the fingernail travels over the nailbed in a tongue-and-groove fashion.

Keratin microfibrils within the nailbed are located at the interface of the nailbed and the nailplate, or fingernail. The method utilizes a broadband interferometer technique to detect polarized phase changes in back-scattered light introduced through the nailplate and into the birefringent cell



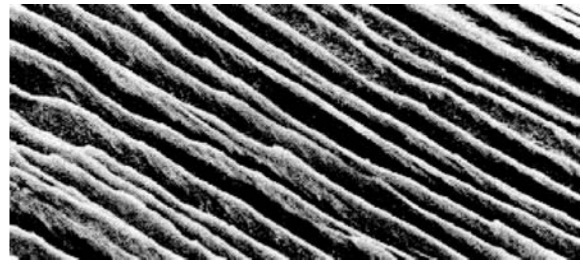


Fig. 6 (**a**) Schematic representation of nail, (**b**) Microscopic picture of nailbed [49]

layer. This is similar to the ordinary process of inspecting microscopic structures on a multi-layered semiconductor. 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. The identification process generates an one-dimensional map of the nailbed, a numerical string much like a "barcode" which is unique to each individual. This design may result in an in-expensive hardware scanning assembly.

This technology may be more efficient than other relevant modalities, such as fingerprints and hand geometry. The nailbed, residing beneath the nailplate, is not externally visible and hence difficult to alter or duplicate. The inventors even argue that the system can also be accessed through surgical gloves. However so far, there is no published work showing the true capabilities and performance of this system.

2.10 Skin spectroscopy

In [50], a new commercial biometric technology based on the unique spectral properties of human skin is described. Skin is a complex organ made of multiple layers, various mixtures of biochemical substances and distinct structures, such as hair follicles, sweat glands and capillary beds. While every person has skin, each person's skin is unique. Skin layers vary in thickness, interfaces between skin layers have different undulations and other characteristics, collagen fibres and elastic fibres in the skin layer and capillary bed density and location differ. 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 system hardware and software are reported to recognize these skin differences and 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 (Fig. 7). The changes to the light as it passes through the skin are analyzed and processed to extract a characteristic optical pattern that is

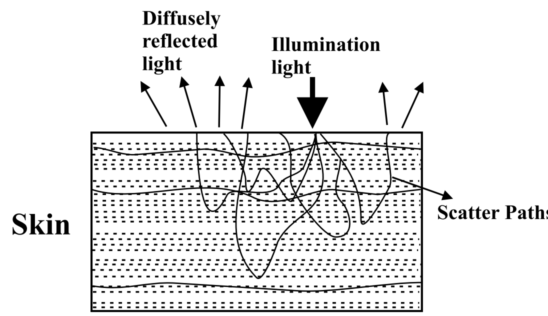


Fig. 7 Illustration showing light undergoing optical scatter as it passes through skin, resulting in a portion of light that is diffusely reflected [50]

then compared to the pattern on record or stored in the device to provide a biometric authorization.

Since the optical signal is affected by changes to the chemical and other properties of human skin, it also provides a very sensitive and easy way to confirm that a sample is a living human tissue. Non-human tissue or synthetic materials have very different optical properties than the human skin, which cause a corresponding change to the resulting optical signal. Likewise, excised or amputated tissue undergoes rapid changes in biochemistry, temperature and distribution of fluids within the various physiological compartments that also alter the optical signal. These optical differences ensure that a sample authorized by the biometric sensor is truly that of a living human (aliveness detection). The sensor used to perform these non-imaging optical measurements is a small, solid-state device made up of light emitting diodes and silicon photo detectors embedded in an alumina ceramic housing shown in Fig. 8 [51]. 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.

A multi-person performance evaluation was conducted by the investors of the solid-state spectral biometric sensor over a 4-month period [51]. In total, 113 volunteers from different ethnics and ages, participated in the study and were measured over multiple visits. More than 11,000 individual measurements were collected. Study participants were requested to come in "as is" during their scheduled time. Prior to performing the spectral measurements, an interview was

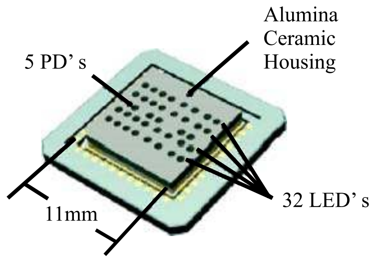


Fig. 8 Solid-state biometric sensor [51]

conducted to collect any potentially noteworthy information that could potentially correlate with error sources. Many people indicated recent applications of lotion and other topical substances on their hands, and dirt was noted on some subjects' hands. The overall equal error rate (EER) given for this system for single-try data is 2.7%. However, the researchers maintain that the overall performance improved remarkably after the volunteers successfully used the sensor a small number of times. After each person successfully used the sensor 20 times the overall EER obtained was decreased to 1.7%.

Spectroscopic approach as a biometric offers a grate advantage over other conventional technologies. Since skin is a such a complex organ, it cannot be copied or replaced by synthetic materials offering in parallel, liveness detection. Such an approach that examines spectroscopy as aliveness detection solution for biometric systems, is presented in [52].

2.11 Ear prints

Using ears in identifying people has been a subject of investigation for at least 100 years. The researches still discuss if ears are unique, or unique enough to be used as a biometric modality. Ear shape applications are not commonly used yet, but the topic is interesting, especially in crime investigation. Burge and Burger think that ear biometrics is a "viable and promising new passive approach to automated human identification" [53]. When a burglar listens at, for instance, a door or window before breaking and entering, oils and waxes on the ear leave a print that can be made visible using techniques similar to those used when lifting fingerprints. The 'FearID' research project, a collaboration of several European institutes, was aimed at the individualisation of such an ear print to a person. The study presented in [54] is compiled within the framework of this project.

Ear data can be received from photographs, video or earprints produced by pressing the ear against a firmed transparent material, for instance glass. Ear print geometry is shown in Fig. 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'):

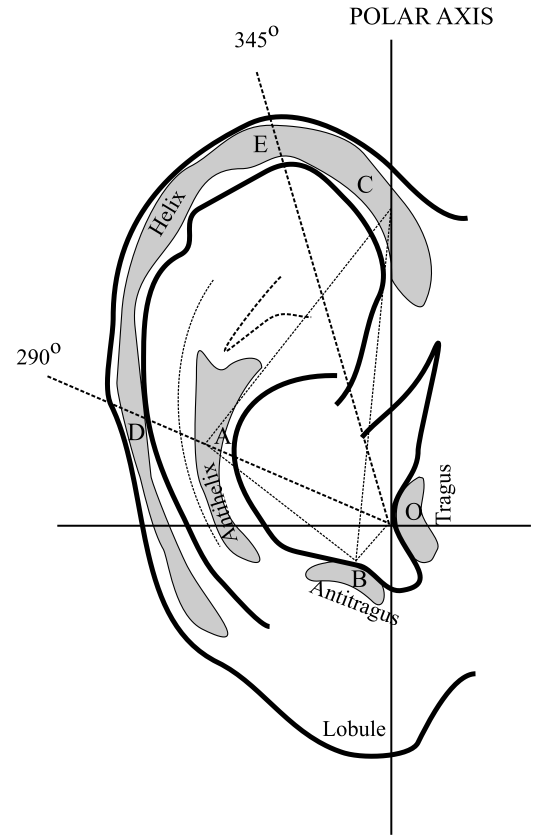


Fig. 9 Reference points for metrical characteristics ('cues') of an earprint [58]

- (A) Intersection of the 290ø 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 345ø 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*

In [55] researchers suggest that the ear may have advantages over the face for biometric recognition. Their previous experimental results working on ear and face recognition tasks, using the standard principal component analysis, indicated an almost equal recognition performance for the two different types of data. The dataset consisted of 197 subjects used in training. Each sample had both, face and ear images taken under the same conditions and same image acquisition session. After testing the database under pose and lighting variation, they found that the recognition performance is not significantly different between the face and the ear. Their published work indicates 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.

Although there are many methods that use ear biometrics, [56], their performance is not sufficient yet. Probably the most important argument against the use of this biometric modality comes from its discriminant capacity. A Netherlands court decided that the earmarks are not reliable enough for judging [57]. It was also decided that when there are no dependable proofs that ears are unique, ear identification cannot be used as evidence.

2.12 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 [59].

It employs a similar idea to keystroke dynamics. Keystroke dynamics is a common and widely known technique since the beginning of the past decade [60]. 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.

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 Fig. 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.

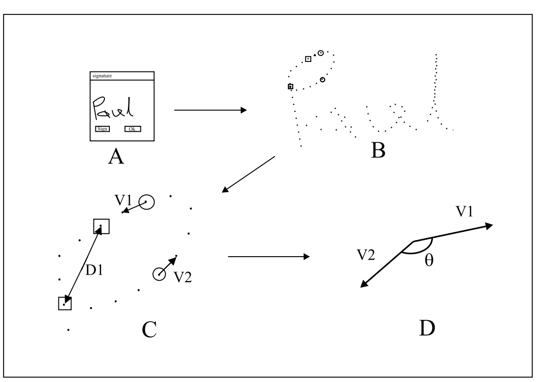


Fig. 10 Main idea of the mouse dynamics recognition system [59]

In order to increase the improvement 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 and false rejection rate of around of around 4.4% and 1% respectively. In these trials, it was assumed that the password was known, whereas in reality it would not be.

In [61], 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 user’s usage. The authors develop a mouse dynamic signature (MDS) for each user using a variety of machine learning techniques. The data collected for the experiments comprise of 22 participant 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 that in following, makes the classification. The FRR and the FAR obtained for this study was 2.4649% respectively. This approach according to authors, could also applied for continuous user authentication.

Mouse dynamics presents a number of advantages: 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 on-line biometric verification solution. On-line banking, internet shopping, or accessing web based e-mail, could be a few of its possible applications. However, mouse dynamics can be applied only on those applications where a computer founds a natural match [62].

2.13 Electrocardiogram (ECG)

An electrocardiogram is an electrical recording of the heart and is routinely used in the investigation of heart diseases. ECG is widely known from its clinical usage and has been used since the beginning of the 20th century for the diagnosis of different cardiac diseases. Recently, several researchers characterized the ECG as unique to every individual [63–65].

In [66] the ECG processing with quantifiable metrics was proposed as a biometric modality. Data filters were designed based upon the observed noise sources. Fiducial points were identified on the filtered data and extracted digitally for each heartbeat. From the fiducial points, stable features were

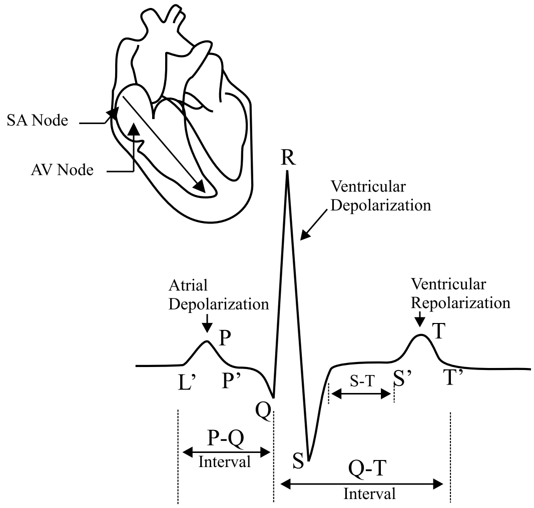


Fig. 11 ECG trace based upon cardiac physiology. L' and P' indicate the start and end of atrial depolarization, the R complex indicates ventricular depolarization, and the T complex indicates the ventricular repolarization [66]

computed that characterize the uniqueness of an individual. The locations of the fiducial positions, noted by an apostrophe ('), are illustrated in Fig. 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. Collectively, the fiducials describe the unique physiology of an individual. The extracted features are based upon cardiac physiology and have fixed positions relative to the heartbeat.

The tests show that the extracted features are independent of sensor location, invariant to the individual's state of anxiety, and unique to an individual. The above experimental data were collected from males and females between 22 and 48 years old. Twenty-nine individuals were tested 12 repeat times, for each of the 41 total sessions within the dataset. Each individual session contained a set of recordings during seven two-minute tasks. The tasks where designed to stimulate different states of anxiety. Unlike conventional ECG data, the hardware for this series of experiments collected ECG data at a high temporal resolution of 1 ms. Trying tests measuring the heartbeats in two different points (neck and chest), researchers managed to classify 82% and 72% of the heartbeats for the two different points respectively, while in both cases 100% of subjects' identification was achieved.

The dataset was used to identify a population of individuals. Additional data collection is being tried in order to test the scalability of the features to characterize a large population as well as the stability of those features over long time intervals.

In [67], researchers simplify the procedure and demonstrate ECG's use as a biometric under conditions that include intra-individual variations and a simple user interface (electrodes held on the pads of the subject's thumbs). ECG person identification was accomplished through quantitative comparisons of an unknown signal to enrolled signals. The quantitative comparisons were: the correlation coefficient and a wavelet distance measure. It was found that the combination of these two methods provided improved performance, relative to either individual method. ECG person identification accuracy on 59 subjects was 90.8%. While this accuracy is relatively low compared to conventional biometrics, such as fingerprints, the ECG according to authors can be used as supplementary information for a multi-modal biometric system. A multi-modal system that includes the ECG would have increased accuracy and robustness, without necessarily requiring any change to the perceived user interface. At minimum, the ECG would be useful in providing liveness detection.

It is important to be mentioned that the technique is rather difficult to use, since it requires the placement of electrodes on subject's body, making the enrolment and testing procedures time-consuming. An evaluation on how easy an ECG biometric system can be fooled by the morphology of the electrocardiogram can be found in [68].

2.14 Electroencephalogram (EEG)

It has been shown that the brain activity measured in electric waves is unique to every individual [69, 70]. A new study in [71], uses the brain wave pattern for person authentication. The authors hold that the use of EEG as a biometric solution has several advantages as: it is confidential (as it corresponds to a mental task), it is very difficult to mimic, and is almost impossible to be copied or to be stolen.

In general, only a few things have been proposed in this area and this is the first method concentrated on person authentication. The authors propose a statistical framework used in other biometric authentication approaches such as face and speaker authentication. More specifically, they use a statistical framework based on Gaussian Mixture Models and Maximum A Posteriori model adaptation which can deal with only one training session. They perform intensive experimental simulations using several strict train/test protocols to show the potential of the specific method. They also show that there are some mental tasks that are more appropriate for person authentication than others.

The EEG is a very noisy signal and its processing is a difficult task. For the feature extraction, researchers spatially filter the signal by means of a surface Laplacian the EEG raw potentials. In following they increase the signal-to-noise ratio and extract the features that better describe the mental state to be recognized. The choice of the electrodes and frequency band is based on the expertise available in the Brain Computer Interfaces (BCI) community [72].

The experimental results indicated that EEG could be an effective modality for person authentication and that the specific method performs satisfyingly for the specific task. By having a closer look on the experiment protocol though, one can see that although the number of simulations that take place is large, the number of individuals that are involved, is very small (3 persons). It is obvious that no conclusions can be drawn on such a small database. Another matter that authors note, is that mismatching between testing and training increases from day to day. So, data collected in one day is not enough for training robust models.

After authors in [73] showed that the energy of brain potentials evoked during processing of visual stimuli appear to have potentials in applications for such as stand alone individual identification system or as a part of a multi-modal individual identification system, they pushed their research forward. In their following study [73], they analyze the potential of dominant frequency powers in gamma band Visual Evoked Potential (VEP) signals as a biometrics. Techniques used include those based on the k-Nearest Neighbors (kNN), Elman Neural Network (ENN) classifiers, and 10-fold Cross Validation Classification (CVC). The feature extraction is achieved by a subspace technique called Multiple Signal Classification (MUSIC) while the classification techniques used include those based on the k-Nearest Neighbors (kNN), Elman Neural Network (ENN) classifiers, and 10-fold Cross Validation Classification (CVC). For the experimental procedure of the specific work, a total of 3,560 VEP signals from 102 subjects were used. There was a minimum of 10 and a maximum of 50 eye blink free VEP signals from each subject (in multiples of 10). Three different experiments were conducted with features produced by the EL, SMT, and the proposed features. The maximum ENN classification accuracy for the improved feature extraction method was 98.12 ± 1.26, while the classification performances for EL and SMT methods were $96:94 \pm 1:44$ and $96:54 \pm 1:23$. For kNN, the corresponding maximum classification accuracies were 92.87 ± 1.49, 91.94 ± 1.54, and 96.13 ± 1.03 and were obtained for $K = 1$. Authors argue that their results have clearly indicated the significant potential of brain electrical activity as a biometric.

On this research topic a recent study [74] proposes a multitask learning approach which is in contrast with previous EEG based methods. While EEG techniques use for classifier design and subsequent identification a single task (signals recorded during imagination of repetitive left hand movements or during resting with eyes open), the proposed method uses multiple related tasks simultaneously. The advantage obtained, is that classifier learning can be more effectively guided in a hypothesis space as it integrates information from the extra tasks. For the experiments 180 recorded trials for 9 subjects where used. Accuracy rate proved to reach 95.6% for imaging left index finger movements.

Summarizing the elements provided in the specific works, we could say that brain activity could be proven to be a promising modality for individual authentication. As mentioned above, due to its special character and the advantages that presents against other type of biometrics (confidentiality, difficulty of mimicry, not easy to be stolen) it could be useful to application with special demands. There is a lot of things to be done though in order this method to support a full real time authentication system. The procedure requires the absolute participation of the subject, it is dependent on it's current mental condition, while the placement of the electrodes to the right position and the process of the (EEG) signal is significantly time consuming.

2.15 Cognitive biometrics

An alternative biometric is described in [75]. In this study, the simplicity of interface is kept while the restriction of typing specific patterns is alleviated. The present work was motivated by recent, independent studies in cognitive neuroscience and psychiatry reporting that the generation of random rhythms or numbers is a demanding cognitive task and carries enough information to discriminate between different clinical populations. When someone is asked to generate (verbally or via keyboard) random numbers, there is a cognitive load implied. This is due to the close interaction between short-term memory and internalized decision making mechanisms. A closely related task is the generation of 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.

At an experimental level, this is the first approach where human-generated time-series of random latencies are tested as biometric. The procedure for generating the RTI signals is simple. The subject is asked to press the space key of the computer with the index finger of his/her dominant hand as irregularly as possible, until the screen shows the end of the exercise. The first time the subject encounters this task, is provided beforehand with an example consisting of a square 4×4 cm, which appears and disappears in the screen at random rhythm and is synchronized with a sequence of beeps. The particular example is indicative of the sort of time series one has to create and—as it is explicitly stated—its exact reproduction is not the objective of the task.

Moreover, the dynamics showed a prominent idiosyncratic character when realizations from different subjects were contrasted. Researchers established an appropriate similarity measure to systematize such comparisons and experimentally verified that it is feasible to restore someone's identity from RTI signals. By incorporating it in an SVM-based verification system, which was trained and tested using a medium sized dataset (from 40 persons), an equal error rate of $\simeq$5% was achieved. The method though, has a major drawback. The enrolment procedure at the moment takes

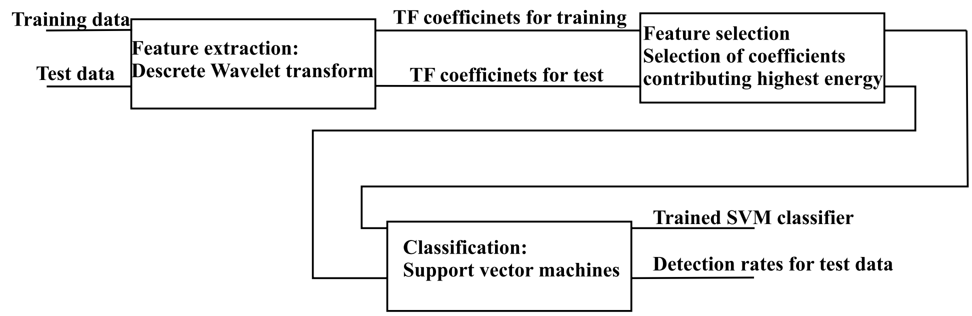


Fig. 12 Overview of the detection system for cochlear hearing loss [78]

almost two minutes and requires the foul user cooperation. Such an enrolment procedure is considered as highly intrusive for any kind of biometric application.

2.16 Otoacoustic emissions recognition (OAE)

A research project at the University of Southampton is examining whether hearing could be effective in recognizing individuals by otoacoustic emissions [76]. If audio clicks are broadcasted into the human ear, a healthy ear will send a response back [77, 78]. These are called otoacoustic emissions. OAE testing is often used to screen newborns for hearing problems and it is done, by placing a small, soft microphone in a person's ear canal. Sound is then introduced through a small flexible probe inserted in the ear. The microphone detects the inner ear's response to the sound. The overview of the detection system for cochlear hearing loss is illustrated in Fig. 12. The researchers are examining the reliability of using this source as a biometric modality. From the total of 704 measurements reported in [76], 570 (81%) were correctly classified.

The specificity of otoacoustic emissions to an individual and their stability over a 6 month period time is demonstrated in [79]. Experiments performed on 760, 561 subjects and a smaller dataset indicated that otoacoustic emissions are surprisingly individual. Use of simple statistic techniques indicated an equal error rate of 3.53% with 95% confidence improving to 2.35% at 90% confidence. The research suggest a level of permanence of at least 6 months.

Even though otoacoustic emissions seems to be strange by its nature as far as it concerns it possible applications, it could be easily used in many commercial products. For instance, it could be used to guard against mobile phone theft, where such a modality could be used to check whether the user matches the profile of the owner. It could also be used together with a special telephone receiver for card transactions, presumably in conjunction with a PIN number. A cardholder would pick up the receiver and listen to a series of clicks. His otoacoustic response would be measured and checked against the information stored on the card and the records held by the Credit Card Company or bank. Portable music devices and cell phones could be equipped with an acoustic biometric security device to prevent their use by anyone other than a registered user.

2.17 Eye movement

A completely new type of biometric is based on eye movement characteristics [80]. This work examined the reaction of human eyes to visual stimulation. The person to be identified is asked to follow a point displayed on a computer's monitor. An eye tracker is used to collect information relevant with the eye movement during the test. A very fast and accurate tracking system that is based on infrared reflection was used for this reason.

The main challenge for this system was to convert the recorded eye movements to a set of features that may be directly used for identification. The dataset consists of probes. Each probe is the result of recording one person's eye movements during 8 seconds stimulation lasting. The experiments were made with frequency 250 Hz, which means that the probe consists of 2048 single measurements. Each measurement consists of six integer values, which give the position of the stimulating point on the screen and the position of the points the right and the left eye are looking at, respectively. In order to extract a set of discriminant features, the spectrum was used [81]. The experiment was performed on nine subjects. Each person was enrolled more than 30 times and the last 30 trials were used for classification, giving 270 probes for a training set. The validation experiment gave an average false acceptance rate of about 2% and a rather high average false rejection rate of about 25%.

The continuous movement of the eye for biometric purposes is also suggested in [82]. The proposers of the method, have conducted a case study to investigate the potential of the eye-tracking signal. They argue that the distance between 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 week 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.

For a comparison, the researchers created a static user template by taking the time averages for each subject. As long-term statistics, these were expected to carry the information about the physiological properties of the subject's eyes we created a static user template by taking the time averages for each subject. As long-term statistics, these were expected to carry the information about the physiological properties of the subject's eyes. The dynamic user templates were formed by considering the time signal as a feature vector. In summary, eye movement show to provide discriminatory information. Considering that both the training and test signals had the 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).

In contrast to many biometric systems like fingerprint and face recognition, which are based on physiological characteristics, the eye movement identification combines both physiological and behavioral (brain) characteristics. This is an advantage against other biometric modalities, considering that aliveness detection is embodied in this method. On the other hand, the specific method requires a conscious effort on behalf of the subject, which means that the system would fail in the case of, e.g. a drunken person. Researchers mention that there is a lot of work to be done to improve their methodology. The first experiments though, show that eye movement identification may have potentials.

2.18 Dental biometrics

Dental biometrics utilize dental radiographs for human identification. Radiographs are able to provide information about the condition of teeth, their roots, jaw placement, and the overall composition of the facial bones. The radiographs acquired after the victims death are called postmortem (PM) and the radiographs acquired while the victim is alive are called antemortem (AM). A proposed method in [83] uses this information to identify individuals in the forensic domain. The paper presents an automatic method for matching dental radiographs that has two main stages: feature extraction and matching. The feature extraction stage uses anisotropic diffusion to enhance the images and a Gaussian mixture of model to segment the dental work, if there is any. The matching stage has three sequential steps. In the first step (called as tooth-level), a shape registration method aligns the tooth contours and computes the distance between them. If dental work is present, an area-based metric is used for matching it. The two matching distances are then combined using posterior probabilities. In the second step, the tooth correspondence is established for a PM and an AM image and it is used to compute the similarity between the pair of images. In the third step, the distances between subjects are computed and used to retrieve the identities from a database. Some examples of extracted tooth shapes are presented in Fig. 13.

The results provided in this paper are presented in three main steps. The first step is matching at the tooth level, where 414 PM and 738 AM teeth are used. In the second step, teeth in the same rows are viewed as a unit and 166 PM images are matched against 235 AM images. Finally, at the third step, the identification task is performed. In this step, 11 PM subjects are matched to the 25 AM subjects. For the two first steps, the hit rate given is 95% and 90%, respectively, while for the final step the retrieving accuracy is 72%, 91% and 100%, percent according to the number of top retrievals used (1, 4 and 7 top retrievals).

Dental work (DW) information is exclusively used in a newer approach [84]. The proposed method for person identification is based on dental work and consists of three main processing steps. Firstly the segmentation of the dental work is achieved after pre-processing of the dental radiograph images. The information obtained containing the dental work, contains details about the position of it on both jaws, size and distance between neighboring DW. This information actually creates a "dental code" (DC) which is finally matched with the corresponding DC within the database.

The segmentation of the DW is performed by a snake (active contour). Each DW is segmented with a separate snake. In order to speed up the process and improve segmentation, the initial curves for all DWs are computed from a binary mask. Edit distance (Levenshtein distance) is used for matching. To evaluate the proposed method, the researchers used 68 dental radiographs from a total of 46 subjects. To test the matching performance of the method, the implemented algorithm to compares DRs of the genuine class and DRs of the impostor class. The equal error rate obtained for the proposed method on 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 [83]. 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 could be easily applied to just 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 right now. Is very possible to appear in the near future though.

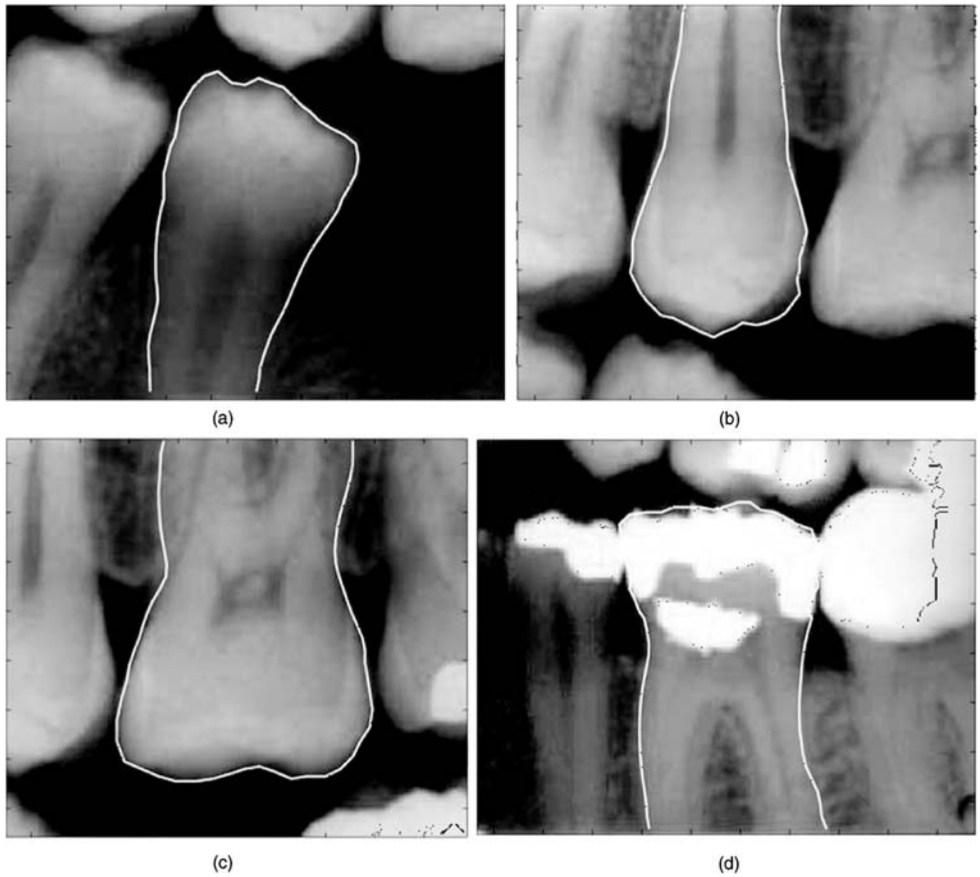


Fig. 13 Some examples of extracted tooth shapes [83]

2.19 DNA

DNA data differ from standard biometrics in several ways. It requires a tangible physical sample as opposed to an impression, image, or recording. Their matching is not done in real-time and, currently, not all stages of comparison are automated. Usually DNA matching does not employ templates or feature extraction, but rather represents the comparison of actual samples [85].

In the matching procedure, DNA is isolated and cut up into shorter fragments containing known areas. In following, the fragments are sorted by size using gel electrophoresis and are compared in different samples. A representative example of the identification that occurs with DNA method is described in Fig. 14 for a sexual assault case. DNA from suspects 1 and 2 are compared to DNA extracted from semen evidence. In this sample, it can be seen that suspect 1 and the sperm DNA found at scene match. Suspect 2 has a profile totally different from the semen sample. DNA isolated from the victim as well as human control DNA (K562), serve as a standard size reference and they are included as controls [86].

DNA provides an extremely high counterfeit barrier, because a counterfeiter can never replicate the unique DNA sequence that identifies a person. Although DNA could be the ultimate biometric technology, it still presents a lot of problems, as it is not yet fully automated (and fast). According to [87, 88] automatic detection is feasible. The authors measured the intrinsic charge of DNA molecules with an array of silicon transistors, which allowed them to avoid the markers and labels used in conventional detection techniques.

The interest the DNA identification systems raise can be easily understood by contemplating the amount of money that is spent every year for research on this topic. In particular, the USA federal funding that reached the amount of 232.6 million dollars for year 2004, increased by 100.7 million dollars for the following year. This amount had been asked to aid local, state and federal services in improving their DNA collection systems with added funding for staff, technology, training and assistance [89].

3 Conclusion

In this paper the emerging technologies in biometrics were presented. There is a large number of body parts, personal, behavioral characteristics and imaging methods that have been suggested over the past years containing face, eyes, mouth, teeth, ears, hands, signatures, typing styles and others. Although the maturity of most of the proposed techniques has reached a certain level, a variety of unsolved

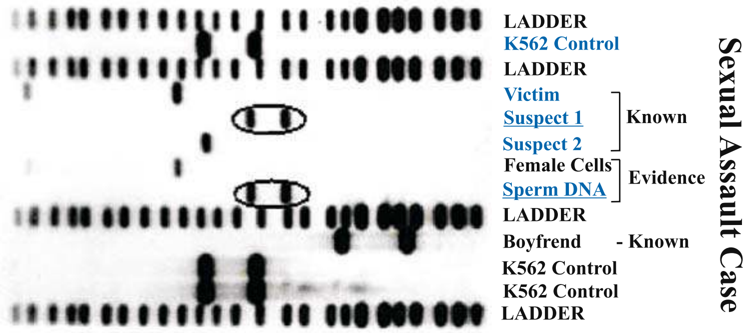


Fig. 14 Example of DNA identification [86]

problems still remain, while the demand for various kind of applications that will be able to minister the various needs for security, is increasing. The besetting research on new ideas as well as the continual growth of new modalities, give evidences of the above deficiency.

Methods that use more advanced human features and sophisticated electronic devices have been proposed. Thermogram, ECG, DNA, veins, nails, otoacoustic emissions, skin spectroscopy and infrared palms are some of them. However, even in the most recent technologies, there are a lot of problems concerning the efficiency of each system. Some techniques require expensive equipment of high technology while others require time consuming enrolment procedures of high intrusiveness. Although researchers publish results that usually outperform their competitors, there is still no system that can guarantee reliably high performance for real security applications. Furthermore, most of the emerging biometric systems have not been tested on large databases. An issue for the following years would be the independent performance analysis on multimodal data bases that would be essential to assess performance and compare modalities to each other. However, the remarkable variety as well as the promptness of the new biometric methods and modalities development, predisposes us for the amazing developments that we will meet in the near future.

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