Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 1 (2010) 2505–2513
Procedia Computer Science
www.elsevier.com/locate/procedia

International Conference on Computational Science, ICCS 2010

Beyond Biometrics

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Abstract

Throughout the last 40 years, the essence of automated identification of users has remained the same. In this article, a new class of biometrics is proposed that is founded on processing biosignals, as opposed to images. After a brief introduction on biometrics, biosignals are discussed, including their advantages, disadvantages, and guidelines for obtaining them. This new class of biometrics increases biometrics' robustness and enables cross validation. Next, biosignals' use is illustrated by two biosignal-based biometrics: voice identification and handwriting recognition. Additionally, the concept of a digital human model is introduced. Last, some issues will be touched upon that will arise when biosignal-based biometrics are brought to practice.

Keywords: biometrics, biosignal processing, digital human model, validation, robustness

1. Introduction

Four decades ago, IBM envisioned the identification of persons (ID) by machines [1]. IBM stated that this could be achieved through:

1. *something the user knows or memorizes*
2. *something the user carries*
3. *a personal physical characteristic*

From this concept, a new field of research emerged: biometrics[1]. Anil K. Jain, Patrick Flynn, and Arun A. Ross [2, p. 1] start their Handbook on Biometrics with its definition: "Biometrics is the science of establishing the identity of an individual based on the physical, chemical or behavioral attributes of the person." The attention for biometrics fluctuated throughout the last decades, following the attention in society for security issues [1]. During this century the attention for biometrics was reinforced by the need for large-scale identity management systems.

Essentially, biometrics is a pattern recognition problem; e.g., see [2]. It can be applied to either verify or identify a person's identity. In the former case, biometric data of a person is captured and compared with that person's biometric

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[1]Biometrics is derived from the Greek language, meaning: life measuring.

1877-0509 © 2010 Published by Elsevier Ltd.
doi:10.1016/j.procs.2010.04.284

data stored in a database (DB); i.e., 1:1 matching. In the latter case, the biometric data captured is compared with all biometric data available in a DB, with the aim to identify the person who's biometric data was captured [2]; i.e., 1:n matching, with n being the size of the DB.

In this paper, the difference between identification and verification will not be discussed in depth, as they are in essence identical. The following formal definition of ID illustrates this:

$$I_x = \begin{cases} I_n \text{ if } \max_n\{D(I_x, I_n)\} < T \\ I_x \text{ otherwise} \end{cases} \quad (1)$$

where I_x is the representation (e.g., a vector) of an unidentified person, his bioprofile. I_n is the n^{th} sample from the DB. D is a distance metric (e.g., a Minkowsky or quadratic metric) [3] and T is a threshold. Note that in the case Eq. 1 results in $I_x = I_x$, the person remains unidentified after the DB is consulted.

In case of verification of persons, 1:1 matching is applied. So, the DB, as depicted in Eq. 1, contains one profile. Then,

$$\max_n\{D(I_x, I_n)\} < T \quad (2)$$

still holds but can be simplified to

$$D(I_x, I_n) < T. \quad (3)$$

In practice, frequently a way in between 1:1 and 1:n matching can be employed. Such a search can be classified as neither verification nor identification. Having (some) knowledge on the ID of an unknown person (I_x), a subset (s) of the DB (i.e., $s \subset n$) can be queried instead of the complete DB.

The tremendous boost of technology in the last decades has had its influence on the field of biometrics. IBM's original methods for ID have been adapted. ID is nowadays mostly approached through one of the following two types of methods or a combination of them:

1. Manual ID:
   (a) through an object; e.g., ID card, its reader, or a USB stick.
   (b) via knowledge; e.g., personal identification number, password, and secret questions.
2. Biometrics:
   (a) Behavioral attributes; e.g., signature, keystroke dynamics, and gait;
   (b) Physical attributes: fingerprint, iris and retina, facial image and facial thermogram, geometrical features of the face; e.g., ear and nose [4], and geometrical features of the hand (incl. vein pattern) and feet [5].
   (c) Other: audio-based (e.g., voice), chemical attributes (e.g., odor), and DNA.

The combination of ID methods is, in practice, also based on several trade-offs; e.g., level of accuracy, ease of use / intrusiveness / convenience, security / barrier to attack, public acceptability, long-term stability, costs, and size. In addition, issues such as speed, connectivity, and compatibility (e.g., ports, operating systems, and CPU) play their role.

From the two types of methods and the trade-offs, one can extract a taxonomy on biometrics. This can help in understanding and, consequently, in describing biometrics. A taxonomy on biometrics can be defined on several dimensions, of which the most important are [2]:

- universality: all persons should possess the trait
- uniqueness: the level of discrimination it provides between persons
- permanence: invariance or stability of the trait.
- measurability: effort related to acquisition and processing in practice; e.g., to what extent a person needs to cooperate in obtaining the biometric and in how far the environment needs to be controlled?
- performance: the reliability of the biometric.
- acceptability for the people.

- circumvention: sensitivity to fraud.

In addition, other dimensions are mentioned in literature, such as:

- Overt versus covert: To what extent measurement of a biometric can be covered?
- Requirement of supervision: Results on some biometrics need to be manually checked; hence, they cannot be processed automatically or only to a certain extent.
- Optional versus mandatory: Is the biometric required for ID or can it be replaced by another? This refers to a biometric's concurrent validity: its reliability and discriminative power compared to the other biometrics applied.

Using these dimensions, a well argued choice of biometrics can be made for an application, taking into account its characteristics. For example, in case an ID is needed for physical access, the choice of biometrics will be completely different from when ID is needed for computer logon/logoff.

Although different biometrics are clearly distinct, their processing pipeline is identical. First, persons have to be enrolled and signals, most often images, need to be captured of parts of them. Capturing is done through various sensors and materials; e.g., optical, capacitance, resistance, thermal, and polymer [6, 7, 8]. Second, these images are processed and features are extracted [9, 10]. Third and last, the extracted features are used for verification (i.e., 1:1 matching) and identification (i.e., 1:n matching) [2]; see also Eq. 1–3. In practice, this processing pipeline suffers from the following problems:

- Capturing images requires highly controlled environmental circumstances.
- Templates for biometrics are not compatible among vendors.
- Template size (i.e., from $< 10^2$ to $> 10^4$ bytes) and type (e.g., vectors and minutiae) varies.

As a result of these issues both speed and accuracy of biometrics differs significantly.

Given the attention for biometrics, it is not surprising that frequently new processing paradigms, fusion methods, and even new physical characteristics are proposed to enhance biometrics. For example, the nose was recently proposed as a new element for biometrics [4]. However, in the majority of cases, more advanced schemes or extensions of known methods are introduced, instead of introducing new elements or even classes into the field of biometrics; cf. [2, 5, 10, 11, 12]. In contrast, in this article, a new class of biometric methods will be introduced.

The new class of biometrics concerns the utilization of biosignals for ID, as will be explained in Section 2. It will be explained how biometrics can be used to validate traditional, image processing based, methods and can enhance their robustness. Moreover, this section discusses both the advantages and disadvantages as well as guidelines for biosignals, as class for biometrics. Next, in Section 3, two examples of this new class of biometrics will be discussed. Section 4 introduces the more general concept from which it originated: digital human modeling. This paper ends with a brief discussion and conclusions in Section 5.

2. Processing biosignals

A new class of biometrics, biosignals, is introduced and depicted in Fig. 1. Biosignals (or physiological signals) originate as electrochemical changes in neurons (nerve cells), muscles, and gland cells. These biosignals spread from their sources throughout the body to the surface of the skin. Via surface electrodes attached (or close) to the body surface, these signals can be recorded. Signals from a broad range of sources can be recorded. For example, from the heart, the electrocardiogram (ECG) can be recorded; the muscles' activity can be recorded through the electromyogram (EMG); and the sweat glands determine the electrodermal activity (EDA).

Biosignal processing is expected to be of significant value for biometric applications. This can be illustrated by mentioning problems that can occur with traditional biometrics [2]; e.g.,

1. facial image: recording, processing, and matching is notoriously problematic,
2. movement analysis (e.g., gait): often simply not feasible in practice, and

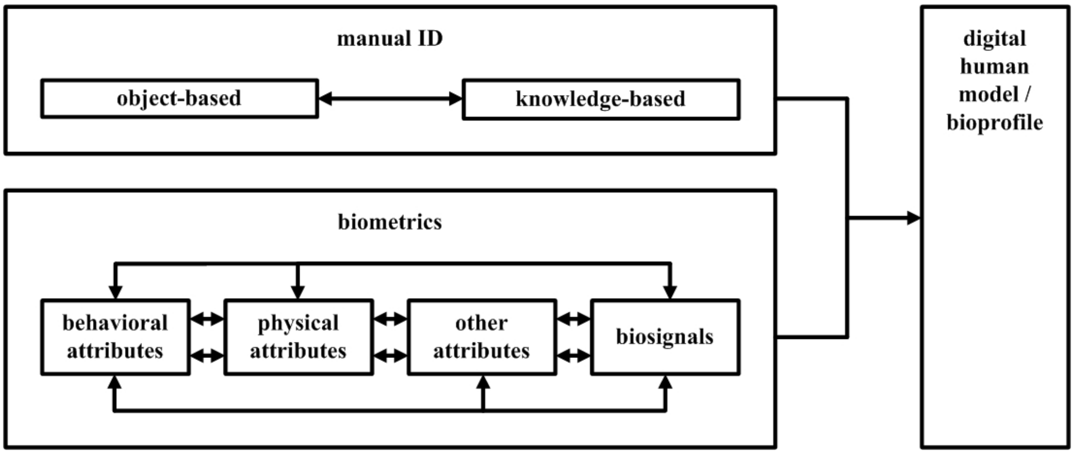

Figure 1: The general proposed processing scheme for ID. Manual ID based on objects and knowledge is included. The two methods based on image processing for biometrics (i.e., behavioral and physical attributes) as well as a set of other attributes (e.g., audio, chemical, and DNA) are also included; see also 1. Additionally, the new class of biosignal-based biometrics is included; see also Section 2. With the latter class included, the robustness and the cross validation of ID can be even further enhanced. In time, this will show to provide a richer and more reliable bioprofile or human digital model; see also Sections 3–4. Robustness of profiles can be improved and cross validation can be applied. These processes are indicated by the arrows in the scheme; see also Section 2.

3. voice: speech is often either absent or suffering from severe distortions in many contexts.

However, it are not only limitations such as these that stress the need of introduction of biosignals as a new class of biometrics. It is also the rapid progress sensor development made over the last decade; e.g., [6, 7, 8]. Sensors that enable biosignal recording have become cheaper, more reliable, and can be applied in a wireless manner [7, 8].

In this section, advantages and disadvantages of biosignals as biometrics will be discussed. After this, some guidelines for the application of biosignal-based biometrics will be denoted.

2.1. Advantages

Traditional biometrics can be manipulated; biosignals, in contrast, are free from social masking. With the development of non-invasive and even wireless sensors [6, 7, 8], they are suited for a wide range of applications [13, 14]. Hence, such biosignals can act as a very useful interface between man and machine.

In combination with traditional biometrics, biosignals increase the information available on a person. This is in particular the case as biosignals are known to discriminate among people, like traditional biometrics do. Consequently, a more reliable profile can be generated. In generating persons' profiles this can provide the following advantages (see also Fig. 1):

1. Enhancing robustness: Information obtained through biosignals can be used to verify information obtained through traditional ID methods; see Section 1. Missing data in the profile can be complemented with information extracted from biosignals. Also, noise canceling can be enhanced through integration of these sources.
2. Cross validation: Traditional (image processing based) biometrics can be validated against biosignals. The same constructs can be mapped to both biometric features and features extracted from biosignals. In the next section, two examples of this advantage will be provided. Where the added value of robustness is expressed on signal processing and pattern recognition level, the added value of cross validation is expressed on a conceptual level. It concerns the mapping of bio-information on the representation of a person's characteristic; e.g., his voice or handwriting.

2.2. Disadvantages

As with all processing techniques, also biosignal processing has its downside. Several crucial concerns that limit both their acceptation and application in practice have to be acknowledged; see also Section 1. Some of the most important concerns are:

1. Sensors are still obtrusive to a certain extent [6, 7, 8]
2. Sensors are unreliable; e.g., movement artifacts, bodily position, air temperature, and humidity [6, 7, 8]
3. Many-to-many relationships: Multiple biosignals can be used as indicator for multiple constructs from psychology as well as for various physiological processes. This makes biosignals inherently noisy [13, 15]
4. Time windows of biosignals vary
5. Humans are not linear time invariant; e.g., they habituate

It should be acknowledged that, although a significant progress in biosignal processing has been realized, these issues still have not been solved.

2.3. Guidelines

Biosignals can become a promising new class of biometrics. This is best illustrated by its advantages, as expressed in the former subsections. However, as denoted in the latter section, there is still a long way ahead of us in bringing biosignals to biometrics. One of the core issues in making biosignal-based biometrics a success is the acquisition of these signals. For this reason, this section is devoted to presenting guidelines for biosignal recording.

One of the main problems with biosignal processing, so far, has been the lack of a coherent and concise set of guidelines for obtaining them. Literature on biosignal processing is scattered as are its guidelines. A set of main guidelines that can improve the quality of recording biosignals will now be provided:

1. Validation; in particular:
   (a) content validity: agreement among experts and the degree of representation of construct through signals
   (b) concurrent validity: reliability of the biometric in relation to the ground truth
   (c) ecological validity: unravel the context of measurements
2. Integration of data sources, in particular triangulation (i.e., using multiple operationalizations of constructs).
3. Physical characteristics; e.g., type of electrodes (i.e., dry or wet), gel, location of electrodes, and environmental characteristics.
4. Temporal construction, which is important as:
   (a) people habituate and physiological activity tends to move to a neutral state
   (b) physiological processes develop over different time windows
   (c) physiological responses are likely to be layered.
5. Baselining; i.e., applying suitable corrections to the biosignals

These guidelines do not solve all disadvantages mentioned in the previous subsection. However, perhaps they can help in making progress in the field of biosignal-based biometrics or at least in comparing studies in this field.

In addition to the five guidelines mentioned above, the importance of respecting the rich history on biosignal processing needs to be stressed. Please note that biosignals are already processed since the 17th century. Regrettably, this rich history is ignored to a large extent; hence, a vast amount of knowledge remains unused.

3. Towards biometrics based on biosignals

This section will first introduce two recently presented methods. Of both methods, their use in general has been shown and now their use for biometrics will be explained. Both methods can be considered as instances of the new proposed class of biometrics.

3.1. Speech interface

Recently, it has been shown that speech recognition can be achieved even without sound, without processing the speech signal itself [16]. This new technique relies on surface electromyography (EMG) [14] and is baptized silent speech interfaces [16]. It also enables the development of tools for advanced speech synthesis [14]. Such silent speech interfaces are envisioned to improve verbal communication in noisy environments; e.g., in combat or disaster situations [14]. In addition, such interfaces enable speaker identification and verification [17]; see also Section 1. With the latter applications, silent speech interfaces become of interest to biometrics.

The EMG signals obtained through silent speech interfaces can be combined with voice recordings and, as such, a multi-modal voice identification and verification can be realized. Such an approach will provide more robust results than solely processing the speech signal for voice identification and verification. Moreover, the speech signal and EMG signals can be validated against each other; see also Fig. 1. Consequently, recording of both signals can aid the understanding of the voice, as is now used for identification and verification purposes. In time, this will result in more robust identification and verification of persons.

3.2. Handwriting recognition

Handwriting recognition (HWR) has a long tradition within the field of biometrics [2, 12] but also outside this field; e.g., [14, 18]. Its challenge is well illustrated by the "... very broad field dealing with numerous aspects of this very complex task. It involves research concepts from several disciplines: experimental psychology, neuroscience, physics, engineering, computer science, anthropology, education, forensic document examination, etc." [19].

In the field of biometrics, off-line HWR is applied, which is a much harder task than on-line HWR. [19]. With the birth of biometrics, this was a choice founded on technical limitations. However, nowadays these limitations have vanished and on-line HWR can as easily be conducted as off-line HWR, using simple, cheap tablets. So, the use of on-line HWR should be included much more in biometrics applications.

On-line HWR can even be taken a step further than its acquisition through a tablet. As has been recently shown, HWR can be realized through processing EMG signals [14, 18]. It has even been shown that EMG-based HWR can be of help in the discrimination among persons, as each person has his own bioprofile with this application [18].

Although HWR is still the dominant application for pen-based computing, pen input can also be used for a range of other applications. Not only writing but, for example, also drawing would be of use. Moreover, using on-line pen-based acquisition methods, a parameter such as the pressure imposed on the pen is of interest.

4. Digital human modeling

In the previous section, two applications of biosignal-based biometrics were discussed. However, as introduced in Section 2, there are many more biosignals that are of interest for the new class of biometrics. Moreover, not only the distinct biosignals are of interest but also their combinations. Multi-modal biosignal processing provides a rich source of information. It can reveal both physiological and psychological aspects of a person [13, 15]. From multi-modal (traditional) biometrics, a range of behavioral, chemical, and physical characteristics can be derived (see also Section 1). Together these two multi-modal sources can provide the foundation for a digital human model (DHM); e.g., see Fig. 1 and [20], in particular Ch. 16 and 35.

A DHM of persons can be seen as the ultimate model for biometrics, also including biosignal-based biometrics; see also Fig. 1. It is envisioned that in time, modules for a DHM will be defined in which both traditional biometrics and biosignals will take a prominent place. However, so far, there is only limited progress in the development of models that relate biometrics and biosignals to each other as well as to physiological and psychological characteristics [20].

An exhaustive discussion on DHM is well beyond the scope of this article. In the previous section, two examples of classical biometric applications were given, which illustrated the relation between biosignals and traditional biometrics. The knowledge extracted from such examples could be integrated in DHM. As opposed to the previous section, this section adopts an atypical aspect of DHM: people's affective profile [13, 15]; i.e., the relation between biosignals and the concepts arousal, emotion, and personality. In the remainder of this section the measurement of a person's affective profile will be explained, as this can be a valuable contribution to a range of applications of biometrics; e.g., security issues.

Arousal is most often addressed as being related to unspecific excitation processes in the central nervous system. As such, it is considered as a basic process that catalyzes the transfer from percept to behavior. Most often, arousal is approached as a one dimensional concept. This is in particular the case in applied sciences and engineering; e.g., the field of affective computing [13, 15]. Although often ignored, there is a significant amount of research that showed that arousal is a complex, multi-dimensional phenomenon, which possibly needs up to four dimensions to be described accurately [20, Ch. 35]. In practice, various biosignals can be applied to assess arousal; e.g., ECG, blood pressure, EDA, and (skin) temperature [13, 15].

Despite the tremendous amount of research conducted on the concept of emotion, it still lacks a generally accepted definition [20, Ch. 35]. Although the debate on the physiological origin of emotion is still ongoing, there is general consensus on the limbic system being a part of it. Often emotion is described in terms of arousal and valence (i.e., (dis)pleasure), using a two, three, or four dimensional model. Arousal was already addressed, as it is also considered frequently separate from valance. Valence is assessed through the same biosignals as arousal and, in addition to these, EMG is often included and even regarded as a ground truth for valence [15].

Personality can be of key importance for forensics and, as such, also for biometrics. Traditionally, personality traits are assessed through interview techniques, observation, tests, questionnaires, and so forth [13]. However, it is known that through biosignals people's personality traits can also be assessed. For personality assessment, the same biosignals can be applied, as with arousal and valence. The latter gives rise to the question, what the relation is between this set of biosignals and the three concepts (i.e., arousal, valence, and personality) discussed; see also Section 2. Moreover, it illustrates the lack of large scale research, which integrates these three concepts and tries to untangle them.

The development of a DHM is an endeavor that will be passed from generation to generation. Although, with the increasing interest of both science and engineering in human-centered computing and cognitive engineering, the future looks promising. A DHM can be considered as the ultimate goal for biometrics. It can include behavioral, chemical, and physical attributes as well as psychological attributes, as denoted in this section. In addition, brain activity could be recorded and automatically analyzed, as is done with brain-computer interfaces (BCI) [21]. For now, however, a combination of traditional biometrics and biosignal-based biometrics can be considered as a bioprofile or DHM. A such, it will already serve as a rich source of information. Such a rich profile would already be of great value for all application areas of biometrics.

5. Discussion

This paper started with an introduction on biometrics. Next, in Section 2, a new class of biometrics was introduced: biosignals, as opposed to more traditional approaches to achieving progress in biometrics [11]. Both advantages and disadvantages of biosignal-based biometrics were denoted as well as guidelines for their application. Section 3 provided two examples of applications of biosignals that can aid biometrics. Section 4 introduced a more general goal: the development of a digital human model (DHM). This can be considered as the ultimate bioprofile, consisting of both traditional biometrics and features derived from biosignals; see also Fig. 1.

With the application of biosignals, filtering becomes a core issue of these signals [22]. In the case of biometric applications, traditional sources of noise have to be considered, see also Section 2. However, in addition, various types of noise have to be filtered, as introduced on purpose by the persons, whose biosignals are recorded. This makes it an even more challenging issue than it already would have been without these type of noise sources. Luckily, progress in the development of sensors has accelerated in the last decade; cf. [6], [7], and [8]. It is expected that this development will continue as sensor's prices have made it feasible to integrate them in consumer electronics on much larger scale than has been possible until recently [7, 8].

Obtaining the highest possible quality of signals is the first phase in the processing pipeline of biometrics. The second is the pattern recognition process, which heavily relies on the first phase. In Section 2 it was posed that one of the advantages of including biosignals for biometric applications is the information it adds to a person's profile. However, this has its downside. The dimensionality of the information increases significantly with incorporating such a new class of biometrics. Hence, dimension reduction [23] becomes even more important than it already was. This is in particular important as the current trend is to collect biometrics of more and more persons; consequently, the size of biometric databases increases rapidly; cf. Eq. 1, with $n \to \infty$. In combination with an increase of the amount of information (i.e., features [9, 10]) per person (i.e., the vectors or minutiae (I) in Eq. 1), as will be the case when biosignals would be included, this stresses the need for i) dimension reduction of biometric data, ii) identifying efficient distance or similarity metrics [3], and iii) developing efficient data mining schemes.

With applications such as silent speech and handwriting recognition (see Section 3), both via the biosignal EMG, it has been illustrated that the integration of traditional biometrics with biosignals, as posed in Section 2, would provide a much richer bioprofile of persons. Section 4 posed an even more ambitious goal: the development of a DHM. Although the ultimate DHM is far beyond science reach, simplified models can already be of great use. This is already illustrated by work on BCI [21]. Using EEG signals rough estimations of significant brain activity can be made. But even this can already be of use, as is shown in various clinical application areas.

With the introduction of a new class of biometrics not only technical issues will play a role, also issues concerning both law and ethics are of importance. Law considerations comprise: i) rules of privacy, ii) the constitutional background, and iii) privacy under law, including physical, decisional, and information privacy [2, Ch. 18]. Biosignal-based biometrics deviate in multiple ways from traditional biometrics. They require other registration and processing schemes. Possibly even more important, they enable much broader information collection than solely a person's ID. As such, they can be considered as possibly even more intrusive than traditional biometrics. One of the ethical issues is that biometrics introduces the risk of social exclusion [24], which would increase with the introduction of biosignal-based biometrics, as it enables the extraction of much more information than solely traditional biometric data; see also Section 4.

Although there is still a long way to go, it would be good if biosignals will find its way through, as a new class of biometrics. With the rapid developments in biosignal processing and, even more, in unobtrusive sensor technology, biosignal-based biometrics should have a bright future. Consequently, dual modal biometrics, including both traditional, mostly image-based, biometrics and biosignal processing, will become the next step in the evolution of biometrics.

Acknowledgments

The author gratefully acknowledge the support of the BrainGain Smart Mix Programme of the Dutch Ministry of Economic Affairs and the Dutch Ministry of Education, Culture, and Science. Frans van der Sluis and Winnie Teunissen are acknowledged for reviewing preliminary versions of this article.

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