Cogn Comput (2013) 5:136–151
DOI 10.1007/s12559-012-9169-9

Biometric Applications Related to Human Beings: There Is Life beyond Security

Marcos Faundez-Zanuy · Amir Hussain · Jiri Mekyska · Enric Sesa-Nogueras · Enric Monte-Moreno · Anna Esposito · Mohamed Chetouani · Josep Garre-Olmo · Andrew Abel · Zdenek Smekal · Karmele Lopez-de-Ipiña

Received: 1 December 2011 / Accepted: 10 July 2012 / Published online: 3 August 2012

Abstract The use of biometrics has been successfully applied to security applications for some time. However, the extension of other potential applications with the use of biometric information is a very recent development. This paper summarizes the field of biometrics and investigates the potential of utilizing biometrics beyond the presently limited field of security applications. There are some synergies that can be established within security-related applications. These can also be relevant in other fields such as health and ambient intelligence. This paper describes these synergies. Overall, this paper highlights some interesting and exciting research areas as well as possible synergies between different applications using biometric information.

Keywords Biometrics · Security · Healthcare · Ambient intelligence

Introduction

The term "biometrics" originates from the Greek words Bio (life) and metron (measure) and is defined as the science and technology of measuring and statistically analysing biological data. Although many people consider biometrics only relevant to security applications, in reality, the relevance of biometrics is very far reaching. This field has applications relevant to animals, plants and human beings. Some examples are:

M. Faundez-Zanuy (✉) · E. Sesa-Nogueras
Escola Universitària Politècnica de Mataró, Tecnocampus Mataró Maresme, Avda. Ernest Lluch 32, 08302 Mataró, Spain
e-mail: faundez@eupmt.es

E. Sesa-Nogueras
e-mail: sesa@eupmt.es

A. Hussain · A. Abel
Department of Computing Science and Mathematics, University of Stirling, Stirling FK9 4LA, UK
e-mail: ahu@cs.stir.ac.uk

J. Mekyska · Z. Smekal
Department of Telecommunications, Brno University of Technology, Brno, Czech Republic
e-mail: j.mekyska@phd.feec.vutbr.cz

Z. Smekal
e-mail: smekal@feec.vutbr.cz

E. Monte-Moreno
TALP Research Center, UPC, Barcelona, Spain
e-mail: enric.monte@upc.edu

A. Esposito
IIASS (International Institute for Advanced Scientific Studies), Vietri sul Mare, Italy
e-mail: iiass.annaesp@tin.it

M. Chetouani
Pierre Marie Curie University, Paris, France
e-mail: Mohamed.chetouani@upmc.fr

J. Garre-Olmo
IAS (Sanitary Assistance Institute), Salt, Spain
e-mail: josep.garre@ias.scs.es

K. Lopez-de-Ipiña
EHU (Basque Country University), Donostia, Spain
e-mail: karmele.ipina@ehu.es

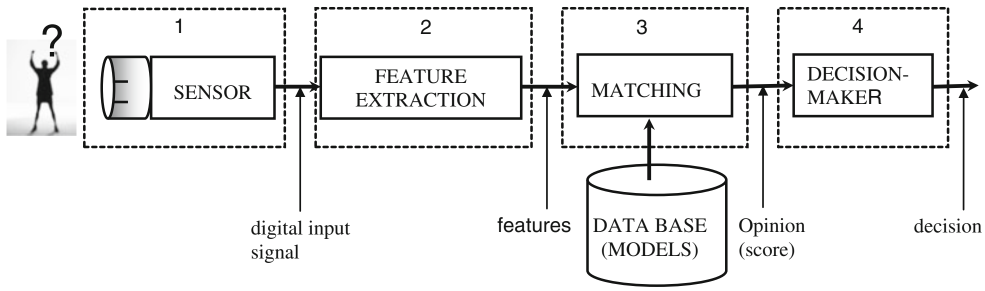


Fig. 1 Main blocks of a hypothetical biometric application system

- Statistical methods for the analysis of data from agricultural field experiments to compare the yields of different varieties of wheat.
- Analysis of data from human clinical trials evaluating the relative effectiveness of competing disease therapies.
- The analysis of biometric characteristics for animal/human verification or identification.

The main components of a hypothetical biometric application system are shown in Fig. 1. The first block deals with the acquisition of input signals. Depending on the application and the kind of sensors, a variety of different signals may be obtained. Nowadays, most signals are acquired in a digital format or are converted to digital in order to make computerized analysis more feasible. While some signals can be acquired from both human beings and animals (such as iris and retinal analysis of the eye), others are specific to humans (such as speech, handwriting, etc.).

This paper is focused exclusively on applications that are relevant only to human beings. Therefore, we will limit discussion to only human-specific signals. The set of these signals can be split into two categories:

1) Behavioural biometrics: this category is based on the measurements and data derived from an action performed by a user and thus indirectly measures some characteristics of human body. Signature, gait, gesture and key stroking recognition belong to this category.
2) Morphological biometrics: this category is based on direct measurements of parts of the human body. Fingerprint, face, iris and hand-scanning recognition belong to this category.

However, this classification is quite artificial. For example, speech signals are dependent on behavioural traits such as semantics, diction, pronunciation, idiosyncrasy, etc. A speech signal might also be related to factors such as socio-economic status, education, place of birth, etc. Moreover, it is also dependent on individual speaker physiology, such as the shape of the vocal tract. On the other hand, physiological traits are also influenced by human behaviour, for example, the manner in which a user presents a finger and looks at a camera, etc.

Figure 2 summarizes possible biometric applications as well as the input signals that can be used for these applications. While a large set of signals can be utilized for biometric security applications, some offer much more potential in other fields, especially in the case of behavioural signals. For the remainder of this paper, we will concentrate exclusively on health and ambient intelligence applications.

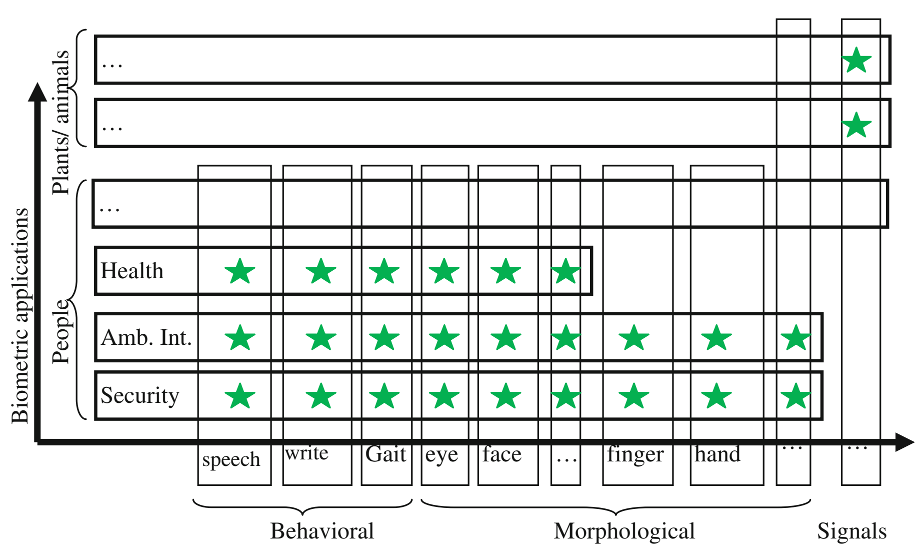


Fig. 2 Summary of main biometric applications and possible associated signals. Each star indicates the applicability of a given signal for a specific application

Health Applications

The skill level of humans is strongly related to their health state. An important example is the way our cognitive functions are related to the ageing process. Cognitive decline is a natural part of the ageing process. However, the extent of decline varies across subjects and across functions. For instance, handwriting and speech production is a fine motor control performed by our brain. When these signals are degraded, it is indicatory of health problems. Figure 3 shows the handwriting of one elder person as an example.

One important unsolved problem is how the dementia syndrome is associated with diseases such as Parkinson's and Alzheimer's, etc. In the case of Alzheimer's, it is estimated that the cost per year for a single patient is 35,000 USD in the USA. One in ten patients is below 60 years old. The incidence of Alzheimer's is doubled for every 5 years after 65, and beyond 85 years old, the incidence is between one-third and half of the amount of population. If a solution is not found, this problem will be unbearable for society. A relevant issue related to dementia is its diagnostic procedure. For example, Alzheimer's disease (AD) is the most common type of dementia and it has been pointed out that early detection and diagnosis may confer several benefits. However, intensive research efforts to develop a valid and reliable biomarker with enough accuracy to detect AD in the very mild stages or even in presymptomatic stages of the disease have not been conclusive. Nowadays, the diagnostic procedure includes the assessment of cognitive functions by using psychometric instruments such as general or specific tests that assess several cognitive functions. A typical test for AD is the clock drawing test (CDT) [84] that consists of drawing a circle and distributing the 12 h inside. An example of this is shown in Fig. 4. The top row shows the initial results produced by a person (baseline) on the left, and on the right, several samples of the same person after 6, 12 and 18 months of being damaged are also shown. This same test has also been used for detecting drug abuse, depression, etc. The bottom row of Fig. 4 shows a similar situation when copying two interlinking pentagons, which is

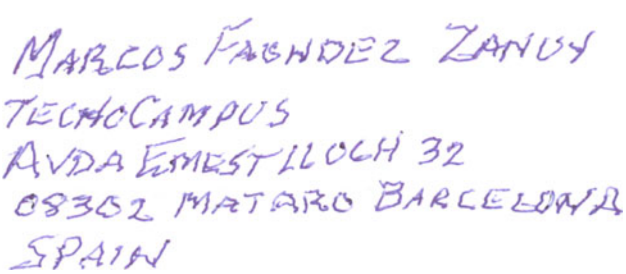


Fig. 3 Handwriting of an elder person

one of the tasks of the mini-mental state examination (MMSE) [30]. The MMSE or Folstein test is a brief 30-point questionnaire test that is used to screen for cognitive impairment. It is also used to estimate the severity of cognitive impairment at a specific time and to follow the course of cognitive changes in an individual over time, thus making it an effective way to document an individual's response to treatment.

Research by Forbes et al. [31] showed the correlation between handwriting skill degradation and AD. Initially, it is possible to detect the disease using handwriting, especially in the case of cursive letters. Work by Neils-Strunjas et al. [60] established that some handwriting aspects are more open to vulnerabilities than others and thus can be good indicators for AD diagnosis.

Handwriting tests are also very useful for determining the relevance of medication. For instance, Fig. 5 shows on the left the result of drawing an ellipsoid on a digitizing tablet. As can be seen, the *Y* plot, the velocity and acceleration of this coordinate are quite periodic for a healthy person (on the left). In the centre, we can see the results of a Parkinson disease (PD) patient and on the right a PD patient taking medication. It is evident that the medication permits the recovery to a large extent the skill of a healthy person. Obviously, this kind of analysis can be used for determining the dosage of drugs for a specific patient. This example has been extracted from [21]. Similar research line is exploited here [11].

There are similar experiences using the letter "ll" Tucha et al. [89, 90] and drawing an Archimedes spiral [75]. Werner et al. [94] showed the differences in handwriting between patients with mild AD and mild cognitive impairment. Ericsson et al. [23] evaluated the dictated handwriting and signature and observed that it remained unaltered longer than spontaneous writing. Heinik et al. [42] used the drawings for analysing depressive disorders in older people. Other interesting works using handwriting include:

a) Changes in handwriting due to Alcohol [27, 65]
b) Effects of caffeine on handwriting [90]
c) Effects of marijuana and alcohol [29]
d) Study of kids with perceptive/motor difficulties [48, 72]

Handwriting analysis using a digitizing tablet with an ink pen has an advantage over the classic method based on handwriting and posterior scanning, namely that the machine can acquire the information "in the air". That is, where there is no contact between pen and paper. Figure 6 shows the acquisition of the ten digits from 1 to 0 using an Intuos Wacom digitizing tablet (http://www.wacom.eu). The tablet acquired 100 samples per second including the spatial coordinates (x, y), the pressure, and a couple of

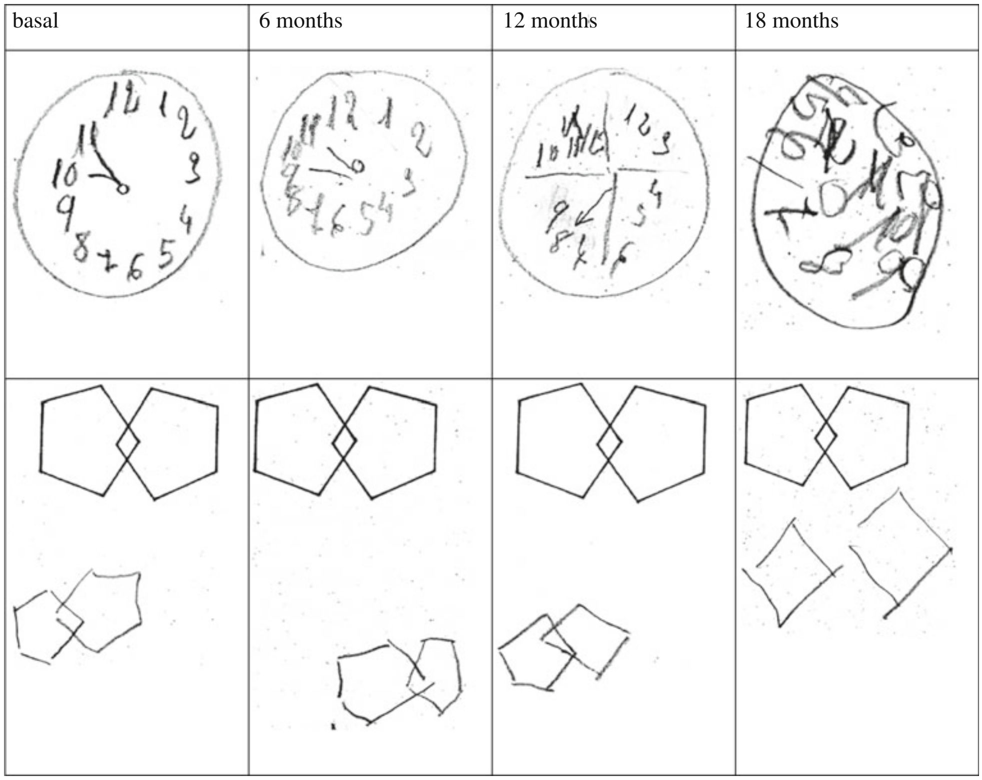


Fig. 4 Clock drawing test (*top*), pentagons of MMSE (*bottom*) for a person with AD, showing initial baseline on the *left*, and then from *left* to *right*, samples from the same person after 6, 12, and 18 months

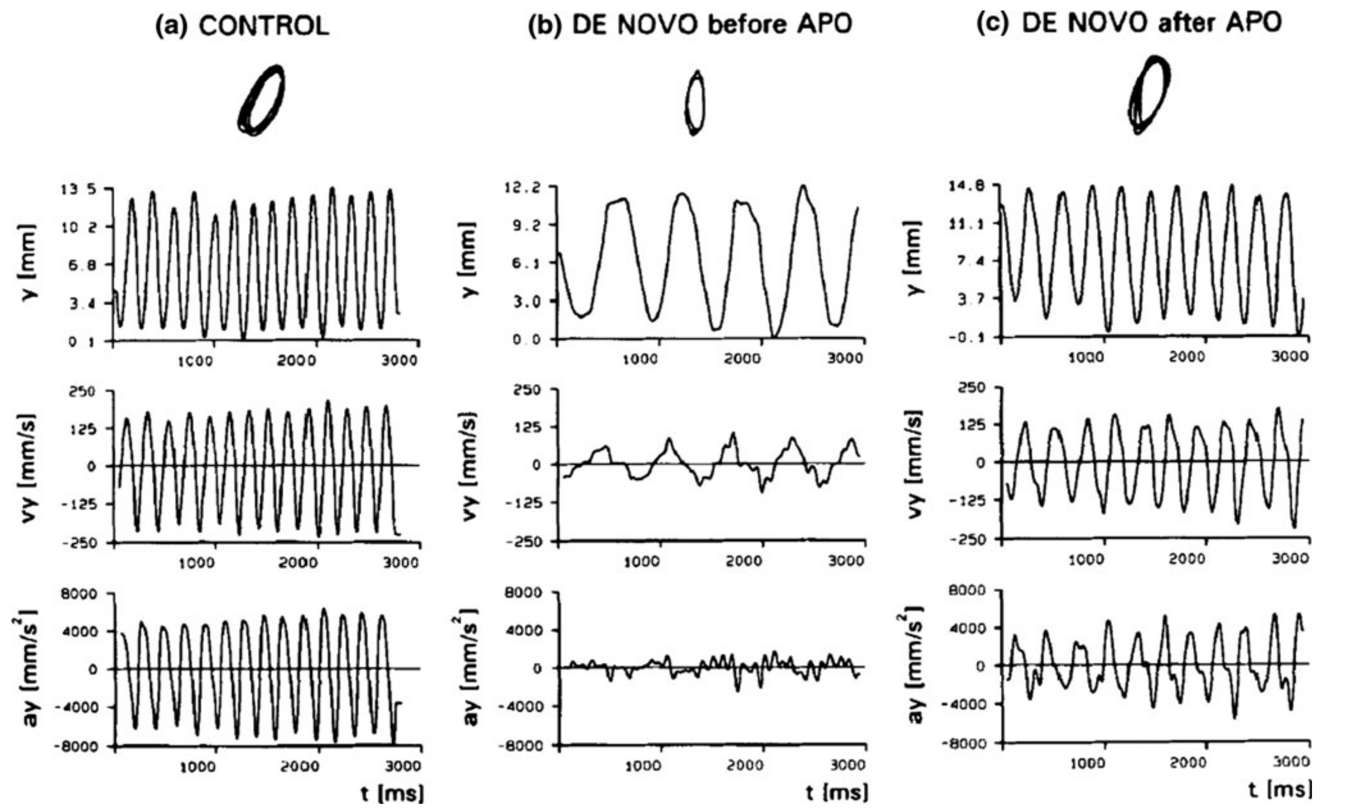


Fig. 5 Signals $y(t)$, $v_y(t)$, $a_y(t)$ (position, velocity and acceleration, respectively, of coordinate y) when drawing an ellipsoid by a healthy person (*left*), a PD patient (*centre*) and a PD patient taking apomorphine (APO)

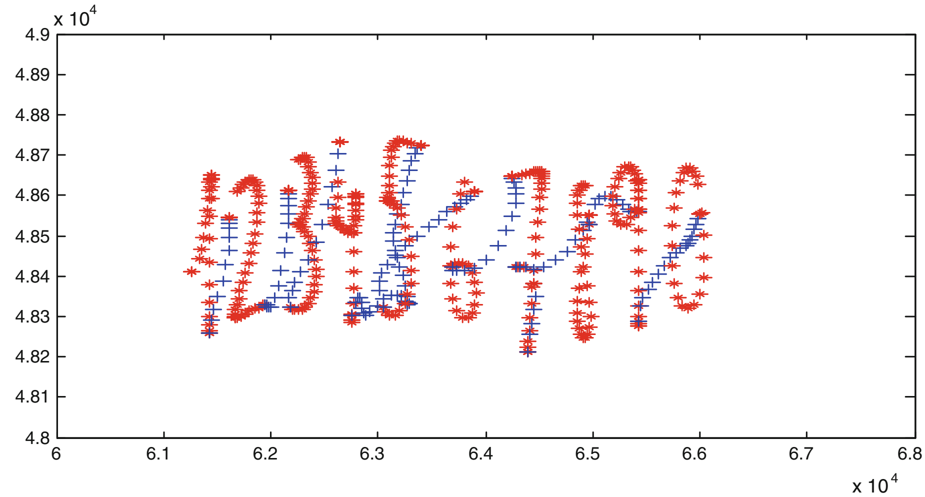


Fig. 6 Example of handwritten numerical digits input onto a digitizing tablet. *Asterisks* (*) represent pen-down information and crosses (+) the pen-up

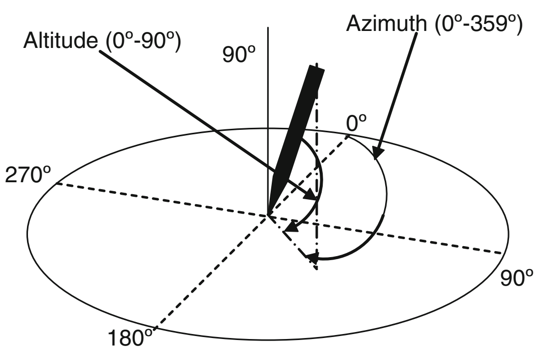


Fig. 7 Handwriting angle information acquired by the Intuos Wacom (*X*, *Y*, pressure, Azimuth, Altitude)

angles (see Figs. 7, 8). The pen-up information is represented in Fig. 6 using "+", while the pen-down is marked with "*". Our experiments on the biometric recognition of people reveal that these two kinds of information are complementary and in fact, contain a similar discriminative capability, even when using a database of 370 users [78, 79].

Speech signals represent another important possibility for health analysis. Hypokinetic dysarthria is a speech production alteration based on neurological problems [53]. There are multiple causes for this illness, such as brain paralysis, thrombosis, embolia, hemorrhagia, tumours and degenerative diseases (Alzheimer's, Parkinson's, Amyotrophic lateral sclerosis, etc.). Dysarthria affects speech quality (articulation, speech, intonation, speed, breath control, etc.) [57]. One possible analysis based on speech signals is of emotion analysis, because people affected by dementia display fewer emotions [80]. Moreau et al. [58] dealt with oral festination in PD. Festination is the tendency to speed up during repetitive movements. It appears

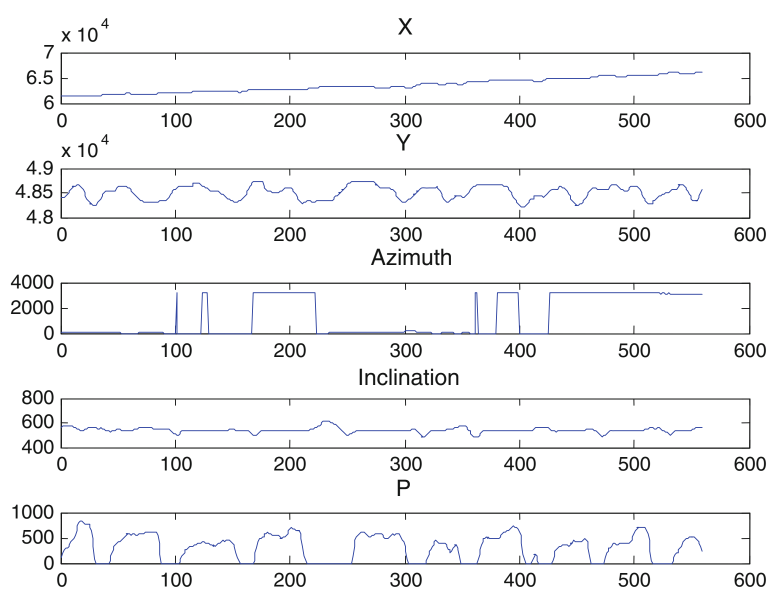


Fig. 8 Temporal evolution of the acquired parameters when drawing the numbers shown in Fig. 6

first with gait in order for sufferers to avoid falling down, and it subsequently appears in handwriting and speech. Ozsancak et al. [63] used speech signals to study PD. Ackermann et al. [5] analysed the trajectory of the lower lip when articulating speech signals, in order to study Parkinson's, Huntington's, cerebellum atrophia and pseudobulbar paralysis. Goberman and Coelho [36, 37], Nagulic et al. [59], Stewart et al. [83] used speech to evaluate the improvement of PD after treatment. [93] analysed the required time taken for sufferers to find the suitable word as well as time taken to articulate, and they found that AD specially affected the time taken to find the correct word, and to a lesser extent the articulation time. Rapcan et al. [69] used several measures (pitch, energy, etc.) for schizophrenia detection. They obtained promising results, which are especially interesting because there are no biological markers for this kind of disorder. Ferrand [28] used harmonic-to-noise ratio (HNR), jitter, fundamental frequency (F0), etc., and found that the most relevant of these parameters for studying the ageing process is the HNR.

Ringeval et al. [70] developed an automatic intonation recognition systems exploiting static (e.g. k-NN) and dynamic classifiers (e.g. HMMs) for the characterization of verbal productions of language-impaired children. The main results show that it is possible to characterize the prosodic abilities of those children and providing results in agreement with the clinical descriptions of the subjects' communication impairments.

Figure 9 shows a speech sentence pronounced by a healthy person and the same sentence pronounced by a PD affected person. It can be seen that the intonation is very flat for the PD sufferer, matching similar results as those reported in [41]. AD causes the changes in prosody [71]. The reason is based on the alteration of brain areas devoted to speech processing [44, 62]. In its initial stages, AD can be confused with multiple sclerosis, and speech analysis can differentiate between both [9]. Another classical

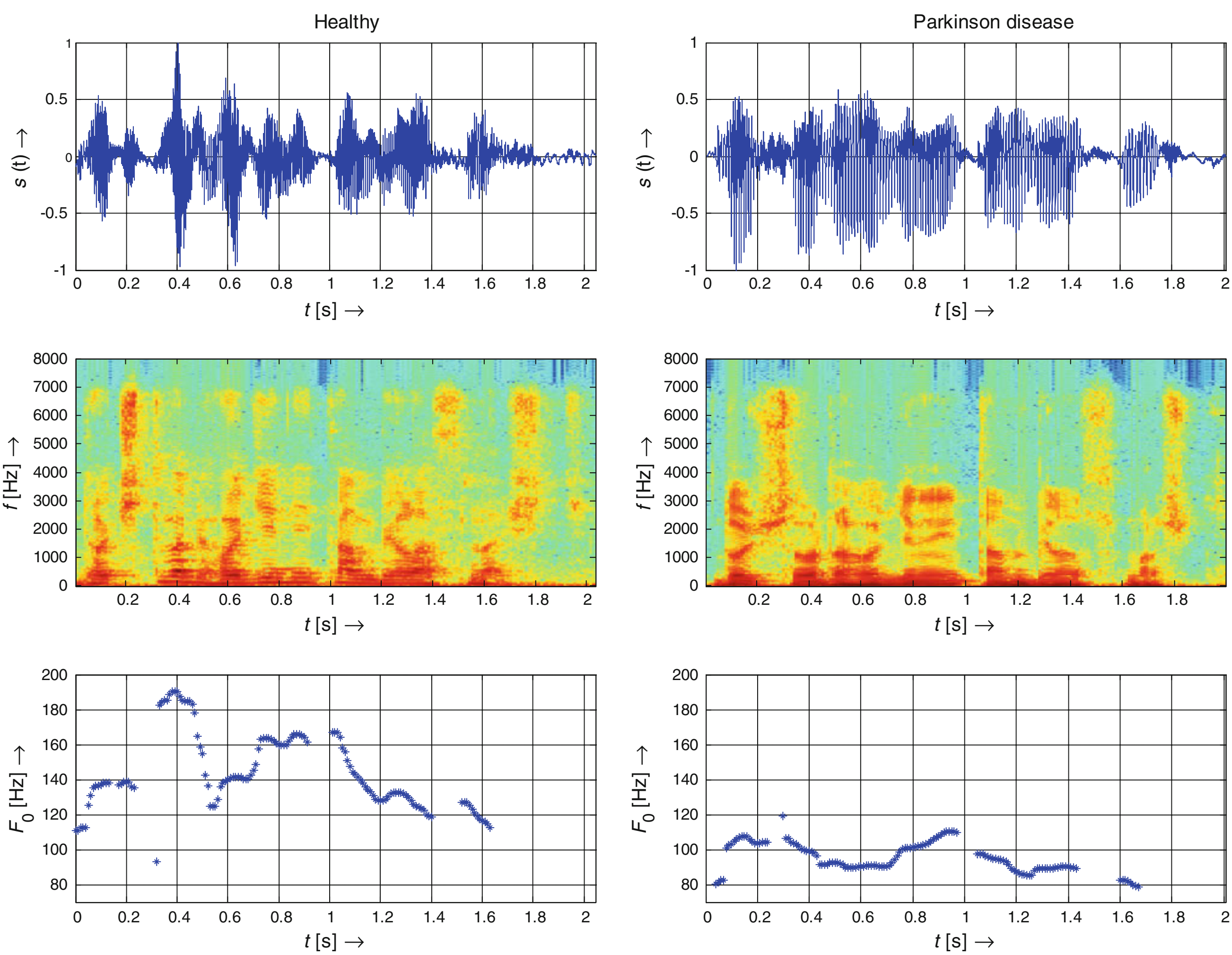


Fig. 9 Speech sentence uttered by a healthy person (*left*) and a PD person (*right*). Waveform (*top*), spectrogram (*middle*) and pitch frequency (*bottom*)

application of speech processing can be useful for dementia studies. For instance, AD patients exhibit a reduced vocabulary [19, 47]. Thus, speech recognition applications can be useful for evaluating the reduction of vocabulary in spontaneous speech.

Thus, speech signals offer significant potential for health analysis. Nevertheless, its acquisition can be more complicated than handwriting due to microphone position, recording level adjustment, etc. Some studies, such as [40], studied jointly handwriting and speech, although they were focused on lexical issues. Obviously, possibilities with other signals exist, such as the pupil reaction to light [32] and SPECT (single-photon emission computed tomography) [39], PET (positron emission tomography) [45], and MRI (magnetic resonance imaging) image analysis [88].

An interesting application of iris recognition might be to use this technology for characterizing the relationship of the change of pupil to the mood state of one person [33]. It is known that depressed patients manifest a shorter latency for constriction than control subjects, which is related to the fact that in depression, the activity of the neurotransmitters' decreases. Another application of biometric iris recognition technologies can be to predict the risk of age-related macular degeneration. Macular degeneration is one of the main causes of loss of sight in elderly people, and changes in iris colour are a sign of the risk of this illness [43]. Another extremely promising use of biometric technologies can be for a noninvasive estimate of cholesterol, through the changes in the iris of a patient [67].

Another potential use for biometric information is to develop the next generation of hearing aids. The previous audio-only developments in the field of speech enhancement (such as multi-microphone arrays and speech enhancement algorithms) have been developed academically and then been implemented into commercial hearing aids for the benefit of the hearing impaired community. In recent years, hardware has developed to an extent that very sophisticated multiple microphone hearing aids have been developed that exclusively exploit the audio modality. It is expected that in the future, conventional hearing aids will be transformed to make use of visual information with the aid of cameras for input in addition to conventional audio input, demonstrating that it is possible to combine audio and visual information to further improve the quality and intelligibility of speech in real-world noisy environments.

Speech is produced by vibration of the vocal cord and the configuration of the vocal tract that is composed of articulatory organs, and due to the visibility of some of these articulators such as tongue, teeth, and lips, there is an inherent relationship between the acoustic and visible properties of speech production. The speech perception connection between audio and visual aspects of communication has been established since pioneering works in 1954 [87] and subsequent developments such as the McGurk effect [56]. In addition, audiovisual speech correlation has been deeply investigated in the literature [7, 8, 74], including in the work by [4, 18], showing the connection between lip movement and acoustic speech and that this connection could be used for enhancing noisy speech.

Multimodal correlation is of interest because of the application of visual information to the speech enhancement domain. To the best knowledge of the authors, the first example of a functioning audiovisual speech filtering system was proposed in 2001 [35], and this was then followed by other related work [38, 81, 82]. The increased processing power of computers and the miniaturized and improved capability of relevant technical components such as video cameras and processors have made the concept of utilizing cameras for speech processing, possibly even as part of a hearing aid system, much more feasible. There are both strengths and weaknesses with the use of visual information for speech enhancement, but it has proved practical for further development. Following the pioneering work by Girin et al. [35], more recent work has focused on the use of visual information as part of a source separation-based system [81, 82]. In addition, [6] has made use of visual information as part of a Wiener filtering speech processing system. The use of visual biometric information, applied intelligently, has the potential to improve the quality of future hearing aid devices and aid the lives of those who suffer from hearing impairment.

Multimodal signal processing plays an important role in human communication analysis due to its integrative process. Indeed, correlations between speech and visual information (e.g. gestures, movements) make it possible to extract intra- and inter-coordination. In Delaherche and Chetouani [20], a general framework is proposed for the characterization of dyadic interactions for the automatic assessment of the interactional synchrony, which is considered as a measure of the quality of interaction.

Ambient Intelligence

In computing, ambient intelligence refers to electronic environments that are sensitive and responsive to the presence of people. According to [1, 96], it is characterized by systems and technologies that are:

- Embedded: many networked devices are integrated into the environment;
- Context aware: these devices can recognize you and your situational context;
- Personalized: they can be tailored to your needs;
- Adaptive: they can change in response to you;

- Anticipatory: they can anticipate your desires without conscious mediation.

While probably the highest level of intelligence that a machine can posses is the knowledge about the health condition of the human beings in front of machine, there is much other possible information that the machine can infer, such as

- Who is in front of the machine? (man/woman)
- How old are they? (child, elder, etc.)
- What is their emotional state? (angry/sad/happy, etc.)
- Who is speaking in a given room?

In a daily body-to-body interaction, emotional expressions play a vital role in creating social linkages, producing cultural exchanges, influencing relationships and communicating experiences. Emotional information is transmitted and perceived simultaneously through verbal (the semantic content of a message) and nonverbal (facial expressions, vocal expressions, gestures, paralinguistic information) communicative tools, and contacts and interactions are highly affected by the way this information is communicated/perceived by/from the addresser/addressee. Therefore, research devoted to the understanding of the relationship between verbal and nonverbal communication modes, and to investigate the perceptual and cognitive processes involved in the perception of emotional states, as well as the role played by communication impairments in their recognition, is particularly relevant in the field of human–human and human–computer Interaction both for building up and hardening human relationships and for developing friendly and emotionally coloured assistive technologies.

Emotions are considered as adaptive reactions to relevant changes in the environment, which are communicated through a nonverbal code from one organism to another [66]. This perspective is based on several assumptions, among which, the most important is that there exists a small set of universally shared discrete emotional categories from which other emotions can be derived [22, 46]. This small set of emotional categories includes happiness, anger, sadness and fear, which can be reliably associated with basic survival problems such as nurturing offspring, earning food, competing for resources, avoiding and/or facing dangers. In this context, basic emotions are brief, intense and adapted reactions to urgent and demanding survival issues. These reactions to goal-relevant changes in the environment require “readiness to act” and “prompting of plans” in order to appropriately handle (under conditions of limited time) the incoming event producing suitable mental states, physiological changes, feelings and expressions [34].

The categorization of emotions is, however, debated among researchers and different theories have been proposed for its conceptualization, among these dimensional models [73, 77]. Such models envisage a finite set of primary features (dimensions) in which emotions can be decomposed and suggest that different combinations of such features can arouse different affective states. Bringing the dimensional concept to an extreme, such theories suggest that, if the number of primary features extends along a continuum, it would be possible to generate an infinite number of affective states. This idea, even though intriguing, clashes with the principle of economy that seems to rule the dynamic of natural systems, since in this case, the evaluation of affective states may require an infinite computational time. Moreover, humans tend to categorize, since it allows for them to make associations, rapid recovery of information, and facilitates handling of unexpected events, and therefore, categories may be favoured in order to avoid excessive processing time. Furthermore, this discrete evolutionary perspective of basic emotions has been supported through several sources of evidence, such as the findings of (1) an emotion-specific autonomic nervous system’s (ANS) activity[1] [50]; (2) distinct regions of the brain tuned to handle basic emotions [64]; (3) presence of basic emotional expressions in other mammalian species (as the attachment of infant mammals to their mothers) [61]; (4) universal exhibition of emotional expressions (such as smiling, amusement and irritability) by infants, adults, blind and sighted [61]; (5) universal accuracy in recognizing facial and vocal expressions of basic emotions by all human beings independently of race and culture [22, 46, 76].

Most of the relevant applications in information communication technologies exploit what are called the “expressions of emotions”, that is, changes in expressions that allow interactants to perceive an emotional state during face-to-face interaction. In this sense, the perceptual appearance of emotional states is attributed to perceptual changes in the facial, vocal and gestural expressions [24–26].

In the field of human computer interface (HCI), the research objectives are to identify methods and procedures capable of automatically identifying human emotional states exploiting the multimodal nature of emotions. This requires the consideration of several key aspects, such as the development and the integration of algorithms and procedures for applications in communication, and for the recognition of emotional states, from gestures, speech, gaze and facial expressions, in anticipation of the implementation of intelligent avatars and interactive dialog systems

[1] It should be noticed that not all these findings proved to be strong enough, as, for example, [10, 13] disconfirmed the existence of an autonomic specificity and distinctive ANS’s activity patterns for each basic emotion.

that could be exploited to improve the learning and understanding of emotional behaviour and facilitate the user's access to future communication services.

Emotional processes in disabilities and health disorders follow in some aspects the same paths exploited in typical normal conditions and are different in other aspects. Impairments and developmental disorders may change emotional expressions and needs with respect to normal emotional processes.

Emotional reactions may be different. Questions on how these differences are expressed, felt and relevant to social interaction are still open and can be considered to still be at a theoretical level. Comparing normative and disordered expressions of emotional states can be useful not only for implementing effective intelligent systems able to interact with disabled people, but also to improve the performance of these systems. To the best of our knowledge, very little research has been done up to now in this direction.

Given the complexity of the problem, there has been a branching of the engineering approach toward the improvement and the development of video–audio techniques, such as video and image processing, video and image recognition, synthesis and speech recognition, object and features extraction from audio and video, with the goal of developing new cutting edge methodologies for synthesizing, analysing and recognizing emotional states from faces, speech and/or body movements.

One example of an emerging ambient intelligence technology is the novel emotion and sentiment mining approach, termed sentic computing, that has been developed by Cambria and Hussain et al. [14], which aims to extract cognitive and affective information associated with natural language and, hence, better understand the current state of the user, including factors such as his/her emotional state, current needs and intent. Cambria et al. [14] also employed affective ontologies and common sense reasoning tools to analyse text not only at document, page or paragraph level, but also at sentence and clause level.

Sentic computing involves the use of AI and Semantic Web techniques, for knowledge representation and inference; mathematics, for carrying out tasks such as graph mining and multi-dimensionality reduction; linguistics, for discourse analysis and pragmatics; psychology, for cognitive and affective modelling; sociology, for understanding social network dynamics and social influence; and finally ethics, for understanding related issues about the nature of the mind and the creation of emotional machines.

In the field of health, in particular, sentic computing has been used for the development of patient-centred applications [15], which empower the real end-users of the health system by bridging the gap between unstructured and structured health-care data [16]. Sentic computing is also employed for the development of intelligent multimodal affective interfaces, in which many different technologies are concurrently applied and integrated, for example, a facial emotional classifier and a multimodal animation engine for managing virtual agents and 3D scenarios [17].

Different sensors usable in a home environment are nowadays available at reasonable prices. In the last few years, many efforts have been made to build different frameworks capable of integrating unstructured signals received from different sources. The main aim of such systems is to enhance everyday living (e.g. for home automation system) but also to allow people who require care to safely live in their home environment [55].

An interesting example of ambient intelligence has been given in Rantz et al. [68] where a number of sensors have been installed in an apartment within a retirement community. The sensor network (including bed, chair, stove temperature and motion sensors) passively collected data to detect the presence of the person in different rooms and to infer when the person is carrying out specific activities. Data from sensors are then aggregated for each patient and made available to clinicians and researchers; graphical representations of the activity level could help healthcare providers to detect any changes in activity patterns, after receiving automated alert from the system. It has been shown the potential of this kind of system for early detection of specific pathologies (e.g. for urinary treat infections).

There are a number of diverse applications for ambient intelligence-based technologies and systems that are expected to impact our daily life in the future. For example, consider the case of future intelligent transportation systems for tackling drink driving. One hypothetical example could be a scenario where a driver intends to drive his/her car after a night out drinking with friends, an embedded ambient intelligent system within his car will be able to automatically detect this situation and judge whether the level of alcohol is below the legal limit or not. If the system finds the driver might be illegally driving, it may send a signal to alert the driver and in an extra case it can stop the driver from starting his/her car. Another potential application of intelligent transport is where ambient intelligence can also help to alert the driver to be aware of speeding if the intelligent system can recognise the driving situation and detect the speed limit.

In adaptive cruise and steering control (ACC) of future cognitive or "smart" vehicles, ambient intelligence may also play a key role. Figure 10 illustrates such a typical system where an intelligent multivariable multi-controller approach is employed to realize speed tracking by using a longitudinal and lateral vehicle model and a switching strategy from one mode to another [2, 3]. One example is given in Fig. 11 showing how the intelligent system is able

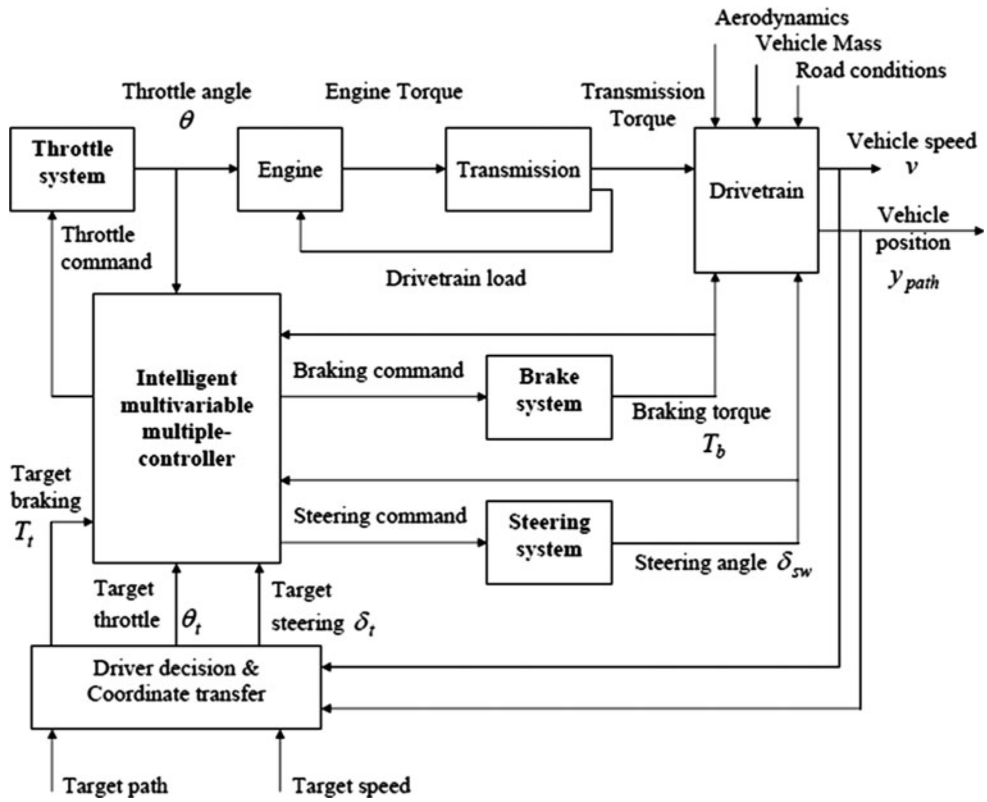


Fig. 10 Intelligent multivariable multi controller approach to adaptive cruise control

to track the target speed of vehicle by switching the controllers between two modes [2, 3].

Synergies and Interactions between Health and Security Applications

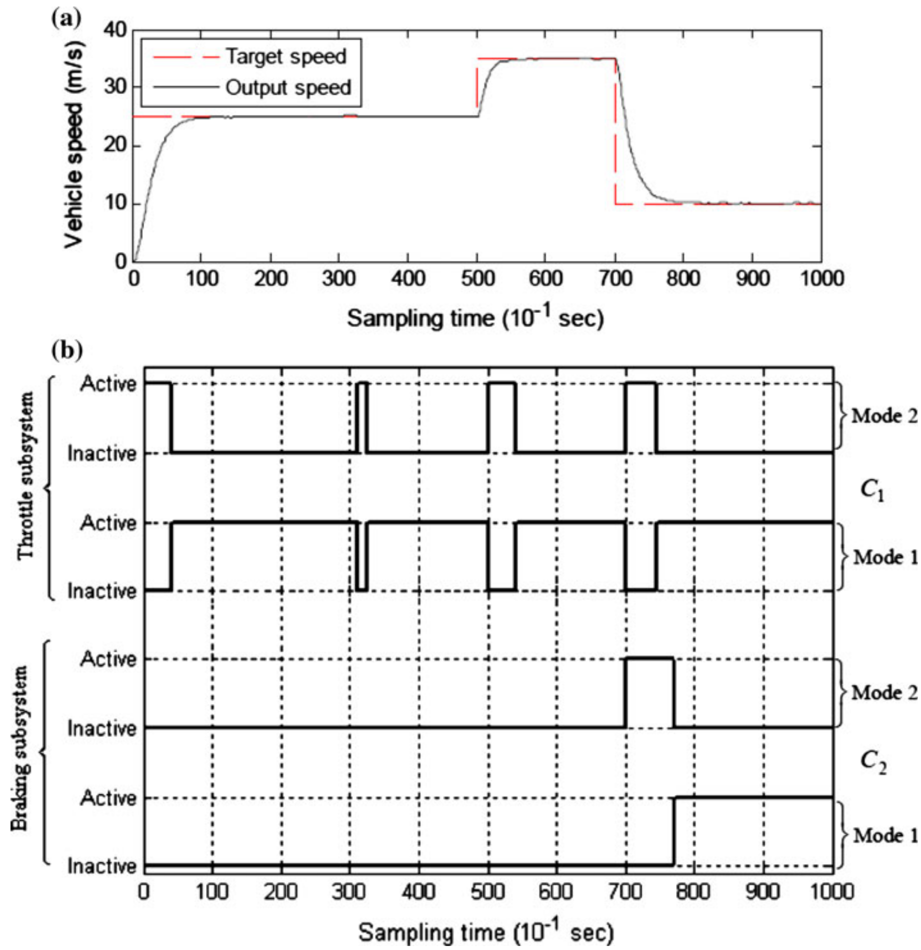
Ideally, a system with ambient intelligence should be able to detect the age of the persons in front of it, and their gender, health condition, emotional state, etc. This information should be inferred from the signals described in Section 2. Some security systems are also able to detect heart rates. If the heart rate is higher than a predetermined threshold, a silent alarm is activated because the system considers that the person is providing their biometric trait in a situation where they may be under duress.

One of the main concerns of biometrics applied to security is about privacy issues. Technological advances let to store, gather and compare a wide range of information on people. Using identifiers such as name, address, passport or social security number, institutions can search databases for individuals' information. This information can be related to salary, employment, sexual preferences, religion, consumption habits, medical history, etc. Though in most of the scenarios there should be no problem, there is a potential risk. Let us think, for instance, in sharing medical information. Obviously, in case of emergency, this sharing between hospitals would be beneficial. On the contrary, if this information is transferred to a personal insurance company or a prospective employer, the insurance or the job application can be denied. The situation is especially dramatic when biometric data collection is intended for security purposes but a third party tries to infer the health condition of the subject. For instance, in the case of retina and iris recognition, an expert can determine that a patient suffers from diabetes, arteriosclerosis, hypertension, etc.

For any biometric identifier, there is a portion of population for which it is possible to extract relevant information about their health, with similar implications to the ones described in previous paragraph, for example, speech disorders, hair or skin colour problems, etc. An important question is what exactly is disclosed when biometric scanning is used. In some cases, additional information not related to identification might be obtained. For instance, [95] presents a list of these cases that includes

- Some studies suggesting that fingerprints and finger images may disclose medical information about a person (chromosomal disorders such as Down syndrome, Turner syndrome and Klinefelter syndrome, and nonchromosomal disorders, such as chronic, intestinal pseudo-obstruction, leukaemia, breast cancer and Rubella syndrome).
- Several researchers reporting a link between fingerprints and homosexuality.

Fig. 11 Intelligent multiple controller in tracking target vehicle speed: (**a**) output speed trajectory, (**b**) multiple controller switching scheme among throttle and wheel brake subsystems



In (Maltoni et al. [54], p. 46), there is a set of references about statistical correlation between malformed fingers and certain genetic disorders.

While the relationship between genetic disorders and fingerprints may be possible, it is hard to believe that a fingerprint, which is fully formed at about 7 months of foetus development and does not change throughout the life of an individual (Maltoni et al. [54], p. 24), could be correlated with sexual preferences that can vary, or diseases that can appear and disappear during a lifetime.

Most biometric traits evolve through time. Feature extraction is a key point of classification, but nowadays there are no powerful studies about the evolution of different parameters: Which are more long lasting? Which phenomena affect these parameters? How can we use this information for a robust biometric security/health application? Is the person in front of the machine in good health condition and he/she can be responsible of his/her own acts? Fig. 12 shows a real case extracted from [92]. In this case, several women made an elder woman sign her name on blank sheets of paper (Fig. 13). Theoretically, it was to solve some issues related to medicines. When the elder person died, the other women took advantage of the signed sheets in order to write a rental agreement. The theoretical date of this agreement was 1985 (Fig. 12 on the bottom), but several documents signed in 1986 (Fig. 12 on the top) showed better control of calligraphic movements. In fact, the hesitantly written signature document signed in 1985 was closer in appearance to the blank sheets signed when the elder woman had dementia than to the 1986 document. Thus, it was demonstrated that in fact the rental document was not signed in 1985. It was signed later.

An interesting application of biometric system combined with ambient intelligence to health is the use of gait recognition for predicting falls of elderly people. From a healthcare perspective, different applications for exploiting ambient intelligence have been recently proposed. Among them, we can recall here an automated fall detection system [52] whose main aim is to promptly detect falls especially in older people to ensure a rapid medical intervention. In that study, falls are reported as the leading causes of accidental death in the US population over 65, with a large percentage of all people who died as a result of a fall being over 65. An inexpensive system based on Doppler radar sensors has been set up and a k-NN (nearest neighbour)-based classification system has been developed showing

Fig. 12 Documents signed in 1985 (hesitated) and 1986

excellent performance (with an AUC equal to 0.96) in detecting falls at home.

On a similar topic, [86] proposed a preliminary study on a depth camera device in home environments with a view of building a fall risk model. That study has shown how measurements of temporal and spatial gait parameters could be inexpensively and passively (i.e. without the active involvement of the person being observed) obtained by a depth camera (such the popular Microsoft Kinect) combined with a motion capture system for ground truth.

In biometric systems, the use of gait information has been used not only for recognizing the identity of people but also for indentifying gender [49]. The technology for gait recognition is based on deriving parameters from silhouettes, such as approximating ellipses, from which time-dependent features are extracted, which are fed into a classifier that gives as output the identity and/or the gender of the person in the image.

A straight forward extension of this idea might be to determine a specific gait sequence of a given person, and detect whether the gait process suffers changes. In the case of elderly people, it might be a good predictor of the probability of falling [91]. In this paper, the authors analysed the set of features that gave the best prediction of the risk of falling, which from a set of 7 gait markers, the feature that explained most of the variance was a slower gait speed. The technology for detecting gait anomalies does not need to be based on expensive video signal processing, but can be based on simple accelerometers [51], which can be implemented in a wrist wearable device or even on a mobile telephone. The same technology can be used for training and correcting the gait of elderly people and, therefore, diminishing the fall risk [85].

The use of the current technology on gait recognition not only can identify the danger of fall, but also can be used to train elderly people to reduce the risk of falling. As a matter of fact, the combination of biometric and ambient intelligence technologies may allow to improve the quality of living and autonomy of elderly or handicapped people, which improves the independence and auto-sufficiency and at the same time might lower the cost of attending a growing fraction of the population that needs specific care, but not on a 24 h basis.

A last straightforward question is about the physical "apparent" age and the real age. For instance, [12] reveal a loss of writing speed in later life, particularly in individuals suffering from senile psychoses. The differences in writing speed between senile subjects and "normal elderly" ones were less than the differences between normal elderly and young subjects. They also provide a plot that relates age with writing speed. Thus, theoretically, an apparent age estimation is possible looking at the writing speed, and some categorization of people could be possible: those with health condition below the average of those born the same year and those in better condition than the average. This classification could probably be considered very sensible and private data.

Conclusions

In this paper, we have discussed several applications of biometrics related to human beings beyond security applications. Mainly, we have investigated the possibilities in health and ambient intelligence, as well as the relationship between these applications. The most important issue is that the same signals used for security applications can be used for detecting diseases such as dementia, drug abuse, diabetes, arteriosclerosis, hypertension, genetic disorders, etc. This is a double-edged sword because biometric data can be used to assist in obtaining accurate and fast health diagnoses, but this information can also be illegally inferred without the consent of the user. Another synergy worth considering is when health issues are important for identity verification, that is, when the health

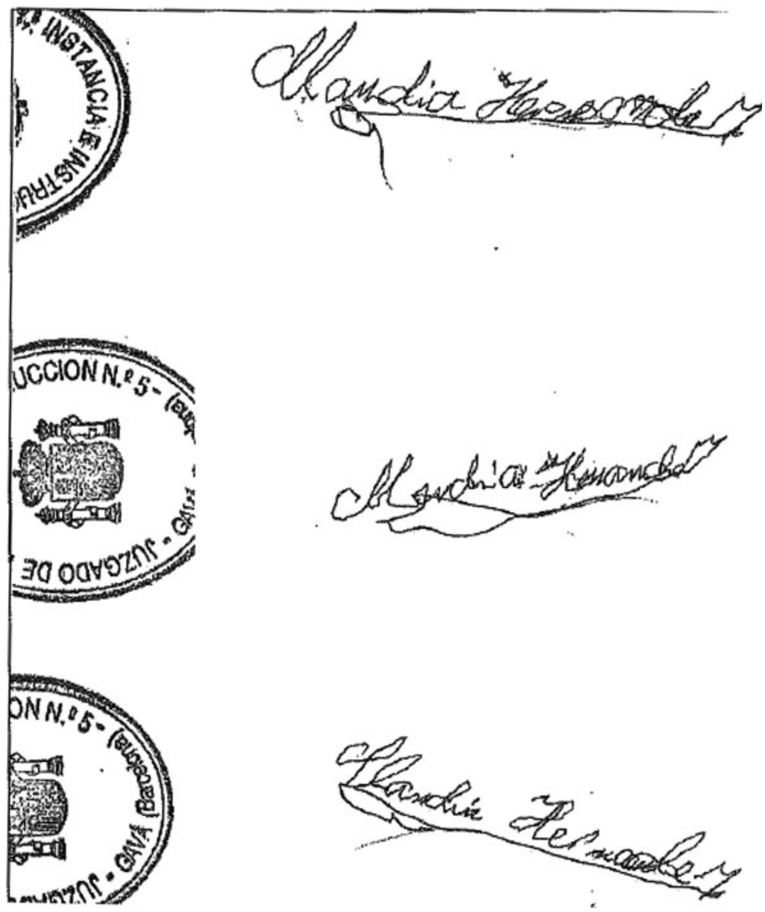


Fig. 13 Some signatures on blank sheets, when the elder woman was suffering dementia

state can change the validity of the authentication. These are the cases where the user has provided his biometric data, such as the signature, under pressure or affected by dementia.

Thus, this is a hot research topic that must be addressed, probably by signal processing teams cooperating with medical doctors and working on both biometric research fields: health and security.

Acknowledgments This work was supported by FEDER and MEC, TEC2009-14123-C04-04. SIX (CZ.1.05/2.1.00/03.0072), CZ.1.07/2.3.00/20.0094, VG20102014033, GACR 102/12/1104 and KONTAKT ME10123. We also thank Francesc Viñals and Mari Luz Puente for providing the examples in Figs. 12 and 13.

References

1. Aarts E, Harwig R, Schuurmans M. Ambient intelligence. In: Denning PJ, editor. The Invisible future: the seamless integration of technology into everyday life. New York: McGraw-Hill; 2001. p. 235–50.
2. Abdullah R. Intelligent methods for complex systems control engineering. PhD thesis with Dr Amir Hussain. UK: The University of Stirling; 2007.
3. Abdullah R, Hussain A, Warwick K, Zayed A. Autonomous intelligent cruise control using a novel multiple-controller framework incorporating fuzzy-logic-based switching and tuning. Neurocomputing. 2008;71:2727–41.
4. Abel A, Hussain A, Nguyen QD, Ringeval F, Chetouani M, Milgram M. Maximising audiovisual correlation with automatic lip tracking and vowel based segmentation. In: Biometric ID, editor. Management and multimodal communication. Berlin: Springer; 2009. p. 65–72.
5. Ackermann H, Hertich I, Daum I, Scharf G, Spieker S. Kinematic analysis of articularoty movements in central motor disorders. Mov Disord. 1997;12(6):1019–27.
6. Almajai I, Milner B. Effective visually-derived Wiener filtering for audio-visual speech processing. In: Proceedings of the inter-speech. Brighton, UK; 2009.
7. Almajai I, Milner B. Maximising audio-visual speech correlation. In: Proceedings of the AVSP. 2007.
8. Barker JP, Berthommier F. Evidence of correlation between acoustic and visual features of speech. In: Proceedings of the ICPhS '99. 1999; p. 199–202.
9. Beatty WW, Orbelo DM, Sorocco KH, Ross ED. Comprehension of affective prosody in multiple sclerosis. Multiple Scler J. 2003;9(2):148–53.
10. Bermond B, Nieuwenhuyse B, Fasotti L, Schuerman J. Spinal cord lesions, peripheral feedback, and intensities of emotional feelings. Cognit Emot. 1991;5:201–20.
11. Bidet-Ildei C, Pollak P, Kandel S, Fraix V, Orliaguet J-P. Handwriting in patients with parkinson disease: effect of l-dopa and stimulation of the sub-thalamic nucleus on motor anticipation. Hum Mov Sci. 2011;30(4):783–91.
12. Birren JE, Botwinick J. The relation of writing speed to age and to the senile psychoses. J Consult Psychol. 1951;15(3):243–9.

13. Caccioppo JT, Klein DJ, Bernston GC, Hatfield E. The psychophysiology of emotion. In: Lewis JM, Haviland-Jones M, editors. Handbook of emotion. New York: Guilford Press; 1993. p. 119–42.
14. Cambria E, Hussain A, Havasi C, Eckl C. Sentic computing: exploitation of common sense for the development of emotion-sensitive systems. Lect Notes Comput Sci. 2010;5967:148–56.
15. Cambria E, Hussain A, Durrani T, Havasi C, Eckl C, Munro J. Sentic computing for patient centered applications. In: 10th IEEE international conference on signal processing (ICSP), 2010. p. 1279–82.
16. Cambria E, Hussain A, Eckl C. Bridging the gap between structured and unstructured health-care data through semantics and sentics. In: Proceedings of the ACM WebSci'11; 2011. p. 1–4.
17. Cambria E, Hupont I, Hussain A, Cerezo E, Baldassarri S. Sentic avatar: multimodal affective conversational agent with common sense. LNCS, vol. 6456. Berlin, Heidelberg: Springer; 2011. p. 81–95.
18. Cifani S, Abel A, Hussain A, Squartini S, Piazza F. An investigation into audiovisual speech correlation in reverberant noisy environments. Lect Notes Comput Sci. 2009;5641:331–43.
19. Chan D, Fox NC, Scahill RI, Crum WR, Whitwell JL, Leschziner G, Rossor AM, Stevens JM, Ciplolotti L, Rossor MN. Patterns on temporal lobe atrophy in semantic dementia and Alzheimer's disease. Ann Neurol. 2001;49:433–42.
20. Delaherche E, Chetouani M. Multimodal coordination: exploring relevant features and measures. In: SSPW '10 Proceedings of the 2nd international workshop on Social signal processing; 2010. p. 47–52.
21. Eichhorn TE, Gasser T, Mai N, Marquardt C, Arnold G, Schwarzy J, Oertel WH. Computational analysis of open loop handwriting movements in Parkinson's disease: a rapid method to detect dopamimetic effects. Mov Disord. 1996;11(3):289–97.
22. Ekman P. An argument for basic emotions. Cognit Emot. 1992;6:169–200.
23. Ericsson K, Forssell LG, Holmén K, Viitanen M, Winblad B. Copying and handwriting ability in the screening of cognitive dysfunction in old age. Arch Gerontol Geriatr. 1996;22:103–21.
24. Esposito A. The amount of information on emotional states conveyed by the verbal and nonverbal channels: some perceptual data. In: Stilianou Y, et al., editors. Progress in nonlinear speech processing. Lecture notes in computer science, vol. 4392. Berlin: Springer; 2007. p. 45–264.
25. Esposito A. Affect in multimodal information. In: Tao J, Tan T, editors. Affective information processing. Heidelberg: Springer; 2008. p. 211–34.
26. Esposito A. The perceptual and cognitive role of visual and auditory channels in conveying emotional information. Cogn Comput J. 2009;1(2):268–78.
27. Faruk A, Turan N. Handwritten changes under the effect of alcohol. Forensic Sci Int. 2003;132(3):201–10.
28. Ferrand C. Harmonics-to-noise ratio: an indexing of vocal aging. J Voice. 2002;16(4):480–7.
29. Foley RG, Miller L. The effects of marijuana and alcohol usage on handwriting. Forensic Sci Int. 1979;14(3):159–64.
30. Folstein MF, Folstein SE, McHugh PR. Mini mental state: a practical method for grading the cognitive state of patients for the clinician. J Psychiatr Res. 1975;12:189–98.
31. Forbes KE, Shanks MF, Venneri A. The evolution of dysgraphia in Alzheimer's disease. Brain Res Bull. 2004;63:19–24.
32. Fotiou DF, Stergiou V, Tsiptsios D, Lithari C, Nakou M, Karlovasitou A. Cholinergic deficiency in Alzheimer's and Parkinson's disease: evaluation with pupillometry. Int J Psychophysiol. 2009;73(2):143–9.
33. Fountoulakis K, Fotiou F, Iacovides A, Tsiptsios J, Goulas A, Tsolaki M, Ierodiakonou C. Changes in pupil reaction to light in melancholic patients. Int J Psychophysiol. 1999;31(2):121–8. ISSN 0167-8760.
34. Frijda NH. Moods, emotion episodes, and emotions. In: Lewis JM, Haviland-Jones M, editors. Handbook of emotion. New York: Guilford Press; 1993. p. 381–402.
35. Girin L, Schwartz JL, Feng G. Audio-visual enhancement of speech in noise. J Acoust Soc Am. 2001;109(6):3007–20.
36. Gobermana AM, Coelho C. Acoustic analysis of Parkinsonian speech I: speech characteristics and L-Dopa therapy. NeuroRehabilitation. 2002;17:237–46.
37. Gobermana AM, Coelho C. Acoustic analysis of Parkinsonian speech II: L-Dopa related fluctuations and methodological issues. NeuroRehabilitation. 2002;17:247–54.
38. Goecke R, Potamianos G, Neti C. Noisy audio feature enhancement using audio-visual speech data. In: Acoustics, speech, and signal processing, Proceedings (ICASSP'02), vol. 2. IEEE International Conference; 2002. p. 2025–2028.
39. Gorriz JM, Segovia F, Ramirez J, Lassl A, Salas-Gonzalez D. GMM based SPECT image classification for the diagnosis of Alzheimer's disease. Appl Soft Comput. 2011;11:2313–25.
40. Groves-Wright K, Neils-Strunjas J, Burnett R, O'Neill MJ. A comparison of verbal and written language in Alzheimer's disease. J Commun Disord. 2004;37(2):109–30.
41. Gustaw K, Gonet W. Speech disorders in multiple system atrophy of parkinson type. Clin Res. 2008;1(2):185–8.
42. Heinik J, Werner P, Dekel T, Gurevitz I, Rosenblum S. Computerized kinematic analysis of the clock drawing task in elderly people with mild major depressive disorder: an exploratory study. Int Psychogeriatr. 2010;22(3):479–88.
43. Holz FG, Piguet B, Minassian DC, Bird AC, Weale RA. Decreasing stromal iris pigmentation as a risk factor for age-related macular degeneration. Am J Ophthalmol. 1994;117(1): 19–23.
44. Iliadou V, Kaprinis S. Clinical psychoacoustics in Alzheimer's disease central auditory processing disorders and speech deterioration. Ann Gen Hospital Psychiatr. 2003;2:12.
45. Illán IA, Górriz JM, Ramírez J, Salas-Gonzalez D, López MM, Segovia F, Chaves R, Gómez-Rio M, Puntonet CG, the Alzheimer's Disease Neuroimaging Initiative. 18F-FDG PET imaging analysis for computer aided Alzheimer's diagnosis. Inf Sci. 2011;181(4):903–16.
46. Izard CE. Innate and universal facial expressions: evidence from developmental and cross-cultural research. Psycholog Bull. 1994;115:288–99.
47. Kempler D, Curtiss S. Catherine jackson "synthactic preservation in Alzheimer's disease". J speech Hearing Res. 1987;30:343–50.
48. Kushki A, Chau T, Anagnostou E. Handwriting difficulties in children with autism spectrum disorders: a scoping review. J Autism Dev Disord. 2011;41(12):1706–16.
49. Lee L, Grimson WEL. Gait analysis for recognition and classification. Automatic face and gesture recognition, 2002. In: Proceedings of the fifth IEEE international conference; 2002. p. 148–55.
50. Levenson RW. Human emotion: a functional view. In: Ekman PP, Davidson RJ, editors. The nature of emotion: fundamental questions. New York: Oxford University Press; 1994. p. 123–6.
51. Liu R, Zhou J, Liu M, Hou X. A wearable acceleration sensor system for gait recognition. In: 2nd IEEE Conference on industrial electronics and applications, ICIEA 2007; 2007. p. 2654–59.
52. Liu L, Popescu M, Rantz M, Skubic M, Cuddihy P, Yardibi T. Automatic fall detection based on Doppler radar motion signature. In: 5th International conference on pervasive computing technologies for healthcare; 2011. p. 222–5.

53. Llau Arcusa MJ, Gonzalez Alvarez J. Medida de la inteligibilidad en el habla disaártrica. Rev Logop Foniatr Audiol. 2004;24: 33–43.
54. Maltoni D, Maio D, Jain AK, Prabhakar S. Handbook of fingerprint recognition. 1st ed. New York: Springer; 2003.
55. Maternaghan C, Turner KJ. A component framework for telecare and home automation. In: CCNC'10 Proceedings of the 7th IEEE conference on consumer communications and networking conference; 2009. p. 886–870.
56. McGurk H, MacDonald J. Hearing lips and seeing voices. Nature. 1976;264:746–8.
57. Mekyska J, Smekal Z, Kostalova M, Mrackova M, Skutilova S, Rektorova I. Motor aspects of speech imparment in Parkinson's disease and their assessment. Cesk Slov Neurol N. 2011;74: 662–8.
58. Moreau C, Ozsancak C, Blatt J-L, Derambure P, Destee A, Defebvre L. Oral festination in parkinson's disease: biomechanical analysis and correlation with festination and freezing of gait. Mov Disord. 2007;22(10):1503–6.
59. Nagulic M, Davidovic J, Nagulic I. Parkinsonian voice acoustic analysis in real-time after stereotactic thalamotomy. Stereotact Funct Neurosurg. 2005;83(2–3):115–21.
60. Neils-Strunjas J, Groves-Wright K, Mashima P, Harnish S. Dyspgraphia in Alzheimer's disease: a review for clinical and research purposes. J speech Lang Hearing Res. 2006;49(6): 1313–30.
61. Oatley K, Jenkins JM. Understanding emotions. 2nd ed. Oxford: Blackwell; 2006.
62. Ohn TG, Braak H. Auditory brainstem nuclei in Alzheimer's disease. Neurosci Lett. 1989;2:60–3.
63. Ozsancak C, Auzou P, Jan M, Defebvre L, Derambure P, Destee A. The place of perceptual analysis of dysarthria in the differential diagnosis of corticobasal degeneration and Parkinson's disease. J Neurol. 2006;253(1):92–7.
64. Panksepp J. Emotions as natural kinds within the mammalian brain. In: Lewis JM, Haviland-Jones M, editors. Handbook of emotions. 2nd ed. New York: Guilford Press; 2000. p. 137–56.
65. Phillips JG, Ogeil RP, Muller F. Alcohol consumption and handwriting: a kinematic analysis. Hum Mov Sci. 2009;28: 619–32.
66. Plutchik R. Emotions as adaptive reactions: implications for therapy. Psychoanal Rev LIII. 1966;2:105–10.
67. Ramlee RA, Ranjit S. Using iris recognition algorithm, detecting cholesterol presence. In: International conference on information management and engineering; 2009. p. 714–7.
68. Rantz MJ, Skubic M, Koopman RJ, Phillips L, Alexander GL, Miller SJ, Guevara RD. Using sensor networks to detect urinary tract infections in older adults. In: Proceedings of the IEEE 13th international conference on e-health networking, applications and services. 2011.
69. Rapcan V, D'Arcy S, Yeap S, Afzal N, Thakore J, Reilly RB. Acoustic and temporal analysis of speech: a potential biomarker for schizophrenia. Med Eng Phys. 2010;32(9):1074–9.
70. Ringeval F, Demouy J, Szaszak G, Chetouan M, Robel L, Xavier J, Cohen D, Plaza M. Automatic intonation recognition for the prosodic assessment of language impaired children. IEEE Trans Audio Speech Lang Process. 2011;19(5):1328–42.
71. Roberts VJ, Ingram SM, Lamar M. Prosody impairment and associated affective and behavioral disturbances in Alzheimer's disease. Neurology. 1996;47:1482–8.
72. Rosenblum S, Parush S, Weiss PL. The in air phenomenon: temporal and spatial correlates of the handwriting process. Percept Mot Skills. 2003;96(3):933–54.
73. Russell JA. A circumplex model of affect. J Pers Soc Psychol. 1980;39:1161–78.
74. Sargin ME, Yemez Y, Erzin E, Tekalp AM. Audiovisual synchronization and fusion using canonical correlation analysis". IEEE Trans Multimed. 2007;9(7):1396–403.
75. Saunder-Pullman R, Derbym C, Stanley K, Floyd A, Bressman S, Lipton RB, Deligtisch A, Severt L, Qiping Yu, Kurtis M, Pullman SL. Validity of spiral analysis in early Parkinson's disease. Mov Disord. 2008;23(4):531–7.
76. Scherer KR, Banse R, Wallbott HG. Emotion inferences from vocal expression correlate across languages and cultures. J Cross Cult Psychol. 2001;32:76–92.
77. Schlosberg H. Three dimensions of emotion. Psychol Rev. 1953;61(2):81–8.
78. Sesa E, Faundez-Zanuy M. Biometric recognition using online uppercase handwritten text. Pattern Recognit. 2012;45(1): 128–44.
79. Sesa E, Faundez-Zanuy M, Mekyska J. An information analysis of in-air and on-surface trajectories in online handwriting. Cognit Comput. 2012;4:195–205.
80. Skodda S, Schlegel U. Speech rate and rhythm in parkinson's disease. Mov Disord. 2008;23(7):985–92.
81. Sodoyer D, Schwartz JL, Girin L, Klinkisch J, Jutten C. Separation of audio-visual speech sources: a new approach exploiting the audio-visual coherence of speech stimuli. EURASIP J Appl Signal Process. 2002;11(1):1165–73.
82. Sodoyer D, Girin L, Jutten C, Schwartz JL. Developing an audio-visual speech source separation algorithm. Speech Commun. 2004;44(1–4):113–25.
83. Stewart C, Winfield L, Junt A, Bressman SB, Fahn S, Blitzer A, Brin MF. Speech dysfunction in early Parkinson's disease. Mov Disord. 1995;10(5):562–5.
84. Sunderland T, Hill JL, Mellow AM, et al. Clock drawing in Alzheimer's disease: a novel measure of dementia severity. J Am Geriatr Soc. 1989;37:725–9.
85. Trombetti A, Hars M, Herrmann FR, Kressig RW, Ferrari S, Rizzoli R. Effect of music-based multitask training on gait, balance, and fall risk in elderly people: a randomized controlled trial. Arch Intern Med. 2011;171(6):525–33.
86. Stone EE, Skubic M. Evaluation of an inexpensive depth camera for passive in-home fall risk assessment. In: Proceedings of the 4th International conference on pervasive computing technologies for healthcare. Dublin; 2011.
87. Sumby WH, Pollack I. Visual contribution to speech intelligibility in noise. J Acoust Soc Am. 1954;26(2):212–5.
88. Tripolitia EE, Fotiadisb DI, Argyropoulou M. A supervised method to assist the diagnosis and monitor progression of Alzheimer's disease using data from an fMRI experiment. Artif Intell Med. 2011;53(1):35–45.
89. Tucha O, Mecklinger L, Thome J, Reiter A, Alders GL, Sartor H, Naumann M, Lange KW. Kinematic analysis of dopaminergic effects on skilled handwriting movements in Parkinson's disease. J Neural Transm. 2006;113:609–23.
90. Tucha O, Mecklinger L, Walitza S, Lange KW. The effect of caffeine on handwriting movements in skilled writers. Hum Mov Sci. 2006;25(4–5):523–35.
91. Verghese J, Holtzer R, Lipton RB, Wang C. Quantitative gait markers and incident fall risk in older adults. J Gerontol Ser A Biol Sci Med Sci. 2009;64A(8):896–901.
92. Viñals Carrera F, Puente Balsells ML. "Grafología criminal", capítulo 3, alteraciones neurológicas y biológicas. Editorial Herder, 2009.
93. Warkentin S, Erikson C, Janciauskiene S. rCBF pathology in Alzheimer's disease is associated with slow processing speed. Neuropsychologia. 2008;46(5):1193–200.
94. Werner Perla, Rosenblum Sara, Bar-On Gady, Heinik J, Korczyn A. Handwriting process variables discriminating mild Alzheimer's

disease and mild cognitive impairment". J Gerontol. 2006;61B(4): 228–36.
95. Woodward J. Biometrics: identifying law and policy concerns. In: Jain AK, Bolle RM, Pankanti S, editors. Biometrics: personal identification in networked society. New York: Springer; 2005. p. 385–405.
96. Zelkha E, Epstein B, Birrell S, Dodsworth C. From devices to "ambient intelligence". Digital Living Room Conference, June 1998. http://www.epstein.org/brian/ambient_intelligence/DLR%20Final%20Internal.ppt.