A Preliminary Review of Behavioural Biometrics for Health Monitoring in the Elderly

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Abstract: This article explores the potential of ICT-based biometrics for monitoring the health status of the elderly people. It departs from specific ageing and biometric traits to then focus on behavioural biometric traits like handwriting, speech and gait to finally explore their practical application in health monitoring of elderly.

1 INTRODUCTION

The word biometrics comes from the Greek words "bios" (life) and "metrikos" (measure). Strictly speaking, biometrics refers to a science and technology involving the measuring and statistical analysis of biological characteristics.

According with Faundez-Zanuy and Chetouani (2005), biometric recognition offers a promising approach for security applications, with some advantages over the classical methods that depend on something you own (key, card, etc.) or something you know (password, PIN, etc.). An interesting feature of biometric traits is that they are based on something you are or something you do, so you do not need to remember anything or to hold any token. But security is not the only field in which biometrics can be used. For instance, biometric techniques can be used for the analysis of data in agricultural field experiments to compare, for example, the yields of different varieties of wheat; or for the analysis of biometric characteristics for animal classification. Among others, one of the most promising fields of biometrics application is the analysis of data from human clinical trials to evaluate the possible illness or malfunction of human body.

Population ageing has become one of the major challenges for the future of our societies and various technological innovations have been developed to promote and enhance an active and healthy ageing. In Europe, in the last three decades, birth and death rates have gradually decreased while longevity and life expectancy rates have significantly increased. By 2050, the European population segment of over 50 will increase by 35 percent and the one over 85 will triple (Eurostat, 2012). Beside a steady decrease in fertility and birth rates, strongly linked to the progressive inclusion of women in the labour market, scientific developments in different fields such as medicine, healthcare or hygiene also account for this process of population ageing.

The use of biometric systems for health diagnosis/monitoring/screening/ could mark an important step in dealing with population ageing due to aspects related to:

- The prevalence of diseases, especially those related with brain deterioration; and
- Particular characteristics of biometrics traits.

This article aims to provide an exploratory review of ICT-based biometrics and how this technology can be used to improve the quality of life of elderly people.

This paper is organized as it follows: in section 2, we present various ageing and biometric traits; in section 3, we focus on behavioural biometrics and provide three different examples of biometrics traits for health monitoring; finally, in section 4, we present the final conclusions and discussion aspects.

2 AGEING AND BIOMETRIC TRAITS

In order to use biometrics, we first have to decide which characteristics can be used for biometric recognition, and which ones can be used for health applications. As common sense says, a good biometric trait must accomplish a set of properties. Among these properties, we could mention the following (Clarke, 2014):

- Universality of coverage: every relevant person should have an identifier;
- Uniqueness: each relevant person should have only one identifier, so two persons cannot have the same identifier;
- Permanence: the identifier should not change, nor be changeable;
- Indispensability: the identifier should be one or more natural characteristics, which each person has and retains; if artificial, the identifier should be enforcedly available at all times;
- Collectability: the identifier should be collectible by anyone on any occasion;
- Storability: the identifier should be storable in manual and in automated systems;
- Exclusivity: no other form of identification should be necessary or used;
- Precision: every identifier should be sufficiently different from every other identifier that mistakes are unlikely;
- Simplicity: recording and transmission should be easy and not error-prone;
- Cost: measuring and storing the identifier should not be unduly costly;
- Convenience: measuring and storing the identifier should not be unduly inconvenient or time-consuming;
- Acceptability: its use should conform to contemporary social standards.

If we focus on health applications, some of these characteristics may be very relevant while others not. In health applications, the focal point is not so much the subject (like, for example, in security applications) than the state of health of the subject. Since health applications are generally designed to enhance health conditions, the biometric traits used in this case should accomplish properties related to the state of health of the individual and not with the individual *per se*. In this new scenario, the *exclusivity* property, for example, may not be necessary *stricto sensu*, but the *permanence* property may be really essential.

The aging process may produce changes in biometric traits, and these changes are of particular interest as they can tell us a lot of things about the state of health of an individual. A good example is the way in which 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 body functions. For instance, handwriting and speech production are a fine motor control performed by our brain. When these signals are declining, health problems might be detected.

Some physical and mental characteristics change during the lifetime of a human (Sasse and Krol, 2013). In terms of height, physical maturity is reached around age 20, but different body tissues mature at different rates. Body height declines from the age 50 onwards due to bone shrinkage, and the acuity of sight and vision can start to decline even earlier. Age-related changes can affect biometric traits, and make it more difficult to operate the systems through which users interact with them. Ageing affects the biometric templates of all biometric traits in different ways.

Biometric traits can be split into two main categories:

- Physiological Biometrics: based on direct measurements of a part of the human body; fingerprint, face, iris, and hand-scan recognition belong to this group.
- Behavioural Biometrics: based on measurements and data derived from an action performed by the user, and thus indirectly measuring some characteristics of the human body; signature, gait, gesture, and key stroking recognition belong to this group.

For health applications for elderly, we are interested in the second category of biometric traits, behavioural biometrics, in order to characterize the state of health of the subject. Of course, we have to keep in mind that, for instance, the speech signal depends on behavioural traits such as semantics, diction, pronunciation, idiosyncrasy, etc. (related to socio-economic status, education, place of birth, etc.), but it also depends on the speaker's physiology, such as the shape of the vocal tract. Hence, what is really useful (in some cases) in behavioural biometrics is the evolution of biometric traits for each subject (intrasubject variability), and not the global characterization of the state of health of each subject (intersubject variability).

3 BEHAVIOURAL BIOMETRICS

In this section, we review three of the most important behavioural biometrics traits for health monitoring in the elderly, and emphasise some practical applications.

3.1 Handwriting

Handwriting refers to a person's writing created with a writing utensil such as a pen or pencil. This creation may include not only text but also drawings or other kind of graphs. Handwriting has been used extensively for biometric recognition, for example, as a signature: it is frequently used when signing credit card receipts, checks, etc.

In the past, the analysis of handwriting had to be performed in an offline manner. Only the writing itself (strokes on a paper) were available for analysis. Nowadays, modern capturing devices, such as digitizing tablets and pens (with or without ink) can gather data without losing its temporal dimension. When spatio-temporal information is available, its analysis is referred to as online. Modern digitizing tablets not only gather the *x-y* coordinates that describe the movement of the writing device as it changes its position, but it can also collect other data, mainly the pressure exerted by the writing device on the writing surface and also the azimuth, the angle of the pen in the horizontal plane, and the altitude, the angle of the pen with respect to the vertical axis. A very interesting aspect of the modern online analysis of handwriting is that it can take into account information collected when the writing device was not exerting pressure on the writing surface. Thus, the movements performed by the hand while writing a text can be split into two classes:

a) On-surface trajectories (pen-downs), corresponding to the movements executed while the writing device is touching the writing surface; each of these trajectories produces a visible stroke; and

b) In-air trajectories (pen-ups), corresponding to the movements performed by the hand while transitioning from one stroke to the next; during these movements, the writing device exerts no pressure on the surface.

Handwriting signals have been used for cognitive impairment detection. For instance, handwriting skill degradation and Alzheimer’s disease (AD) appear to be significantly correlated (Forbes, Shanks and Venneri, 2004) and some handwriting aspects can be good indicators for its diagnosis (Neils-Strunjas et al., 2006) or help differentiate between mild Alzheimer’s disease and mild cognitive impairment (Werner et al., 2006). As demonstrated in Faundez-Zanuy et al. (2014), the visual inspection of the pen down images suggest a progressive degree of impairment, where drawing becomes more disorganized and the three dimensions effect of the drawing (a house) is only achieved in the mild case. The visual information provided by the pen up drawing between AD individuals also indicates a progressive impairment and disorganization when the individuals try to plan the drawing. In addition, the pressure is also different. AD people produce softer and simpler strokes.

For Parkinson’s disease (PD), handwriting is thought to be impaired mainly due to hypokinesia (decreased amplitude of movements) and bradykinesia, as detailed in Broderick et al. (2009) and Tucha et al. (2006). As compared to on-surface movements (Drotár et al., 2014), the in-air movements elicited during handwriting of a sentence may involve additional cognitive processes such as motor planning, programming of the alternating motor sequences, and movement initiation that may also have impacted on the kinematic features and our results. In-air movement possess significant amount of information relevant to diagnosis of PD and could be incorporated in decision support systems that are the important part of the next generation health-care (Drotár et al., 2014).

Also, the analysis of handwriting has proven useful to assess the effects of substances such alcohol (Asıcıoglu et al., 2003; Phillips et al., 2009), marijuana (Foley and Lamar Miller, 1979) or caffeine (Tucha et al., 2006). Aided by modern acquisition devices, the field of psychology has also benefitted from the analysis of handwriting. For instance, Rosenblum et al. (2003) link the proficiency of the writers to the length of the in-air trajectories of their handwritings.

3.2 Speech

Speech processing is the study of speech signals and the processing methods of these signals. It is also closely related to natural language processing (NLP), and includes several areas of study as for example Speech recognition, Speaker recognition, Speech synthesis, Speech enhancement or Voice analysis for medical purposes, among others. This last area is the one in which we are interested in our work, in which biometric techniques can be applied for different diseases.

Alzheimer’s disease is the most common type of dementia among the elderly. The cognitive deficits and behavioural symptoms are severe enough to limit the ability of an individual to perform everyday professional, social or family activities. An early and accurate diagnosis of AD helps patients and their families to plan for the future and offers the best opportunity to treat the symptoms of the disease. Various researchers have explored different solutions to help on the early diagnose of AD using continuous speech signal. Non-invasive intelligent diagnosis techniques would be very valuable for this purpose. Lopez-de-Ipiña et al. (2013) analysed non-invasive methods based on continuous speech and used them to design an automatic system that can offer medical doctors another point of view for the early diagnosis of AD. By analysing continuous speech, the system calculates an index whose values show whether the subject can be classified as being affected by AD. Emotional Temperature (ET) is another parameter that, combined with other traditional speech parameters, can improve and facilitate the early diagnosis of AD (López-de-Ipiña et al., 2013). In López-de-Ipiña et al. (2014), the Fractal Dimension (FD) of the speech signals is combined with linear parameters in the feature vector in order to enhance the performance of the original system while controlling the computational cost. The advantage of using spontaneous speech tests for the early diagnosis of AD is that these are not perceived as stressful. Moreover, the cost of speech analysis techniques is lower, as they do not require extensive infrastructure or the availability of medical equipment.

Another interesting example of speech processing used in health applications is the detection of Obstructive Sleep Apnea (OSA) (Solé-Casals et al., 2014). OSA is a common sleep disorder that manifests itself by daytime sleepiness caused by a cease in breathing occurring repeatedly during sleep, often for a minute or longer and as many as hundreds of times during a single night. Diagnosis of the sleep condition is based on the calculation of the apnea–hypopnea index (AHI) which measures the frequency of reductions in airflow associated with upper-airway collapse or narrowing that occurs with the state change from wakefulness to sleep (Caples and Gami, 2005). The gold standard procedure to determine the AHI is polysomnography, however it is a quite costly methodology (Kushida et al., 2005). No other measure has proven to be superior to AHI in assessing the overall effect of obstructive sleep apnea. The results presented in Solé-Casals et al., (2014), in terms of Correct Classifications Rate, Sensitivity and Specificity, all above 80% for several classifiers, point out the good potential of voice as a discriminating factor between healthy subjects and severe OSA.

3.3 Gait

Human gait is the pattern of movement of the extremities during locomotion. Minor variations in gait style can be used as a biometric identifier to identify individual people. For example, it's well known that stride parameters (stride length and cadence) are function of body height, weight, and gender (Abdelkader, Cutler and Davis, 2002). In health applications we want to detect physiological, pathological and mental characters of people by their walk style. The technique of gait recognition, as an exciting research area of biomedical information detection, attracts more and more attention.

Several techniques can be used nowadays for gait analysis: stopwatch and marks on the ground; march on a pressure mat; range laser sensors scanning a plane a few centimetres above the floor; video recordings, etc., but new devices like mobile phones or other wearable can also be used if they are equipped with inertial sensors (gyroscopes and accelerometers). An extensive review about gait analysis using wearable sensors can be found in (Tao et al., 2012). The gait analysis is modulated by many factors, including extrinsic (terrain, clothing, etc.) and intrinsic (gender, weight, age, etc.) ones, but also psychological (e.g. emotions) and pathological (e.g. neurological diseases or psychiatric disorders) ones. Focussing in these last factors, gait can be used in elderly people for early diagnostic of Parkinson's disease (PD) (Barth et al., 2011), for the screening of knee osteoarthritis disease (Turcot et al., 2008), for detecting walking behaviour abnormalities that may indicate the onset of adverse health problems, or for the progression of neurodegenerative diseases (El Sayed et al., 2010). The presence of gait abnormalities in elderly persons is often a significant predictor of the risk of the development of dementia, especially non-Alzheimer's dementia (Verghese, et al., 2002). Also, gait can be used in the mobility and fall risk assessment of elders (Stone et al., 2014).

One of the most typical applications of gait analysis is in Parkinson's disease (PD) because PD is commonly characterized by motor dysfunctions, such as resting tremors, slowing of movement, gait difficulty, and limb rigidity. Hence, gait has been verified as one of the most reliable diagnostic signs of this disease. Early diagnosis and effective therapy monitoring of PD is an important prerequisite to treat patients and reduce health care costs. In Barth et al. (2011), a mobile sensor based gait analysis system was developed to measure gait patterns in PD and to distinguish mild and severe impairment of gait. Examinations of 16 healthy controls, 14 PD patients in an early stage, and 13 PD patients in an intermediate stage were included. The system was able to classify patients and controls (for early diagnosis) with a sensitivity of 88% and a specificity of 86%. In addition it was possible to distinguish mild from severe gait impairment (for therapy monitoring) with 100% sensitivity and 100% specificity.

The other common application of gait analysis is related to fall detection. One third of elderly people fall each year, and half of them experience recurrent falls (Mortaza, Osman and Mehdikhani, 2014). A fall could be defined as a situation in which the individual comes to rest at a lower level (e.g. floor) accidentally. Daily activity monitoring and fall detection is important to healthcare for the elderly and patients with chronic diseases. Different devices can be used to measure the spatio-temporal parameters of gait for fall detection. Video cameras or infrared cameras are the most common methods, but also accelerometers are well used these last years. Typically, measured variables are the cadence, the stride time, the duration of single and double support, the walking speed, the stride length the step length, and the step width. According to Mortaza, Osman and Mehdikhanim (2014), effect size analysis showed that time variability, gait speed, stride length and step length were the spatio-temporal parameters that were the most different between elderly fallers and non-fallers. Finally in Patel et al. (2012), a low-cost, continuous, environmentally mounted monitoring system based in a Kinect device is used in order to compute a new metric, the average in-home gait speed (AIGS). Results demonstrate that AIGS outperforms traditional instruments used for mobility and fall risk assessment of elderly adults.

4 DISCUSSION AND CONCLUSIONS

This work has aimed to explore behavioural biometrics for health monitoring in the elderly. In this scenario, biometrics has been presented as a technical tool to be considered due to its capacity in dealing with these tasks. Three different examples of biometric traits have been presented, covering applications like AD, PD, OSA or falls.

We can observe that behavioural characteristics are good traits in order to early detect changes in the health status. On the other hand, due to the great variability of these traits (we have to remember that behavioural traits are also affected by many other characteristics like physiology, changing environment, etc.), it is very interesting to develop a particular biometric system to follow the dynamics of changes for each individual. For example, we can be interested in monitoring the speech characteristics of an elderly subject in order to detect when he/she starts using shorter sentences and long pauses. This change in speech may indicate the start of some cognitive impairment. We can also monitor the handwriting evolution of an individual during a certain period of time in order to detect the beginning of imperceptible tremors in the hands.

Thanks to new wearable devices (a very interesting review of wearable sensors and systems with application in rehabilitation can be found in Patel et al., 2012) and the new capabilities of mobile phones, new apps can be designed using signal processing algorithms for health biometrics. This fact links our field of interest with big data analysis, in which the main focus and challenges are related to the acquisition, analysis, sharing, storage, transfer, visualization or privacy violations of the amount of personal data collected.

Therefore, a very interesting field of research, combining behavioural biometrics, health, wearable and big data may emerge and become a challenge for the scientists coming from these disciplines.

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