Prospect of Smart Home-Based Detection of Subclinical Depressive Disorders

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***Abstract* - Aging is associated with changing physical, social, emotional, and financial circumstances that are often new to the elder. The affective distress that stems from coping with them could play a negative effect on the health of seniors and lead to severe cases of depression, an emotional disorder that could lead to fatal consequences.**

The combination of novel methods of ambulatory detection of emotional states, body area networks providing information from numerous bodily parameters, and sophisticated pervasive technologies offers new possibilities in the detection of and intervention in cases of subclinical depression. In this paper we present the technical aspects and rationale behind systems that can use emotional valence monitoring to quantify prolonged emotional negativity and identify the activities associated with such negativity. We argue that this as a suitable mechanism to facilitate ambient-mediated self-regulation and remote peer-support.

***Index Terms*—Depression, Affective Pervasive Computing, Smart Home**

I. Introduction

EUROPEANS enjoy longer lives than citizens from other world regions. However, perhaps more important than life expectancy for the elderly is the quality of life as it is this element that most affects individuals, their families and friends. The EU recognizes: "Chronic disease, frailty, mental disorders and physical disability tend to become more prevalent in older age, and the burden of these conditions may impact on healthcare and pension provisions, while resulting in a low quality of life for those who suffer from such conditions" [1]. Although the number of disability-free years that people at 65 can expect to live varies across countries, and does not seem solely to be connected with life expectancy, the social, economic, political and technological implications of facilitating a healthy life in old age represent a pressing challenge for all EU countries. In this context, the convergence of longer life expectancies and a fast growing number of elderly people represents a huge market for assistive technology and a fertile ground for innovation that cares for hitherto unmet needs.

Along these lines it is perhaps surprising that despite the long-known effects of emotions on cognitive and physical aspects of health, assistive technology founded specifically on principles of affective computing remains relatively unexplored. The experience of affective states varies in intensity and may have positive or negative effects on the individual depending on their perception of external or internal stimuli. Not only our relationships with the different elements of our environment become largely determined by how we feel but also our vulnerability to a number of illnesses and health afflictions. In other words a healthy affective life is integral with a good quality of life. Since the susceptibility of a person to be affected by poor health increases with age, the negative influence of emotions on our state of mind and body becomes more significant. Pervasive systems that efficiently detect and use affective information to support self-regulation and reduce the impact of negative emotional states may therefore become a tool for a healthier emotional life.

In this paper we present the technical aspects and rationale behind systems that can use affective information, more specifically emotional valence, to support the identification of early signs of depressive disorders and facilitate affective support and care. In section 1, we provide a theoretical framework that includes an introduction to the aspects of emotion detection and behaviour modelling. Section 2 presents the elements of two existing systems that show the feasibility of ambient-assisted detection of subclinical depression. Section 3 outlines the main conclusions and on-going and future work.

II. Affective Pervasive Computing

The concept of Affective Pervasive Computing stems from the intersection of physiological emotion detection and ambient intelligence and integrates elements from sensor design and body area networks.

A. Affective wearables

Along with facial and speech recognition, the collection of information from the brain and the autonomic nervous system is the third major approach to emotion detection in affective computing. It is based on the idea that affective states are associated with specific physiological patterns and thus can be ascertained from measured bodily reactions. This can be automatically done with continuous collection of data from tethered or wireless sensors that measure heart rate, blood volume, blood pressure, or Electrodermal Activity for example. Emotional states are usually classified into dimensions (e.g. valence, arousal), or discrete classes such as anger or joy. Some relevant approaches to physiological

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emotion detection include the work of Nasoz, Alvarez et al. (2003) [2], Kim et al. (2004) [3], or Leon et al. (2007) [4].

There are various reasons why physiological signals have become an increasingly popular choice among researchers interested in emotion detection. First of all physiological signals are one of the most recommended techniques to measure behaviour under real-life condition [5]. Additionally, one of the main arguments in favour of bodily signals is that physiological concomitants of emotional states offer two advantages over facial and speech counterparts. First, facial and speech recognition are usually based on fixed models that require well-defined gestures or utterances that limit movement and thus make real-life emotion detection unfeasible. Physiological signals can on the other hand be obtained during normal activity without the need for cumbersome equipment thus making data acquisition less intrusive. Secondly, there is a well-documented tendency of people to alter their behaviour when they become aware of the presence of video-cameras or microphones (Hawthorne Effect). Thus, whilst facial expressions and vocal utterances can be more easily disguised, faked or hidden, physiological measures are difficult to be consciously concealed or manipulated, and enable a more reliable representation of inner feelings. Finally, advances in medicine, biomedical engineering and computing enable us to use sensing devices that provide high levels of portability, comfort, and reliability in the measure of physiological parameters in real-life situations.

Affective wearables (AWs) can be seen as the embodiment of physiological emotion detection methods. AWs have come a long way since initial investigation of the concept in the mid nineties. The two main components of an affective wearable are 1) an emotion detection method and 2) wearable physiological sensors. An important open question is which method provides the best trade-off between comfort and reliability. This trade-off is based on 1) robust online detection of discrete emotional values or dimensions, and 2) a reduced number of input signals that reduces cumbersomeness. Two illustrative examples of AWs that have attempted to tackle this problem are: 1) The Modular Autonomous Recorder System For Measurement Of Autonomic Nervous System Activity, MARSIAN [6] and 2) The Human++ BAN [7].

B. Smart home-base Behaviour Modelling

Human behaviour has been the focus of many studies from different theoretical, philosophical and historical perspectives over the centuries, but it is generally agreed upon that the way we think and act is a highly complex phenomenon that is difficult to observe and predict. After careful long-time observation and under very specific, controlled situations theorists have been able to determine what actions we are likely to take in response to certain internal or external stimuli. In fact this form of behavioural assessment relies heavily on a very simple principle: the changes of internal conditions and external stimuli are followed by modifications in behaviour.

Intelligent Inhabited Environments (IIE) such as Smart Homes attempt to build a model of user's preferences and behaviour based on continuous observation of their actions. The numerous intricacies of human behaviour make such modelling very difficult and thus numerous efforts have been directed at advancing the capacity of IIEs to faithfully represent user actions. Two examples of methods to model behaviour include:

1) AOFIS by Faiyaz, Hagras and Callaghan. The Adaptive On-line Fuzzy Inference System Agent (AOFIS) is an intelligent mechanism that is not only able to learn rules for the Fuzzy Logic Controller (FLC) but also the membership functions associated with the environmental variables. After an initial monitoring phase in which the user interacts naturally with the environment, AOFIS's FLC learns a descriptive model of the user's behaviour based on the event-related data that have been accumulated. The latter is done using a combination of two mining algorithms namely Fuzzy-C-Means (FCM) and hierarchical clustering. Once a preliminary behavioural model has been constructed, AOFIS initiates an automatic control of the environment on behalf of the user using the knowledge previously acquired [8].

2) D-HTN by Amigoni, Gatti, Pinciroli, and Roveri. This pervasive system is built on an agent configuration called D-HTN (Distributed Hierarchical Task Network) and it is an example of a Multiagent System featuring hierarchical control. Instead of having a community of independent agents with its own perception of the environment, D-HTN utilises a global centralized planner that decomposes plans into tasks and resources among the elements of the system. The different roles each agent plays are embedded into the agents themselves in the form of plan libraries that allow them to become aware at any moment of what their response to a given situation should be. Learning about the tasks associated with user behaviour is achieved by updating agent libraries at the end of the day depending of which agents were relevant to successfully achieving a given goal [9].

C. Affective and behavioural monitoring

It is notable that smart home systems that integrate contextual and emotional information are uncommon. This ignores the evidence that links emotions and decision making and thus overlooks the user's emotional needs. We assert the argument that if emotions participate in our decisions and actions then pervasive systems whose functioning is based on accurate modelling of user behaviour may in principle be able to learn and identify user activities using a combination of contextual and affective information.

Smart home technology integrating physiological emotion detection represents an opportunity for the study of emotions that motivate behaviour and provide a valuable tool to support self-regulation. This technology facilitates the process of understanding, compensating for, and potentially anticipating factors affecting our health by analysing the external conditions and the inner processes that elicit negative emotions.

III. Detection of Signs of Depression

It is clear that aging is not only associated with physical changes but also with an entire new array of social, emotional and financial circumstances. Perhaps not surprisingly such circumstances put additional pressure on the individual and often cause negative feelings and emotions including stress, frustration and isolation. Damage to self-confidence, disability, discrimination, loss of independence, lack of mobility and proper accessibility tools, the use of certain medicines, fear of death, chronic illnesses, and alcoholism or other substance abuse can all exacerbate affective disorders thereby affecting health and posing life risks. These coexisting circumstances and the affective distress that stems from coping with them could play a negative effect on the health of senior people and lead to severe cases of depression, an emotional disordered that, if untreated, could have fatal consequences. Moreover, these external factors exacerbate a declining immune system and contribute to increased mortality and morbidity in old age [10][11].

Along these lines and despite increasing awareness, depression in old age remains largely under-recognized and undertreated, which exacerbates physical and mental health problems [12]. An unhealthy affective life populated with sustained emotional negativity shortens life expectancy and hinders independence. Prevention, appropriate diagnosis, and timely intervention are thus crucial to reduce the adverse socioeconomic impact of both subclinical and major depressive disorders (MDD).

Although those who suffer from major depression disorders (MDD) usually respond very well to treatment, there are two main problems associated with depression in the elderly population: 1) how to detect depression given the number of comorbid factors that normally accompany old age, and 2) how to prevent milder depressive symptoms from developing into more severe forms of depression given the social and physical burden elders face. Note that in the present paper we utilize a definition of depression that is related to prolonged emotional negativity and therefore assume that this can be related to states of long-lasting negative valence.

The combination of the affective wearables and smart-home based behaviour modelling methods opens the door to the detection of depression symptoms. The feasibility of this enabling technology is shown in two existing projects that are presented next.

A. Sentient

As part of the Sentient project at the Health and Quality of Life Unit of Tecnalia we are investigating methods to detect the valence of emotional changes and measure its intensity and duration. Using commercial physiological sensors and long term adaptation, SENTIENT is capable of providing real-time indication of negative or positive emotional valence. SENTIENT's methodology, based on AI and statistical methods, can also measure how intense and recurrent emotional reactions are. The two main components of SENTIENT are 1) the Bluetooth heart monitoring device and 2) the processing unit (Smartphone or PC). Additionally, this basic kit may be supplemented with 3) an ambient electronic device (AED) or automatic-controlled household device (see Figure 1).

The SENTIENT project primarily aims at improving the well-being of elderly people by providing tools that enable emotional self-regulation and facilitate detection of early signs of depressive disorders. Such tools are based on the combination of physiological emotion detection (affective wearables) and pervasive technologies that allow the person to orchestrate a response from the environment that in fact is a realization of their own coping strategy response. Such response can be either an activation of an object, an action on the mobile phone itself (SMS, Music) or a call to a relative or friend.

Sentient's emotional valence algorithm is based on the utilization of artificial neural networks and change point detection. We have undertaken tests on the performance of

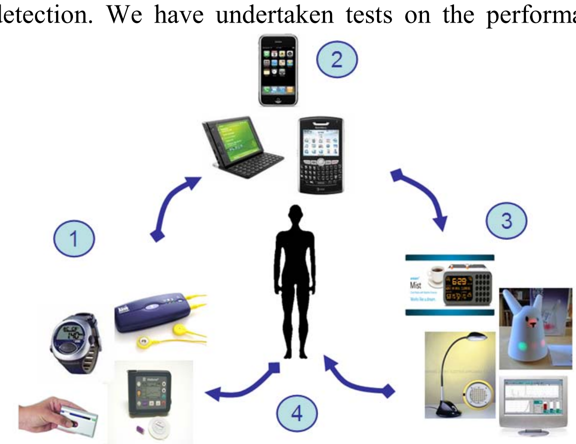

Fig. 1. Sentient components and operation. 1) the user wears a physiological sensor, 2) the algorithm detects an emotional state, 3) the smartphone interacts with the user and the environments, and 4) the user receives feedback.

this algorithm to detect and classify emotional valence using commercial HR monitors. Initial results from trials on 9 individuals have delivered 76% averaged recognition rate (Specificity 96.6%, Sensitivity 68.6) measured against self-reporting (see Table I) using movies to elicit emotions.

There are a number of advantages of Sentient with respect to existing commercial and research approaches:

1) It can provide real-time indication of the polarity and intensity of the emotional valence.
2) System configuration is highly customizable to match the user's own coping strategy.
3) The algorithm performs life-long learning and adaptation based on user feedback.
4) The number of physiological signals can be adapted to include a number of Bluetooth commercial sensors.
5) The system can operate in non-ambulatory conditions using heart rate monitoring only and still provide the same functionalities.

The ultimate goal of Sentient is to be able to offer a cross-platform portable system that can assist in providing care solutions that look after the person's emotional well-being. Sentient is currently undergoing tests to be released as a commercial product.

Some of these tests involve the use of Kahneman's Day Reconstruction Method (DRM), an instrument developed to evaluate well-being by combining time-allocation analysis with a technique for recovering affective experiences that linked to a person's activities [13]. The DRM provides a measure of well-being as indicated by the quality and duration of daily life experiences.

Using the DRM, it is possible to see how closely Sentient reflects the person's own reports of emotional fluctuations throughout the day. In the future, affective wearables may become part of systems used to assess well-being that reduce or even eliminate the need of self-questionnaires.

TABLE I
NUMBER OF CORRECTLY IDENTIFIED VALENCED CHANGES

ID	% Rate
1	83.64%
2	87.27%
3	95.45%
4	47.27%
5	46.36%
6	77.27%
7	91.82%
8	65.45%
9	91.82%

The current implementation of Sentient is built on an Android mobile phone and employs a commercial Bluetooth heart monitor (Figure 2). The system can take actions using the mobile phone functionalities (music, SMS, etc.) or interact with WiFi-enabled domestic objects.

Fig. 2. Sentient Interface on Android OS.

B. The iSpace

As an example of the potential of affect-aware systems to recognize behavioural clues associated with emotions, we show results from our previous work involving a smart-home called the iSpace. The Intelligent Inhabited Group at the University of Essex have developed an affect-aware intelligent environment that features affective wearables called the X-Vest and an AOFIS control system. The X-Vest utilizes an emotional valence detection algorithm based on data from heart rate, skin conductance and blood volume pressure (See Figure 3).

Once inside the iSpace, the user wearing the X-Vest can initiate control (after a learning period) using the interface on the PC.

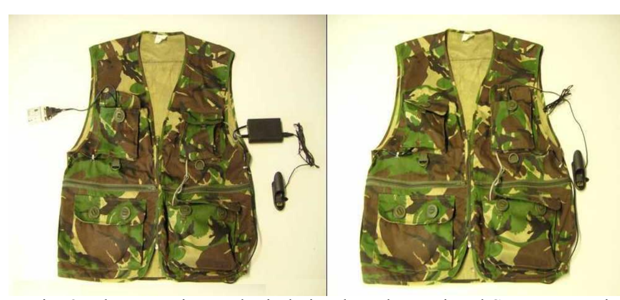

Fig. 3. The eXperimental Vital-sign-based Emotional State Transmitter X-Vest

Using this system, it is possible to establish relationships between a number of user activities and their emotional content (see Table II). For example, in experiments involving one person living inside the iSpace for a number of days, we found that watching TV and playing videogames elicited the highest number of emotional changes (from positive to neutral) while work activities did not seem to provoke as many emotions.

Results correlated with the participant's self-questionnaires and own emotional experience. Using this affect-aware smart home we were also able to find initial evidence proving that pervasive systems that include emotions in their decision systems are more effective in learning user preferences than those systems based only on contextual information. Our conclusion was the reason for these results lies in the link between. For more information we refer the reader to our published work [14].

TABLE II
NUMBER OF EMOTIONAL CHANGES DETECTED BY AN AFFECTIVE WEARABLE OVER A TWO-DAY PERIOD

Time Slot	Activities	Number of Valenced Emotional Changes
Morning	Reading and responding to email messages	18
	Computer work	
Afternoon	Computer Work	36
	Desk Work	
Evening	Watching TV	79
	Playing videogames	

IV. CONCLUSIONS

Affective and pervasive computing complement each other to provide ways to better understanding behaviour in the elderly and ways to cater for enhanced emotional well-being. Thanks to this orchestrated partnership it is possible to detect potential hazards to personal safety, monitor health conditions, and endow inanimate household objects with the capacity to interpret the state of mind, be empathetic, proactive, helpful and cost-saving towards old persons' needs.

Depression in old age is one of the most frequent reasons for emotional suffering [15] and significantly decreases quality of life. While there is no empirical evidence of psychosocial primary prevention of depression in the elderly population [15], early diagnosis of depressive disorders is crucial to initiate treatment and prevent that mild depressive disorders develop into chronicity [16]. The identification of subclinical forms of depression in late life is still one the main problems affecting this age group primarily due to the numerous comorbid factors. In this paper we propose to apply the methods of Affective Pervasive Computing as a new way to tackle this issue. Two different projects have been presented showing the technical feasibility of this idea. The SENTIENT project which combines physiological emotion detection tools with ambient interaction to facilitate self-regulation and the iSpace, affect-aware smart home, enabling the combination of behavioural monitoring and measurement of emotional valence intensity. Although a number of unanswered question remain, the initial evidence is encouraging.

Our future work involves the development of smart-home systems that are capable of automatically organizing appropriate coping strategies that reduce the intensity of negative emotions and interrupt sustained emotional negativity. We are also interested in developing commercial products that allow a person to more effectively self-regulate at home.

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