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A home daily activity simulation model for the evaluation of lifestyle monitoring systems

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ABSTRACT

Lifestyle monitoring (LM) technology is part of a new generation of telecare which aims to observe the daily activities of older or vulnerable individuals and determine if a medical or care intervention would be beneficial. The development and validation of new LM systems should ideally involve extensive trials with users in real conditions. Unfortunately, effective user trials are very challenging, generally limited in scope and costly. In this paper, a simulator is proposed that can serve to generate synthetic data of daily activity which can then be used as a tool for the validation and development of LM systems. The most challenging part of the simulator is to replicate people′s behaviour. In the paper, a novel model of daily activity simulation is proposed. Such daily activities are dependent on a number of external factors that control the need or desire to perform the activity. The proposed simulator aims to reproduce behaviour such that the probability of performing an activity increases until the need is fulfilled. It is possible to parameterise the behavioural model according to a set of features representing a particular individual. The simulator parameters have been populated using real world experiments through hardware testing and data collection with older people. Experimental verification that the desired features are reasonably reproduced by the simulator is provided.

1. Introduction

In England, over the next fifty years, the number of people over 65 is expected to rise by 56% and a similar trend is observed in most other western countries. As a consequence, researchers and governments are looking at novel solutions to support people in their own home by automatically monitoring their daily activities [2,3,6,9,12,15,18,20]. As part of the newer generations of telecare, lifestyle monitoring (LM) aims to observe the activities of older or vulnerable individuals and if circumstances change determine if a medical or care intervention may be beneficial. Generally, LM uses a set of sensors fitted in the house and aims to detect those deviations from 'normal' behaviour that could be indicative of a change in care needs (e.g. Mobility problems, difficulty of toileting, etc.).

LM has attracted a lot of interest in the last few years, however, most of the research publications in this domain present results based on only a small number of users. Indeed, a review of the literature suggests that to the end of 2009 only 4 trials have been conducted with more than 20 participants [5]. The limited scale and scope of trials can largely be attributed to the difficulty of performing such experiments. Indeed, while it is desirable to evaluate a lifestyle monitoring system under real conditions, several issues generally arise which act to limit the scope of the trials. These include:

a. Difficulty in recruiting participants who will accept a relatively intrusive system installation in their home without direct immediate return.
b. Data should be observed over a long period of time.
c. Difficulties in collecting ground-truth information. Indeed, to validate and develop a system that is supposed to observe individual activity, it is essential to know which activity that individual is actually involved in at any time. This information could be collected by means of diaries, but these are not always accurate and can be very demanding for the participants if they need to be maintained over a long period of time. Another approach could be to visually monitor and manually annotate individual activity using video cameras on site, but this can be considered intrusive and would require a laborious video transcription and annotation phase.
d. In order to validate a system that aims to detect abnormality, a significant number of abnormal events must be observed. By definition, such abnormal events are rare.

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Given these constraints, it becomes clear that trials with users, while ultimately essential, can also be limited, especially at the early stages of development. As a consequence, thorough and large scale testing on synthetic data can be of great benefit to the development of novel LM systems.

By using a simulation tool, it becomes possible to simulate virtually any condition, and it becomes possible to test the effect of any change on the system or on subject behaviour. With a simulator it is possible to create a change in behaviour on demand, rather than running a real system while hoping to encounter specific types of change. Likewise, a simulator could provide information on the effect of including a new sensor (with known specifications) in the system before having to encounter the costs in both time and money of real world experiments.

Verone et al. [19] attempted to simulate behavioural data from a patient living in an intelligent home. Their paper presents some interesting ideas and appears to provide a useful background in developing the simulator being proposed here. However, Verone et al. only simulate room transitions based on daily behaviour profiles. More importantly, they do not propose any mechanism to modify behaviour according to specific changes in the subject′s condition or care need. More recently, Noury et al. [13] proposed a similar approach based on Markov models corresponding to activities corresponding to seven periods of the day. This model do not allow long term dependences of activities to be taken into account, i.e. the decision on the activity to perform at time t is only dependant on the activity performed at time $t-1$. In this paper, a simulator is proposed that can serve to generate synthetic data of daily activity which could be used as a tool for the evaluation of LM systems. The evaluation of such a system should ideally involve trials with users in real situations. Issues regarding the evaluation of medical informatics are discussed in [10]. As argued by the authors in [1], computer simulation provides a flexible approach to evaluation in health informatics.

The proposed simulation model aims to be used to evaluate the capability of LM systems to detect unusual change in activities indicative of changes in health conditions. To achieve this, we aim to generate realistic sequences of daily activity. The simulator allows simulating circumstances such as a reduction in mobility or illness that could lead to a change in care need. With such a scheme it becomes possible to evaluate abnormality detection algorithms but also the effect of a new sensor, before physically integrating them, and consequently could significantly reduce development costs.

It is believed that the modelling of the daily pattern of activities is the key step toward the development of the simulator and can be considered as the most challenging aspect. Indeed, the activities undertaken by an individual during a day are driven by a number of factors and, unlike machines, human behaviour can be unpredictable. In terms of the simulation this unpredictability is reproduced through the use of stochastic models.

2. Method

The primary objective of the simulator is to generate data that can be used for evaluating the performance of a LM system and should be able to reproduce sensor activations that correspond to specific user behaviours. Note that there is a differentiation between those key features which are characteristic of behaviour or the system and those key parameters that translate these features into the values used by the simulator. Key features could for example be the number of times the subject has a drink in a day, the average time the subject takes lunch or the expected error rate of a sensor. Key parameters are parameters of the mathematical model that reproduce these features. Some of these features can change with time when circumstances that result in a change in care needs are simulated.

The proposed simulator follows a three level mechanism where first activities are generated which are subsequently represented as sequences of actions and finally translated into sensor activations. It can be assumed that subject behaviour is independent of the LM system (sensors), and therefore can be generated independently. The simulator can therefore be decomposed in two parts: the first part simulating subject′s behaviour and the second simulating the response of the LM system to these behaviours. Subject behaviour can in turn be decomposed into two hierarchical levels. The first of these levels is the activity sequence, defining WHAT the subject is doing. The second level is then a sequence of actions, defining HOW the activity is performed. For example, having dinner is an activity and turning the kettle on, opening the fridge, sitting on a chair and so on could be the associated actions. While activities are enduring processes, actions are considered as instantaneous and are not associated with any duration. This hierarchical structure was chosen for the simulator in order to imitate human behaviour, in that subjects tend to decide what they want to do (activities) according to a number of motivating factors and then to do it in a defined way (actions). Fig. 1 thus represents the flow of information of the simulation system. Note that the activity generation determines the start time of the activity while its length is decided from the timing of the actions involved in this activity.

2.1. Activity simulation

Simulating realistic daily activities is a challenging task since activities performed are usually driven by a large set of factors. These include; basic needs, lifestyle, weather, TV programming, family visits among many others. The proposed approach to generating the sequence of daily activities is described in this section.

Because of the dynamic nature of daily activity simulation, it is necessary to keep track of the current value of the simulated time as the simulation proceeds. The simulation clock is a variable that gives the current value of time which is then incremented by a fixed value. The unit of the increment can be chosen according to the level of precision needed. Furthermore, as previously stated, daily activities are dependent on a number of external factors that control the need or desire to perform them. Arguably, a desire can be the consequence of a need, generalised here by using the word need even though in some cases desire could be considered more appropriate.

The aim is to build a model of the need to perform a specific activity. It provides at each time the probability of acting on a need. The main assumption of the proposed model is that the need to perform a specific activity will increase with time until the need is fulfilled and the activity is performed. The proposed model will not cover all the parameters which could be involved in more sophisticated behavioural or cognitive models such as in [14]; however such models would be impractical for this application. Moreover we believe that the proposed model adds a degree of realism compared to other models previously introduced in this context. Indeed, the models proposed in [19] and [13] are based on the Markov assumption [8] and infer the next activity based solely on the state at the previous time step, which does not allow long term temporal dependence to be considered, as is the case here. Fig. 2 presents the simplest form of the need model where the probability of performing an activity increases linearly with time. This model can be defined such that:

$$\begin{aligned} p_t &= \lambda \times t \text{ when } 0 < t < \frac{1}{\lambda} \\ p_t &= 1 \text{ when } t \geq \frac{1}{\lambda} \end{aligned} \quad (1)$$