

Knowledge Discovery from Lifestyle Profiles to Support Self-Management of Chronic Heart Failure

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Abstract

In this paper, we explore the feasibility of integrating data gleaned from home-based sensors and information from self reporting to support the self-management of Chronic Heart Failure. Time spent sleeping, television usage and utility usage were recorded by sensor based technology within the home environment for one participant over a 30 day period. Information in relation to a participant's daily self report was used to assist analysis in an effort to provide more meaningful and relevant feedback to the participant in relation to how they should manage their condition. The results indicate that trends which could lead to lifestyle change can be discovered. For example, whilst no particular cause of an unusual sleeping pattern event was discovered, the ability to identify such events could be important over longer periods of time. In conclusion, the findings from the study have suggested that feedback used to support self-management can be generated using both activity information and self report, and potentially benefits for the combination.

1. Introduction

Approximately 900,000 people in the United Kingdom suffer from a form of heart failure [1]. Chronic Heart Failure (CHF) has a major impact on a patient's quality of life (QoL) and is characterized by symptoms of distress, compromised physical functioning, feelings of reduced energy and hopelessness; indeed it affects most aspects of a person's social function and societal role [2]. It has been shown that the lifestyle of a CHF patient is correlated with health status [3]. Professional lifestyle advice can therefore impact upon a patient's perception such that they are able to take control of their condition. Studies have demonstrated that when patients receive the correct lifestyle advice they are better placed to adopt self-management strategies and as a result they can witness an improved QoL [3][4]. Given recent developments within the domain of Information and Communication

Technologies there are now a number of opportunities to utilize technology based solutions to assist patients with the management of their long term condition. A number of studies have shown that using such technologies can be an effective strategy for disease management in CHF patients [5].

Although many advances have been made, there are still a number of outstanding issues that need to be addressed to improve the overall paradigm of technology mediated self-management. Examples of these challenges include: How to obtain a patient's activity trend over a given period of time? How does a patient's activity trend relate to health status? What lifestyle advice can be provided? The aim of this paper has been to explore these issues.

The remainder of the paper is organized as follows: in Section 2 related work is reviewed, in Section 3 the proposed method is described, in Section 4 validation results are presented; finally, in Section 5 pertinent issues are discussed and conclusions are drawn.

2. Related work

Self-reporting is the use of questionnaires by patients to record their health related information. Questionnaires for patients with chronic diseases normally consist of information relating to the three areas of physical, mental and social wellbeing [6]. Doctors and health professionals can obtain details of a patient's overall functioning from such a questionnaire. Self-reporting can be used to identify a patient's health status and can also be used for self-management purposes [7]. The advantage of using self-reporting is that it is a low cost method and easy to undertake. Nevertheless, the information from the report is subjective and may suffer from bias and inaccuracies [8].

Recently, sensor based system for both healthcare and disease management have been deployed. The HeartCycle Project aimed to provide personalized care to patients with cardiovascular disease by using sensors to monitor vital signs [9]. The project has developed technologies

and services which have the capabilities to facilitate remote disease management for patients at home, in addition to developing strategies to encourage patients to adhere to their treatment and adopt a healthy lifestyle. Bed sensors and Passive Infra Red (PIR) sensors to detect sleep patterns in people with dementia have been considered in [10]. The person’s weekly and monthly sleep patterns could be extracted from sensor data and subsequently visualized. The results demonstrated that such assistive technologies could provide objective information in relation to sleep patterns which were useful for health care purposes.

In this paper, we explore the feasibility of combining a home-based sensor network in conjunction with a self-reporting system to support the self-management of patients with CHF.

3. Methods

A patient’s health and wellbeing can be improved by promoting behaviour and lifestyle change. Certain anomalies can be detected and analysed, such as high blood pressure and lack of water intake. This study explores a practical approach for generating useful feedback to help users self-manage their conditions. A patient’s activity can be detected through the analysis of a series of sensor activations. Identification of an activity is the prerequisite to the analysis of a patient’s behaviour change over time. A patient’s behaviour change may be assumed to be affected by either the underlying disease or its recommended treatment (or both). This information is therefore important for the purposes of disease management.

3.1. Overall framework

Figure 1 describes the process of generating alerts for abnormal behaviour.

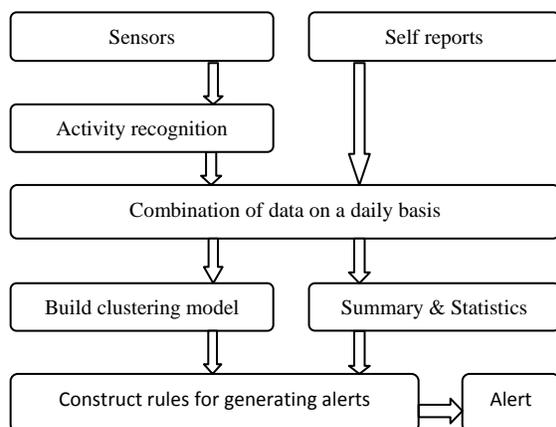


Figure 1. Overall framework for abnormality detection.

When all the activities in the period of time are identified, the unsupervised learning method *k*-means can be applied to analyze behaviour changes. The data from sensor and self report is pre-processed and classified as ‘observations’. An observation consists of all the activities and self reporting information within a day. Following this, all observations are used as input to build a clustering model; all the observations are partitioned into two clusters, i.e. normal day (cluster 0) and abnormal day (cluster 1). The clustering results and statistics of activities are then used to construct rules of generating alerts for new data.

3.2. Data collection

A participant suffering from CHF was monitored within a ‘sensorised’ one bedroom apartment for a period of one month. The technology consisted of a bed occupancy sensor, a PIR movement detector, a door usage sensor and an electrical appliance usage monitor. Table 1 provides an example of the data collected from the environment.

Table 1. Example of data from sensors

Sensor	Location	Status	Time
Bed	Bedroom	In	30/10/2006 22:45:49
Bed	Bedroom	Out	30/10/2006 23:28:12
Door usage	Food cupboard	Opening	01/10/2006 18:34:49
Door usage	Food cupboard	Closing	01/10/2006 18:34:55
Appliance	Kettle	On	10/09/2006 16:05:41
Appliance	Kettle	Off	10/09/2006 16:07:50
PIR	Bathroom	Room visit	27/09/2006 22:03:38

Self-reporting information was collected via the Docobo healthcare device (www.docobo.co.uk). This device also has the ability to record a patient’s vital signs, for example blood pressure and pulse rate. In addition, questions related to health status were also recorded. For example, a sample question asked was: ‘Have you felt more tired today?’ The answer could be ‘No/Less than usual/As usual/More than usual’.

3.3. Activity identification

A patient’s activity can be detected through the analysis of a series of sensor activations. An activity could be using the kettle to boil water, opening the food cupboard to prepare lunch or usage of the bathroom.

A preliminary analysis has been conducted on three types of activity information: amount of sleeping time, television (TV) usage and food-related activity. Following investigation of the sensor dataset, it was found that the bed sensor data was very noisy. The bed sensor gave ‘in’ status messages more than once prior to the person entering the bed. This situation also occurred when the patient left the bed with multiple ‘out’ [of bed] messages being recorded. In order to obtain more accurate sleep (bed occupancy) information, we applied a

number of rules to ameliorate this problem. We refer to this rule as ‘first in and last out’.

$$time_{episode} = time_{last_out} - time_{first_in} \quad (1)$$

$$time_{sleep} = \sum time_{episode} \quad (2)$$

We define a day from 12:00 noon until 12:00 noon the following day. Each sleep episode represents the time a patient stayed in bed, and the total sleep time for one day sums up all episodes in 24 hours.

The TV usage information, extracted from electric appliance sensor, records the time for TV on and off, the total time of TV usage each day calculated by equation 3.

$$time_{TV} = \sum (time_{TV_off} - time_{TV_on}) \quad (3)$$

Daily food-related ‘event’ information can be inferred from the number of events associated with the usage of the food cupboard, the fridge door opening and kettle usage. Though this information is not sufficient to provide an accurate insight to nutritional information, it provides related information about patients preparing food and water intake. If this information deviated from an expected value on a specific day, the system may provide an alert and advice. For example, if the kettle usage is 50% lower than usual, the system could provide advice that the patient should take more drinks.

The use of self report can assist to provide feedback to the patient. For instance, according to the self report on a

specific day, a patient may have undertaken more exercise than usual, but did not eat very well and thus the system could provide advice that the patient should intake more calories in order to keep healthy.

4. Results

29 days were clustered into cluster 0 by *k*-means, and one day (day 8) was clustered into cluster 1. Trend results for blood pressure, sleeping time, TV usage and nutritional information over a period of 30 days, were derived.

Figure 2 (a) indicates that the patient has a consistent sleeping time during this period. The daily sleeping time ranged from 6 hours to 8 hours with a mean sleeping time of 7.35 hours. There were 12.85 hours of sleep time on day 9, which deviated from the norm. Thus an intervention may be required to decide if there was any abnormal condition. A subsequent visual investigation of vital signs and self reporting was carried out on days, 8 – 10 (around this ‘event’). There was no significant abnormality during those three days. The TV usage is around 12 hours to 14 hours daily. The trend line demonstrated that the TV usage increased more than 20% during the 30 day period.

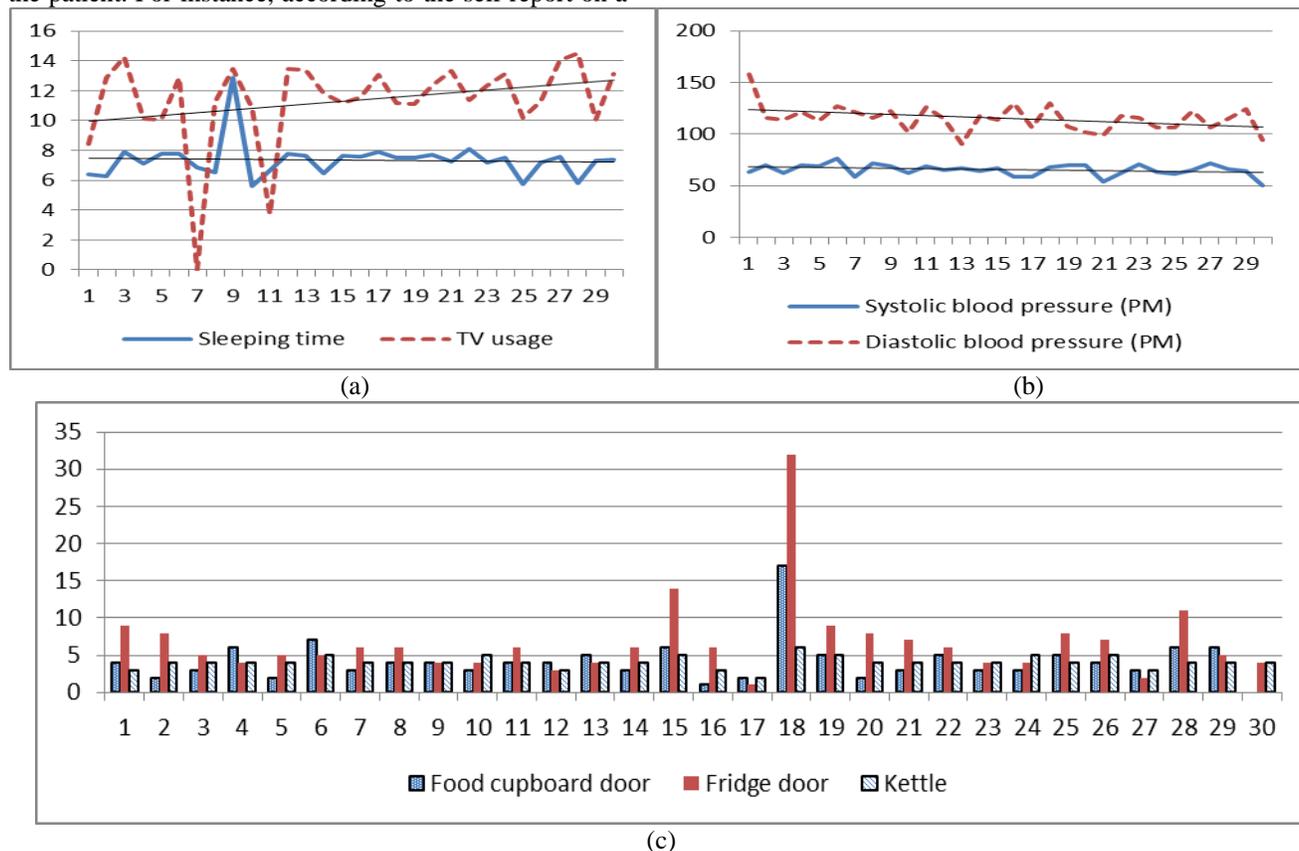


Figure 2. (a) Summary of 30 days sleeping time and TV usage. The daily sleeping time is from noon on one day until noon the following day, the daily TV usage is from 0.00 o'clock to 24.00 o'clock. (b) Summary of 30 days blood pressure. (c) Summary of 30 days for utilities usage. The trend lines for (a) and (b) are drawn to indicate the changes over the 30 days.

Figure 2 (b) demonstrates that the patient's blood pressure was in the normal range during the 30 days, with most days being below 140/90 mmHg. Both trend lines for the systolic and diastolic values decreased during this period.

Figure 2 (c) depicts that the average daily usage of the kettle is 4 times. The average number of times opening the food cupboard door and the fridge door were 4 and 7 respectively. According to figure 2, the patient used the fridge and kettle less than usual in day 17. The usage of utilities increased dramatically in day 18. An investigation into the vital signs and self-reporting was carried out around day 18. No abnormalities were found in the data during this period.

5. Discussion

This study aimed to explore an approach to support chronic condition self-management. Activity related information and vital signs data were visualized. 'Abnormal' events were detected with the aim of providing feedback to the user. This is a direct method to analyse user lifestyle and trends within vital signs. This preliminary study demonstrates that the pervasive home-based sensor and self reporting approach can be applied to monitor a patient's lifestyle.

The patient's data in this study is consistent, with a limited number of what could be inferred as abnormal events. For data that has sufficient instances of deviations of behaviour change the system has the ability to generate further automated feedback. Nevertheless, it is not always necessary for interventions to be delivered when an abnormal activity occurs.

In this research context, we have assumed that there was only one person in the apartment and all sensor activations were associated with this person. Nevertheless, this is somewhat different in the real world context. While there is a visitor in the apartment, some sensors will be fired more often than usual. For example, it is likely that the usage of the fridge, kettle and food cupboard increases when visitors are present. This may generate unnecessary feedback to the user unless such a context is taken into account. One solution is that a question can be added to the self report process in relation to hosting visitors.

Whilst no particular cause of an unusual pattern (prolonged sleeping, more use of cupboard/kettle) was discovered in this study, the ability to identify such events could be important over longer periods of time for the purposes of understanding chronic diseases. Feedback used to support self-management can be generated using both activity information and self reporting, and potentially benefits for the combination.

Future work will be carried out on a larger dataset and additional methods will be investigated for the purposes of data analysis and correlation analysis.

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