Deriving Relationships between Physiological Change and Activities of Daily Living Using Wearable Sensors

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Abstract. The increased prevalence of chronic disease in elderly people is placing requirements for new approaches to support efficient health status monitoring and reporting. Advances in sensor technologies have provided an opportunity to perform continuous point-of-care physiological and activity-related measurement and data capture. Context-aware physiological pattern analysis with regard to activity performance has great potential for health monitoring in addition to the detection of abnormal lifestyle patterns. In this paper, the successful capture of the relationships between physiological and activity profile information is presented. Experiments have been designed to collect ECG data during the completion of five predefined everyday activities using wearable wireless sensors. The impact of these activities on heart rate has been captured through the analysis of changes in heart rate patterns. This has been achieved using CUSUM with change points corresponding to the transition between activities. From this initial analysis a future mechanism for context aware health status monitoring based on sensors is proposed.

Keywords: Wireless Sensors, Physiological Profile, Activities of Daily Living, Health Status, Wellbeing.

1 Introduction

Over the next 40 years, the worldwide demographic for the elderly population is projected to increase significantly, with the number of people aged over 60 rising from approximately 700 million in the year 2009 to 2 billion by the year 2050 [1]. Due to the prevalent onset and advancement of chronic disease with age, the overall number of people suffering from some form of chronic condition will potentially increase in correspondence with the estimated growth in the size of the elderly population. For a large number of elderly sufferers, the progression of a chronic condition can make it even more difficult to live independently in terms of maintaining and managing health, wellbeing and lifestyle. This, in turn, places pressure on the resources of health and social

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care services, as the traditional reactive model of healthcare undertakes the provision of support for monitoring and management of chronic diseases [2, 3]. Therefore, in order for healthcare services to retain the ability to effectively monitor and manage the health of an ever increasing, ageing population, a more sustainable form of care provision is required. Subsequently, the challenge for a pro-active healthcare model is to provide an improved quality of service at a lower cost, in terms of both financial resources and the workload required from healthcare professionals and members of the patient's family. Additionally, support should also be provided for elderly patients and their families that facilitates independent living, thus permitting chronic disease monitoring and management within a familiar, comfortable environment [4]. Such approaches also have the potential to extend the period of time living within the home environment.

Connected Health is an overarching concept that utilizes *Assistive Technologies* in order to provide remote healthcare and wellness solutions for the purpose of maximising healthcare resources, patient self-management and patient engagement with healthcare professionals [3]. Characteristically, *Point of Care* devices are employed to acquire and monitor a patient's physiological information. Such devices are typically deployed within the patient's living environment and provide both local and remote wireless communications, thereby facilitating remote monitoring and management of the patient's vital sign information within the convenience of the home environment. By supporting timely access to a patient's physiological record in addition to information relating to how they have interacted within their environment, a more pro-active, efficient and cost effective approach to patient assessment and chronic disease management may be realized. Moreover, immediate access and analysis of the current health status of a patient also makes it potentially possible to detect and act upon the early stage symptoms of chronic conditions [5], [6].

The aim of this paper is to capture and investigate the underlying relationships between an individual's physiological profile and their activity profile. Data have been acquired from a number of healthy participants using wireless sensor technologies during a predefined set of daily activities. With the future goal of providing context aware monitoring of health status based on information derived from wearable sensors, an indication of an individual's health and wellbeing may be inferred from the relationships between the health status and performance observed when a selection of *Activities of Daily Living* (ADLs) are carried out [5], [6], [7], [8], [9]. It is anticipated that the discovery of such relationships will provide valuable information that may be further utilized to carry out interventions in an individual's lifestyle in order to maintain or improve overall health status, e.g. the elimination of potentially dangerous activities for cardiovascular conditions based on key physiological patterns observed. In addition, the physiological information may also be used to assist in the inference of ADLs, thus providing support for the completion of these activities. By utilizing healthy participants within the trial study, a baseline set of relationships has been established, which may subsequently be used to inform further research, and provide an initial contribution to the goal of context aware health monitoring and analysis. This paper is organized as follows: Section 2 provides a brief synopsis of related research, followed by a description of the methodology employed in Section 3, including an overview of the wireless sensor technologies, predefined activity scenarios, pre-processing and data analysis techniques used. Results are subsequently presented and discussed in Section 4. The paper then concludes in Section 5 by proposing future research that may be conducted in order to continue and extend the current work.

2 Related Research

Throughout the research literature physiological profile data have been utilized exclusively [10], [11], or in conjunction with activity profile data [7], [8], and environmental information [6], [9], [12], for a variety of Connected Health purposes. These include the automated observation and analysis of physiological function, and health and wellbeing status [6], [12], the analysis of relationships between physiological and activity profiles [7], [9], and the classification and prediction of vital signs, ADLs, and health and wellbeing status [6], [7], [8], [9], [10], [11].

In [10], Pawar et al. conducted research into the use of physiological profile data for the classification of activities. A single-lead wearable ECG sensor device, configured for Lead II, was employed in order to obtain ECG signal data from a number of healthy participants over a range of ADLs, including ascending and descending stairs, sitting in a chair, and upper-limb motion. Motion artifacts inherent in the ECG signal were analyzed using a supervised learning approach based on Principle Component Analysis (PCA) in order to classify the ADLs. Subsequently, the authors demonstrated the potential use of physiological data for activity classification and suggested the use of class-specific PCA-filtering for the attenuation of motion artifacts within ECG signals [10]. Jakkula et al. also used physiological profile data exclusively for the classification and prediction of health trends within the investigations reported in [11]. Employing Support Vector Machines in conjunction with vital sign data, heartbeat and blood pressure were individually classified using a binary taxonomy, which indicated whether a vital sign was likely to increase or decrease. The authors have suggested that the use of physiological information with such a technique may provide a useful measure of deterioration in health status [11].

Extending the research in [8], Jakkula discussed the use of both physiological and activity profile data for the classification and prediction of health status. A classifier was developed using the K-Nearest Neighbor (K-NN) algorithm, trained with input vectors comprised of physiological data, including heartbeat, blood pressure, weight and temperature, and activity data, including the type of ADLs performed. By classifying labeled training examples as either healthy or unhealthy, the resulting model can be used to predict health status from unseen input vectors [8]. In [7], Yuchi and Jo investigated the relationship between an individual's physiological and activity profiles in order to perform heart rate prediction. Using a single-channel ECG monitor with integrated 3-axis accelerometer, heart rate and accelerometer data were captured in real-time from a single healthy participant over a range of ADLs for a period of 90 minutes. The relationship between the physiological and activity profile was modeled with a feed-forward Neural Network trained using examples from the captured, pre-processed data, which comprised of inputs corresponding to the heart rate and acceleration for the current time step and an output corresponding to the heart rate for the next time step. The authors found that predicted heart rate was close to the actual heart rate and suggested that modeling the relationship between an individual's physiological and activity profile in such a manner may be potentially useful as an indicator for cardiac problems [7].

Both physiological and activity profile data were also used in conjunction with environmental information in the research conducted by Ogawa et al. In [12], investigations were carried out into the continuous and automated monitoring of physiological data within the home in order to provide support for the long-term management of physiological function. By employing sensor devices within areas of the home associated with daily activities, including an ECG monitor in the bathroom and a temperature sensor in the bedroom, information pertaining to the participant's physiology and activity levels was monitored along with environmental information when daily activities such as bathing and sleeping were performed. Although the authors did not conduct further analysis on the derived data, the research suggests that the focus of future efforts would be the selection and development of algorithms for the analysis and interpretation of such profile data [12]. The relationship between an individual's health status and ability to perform ADLs, based on physiological, activity and environmental information, was investigated in research conducted by Celler et al. In [6], it was suggested that changes in everyday activities, such as bathing and sleeping patterns, could potentially indicate changes in health status. By monitoring information related to both the activities being performed and the state of the environment, in conjunction with an individual's physiological profile, inferences made on the status of health and wellbeing may be improved. Such measures were used to automatically monitor and assess the health status of elderly people for the prediction of health and wellbeing status, and to provide further insight into the behaviours observed during ADLs [6]. The relationship between an individual's lifestyle and health and emotional wellbeing was also investigated by Jakkula et al. based on the use of physiological data, together with activity and environmental information [9]. The lifestyle of a single participant was monitored over a period of 40 days and comprised physiological profile information, such as heartbeat, activity profile information, such as upper and lower-body movement, and environmental information, including distances travelled and room usage statistics. By explicitly labeling the captured data in terms of a discrete set of classes associated with levels of wellbeing, a model of the relationship was developed using the K-NN algorithm in order to perform classification and prediction of the future status of health and wellbeing of the participant [9].

Although a variety of approaches to the collection and use of ADL-based information have been reported within the literature, the brief review reveals that the predominant application of such data is in the classification and prediction of health status. For the majority of cases, both physiological and activity profile information has been utilized during classification, and a relatively straightforward taxonomy has been employed. Where physiological information has been exclusively used during the classification of ADLs, research efforts have focused on the use of implicit features derived from the sensor data. Correspondingly, within the preliminary research presented herein, the heart rate has been obtained from sensor data, however such physiological information has been utilized alongside activity profile data in order to examine the effect on heart rate caused by the transitions that occur during various commonplace activities. Before classification and prediction of such activities can be performed based on the explicit use of physiological information, an improved understanding of the relationship between the physiological profile and activity profile is required.

3 Methodology

In order to investigate the relationship between an individual's physiological and activity profile on a number of tasks, a methodology for the real-time collection and subsequent analysis of activity-related data was initially specified. The following subsections outline the methodology adopted, including an overview of the wireless sensor devices used during data capture, a description of the activity scenarios performed by participants and details of the statistical techniques employed for data pre-processing and analysis.

3.1 Shimmer Wireless Sensor Platform

To facilitate data acquisition during the activity scenarios, the Shimmer[1] wireless sensor platform developed by Shimmer Research was utilized. Employing two Shimmer devices, upper-body and lower-body motion performance on activities were captured using the devices' integrated 3-axis MEMS accelerometer, with a sample rate of 50Hz and accelerometer sensitivity specified within the range [-1.5, 1.5] g. Physiological data was simultaneously acquired using the 3-lead electrocardiograph expansion module in conjunction with the accelerometer. The expansion module employs three recording electrodes to record bipolar leads in the Einthoven limb lead configuration. Due to restrictive cable length, the recording electrodes were placed in the left pectoral region to record variants of Lead II and Lead III. Both channels of ECG data were sampled simultaneously at 100Hz [13]. In order to effectively detect changes in anterior-posterior and lateral movement, the upper-body device was placed in the middle of the participant's left pectoral, while the lower-body device was placed at the mid-point between the thigh and knee on the anterior of the participant's right leg [14]. Accelerometer data from both devices, together with the ECG signal from the upper-body device, were transmitted wirelessly to a receiving computer via the IEEE 802.15.1 Bluetooth communications protocol. A custom Windows-based application, developed using the BioMOBIUS application development platform [15], was used for the real-time reception and storage of the transmitted data, in addition to the overall configuration of the sensor devices.

3.2 Activity Scenarios

ADLs consist of a wide range of possible actions, and interactions with objects, within a variety of environments [16]. For the investigations presented in this paper, two high-level activity scenarios were defined, which provide a rudimentary simulation of some basic activities a person may perform within the home environment. The first activity scenario, entitled *Arrive Home*, comprises the subset of activities: {*Ascend Stairs*, *Walk*, *Sit Down*}. Likewise, the second activity scenario, entitled *Leave Home*, is composed of the subset of activities: {*Stand Up*, *Walk*, *Descend Stairs*}. Although the scenarios have been specified within a home

[1] Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability.

environment, the activities involved are also commonplace within a hospital environment or workplace. The entire subset of activities for each high-level activity scenario must be performed in order to consider the high-level activity completed [2]. Subsequently, for Scenario I the participant must ascend a number of flights of stairs, walk along a corridor for a given distance then sit down in a sitting straight position from a standing straight position to accomplish the high-level activity *Arrive Home*. Similarly, for Scenario II the participant must stand up in a standing straight position from a sitting straight position, return along the corridor and finally descend the three flights of stairs to complete the high-level activity *Leave Home*.

For the purposes of generating data for use in the preliminary investigations, a number of healthy participants were asked to repeatedly perform both activity scenarios, as previously outlined in Section 3.1. As each scenario comprises a number of activities, data from both accelerometers and the ECG signal were continuously captured before, during and after the participant's performance of each activity. In order to obtain baseline physiological and motion values for each activity, data capture started approximately 30 seconds prior to commencement of the activity, with the participant adopting a standing straight or sitting straight posture, depending on the activity. Similarly, once the activity was performed, data capture was continued for approximately 30 seconds, with the participant remaining in a standing straight or sitting straight posture, in order to record any ECG recovery information that may have occurred. A single occurrence of either Scenario I, or Scenario II, was considered complete after the participant performed the associated set of activities. During the data capture phase of the preliminary investigations, two participants performed both activity scenarios five times each, resulting in physiological and activity information being captured from a total of 60 activities.

3.3 Pre-Processing Techniques

Prior to data analysis, pre-processing was performed on the raw data values acquired from the accelerometer and ECG sensors in order to reduce the noise inherent in the devices along with the noise generated due to motion artefacts. For the accelerometer data, a Finite Impulse Response (FIR) filter was employed as a low-pass filter to produce a set of acceleration values for each activity. As such, the FIR filter was independently applied to the raw data values obtained from each axis of the accelerometer and utilized a Barlett Window to attenuate frequencies above 20Hz. The resulting sets of values were subsequently normalized within the range [-1, 1] in order to give a direct mapping from individual accelerometer values to gravitational acceleration values within the range [-1, 1] g. The values for gravitational acceleration were used to represent the activity profile of the participant for a given activity, thereby providing a contextual reference during analysis of the ECG signal.

For the ECG signal values, a Fast Fourier Transform was applied during pre-processing to attenuate low-frequency noise and waveform irregularities within the recorded signal. In order to obtain heart rate from the ECG signal, automated R-peak detection was performed on the resulting ECG signal, using an adaptive filter with a threshold of 70% of the maximum level of the signal, and the average heart rate for each activity calculated from successive R waves after two passes of the filter have been applied.

3.4 CUSUM Data Analysis Technique

In order to reveal the significance of any underlying relationships discovered between the ECG data and the ADLs, analysis of the heart rate values during each activity was performed using the statistical technique Cumulative Sum Control Chart (CUSUM). As a tool for detecting shifts in the mean of a process, the application of CUSUM analysis to the heart rate values permits the discovery of changing patterns normally associated with performance of an activity [17]. Such patterns can then be used to monitor and identify any abnormal cases that may arise during the activity. The CUSUM technique [18], as applied to the set of heart rate values for a given activity, is given in Figure 1. As may be observed, the analysis comprises a two-step process. In the first step, the cumulative sum of the difference between the values of each data point and the process mean are calculated over time, where the process mean, is an estimate of the control mean. In the case of the set of heart rate values, the process mean is the average heart rate value during the activity process. The difference, S_{diff}, between the maximum and minimum CUSUM values, S_{max} and S_{min} respectively, is then calculated and utilized within a bootstrapping process in order to identify the significance of S_{diff}, thus identifying the change in the trend associated with the heat rate values. During the bootstrapping process, the data points are randomly re-ordered, the corresponding difference in CUSUM values determined and compared with the difference from the original data. The confidence for the change in trend is then given as the percentage of bootstrapping cases that have smaller values for the CUSUM difference than the values for the difference from the original data points. Once a change in the trend is evaluated as significant, a change point can be identified in order to split the set of data points into two segments with individual characteristics. If the confidence value is greater than a pre-specified threshold, then Step 2 of the CUSUM algorithm is performed in order to identify the point of significant change within the dataset. Consequently, the change point is the point in the data sets at which the variance in the two separate segments is minimised. For the investigations presented herein the bootstrapping sample size, L, was set to 1000 to cover a sizeable distribution of S_{diff} during the re-ordering of data. Additionally, a value of 1 was utilized for the significance in the change of trend.

During the analysis conducted for the investigations, once a change in the pattern of the heart rate had been identified, information from the activity profile of the participant, contained within the acceleration data, was utilized in order to provide further contextual information regarding the possible reason for the change. Correspondingly, the points of transition within the activity profiles are compared with the change points determined for the associated heart rate in order to reveal the underlying relationship between the physiological and activity profile for an activity.

Step 1:

Calculate difference of maximum and minimum of cumulative sum:

Calculate the process mean:

$$\bar{x} = \sum_{i=1}^{N} x_i / N$$

where N is the number of data points (i.e. heart rate values)

$$S_i = S_{i-1} + (x_i - \bar{x}),\ i = 1,\ldots N \quad \text{and} \quad S_{diff} = S_{\max} - S_{\min}$$

Use bootstrapping to estimate significance of change in trend:

Repeat (i = 1,…,L)

Randomly re-order data points (bootstrap samples)
Calculate CUSUM value for bootstrap samples:

$$S_{diff}^{i} = S_{\max}^{i} - S_{\min}^{i}$$

End (i = L)

M is the number of bootstraps with index j such that:

$$S_{diff}^{j} < S_{diff}$$

Trend confidence value, Conf = (M/L). If the confidence value is greater than 95%, proceed to Step 2, otherwise the change in trend is not significant

Step 2:

Repeat (for data point (m >= 2) to calculate Mean Square Errors)

$$MSE(m) = \sum_{i=1}^{m-1} (x_i - \bar{x}_1)^2 + \sum_{j=m}^{N} (x_j - \bar{x}_2)^2$$

Where $$\bar{x}_1 = \sum_{i=1}^{m-1} x_i \Big/ (m-1) \quad \text{and} \quad \bar{x}_2 = \sum_{i=m}^{N} x_i \Big/ (N-m+1)$$

End (m = N-1)

The change point is the data point that minimises the MSE value:

$$\beta = \arg\min_{k} MSE(k)$$

Fig. 1. CUSUM: Two-Step Process Applied to Heart Rate Values from a Single Activity

4 Results and Discussion

For the investigations, physiological and activity profile data were captured from two healthy participants over five repetitions of both activity scenarios, where each activity scenario consisted of three activities. Although data from a total of 60 activities were recorded, only 83.33% of the datasets contained complete information, due to issues with the Bluetooth communications between the wearable sensor devices and the receiving computer. Initially, detailed results from one participant for a single performance on one activity will be given, along with the corresponding analysis. This will be followed by selected results and analysis from a single participant on the remaining set of activities performed.

Figure 2 illustrates the set of values for the heart rate, as determined using the R-peak detection method previously described in Section 3.3, alongside the corresponding set of values obtained for the Mean Square Error (MSE) during CUSUM analysis. The activity profile information captured for the activity, in terms of the sets of normalized acceleration values from both the upper-body and lower-body accelerometers, are subsequently presented in Figure 3.

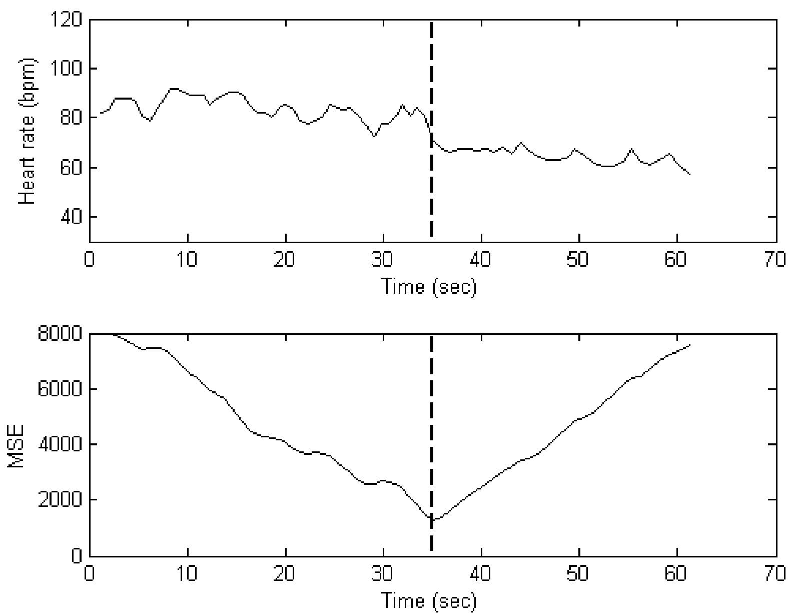

Fig. 2. Activity *Sit Down*: Heart Rate & Mean Square Error (MSE). CUSUM result is given in both graphs (*dashed vertical line*).

From the CUSUM analysis, it has been discovered that there is a significant change in the trend associated with the heart rate values during the activity. The corresponding change point of the trend is identified during CUSUM analysis by minimizing the total individual variances for the data points within the two segments separated by the change point. In Figure 2 the position of the change point is illustrated with a dashed vertical line at 35.04 seconds in both the graph depicting the set of heart rate values and the graph showing the corresponding set of values for the MSE. As can be seen in the graph of MSE values, the change point corresponds to the data point for which the smallest MSE value has been determined. Based on the CUSUM analysis, the data points before the change point represent a pattern of values that are distinct from the pattern formed by the data points after the change point. Consequently, the range of values for the heart rate before the change point is [72.28, 91.70], whereas the range of heart rate values after the change point is [56.89, 71.44]. In order to determine the potential cause of the change in heart rate pattern, the activity profile obtained during the activity over the same period may be examined.

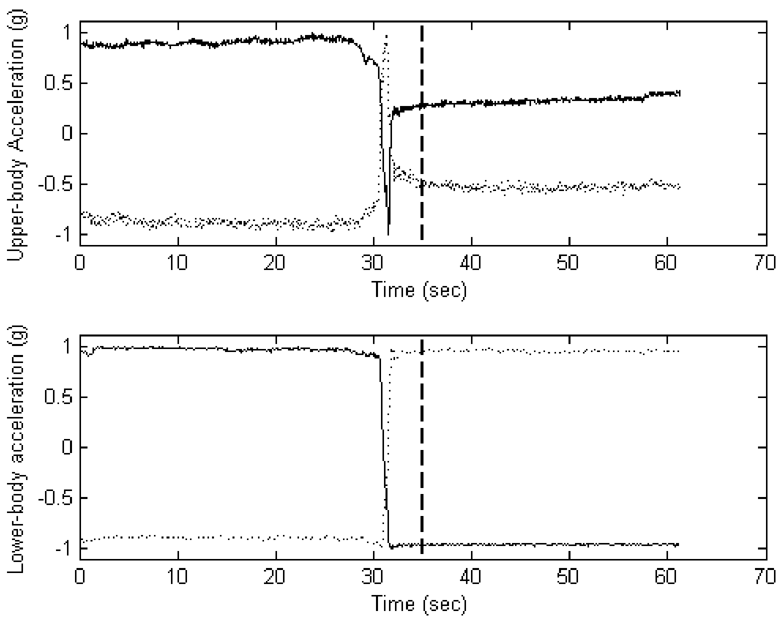

Fig. 3. Activity *Sit Down*: Upper & Lower-Body Acceleration Values. Anterior-posterior acceleration (*solid line*) and vertical acceleration (*dotted line*) are shown on both graphs. CUSUM result is also given in both graphs (*dashed vertical line*).

Figure 3 provides an illustration of the corresponding activity profile, with the set of acceleration values from the upper-body and lower-body accelerometers being displayed in the top and bottom graphs respectively. Although a 3-axis accelerometer was used during the activities, only the two most dominant axes are shown in order to increase the clarity of the figures. In Figure 3 it can be seen that both of the accelerometers show a consistent change in values during the transition from the initial standing position to the seated position, prior to the change in the pattern of the heart rate. For the upper-body accelerometer, the chest is recorded as moving briefly from an anterior position to a posterior position, then back to a more anterior position as the participant moves through the activity of sitting down. Simultaneously, there is a rapid increase in vertical acceleration of the chest, which is followed by a quick decrease as the participant settles in a seated position. In a similar manner, the lower-body acceleration values show a rapid transition from an anterior position to a posterior position, coupled with a rapid increase in vertical acceleration, as the sensor device rotates by 90° around the lateral axis during the activity. Although the activity begins before the change point at approximately 30.53 seconds, a comparison with the graph of the heart rate in Figure 2 shows a brief fluctuation in heart rate around the time of the activity. Subsequently, the change in the pattern of the heart rate reflects the fact that the participant has just performed the activity. Results from the set of values for the heart rate, together with the corresponding set of values from the upper-body accelerometer, obtained during the *Stand Up* activity, are presented in Figure 4.

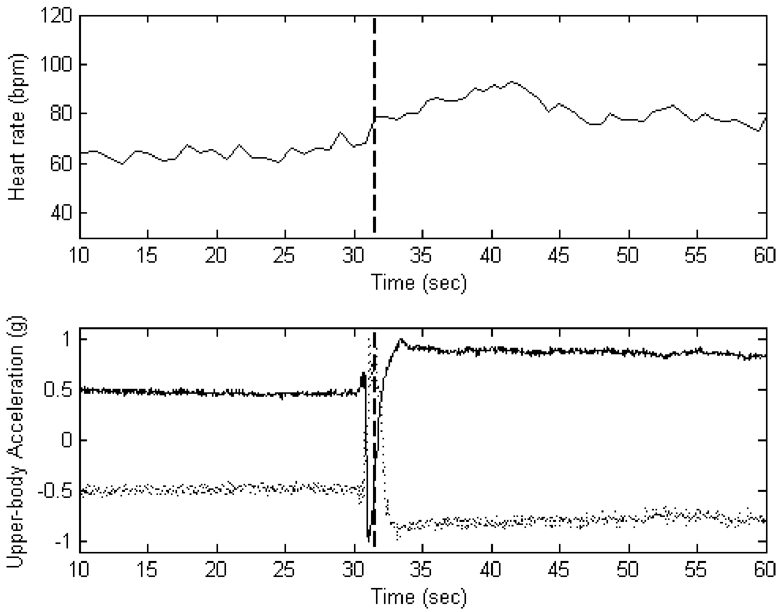

Fig. 4. Activity *Stand Up*: Heart Rate & Upper-Body Acceleration. Anterior-posterior acceleration (*solid line*) and vertical acceleration (*dotted line*) are shown on the Upper-body Acceleration graph. CUSUM result is given on both graphs (*dashed vertical line*).

In Figure 4 it can be viewed that the activity commences at approximately 30.49 seconds, immediately prior to the change in heart rate pattern at 31.59 seconds. Similar to the transition from standing to sitting, previously shown in Figure 3, the acceleration values indicate the chest initially moves in the posterior direction, followed quickly by a move in the anterior direction as the participant moves from a sitting to standing position. Likewise, there is an initial increase in vertical acceleration, with a subsequent decrease before the acceleration during the activity. Although a comparison of the upper-body acceleration values from both the *Sit Down* and *Stand Up* activities shows that they have similar patterns, the corresponding values before and after the activities are significantly different. Moreover, an overall increase in the value of the heart rate for the *Stand Up* activity can be seen in Figure 4, with values for the heart rate before and after the change point occurring within the ranges [59.65, 72.28] and [73.14, 93.09] respectively. By contrast, the heart rate illustrated in Figure 2 for the *Sit Down* activity shows an overall decrease in value.

Figure 5 illustrates the results for the heart rate and corresponding lower-body acceleration for the activity *Walk*. In the lower-body acceleration graph in Figure 4, the regular, repeated movement of the leg that occurs during the *Walk* activity is clearly depicted by the acceleration values. As with the previous results from the *Sit Down* and *Stand Up* activities, the activity begins at approximately 31.56 seconds, immediately prior to the change point at 33.96 seconds. From the graph of the heart rate presented in Figure 5, a general fluctuation in the heart rate may be observed, with an overall rise occurring after the change point as the participant continues to perform the activity. Subsequently, the values for the heart rate before the change point are within the range [66.06, 83.03], whereas after the change point the values for the heart rate are in the range [84.16, 102.40].

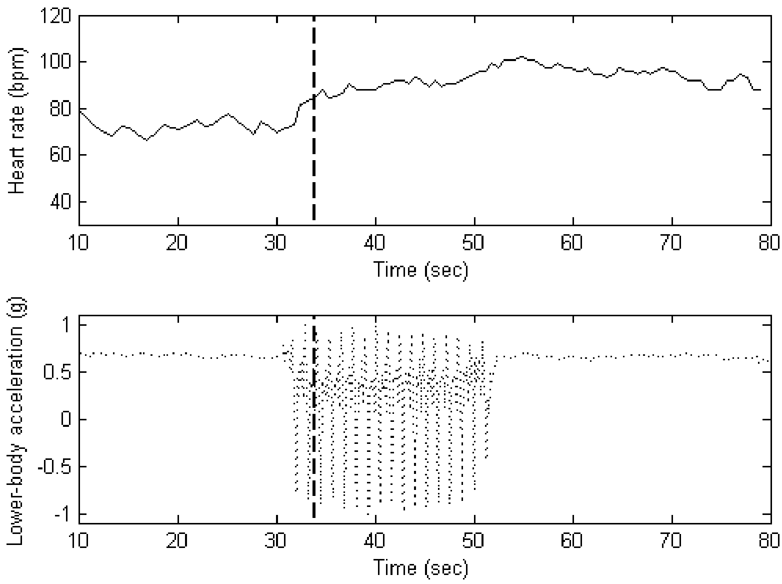

Fig. 5. Activity *Walk*: Heart Rate & Lower-Body Acceleration. Anterior-posterior acceleration (*dotted line*) is shown on the Lower-body Acceleration graph. CUSUM result is given on both graphs (*dashed vertical line*).

A similar correlation between the heart rate values and the acceleration values can also be discerned in the results from the activities *Ascend Stairs* and *Descend Stairs*, which are presented in Figure 6 and Figure 7 respectively. Similar to the results presented in Figure 5, in both Figure 6 and Figure 7 the regular, repeated movements of the leg may again be seen in the lower-body acceleration graphs, as the participant performed the activities of *Ascend Stairs* and *Descend Stairs* respectively. As the stairwell used during the activities contained 3 flights of stairs with a small mezzanine level in-between each flight, the increased acceleration during the flights can be recognized in both of the acceleration graphs.

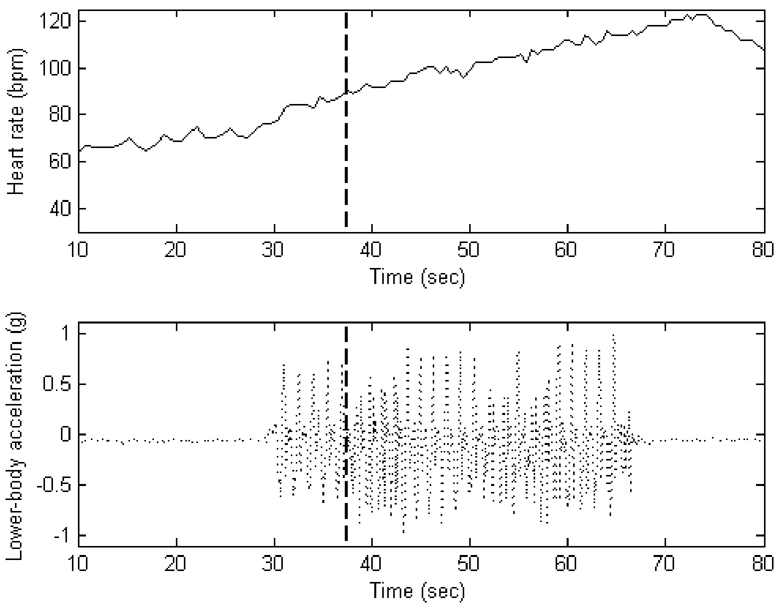

Fig. 6. Activity *Ascend Stairs*: Heart Rate & Lower-Body Acceleration. Vertical acceleration (*dotted line*) is shown on the Lower-body Acceleration graph. CUSUM result is given on both graphs (*dashed vertical line*).

In Figure 6 and Figure 7 it may also be observed that the activities start at approximately 30.00 seconds and 32.09 seconds respectively, yet continue after the corresponding changes occur in the heart rate patterns at 37.43 seconds and 35.50 seconds. Comparing the graph of the heart rate in Figure 6 with the equivalent graph in Figure 7, it is readily apparent that considerably more effort is required by the heart when performing the activity *Ascend Stairs*. Subsequently, the heart rate during *Ascend Stairs* continues to increase for a short period after the activity is performed before it begins to recover to a resting rate. For the *Ascend Stairs* activity, as illustrated in Figure 6, the heart rate has a value within the range [63.34, 87.77] before the change point and a value within the range [89.04, 122.88] after the change point. Likewise, during the *Descend Stairs* activity, shown in Figure 7, before the change point the values for the heart rate occur within the range [65.36, 76.80], whereas after the change point the values for the heart rate occur within the range [77.77, 97.52]. Again, the heart rate graphs in Figure 6 and Figure 7 show distinct patterns of the heart rate before and after the respective change points, thus reflecting the response by the heart to the activities performed.

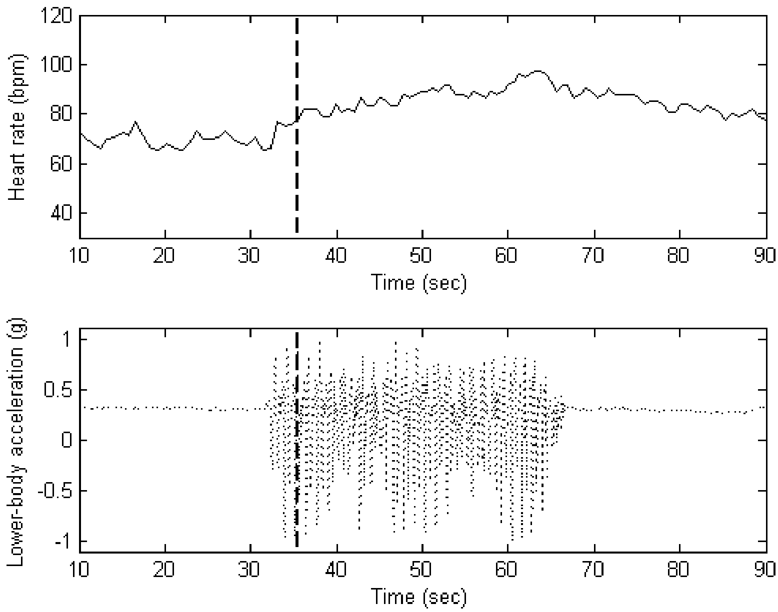

Fig. 7. Activity *Descend Stairs*: Heart Rate & Lower-Body Acceleration. Vertical acceleration (*dotted line*) is shown on the Lower-body Acceleration graph. CUSUM result is given on both graphs (*dashed vertical line*).

From the investigations, it has been observed that there is a high correlation between the time when an activity takes place and the time when the change point occurs, with the change point occurring shortly after the activity commences. Subsequently, it has been shown that a transition to an activity results in a corresponding change in the pattern of the heart rate, which is potentially due to an increase in the function of the heart in response to the effort required to perform an activity. Within the results, it has also been shown that even the least significant activities, such as *Sit Down* and *Stand Up*, have an obvious effect on the patterns of the heart rate. Thus the relationship between the physiological and activity profile provides crucial information that may be further used in order to develop algorithms that determine if physiological profile information derived from sensors is abnormal or alarming, given the context from corresponding activity profile information. Ranges of values for the heart rate for different ADLs can potentially be determined, as different activities have a different effect on the change in the pattern of the heart rate. Consequently, threshold values for heart rate *alarms* on individual activities may be determined based on derived features of the heart rate in order to detect abnormalities during ADLs. Given the context of the current activity, it is expected that the values of the heart rate after the activity will occur within a range defined by the associated threshold value. Any heart rate values that are detected outside the threshold for an activity can be reported in order to prompt a further investigation by a clinician. Subsequently, mechanisms that provide context aware monitoring of health status, based on physiological information derived from wireless sensor technology may be further developed.

As previously stated, during the data acquisition phase of this study there was a periodic problem with packet loss occurring from the Bluetooth transmission between sensor devices and receiving computer. Potential causes for such packet loss include faulty wireless sensors, interference from other wireless transmission signals and the implementation of the Bluetooth stack on the receiving computer. Consequently, the problem of packet loss is potentially significant for the practical deployment of wireless sensors for health monitoring and analysis. In order to address this problem, a number of approaches may be adopted, such as the use of a more robust communications protocol, or the use of duplicate sensor devices to facilitate signal validation and fault tolerant communications. Likewise, the use of adaptive data analysis techniques, which permit effective analysis from incomplete information, may be applied to aid in the resolution of this problem.

5 Conclusion and Future Work

The relationship between physiological profile and activity profile information, obtained from performance of ADLs, has considerable potential for use in the inference of health and wellbeing status. Consequently, such relationships may be used by healthcare services in order to provide the facility for elderly patients to *age in place*. In this paper, the first steps towards this goal have been made through preliminary investigations that verify the ability to capture changes in the patterns associated with heart rate, which occur as a direct result of performing daily activities. Using five distinct activities, the relationship between physiological and activity profile information for each activity has been successfully determined through application of the CUSUM analysis technique. Based on this work and the relationships discovered, the research should initially be extended to incorporate intelligent data analysis techniques for the modeling and classification of the activities based on the physiological profile information. Although participants within this preliminary work performed an exclusive set of predetermined activities, the research should also be extended to permit the continuous monitoring and analysis of both performance and activity profiles of participants freely conducting activities within a sensor-based, smart environment. Furthermore, the problem of packet loss during data acquisition has a potentially significant impact on the deployment and utilization of wireless sensors for the purpose of health monitoring. Although a number of approaches from both communications protocol and data analysis points of view have been suggested to help resolve the problem, these provide further challenges for the effective management of network traffic within sensor-based environments and challenges for the development of effective data analysis methods that operate effectively on incomplete datasets. Subsequently, both of these aspects provide additional areas in which to extend the current research.

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