PREDICTION OF ELEVATED PULSE PRESSURE IN ELDERLY USING IN-HOME MONITORING SENSORS: A PILOT STUDY

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Abstract

In this paper we describe the possibility of employing the data generated by a continuous, unobtrusive home monitoring system for predicting abnormal blood pressure (BP) in elderly. Blood pressure may be used for both early detection of clinical conditions (such as heart attacks or strokes) and long term assessment of functional or cognitive decline. We investigated several factors that influence abnormal BP prediction such as sensor type, number of days prior to the BP measurement and algorithm choice. In our algorithms we used the pulse pressure (the difference between systolic and diastolic BP) that is believed to be a better predictor for clinical events. We conducted a retrospective pilot study on two residents of the TigerPlace aging in place facility with age over 70, that had blood pressure measured between 100 and 300 times during a period of two years. The pilot study suggested that abnormal pulse pressure can be reasonably well estimated (an area under ROC curve of about 0.75) using apartment bed and motion sensors.

1 Introduction

The proportion of elderly in the population is growing at a rapid rate in countries around the world. Many of these seniors prefer to live independently for as long as they are able, despite the onset of conditions such as frailty and dementia. Solutions are needed to enable independent living while enhancing seniors' safety and their families' peace of mind [2, 9].

Aging adults are often stereotyped as purposefully masking any decline in abilities to avoid outside intervention and this fact leads to the concern held by adult children about their aging parents [9]. Elderly patients are particularly at-risk for late assessment of cognitive changes due to many factors: their impression that such changes are simply a normal part of aging, their reluctance to admit to a problem, their fear of being institutionalized and even the failure of physicians to fully assess their cognitive function due to the belief that no intervention is possible [5]. Relying on self-report by the patient or their family is also unreliable. Current clinical monitoring approaches may miss important fluctuations in behaviour and health state [5]. In addition, presenting the long term patterns to the elders may encourage them to seek help [3].

One approach to solving the above problems is to use unobtrusive sensors placed in the living environment to alert caregivers to a potential need for medical intervention.

The rest of the paper is structured as follows: in section 2 we show the reasons for investigating pulse pressure in our study, in section 3 we present the methodology of the current study, in section 4 we describe the data used, section 5 contains the results and section 6 the conclusions and future work.

2 Pulse pressure as a predictor of multiple diseases

Pulse pressure (PP) is defined as the difference between the systolic blood pressure (SBP) and the diastolic blood pressure (DBP). The majority of individuals older than 70 years have an increased pulse pressure resulting from age-related stiffening of the central elastic arteries and systolic hypertension. A high PP is associated with cardiovascular risk factors such as diabetes, hypertension, and smoking. It also predicts a higher risk of subsequent cardiovascular events [7], coronary heart disease [4], renal disease, heart failure [11] and mortality [10], particularly in the elderly. According to Safar et al. [10], a PP of 60 mm Hg is a strong mechanical factor predicting cardiovascular mortality. Based on epidemiological studies, it is well accepted that PP above the critical levels of 60 mm Hg cause particular risk in patients. Such a threshold has been established for PP on the basis of epidemiological studies indicating the lower level of PP at which renal, cerebral, and most ischemic cardiopathies (myocardial infarctions) occur [10]. However, according to Peters et al. [7] and Swannacker and Alexander [11] no practical cut-off value exists for differentiating normal pulse pressure from abnormal pulse pressure. In addition, PP seems to increase with age [10] and for any given age over 70, men have a 5%-10% higher PP than women [11]. In our study we considered elevated high pressure (abnormal) if PP>60. In further work we will consider adapting the threshold for sex and age.

In summary, by signalling to nursing staff the possibility of high pulse pressure we may be able to prevent a subsequent cardiovascular event. In addition, the trend of the pulse pressure may be used in evaluating the functional and cognitive decline of the elders.

3 Methodology

TigerPlace [8] is an independent living facility for seniors designed and developed as a result of collaboration between Sinclair School of Nursing, University of Missouri and Americare Systems Inc. of Sikeston, Missouri. A primary goal of TigerPlace is to help the residents not only manage their illnesses but also stay as healthy and independent as possible. Each resident included in the study has a Data Logger in his or her apartment that collects data from wireless sensors (Fig. 1). The Data Logger date-time stamps the data, and logs them into a file that is sent to a database in a secure server via a wired network connection. Fourteen networks (without video) have been installed in TigerPlace apartments, the video part of the network is currently under development.

The sensor network consists of several types of sensors mounted in different places throughout the residents' apartments, including motion sensors, bed sensors, and stove temperature sensor. The motion sensors are placed in various places, such as bathroom, bedroom, kitchen, living room, etc. and some of the residents have this type of sensor installed on the door of the refrigerator, kitchen cabinets and even drawers.

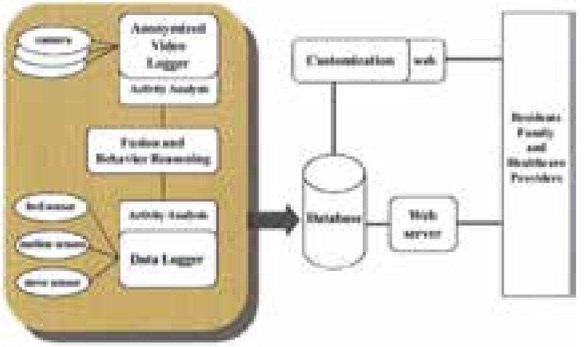

Figure 1. The sensor network. Motion and bed sensors were used in this study.

They capture resident motion through his/her apartment by emitting a signal (firing) as often as there is movement around them. The bed sensors are in fact sets of sensors, composed of a pneumatic sensor strip across the bed and a motion sensor attached to the bed headboard [1]. The sensor strip is able to keep track of the resident's movement in the bed, namely restlessness, pulse and breathing, as long as the resident is in the bed. The sensor strip and motion sensor attached to the bed are connected together and they function similarly to the motion sensors mentioned previously: they fire as long as they detect activity. Unlike the motion sensors, the bed sensor strip captures three types of activities, which are structured on three or four levels of severity.

The prediction of the elevated PP is based on the intuition that if the resident does not feel well, his/her sleep and motion patterns are altered. In this study, we used the following values for PP prediction:

- the total number of motion sensor firings from the day (from 7am to 9pm) and from the night (from 9pm to 7am) previous to the PP measurement;

- the total number of bed restlessness (level 1: movement for 1 to 5 seconds) firings from the day (from 7am to 9pm) and from the night (from 9pm to 7am) previous to the PP measurement;

- the total number of low heart rate (HR<50 beats/min) firings from the day (from 7am to 9pm) and from the night (from 9pm to 7am) before the PP measurement.

We also considered using two consecutive days of motion and bed restlessness for predicting PP. However, in PP prediction we did not use any PP values from previous days since the current BP measurements were not available daily. In future research we plan to measure the BP data daily which will allow for using past PP values in the prediction process.

Although each considered resident lives alone in his apartment, some extra motion hits were possible due to housekeeping or occasional visits. In this research we did not consider factors that affect the total number of motion firing such as visitors, the duration of the sleep and the time out of the apartment. We are currently working on algorithms for detecting these factors and plan to account for them in the future. Instead, we considered the night sleep occurring from 9pm to 7am and we removed the samples where there were no motion hits for at least three hours (the resident was probably out of the apartment).

We decided to treat the detection of elevated blood pressure as a two class problem: normal PP (PP≤60 mmHg) and elevated PP (PP>60 mmHg). For this task, we used three classification approaches: neural networks (NN), Support Vector Machines (SVM) and linear regression. The training values for the classifiers were 0 (for the normal PP values) and 1 (for the elevated ones). Leave-one-out cross-validation was used in each case in order to evaluate the classification accuracy. Receiver Operating Characteristic (ROC) curves were used for assessing the performance and comparing the classification models. The following algorithm for computing the ROC curves has been used for NN and SVM:

Let $Y_t(i)$ be the ground truth labels, where $Y_t(i) = 0$ if $PP(i) < 60$ and $Y_t(i) = 1$ if $PP(i) \geq 60$, $i = 1,\dots,N$. Let $X(i)$ be the M sensor input vector, $X(i) \in R^M$, and $Y_a(i) \in [0,1]$ be the related algorithm output. Consider a set of output thresholds $\{T(k)\}_{k=1,\dots,K}$ such as {0, 0.1, 0.2, ... ,1}.

For each threshold $T(k)$, $k = 1,\dots,K$

  For $i = 1,\dots,N$

    -calculate the predicted output $Y_p(i) \in \{0,1\}$ using $\{X(i)\}_{i=1,\dots,N}$ and threshold it as:

      If $Y_a(i) \geq T(k)$

        $Y_p(i) = 1$

      else $Y_p(i) = 0$

  end

  -Calculate the false positive rate, x(k) = normal PPs identified as abnormal / total normal PPs, as:

    $x(k) = 1 - \mathrm{sum}((1-Y_t(i))*(1-Y_p(i)))/\mathrm{sum}(1-Y_t)$

  - Calculate the true positive rate, y(k) = abnormal PPs correctly identified / total abnormal PPs, as:

    $y(k) = \mathrm{sum}(Y_t(i)*Y_p(i))/\mathrm{sum}(Y_t)$,

    where $i = 1,\dots,N$.

end.

4. Plot the ROC curve $\{y(k)\}$ vs $\{x(k)\}$ for $k = 1,\dots,K$.

The ROC curves are obtained by varying the threshold T(k) over which the output of a classifier ∈[0,1] is classified as "elevated". For each threshold value T(k), a pair of points {x(k), y(k)} is obtained that represent the portion of the number of normal PP points that were predicted as elevated out of all normal PP points (false positives rate) and the portion of elevated PP detected out of all elevated PP points (detection rate), respectively.

The above algorithm was implemented in MATLAB. For the NN approach we used the MATLAB Neural Networks Toolbox, for the SVM we used the MATLAB Bioinformatics Toolbox and for the robust linear regression [6] we used the MATLAB Statistics Toolbox. The size of the neural network was M-M-1, meaning that the hidden layer had size M, where M was the number of sensor inputs.

4 Data set

The data available for the two residents considered in the study is shown in Table 1.

	Total records	Out of the room	Final data set
Male1	93	[illegible]	41 (30 PP>60)
Female1	138	48	90 (35 PP>60)

Table 1. The data for the two residents considered in the study

The "out of the room" data was due to the resident being out of his apartment for more than three hours. We are currently working on an algorithm that will reliably detect when the resident is out of his apartment which will increase both the PP prediction accuracy and the amount of available data.

The results of the classification algorithms mentioned above for the residents Male1 and Female1 are given in next section.

5 Results

The goal of this work was to determine the feasibility of the PP prediction based on the sensor data. We were interested in several computational aspects of the PP prediction:

- whether to use the sensor readings from one or two days previous to the PP measurement;
- what is the best algorithm for this problem;
- what choice of sensor data input provides the best prediction;

The answers to the three above questions are shown in the next subsections.

5.1 Number of days previous to the PP measurement

In this experiment we considered four features (variables) for each day before the measurement: the total number of motion firings from 7am-9pm, the total number of motion firings from 9pm to 7am and the total number of restlessness level 1 firings for the same two time intervals. The ROC curves for residents Male1 and Female1 and the two cases considered (previous day, M=4, and previous two days, M=8) are shown in Figure 2 (linear regression was employed).

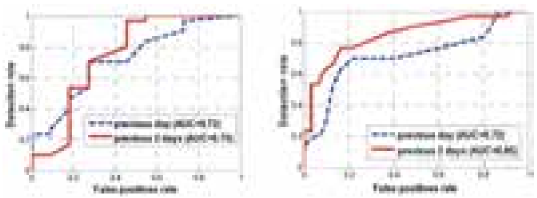

Figure 2. ROC curves for Male1(left) and Female1(right) and measurements from one (M=4) or two (M=8) previous days - linear regression algorithm.

We see that using two days increases the performance of the prediction (AUC=0.85 and AUC=0.75 > AUC=0.72, where AUC=Area Under the Curve). The increase is not that great for Male1 due to, probably, the smaller sample size (41 vs. 90).

5.2 Classifier comparison

We used three classifiers: SVM, linear regression and neural nets. For SVM we did not compute the ROC curve (we show just one pair {true positive rate, false positive rate}). A comparison of the three algorithms is shown in figure 3.

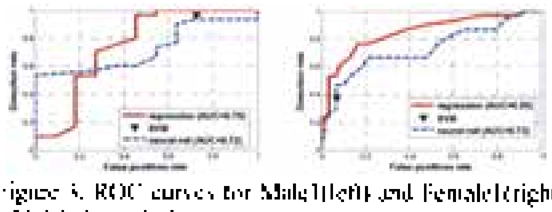

Figure 3. ROC curves for Male1(left) and Female1(right) with M=8 and 3 algorithms.

It seems that for the conditions of our pilot study (limited amount of training data) the robust linear regression algorithm (*robustfit* function in MATLAB) performs the best.

5.3 Using HR sensor data for PP prediction

By inspecting the collected data using our user data visualization interface for several patients, our nursing collaborators suggested that the daily total of low pulse hits acquired by the bed sensor may be a predictor of clinical events. To validate these events, we added two more features (low pulse during previous day from 7am to 9pm, and during previous night from 9pm-7am) to the M-4 case (previous day motion and bed restlessness). The related ROC curves are given in Figure 4.

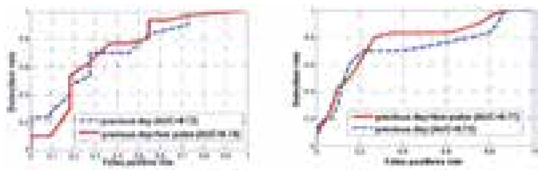

Figure 4. The ROC curves for M-4 and M-6 (added low pulse) for Male1 (left) and Female1 (right)

From Figure 4 we see that the low heart rate increases the PP prediction accuracy, validating the observation that our nursing collaborators made. The increase is higher for 3047 due to, we believe, larger sample size (90 vs. 41).

6 Conclusions

In this paper we investigated methods for predicting elevated pulse pressure in elderly residents using unobtrusive monitoring sensors. The prediction of elevated PP may help nursing staff provide interventions that might prevent grave clinical events such as heart attacks or strokes. The trend of predicted PP may be also used for assessing the functional decline of the elders.

We investigated several sensor inputs that could be used to predict elevated PP such as the bed restlessness, room motion and low heart rate. The conclusion of our study was that the above variables predict reasonably well (AUC between 0.72 and 0.85, where AUC=1 denotes perfect prediction) the elevated PP events.

However, our study had several limitations. First, the sample size and the data sets were small. We plan to measure BP of three elders daily for 3 months in order to have a larger data set. Second, the sensors readings were influenced by factors such as the presence of visitors, the time out of the apartment and the sleep duration that we only partially accounted for. We are currently working on algorithms to detect and correctly integrate for the above factors.

Acknowledgements

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