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Development of remote health monitoring devices: towards IoT for manic-depressive, ageing and obese people

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Abstract: This work presents the development of devices for remote monitoring of manic-depressive, elderly, and obese people to be used at IoT (Internet of Things) context. These people are monitored through a wearable device and an instrumented digital scale. For monitoring of manic-depressive and ageing people, several techniques were analyzed (Decision tree, k-Nearest Neighbor, Naive Bayes, and Artificial Neural Network) to allow human activity recognition. k-Nearest Neighbor got the best result (86% of accuracy) for four different trials in six different activities (walking, running, going upstairs, going downstairs, standing up, and sitting). For monitoring of obese people, an app was developed for a smartphone, which obtains remote weight measurements with 0.01 kg of accuracy.

Keywords: health monitoring, wearable device, manic-depressive disorder, obesity, elderly.

Introduction

The Internet of Things (IoT) has created new possibilities for using the Internet as a communication medium with potential for monitoring and control. Many applications have been developed to communicate with "objects" from a distance, creating new ways to achieve intelligent environments. According to Intel, the IoT is predicted to grow from two billion objects in 2006 to 200 billion by 2020 – around 26 smart objects for every human being on Earth. Although "objects" could theoretically be anywhere and in any state, IoT is currently only practical when objects and users of such objects are relatively close.

According to the International Data Corporation (IDC), there is relatively low awareness of IoT technology and potential benefits to businesses in Brazil. In contrast, the market value of IoT in the EU is expected to exceed one trillion euros by 2020. One specific area of developing IoT in Brazil that could have a great impact on the society and businesses is health and wellbeing related applications. Overcrowded hospitals, shortage of medicines, occasional strikes and poorly maintained buildings are a few major problems faced by the healthcare infrastructure in Brazil. The middle class who are financially secure have to seek supplementary health plans and care systems. The IoT could be used to relieve some of the costs of these systems, and reduce the burden on healthcare for the rest of the population.

The IoT claims to allow diverse elements to communicate and provide information for more sophisticated uses. However, many examples of IoT seem to offer little more than basic monitoring and control (e.g. home heating monitoring and control). This work uses off the shelf IoT enabled devices and appliances from different suppliers and address how they can be appropriately integrated to achieve high level outcomes to monitoring, reacting, and communicating (e.g. a person has just had his/her breakfast) or as longer-term information (e.g. this person has slept poorly or had an expressive increase of weight for the last week), and, on the other hand, low level to indicate an urgent worry (for example, an elderly has just fallen down).

In this work, we develop and propose devices for remote health monitoring, mainly for manic-depressive, ageing, and obese people, in order to trigger immediate warnings to the relevant parties (e.g. carers and/or doctors).

IoT use cases: monitoring and management of health status

Manic-depressive and ageing people often have limited mobility and they are living some distance away from their friends and family. They can lose touch with their beloved ones and friends, becoming socially isolated and lonely. The first use case of this work is the monitoring of manic-depressive and single elderly people in their own homes, so that their Activities of Daily Living (ADL) can be evaluated, diet monitored and incidents identified. This demands a system that can provide immediate data for risk situations, so as to inform emergency services; provide reports to care organizations and feedback to these people; and long-term trend data whereby changes can be inferred and informed to local health care professionals e.g. doctors.

In terms of detecting excess and lack of human movements, it is known that manic-depressive symptoms are characterized by alternate episodes of depression and mania. When in depression, patients describe sleeping too much, needing to be alone and feeling tired. For mania, the major symptoms are difficulty to sleep, not needing much sleep, racing thoughts, and feeling more talkative. This demands a system that can provide immediate data for risk situations, so as to inform emergency services; integrated data from the ADL so as to provide reports to care organizations and feedback to

these people; and longer-term trend data whereby changes can be inferred and informed to local health care professionals e.g. doctors. In this same context is the case in which an elderly has fallen down for long term. The other case study is for those suffering clinical obesity. The monitoring makes use of a scale, in which a summative information is sent to doctors to allow them to follow the increase/decrease of weight, and longer-term data (including that relating to the interventions) goes to local healthcare organizations to allow prediction for needs for local facilities.

Human activity recognition (HAR) for manic-depressive and ageing people

For manic-depressive and ageing people, Activities of Daily Living (ADL) should be monitored to detect risk situations. In this context, it is necessary to take advantages of HAR systems. HAR has emerged as a key research area in the last years and is gaining increasing attention by the pervasive computing research community, especially for the development of context-aware systems. The processes embedded in HAR is composed of data acquisition, pre-processing, segmentation, feature extraction, and classification.

a) Data acquisition

According to L. Gao et al. (2014) [4], a long-time remote HAR must establish an optimal relation between confident data e requirements as battery duration and capacity of data storage. In addition, the sample rate used for data acquisition plays a very important role, as it affects the energetic consumption, amount of data and requirements of frequency-range for data transmission. In [4] the relation between sample rate and accuracy of different classifiers for HAR was studied, establishing that the mean accuracy increases around 1% for sample rate between 20 to 50 Hz, although the increasing of the sample rate implies higher computational cost.

b) Pre-processing

As inertial sensors are normally used in HAR, the data must be pre-processed in order to reduce the noises and eliminate possible artifacts generated by unexpected sensor movements. Normally, low-pass filters (median, Gaussian, or Laplacian) to eliminate high frequency noises. On the other hand, a high-pass filter can be used to obtain the human body acceleration.

c) Segmentation

Sliding window is one of the most common techniques used for segmentation in HAR [6]. In this technique, the data are divided in several consecutive windows or even with overlapping. At the sequence, features are extracted and activities are assigned to each window, according to the classification result. The choice of the window size plays important role for the HAR performance. With a short window, it is possible to recognize an activity in a faster way, reducing the computation cost and energetic consumption. However, a very short window may not include a complete cycle of activity. A wide window is normally used for complex activity recognition, however, implying higher computational cost.

d) Feature extraction

This step consists of finding an efficient way to represent the original data with a reduced set containing its more relevant features. A suitable feature selection improves significantly the algorithm performance, but selecting redundant and irrelevant elements can demand higher computational cost and deteriorate the classifier performance. In HAR systems, features are extracted from the sliding data-window defined at the segmentation step, and can be divided in two categories: time domain and frequency domain. Table 1 shows the main features used in HAR. At the time domain, the use of mean and variance is especially high, due to their efficient implementation. Mean is normally used to detect the local body posture, and variance is used to describe the amount of movement is present at the signal. On the other hand, features of the frequency domain include entropy and energy of the acceleration, which are normally used as measurement of periodicity of a data-window. In addition to the feature extraction, dimensionality reduction is normally used to increase the classifier accuracy and reduce the computational cost. There are two kinds of strategies to execute this step: feature selection and data transformation. At the first, the classifier performance is evaluated with different feature sets, in order to reach the optimal result. At the second, the data transformation is executed through techniques as Principal Component Analysis (PCA) and Local Discriminant Analysis (LDA), which transform the feature space, searching for the maximization of the variance among data and eliminating redundancy.

e) Classification

The vector of features extracted from the data is inputted to the classifier algorithm of the HAR. The main classifiers used for HAR are: decision trees, k-Nearest Neighbors (k-NN), Naive Bayes, and Artificial Neural Networks (ANN) with architecture Multilayer Perceptron (MLP) [6].

- Decision tree (DT)

A decision tree is an algorithm that predicts a class associated with a sample, traveling from a root node of a tree to a leaf. Generally, the division of each node is based on a separation rule related to sample attributes, while the leaf contains a specific class. In Phan (2014), a decision tree with automatic pruning is proposed to classify five human activities ("Idle", "walking", "running", "cycling" and "driving") using a smartphone for data collection, obtaining 98.1% of mean accuracy in classification.

In [3] a decision tree was developed to classify five activities ("Standing up", "walking", "running", "going upstairs" and "going downstairs"), using eight parameters from the time domain and two from the frequency domain. These parameters are extracted from accelerometer data, collected with a smartphone. The authors obtained 80.29% of accuracy in classification.

- k-Nearest Neighbor (k-NN)

This algorithm memorizes the set of training and classifies a new sample according to the class of the

nearest neighbor to that sample, associating the sample to the predominant class among the classes of the k nearest neighbors. In [8] k-NN was used to recognize four activities ("Standing", "sitting", "walking" and "running"), collecting data with a smartphone, and using as features: mean, standard deviation, maximum value, and minimum value, obtaining 92% of accuracy, which is considered a low accuracy, taken into account the activities are considered simple ones. In [2], k-NN is used to recognize 13 activities, among them some complex activities as “dish wash”, “sweep” and “vacuum clean”. The sample are part of database of 19 health subjects, which used four wearable devices composed of accelerometer and 3-D gyroscope attached in different body limbs. The features used were: mean, standard deviation, variance, median, amplitude, RMS, kurtosis, obliquity, energy, and area under signal (SMA, Signal Magnitude Area). The authors reached 97.38% of accuracy, however, they emphasize that four wearable devices are a high number of devices in HAR systems, when requirements as usability, battery autonomy and data storage are evaluated.

- Naive Bayes (NB)

Naïve Bayes is a known classification technique, which is popular due to its simplicity of implementation. In this classifier, the features (inputs) are assumed as independents, while the conditional probability function of each activity can be expressed by the product of probability density functions (Attal et al., 2015). In [9], a Naive Bayes classifier is used to identify eight different activities: "Standing", "walking", "running", "going up stairs", "going down stairs", "sitting", "using the vacuum cleaner" and "brushing teeth". The data are collected with a 3-D accelerometer attached close to the pelvic region, using a sample rate of 50 Hz and window of 5.12 s. The features used are: mean, standard deviation, energy, and correlation. The accuracy obtained was 98.86%, for training and testing for a same subject in different days, and 64.00% for training with a person and testing with other person, in different days.

- Artificial Neural Network (ANN)

A neural network is a distributed processor with high degree of parallelism built with single processing units (neurons), with capacity of knowledge storage and generalized way of application. The knowledge is acquired by mean of a training process, and the connection among neurons, known as synaptic weight, are used to storage that acquired knowledge [5]. Basically, a model of artificial neuron is formed by input signals, synaptic weights, a linear combiner, an activation threshold, and an activation function, which generates the neuron output. The more elemental model of an ANN is a perceptron, formed by an input layer, and an output layer composed of a unique neuron. The output produced by the perceptron assumes only two different values. Thus, the perceptron can classify a set of samples in only two classes, which are linearly separable by a hyperplane. On the other hand, a multi-layer perceptron (MLP) is formed by at least one hidden neuron layer, between the input and output, and its layers are constituted by several neurons, which have a non-linear activation function. This kind of ANN can classify a set of samples in a number of different classes, even they are not linearly separable. Artificial neural networks are also used for human activity recognition. For example, in [1], a multi-layer perceptron (MLP) is trained with a backpropagation ANN to recognize daily and sports activities, using five sensor units worn by eight subjects on the chest, the arms, and the legs (with 86,9% of accuracy). Each sensor unit comprises a triaxial gyroscope, a triaxial accelerometer, and a triaxial magnetometer algorithm.

In this work, a wearable device human activity recognition (HAR) was developed (Figure 1) to acquire data from manic-depressive and ageing people.



Fig. 1 – Wearable device developed: a) on the belt; b) on the wrist.

In this device, the accelerometer collects data and transfer them to the microcontroller, which runs the algorithm for data processing. The result is sent to the user’s smartphone through a BLE (Bluetooth Low Energy) module. The wearable device can be also used to detect fall, as well as the device Myo, which is a very important situation for ageing people. Figure 2 shows pictures of trials with four different fall movements, in addition to raw accelerometer signals for some fall movements. Fifty fall movements and fifty rough movements (not meaning fall) were analyzed, and k-NN was used to data classification. A 100% of accuracy was obtained for fall detection.

Monitoring of obese people

For monitoring of people suffering clinical obesity, a commercial digital scale was used, which was instrumented to send its measurements to a smartphone. The weight is converted to digital data through a HX711 A/D converter, and a HC-05 bluetooth module was used together an Arduino to transmit the data to a smartphone.

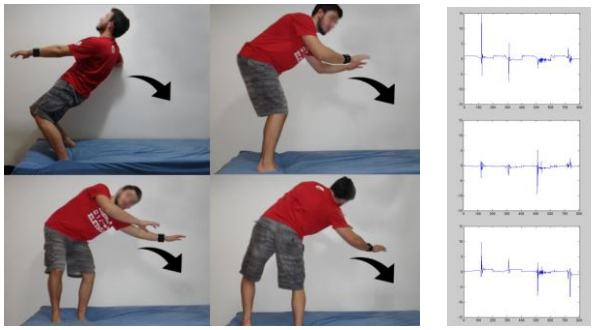

Fig. 2 – Four different fall movements, and some raw accelerometer signals captured.

Results

The wearable device of UFES/Brazil can use its accelerometer to measure the ADL of manic-depressive and ageing people during the day, associated with six different activities: "walking", "running", "going upstairs", "going downstairs", "standing up" and "sitting" from a data-window of 2 s with a sample rate of 10 Hz. Table 1 shows classification results obtained for these movements carried out for six volunteers in four trials.

Table 1 – Results for preliminary tests using different classifiers.

Classifier	Accuracy				
	Trial 1	Trial 2	Trial 3	Trial 4	Average
NB	84.64%	87.15%	64.25%	75.70%	77.94%
k-NN	88.55%	92.46%	77.65%	84.08%	85.69%
DT	82.96%	79.05%	66.20%	77.37%	76.40%
ANN – MLP	86.98%	91.56%	73.85%	83.63%	84.01%

Regarding obese people, an app was developed to monitor daily the weight of these people (Figure 4), with an accuracy of 0.01 kg.



Fig. 4 App developed for weight monitoring in a smartphone (Android).

Conclusion

This work presented the development of devices for remote monitoring of manic-depressive, elderly, and obese people to be used at the IoT context. The first two group of people are monitored through a wearable device, which considers the people movements during their Activities of Daily Living. The third group of people are monitored through an instrumented digital scale.

Regarding manic-depressive and ageing people, several techniques were analyzed (Decision tree, k-Nearest Neighbor, Naive Bayes, and Artificial Neural Network) for human activity recognition. Among these, k-Nearest Neighbor got the best result (86% of accuracy) for four different trials in six different activities (walking, running, going upstairs, going downstairs, standing up, and sitting). Regarding obese people, the instrumented scale provides an accuracy of 0.01 kg in weight measurements, which are sent to a smartphone containing an app developed in this study. The next step of this work is to integrate these measurements in a monitoring platform to be used at the IoT context.

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