Hi-Res activity recognition system based on EEG and WoT

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Abstract

Nowadays, the recognition of physical activity (PA) is a well-known problem with many solutions. Several kind of algorithms, using MEMS sensors, allow determine the most likely activity. Indeed, these applications work well when physical activity is performed for long periods of time and steadily. However, indoors, these systems are not entirely suitable and have several problems. In this paper, thanks to the introduction of new context information, such as EEG, and through communication between WoT based elements interface at home, it would be possible to perform a more accurate and low-level recognition. By using uPnP protocol and additional services, information from other smart housing elements with user device itself can be shared, enriching traditional systems based on ac-celerometry.

1 Introduction

Just 30 minutes of moderate activity five days a week, can improve your health according to the Centers for Disease Control and Prevention. By enabling activity monitoring on an individual scale, over an extended period of time in a ubiquitous way, physical and psychological health and fitness can be improved. Studies performed by certain health institutes initiative [Manson *et al.*, 2002, Ellekjaer *et al.*, 2000, Sattelmair *et al.*, 2010, Lee, 2001] have shown significant associations between physical activity and reduced risk of incident coronary heart disease and coronary events. Their results can be seen in Figure 1, where the inverse correlation between the risk of cardiovascular incidents and physical activity level is shown through the comparison of four separate studies.

In recent years, thanks largely to the increased interest in monitoring certain sectors of the population such those of as elderly people with dementia and of people in rehabilitation, activity recognition systems have increased in both number and quality. Furthermore, communication between relatives, friends and professionals can be improved by means of graphs of weekly activity (high relevant for sportsmen and for the relatives of elderly people) whereby the doctor can be automatically alerted if any strange activity is detected. By using data acquired from accelerometer, *NFC*, or even microphone sensors and applying some classification algorithm, it is possible to recognize human activities. Artificial neural networks (*ANN*) method will be analyzed and compared with our work. Results show the main differences between different studies, and certain drawbacks are determined which rules them out for development on users' smartphones To reduce the cost related to process accelerometer signals, this paper opts for an innovative technique, through which the work is performed in the field of discrete variables. Thanks to a discretization process, the classification cost is much lower than that obtained when working with continuous variables. Any dependence between variables during the recognition process is therefore eliminated and, on the other hand, energy consumption from the process itself is minimized.

Activity recognition

1.1 Data Collection

Certain related studies attain results on activity recognition off-line. A comprehensive training set from the accelerometer output is first needed before data can be classified into any of the recognized activities. However, this paper has sought to minimize the waiting time for recognition, thereby providing valid information of the activity very frequently. To this end, both training and recognition sets are obtained using time windows of fixed duration. After having conducted a performance and system accuracy analysis, it is determined that the optimum length for these windows is 5 seconds. Five seconds windows was chosen due to for our system it's extremely important to ensure that in each time window there is, at least, one activity cycle. Where activity cycle is define as an complete execution of some activity pattern. For instance, two steps are an activity cycle for walking and one pedal stroke is the activity cycle for cycling. If at least one activity cycle can not be ensure in each time window, it's not possible to determine, basing on accelerometer patterns, the activity performed. This statement could be seen in the next example. Suppose a two second cycle is having and the actor is jumping continuously, that is, we have a cadence of one jump for each two seconds. The system is configured with one second time window and thus, for each activity cycle will have two windows. In the first one, while the user is rising, vertical acceleration is negative. In the other one, because the

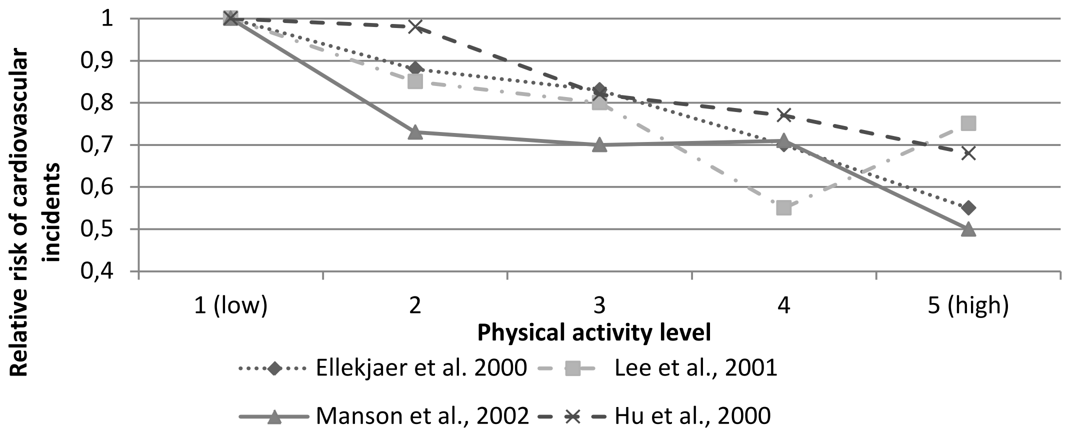

Figure 1: Associations between physical activity and reduced risk of incident coronary heart disease and coronary events

user is falling, vertical acceleration will positive. If user increase the cadence by two, mean between acceleration set is close to , due to vertical positive and negative accelerations will be counteracted. For this reason, it's very important to ensure that one cycle of all activities, regardless of the speed performed, is contained in a time window. Segmentation process and activity cycle is shown in Figure 2.

Based on these time windows, which contain data for each accelerometer axis, the signal module has been chosen in order to reduce the computational cost of the new solution. In addition to rendering the system more efficient, this choice of module eliminates the problem caused by device rotation [He and Jin, 2009]. Furthermore, user comfort with the system is decreased by removing the restriction that forces its orientation to be maintained during the process of learning and recognition. Using the accelerometer module, a data from each of the different readings taken within a time window $a_i = (a_{x,i}, a_{y,i}, a_{z,i})$ for the x, y, and z axes is defined as follows

$$|a_i| = \sqrt{(a_{x,i})^2, (a_{y,i})^2, (a_{z,i})^2} \quad (1)$$

For each temporal window is obtained Arithmetic Mean, Minimum, Maximum, Median, Std deviation, Geometric mean and other measures. In addition to the above variables, hereafter called temporal variables, a new set of statistics from the frequency domain of the problem is generated. This second set of variables will be called frecuencial variables. In order to obtain the frequency characteristics, the Fast Fourier Transform (*FFT*) for each time window is applied. In this way, and based on the frequency components obtained.

2 Qualitative method

2.1 Ameva Algorithm

Let $X = \{x_1, x_2, \ldots, x_N\}$ be a data set of a continuous attribute $\mathcal{X}$ of mixed-mode data such that each example x_i belongs to only one of ℓ classes of the variable denoted by

$$\mathcal{C} = \{C_1, C_2, \ldots, C_\ell\}, \quad \ell \geq 2$$

A continuous attribute discretization is a function $\mathcal{D} : \mathcal{X} \to \mathcal{C}$ which assigns a class $C_i \in \mathcal{C}$ to each value $x \in \mathcal{X}$ in the domain of the property that is being discretized.

Let us consider a discretization $\mathcal{D}$ which discretizes the continuous domain of $\mathcal{X}$ into k discrete intervals:

$$\mathcal{L}(k; \mathcal{X}; \mathcal{C}) = \{[d_0, d_1], (d_1, d_2], \cdots, (d_{k-1}, d_k]\}$$

In this discretization, d_0 is the minimum value and d_k is the maximum value of the attribute $\mathcal{X}$, and the d_i values are in ascendent order.

If L_1 is the interval $[d_0, d_1]$ and L_j is the interval $(d_{j-1}, d_j]$, $j = 2, 3, \ldots, k$, then

$$\mathcal{L}(k; \mathcal{X}; \mathcal{C}) = \{L_1, L_2, \cdots, L_k\}$$

Therefore, the aim of the Ameva method [Abril *et al.*, 2009] is to maximize the dependency relationship between the class labels $\mathcal{C}$ and the continuous-values attribute $\mathcal{L}(k)$, and at the same time to minimize the number of discrete intervals k.

As a result from applying the above algorithm to each statistical value of the system, a series of intervals associated with a particular $\mathcal{C}$ tag is obtained. Thus, after processing all system statistics, a three-dimensional matrix is obtained. In the first two dimensions, the label of the activity $\mathcal{C}$ associated with the interval $L_i = (L_i^l, L_i^s]$, as well as with the lower limit L_i^l and the upper limit L_i^s of that range is stored. In a third dimension, the matrix contains the above data for each statistic $\mathcal{S} = \{S_1, S_2, ..., S_{\mathbb{S}}\}, \mathbb{S} \geq 2$. This three-dimensional matrix containing the set of interval limits for each statistic is called the *Discretization Matrix* and is denoted by $Dm\{\mathcal{C}, L^{l,s}, \mathcal{S}\}$. The *Discretization Matrix* therefore determines the interval to which each item of data belongs with respect to each statistical value, by means of carrying out a simple and fast discretization process.

Class Integration

The next step of the algorithm determines the probability associated with the statistical data for each of the activities based on previously generated intervals. To this end, each element of the training set $x = \{\mathcal{X}; \mathcal{C}\}$ is processed, to which,

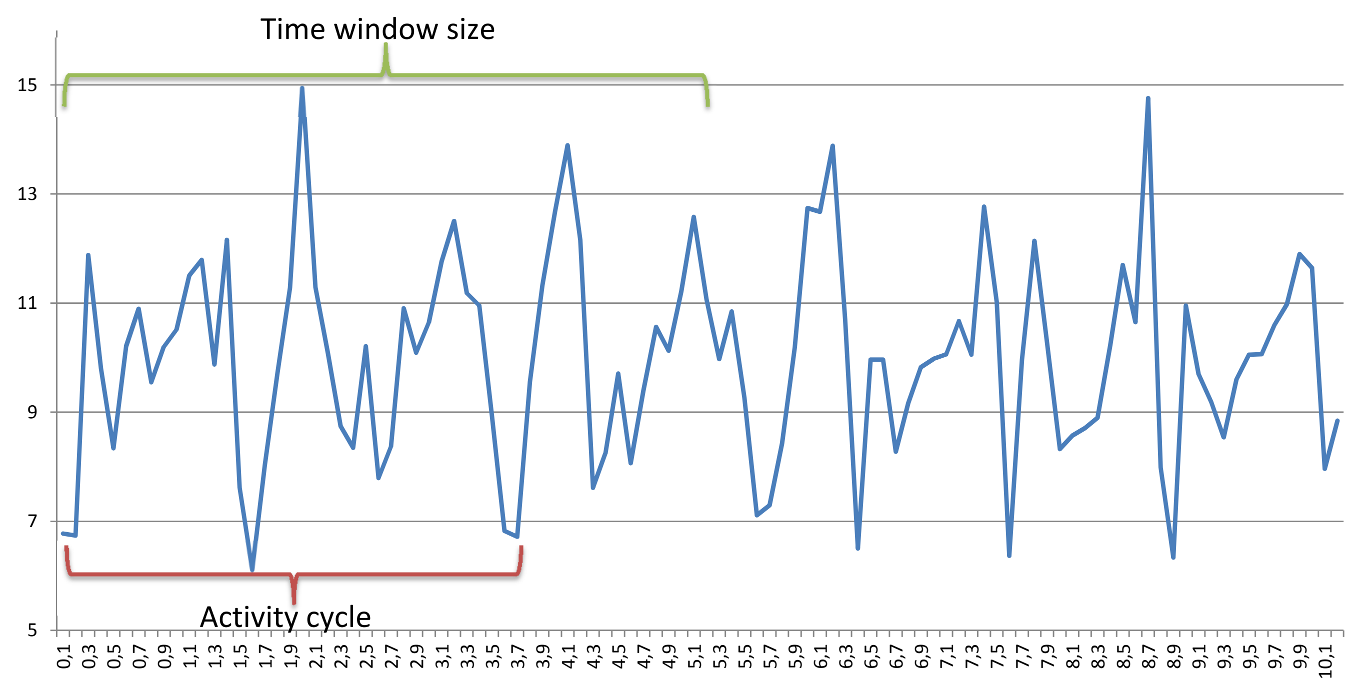

Figure 2: Time windows split method over accelerometer signal

in addition to the value of each statistic whose calculation is based on the time window, is also associated the label of the specific activity in the training set. In order to carry out this process, *Class-Matrix* is denoted by $Cm\{x, L_i, \mathcal{S}\}$ and is defined as a three-dimensional matrix that contains the number of data x from the training set associated with each L_i interval for each statistical $\mathcal{S}$ of the system. This matrix is defined as follows,

$$Cm_{x,i,s} = |x \in \mathcal{X}|x \geq L_i^l \wedge x < L_i^s \wedge x\{\mathcal{C}\} = C_s \quad (2)$$

Therefore, by this definition, each position in the *Class-Matrix* is uniquely associated with a position in the *Discretization-Matrix*, as determined by its range.

At this point not only is it possible to determine the discretization interval likelihood, but the *Class-Matrix* also helps to obtain the probability associated with the discretization process performed with the *Ameva* algorithm.

Activity-Interval Matrix

The next step in the learning process is to obtain the matrix of relative probabilities. This three-dimensional matrix, called the *Activity-Interval Matrix* and denoted by $AIm\{x, L_i, \mathcal{S}\}$, determines the likelihood that a given value x associated to an $\mathcal{S}$ statistic corresponds to a specific C_i activity. This ratio is based on the quality of the discretization performed by *Ameva*, and in order to determine the most probable activity from the generated data and the intervals of the training set. First the contents of the array *AIm* is defined as follows,

$$AIm_{c,i,s} = \frac{Cm_{c,i,s}}{total_{c,s}} \cdot \frac{1}{\ell - 1} \sum_{j=1, j\neq c}^{\ell} (1 - \frac{Cm_{j,i,s}}{total_{j,s}}) \quad (3)$$

where $total_{c,s}$ is the total number of time windows of the training process labeled with the c activity for the $\int$ statistic.

Figure 3 shows the overall process described on this section for carry on data analysis and interval determination.

2.2 Classification Process

Having obtained the discretization intervals and the probabilities of belonging to each interval, the process by which the classification is performed can be described. This classification is based on data from the analysis of time windows. The process is divided into two main steps: the way in which to perform the recognition of physical activity is first described; and the process to determine the frequency at which some particular activity is then presented.

Classifying Data

For the classification process, the most probable activity is decided by a majority voting system. This process starts from the *Activity-Interval Matrix* and uses a set of data $x \in \mathcal{X}$ for each of the statistics belonging to the $\mathcal{S}$ set. The process consists of finding an activity $mpa \in \mathcal{C}$ such that the likelihood is maximized. The above criterion is included in the following expression,

$$mpa(\mathcal{X}) = \max \sum_{s=1}^{s} AIm_{c,i,s}|x_s \in (L_i^l, L_i^s] \quad (4)$$

Figure 4 shows the overall process described on this section for recognition process from Activity-Interval Matrix calculated in the previous stage.

The expression shows that the weight contributed by each statistic to the calculation of the probability is identical. This

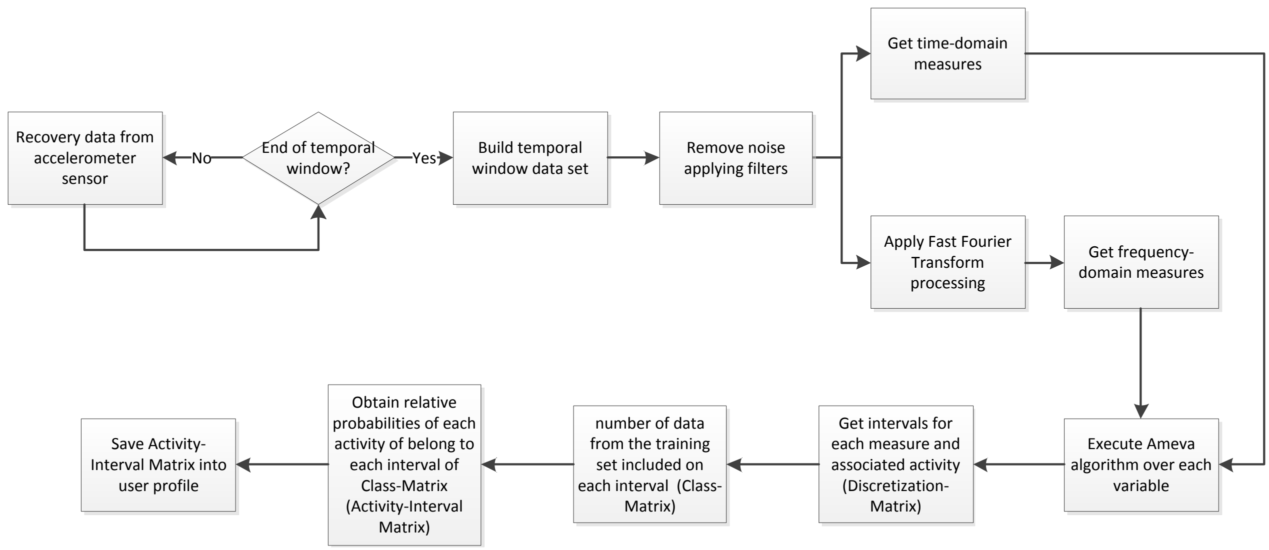

Figure 3: Overall process of data analysis and interval determination

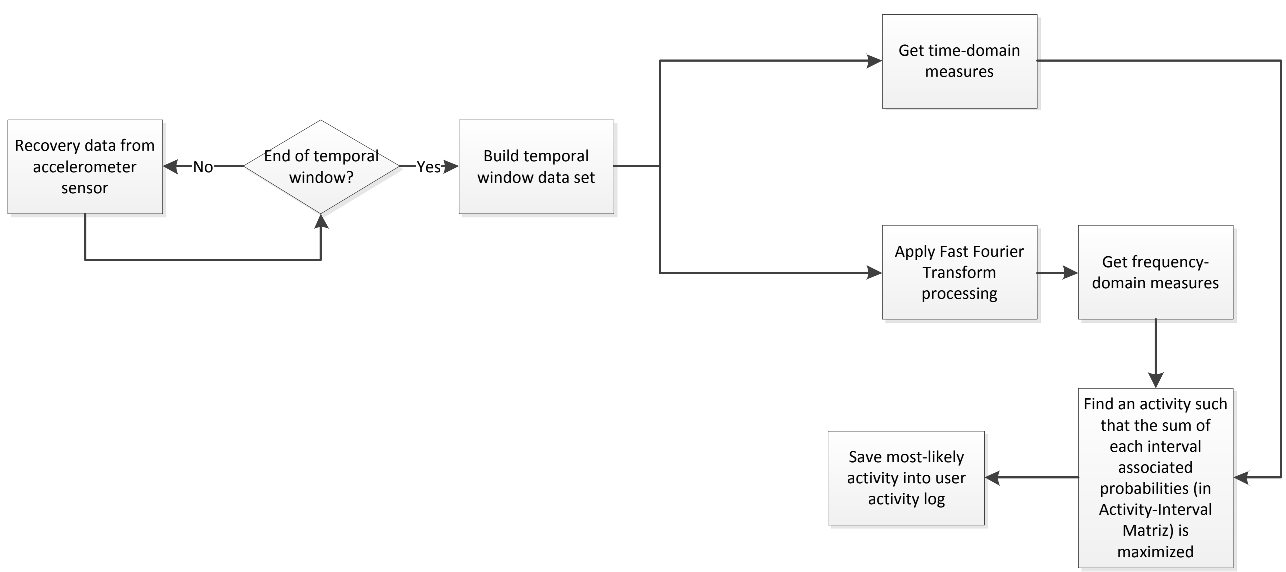

Figure 4: Overall recognition process from data sensors

can be carried out under the assumption that all statistics provide the same information to the system, and that there is no correlation between them. Thus, the most probable activity, or mpa, represents those activities whose data, obtained through the processing time window, is more suited to the AIm set values. In this way, the proposed algorithm not only determine the mpa, but also its associated probability. From this likelihood, certain activities that do not adapt well to sets of generic classification can be identified. This could be an indication that the user is carrying out new activities for which the system has not been previously trained.

3 Conclusions and future work

In this work, a highly successful recognition system based on discrete variables is presented, which uses the *Ameva* discretization algorithm and a new *Ameva*-based classification system. It has therefore been possible to achieve an average accuracy of 98% for the recognition of 8 types of activities. Furthermore, working with discrete variables has significantly reduced the computational cost associated to data processing during the recognition process. By using this process to increase recognition frequency, it has been possible to obtain a physical activity reading every 5 seconds and to enter these readings into the user activity log. However, the main problem of this system based on statistical learning is the limit to the number of activities that can be recognized. Working only with accelerometer sensors implies a limit to the number of system variables and therefore may lead to a strong correlation between these variables.

Acknowledgments

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