Human Activity Recognition and the Activities Holter

Brain disorders cost Europe almost €800 billion a year [1] and, according to the World Health Organization [2], one in four people suffer mental illness throughout his life, and the percentages of the European population who suffer from illnesses such as bipolar disorder or schizophrenia are, respectively, 2 and 1%. Many of these diseases have as symptoms some specific patterns of behavior, and knowledge of all activities undertaken by the patient can be extremely useful information for establishing a diagnosis and evaluation of the effectiveness of subsequent treatment. Nevertheless, these data are provided in most cases by a subjective source: the patient. Despite the high prevalence of these diseases and the potential impact in the quality of life of patients and the cost of health care, there is still no objective way to monitor the activities undertaken by the patient, and this is the purpose of what we call an "activities Holter."

The word Holter means a medical device performing the ambulatory monitoring of electrocardiographic activity over an extended period (one or several days) [3] and its name comes from its inventor, Norman J. Holter [4]. By extension, other devices capable of monitoring for long periods outside the hospital setting also receive this name, such as EEG Holter [5] or blood pressure Holter [6]. Thus, an activity Holter would be a device that makes a temporary record of the various activities carried out by a person (walking, running, sitting, standing, climbing stairs, etc.) over a long period and in normal life.

The activity Holter shares with the rest of monitoring procedures the need for little or no intrusiveness and to be usable for long periods of time (in this case, it could be even weeks) or an outpatient basis, but unlike, for example, a cardiac Holter it can not be limited to the acquisition and storage of a biological signal, but must incorporate enough intelligence to automatically determine the activity being undertaken by the subject and the main parameters of this activity. This feature is, precisely, the main obstacle to its implementation and the purpose of this research project.

There are two main methods for human activity recognition: vision-based, e.g. [7], and inertial sensor-based, e.g. [8]. The main disadvantages of vision-based systems are that they can only be used in a confined space, they interfere with the privacy of the individual and they produce an excessive amount of information that must be processed. On the other hand, the size, weight and power consumption of inertial sensors has been a traditional barrier for use as portable sensors. Due to recent advances in MEM ("Microelectromechanical") technologies, miniature inertial sensors have been made wearable and have became the ideal platform for the analysis of human movement [8], falls detection [9], medical diagnosis and treatment [10], and tele-rehabilitation [11]. Currently there are devices available like [12], which integrate high accuracy accelerometers, gyroscopes, magnetometers and thermometers in a tiny device with real time wireless transmission capabilities. All these features make these devices ideal candidates for data capturing in our activities Holter.

Our Holter will consist, therefore, of one or more wearable inertial sensors with wireless transmission (and synchronization if needed), and an automatic human activity recognition system that, according to a standard methodology [13], will include a preprocessing and/or feature extraction module followed by a classifier/regressor. In order to ensure that the global performances of the system are satisfactory, we must address the following issues:

1 - Number of sensors: it is well known that there is a compromise between the number of inertial sensors and the number and/or the complexity of the activities the system can recognize [14], although the limit that can be achieved using a single sensor is not well known. This is, in part, due to the influence of the type of activities, the sensor position, or the preprocessing and feature extraction methods.

2 - Feature extraction: the ability to discriminate between one activity and another, or the invariance of the system with respect to the orientation and precise location of the sensors depends largely on the feature extraction stage [15]. Due to the high sampling rate (even above 100 Hz), usually this stage consists of obtaining a redundant set of the signals' statistical parameters using a time window of length between 0.5 and 2 seconds, followed by a feature selection using filtering methods [16] which can be either supervised (e.g., linear discriminant analysis or LDA) or unsupervised (Principal Component Analysis or PCA). The irreversible nature of this stage means that it is advisable to avoid aggressive stages of feature extraction that may cause loss of relevant information but, at the same time, it must provide a set of parameters, which are invariant with respect to the location and orientation of the sensors.

3 – Activity classification: there are basically two approaches to activity classification, depending on the use of the movement dynamics: explicit in Bayesian methods and implicit in block discriminative methods. In [17] we can find a recent comparison between the two approaches that demonstrates the superiority of the first one. Among the Bayesian methods, the most popular in this application are Hidden Markov Models (HMM) [18] [19], although it is not trouble free. The first problem is not directly attributable to the HMM but lies in the activity modeling, usually too simple or imprecise to incorporate the activities' dynamics. In this regard, the preliminary results presented in [20] that make use of hierarchical dynamic model with a HMM per activity are promising, because they prove the effectiveness of a two-level modeling (activities in the upper level and movements within the activity in the lower one), even working directly with the data without any preprocessing. The second and more serious problem of HMM comes from its parametric nature, in which the number of states and possible transitions has to be determined in advance. To solve this problem methods such as the infinite HMM [21] have been proposed, where the number of states is not specified a priori, but its distribution via a hierarchical Dirichlet process that defines the transitions between states. These Bayesian methods, which replace parameters with distributions, have been called non-parametric Bayesian methods [22]. Recent results [24] [23] support the validity of these methods in dynamic models.

4 - Measures in activities: the knowledge of the activity, in some cases, does not provide enough information on the status of the subject, and often additional

measures are required, such as energy consumption, complexity of the movements or the position and trajectory of the subject. The latter is very difficult to obtain from inertial sensors because even a small and unbiased measurement error in the accelerometer results in a random walk process in speed. In certain positions of the sensors and for certain activities such as walking or running, this problem is solved by resetting the speed when it is certain that the true speed is zero [25], which is the method used in pedometers, but unfortunately there are no general methods to correct the drift in the position generated by these measurement errors. One promising method to explore, and it is in the intentions of this project, is to adapt the dynamic model and the instants of zero activity according to the result of the activities classifier.

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