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# Fusing actigraphy signals for outpatient monitoring

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ABSTRACT

Actigraphy devices have been successfully used as effective tools in the treatment of diseases such as sleep disorders or major depression. Although several efforts have been made in recent years to develop smaller and more portable devices, the features necessary for the continuous monitoring of outpatients require a less intrusive, obstructive and stigmatizing acquisition system. A useful strategy to overcome these limitations is based on adapting the monitoring system to the patient lifestyle and behavior by providing sets of different sensors that can be worn simultaneously or alternatively. This strategy offers to the patient the option of using one device or other according to his/her particular preferences. However this strategy requires a robust multi-sensor fusion methodology capable of taking maximum profit from all of the recorded information. With this aim, this study proposes two actigraphy fusion models including centralized and distributed architectures based on artificial neural networks. These novel fusion methods were tested both on synthetic datasets and real datasets, providing a parametric characterization of the models' behavior, and yielding results based on real case applications. The results obtained using both proposed fusion models exhibit good performance in terms of robustness to signal degradation, as well as a good behavior in terms of the dependence of signal quality on the number of signals fused. The distributed and centralized fusion methods reduce the mean averaged error of the original signals to 44% and 46% respectively when using simulated datasets. The proposed methods may therefore facilitate a less intrusive and more dependable way of acquiring valuable monitoring information from outpatients.



## 1. Introduction

In recent years there has been growing interest in the development of computer based health systems to facilitate prevention, early diagnosis, and treatment through the continuous monitoring of patients outside clinical institutions. These systems are able to provide immediate and personalized health services to individuals regardless of location, facilitating normalization of the patient's lifestyle during treatment thereby enhancing their life quality.

One of the biggest challenges in the development of these computer based systems is the monitoring of the mental, physiological, and social signals from the patient without influencing or changing the patient's daily life activities. Due to advances in wireless technologies and wearable electronics, today it is possible to integrate sensors in small and discrete devices, allowing long time non-invasive studies of free-living patient activity [1]. Nevertheless, greater efforts are still required to make these devices as unobtrusive as possible for the target users and those around them.

In order to improve these properties, a multi-sensor based strategy consisting of the use of different devices to monitor the same activity (e.g. wrist watch, smartphones, or undermattress actigraphs) can be used. This strategy gives more flexibility to the patient, allowing the use of one device or another, thus adapting the system to the individual patient's lifestyle and behavior. This methodology minimizes the user's responsibility for the operation of the system, making the system more robust to individual sensor data loss, and making the monitoring system more transparent to the user.

Outpatient monitoring using a multi-sensor based strategy requires a data fusion model capable of taking maximum profit from all of the generated information, which in most cases is redundant, with non-linear dependencies, long periods of missing

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data, and different sensitivity levels. In this sense, this study proposes two novel multi-sensor fusion methodologies at the raw level of actigraphy signals. The main goal of the fusion methodology presented here is to obtain a single fused activity signal that improves the information contained in each single original signal, avoiding common artifacts such as noise, missing data, or spurious data, and complementing the loss of sensitivity of some of the sensors used. That is, to design a low signal abstraction level multi-sensor fusion method (data in-data out) for actigraphy signals [2,3]. In recent years different multi-sensor data fusion techniques have been presented in the literature [4–6]. These fusion techniques were designed to deal with the main challenging problems in multi-sensor fusion [5] such as: data imperfection, outliers, conflicting data, multi-modality data, correlation, alignment, data association, processing framework, operational timing, dynamic phenomena, and dimensionality. In the specific case of fusing actigraphy signals for outpatient monitoring, the main problems to overcome are related to data imperfection (impreciseness and uncertainty in the measurements), outliers (artifacts and missed data) and heterogeneous sensors (different sensors, devices, or event placement in the patient body). Each of these problems was addressed separately in the literature considering different approaches. In the case of imperfect data the main approaches followed were the probabilistic [7,8], the evidential [9–11], fuzzy reasoning [12–14], possibilistic [15,16], rough set theoretic [17–19], hybridization [14,20] and random set theoretic [21,22]. In the case of outliers and missing data, the most common approaches are based on sensor validation techniques [23–25] and on stochastic adaptive sensor modeling [26]. Finally the approaches followed to solve the problems related to heterogeneous sensors were highly depending on the sensors used and the desired target. Multi-sensor data fusion techniques were successfully applied in the specific problem of fusing actigraphy signals. In [27] the authors proposed the use of a Hidden Markov Model to classify daily activities by combining the data coming from three different accelerometers. In [28] a system for activity recognition using multi-sensor fusion based on a Naïve Bayes classifier was presented achieving a 71%–98% recognition accuracies when using 1–4 sensors. In [29] the authors used a hierarchical classifier for activity recognition that combines a decision three classifier (to select a optimum sensors subset) with a Naïve Bayes classifier (to classify the activities), in order to reduce energy consumption of the system while maintaining the recognition accuracy. In [30] the authors presented a multi-sensor based method for classification of daily life activities based on a hierarchical classification algorithm and compare their performance with state-of-the-art algorithms by using a benchmark dataset. In [31] the authors fused the features obtained using a set of actigraphy sensors placed in different parts of the body for activity recognition, comparing the performance of five types of classifiers including ANNs, decision tree classifiers, KNN classifier, the Naïve Bayes classifier, and the support vector machine classifier. Guiry et al. studied in [32] the role that smart devices, including smartphones and smartwatches, can play in identifying activities of daily living. They trained different classifiers including C4.5, CART, Nave Bayes, Multi-Layer Perceptrons and Support Vector Machines using both single and multi-sensor approaches (including not only accelerometer but also gyroscope and magnetometer). They conclude that the fusion of the different signals improve the accuracy of the activity identification. In [33] the authors used a set of smartphones including gyroscope, magnetometer and accelerometer placed in different parts of the body for physical activity recognition. One of the main interesting conclusions obtained is that the combination of the different smartphones used only improved the overall recognition performance when their individual performances were not very high. Finally in [34,35] the authors presented a sensor fusion method for assessing physical activity of human subjects, based on support vector machines by using acceleration and ventilation data measured by a wearable multi-sensor device. Their results show that the fusion approach improved the results of the traditional accelerometer-alone-based methods. The above-mentioned methods were successfully applied to fuse different actigraphy signals [27–29,32,33] or even to fuse actigraphy signals with other types of sensors [32–35]. However, in most cases the result of these techniques have been to obtain better estimates of energy consumption [34,35] or to improve activity recognition [27–30,32,33], but not to obtain a more robust fused signal based on a low signal abstraction level approach.

The proposed fusion models are based on the transformation of the input signals to a common representation space where they can be combined linearly. To do this, one sensor is chosen as the reference, and a non-linear regression model is designed to transform the rest of the sensor signals to the representation space of the reference sensor. Once the signals are transformed they are comparable and, as a result, a mixing strategy based on a weighted sum can be applied to obtain a final fused signal. This mixing strategy should avoid the missed data periods that may distort the fused signal.

In this work the non-linear regression models are based on Artificial Neural Network (ANN). We have considered the two principal multi-sensor data fusion approaches: The first one is a centralized fusion model, in which all the signals (except the reference one) constitute the inputs to a single ANN trained with the reference signal as output. The second one is a distributed fusion model in which each non-reference signal constitutes the input of a different ANN trained with the reference signal as output.

In order to test the proposed fusion method we focus on a real case application where the system properties of transparency to the user, non-stigmatizing technology, and non-obstruction to lifestyle are mandatory. This is the case of monitoring patients who are recovering from major depression. These patients require constant monitoring to assess their emotional state at all times in order to make recommendations for healthy practices and to prevent relapses. Several studies have shown the importance of motor activity as a relevant behavior pattern for assessing patients with depression [36,37], and for measuring treatment outcomes in major depression [38–42]. Moreover, in recent years different research initiatives has focused their efforts in the development of computer based health systems for following up outpatients and for the automatic prescription of healthy practices. Some examples of these projects are the Help4Mood [43], Monarca [44], ICT4Depression [45], and Optimi [46] EU projects. In these projects different actigraphy devices such as smartphones, wrist watches, key-rings, and even undermatress sensors have been used to monitor patients with major depression.

The evaluation of the fusion methodology has been performed using both synthetic and real datasets. This allows a precise characterization of the behavior of the fusion models in controlled conditions, and also the evaluation of the performance of the fusion models in a real case application. In this work a novel methodology for synthetic actigraphy data simulation has been prepared to perform an exhaustive evaluation. This simulation methodology includes: a pipeline for signal preprocessing, a non-linear pre-processing algorithm based on Functional Data Analysis (FDA), a feature extraction module based on FDA, and a signal modeling step based on Multivariate Kernel Density Estimation (MKDE).

The adequate functioning of the proposed fusion methodologies will constitute a significant improvement in the monitoring of the physical activity of outpatients, allowing a less invasive means to acquire more data. Moreover these methods will increase the robustness of the acquisition systems, reducing the effect of