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BSN-based Activity Classification: a Low Complexity Windowing-&-Classification Approach

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Abstract. Wireless sensor networks (WSNs) are becoming more and more attractive because of their flexibility. In particular, WSNs are being applied to a user body in order to monitor and detect some activities of daily living (ADL) performed by the user (e.g., for medical purposes). This class of WSNs are typically denoted as body sensor networks (BSNs).

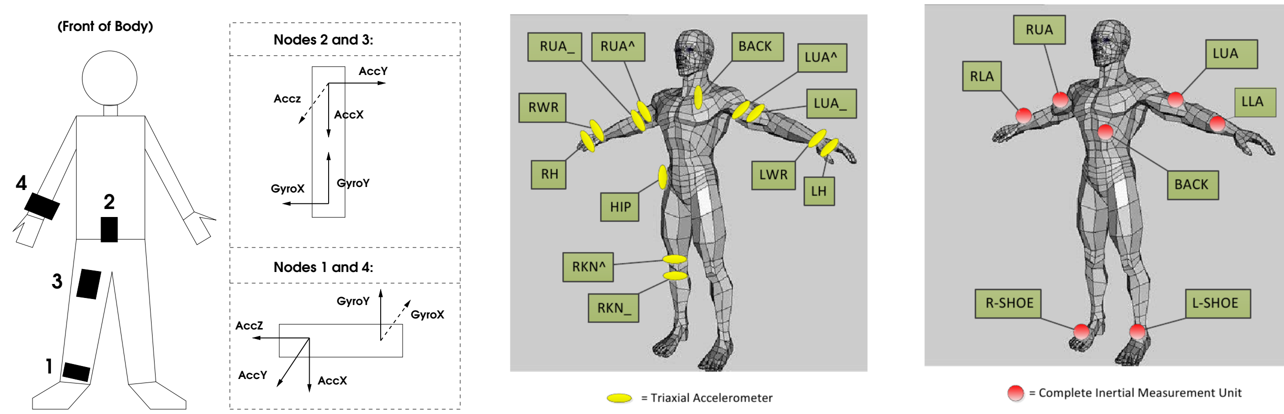
In this paper, we discuss BSN-based human activity classification. In particular, the goal of our approach is to detect a sequence of activities, chosen from a limited set of fixed known activities, by observing the outputs generated by accelerometers and gyroscopes at the sensors placed over the body. In general, our framework is based on low-complexity windowing-&-classification. First, we consider the case of disjoint (in the time domain) activities; then, we extend our approach to encompass a scenario with consecutive non-disjoint activities. While in the first case windowing is separate from classification, in the second case windowing and classification need to be carried out jointly. The obtained results show a significant detection accuracy of the proposed method, making it suitable for healthcare monitoring applications.

Introduction

Wireless sensor networks (WSNs) are attracting a relevant interest in many applications, typically associated with monitoring of a specific environment. Body sensor networks (BSNs) are a special class of WSNs, where wireless nodes are applied to a user body in order to monitor and detect some activities of daily living (ADL) performed by the user (e.g., for medical purposes).

Past work on sensor-based activity recognition algorithms has taken into consideration a single type of sensor, typically accelerometers, placed in multiple locations over the body [1, 2]. More recent systems tend to use multiple motion sensors [3, 4]. Depending on the considered type of sensor, an activity classification system is typically composed of two modules: a feature extraction module and a classification module. Concerning feature extraction, there are different approaches in the literature, among which the most popular are manual segmentation [4] or auto-segmentation [5]. Regarding classification, most of the previous works tend to adopt thresholding or to use k-nearest neighbors algorithms, because of their simplicity and applicability to mobile devices [2]. However, more sophisticated techniques have also been considered, such as those based on the use of decision trees [1] or hidden Markov models [3].

In this work, we focus on the formulation of a BSN-based activity classification framework to detect and classify a sequence of activities, chosen from a list of fixed known activities, just observing the outputs generated by accelerometers and gyroscopes. Our approach can be divided into two main phases: a *windowing* phase, whose objective is to isolate different activities from an inertial data stream; and a *classification* phase where previously identified activities are classified on the basis of a list of known possible activities. Our goal is to derive a general approach flexible enough to process different types of data. In this work, the used experimental data have been provided by different research groups in the context of two activity classification contests: the BSN Contest [6] and the Opportunity Challenge [7].



(a) (b) (c)

Fig. 1: Specific setups: (a) BSN Contest with four sensor devices; (b) accelerometer nodes of Opportunity Challenge; (c) Inertial Measurement Unit (IMU) nodes of Opportunity Challenge [7].

Contests' Description

The research in the field of activity classification through BSNs is often limited both by the specificity of the data used to train and test a new algorithm and by the types of activities that have to be recognized. This makes a comparison between different algorithms not straightforward. The necessity to have an accurate benchmark to evaluate different algorithms has led to the creation of large shared datasets that can be used to obtain consistent performance analyses.

In the last year, two contests were promoted: the BSN Contest [6] and the Opportunity Challenge [7]. In both cases, a unique dataset is shared with the participants, who can use it to test their algorithms and estimate the correct sequence of activities.

The BSN Contest was promoted by the University of Texas in Dallas, TX, USA [6]. The provided datasets differ in the number, the type, and the positions of the BSN nodes. Generally, accelerometer and gyroscope outputs were provided. One of the given BSN setup is shown in Fig. 1 (a)—this corresponds specifically to Task 1 of the BSN contest [6]. In order to clearly develop/test a classification strategy, some training data streams were given, together with the list of true activities performed in the given data segments. In the real contest (2 hours), activity sequences had to be detected just by observing and analyzing one or more data streams then given.

The set of known activities contains both transistional movements between different postures (e.g., sit to stand, sit to lie, ..) and other simple movements (e.g., step forward, turn right/left, ..).

The main feature of the data of this contest is the fact that the users that recorded the stream of activities performed each of them in the most compact and clean way. Moreover, every activity is well separated (time-wise) from the previous and the following activities.

The Opportunity Challenge was born in the context of the European project “Opportunity” coordinated by the ETH, Zurich, Switzerland [7]. The provided datasets were recorded by four different subjects, each of them wearing a large number of sensor nodes placed in positions that cover almost uniformly his/her body. Accelerometer measures were mainly provided and, for some nodes, also gyroscope and magnetometer measurements were given [8]. Fig. 1 (b) and Fig. 1 (c) show the BSN setup for the Opportunity Challenge. Some training data streams were given, in order to clearly develop/test a classification strategy, together with the list of known activities that could have been performed in the given data segments. In the effective contest, activity sequences had to be detected just observing and analyzing one or more unlabeled data streams. These test data were available from the beginning along with the training data.

The set of known activities among which the user has to classify the data streams contains two levels of activities: (i) states of locomotion (e.g., stand, walk, sit, and lie) and (ii) gestures (e.g., open/close door, open/close drawers, drink cup, clean table, ..).

The main problem in the datasets of the Opportunity Challenge is that the way to perform a specific activity is subjectively interpreted by the user who performs it. Furthermore, consecutive activities are not necessarily well separated (time-wise) nor clean and compact. Therefore, the datasets in the Opportunity Challenge were much "rougher" than in the BSN contest.

A General Approach

The aim of this work is to formulate a general approach to the activity classification problem. This general approach consists of a "windowing-&-classification" process which is based, first, on a segmentation of the data (i.e., windowing) and, then, on their classification into activities chosen in a set of predefined activities.

BSN Contest Algorithm We describe the algorithm presented in [9]. Provided that the sensor data are calibrated (i.e., the acceleration is expressed in g units and the angular rate in m/s) and low-pass filtered (the interested user can find more details in [9]), the following algorithm is applied to the data.

A windowing phase is first performed in order to isolate the data segments corresponding to user movements. Our approach to the segmentation of the data stream is based on the idea of recursively evaluating the standard deviation of the norm of the acceleration data, measured over a sliding window of samples, and comparing it with a properly selected threshold.

More formally, let us define the measured acceleration vector as $\boldsymbol{a_i} = (a_{xi}, a_{yi}, a_{zi})$ and the norm of $\boldsymbol{a_i}$ as $\overline{a}_i \triangleq |\boldsymbol{a_i}| = \sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2}$ with $i \in \{0, 1, \ldots, N-1\}$.
Taking into account border effects, the starting and ending epochs of the sliding window centered at the k-th sample and of side length s, denoted as $W_k^-(s)$ and $W_k^+(s)$, can be expressed as follows:

$$W_k^-(s) \triangleq \begin{cases} k-s & k-s \geq 0 \\ 0 & \text{elsewhere} \end{cases} \qquad W_k^+(s) \triangleq \begin{cases} k+s & k+s \leq N-1 \\ N-1 & \text{elsewhere} \end{cases} \tag{1}$$

Finally, we define the standard deviation computed on the set of acceleration samples, between the i_S-th and the i_E-th, as $\sigma(i_\mathrm{S}, i_\mathrm{E}) \triangleq \sqrt{\sum_{i=i_\mathrm{S}}^{i_\mathrm{E}} [\overline{a}_i - \mu(i_\mathrm{S}, i_\mathrm{E})]^2/(i_\mathrm{E} - i_\mathrm{S})}$ where $\mu(i_\mathrm{S}, i_\mathrm{E}) \triangleq \sum_{i=i_\mathrm{S}}^{i_\mathrm{E}} \overline{a}_i/(i_\mathrm{E} - i_\mathrm{S} + 1)$. In our specific case, we will denote as $\sigma_k(s)$ the standard deviation computed on the set of acceleration samples in the sliding window centered at epoch k, i.e., $\sigma_k(s) \triangleq \sigma(W_k^-(s), W_k^+(s))$.

At this point, we decide if a user is moving or not, at epoch k, simply by comparing $\sigma_k(s)$ with a threshold t. More precisely, let us define the "motion labels" related to the i-th sensor device $M(i)$ as the vector whose k-th element is set as following

$$M_k(i) \triangleq \begin{cases} 1 & \sigma_k(s) \geq t \\ 0 & \sigma_k(s) < t. \end{cases} \tag{2}$$

It is now easy to see that the segments of the data in which the i-th sensor device is moving ("movement windows") are clearly distinguishable as the segments of adjacent "1s" in $M(i)$.

Because some sensor device may not detect every movement, all devices in the BSN have to be taken into account. Conservatively, a potential movement is declared to be detected if at least one of the sensor devices detects it. Practically, this process can be used to detect every movement of the user.

Fig. 2: General structure used (a) in the BSN Contest and (b) in the Opportunity Challenge.

More formally, if we define the set of the sensor devices involved in a specific movement as $\mathcal{MS}$, the estimated motion labels $\{M_k\}$ for that movement are obtained as follows:

$$M_k \triangleq \begin{cases} 1 & \sum_{i \in \mathcal{MS}} M_k(i) > 0 \\ 0 & \text{else.} \end{cases} \tag{3}$$

The proposed windowing approach leads to a first, and possibly coarse (inaccurate), segmentation of the data stream. Indeed, it is possible that some little pauses within a single movement lead the system to miss the detection of a single movement and, possibly, to interpret it as a sequence of two distinct movements. This can be avoided by applying to the windowing output a refinement process which takes into account the size of the estimated movement windows. More specifically, in our implementation the refinement is based on the following sequential steps:

1. every *still* window, i.e., window of samples where the user is declared still, with a length (given by the number of samples) shorter than ℓ_1, is switched to a *movement* window (and incorporated in the preceding and following movement windows, which are then fused together);
2. every *movement* window with a length shorter than ℓ_2 is turned into a *still* window ($\ell_2 \simeq \ell_1$);
3. step 1 is repeated considering now every *still* window with a length shorter than ℓ_3 ($\ell_3 \simeq 2 * \ell_1$).

The thresholds ℓ_1, ℓ_2, and ℓ_3 must be properly tuned considering the specific context under analysis. In particular, for the BSN contest their values were heuristically chosen observing their behavior on the training data.

Finally, the classification step is performed relying on the windows estimated at the end of the previous steps. Specifically, every movement window is analyzed singularly and the activity type is evaluated observing the sensors' outputs (i) at the beginning, (ii) at the end, and (iii) along the window. Eventually, the system tries to classify each activity choosing from a set of known activities. Generally, the classification follows a decision tree that gives a specific level of priority to a type of activity on the basis of the "shape" of the data stream generated by one or more (properly chosen) sensors. For example, if the data appear different at the beginning and at the end of a specific movement window, this window represents a transitional movement between two different states of locomotion.

In Fig. 2 (a), a block diagram of the algorithmic approach followed in the BSN Contest is shown.

Opportunity Challenge Algorithm As it may be clearly observed, in the previous algorithm the windowing and classification steps are well distinguishable, mainly because of the nature of the data. Indeed, the data provided for the BSN Contest derive from users who performed isolated atomic activities (e.g., a "step forward" or a "sit to stand" action) and, thus, the movement windows generated through the proposed approach represent, most of the time, a whole easily classifiable activity. On the other hand, the data provided for the Opportunity Challenge correspond to a more complex set of activities, often mixed together and performed in a continuous way by the user. This kind of data, though more realistic, introduces many difficulties, especially in the windowing step. This led us to an approach that mixes the windowing and classification steps: more specifically, data segmentation is obtained as a result of the classification step itself.

The classification is performed independently, activity by activity, by fusing the movement windows (labeled as $\{M_k\}$) generated measuring the standard deviation of the norm of the acceleration of specific devices (as described in the previous subsection) with other activity windows generated through a thresholding process on the accelerations measured by some other specific sensor devices. More formally, for a specific activity, the k-th element of the "activity labels" vector associated with the i-th sensor device is defined as

$$A_k(i) \triangleq \begin{cases} 1 & condition(\boldsymbol{a}_k^i) = \text{true} \\ 0 & \text{else} \end{cases} \tag{4}$$

where $condition(\boldsymbol{a}_k^i)$ is a specific thresholding condition to be verified on the k-th epoch acceleration vector measured by the i-th sensor device.

At this point, if we define the set of the sensor devices involved in a specific activity as $\mathcal{AS}$, the estimated activity labels $\{A_k\}$ for this activity are obtained as

$$A_k \triangleq \begin{cases} 1 & \prod_{i \in \mathcal{AS}} A_k(i) = 1 \\ 0 & \text{else.} \end{cases} \tag{5}$$

Finally, for the considered activity, the estimated output labels, defined as $\{L_k\}$, are obtained by fusing the previous labels together as follows [1] :

$$L_k = \begin{cases} M_k \cap A_k & \text{dynamic activity} \\ \neg M_k \cap A_k & \text{static activity.} \end{cases} \tag{6}$$

A refinement step, similar to the one described in the previous subsection, is performed here as well, in order to avoid the identification of too short windows or to merge close short windows. Eventually, just to emphasize the roles of the windowing and the classification steps, in Fig. 2 (b) it can be noticed that the classification step output is actually evaluated in order to perform the windowing step itself.

Performance Analysis

In order to evaluate the performance of the developed algorithms, their parameters were optimized and the predicted activity labels were compared with the actual (true) labels provided by the organizers of the contests. In the following, the performance of our approach in the two contests is presented after having described how we optimized the parameters of the system.

Parameters' Optimization The values of all parameters were optimized heuristically by making different trials on the training data provided by the organizers in the two contests. However, for lack of space, we do not report them here explicitly.

Numerical Results The performance results of the algorithms is evaluated differently in the two contests. Specifically, according to the rules of the BSN Contest, an activity is positively classified if the right activity is detected *and* if the starting and ending epochs of activity window differ at most 1 s from the actual limiting epochs of the movement window. Given this tolerance margin, our algorithm positively classified 87% of the activities. Furthermore, most of the errors were made in correspondence to long activities. In these cases, indeed, the system may detect these activities as two different activities, thus leading to a wrong classification of the activities in both windows.

On the other hand, according to the rules of the Opportunity Challenge, the performance is computed using the F1-score metric for the predicted and the actual activity labels, conveniently weighed on the basis of the frequency of a specific activity with respect to that of the others [10]. Using this metric, our algorithm positively classified more than 84% of the activities.

Our approach led us to win the BSN Contest and to rank second in the fourth Task of the Opportunity Challenge.

[1] Note that in Eq. the motion labels are logically negated in the case of a static activity (e.g., walk).

Discussions and Future Work

On the basis of inertial data provided by some research groups for the first BSN contest [6] and for the Opportunity Challenge [7], we have proposed a simple, yet very effective, approach to the activity classification problem. Our approach can be separated into two main phases: a *windowing* phase, where the data stream is segmented and every activity is isolated; and a *classification* phase, where each activity window is analyzed in order to classify the related activity among a list of known activities. Given the type of data, these two phases have been linked into different structures. The obtained performance is very promising, as a successful classification rate between 84% and 87% was obtained in the two contests.

The parameters used in the windowing and classification phases have been optimized in an heuristic way. Future work will include automatic optimization of these parameters. Another interesting extension, in order to improve the performance of our approach, consists in estimating the orientation of each sensor device through a joint utilization of accelerometers, gyroscopes, and possibly magnetometers, thus using this information in the classification phase.

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