Posture recognition using the interdistances between wearable devices

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Abstract—Recognition of user's postures and activities is particularly important, as it allows applications to customize their operations according to the current situation. The vast majority of available solutions are based on wearable devices equipped with accelerometers and gyroscopes. In this paper a different approach is explored: the posture of the user is inferred from the interdistances between the set of devices worn by the user. Interdistances are first measured using ultra-wideband transceivers operating in two-way ranging mode, and then provided as input to a classifier that estimates current posture. An experimental evaluation shows that the proposed method is effective (up to $\sim 98.2\%$ accuracy), especially when using a personalized model. The method could be used to enhance the accuracy of activity recognition systems based on inertial sensors.

Index Terms—Ultra-wideband, distance sensing, wearable, posture.

1 Introduction and Related Work

Applications greatly benefit from knowing the user's posture and/or the activities the user is carrying out at a given time. For instance, this information can be used to customize the way of operation of applications according to the current situation and thus provide an enhanced service. Additionally, logging the activities and posture of users during their daily routine enables automatic assessments of their health and well-being status [1]. During the last years, research on this topic, pushed by the availability of low-cost MEMS sensors, has been particularly intense. Most of the methods in the literature rely on the use of body-worn accelerometers, due to their low cost and proved effectiveness in describing human locomotion [2].

A pioneering work related to wearable sensor-based activity recognition was presented in [3]. In that work, five biaxial accelerometers were worn simultaneously at different positions, and 20 subjects were asked to perform everyday activities under semi-naturalistic settings. Results showed an overall accuracy of 84% using decision trees.

In more recent times, the widespread adoption of smart devices embedding inertial sensors has generated a great interest in smartphone-based activity recognition systems. A relevant work in this area is [4]. Twenty-nine users performed supervised activities while carrying a smartphone in a trouser pocket. Six activities were considered: walking, jogging, ascending or descending stairs, sitting, and standing. Data was split into 10-second segments and then processed to extract features. Multilayer Perceptron classification achieved an average accuracy above 90%. The same research group discussed the impact of personalization (i.e., of using subject-specific training data) on smartphone-based activity recognition [5]. Results highlight the importance of using personalized models whenever possible.

Among everyday activities, particular attention has been devoted to the detection and analysis of gait patterns. While simple information such as the step count can be used to track users' fitness level, more advanced gait analysis techniques have been proposed as a means to detect and monitor medical conditions that affect motor ability, such as the frailty syndrome in older adults [6].

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Besides normal activities like walking or jogging, activity recognition techniques can be used to identify hazardous situations. In particular, researchers have devoted a significant effort in finding reliable solutions to automatically detect accidental falls [7], [8]. In fall detection systems, it is paramount to distinguish falls from normal activities with high sensitivity and specificity values. To tackle this problem, researchers exploited activity and posture recognition techniques to identify the everyday activities that typically lead to false alarms [9], [10].

Some works have investigated the use of different wireless technologies to achieve device-free activity recognition [11], [12]. In particular, in [13] an approach based on Wi-Fi channel state information (CSI) analysis is proposed. Two Wi-Fi devices are required: one as sender and one as receiver. When an activity is performed in the range of these two devices, CSI value changes are used for recognition. Eight activities were performed by 25 volunteers—results show an accuracy of 96%. A major limitation of device-free approaches is that such systems only work in properly equipped environments. Conversely, wearable sensors may enable continuous monitoring of users' activities at any time and in any environment.

Recently, researchers have evaluated the use of ultra-wideband (UWB) radars to monitor vital signs [14]. In [15], eight volunteers placed a UWB antenna on their thorax to monitor breath frequency, whereas a piezoelectric belt was used as a comparison. Evaluation with a time reflectometry technique showed that the results achieved by the UWB-based radar are comparable with those achieved by the piezoelectric belt, which is a widely adopted setup to monitor respiratory activity.

In this work, we propose a novel wearable-based approach to exploit ultra-wideband technology for activity and posture recognition. Users carry UWB transceivers at different body positions, and there is no need for external sensors. The estimated interdistances between the transceivers are used as raw inputs to feature extraction and classification techniques, so as to recognize different postures and activities. To the best of our knowledge, this is the first time that body-worn UWB transceivers are exploited in this context. The promising results suggest that the additional information provided by UWB transceivers could be used to improve the accuracy of activity recognition systems based on inertial sensors.

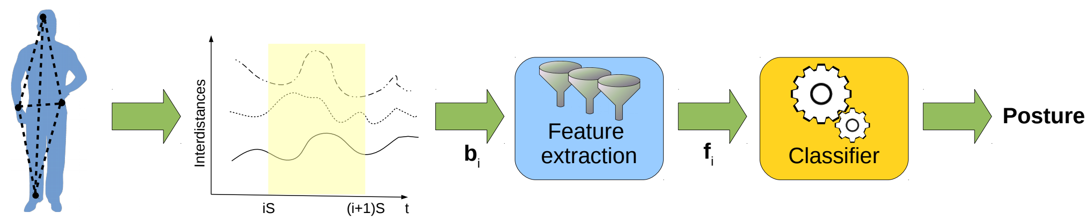

Fig. 1: Overview of the method.

2 Method

The method is based on the idea of recognizing the current posture of the user by observing the interdistances between a set of worn devices. This approach is motivated by the increasing number of wearable devices adopted by the general public. Examples include smartphones, smartwatches, smart wristbands, smart glasses and smart shoes. Each device is supposed to be equipped with an UWB transceiver, as the ones compatible with the IEEE 802.15.4-2011 specifications. UWB transceivers are able to determine the distance from another transceiver by measuring the time-of-flight of the UWB signal. This enables accurate estimation of the distance between the two devices, and in turn of the distance between the two body parts where the devices are placed.

If n devices are worn by the user, then there are $N = n(n-1)/2$ different interdistances. Let us call d_{ab} the interdistance between node a and node b, with a and $b \in 1..n$ and $a < b$. These interdistances are collected with period T. Samples are organized in blocks with a duration equal to S. Thus, the ith block ($\mathbf{b}_i$) contains the kN samples acquired in the interval $[iS, (i+1)S)$, with $k = \lfloor S/T \rfloor$. Each block is processed to extract a vector of relevant features ($\mathbf{f}_i$). The feature vector (also called *instance*) is then provided as input to a classifier where it is used to estimate the posture of the user during the corresponding time interval. An overview of the system is shown in Fig. 1.

2.1 Modes of operation

Two modes of operation were considered: *generic* and *personalized*. In the generic mode of operation, the system is trained on a set of subjects during the development and engineering phase. Then, the system can be used by new subjects without requiring additional training. In the personalized mode of operation, the system requires a training phase that is user specific. Thus, during the first period of use the system learns the characteristics of the specific user and then becomes ready for actual use.

3 Evaluation

The proposed method was implemented and evaluated as follows.

3.1 Experimental setup

A prototype of the proposed method was implemented using four UWB-enabled boards produced by DecaWave [16]. Each board includes an ARM Cortex M3 processor (STMF32105) and a DW1000 IEEE802.15.4-2011 UWB wireless transceiver. One board was attached to a hard hat to emulate the presence of a transceiver embedded in a pair of smart glasses (or an ear-worn device [17]). The other three boards were enclosed in small plastic containers. Two of them were attached to the users' right wrist and right ankle using elastic bands, to mimic a smartwatch and a smart shoe respectively. The last one (mimicking a smartphone) was placed in the left pocket of users' trousers or jacket, depending on the clothes of the subjects. UWB transceivers were configured to communicate using a 6.8 Mbps datarate at 3.993 GHz. UWB transceivers operated in two-way ranging mode: each node exchanged ranging messages with the other nodes and calculated the time-of-flight, which was then used to estimate the distance. This produces two possibly different estimates of distance d_{ab}, the one computed by node a and the one computed by node b. The two values were averaged to obtain the value of d_{ab} used in feature extraction and thus classification. Interdistances were acquired with 10 Hz frequency using a tablet carried by the users. Interdistances between nodes were logged on a file and then processed off-line, to enable tuning of parameters and ensure repeatable experiments.

Twelve volunteers took part in data collection experiments. Their characteristics are summarized in Table 1. Each user was asked to change posture every 30 s according to the following scheme: i) standing, ii) walking, iii) sitting, iv) walking, v) standing, vi) sitting. The order of the first three postures is different from the order of the last three postures to include more variations in the set of transitions. The execution of each user was recorded using a video-camera—the videos were used to manually annotate the traces.

Traces were segmented in intervals with a duration of 3 s (i.e. $S = 3$ s, and hence $k = 30$). A label corresponding to the real posture of the user was manually assigned to all intervals (*standing*, *sitting*, *walking*). A fourth label was used to mark the intervals corresponding to a change in the user's posture (*transition*). Annotated traces are available at the following address: `http://vecchio.iet.unipi.it/vecchio/data`.

Fig. 2 shows one of the collected traces. The six interdistances between the four nodes have been divided in two groups of three, for the sake of image clarity. The first group includes the distances of the body-mounted nodes from the head (head-ankle, head-wrist, head-pocket). The second group includes the interdistances between body-mounted nodes (wrist-ankle, wrist-pocket, ankle-pocket). The two groups are also depicted in Fig. 3.

TABLE 1: Users' characteristics.

User	Gender	Age	Height [cm]	Weight [kg]
1	M	19	179	69
2	M	23	179	65
3	M	28	186	70
4	M	19	176	65
5	M	22	179	63
6	M	30	192	80
7	F	25	155	56
8	F	21	156	60
9	M	25	172	73
10	M	25	173	67
11	M	25	179	95
12	M	44	177	81

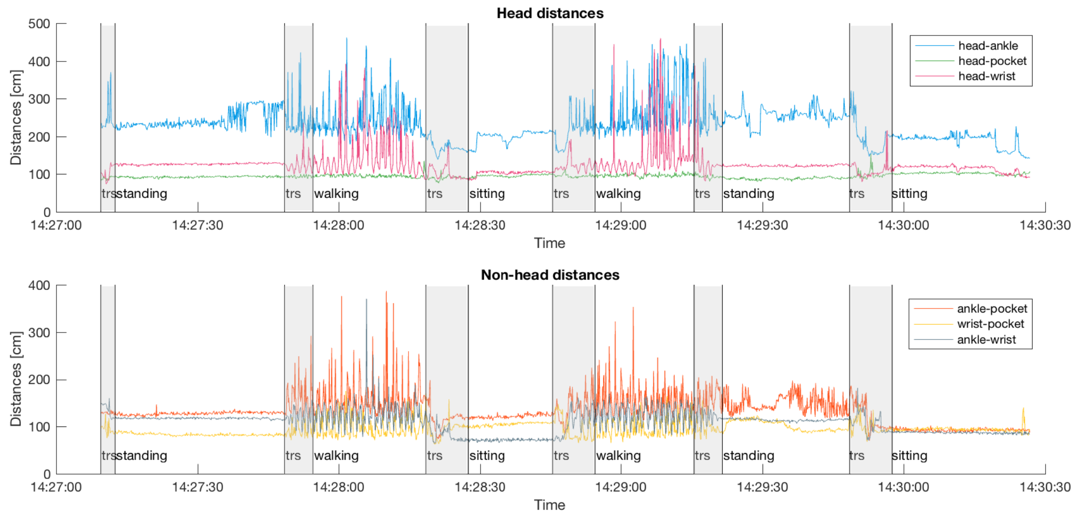

Fig. 2: A trace produced by one of the users. Interdistances are divided into two groups, as illustrated in Fig. 3, for the sake of image clarity.

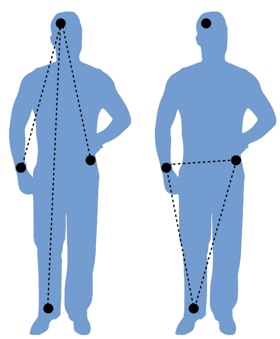

Fig. 3: The six interdistances between the four devices are organized in two groups: {head-ankle, head-wrist, head-pocket}, {wrist-ankle, wrist-pocket, ankle-pocket}

The gray vertical bands in Fig. 2 are transitions (trs) between different postures. Transitions are not used in the training phase. The regions associated to each different posture are easily identifiable. During standing and sitting, interdistances are relatively stable. Conversely, during walking periods interdistances are subject to large oscillations (as expected). Sitting is, in general, characterized by shortened distances with respect to standing. The interdistances collected using the prototype are generally characterized by a positively biased measurement error. This is due to i) the close distance between antennas and the surface of the human body, and ii) the obstruction between antennas caused by the body itself (the signal-to-noise ratio is worsened and the effect of multi-paths is amplified). The reader is forwarded to [18], [19] for a detailed discussion of TOA-based ranging error when using body-mounted UWB devices. In any case, this ranging error does not affect significantly the performance of the proposed system, as will be shown in the following, and even better results could be obtained by using antennas specifically designed for being used on-body.

For each interdistance signal block, the following features were extracted: mean, min-max difference, skewness, median, standard deviation, kurtosis, root mean square, mean crossing rate (the number of times the signal crosses the average value).

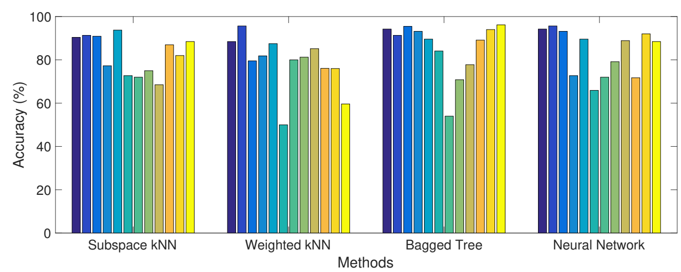

Fig. 4: Classification accuracy for the different users (generic mode of operation).

TABLE 2: Average accuracy (generic mode of operation)

Subspace kNN	82.44%
Weighted kNN	78.42%
Bagged Tree	85.81%
Neural Network	83.62%

These are all features frequently used in the signal processing domain, and they proved to be effective in similar applications (e.g. [20]).

3.2 Results

The following classifiers were used: Neural Network [21], Bagged Tree [22], Weighted kNN (k-Nearest-Neighbor with weight equal to the inverse of the squared distance [23]), and Subspace kNN [24]. In particular, we adopted the implementations of these classifiers as provided by MATLAB 2016b. Each classifier was trained with part of the dataset and evaluated on previously unseen data.

For the generic mode of operation, leave-one-user-out cross validation was used: the system was trained using the data of all the users but one, and its classification accuracy[1] was evaluated on the remaining user. Per-user accuracy is shown in Fig. 4, whereas average classification accuracy is shown in Table 2.

1. Accuracy is defined as the percentage of correct classification results among the total number of examined instances.

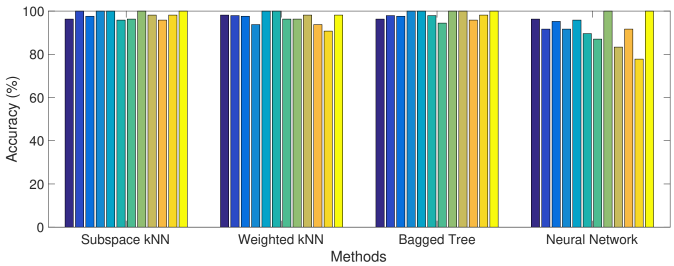

Fig. 5: Classification accuracy for the different users (personalized mode of operation).

TABLE 3: Average accuracy (personalized mode of operation)

Subspace kNN	98.18%
Weighted kNN	96.73%
Bagged Tree	98.18%
Neural Network	91.67%

The users with extreme values in terms of height (users 6 and 7) are characterized by an accuracy that is significantly lower than the other users ($\sim 13\%$ lower, on average). This is due to their difference, in terms of length of limbs and thus interdistances, from the other users.

Overall, the classifier that provides the best results is Bagged Tree with $\sim 86\%$ accuracy.

For the personalized mode of operation, six-fold cross validation was applied to each user's data. In n-fold cross validation, the dataset is partitioned in n disjoint sets: $n - 1$ sets are used to train the system, and the remaining one is used to evaluate its performance on previously unseen data. The procedure is repeated n times, using all the sets for evaluation and then averaging results. The classification accuracy for all the users is shown in Fig. 5. The overall accuracy obtained by the different classifiers, when using the personalized operation mode, is reported in Table 3.

The use of a personalized model makes the system more accurate (up to $\sim 98.2\%$), as it is now able to take into account the physical characteristics of the user. Results are not only better in terms of average accuracy, but also more consistent: the standard deviation of accuracy across all users is reduced from 8.1% (general) to 1.3% (personal). Finally, the classification accuracy for the tallest user and the shortest one is now in line with the others.

4 Discussion

UWB-based distance estimation between devices can be an important source of information for wearable systems. Experiments show that almost perfect accuracy can be obtained when using a model tailored to the user. Interdistances estimated via UWB transceivers can be combined with other sources of information, such as accelerometers and gyroscopes, to achieve even better results. In other situations, UWB-based distance estimation may represent an alternative to the use of dedicated sensing hardware: if a device already includes a UWB transceiver, it may provide sufficient information to make accelerometers and gyroscopes not strictly needed.

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