A method based on UWB for user identification during gait periods

Alessio Vecchio and Guglielmo Cola

Dipartimento di Ingegneria dell'Informazione, University of Pisa
Largo L. Lazzarino 1, 56122 Pisa, Italy.
E-mail: alessio.vecchio@unipi.it guglielmo.cola@iet.unipi.it

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Everyone has a different way of walking, and for this reason gait has been studied in the last years as an important biometric information source. This paper explores a novel approach, based on ultra-wideband (UWB) technology, for user identification via gait analysis. In the proposed method, the user is supposed to wear two or more devices embedding a UWB transceiver. During gait, the distances between the devices are estimated via UWB and then analyzed by means of a machine learning classifier, which provides automatic identification. Experiments were carried out by twelve volunteers, who walked while wearing four UWB boards (placed on the head, wrist, ankle, and in a trouser pocket). The off-line evaluation considered a set of different possible configurations in terms of number and position of the wearable devices. Despite a relatively low sampling frequency of 10 Hz, the results are promising: average identification accuracy is as high as $\sim 96\%$ with four devices, and above 90% with three devices (wrist, trouser pocket, ankle). This novel approach may enhance the accuracy of inertial-based systems for continuous user identification.

1. Introduction and Related Work: Wearable devices provide the opportunity to gather information about their users with unprecedented detail. The availability of a large amount of personal data, including movement patterns and physiological measurements, paved the way to the development of novel applications in well-being and telemedicine [1, 2, 3]. In this context, there is great interest in techniques for automatic user identification.

Identification can be defined as the recognition of the current user among a set of authorized ones. Applications greatly benefit from this possibility, as they can automatically adapt their mode of operation according to the identity of the current user. In the typical scenario, a device (or a set of devices) is time-shared by a group of users, such as the members of a family, a group of athletes, or a group a patients. Thanks to automatic identification, the wearable device can infer who is the current user and then provide customized services. For example, it may activate user-specific sensors, use personalized pattern recognition parameters, as well as perform automatic labeling of collected data.

Everyone has a different way of walking, and as a consequence gait has been extensively studied as an important biometric information source [4, 5]. Typically, gait-based identification on wearable devices relies on the analysis of the acceleration samples collected by one or more accelerometers. In the seminal work presented in [6], fifty users were asked to walk for 20 m while wearing a tri-axial accelerometer in a front trouser pocket. An analysis based on the absolute distance among acceleration samples in gait cycles showed a recognition rate of $\sim$86%.

More recent work focused on the use of common smartphones as sensing devices. For example, in [7], thirty-six individuals performed a set of supervised activities while wearing a smartphone. As it turned out, the activities offering the best information for identification are jogging and walking, with an accuracy in the 90-92% range. Gait-based identification proved to be effective also in uncontrolled environment: experiments based on acceleration traces from ten volunteers demonstrated that more than 90% accuracy can be achieved [8]. Identification can be performed successfully also when acceleration patterns are collected at the wrist, a position characterized by reduced invasiveness [9].

The use of UWB radios in wearable devices has been recently investigated, as it brings about accurate indoor localization and limb movement tracking [10]. Wearable UWB was adopted in gait analysis to estimate the distance of feet from the ground [11]: small antennas mounted in proximity of the user's heel and toe were used to transmit a signal and receive it after reflection from the ground. Similarly, the flexion angle of a knee was measured using two UWB wearable antennas, positioned at the user's thigh and shank [12]. A preliminary evaluation of UWB-based step length estimation was presented in [13], where collection of data was carried out by means of two UWB antennas mounted on the subject's feet and three anchors. Flexible UWB antennas were developed to ease the adoption of such technology in wearable applications [14]. In particular, the performance of printed antennas based on conductive polymers remains good also when crumpled because of clothes bending. UWB was also used for identification purposes, but according to a non-wearable approach [15]: a transmitter and a receiver were mounted on the top of a door frame; the UWB signals, scattered by the body of people passing through the doorway, were used to predict the identity of the user by means of unsupervised feature learning and classification; accuracy was approximately 80% with eight users. A similar non-wearable approach was proposed for human fall detection in [16], showing promising outcomes.

In this letter, a novel approach to the problem of user identification through gait analysis is presented. The proposed method takes advantage of wearable UWB technology: users are supposed to carry two or more devices embedding UWB transceivers, which enable the estimation of interdistances between worn devices in real time. The pattern of such interdistances during gait activity is analyzed to achieve identification. To the best of our knowledge, this is the first time that gait patterns are analyzed, for identification purposes, by means of distances estimated through UWB.

It is foreseen that wireless technologies, like UWB, will be an integral part of future wearable systems [17]. In such body sensor networks, UWB-based information could be fused with inertial data in order to provide better identification accuracy. Reliable identification, in turn, will play a key role in enabling personalized applications related to healthcare and well-being.

2. Method: The method is based on the idea of identifying the user by observing the interdistances between a set of wearable devices during gait periods. This approach is motivated by the increasingly popular adoption of wearable devices. Examples include smart-watches, smart-glasses, and smart-shoes. Also smartphones are frequently "attached" to the user's body (e.g carried in a pocket) and thus they partially belong to the

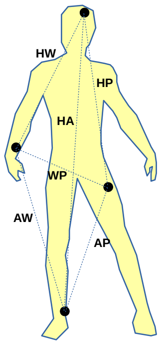

Figure 1: UWB sensors and the six interdistances: ankle-pocket (AP), wrist-pocket (WP), ankle-wrist (AW), head-pocket (HP), head-ankle (HA), and head-wrist (HW).

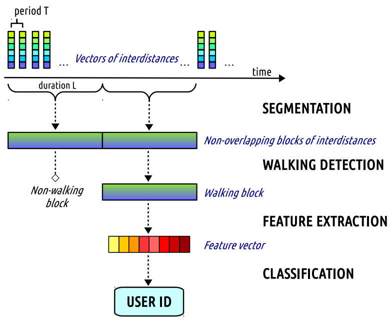

Figure 2: Overview of the proposed method.

wearable category. Another motivating reason is represented by the availability of low-cost transceivers able to estimate, with reasonable accuracy, the distance from another transceiver via UWB. An example is provided by the IEEE 802.15.4-2011 UWB standard.

Let us call XY the interdistance between devices X and Y. Interdistance XY is computed as the average of the measurements provided by the devices at its two ends (namely X and Y). Figure 1 depicts a system based on four devices, and thus characterized by six interdistances. With a period T, each device estimates the distance from all the other devices using two-way ranging. A vector $\mathbf{u}$ of interdistances is thus produced with period T. Let us call $\mathbf{u}_{jT}$ the vector of interdistances produced at time jT with j a non-negative integer. Interdistances are analyzed in non-overlapping blocks with fixed duration (equal to L). The ith block thus contains all $\mathbf{u}_{jT}$ with $jT \in [iL, (i+1)L)$. All blocks that correspond to walking periods are used to identify the user, whereas remaining blocks (i.e. those belonging to other activities) are discarded. To identify the user, first a vector $\mathbf{v}_i$ of features is extracted from the ith block of interdistances. Then, $\mathbf{v}_i$ is fed into a classification system which provides the estimated identity of the user during such interval. The classification system is supposed to be previously trained with labeled data (supervised training). An overview of the main phases of the method is depicted in Figure 2.

2.1. Prototype: A prototype of the proposed method was implemented using four DecaWave EVB1000 boards. The EVB1000 board is based on a DW1000 IEEE 802.15.4-2011 UWB compliant wireless transceiver and an STM32F105 ARM Cortex M3 microcontroller. The four boards were enclosed in small plastic boxes and powered by means of powerbanks connected via USB cables. The user is supposed to wear up to four devices. Thus, two boards were attached to the right wrist and the right ankle to mimic the presence of a smart-watch and a smart-shoe; a board was carried in the left trouser pocket to emulate the presence of a smartphone; another board was attached to a hat to emulate the use of a pair of smart-glasses. Transceivers were set up to operate at 3.993 GHz with a datarate of 6.8 Mbps. Distances were estimated by all transceivers according to the two-way ranging mode. Interdistances between the four nodes were collected at 10 Hz, which is the maximum frequency allowed by the adopted combination of boards and sampling software.

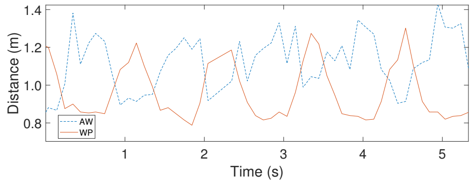

Figure 3: Two of the collected distances during five seconds of gait.

2.2. Collection of data: Twelve volunteers were recruited and involved in a data collection campaign. Age: 24.8 ± 6.5 yr, height: 171.7 ± 8.7 cm, weight: 70.3 ± 10.7 kg, Body Mass Index (BMI): 23.8 ± 3.0 km/m^2 (mean $\pm$ std. deviation). The characteristics of the single users are reported in Table 1. It is interesting to note that eight users fall within a rather small range of height (from 172 to 179 cm). This makes the identification process possibly more difficult, as the length of limbs, and thus interdistances, tend to be characterized by small changes across users.

Each user was asked to walk for approximately 60 s while wearing the four UWB boards. One of the boards was connected to a portable PC via USB, where ranging information was logged using the TREK1000 software [18]. Figure 3 shows the periodic behavior of two distances, AW and WP, during approximately five seconds of gait.

Data was saved onto persistent memory and analyzed off-line to ensure repeatability of experiments. In particular, this allowed us to explore the impact of some parameters of operation on identification accuracy and the efficacy of different classification approaches in the considered problem.

The collected dataset is publicly available at:
`http://vecchio.iet.unipi.it/vecchio/data`.

2.3. Identification: Interdistance samples are organized in non-overlapping blocks. A walking detection technique is supposed to be used to retain only the blocks containing gait data. This is a reasonable assumption, as previous work showed that it is possible to achieve high accuracy in walking detection with body-worn UWB sensors [19]. In addition, a regularity test like the one proposed in [8] could be included to further remove non-walking data, as gait cycles are expected to produce a periodic pattern.

Table 1 Users' characteristics.

User	**Gender**	**Age** (yr)	**Height** (cm)	**Weight** (kg)	**BMI** (kg/m^2)
1	F	25	171	80	27.4
2	F	25	165	70	25.7
3	M	19	179	69	21.5
4	M	23	179	65	20.3
5	M	19	176	65	21.0
6	M	22	179	63	19.7
7	F	25	155	56	23.3
8	F	21	156	60	24.7
9	M	25	172	73	24.7
10	M	25	173	67	22.4
11	M	25	179	95	29.6
12	M	44	177	81	25.9

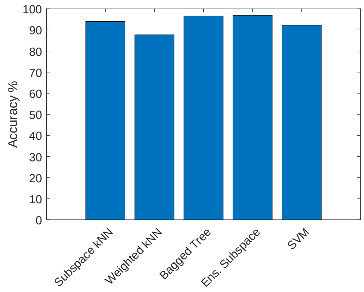

Figure 4: Accuracy obtained by the five considered methods.

In the proposed identification method, blocks associated to gait periods are processed to extract a vector of relevant features (feature extraction). More precisely, the following features are calculated for each interdistance: *mean*, *standard deviation*, *skewness*, *root mean square* (RMS), *min-max* (the difference between the maximum and minimum value in a block), *kurtosis*, *mean crossing rate* (the number of times the mean value is crossed in a block), *inter-quartile range* (IQR), *mean absolute deviation* (MAD, a robust measure of statistical dispersion) [20], *average absolute acceleration variation* (AAV), *min*, *max*. AAV, which has been previously used in similar contexts, is calculated as follows:

$$AAV = \frac{1}{S-1}\sum_{i=1}^{S-1}|x_{i+1} - x_i|$$

where x_i is the ith sample in the block and S is the number of samples in the block [21]. In the end, for each segment, a vector $\mathbf{v}$ containing 72 elements is produced (twelve feature functions, computed on the six interdistances in $\mathbf{u}$). Finally, the vector of features is used to feed a classifier, which returns the predicted user identity.

3. Results and Discussion: Five classification methods were considered: Subspace kNN [22], Weighted kNN [23], Bagged Tree [24], Ensemble Subspace Discriminant [25], and Support Vector Machine (SVM) [26]. In detail, the implementation of the methods provided by Machine Learning toolbox of MatLab 2018b was adopted. To calculate the accuracy of the methods, ten-fold stratified cross validation was used. In ten-fold cross validation, the dataset is divided in ten disjoint subsets of roughly the same size. Nine subsets are used to train the considered classification method, whereas the remaining subset is used to evaluate the method on previously unseen data. The process is repeated so that all the subsets are used in the evaluation phase, then results are averaged. Stratified means that when the subsets are generated, the original frequency of the different classes is preserved.

Identification attempts occurred at every block, and accuracy is defined as the percentage of blocks where the user was correctly identified.

We first evaluated the impact of the block duration on the average performance of the considered classifiers. For L we considered the set of values ranging from 1.0 s to 3.0 s, with step equal to 0.5 s. This interval was chosen because the typical duration of a stride is between 1 and 2 seconds, so the considered values allowed us to explore the effect of blocks with a duration that goes from below the typical stride duration to approximately two times the typical stride duration. Table 2 shows that all block durations equal to or above 1.5 s are able to provide excellent results. A duration of 1 s produces slightly lower accuracy values, probably because it is too short to capture a full gait cycle for most of the users. The other results presented in this section are based on $L = 2$ s. Such value is able to

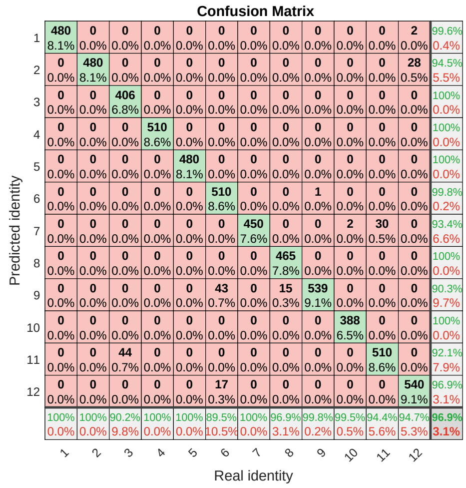

Figure 5: Confusion matrix obtained with Ensemble Subspace Discriminant.

provide the best average results for the considered classifiers, and at the same time provides quicker reaction times with respect to 2.5 s.

The accuracy obtained by the five methods, averaged over all users, is shown in Figure 4. The method that provided the best results is Ensemble Subspace Discriminant (ESD), with an accuracy equal to 96.9%. The performance obtained with the other methods is also almost excellent, with the exception of Weighted kNN that is characterized by a lower accuracy rate. Overall, results confirm that an accurate recognition of the identity of the user is possible when using the proposed method. To further improve identification accuracy, majority voting methods operating on multiple blocks can be used (as the one suggested in [8]). Figure 5 shows the confusion matrix obtained with ESD (30 runs, ten-fold stratified cross validation). The off-diagonal cells correspond to misidentified users. The rightmost column shows the percentages of instances predicted to belong to each user that are correctly and incorrectly classified (usually called precision and false discovery rate, respectively). The bottom-most row shows the percentages of instances belonging to each user that are correctly and incorrectly classified (recall and false negative rate, respectively). For example, User 3 is sometimes misidentified as User 11. The classifier obtained precision rates above 90% for all users, and recall rates above 90% for eleven users out of twelve.

3.1. Varying the number and position of the devices: The above results (Figure 4 and 5) have been obtained using all the available interdistances. We then studied how the single interdistances, and their combinations, contribute to the identification process. Let $\mathcal{I} = \{AP, WP, AW, HP, HA, HW\}$ be the set of all the interdistances

Table 2 Average accuracy obtained by the considered classifiers when varying the duration of blocks.

L (s)	Accuracy (%)
1.0	91.0
1.5	93.3
2.0	93.4
2.5	93.4
3.0	93.3

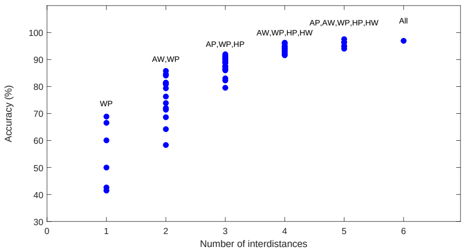

Figure 6: Accuracy obtained when using a subset of the available interdistances.

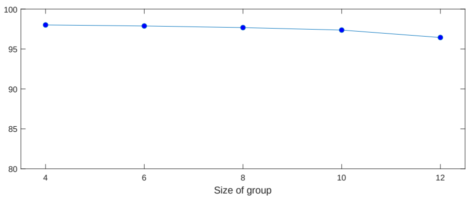

Figure 7: Accuracy when the size of the group of users changes.

(illustrated in Figure 1), and let $\mathcal{P}(\mathcal{I})$ be the powerset of $\mathcal{I}$ (excluding the empty set). We evaluated the identification accuracy for all $p \in \mathcal{P}(\mathcal{I})$ when using the ESD method (the one that provided the best performance). Figure 6 shows the obtained results averaged over all users. When a single interdistance is used, accuracy ranges within 41-69%. As expected, when the number of used interdistances gets larger accuracy gets better. For instance, when using two interdistances, accuracy approximately falls in the 58-86% range. The behavior of the system gets more consistent when using a larger number of interdistances (dispersion gets smaller). Figure 6 also reports the best subset p for each $|p|$. When a single interdistance is used, the one that provides the best identification accuracy is WP. When using two interdistances, the best accuracy is reached when using {AW, WP}. When using three, four, and five interdistances, the best accuracy is obtained when adopting the following subsets respectively: {AP, WP, HP}, {AP, WP, HP, HW}, {AP, AW, WP, HP, HW}.

Table 3 reports the results of a similar analysis when varying the number of devices (results are averaged over all users). When all four devices are used, as previously stated, the obtained accuracy is 96.9%. When three devices are used, the best accuracy is obtained using the ankle, pocket, and wrist configuration (90.9%). Similar results are obtained when using the ankle, head, and pocket configuration (88.7%), and the head, pocket, wrist configuration (87.4%). A lower accuracy is reached with the ankle, head, wrist configuration (83.0%). When using only two devices, the best results are achieved by the wrist, pocket configuration (68.9%).

Table 3 Accuracy when using four, three, or two devices.

N	Accuracy (%) and devices (A: ankle, P: pocket, H: head, W: wrist)
4	96.9 {A, H, P, W}
3	90.9 {A, P, W}
	88.7 {A, H, P}
	87.4 {H, P, W}
	83.0 {A, H, W}
2	68.9 {P, W}
	66.6 {A, W}
	60.0 {A, P}
	50.0 {H, A}
	42.6 {H, W}
	41.4 {A, H}

3.2. Varying the number of users: Accuracy of automatic identification methods is known to be dependent on the size of the group of users (identification in large groups is more difficult with respect to small groups). Figure 7 shows the average accuracy of the proposed method when the size of the group is varied. The average is computed over all k-combinations in the set of twelve users, with k in the 4–12 range (from the size of a family to the size of a team). The performance of the method is almost constant, this means that, for the considered range, the capacity of the method to separate the instances belonging to the different users in the feature space is almost unaffected.

3.3. Discussion and comparison with existing approaches: The results in Table 3 show that the proposed approach achieves high accuracy when at least three devices are used. More specifically, the devices should be placed near the wrist, pocket, and ankle to obtain an identification rate above 90%. This configuration, which may seem cumbersome, may become a reality for a significant portion of users in the near future. In fact, thanks to the recent explosion of the wearable market, it is already common for users to wear two devices placed at pocket and wrist position, like a smartphone and a smart-watch. In addition, smart shoes are already available for the general public and recent studies have shown their potential use in applications related to health and well-being [27, 28]. These three "devices"—smartphone, smart-watch, and smart-shoes—may actually enable the procedure shown in this paper.

As mentioned in the Introduction, wearable systems based on inertial sensors have been extensively investigated for identification [5]. The results shown in this work are in line with the best performing inertial-based approaches presented in the literature. Two recent examples are [8] and [29]. These systems used a single wearable device placed in a pocket or on the wrist, respectively. Estimated accuracy was above 90%. It should be highlighted that it would not be correct to directly compare accuracy values, as they were obtained on different experiments. Nevertheless, we can conclude that both approaches, inertial sensor-based and UWB-based, have shown promising results. As identification and authentication on wearable devices is going to be used even for critical applications (e.g., related to the user's health or to authorize payments), it will be paramount to ensure the best possible accuracy. This could be achieved by combining different biometric approaches, like those based on inertial sensors and the proposed one based on UWB technology.

Some works also investigated a completely different approach, based on ambient sensors like cameras mounted in the user's environment [30]. This approach achieved promising results as well [31], with an accuracy above 91% under cross-view conditions (i.e., using possibly different viewing angles) and above 98% with a single-view approach. However, ambient sensors can provide identification only in properly equipped environments, for instance in a "smart home" context. Instead, wearable sensors pave the way for new applications based on continuous and ubiquitous user identification and authentication.

4. Conclusion: Knowing the identity of the user can be useful for customizing the operations of wearable devices and their applications. Presented results show that the interdistances between wearable devices, collected during gait periods, represent valuable information for user identification. Moreover, the increasing adoption of wearable devices from the general public makes this information easier to be collected. It is important to highlight that the proposed approach represents an addition and not an alternative to current techniques, which are generally based on inertial sensors. Thus, information originating from UWB-enabled transceivers can be combined with information coming from accelerometers and gyroscopes to achieve even better identification results. In future work we plan to perform an in-depth evaluation of power consumption during real-time operation. Adaptive strategies could be exploited to dynamically change the sampling frequency based on the user's current activity. This will enable the system to select low-power modes and preserve battery life when the user is not walking. Another important research direction is the evaluation of the proposed method in uncontrolled environment. We foreseen that advancement in miniaturization will enable unobtrusive experiments during the user's daily routine. Finally, to improve the accuracy of the identification method, the use of a higher sampling frequency and majority voting techniques are worthy of further investigation.

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