Estimation of User's Orientation via Wearable UWB

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***Abstract*—User's orientation in indoor environments is an important part of her context. Orientation can be useful to understand what the user is looking at, and thus to improve the interaction between her and the surrounding environment. In this paper, we present a method based on wearable UWB-enabled devices. The position of the devices in space is used to estimate the user's orientation. We experimentally evaluated the impact of some operational parameters, such as the distance between worn devices, or some environmental conditions, such as the position of the user in the room. Results show that the accuracy of the method suits the needs of a wide range of practical purposes.**

***Index Terms*—ultra-wideband, orientation, wearable device, context-awareness.**

I. Introduction

Methods for estimating the position of the user in indoor environments received significant attention during the last years. The position of the user is, in fact, one of the most relevant information sources in context-aware systems and services [1]–[3]. When the user is located in a specific room, for instance, the set of possible activities the user may be carrying out can be restricted to a relatively small set (if she is in the kitchen, she may be cooking but not having a shower). This, in a smart-home scenario, generally improves the interaction between the user and the surrounding environment. The position of the user is also fundamental for applications in the e-health domain. Examples include recognition of a sedentary lifestyle, remote monitoring of elderly people, and detection of declining physical conditions [4]–[6].

Significant less attention has been devoted to recognizing the orientation of the user in indoor environments. However, this information can be extremely useful in several application domains. For example, in a museum, the orientation of the user could be fused with her position to automatically provide information about the painting/sculpture she is currently looking at. In a smart-home setting, orientation can be important to identify the appliance she wants to interact with. In general, orientation is a relevant component of the user's context, and thus can be useful to improve context-aware services and applications [7]–[9]. An easy way to obtain orientation information is my means of the magnetic sensor available on common smartphones and smartwatches. However, magnetic sensors are known to suffer from calibration problems and are negatively affected by the presence of ferromagnetic objects [10]. In addition, magnetic sensors provide orientation information with respect to the cardinal directions. As a consequence, in many cases, such information has to be converted according to a building-based reference system, because the latter is generally used at the application level. Another possibility is to use the gyroscope available on smartphones and other wearable devices: angular velocity with respect to the vertical axis can be integrated to obtain the orientation of the user. However, this approach, similarly to other dead-reckoning techniques, suffers from accumulation of errors during the integration phase, thus requiring a periodic acquisition of additional information from external sources [11], [12].

In this paper, we explore the use of Ultra-WideBand (UWB) localization methods for estimating the orientation of the user. UWB-based localization systems are gaining popularity to obtain positioning information in GPS-denied environments, such as buildings and factories. A UWB-based localization system generally relies on a set of devices with known and fixed position, called *anchors*. Anchors are able to estimate the distance between themselves and mobile nodes, called *tags*, with good accuracy (the distance estimation error can be in the order of 10 cm). Tags can be carried by users, e.g. embedded in smartphones, smart-wristbands or other smart-devices, or they can be attached to other mobile elements that have to be localized, e.g. robots in a factory. We suppose that the user is equipped with two tags, whose position is used to infer the user's orientation. Besides implementing a prototype, we studied the effects on the accuracy of estimation of a number of factors, such as the position of the user and the distance between the tags. Experimental results show that user's orientation can be estimated with adequate accuracy, and that the method can be compatible with the requirements of a large class of applications.

II. Related Work

The problem of estimating the orientation of the user has been generally faced by relying on Inertial Measurement Units (IMUs), possibly in combination with magnetic sensors.

The smartphone-based approach for indoor localization and tracking described in [13] uses an Improved Pedestrian Dead Reckoning (IPDR) algorithm to determine the route and the orientation of a person walking in a museum. IPDR detects steps when the acceleration magnitude exceeds a dynamic threshold; step length is estimated with a model which considers step frequency and acceleration variance; orientation is computed as a function of angular displacement and acceleration with respect to the vertical axis. The method also uses magnetic information: when the user stops in front

Work partially supported by the Italian Ministry of Education and Research in the framework of the CrossLab project (Departments of Excellence).

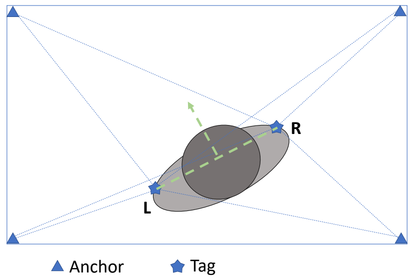


Fig. 1. The distances between tags and anchors are estimated via UWB; the position of tags is computed on the horizontal plane; the two devices are supposed to be positioned on the left-side of the body (L) and on the right-side (R).

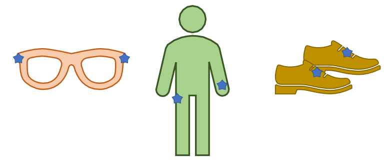


Fig. 2. Examples of possible configurations.

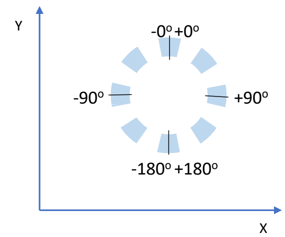


Fig. 3. We suppose that orientation is equal to 0° when the user looks in the same direction of the y-axis. Orientation increases up to +180° when rotating clockwise, and the opposite when rotating anti-clockwise.

of an artpiece, the magnetic sensor measures the magnetic flux densities in parallel and vertical directions with respect to the artpiece. Measurements are compared with previously recorded magnetic maps collected at fixed positions, then a matching algorithm finds the point with minimum error.

The somehow similar problem of finding the distance of the user from an object and the heading angle between the user's current moving direction and the object is studied in [14]. Two possible technologies, Bluetooth Low Energy (BLE) and UWB, are considered, as well as some configurations (with 6 objects or 1 object). Ranging information from the object, in case of BLE, is obtained by means of received signal strength. Ranging information is then fused with pedestrian dead reckoning to compute the desired output (the user is supposed to carry a smartphone). Results show that, when using 6 objects equipped with UWB transceivers, the orientation error is below 30° in approximately 80% of the cases.

An accurate estimate of the position and pose of a human operator is essential to guarantee safety in human-robot interaction environments. In [15], a *GypsyGyro-18* inertial motion capture system is used to determine the operator's pose and position. An additional UWB localization system is used to correct the error accumulation caused by the integration of acceleration data. In particular, UWB measurements are fused with inertial information by means of a Kalman filter.

A user tracking system for indoor scenarios, based on UWB and IMUs, is presented in [16]. Inaccuracies in UWB ranging are mitigated by means of information produced by accelerometers and gyroscopes. The system is able to produce a continuous trajectory by filling the gaps when not enough data are present.

A technique useful to estimate the posture of the user with UWB was presented in [17]. The distances between a set of wearable devices were processed to extract a set of feature and then given as input to a classifier, trained to recognize the current posture of the user (standing, sitting, walking, etc). Other examples of applications relying on wearable devices equipped with UWB also include [18], [19].

III. Method and Prototype

The user is supposed to wear two (or more) devices equipped with UWB transceivers. The distance of such devices from the anchors is used to compute their position in the adopted reference system. Then, their projected positions on the horizontal plane are used to estimate the orientation of the user (Fig. 1). The devices are supposed to be attached to the user's body and their mutual distances must be approximately constant. In addition, the worn devices must be separated by a non negligible distance on the horizontal plane. Possible configurations include a pair of smart-glasses, or a pair of smart-shoes equipped with two UWB transceivers (Fig. 2). The technique can also be applied to a user wearing a smartwatch on one of her wrists and carrying a smartphone in a pocket on the opposite side of her body. Let us call L and R the device on the left-side and right-side of the body, respectively.

The distances between anchors and tags are estimated with period T. Since the position of anchors in the considered reference system is known, the coordinates of the tags can be computed using multi-lateration. Once the position of the two devices is known, it is possible to compute the orientation of the segment connecting them (the dashed line from L to R in Fig. 1) and then the orientation of the user. In the above mentioned examples, the devices are placed at the sides of the user's body, thus the orientation of the user is orthogonal with respect to the segment connecting L and R. However, nothing prevents adapting the method to scenarios where the orientation is not orthogonal to the L-R segment. The only requirement is, from this point of view, that the position of the devices remains approximately fixed with respect to the body. When tags are worn on limbs (e.g. at the wrist, or at the feet), they are subject to spurious movements. To reduce the impact of spurious movements, a low-pass filter can be applied to the position of tags. This obviously reduces the rate of orientation estimates ($\leq 1/T$), as multiple values must be aggregated to produce a single output. Beside spurious movements, the position of tags is generally affected by errors, introduced by inaccurate range estimates. Thus, the adoption of a low-pass filter is going to be beneficial also from this point of view.

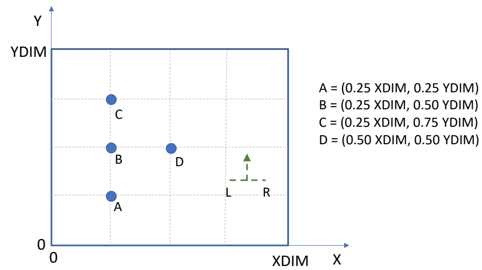


Fig. 4. Positions considered in the rooms.

In this paper, orientation is computed according to the reference frame illustrated in Fig. 3. Let us indicate the real orientation of the user as θ, and the estimated orientation as $\hat{\theta}$. The difference $e = \theta - \hat{\theta}$ is the estimation error. The proposed method is rather simple but, as far as we know, it was not explored in the past.

We built a prototype of the system using the Decawave MDEK1001 development kit. The kit includes 12 development boards, equipped with a UWB transceiver compatible with the IEEE 802.15.4-2011 standard. Each board is controlled by a Nordic nRF52832 MCU, which also provides Bluetooth connectivity (which can be used to communicate with smart-phones and/or tablets). Four boards were used as anchors and were placed at the corners of a room. Other two boards were used as tags, according to the proposed scheme. Each anchor estimated the distance from the tags with $T = 0.1$ s. Distances were transmitted to a sink where they were used to estimate the positions of the tags in the room coordinate system. Data was logged and then analyzed offline.

IV. Experimental Evaluation

We experimentally evaluated the performance of the method in two scenarios, the static scenario and the mobile scenario.

Static Scenario. The goal was to evaluate the accuracy of the system when varying i) the distance between the two tags, ii) the position of the user in the room. The rationale for the evaluation of the impact of the L-R distance comes from considering the geometrical nature of the problem: if the position of a tag is affected by some error, then the error in the orientation estimate is going to be larger for small L-R distances than with large L-R distances. We decided to evaluate the performance of the system when varying the position of the user in the room because the distance estimation phase, between tags and anchors, is known to be slightly influenced by the presence of obstacles and/or walls.

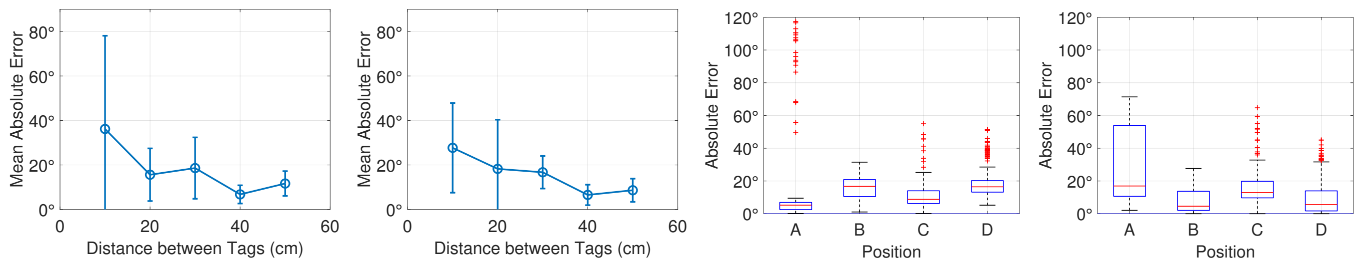
Experiments were carried out in two rooms. The first (room 1), had size XDIM = 3.6 m and YDIM = 3.6 m, the second (room 2) had size XDIM = 6.39 m and YDIM = 6.56 m (Fig. 4). Anchors were placed at the corners, attached to walls 2 m from the ground, in both rooms. Two tag nodes were placed on a table equipped with alignment guides. The tags were 0.79 m from the ground. The tags were accurately placed to have θ equal to 0°. The table, with the two tags, was placed in the four positions illustrated in Fig. 4. The four positions were selected according to the following reasons: D is the center of the room, B involves a shift towards one of the sides of the room, wheres A and C are aimed at understanding the behavior of the system when the user is close to one of the corners. We decided to include both A and C to understand if the symmetry of placement was preserved in terms of estimation errors. For every considered position (A, B, C, and D) we collected data using different L-R distances. In particular, for each position the L-R distances in the [10 cm, 50 cm] interval were considered (with step 10 cm). Thirty seconds of data were collected for each position and L-R distance. Fig. 4 shows also the L-R segment and the orientation of the user as an arrow. Figures 5a and 5b show the mean absolute orientation error ($avg(|e|)$) when varying the distance between the two tags, in room 1 and 2 respectively. In general, when the distance between the two tags increases, the estimation error becomes smaller. When the distance between the tags is in the 40-50 cm range, the absolute estimation error is in the order of 10°. Figures 5c and 5d show the absolute orientation error at the considered locations, for the two rooms. In this case, there is no clear picture: the method is slightly influenced by the position of the user in the room, but without a defined pattern. In fact, despite being geometrically better placed[1], position D does not provide significantly better orientation estimates. Moreover, the differences between room 1 and 2 may suggest that the system is somehow affected by the environment of operation.

Mobile Scenario. The experiment involving a real mobile user was carried out in room 2. The user wore the L device at the left wrist and the R device in the right pocket. The user moved back and forth along a straight line parallel to the x-axis. U-turns were always carried out clockwise. Fig. 6 shows the estimated orientation of the user when walking according to the previously illustrated scheme. The orientation is correctly estimated as $+90°$ when walking towards the right-hand side of the room (i.e. with the same orientation of the x-axis). Similarly, the orientation is correctly estimated as $-90°$ when walking in the opposite direction. The rising spike at the end of each $+90°$ plateau is due to the clockwise rotation of the user, when performing the u-turn at the right-hand side of the room: the orientation increases up to $+180°$, then goes to $-180°$, and finally increases to $-90°$ when the rotation is complete. Then the user starts walking in the opposite direction. Spikes do not reach the $\pm180°$ values just because of the relatively low sampling rate. The u-turn performed on the left-hand side of the room does not present discontinuities, as the orientation goes from $-90°$ to $+90°$.

V. Conclusion

UWB is increasingly used in consumer electronics as an effective solution of the indoor localization problem, which, as known, cannot be faced using GPS and similar technologies. The availability of an UWB chip in recent iPhone models

[1]Being the anchors placed at the corners of the room, central position are characterized by a better Geometric Dilution of Precision.



(a) Room 1 (b) Room 2 (c) Room 1 (d) Room 2

Fig. 5. Orientation estimation error when varying the distance between tags (5a, 5b: average value ± standard deviation), and when changing position in the rooms (5c, 5d).

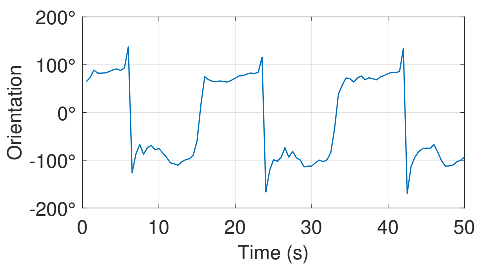


Fig. 6. Orientation of a user walking back and forth.

demonstrates that this technology is ready for mass-market adoption. In this paper, we propose to use UWB not only as a technology useful for localizing the user, but also for estimating his/her orientation in indoor environments. Orientation is an important element of users' context, and can be useful in a wide range of application scenarios. Experimental evaluation of the proposed method shows that the accuracy is adequate for the considered applications, with errors as low as $\sim 10°$. It is important to highlight that such results have been obtained without any calibration, without changes to distance-estimation mechanisms, and just processing the output of the localization system. It is thus reasonable to suppose that there is space for further improvements, e.g. by tuning the low-level mechanisms to the specific goal or by using antennas that are specifically designed to be used in proximity of the human body [20], [21]. The experiments involving a mobile user demonstrate that, despite the spurious movements caused by walk, the method still provides good results.

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