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WhereAreYou: an UWB relative tracking system for pedestrian using only ranging information

Luca Santoro, Matteo Nardello, Davide Brunelli, Daniele Fontanelli
Department of Industrial Engineering,
University of Trento, Trento, Italy
name.surname@unitn.it

***Abstract*—Wireless Sensor Networks have been applied to many application fields, such as building automation, assisted living, health care, positioning and tracking. One of the most active research area is the relative localisation, that is localising the nodes of the network with respect to each other but without a fixed, external and global reference. A common drawback of any relative localisation algorithm is that the solution can be only be found up to an isometric transformation. In this article, we propose a solution based on multidimensional scaling that identifies and adopts the minimum set of information to remove the geometric ambiguity and, unique in this respect, uses only ranging measurements. The characteristics of the algorithm are investigated via Monte Carlo simulation, validating the proposed system with an experimental test. In addition we propose a compact device prototype, based on ultrawide-band technology, used for the experiments and to practically show the technical viability of the solution.**

***Keywords*—Ranging-based positioning, Ultra-Wide Band, Indoor positioning, Outdoor positioning, Tracking, Pedestrian, Relative localisation**

I. Introduction

Wireless sensor networks (WSN) are becoming a reality in many application fields, manly due to the ever decreasing cost and reduced and effective power consumption. Low energy radio frequency modules for data transmission make WSN a viable solution for, e.g., health care [1], assisted living [2], fitness monitoring [3], building automation [4] and security [5] application scenarios.

WSNs have been widely applied to tracking and positioning systems. This is witnessed by the large literature solutions available in the field, where the adopted technologies range from ultrasound [6] to visible light [7], WiFi [8] to ultrawide-band [9]–[13]. One emerging problem in this research area refers to *relative* localisation, that is localising the nodes of the network with respect to each other but without a fixed, external and global reference. In such a case, each node has to reconstruct the location of all the other nodes with respect to a local reference. Application scenarios where this is turning to be quite useful are coverage, deployment and routing, especially if they are carried out autonomously by either human beings or robots.

Since one of the cheapest, yet effective, measurement that can be collected from WSN nodes is the relative range (e.g., using time-of-flight [14] or RSSI [15]). From the problem of relative localisation, distance-based solutions are commonly adopted, leveraging different techniques, such as trilateration, multilateration and multidimensional scaling (MDS) [16]–[18]. MDS algorithm represents the dissimilarity among the data as distances in a $\mathcal{N}$-dimensional space and it is used to create a map of the measurements. In the field of robot localisation, MDS is widely used to build the relative map of the agents whenever the system cannot rely on an external infrastructure [19]. Albeit the MDS turns out to be simple, it suffers geometric ambiguities, hence the map can be only estimated up to an isometric transformations, a common disadvantage of any relative localisation algorithm.

The problem of relative localisation and tracking has been addressed extensively using the MDS algorithm for robotic applications in conjunction with known positions of some team members. For example, in [16], [20], the authors extend and generalise the MDS algorithm including the knowledge of some nodes positions. In [21], [22], the geometric ambiguities are mitigated by the knowledge of the node velocities, which are used to correlate the relative maps at two consecutive time instants. A similar problem is investigated in [23], [24] considering the additional complexity enforced by the partial connectivity between the nodes. In [25], the authors build a cooperative navigation for coordinated-team based on dead reckoning, ranging data and particle filters, while [26] uses inter-node range measurements and odometry data to estimate the nodes positions. Wenchao et al. [27] address the ambiguity problem by letting one agent to move and using the displacement vector computed via inertial information to produce an analytical solution for the ideal noise-free case. All the presented literature entries are based on the (partial) knowledge of a subset of the node positions, thus automatically solving the roto-translation and flipping geometric ambiguities, or mitigating the inconsistencies induced by the MDS algorithm fusing additional available data, such as velocity and acceleration, to the ranging measurements. It turns then out that none of the solutions available may be applied when ranging measurements are the only source of information available, which makes the nodes lighter from a computation and a communication view point, not to mention the inherited node

Authors are with the Department of Industrial Engineering, Via Sommarive 9, 38123, Trento, Italy (e-mail: {luca.santoro, matteo.nardello, davide.brunelli, daniele.fontanelli}@unitn.it).

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power savings. This is the main focus of this paper that, as a side effect, let the solution to be applied to human beings endowed with ranging sensors and moving in a structured or unstructured environment. Our solution can then be applied, e.g., to a group of humans go hiking in the mountains or families going to a massive public event or to a large shopping mall: in all those cases, the knowledge of members' location can be a safety critical information.

More in depth, this paper aims at providing a preliminary study to build a lightweight systems, dubbed Where Are You (WAY), that is able to generate a common map for every agent belonging to the WSN and removing the ambiguities given only pairwise distances. We identify the minimal set of information needed to solve the problem and we additionally provide an uncertainty analysis, investigating via Monte Carlo simulations how the ranging uncertainties impact on the overall final estimates. Finally, we propose a compact device prototype, based on ultrawide-band technology, used for the experiments and to practically show the technical viability of the solution.

The rest of the paper is organized as follows. Section II presents and discusses the background mathematical model of the MDS algorithm and the ensuing ambiguities, formalising the problem to solve. In Section III, we present the relative positioning system with the uncertainty analysis. Finally, experimental results and the realised prototype are presented in Section IV. Section V closes this work with final remarks and possible improvements.

II. Background and Problem Formulation

Let us consider a set of nodes distributed in a certain area, representing a group of mobile agents (i.e., from now on, each agent is assumed to correspond to one node). We can describe each node by its unknown coordinate N_i and orientation γ_i, i.e.

$$N = \begin{bmatrix} N_0 & \cdots & N_n \end{bmatrix} = \begin{bmatrix} x_0 & \cdots & x_n \\ y_0 & \cdots & y_n \end{bmatrix}, \quad \gamma^T = \begin{bmatrix} \gamma_0 & \cdots & \gamma_n \end{bmatrix}. \tag{1}$$

Let us assume that the i-th node has access to the distances

$$\rho_{i,j} = \|N_i - N_j\| = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2}, \tag{2}$$

so that the symmetric squared Euclidean matrix

$$D = \begin{bmatrix} 0 & \rho_{0,1}^2 & \cdots & \rho_{0,n}^2 \\ \rho_{1,0}^2 & 0 & \cdots & \rho_{1,n}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n,0}^2 & \rho_{n,1}^2 & \cdots & 0 \end{bmatrix}, \tag{3}$$

can be built. Using the double centring matrix

$$H = I_{n+1} - \frac{e\ e^T}{n+1}, \tag{4}$$

where $e\ e^T = \mathbf{1}_{n+1} \times \mathbf{1}_{n+1}^T$, $\mathbf{1}_{n+1}$ is a column vector filled with $n+1$ ones and I_{n+1} is the identity matrix of dimension $n+1 \times n+1$ to transform 3, we obtain the Gram matrix

$$G = -\frac{1}{2} HDH, \tag{5}$$

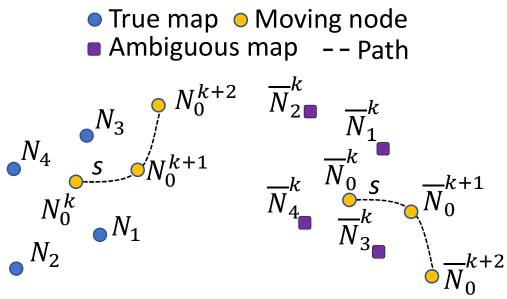

Fig. 1: MDS algorithm may generate an ambiguous map (purple squares), resulting in a wrong final reciprocal position reconstruction.

that turns pairwise Euclidean distances into pairwise inner products of vectors. Let us define with $P = [p_0, p_2, \ldots, p_n]^T$ the matrix of node coordinates that generates the symmetric Euclidean matrix in (3) and that is a replica of N in (1) but affected by the geometric ambiguities. In order to derive P, the following optimisation problem has to be solved

$$\arg\min_P ||G - PP^T||^2. \tag{6}$$

The solution to (6) is given by the eigen-decomposition of (5), i.e.

$$P = \begin{bmatrix} p_0 & \cdots & p_n \end{bmatrix} = \begin{bmatrix} \tilde{x}_0 & \cdots & \tilde{x}_n \\ \tilde{y}_0 & \cdots & \tilde{y}_n \end{bmatrix} = U\sqrt{V}, \tag{7}$$

where V is the diagonal matrix of the eigenvalues, U the eigenvector matrix of G in (5). As aforementioned, the points P are affine transformations of the original set N, i.e., the points in P are rotated and/or flipped versions of the points in N and both verifying the distance matrix D. More precisely, if there exists an angle $\theta \neq 2k\pi$ with $k \in \mathbb{N}$ such that

$$N = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} P = R(\theta)P \tag{8}$$

then a rotation ambiguity occurs. The flipping problem takes place if

$$N = \pm \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} P = \pm SP. \tag{9}$$

An example of geometric ambiguity is reported in Figure 1.

A. Problem formulation and solution overview

Given, $\forall i = 0, \ldots, n$, the ranging measurements $\rho_{i,j} + \eta_i$, where $\rho_{i,j}$ is given in (2) and where $\eta_{i,j}$ are the ranging uncertainties, we want to estimate the location of all the nodes $\hat{N}$ in a local reference frame centred in one agent, say N_0.

In order to tackle this problem, we first derive an estimate of $\hat{P}$ of the points P, solution of the minimisation problem (6). Then, we infer $R(\theta)$ and $\alpha \in \{-1, 1\}$ such that

$$\hat{N} = R(\theta)\alpha S\hat{P}. \tag{10}$$

For the this second step, we will use minimalistic information, that is the fact than only one agent, say N_0, moves and

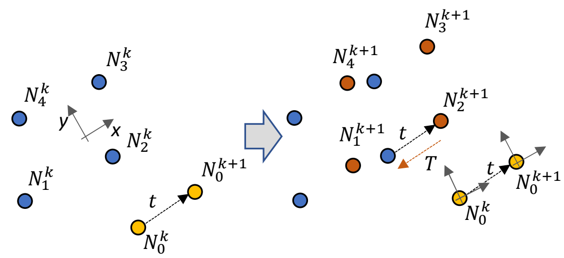

Fig. 2: Geometry of the translation vector T: the displacement computed by the moving node 0 is equivalent to the shift of all the other nodes. Back-projecting T reconstruct the moving node displacements t_k and t_{k+1}.

we assume the knowledge of its turning direction, i.e., if it turns clockwise and counter-clockwise. We will prove that this information is *necessary and sufficient* to solve the problem at hand. It is worthwhile to note that this information does not need a precise measurement, but just an indicator.

III. WhereAreYou: the WAY Algorithm

Let us consider three consecutive time instants, i.e., k, $k+1$ and $k+2$, in which the moving node N_0 starts from position N_0^k and moves towards $N_0^{k+1} = N_0^k + t_k$ and $N_0^{k+2} = N_0^{k+1} + t_{k+1}$, where $t_k = [\Delta x_k, \Delta y_k]^T$ and $t_{k+1} = [\Delta x_{k+1}, \Delta y_{k+1}]^T$ are two generic translation vectors, both different from zero (see Figure 1). Given the measurements $\rho_{i,j} + \eta_{i,j}$ for such three consecutive time instants, it is possible to build the matrices $\overline{D}^k$, $\overline{D}^{k+1}$, $\overline{D}^{k+2}$ described in (3) (we use the $\bar{\cdot}$ notation to denote the measurement results or the function of the measurement results). As described in Section II, it is then possible to compute $\hat{P}^k$, $\hat{P}^{k+1}$ and $\hat{P}^{k+2}$, solution of the optimal problem (6) given by (7).

Then, we first translate $\hat{P}^k$ centred with respect to the moving agent 0, i.e., $\hat{P}_k = \hat{P}_k - \hat{p}_{0,k}$, and then we align $\hat{P}^{k+1}$ to $\hat{P}^k$ by solving the following optimisation problem

$$\arg\min_{\theta,T} \hat{P} = P^k - (R(\theta)\alpha S P^{k+1} + T), \tag{11}$$

where θ and T describes the roto-translation between the two sets of points. The situation after this step is depicted in Figure 2: the moving node 0 at step k and $k+1$ computes the other nodes' position and centre $\hat{P}^k$ to $\hat{P}^{k+1}$ on itself. From the node 0 view point, the displacement t_k it had taken is exactly the translation T in an opposite direction (see Figure 2). As a side effect, the solution of Equation 11, once applied also to the points $\hat{P}^{k+1}$ to $\hat{P}^{k+2}$ returns the sequence of motions, i.e. the path, the node 0 has travelled. In essence, we have solved the problem of the localisation of node 0 in the relative frame (i.e., the one centred on the estimated initial position $\hat{p}_{0,k}$) and have solved the mapping of all the other nodes.

However, as discussed in the previous section and explicitly reported in (10), the roto-translation does not solve the problem entirely. Indeed, the flipping problem, modelled by α and S remains untouched, whatever is the number of measurement collected, as described in the following theorem.

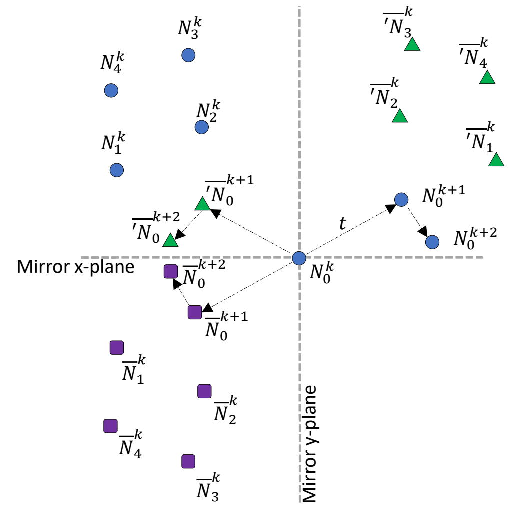

Fig. 3: Removing final ambiguity on the estimated map. Blue circles (N_i) represent the true map, while purple squares ($\overline{N}_i$) and green triangles ($'\overline{N}_i$) are the flipped solutions. Solution to (11) removes the set $\overline{N}_i$, while Corollary 2 removes the flipping given by $'\overline{N}_i$.

Theorem 1: Given a set of $m > 0$ node 0 motions, i.e., $N_0^{k+q} = N_0^{k+q-1} + t_{k+q-1}$, with $q = 1, \dots, m$, it is not possible to determine αS if no knowledge is given about t_{k+q-1}.

Proof: Let us consider the set N in (1) and its flipped version $\overline{N} = \alpha S$. Since $\|x\| = \|\alpha S x\|$ (indeed, $\|x\| = \sqrt{x^T x} = \sqrt{x^T S^T \alpha \alpha S x}$), it turns out that

$$\|N_0^{k+q} - N_i\| = \|\alpha S(N_0^{k+q} - N_i)\| = \|\overline{N}_0^{k+q} - \overline{N}_i)\|,$$

which is true for $q = 0, \dots, m$ and for an arbitrary number of nodes in the network, i.e., $\forall i = 1, 2, \dots$. This case is depicted in Figure 1. As a consequence, given the relative distances (2), we obtain the same set of matrices (3), hence the same solutions to (11). Therefore, without any knowledge about the translations t_{k+q-1}, it is not possible to retrieve αS, which concludes the proof. ■

One immediate consequence of Theorem 1 is that (11) can only estimate the roto-translation but not the flipping. This situation is depicted in Figure 3, where roto-translated locations $\overline{N}_i$ are removed by the solution to (11). The following corollary, instead, expresses the minimum amount of additional information needed to solve the flipping problem.

Corollary 2: Given a set of two node 0 motions, i.e., $N_0^{k+q} = N_0^{k+q-1} + t_{k+q-1}$, with $q = 1, 2$, it is possible to determine αS if the sign of the angle $\beta = \arctan \frac{\Delta y_{k+1} - \Delta y_k}{\Delta x_{k+1} - \Delta x_k}$, i.e., the relative angle between t_k and t_{k+1}, is known.

Proof: The knowledge of the sign of the angle β is equivalent to the knowledge of the change of direction for the moving agent, i.e., if it is rotating clockwise or counter-clockwise. It is evident to note that a flipping operator as αS transform clockwise rotations into counter-clockwise ones: the knowledge of the sign of β, hence, removes the flipping ambiguity. ■

The proof of Corollary 2 is clearly depicted in Figure 3, where the flipped locations ${}^{\bar{\jmath}}N_i$ are removed by the knowledge of the angle β: indeed, to be consistent with the distances among the nodes ${}^{\bar{\jmath}}N_i$, the moving node 0 should rotate clockwise from ${}^{\bar{\jmath}}N_0^{k+1}$ to ${}^{\bar{\jmath}}N_0^{k+2}$. The fact that the node has moved in counter-clockwise direction (motion between N_0^{k+1} and N_0^{k+2}), removes the flipping ambiguity.

A. Uncertainty analysis

To analyse how the ranging uncertainties impact on the final computation, we model the relative distance uncertainties $\eta_{i,j}$ as a white, stationary, zero mean process with standard deviation σ_ρ

$$\overline{\rho}_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} + \eta_{i,j} = \rho_{i,j} + \eta_i. \quad (12)$$

The distance matrix (3) is then computed using the square of (12), i.e.

$$\hat{\rho}_{i,j}^2 = \rho_{i,j}^2 + 2\rho_{i,j}\eta_{i,j} + \eta_{i,j}^2, \quad (13)$$

where $2\rho_{i,j}\eta_{i,j}$ has variance $4\rho_{i,j}^2$ and $\eta_{i,j}^2$ is distributed like a chi-square distribution with one degree of freedom. If we consider that $|\eta_{i,j}| << \rho_{i,j}$, it is possible to approximate

$$\hat{\rho}_{i,j}^2 = \rho_{i,j}^2 + \epsilon_{i,j}, \quad (14)$$

where $\epsilon_{i,j}$ follows a Gaussian probability density function with zero-mean and variance equal to $4\rho_{i,j}^2\sigma_\rho^2$. Since the estimation process of the node positions $\hat{P}$ is based on a non-linear solution 7, which involves an eigenvalue decomposition, it is very complex to derive an explicit solution to propagate the uncertainties starting from the single distance measurements, especially it the number of nodes in the network is larger than 4.

Therefore, the uncertainty analysis has to follow a statistical approach by means of Monte Carlo simulations. In particular, we evaluate the performance of the proposed system against 5 different values standard deviations $\eta_{i,j}$. To randomise on the node configurations, for each level of uncertainty we generated 1000 configurations randomly distributed on an area of 225 m^2. The result of the Monte Carlo simulations are reported in Table I. The system exhibits a linear behaviour with respect to the injected noise $\eta_{i,j}$. Notice that we chose to simulate the ideal case of $\eta_{i,j} = 0$ to validate in simulation the theoretical analysis reported previously.

IV. Results

In this section, the experimental test result is presented to validate the effectiveness of the solution. In addition, a description of the realised prototype and the hardware involved in the experiment is also described.

A. Hardware Implementation

To evaluate the proposed relative positioning system, a custom, battery powered, portable device was developed. The device, presented in Figure 4, is made of COTS components and was developed to be compact, energy-efficient and low-cost. It is based on an Espressif ESP32-S3[1] dual core MCU.

[1]https://www.espressif.com/en/products/socs/esp32-s3

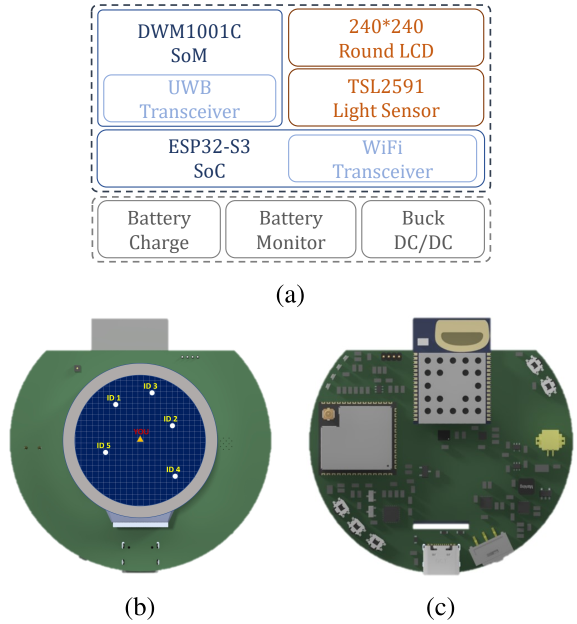

Fig. 4: (a) Schematic block of the proposed device. (b) and (c) 3D rendering of the proposed device.

It integrates a Qorvo DWM1001[2] SoM for distance measurements and it has a 240×240 LCD display for showing to the user the navigation map, remaining battery level and other useful information. Moreover, it is endowed a complete battery management system for both providing power to the device's peripheral and to charge the integrated LiPo battery and a Luminosity sensor to optimise the energy consumption of the LCD by dynamically change its backlight level. Finally, it integrates a 2000 mAh LiPo battery able to power the device for 5 to 8 hours, depending on WiFi connectivity. During the test, the UWB module was configured to use UWB Channel 5 ($f_c = 6489.6$ MHz, $BW = 499.2$ MHz), a preamble length of 128 symbols, the highest Pulse Rate ($PR = 64$ MHz), and the highest Data Rate ($DR = 6.8$ Mbps). Figure 4-(a) presents the architecture overview of the prototype, while device 3D model is presented in Figure 4-(b) and Figure 4-(c).

Regarding the communication protocol, a TWR [28] is adopted to estimate the distance between two nodes. In particular, the communication is organised into two phases: the first one regards the measurements, while the second is meant to share the data, according to Figure 5. The resulting update rate f has a quadratic dependency from the nodes number, i.e.

$$f = \frac{1}{\Delta(n-1)^2}\ , \quad (15)$$

where n is the number of nodes and Δ is a predefined time slot in which a node has to complete one TWR-cycle and share via wifi the measurements. For the experimental test $n = 6$, $\Delta = 5$ ms.

B. Experimental results

The proposed system is finally validated with a laboratory test using 6 anchors, with one that is able to move. We collect

[2]https://www.decawave.com/sites/default/files/dwm1001_datasheet.pdf

TABLE I: Monte Carlo analysis: Theoretical performance of the proposed system against 5 values σ_ρ. All the quantities are expressed in mm

	$\eta_i = 0$ mm				$\eta_i = 100$ mm				$\eta_i = 200$ mm				$\eta_i = 300$ mm				$\eta_i = 400$ mm			
ID	p_1	p_2	p_3	p_4	p_1	p_2	p_3	p_4	p_1	p_2	p_3	p_4	p_1	p_2	p_3	p_4	p_1	p_2	p_3	p_4
μ_x	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	-2	-2	-3	-1	4	-1	-1	-3	-3	-18	-8	-3	11	14	23	7
μ_y	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	-2	-5	-3	-1	1	-6	1	8	5	-11	3	-15	-17	-23	-13	-26
σ_x	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	78	72	75	75	150	157	150	150	229	228	236	222	313	291	289	294
σ_y	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	88	83	89	87	192	191	189	189	257	280	268	285	359	370	381	376

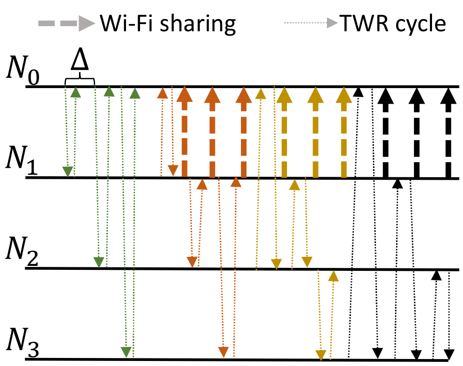

Fig. 5: Scheduling protocol.

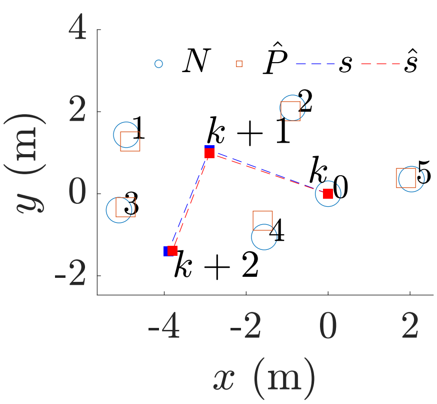

Fig. 6: Experimental results. N (blue circles) represent the true position of the nodes retrieved from the MoCap, $\hat{P}$ (red squares)) represent instead the estimated position using the proposed system. True displacement of the moving node is denoted with s (dashed blue line), while $\hat{s}$ is the estimated displacement retrieved form the algorithm (dashed red line).

100 inter-distance matrices for each positions, supposed to be taken at time k, $k+1$ and $k+2$. The result is reported in Figure 6. To generate a ground truth to assess the obtained results from the UWB relative positioning system, we have acquired the nodes' positions N_i from a Motion Capture (MoCap) system. In particular, the MoCap system adopted is provided by Qualisys with 7 Arqus A9 cameras. The optical tracking system is configured with a working frequency of

TABLE II: Comparison between the true nodes' position N and estimated one $\hat{P}$. All the quantities are expressed in mm.

	e_x	e_y	σ_x	σ_x
$\|N_1 - \hat{P}_1\|$	-95	163	55	119
$\|N_2 - \hat{P}_2\|$	53	82	100	115
$\|N_3 - \hat{P}_3\|$	-160	-70	116	97
$\|N_4 - \hat{P}_4\|$	38	-392	55	310
$\|N_5 - \hat{P}_5\|$	135	-28	175	74
$\|N_0(k+1) - \hat{P}_0(k+1)\|$	-6	-99	-	-
$\|N_0(k+2) - \hat{P}_0(k+2)\|$	81	12	-	-

240 Hz, with a residual error[3] of lees than 1 mm. Nodes coordinate estimation error are reported in Table II. The mean error on the reconstruction of the moving node in position $N_0(k+1)$ and $N_0(k+2)$ is also reported in Table II. Notice that $N_0(k)$ is known from the beginning: indeed, since we are referring to relative positions, $N_0(k)$ is assumed to be known and placed in the origin of the reference frame.

The experimentally retrieved ranging standard deviation is about $\sigma_\rho = 100$ mm. The experimental results shows a nice matching with the Monte Carlo simulations in Table I. We argue that the motivations for the non perfect matching could be traced to the non perfect-isotropic radiation pattern effect of the UWB antenna and the delay introduced by the internal circuitry. Moreover, although the non-line-of-sight (NLOS) condition is beyond the aims of this article, the data gathered during the experiments are intentionally collected without particular attention to possible NLOS conditions, i.e., a realistic conditions, which exacerbate the difference with the theoretical Monte Carlo simulations results. Finally, in the experimental results collection has been performed without a calibration phase, since the nodes are assumed to be deployed randomly in the environment.

V. Conclusion

This paper presents a solution of the relative positioning for people using only ranging information. The WAY algorithm thus defined considers one single node motion and it is able to solve the problem with minimalistic information about moving node, i.e., the fact that the node turns clockwise or counter-clockwise. The UWB is chosen as enabling technology, thanks to its well-known characteristics in this kind of applications. The results obtained by the Monte Carlo simulations and the first validation in-field are very promising, with a mean

[3]The adopted calibration procedure can be found here https://docs.qualisys.com/getting-started/content/getting_started/running_your_qualisys_system/calibrating_your_system/calibrating_your_system.htm

RMSE position error below 20 cm. In addition a prototype was developed to run the proposed algorithm, paying attention to the power consumption and encumbrance of the portable device. In future work, we are aiming to implement the estimated map sharing from the moving node to the others, while we are planning to update the map when all nodes are free to move using a Kalman filter-like approach, avoiding the necessity to compute a minimisation problem and consequently increasing the overall update rate.

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