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Decentralized Positioning Algorithm for Relative Nodes Localization in Wireless Body Area Networks

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Abstract *Wireless Body Area Networks* (WBAN) can offer motion capture capabilities through peer-to-peer ranging and on-body nodes positioning, by relying on transmitted signals and data packets. In this paper, we describe a solution to localize wireless nodes relatively to a body-strapped *Local Coordinate System* (LCS). In particular, we consider coupling a *Constrained Distributed Weighted Multi-Dimensional Scaling* algorithm (CDWMDS), which asynchronously estimates the nodes' locations under geometric constraints related to fixed-length links, with new messages censoring, location updates scheduling and forced measurements symmetry. The idea is to mitigate error propagation (e.g. with respect to the fastest nodes), as well as harmful effects caused by the loss of critical packets. We also introduce a real beacon-aided *Time Division Multiple Access* (TDMA) scheme to suitably support both peer-to-peer ranging and decentralized positioning transactions under real-time constraints. Simulation results are provided to assess the performance of the proposed solution for various levels of connectivity and ranging quality, showing interesting gains on the average location error per node under moderate pedestrian mobility. Comparisons are finally provided with a more conventional centralized and synchronous *Multidimensional Scaling* (MDS) algorithm that would require completing the matrix of measured distances under partial network connectivity.

Keywords Cooperative Localization, Distributed Weighted Multi Dimensional Scaling, Geometric Constraints, Multidimensional Scaling, On-Body Ranging, Time Division Multiple Access, Time Of Arrival, IEEE 802.15.6 Standard.

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1 Introduction

Wireless Body Area Networks (WBANs), which have been subject to growing research interests for the last past years [1], [2], [3], are on the verge of covering unprecedented needs in various application fields such as healthcare, security, sports or entertainment. More recently, such networks have been considered for raw motion capture applications based on opportunistic and stand-alone radiolocation functions. Under mesh or quasi-mesh topologies, mobile on-body nodes can indeed be located in a cooperative fashion out of transmitted radio links, by using peer-to-peer range measurements. In turn, this new WBAN capability could even represent an appealing alternative to costly and geographically restricted video acquisition systems for large-scale indoor motion capture purposes. In this context, the *Impulse Radio - Ultra Wideband* (IR-UWB) technology [4], [5], which benefits from fine multipath resolution capabilities, enables to perform such range measurements through precise *Time Of Arrival* (TOA) estimation. Radiolocation considerations apart, the recent

IEEE 802.15.6 radio standard issued for WBAN applications also promotes IR-UWB as a relevant low power physical layer [6].

But applying cooperative localization into WBAN still imposes to overcome numerous challenges. Wearable sensors are subject to drastic constraints in terms of complexity and consumption, but also to highly specific mobility patterns. Most of the related algorithms described in the literature adversely consider centralized resources and synchronous calculi, which may not be totally compliant with real-time constraints under human mobility [1], [2], [3], [7], [8]. [1] has used the *Non Linear Least Squares* (NLLS) algorithm, which consists in minimizing a global quadratic cost function using the Gradient descent method incorporating the peer-to-peer range measurements. [2] and [8] adapt a centralized classical *Multidimensional Scaling* (MDS) for on-body motion capture applications and pose estimation. In [8], the authors introduce additional constraints relying on the prior knowledge of minimal and maximal feasible distances related to the body dimensions (and thus some kinds of geographical limitations). In [3] the centralized *Maximum Likelihood* estimator has been considered, introducing other constraints relying on the actual positions of on-body mobile nodes. Centralized and synchronous approaches indeed require that all the unknown nodes' locations are simultaneously estimated after relaying inter-nodes measurements to a central coordinator. Moreover, they often under-exploit the available potential of mesh topologies by sticking with non-cooperative links (i.e. uniquely with respect to fixed anchors) [2], [3]. Besides, some of the existing solutions also consider *a priori* parametric models [3] incompatible with the location-dependent and unpredictable mobility. Recently, a new *Constrained Distributed Weighted MultiDimensional Scaling* (CDWMDS) algorithm has been proposed in [9] for WBAN motion capture, providing better immunity against latency effects observed within classical centralized schemes, as well as better adaptability to local nodes velocities. In this solution, originally inspired by the technique described in [10], the locations of mobile on-body nodes are asynchronously estimated in a body-strapped *Local Coordinate System* (LCS), using information from their 1-hop neighbors. Fixed-length links (e.g. between the hand's wrist and the elbow) are also incorporated as geometric constraints, hence limiting the number of required on-line measurements, while still benefitting from the mesh potential. On this occasion it has been illustrated that the fastest nodes (e.g. those placed at legs' extremities) could significantly degrade the average location accuracy. In this context, [11] proposed to improve the nominal CDWMDS formulation, by applying an unilateral censoring and/or a scheduling of the most demanding nodes when updating estimated positions.

In this paper, we propose some new improvements to the nominal CDWMDS [11], by applying an unilateral censoring and/or a scheduling of the most demanding nodes when updating estimated positions, and by forcing the measurements symmetry between each pair of on-body nodes. The idea is to mitigate the effect of outliers or packet losses, but also to avoid error propagation and divergence issues in the retained decentralized positioning approach. Then we introduce a beacon-aided *Time Division Multiple Access* (TDMA) scheme that offers fine synergy between communication and radiolocation means, while supporting both peer-to-peer ranging and decentralized positioning transactions under real-time constraints. We thus make possible a more realistic performance assessment, while accounting for underlying latency issues and investigating the impact of network connectivity or measurements quality. Finally, we compare our solution with a more conventional *Multidimensional Scaling* (MDS) algorithm, which has been considered recently for motion capture applications in a WBAN context [8]. The latter would anyway require completing the matrix of measured distances under partial network connectivity, contrarily to our proposed asynchronous and decentralized approach.

The paper is structured as follows. In Section 2, we introduce the on-body relative localization problem. Section 3 then presents the core cooperative localization algorithms, including the classical *Multi-Dimensional Scaling* (MDS), the initial Constrained DWMDS and the proposed enhancements. Section 4 presents a suitable *Medium Acces Control* (MAC) superframe structure, along with the supported ranging protocols. In Section 5, we describe our evaluation framework, including the simulation set-up and parameters, as well as the localization performances obtained under realistic body mobility. We also provide further comparisons with the standard MDS algorithm. Finally, Section 6 concludes the paper.

2 Problem Formulation

The wireless devices placed on the body can be first classified into two categories. Simple mobile *nodes* with unknown positions (under arbitrary deployment) must be located relatively to reference *anchors* nodes, which are attached onto the body at known and reproducible positions, independently of the body attitude and/or mobility (e.g. on the chest or on the back). A set of such anchors define a stable Cartesian *Local Coordinate System* (LCS), which remains unchanged under body mobility. Mobile nodes are then located in the LCS,

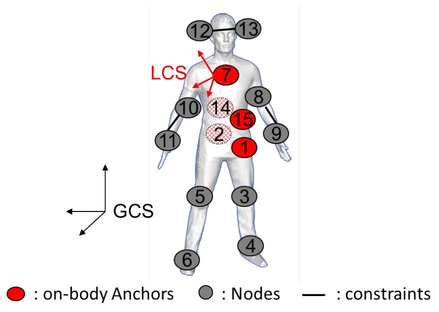

Fig. 1 Typical deployment scenario for the relative localization of on-body wireless nodes (grey circles) with respect to a body-strapped Local Coordinate System (LCS) defined by fixed anchors (red circles).

using peer-to-peer range measurements between pairs of devices (i.e. between mobile nodes or between nodes and fixed anchors).

Figure 1 shows a typical deployment scenario, where the LCS is obviously in movement and misaligned relatively to any *Global Coordinate System* (GCS). In the following, $X_i(t)_{i=1}^{m}$ represent the $3D$ known positions of the m anchors at time t defined into the LCS, where m should be larger than 3. $X_i(t)_{i=1}^{n}$ represent the true $3D$ unknown positions of the n mobile nodes deployed on the body, at time t. Let $\widetilde{d}_{ij}(t)$ be a range measurement available at time t between nodes i and j and let l_{ij} be a constant distance (i.e. constant over body mobility), which will be considered hereafter as a constraint.

Given all the available range measurements, e.g. based on IR-UWB TOA estimation [4], [12], on existing constraints related to the body geometry and on the known anchors' locations, the problem that we want to solve is to estimate the positions of the mobile nodes into the LCS.

3 Localization Algorithms

3.1 Conventional Multi-Dimensional Scaling (MDS)

Applied into our localization problem, the goal of MDS is to find the positions of on-body nodes so that the distances between the estimated positions fit as much as possible to a set of cooperative range measurements between the nodes. Classical MDS formulations are characterized by three basic steps, as follows. The first step consists in constructing a squared distances matrix. The second step consists in locating the nodes into a reference system, which is defined by a geometrical transformation of the LCS (i.e. rotation and translation). The third step is the restoration of the coordinates system by changing the basis of the positions estimated at the second stage [13], [14].

As seen in the previous section, a WBAN is first characterized by n on-body mobile nodes and m anchors, with respective positions $X_i(t)_{i=1}^{m+n}$ forming the overall network-level vector of positions $X(t) = [X_1(t), ..., X_m(t), ..., X_{m+n}(t)]$ at time t. Assuming full network connectivity (i.e. all pair-wise distance measurements are available) and that the observed distance $\delta_{ij}(t)$ between each pair of nodes i and j at time t is equal to the true corresponding distance, then it comes:

$$\delta_{ij}^2(t) = d_{ij}^2(t) = (X_i(t) - Xj(t))^T(X_i(t) - Xj(t)) \quad (1)$$

Writing the squared distance as $d_{ij}^2(t) = X_i(t)^T X_i(t) - 2X_i(t)^T X_j(t) + X_j(t)^T X_j(t)$, and placing the centroid of the configuration at the origin, the matrix of inner products between the nodes can be expressed as follows:

$$B = X(t)X(t)^T = -\frac{1}{2}HDH \quad (2)$$

$$H = I - \frac{1}{n+m}\mathbf{e}^T\mathbf{e} \quad (3)$$

where $D = [d_{ij}^2(t)]_{i,j=1}^{n+m}$ and $\mathbf{e}$ is a $1 \times (n+m)$ vector of ones. Since B is symmetric, positive semi-definite and of rank dimensionality, it can now be written in terms of singular value decomposition as $B = UVU^T$, where V is a diagonal matrix containing the $n+m$ eigen values of B and U is the corresponding matrix of eigen vectors. Thus as $X(t)X(t)^T$, $X(t)$ is now given as:

$$X(t) = UV^{\frac{1}{2}} \quad (4)$$

One major problem with this classical MDS algorithm is the need for complete and noise-free distances matrices, with a full knowledge of all the pairwise distances, what is highly unlikely in realistic wireless cases (e.g. due to connectivity losses or deliberate topology restrictions). Nevertheless, such classical MDS formulation has already considered for WBAN localization in [8], where coarse geometric constraints, relying on the prior knowledge of minimal and maximal feasible distances under radio connectivity, has been introduced to complete empty entries of the input range measurements matrix. Another problem more generally inherent within centralized approaches is the latency effect (i.e. the time elapsed between the collection of the distance measurements and the delivery of location estimates), whereas the body gesture can change rapidly during the measurements collection step, hence degrading significantly localization performances.

Motivated by the possibility to operate under partial connectivity and possibly large measurement errors, by latency reduction gains and by the natural asynchronism potential enabled for node's localization, we thus seek to estimate the nodes' positions using a distributed version of the MDS. A comparison between the classical MDS algorithm used in [8] and our distributed version will be presented in terms of localization accuracy in Section 5.

3.2 Constrained Distributed Weighted Multidimensional Scaling Algorithm (CDWMDS)

As described in [10], a new *Distributed Weighted Multi-Dimensional Scaling* (DWMDS) allows each node i with unknown coordinates to localize itself by minimizing a local cost function as follows:

$$\begin{aligned}\hat{X}_i(t) = \underset{X_i(t)}{\operatorname{argmin}}[&\sum_{j=1}^{n} w_{ij}(t)(\delta_{ij}(t) - d_{ij}(\hat{X}(t)))^2 \\ &+ \sum_{j=n+1}^{n+m} 2w_{ij}(t)(\delta_{ij}(t) - d_{ij}(\hat{X}(t)))^2 \\ &+ r_i(t)||X_i(t) - \overline{X}_i(t)||^2] \end{aligned} \quad (5)$$

where $\hat{X}_i(t)$ is a vector containing the estimated $3D$ coordinates of node i, n and m are respectively the number of mobile nodes with unknown locations (i.e. nodes must be localized) and the number of anchors placed on the body, $\hat{X}(t)$ is the matrix whose columns contain the estimated positions for all the nodes at time t, $\delta_{ij}(t)$ is a so-called observed distance between node i and j at t, $d_{ij}(\hat{X}(t))$ denotes the Euclidean distance between i and j built out of estimated coordinates, which is equal to $\sqrt{(\hat{X}_i(t) - \hat{X}_j(t))^T(\hat{X}_i(t) - \hat{X}_j(t))}$, $w_{ij}(t)$ is a weight value, which reflects the connectivity and the accuracy of the range measurements between nodes i and j at time t, such that inaccurate measurements are down-weighted in the cost function, $\overline{X}_i(t)$ is a vector with prior information about the position occupied by node i at time t, while $r_i(t)$ quantifies the reliability of this prior information.

As described in [10], at each time t, the dynamic equation 5 is iteratively resolved to estimate the nodes' positions. If $\hat{X}^{(k)}(t)$ is the matrix of the estimated positions at iteration k, node i derives its current coordinates update $\hat{X}_i^{(k)}(t)$ as follows:

$$\hat{X}_i^{(k)}(t) = a_i(t)(r_i(t)\overline{X}_i(t) + \hat{X}^{(k-1)}(t)\mathbf{b}_i^{(k-1)}(t)) \quad (6)$$

where

$$a_i(t) = \sum_{j=1}^{n} w_{ij}(t) + \sum_{j=n+1}^{n+m} w_{ij}(t) + r_i(t) \quad (7)$$

	DWMDS	CDWMDS
Fixed links	$\delta_{ij}(t) = \widetilde{d}_{ij}(t)$	$\delta_{ij}(t) = l_{ij}$
Mobile links	$\delta_{ij}(t) = \widetilde{d}_{ij}(t)$	$\delta_{ij}(t) = \widetilde{d}_{ij}(t)$

Table 1 Comparison of the range observations used by DWMDS and CDWMDS algorithms.

and $\mathbf{b}_i^{(k)}(t) = [b_1(t), ..., b_{n+m}(t)]$ is a vector whose entries are given hereafter by

$$\begin{aligned} b_j(t) &= w_{ij}(t)[1 - \frac{\delta_{ij}(t)}{d_{ij}(X^{(k)}(t))}] \qquad j \le n, j \ne i \\ b_i(t) &= \sum_{j=1}^{n} \frac{w_{ij}(t)}{d_{ij}(X^{(k)}(t))} + \sum_{j=n+1}^{n+m} \frac{w_{ij}(t)}{d_{ij}(X^{(k)}(t))} \\ b_j(t) &= 2w_{ij}(t)[1 - \frac{\delta_{ij}(t)}{d_{ij}(X^{(k)}(t))}] \qquad j \ge n \end{aligned} \quad (8)$$

In [9], two first improvements have been proposed to get this nominal DWMDS more adapted into the WBAN relative localization context. One first trivial point consists in taking the latest estimated position available for node i at time $t-1$, as *a priori* information in its local current cost function, i.e. with $\overline{X}_i(t) = \hat{X}_i(t-1)$. The choice accounts for the bounded motion amplitudes of on-body nodes under human mobility. Still relatively to the LCS, this amplitude strongly depends on the node's location itself. The second approach consists in using coarse *a priori* information about the nodes deployment to benefit from geometrical characteristics of the human body. The idea is to introduce fixed links on the body (e.g. links between hand's wrist and elbow) as constraints into the positioning problem. In particular, we use an approximated version of the true constant distances (e.g. learnt out of repeated measurements after averaging, during a preliminary calibration phase under mobility) as inputs, leading to a *Constrained* version of the DWMDS algorithm (CDWMDS).

Table 1 shows the main differences between DWMDS and CDWMDS, where $\widetilde{d}_{ij}(t)$ is the instantaneous distance measured between nodes i and j at time t and l_{ij} is an approximated version of the fixed distance between nodes i and j, which is considered as constant over time independently of the body gesture. Accordingly, no more ranging measurements are required for these links in the steady-state localization regime. Accuracy considerations apart, CDWMDS then theoretically tends to reduce the number of exchanged packets, and hence accordingly, latency and energy consumption.

3.3 Enhanced CDWMDS

We now propose a set of enhancements to the previous CDWMDS algorithm. One first idea is to avoid error propagation in the retained asynchronous and decentralized approach, whereas another point consists in reducing the effects of outlier range measurements and packet losses. We point out that the first two new enhancements have been described in [11].

3.3.1 Unidirectional Censoring of Rapid Nodes' Transmissions

One first goal is to mitigate error propagation while updating nodes locations. It has been illustrated in [9] that the locations estimated for the peripheral nodes are affected by significantly higher errors. It indeed appears that those nodes, typically located at the network edges (e.g. on the ankle) are the most rapid ones -or at least, those subject to the highest accelerations-, less connected -even if the transmission range ensures that they have more than three connected neighbours, so that their estimated locations are not ambiguous- and experiencing poor *Geometric Dilution Of Precision* (GDOP) -for being peripheral and located outside the convex hull defined by on-body anchors-.

Hence, one proposal is to allow only the update of such fast nodes with respect to their 1-hop neighbors but no updates of these neighbors with respect to the fast nodes in return, i.e. performing some kind of unidirectional censoring. The expected gains are two-fold: keep on benefiting at rapid nodes from the reliability of their slow neighbors' estimates, but also improve the average location accuracy in the entire network by avoiding error propagation from less reliable rapid nodes. In equation (5), the unidirectional censoring of any rapid node j would be practically applied by forcing the weight function $w_{ij}(t)$ to be null with respect to any neighboring on-body node i (i.e. $w_{ij}(t) = 0$, $\forall j \leq n$ whereas $w_{ji}(t) \neq 0$).

3.3.2 Scheduling of Location Updates

The objective here is still to avoid error propagation, by forcing the algorithm to converge properly first after updating in priority the slowest and most reliable nodes. Hence, rapid nodes benefit from the consolidated reliability of their slow neighbors' estimates and error propagation is minimized accordingly. Practically, considering a coordinated medium access of the multiple on-body nodes, as it will be seen hereafter, where all the protocol transactions shall be scheduled anyway (i.e. for both range measurements and position updates), one can keep track of the approximated nodes' speeds on the coordinator side, based on the latest available position estimates. Hence, at each new time stamp (and hence, at each superframe), one can draw an ordered list, setting the nodes to be updated in priority. Finally, one more degree of freedom concerns the number of updates per node per localization cycle (i.e. per superframe) or equivalently, the refreshment rate, which can be also dynamically increased for the most demanding nodes.

3.3.3 Forced Measurements Symmetry

The objective here is to jointly mitigate measurement outliers and packet losses. Hence, we propose to force the distance measurements for each pair of nodes into being symmetric, as follows:

$$\delta_{ij}(t) = \delta_{ji}(t) = \frac{w_{ij}(t)\delta_{ij}(t) + w_{ji}(t)\delta_{ji}(t)}{w_{ij}(t) + w_{ji}(t)} \qquad (9)$$

Practically, once the peer-to-peer range measurements between two nodes i and j are recovered independently in both directions (i.e. $\delta_{ij}(t)$ or $\delta_{ji}(t)$), our proposal consists in sharing the related information between each pair of nodes in order to mitigate possible packet losses (and thus missed measurements) that may occur during the ranging transactions. Moreover, if we suppose that the distance observed by node i from node j is strongly affected by measurement noise and/or bias (i.e. $\delta_{ij}(t)$) but that the distance observed by node j is less noisy, outliers are mitigated or more generally speaking, the resulting measurement variance is divided by a factor 2 after averaging, even in case of identically biased distance.

4 Medium Access Control For Localization-enabled WBAN

In our WBAN localization context, one key feature of the *Medium Access Control* (MAC) is to enable ranging between the nodes, as well as further exchanges of any kind of location-dependent information. In [15] a beacon-aided TDMA superframe has been presented, which was adapted for WBAN applications running on the IEEE 802.15.4 radio standard. Figure 2 represents the MAC superframe used in [1] (and inspired from [15]) adapted for localization purposes. In our work, we also consider using this MAC superframe.

As shown in Figure 2, the superframe structure is delimited by a beacon, which is transmitted periodically by the coordinator (e.g. possibly one on-body anchor here) to all the nodes in order to resynchronize all the WBAN (i.e. indicating the beginning of the superframe). The beacon fully describes the MAC superframe, specifying in particular the *Time Slots* (TSs) allocated for each transmitting node. The *Contention Access Periode* (CAP) is devoted to contention based transmissions, while the *Contention Free Period* (CFP) is composed of guaranteed TSs allocated by the coordinator. During the inactive period, the nodes may enter in a sleep mode to reduce energy consumption. The peer-to-peer range information is usually based on *Round Trip - Time of Flight* (RT-TOF) estimation, which relies on *2-Way Ranging* (2-WR) or *3-Way Ranging* (3-WR) handshake protocol transactions and unitary TOA estimates for each involved packets [16]. Two guaranteed TSs are involved in the case of 2-WR protocol to investigate the peer-to-peer range measurements between two nodes i and j, where node i sends its request packet inside the assigned TS at time $\widetilde{T}_{i0}$. Once this packet is received by node j at time $\widetilde{T}_{j0}$, node j sends its response back to the requester node i inside its own dedicated TS at time $\widetilde{T}_{j1}$, after a known time of reply. In turn, node i will receive this packet at time $\widetilde{T}_{i1}$. Hence, the estimated RT-TOF through 2-WR is given as follows:

$$\widetilde{TOF} = \frac{1}{2}[(\widetilde{T}_{i1} - \widetilde{T}_{i0}) - (\widetilde{T}_{j1} - \widetilde{T}_{j0})] \tag{10}$$

One enhancement to the 2-WR protocol consists in asking the responder node j to transmit an additional packet inside a third TS at time $\widetilde{T}_{j2}$, in order to estimate and compensate the relative clock drift between the two nodes. This packet will be received by node i at time $\widetilde{T}_{i2}$, and hence a new 3-WR protocol is considered. Figure 3 shows a simplified representation of the ranging transactions within 3-WR, where the final estimated RT-TOF is given as follows:

$$\begin{aligned}\widetilde{TOF} &= \frac{1}{2}[(\widetilde{T}_{i1} - \widetilde{T}_{i0}) - (\widetilde{T}_{j1} - \widetilde{T}_{j0})] \\ &- \frac{1}{2}[(\widetilde{T}_{i2} - \widetilde{T}_{i1}) - (\widetilde{T}_{j2} - \widetilde{T}_{j1})]\end{aligned} \tag{11}$$

Besides the local timers associated with unitary TOA estimates, which are required to compute range measurements, the payload of the ranging packets are actually exploited to carry additional information (e.g. to collect local estimated positions to the coordinator for synchronous display, to exchange pair-wise ranges in case of forced measurements symmetry, etc.).

Finally, note that *Aggregate-and-Broadcast* (A-B) procedures can be optionally applied to ranging packets [16], [17] so as to limit the localization-specific over-the-air traffic and especially, the number of required slots to perform all the possible pair-wise measurements in a mesh configuration. Accordingly, under full connectivity, $3n + 2m$ transmission slots would be required

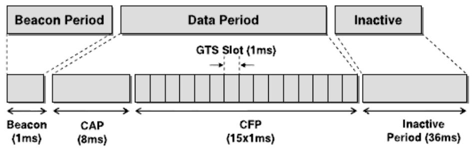

Fig. 2 Beacon-aided TDMA MAC superframe format supporting localization functionalities [1].

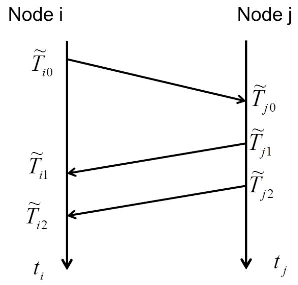

Fig. 3 Peer-to-peer measurement procedure between nodes i and j through 2- and 3-Way ranging protocols.

to guarantee ranging transactions between any pair of nodes, instead of $2n(n + m - 1)$ otherwise. Such A-B procedures enable to share time resource in such a way that each node initiates specific ranging transactions with all the other nodes, and each transmitted packet can play different roles (i.e. either a request, or a response, or even a drift correction packet, depending on the receiving neighbor status and current step in the 3-Way procedure).

5 Results

5.1 Scenario Description

In our evaluation framework, human mobility is based on a mixed model, like in [15]. A first macroscopic mobility *Reference Point Group Mobility Model* (RPGM) accounts for the body center mobility, where the reference point as a function of time is a Random Gauss Markov process [1]. The intra-WBAN mobility pattern is based on a biomechanical cylindrical model [18]. The body extremities are modeled as articulated objects, which consist of rigid cylinders connected to each other by joints. A snapshot of the resulting articulated body under pedestrian mobility is represented in Fig. 4 at an arbitrary time stamp. The biomechanical model enables the generation of true inter-node distances and obstruction conditions, whatever the time stamp.

In our scenario, for each random realization, the reference body moves in a 20 m ×20 m ×4 m $3D$ environment with a constant speed of 1 m/sec for a duration of 80 sec. The network deployment is similar to that

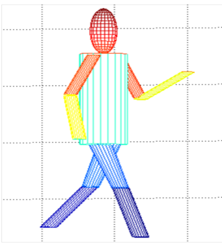

Fig. 4 Biomechanical mobility model based on a piece-wise cylindrical representation, used in the generation of realistic inter-node distance measurements under body mobility.

presented in Fig. 1, where 5 anchors are positioned at fixed locations relatively to the LCS and 10 blind mobile nodes with unknown positions must be positioned.

5.2 Simulation Parameters

Regarding the physical radio parameters, we assume in first approximation that the received power is larger than the receiver sensitivity, enabling peer-to-peer communication links with a worst-case *Packet Error Rate* (PER) of 1 %, as specified by the IEEE 802.15.6 WPAN Task Group 6 [19]. This PER figure is applied onto 3-way ranging protocol transactions to emulate uncomplete ranging (i.e. whenever 1 packet is lost out of 3). Inspired by the TOA-based IR-UWB ranging error model in [12], which has been specified in the IEEE 802.15.6 mandatory band centered around 4 GHz with a bandwidth of 500 MHz, ranging errors are added depending on the current *Line Of Sight* (LOS) or *Non Line Of Sight* (NLOS) channel configuration at time stamp t, as follows:

$$\begin{aligned} \widetilde{d}_{ij}(t) &= d_{ij}(t) + n_{ij}(t) && if\ LOS \\ \widetilde{d}_{ij}(t) &= d_{ij}(t) + n_{ij}(t) + b_{ij}(t) && if\ NLOS \end{aligned} \tag{12}$$

where $\widetilde{d}_{ij}(t)$ and $d_{ij}(t)$ are respectively the measured and the real distance between nodes i and j at time t, $n_{ij}(t)$ is a centered Gaussian random variable with a standard deviation σ, and $b_{ij}(t)$ is a bias term due to the absence of direct path when estimating TOA.

Simplifying the model from [12], our first simulations are carried out using a synthetic and constant σ equal to 10 cm, independently of the *Signal to Noise Ratio* $SNR(t)$, but still in the range of the values observed out of real measurements in [12]. $b_{ij}(t)$ is a positive bias added only into NLOS conditions, which follows a uniform distribution in [0 10]cm. Moreover, $b_{ij}(t)$ is assumed constant over one walk cycle in first approximation (i.e. $b_{ij}(t) = b_{ij}, \forall t$), which is also in compliance with first empirical observations from [12] with dynamic links over NLOS portions (i.e. with reproducible bias from one walk cycle to the next).

Concerning the setting of the CDWMDS algorithm, three fixed-link constraints are imposed, as materialized with black lines in Fig. 1. We also assume that the weight function $w_{ij}(t)$ is equal to 1 in connectivity conditions and 0 when the nodes i and j are disconnected, regardless to neighbor's information reliability (i.e. with no soft weighting under connectivity). The variable $r_i(t)$ associated with the prior estimated position of the current mobile node is also taken equal to 1 [10] for simplification. As for the MDS algorithm, a complete matrix is required with all the distances between all the pairs of nodes. Thus, inspired from the coarse geometric constraints used in [8], which rely for each link on the prior knowledge of minimal and maximal feasible distances under radio connectivity. We then substitute the missed distances $\delta_{ij}(t)$ by random variables, which follow a uniform distribution in $[\min_t(d_{ij}(t)) , \max_t(d_{ij}(t))]$.

After running simulations of the walk cycle with 100 independent realizations of the ranging errors based on the TOA estimation and PER, localization performance is assessed in terms of the *Root Mean Squared Error* (RMSE) per node or average RMSE (i.e. over all the mobile nodes), while considering different approaches. In a first evaluation, we consider updating the positions with a systematic and regular refreshment rate of 30 ms, whereas the latency introduced by the exchanged packets is not taken into account. However, in a second and more realistic approach, we consider a TDMA MAC superframe similar to that presented in Figure 2, where an *Aggregate-and-Broadcast* (A-B) procedure is applied to ranging packets to speed up convergence. Finally, parametric simulation-based studies have also been carried out in order to assess the performance (over all the on-body nodes) as a function of the PER and the standard deviation σ of intra-BAN ranging errors in equation (12).

5.3 Localization Performance

. Figure 5 shows the average RMSE (m) for each blind node placed on the body when applying no scheduling (i.e. random) of the locations' updates. Blue bars then represent the localization performance of CDWMDS, when each measurement constraint is calculated as the mean of the measured distances in an observation window of 9 sec. Red bars show the average RMSE per node in CDWMDS using the unidirectional censoring relatively to the fastest nodes (i.e. 4 and 6). As shown in this figure, the unidirectional censoring may be effi-

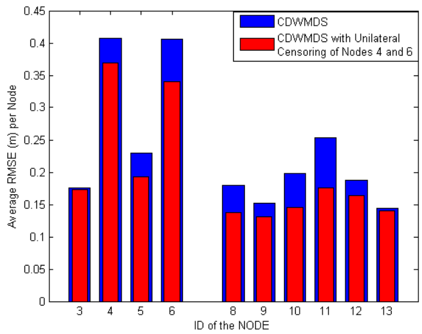

Fig. 5 Average RMSE (m) per node with and without censoring of rapid nodes for $\sigma = 10\ cm$ and a refreshment rate of 30 ms.

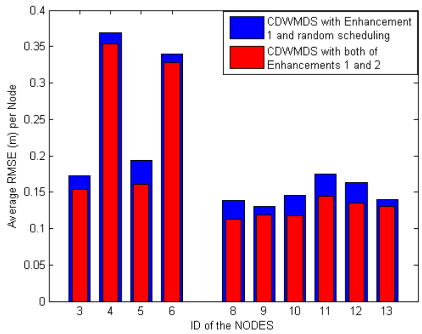

Fig. 6 Average RMSE (m) per node with and without updates scheduling for $\sigma = 10\ cm$ and a refreshment rate of 30 ms.

cient to improve the localization performance, decreasing the average RMSE per node from 23.3 cm down to 19.7 cm, what represents an improvement of 15.4 %.

The effects of introducing scheduling in the sequence of location updates are also illustrated on Figure 6. Blue bars represent the localization performance of CDWMDS using our first enhancement but random scheduling for the update of nodes' locations, whereas red bars account for situations when the slowest nodes are updated in priority and the fast nodes are updated later on (i.e. 4 and 6). The average RMSE (m) per node then decreases from 19.7 cm down to 17.5 cm, representing an improvement by 11.1 %. Moreover the gain is mainly observed for the most poorly positioned nodes. Note that with location updates scheduling, the refreshment rate could be anyway adjusted depending on the local mobile speed in order to favor the most demanding nodes, what was not the case in our simulations.

On Figure 7 the blue bars represent the RMSE per node of the CDWMDS algorithm when applying the two first enhancements (i.e. censoring and scheduling), whereas red bars show the performance while forcing the symmetry of range measurements. The average RMSE (m) per node then decreases from 17.5 cm down to 15.5 cm under symmetric measurements, representing one improvement of 11.4 %.

A comparison between MDS and CDWMDS, with and without MAC superframes, is also provided on Figures 8 and 9. First Figure 8 shows the variation of the average RMSE (over all the nodes) as a function of the PER. Blue, red and green curves represent respectively the localization performance of CDWMDS, CDWMDS under forced measurement symmetry and MDS algorithms, while the dashed curves represent the corresponding RMSE when considering a realistic MAC superframe. It can be seen that CDWMDS outperforms MDS, with and without MAC superframe, for each tested PER value. Moreover, the harmful effects of the latency induced by real MAC transactions (in particular between the collection of measurements and the positioning step) are also illustrated. The effect is however all the more noticeable with centralized approaches, like within MDS. As expected, it appears that forcing measurements symmetry is also an efficient way to mitigate packet losses, outliers or more simply large measurement noise occurrences (even if not outliers). Finally, the localization performance is slowly degraded as PER increases in our solution, most likely due to the jointly cooperative and decentralized nature of the proposed algorithm.

Figure 9 shows the variation of the average RMSE over all the nodes as a function of the standard deviation of the on-body ranging errors defined in equation (12). As expected, the performance is rapidly and rather strongly degraded as measurement errors increase. Indeed, the relative single-link errors become hardly compliant with relatively short true distances in a WBAN context. At very large noise standard deviations (e.g. larger than 20 cm), we even observe that the latency effects introduced by the use of a realistic MAC superframe are minimized, experiencing approximately similar performances (i.e. between dotted and their corresponding continuous curves in Figure 9). The previous observation indicates that measurement errors are far dominating in this case in comparison with latency effects (so far revealed by the presence of realistic MAC constraints), which could hence be neglected.

6 Conclusion

In this paper, we have addressed the problem of motion capture through on-body radiolocation in WBAN. The initial decentralized and cooperative CDWMDS algorithm, which asynchronously estimates unknown nodes' locations under geometric constraints in the form of fixed-length links, has been first enhanced through scheduling and censoring to mitigate error propagation and

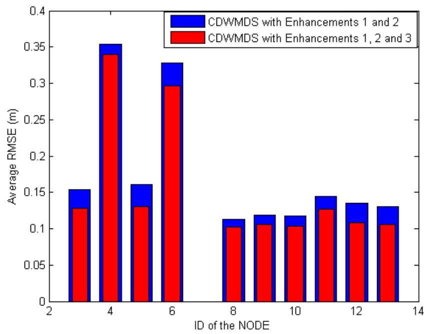

Fig. 7 Average RMSE (m) per node with and without Forced Measurements Symmetry, with $\sigma = 10\ cm$ and a refreshment rate of 30 ms.

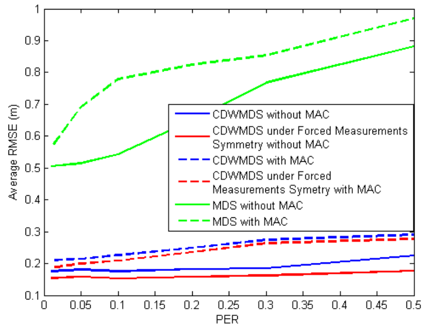

Fig. 8 Average RMSE (m) over all the nodes in the WBAN as a function of PER, with $\sigma = 10\ cm$.

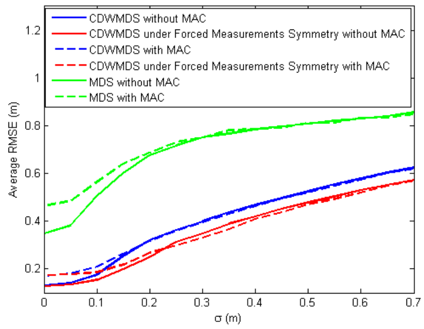

Fig. 9 Average RMSE (m) for all the nodes in the WBAN as a function of the standard deviation of the ranging errors, with PER = 0.01.

harmful effects due to location-dependent node speed disparities. It has been also shown that forced measurements symmetry could help to mitigate outliers and packet losses. Moreover, CDWMDS has been compared with a classical MDS algorithm in terms of localization accuracy for various PER values and ranging standard deviations with and without realistic MAC superframe, hence illustrating latency effects. Given the remaining observed limitations in terms of achieved precision, renewed research efforts have to be committed in the field, for instance by coupling on-body relative localization with absolute indoor positioning capabilities (i.e. with respect to fixed external anchors distributed in the environment) and/or with tracking filters.

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