Nodes Updates Censoring and Scheduling in Constrained Decentralized Positioning for Large-Scale Motion Capture based on Wireless Body Area Networks

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ABSTRACT

Wireless Body Area Networks (WBAN) are endowed with relatively raw but intrinsic motion capture capabilities through radiolocation, which may be of interest for home activity monitoring, large-scale postural rehabilitation or gaming applications. In this context, we propose a solution to localize wearable wireless nodes relatively to a body-strapped *Local Coordinate System* (LCS). More particularly, we consider adapting a *Constrained Distributed Weighted Multi-Dimensional Scaling* algorithm (CDWMDS) that asynchronously estimates nodes' locations under fixed-length constraints. This algorithm is fed by inter-node range measurements based on e.g. *Impulse Radio - Ultra Wideband* (IR-UWB) *Time Of Arrival* (TOA) estimation. Several new enhancements to the nominal CDWMDS, including nodes censoring and updates scheduling for nodes' locations, are herein put forward to mitigate errors propagation and harmful effects caused by fast moving nodes. Simulation results are provided to illustrate the gains observed on the average location error per node under moderate pedestrian mobility, relying on a realistic biomechanical model.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Wireless communication; C.2.4 [**Computer-Communication Networks**]: Distributed Systems; C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and embedded systems

General Terms

Algorithms, Design, Performance

Keywords

Cooperative Localization, Distributed Weighted Multi Dimensional Scaling, Geometric Constraints, IEEE 802.15.6 Standard, Motion Capture, Ranging, Relative Localization, Time Of Arrival, Ultra Wideband, Wireless Body Area Networks.

1. INTRODUCTION

Wireless Body Area Networks (WBANs), which have enjoyed growing research interest for the last past years, can fulfill unprecedented needs in various application fields such as healthcare, security, sports, entertainment and navigation [8], [15]. In the very WBAN context, cooperative localization consists in locating on-body mobile nodes by relying on peer-to-peer range measurements (i.e. out of standard on-body radio links). In turn, this new WBAN functionality shall represent a key enabling feature for opportunistic, stand-alone and large-scale human motion capture applications, as an alternative to costly and geographically restricted video acquisition systems or to specific solutions based on inertial or magnetic sensors. With this respect, the *Impulse Radio - Ultra Wideband* (IR-UWB) technology [5], [14], which benefits from fine multipath resolution capabilities, makes possible such range measurements through precise *Time Of Arrival* (TOA) estimation. Apart from radiolocation considerations, the IEEE 802.15.6 radio standard recently published for WBAN applications promotes IR-UWB as a relevant low power physical layer in the very context [8].

Nevertheless, cooperative localization in WBAN imposes to overcome numerous challenges. Wearable sensors are indeed 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 calculations of all the mobile locations, which are hardly compliant with real-time constraints under realistic human mobility [2], [12] (i.e. estimating all the unknown nodes' locations simultaneously, after relaying inter-node measurements to a central coordinator). Moreover, they often under-exploit the available potential of WBAN mesh topologies by sticking with non-cooperative links (i.e. uniquely with respect to fixed anchors) [15], [11]. A few solutions also consider *a priori* parametric models [11], incompatible with the unknown location-dependent mobility patterns experienced by on-body nodes under arbitrary deployment. Finally, coarse geometric constraints relying e.g., on the prior knowledge of minimal and maximal feasible distances under radio connectivity, have also been introduced [12]. More recently, the new *Constrained Distributed Weighted Multi Dimensional Scaling* (CDWMDS) algorithm proposed in [7] for coarse WBAN motion capture claims better immunity against the latency effects observed within classical central-

BODYNETS 2012, September 24-26, Oslo, Norway

DOI 10.4108/icst.bodynets.2012.249933

ized schemes and better adaptability to local nodes velocities. In this solution, originally inspired by [3], nodes' locations 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, limiting the number of required on-line measurements, while still benefitting from a mesh topology. On this occasion, the harmful effects of the fastest nodes have been illustrated (e.g. those placed at legs' extremities), showing significant degradation of the average location accuracy.

In this paper, we propose several enhancements to the initial CDWMDS formulation, including the unilateral censoring and/or scheduling of the most demanding nodes when updating the estimated mobile positions. One idea is to avoid error propagation and related divergence issues for the asynchronous and decentralized positioning algorithm.

The paper is structured as follows. In Section 2, we introduce the relative localization problem at the body scale. Section 3 then presents the core intended cooperative localization algorithms, including the initial constrained DWMDS and the proposed enhancements. In Section 4, we describe our evaluation framework, including the simulation set-up and parameters, as well as the localization performances obtained under realistic body mobility. Finally, Section 5 concludes the paper.

2. PROBLEM FORMULATION

The wireless devices placed on the body can be classified into two categories. Simple mobile *nodes* (also called *blind nodes* in the following) with unknown positions under arbitrary deployment must be located relatively to reference *anchor* nodes, which are attached onto the body at known and reproducible positions, independently of the body attitude and/or mobility (e.g. on the torso or on the back). At the relative body scale, a set of such anchors defines a stable and time-invariant Cartesian *Local Coordinate System* (LCS), which remains unchanged under body mobility (i.e. a system whose reference inter-anchor distances are constant, whatever the time stamp). Mobile nodes are then located into this LCS, 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) that would be associated with the environment. In the following, $\{X_i(t)\}_{i=1,\dots,n}$ represents the true $3D$ unknown positions of the n mobile on-body nodes at time t, which are to be estimated in the LCS. $\{X_i(t) = X_i\}_{i=n+1,\dots,n+m}$ represents the constant $3D$ known positions of the m anchors defined into the LCS at time t, where m should be at least equal to 3. Let $\widetilde{d(t)}_{ij}$ 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.

The problem that we want to solve is to estimate the dynamic positions of the mobile nodes into the LCS, given all the available range measurements $\{\widetilde{d(t)}_{ij}\}$, e.g. based on the IR-UWB TOA estimation [5], [6], on existing constraints related to the body geometry and on the known anchors' locations.

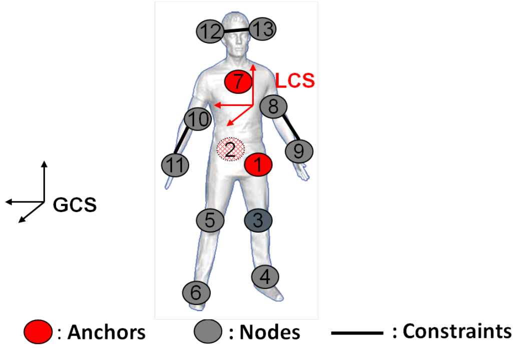

Figure 1: Typical deployment scenario for the relative localization of on-body wireless nodes (grey circles) with respect to a body-strapped Local Coordinate System (LCS) defined by fixed anchors (red circles), with fixed-length geometric constraints (black lines).

3. LOCALIZATION ALGORITHMS

3.1 Constrained Distributed Weighted Multidimensional Scaling (CDWMDS)

Multi-Dimensional Scaling (MDS) is a powerful centralized localization technique, which can estimate nodes' positions from a matrix containing inter-node distances. One major problem of this generic algorithm is the need for complete matrices of distances, with a full knowledge of all the pairwise measurements, what is highly unlikely in realistic wireless cases (e.g. due to connectivity losses or deliberate network topology restrictions). Another problem that can appear within such centralized approaches is the latency effect (i.e. the time elapsed between the collection of the required distance measurements and the delivery of the location estimates), whereas the body gesture can change rapidly during the collection step, hence degrading significantly final localization accuracy. Improvements to the nominal MDS have been provided recently in location-enabled *Wireless Sensor Networks* (WSN), e.g. overcoming the need for cumbersome matrix computations through multiple internal division localizations in static positioning (e.g. [9]) or extending the nominal MDS formalism into dynamic tracking contexts (e.g. [4]). However, motivated by the possibility to operate under partial and varying WBAN connectivity, to be more robust against induced latency and to benefit from asynchronism while localizing the nodes, we thus seek to estimate the nodes' positions using a fully distributed version of the MDS. As described in [3], 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:

$$\begin{aligned}\widehat{X}_i(t) = \underset{\widehat{X}'_i(t)}{\text{argmax}}[&\sum_{j=1}^{n} w_{ij}(t)(\delta_{ij}(t) - \widehat{d}_{ij}(\widehat{X}'_i(t), \widehat{X}_j(t)))^2 \\ &+ \sum_{j=n+1}^{n+m} 2w_{ij}(t)(\delta_{ij}(t) - \widehat{d}_{ij}(\widehat{X}'_i(t), \widehat{X}_j(t)))^2 \\ &+ r_i(t)||\widehat{X}'_i(t) - \overline{X}_i(t)||^2]\end{aligned} \tag{1}$$

where $\widehat{X}_i(t)$ is a vector containing the estimated $3D$ coordinates of node i, $\delta_{ij}(t)$ is a so-called observed distance between node i and j at time t, $\widehat{d}_{ij}(\widehat{X}'_i(t), \widehat{X}_j(t))$ denotes the synthetic Euclidean distance between i and j built out of the current estimated coordinates $\widehat{X}'_i(t)$ and $\widehat{X}_j(t)$, $w_{ij}(t)$ is a weight, which reflects the connectivity and the accuracy of the range measurement between nodes i and j at time t, so that unavailable links are naturally discarded and inaccurate measurements are down-weighted (or reliable neighbors such as anchors could be over-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 such prior information.

As described in [3], at each time t, the dynamic equation (1) is iteratively resolved within a few steps to estimate all the mobile nodes' positions. If $\widehat{X}^{(k)}(t)$ is the matrix whose columns contain all the estimated positions at iteration k, node i derives its current coordinates update $\widehat{X_i}^{(k)}(t)$ as follows:

$$\widehat{X}_i^{(k)}(t) = a_i(t)(r_i(t)\overline{X}_i(t) + \widehat{X}^{(k-1)}(t)\mathbf{b}_i^{(k-1)}(t)) \tag{2}$$

$$a_i(t) = \sum_{j=1}^{n} w_{ij}(t) + \sum_{j=n+1}^{n+m} w_{ij}(t) + r_i(t) \tag{3}$$

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

$$\begin{aligned} b_j(t) &= w_{ij}(t)[1 - \frac{\delta_{ij}(t)}{\widehat{d}_{ij}(t)}] \qquad j \leqslant n, j \neq i \\ b_i(t) &= \sum_{j=1}^{n} \frac{w_{ij}(t)}{\widehat{d}_{ij}(t)} + \sum_{j=n+1}^{n+m} \frac{w_{ij}(t)}{\widehat{d}_{ij}(t)} \\ b_j(t) &= 2w_{ij}(t)[1 - \frac{\delta_{ij}(t)}{\widehat{d}_{ij}(t)}] \qquad j \geqslant n \end{aligned} \tag{4}$$

In the nominal embodiment, one assumes that a localization cycle (to be repeatedly updated) is completed once all the mobile nodes are sequentially updated at least once with respect to their available neighbors.

In [7], 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 the local component of the cost function, i.e. with $\overline{X}_i(t) = \widehat{X_i}(t-1)$. The choice accounts for the bounded motion amplitudes of on-body nodes under realistic human mobility. Relatively to the LCS (still), this amplitude strongly depends on the actual node's location itself.

	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.

The second improvement consists in using coarse *a priori* information about the nodes deployment to benefit from the geometric characteristics of the human body. The idea is to introduce fixed on-body links (e.g. links between the hand's wrist and the elbow) as constraints into the positioning problem (See e.g., Figure 4.1). 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 difference 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 afterwards considered as constant over time, independently of the body gesture. Accordingly, no more ranging measurements are required for these links identified as constrained in the steady-state localization regime (e.g. after initial calibration). Besides accuracy considerations, CDWMDS thus leads to reducing the number of exchanged packets and accordingly, to reducing latency and energy consumption.

3.2 New Proposals

We now propose a set of new enhancements for the previous CDWMDS algorithm. One main idea consists in avoiding error propagation in the retained asynchronous and decentralized updating strategy.

3.2.1 Unidirectional Censoring of Rapid Nodes Transmissions

The first goal is to mitigate error propagation while updating nodes locations. As previously mentioned, it has been illustrated in [7] that the locations estimated for the most rapid nodes are affected by significantly higher errors in comparison with slower nodes. Those rapid nodes also coincide with devices that usually suffer from relatively poor connectivity and bad *Geometric Dilution Of Precision* (GDOP) conditions, from being located at the body periphery (i.e. thus out of the convex hull defined by the anchors on the torso). Hence, we propose to allow only the update of such fast nodes with respect to their 1-hop neighbors but, in return, no updates of these neighbors with respect to the fast nodes, that is, performing unidirectional censoring. The expected gains are two-fold: keeping on benefiting at rapid nodes from the reliability of their slow neighbors' estimates, but also improving the average location accuracy in the entire network by avoiding error propagation from less reliable rapid nodes. Moreover, getting back to equation (1), using the same update framework, the unidirectional censoring of a rapid node j is simply realized by forcing the weight function $w_{ij}(t)$ to be null for every on-body mobile node i (i.e. $w_{ij}(t) = 0$, $\forall i \leqslant n$), whereas $w_{ji}(t) \neq 0$ *a priori*.

3.2.2 *Scheduling of Location Updates*

On top of the unidirectional censoring enhancement, the objective here is also to avoid error propagation by forcing the algorithm to convergence properly first and 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. Practically, within a coordinated medium access scheme of the multiple on-body nodes, where all the protocol transactions shall be scheduled (i.e. for both range measurements and position updates), one can keep track of the approximated dynamic 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 such 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.

4. RESULTS

4.1 Scenario Description

In our evaluation framework, the overall mobility of the human body is based on a mixed model, like in [10]. A macro-mobility *Reference Point Group Mobility Model* (RPGM) model accounts for the body center mobility, where the reference point as a function of time is a Random Gauss Markov process [2]. The intra-BAN mobility is based on a biomechanical cylindrical model [13]. 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 Figure 2 at an arbitrary time stamp. The biomechanical model enables the generation of true inter-node distances, whatever the time stamp. In our scenario, for each random realization, the reference body moves in a 20m × 20m × 4m $3D$ environment with a constant speed of 1 m/sec for 80 sec. The network deployment is similar to that presented in Figure 1, where we have taken 3 anchors positioned at fixed locations, defining the LCS. 10 blind mobile nodes with unknown coordinates must be positioned.

4.2 Simulation Parameters

Concerning the physical radio parameters, we assume that the received power is larger than the receiver sensitivity, thus authorizing peer-to-peer communication on-body links with a worst-case *Packet Error Rate* (PER) of 1 %, as specified by the IEEE 802.15.6 [1], [8]. This PER figure is applied onto each transmitted packets of a 3-way ranging protocol, so as to emulate uncomplete ranging transactions (i.e. whenever one single packet is lost out of the 3 required packets). Practically, the peer-to-peer ranging procedure between two nodes may fail if only one single packet is lost (with a default loss rate equal to PER). Besides, inspired by the TOA-based IR-UWB ranging error model of [6], 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:

$$\begin{aligned} \widetilde{d_{ij}}(t) &= d_{ij}(t) + n_{ij}(t) & \quad if\ LOS \\ \widetilde{d_{ij}}(t) &= d_{ij}(t) + n_{ij}(t) + b_{ij}(t) & \quad if\ NLOS \end{aligned} \tag{5}$$

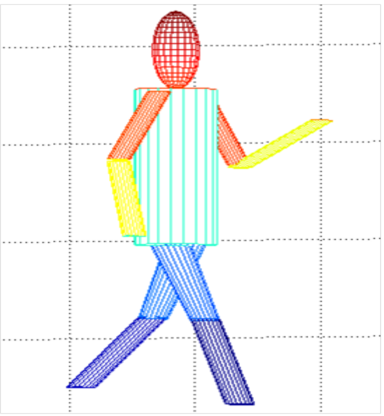

Figure 2: **Biomechanical mobility model based on a piece-wise cylindrical representation, used in the generation of realistic inter-node distance measurements under body mobility.**

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

Simplifying further the model from [6], our simulations are carried out using a synthetic and constant σ_n equal to 10 cm, independently of the *Signal to Noise Ratio SNR*(t), but still in the range of the experimental values observed in [6], based on real measurements. $b_{ij}(t)$ 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 [6] with dynamic links over NLOS portions (i.e. reproducible bias from one walk cycle to the next).

Concerning the localization algorithm parameters, three fixed-link constraints are imposed to the CDWMDS algorithm, as materialized with black lines on Figure 1. We also assume that the weight function $w_{ij}(t)$ is equal to 1 under feasible connectivity and 0 when the nodes i and j are disconnected (i.e. considering the simplest weighting case), regardless to neighbor's information reliability (i.e. with no soft weighting under connectivity). The variable $r_i(t)$ related to the prior estimated position of the node is taken equal to 1 [3], for simplification. Finally, the localization updates (i.e. within one complete localization cycle) are realized in average with a refreshment rate of 30 ms.

4.3 Localization Performances

Simulations have been carried out to illustrate the positive effects of the proposed enhancements on localization performances. After running simulations of the walk cycle with 100 independent realizations of the ranging errors (based on the TOA estimation and applying PER to 3-way ranging transactions), localization performances are measured as a function of the average *Root Mean Square Error* (RMSE) per node.

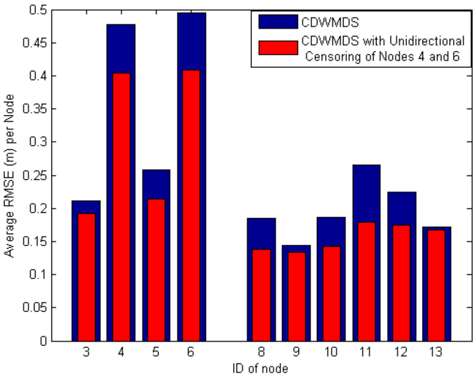

Figure 3: Average RMSE (m) per node with and without censoring of rapide nodes.

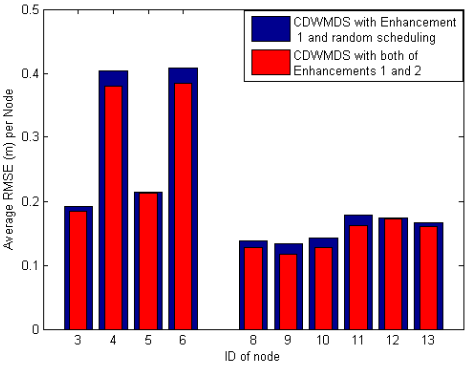

Figure 4: Average RMSE (m) per node with and without updates scheduling.

Figure 3 shows such an error (in m) per blind on-body node under a random scheduling of locations updates. Blue bars represent the localization performances of the constrained DWMDS (CDWMDS) algorithm. The constraints are calculated by averaging the measured distances over the corresponding links within an observation window of 9 sec. Red bars show the average RMSE per node in CDWMDS while applying the unidirectional censoring scheme to the two fastest nodes (i.e. IDs 4 and 6). As illustrated on the figure, applying censoring may represent an efficient way to improve the localization performances, decreasing the average error per node by a factor of 18 %, i.e. from 26.2 cm down to 21.5 cm.

The effects of the scheduling of location updates are represented on Figure 4, where blue bars represent the CDWMDS performances while considering the first enhancement, but still under random scheduling. Red bars show similar localization performances when the slowest nodes are firstly updated and the fastest nodes (i.e. IDs 4 and 6) are updated later on (i.e. at the end of the localization cycle or superframe). The average RMSE (m) per node then goes from 21.5 cm down to 20.2 cm, which represents an additional relative improvement of 6 %.

5. CONCLUSION

In this paper, we have addressed the problem of coarse but opportunistic motion capture through radiolocation in standard WBAN. The decentralized and cooperative CDWMDS algorithm, which asynchronously estimates unknown nodes' locations under fixed-link geometrical constraints, has been enhanced to mitigate errors propagation and harmful effects due nodes' location-dependent speed disparity. Simulations have been carried out to assess the performances of the modified algorithm, showing that both the unidirectional censoring and the scheduling of location updates could be relevant to better the localization performances by more than 20 % overall.

However, achieving very high precision motion capture capabilities through on-body radio means still looks challenging. Hence, based on the remaining observed limitations, more research efforts have to be undertaken in order e.g., to enhance the initialization step, to provide posterior tracking or smoothing of the estimated positions and to assess more carefully the link between the medium access control layer (under realistic packet loss rates) and localization latency.

6. ACKNOWLEDGMENTS

This work has been carried out in the frame of the *CORMORAN* project, which is funded by the *French National Research Agency* (ANR) under the contract number *ANR-11-INFR-010*.

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