Improved Navigation Capabilities in Groups of Cooperative Wireless Body Area Networks

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ABSTRACT
This paper addresses the problem of navigation in cooperative groups of *Wireless Body Area Networks*. On-body radio devices determine their position by estimating their distance to other nodes from the measurement of the Round Trip Time Of Flight of Impulse Radio-Ultra Wideband signals. The nodes not only measure their distance to fixed anchors, but also use device-to-device measurements, which improves spatial diversity and redundancy yielding to a better localization accuracy and robustness. However, such measurements are easily biased by line-of-sight conditions and body shadowing. We propose to apply a biased version of the extended Kalman filter to alleviate the effect of measurement biases in *Non Line Of Sight* (NLOS) conditions and combine this filter with an NLOS detection mechanism from the literature and evaluate, by simulation, the achieved gain.

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, Extended Kalman Filter, Group Navigation, Heterogeneous Networks, Impulse Radio, Ranging, Time Of Flight, Ultra Wideband, Wireless Body Area Networks.

1. INTRODUCTION
Radio-based localization of the on-body devices is a key building block for future WBAN applications and has received a lot of interest from the research community lately [1, 6, 5]. Indeed, the low-power *Impulse Radio - Ultra Wideband* (IR-UWB) technology, which one of the physical layer alternatives for the IEEE 802.15.4a and IEEE 802.15.6 standards, provides short-range and low-power radio channels and receiver strategies that allow precise range measurements. Its fine multipath resolution capabilities enables using *Time Of Arrival* (TOA) estimation over low data rate links to measure device-to-device distances and correlate those distances to locate nodes [1, 3, 9]. Measurements coming from nodes belonging to the same WBAN (intra-WBAN/on-body cooperation), to different WBANs (inter-WBAN/body-to-body cooperation) or from fixed anchors placed in the environment (off-body) can be combined even if they use different technologies. Short-range and low-power standards such as IEEE 802.15.6 can be utilized for on-body links, while larger range technologies, such as IEEE 802.15.4a, could be utilized for off-body links. Impulse Radio-Ultra Wideband (IR-UWB) is a promising technology in this field, as it allows precise Round Trip Time Of Flight measurement, which provides a more accurate distance estimation than narrowband RSSI solutions. However, *Non Line Of Sight* (NLOS) obstructions, e.g. due to body shadowing, significantly degrade this accuracy by biasing the measurements [4]. Given the transmission characteristics, even the body movements are sufficient to create obstruction that modifies sensibly a link characteristics.

At the algorithmic level under mobility, Kalman filtering and its variants represent popular and low-complexity solutions to mitigate such harmful effects. For instance, some *Extended Kalman Filter* (EKF) solutions consider the range biases as state variables to be estimated, in addition to 2D coordinates and speeds. These methods however necessitate *a priori* parametric models (i.e. stochastic or half-deterministic), which account for the time/space correlation of secondary multipath components under mobility [2, 11]. Thus they can hardly be applied in the very WBAN context, due to huge disparities in on-body nodes placements and erratic spatial behaviours and attitudes under realistic human mobility. Other tracking filters are based on the intuitive idea that the standard deviation of ranging errors in NLOS conditions is much larger than that in LOS conditions [2, 10], thus suggesting to increase some marginal terms in the filter observation covariance once *Line Of Sight* (LOS) to NLOS channel transitions are detected on the corresponding links. Besides [10] pointed out side issues within so-called "biased"

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filtering strategies during these NLOS to LOS transitions.

In this paper, we consider adapting such a biased EKF into the context of cooperative on-body nodes localization for navigation purposes, relying on groups of heterogeneous and mobile WBANs. The centralized computation of all the on-body nodes' coordinates and speeds (belonging to a small group of equipped users) is performed as an intermediary step, before estimating the centroid of the located on-body nodes for each single user. Cooperative on-body and body-to-body wireless links, respectively in intra-WBAN and inter-WBAN mesh topologies, are thus used to complement off-body links with respect to a set as fixed anchors. All these links are expected to be mutually beneficial to each other, for the sake of combatting severe obstructions and packet losses. Extra NLOS biases mitigation methods inspired from [10] are also herein extended to cope with our heterogeneous WBAN context. Besides, an adaptive detection scheme of the NLOS range measurements is inspired from [2] is jointly involved with the NLOS biases mitigation methods. We evaluate the localization accuracy by simulation on individual and collective navigation scenarios.

2. DEVICES POSITIONS ESTIMATION

Our aim is to estimate the positions of the on-body nodes at successive moments in time. In the following, we will suppose that measurements are realized every T seconds and we will denote by $\{X_i(k)\}_{i\in\{1\ldots n\}}$ the set of absolute (unknown) 3D positions of the n mobile on-body nodes at time $t = k.T$. Each $\{X_i(k)\}_{i\in\{1\ldots n\}}$ is a column vector of dimension 3. Let us also represent by $\{X_i\}_{i\in\{(n+1)\ldots(n+m)\}}$ the set of the absolute 3D (fixed and known) positions of the m infrastructure anchors. Now let $\widetilde{d}_{ij}(k)$ be the value of the range (or pseudo-range) measured at time $t = k.T$ between one on-body node $i \in \{1\ldots n\}$ and another on-body node or infrastructure anchor, $j \in \{1\ldots m+n\}$. The different $\widetilde{d}_{ij}(t)$ can be obtained, for example, using IR-UWB TOA estimation [4]. We will regroup all the range measurements at step k in a vector $\widetilde{\mathbf{d}}(k) = [\{\{\widetilde{d}_{ij}(k)\}_{j=n+1:n+m}\}_{i=1:n}\ \{\{\widetilde{d}_{ij}(k)\}_{j=1:n}\}_{i=1:n}]$, which has a dynamic length depending on the number of available range measurements.

Given the locations of the infrastructure anchors and $\widetilde{\mathbf{d}}(k)$, the available measurements at step k, the problem that we want to solve consists in estimating the absolute positions of the on-body nodes, $\{X_i(k)\}_{i\in\{1\ldots n\}}$, in a given *Global Coordinates System* attached to the scene.

2.1 Cooperative Extended Kalman Filter

Since TOA-based range measurements are described as non-linear functions of the on-body nodes' coordinates in our case, we consider applying the well-know EKF solution [8, 12], with the following state-space and observation models:

$$\begin{cases} \mathbf{S}(k) = \mathbf{A}.\mathbf{S}(k-1) + \mathbf{u}(k) \\ \widetilde{\mathbf{d}}(k) = h(\mathbf{S}(k)) + \mathbf{n}(k) \end{cases},$$

where $\mathbf{S}(k) = [X_1^T(k)\ V_1^T(k)\ X_2^T(k)\ V_2^T(k) \ldots X_n^T(k)\ V_n^T(k)]^T$ denotes the $6n$ dimensional state-space column vector at step k, that regroups the three-dimensional positions and velocities of the blind nodes to get positioned. $h(.)$ is a function that materializes the non-linear relationship between the observed measurements and the state vector variables and finally. The state transition matrix $\mathbf{A}$, assuming locally linear movements in first approximation, is given by:

$$\mathbf{A} = \mathbf{I_n} \otimes \left(\mathbf{I_6} + \left(\begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \otimes \begin{pmatrix} T & 0 & 0 \\ 0 & T & 0 \\ 0 & 0 & T \end{pmatrix}\right)\right),$$

where $\mathbf{I_n}$ denotes the n-dimensional identity matrix and $\otimes$ is the Kronecker product. Hence $\mathbf{A}$ accounts for some a priori information bridging the occupied positions at two consecutive steps k and $k+1$. In this approach, we assume that each node moves independently of each other. $\mathbf{u}(k)$ is the state-space noise vector, whose covariance matrix is $\mathbf{Q}$. $\mathbf{n}(k)$ is the observation noise vector, whose covariance matrix $\mathbf{\Sigma}(k)$. Note that the latter can be adjusted dynamically over time depending on the availability and/or quality of the measurements. After the initialization phase, the prediction phase of our cooperative EKF is defined as follows:

$$\begin{cases} \hat{\mathbf{S}}(k|k-1) = \mathbf{A}.\hat{\mathbf{S}}(k-1|k-1) \\ \mathbf{M}(k|k-1) = \mathbf{A}.\mathbf{M}(k-1|k-1).\mathbf{A}^T + \mathbf{Q} \end{cases},$$

where $\hat{\mathbf{S}}(k|k-1)$ is the predicted state at step k based on the latest available state estimate at step $k-1$ $\hat{\mathbf{S}}(k-1|k-1)$ (i.e. the latest filter output), starting with the initial guess $\hat{\mathbf{S}}(0|0)$. $\mathbf{M}(k|k-1)$ is the corresponding prediction *Minimum Mean Squared Error* (MMSE) matrix. We then correct the prediction error as follows:

$$\mathbf{K}(k) = \mathbf{M}(k|k-1).\mathbf{H}^T(k).\left(\mathbf{\Sigma}(k) + \mathbf{H}(k).\mathbf{M}(k|k-1).\mathbf{H}^T(k)\right)^{-1},$$

where $\mathbf{K}(k)$ is the filter gain and $\mathbf{H}(k)$ is the Jacobian observation matrix:

$$\mathbf{H}(k) = \frac{\partial h(\mathbf{S}(k))}{\partial \mathbf{S}(k)} |_{\mathbf{S}(k)=\hat{\mathbf{S}}(k|k-1)},$$

$$\begin{cases} \hat{\mathbf{S}}(k|k) = \hat{\mathbf{S}}(k|k-1) + \mathbf{K}(k).\left(\widetilde{\mathbf{d}}(k) - h\left(\hat{\mathbf{S}}(k|k-1)\right)\right) \\ \mathbf{M}(k|k) = \left(\mathbf{I}_{6n} - \mathbf{K}(k).\mathbf{H}(k)\right).\mathbf{M}(k|k-1) \end{cases},$$

where $\hat{\mathbf{S}}(k|k)$ is the final (corrected) state estimate at step k based on the current prediction $\hat{\mathbf{S}}(k|k-1)$ and observation $\widetilde{\mathbf{d}}(k)$, and $\mathbf{M}(k|k)$ is the related estimation MMSE matrix.

2.2 Biased EKF for NLOS Mitigation

So as to mitigate NLOS effects, it has been initially proposed in [7] a so-called "biased" filter to detect and compensate mostly positive measurement errors. The simple idea consists in adjusting the marginal diagonal elements of the measurement noise covariance matrix $\mathbf{\Sigma}(k)$ based on immediate feedback from the monitoring of the innovation terms in $\widetilde{\mathbf{d}}(k) - h(\hat{\mathbf{S}}(k|k-1))$ (i.e. before applying the correction step), as follows:

$$\hat{\sigma}^2_{ii}(k) = \begin{cases} \alpha^2\sigma_n^2, & \text{if } \{\widetilde{\mathbf{d}}(k) - h(\hat{\mathbf{S}}(k|k-1))\}_i > 0 \\ & \text{and NLOS detected;} \\ \sigma_n^2, & \text{otherwise} \end{cases},$$

where σ_n is the observed noise deviation in a steady-state LOS regime and α is a scaling factor chosen experimentally.

Nonetheless [10] has highlighted extra needs to resolve side effects caused by NLOS/LOS transitions, hence suggesting an improved filter version, in which the adjustment affects both the noise variances or the MMSE of the predicted ranges alternatively. We consider herein adjusting only the observation noise variance terms, but now as explicit functions of the marginal innovation terms. More precisely, if $\{\widetilde{\mathbf{d}}(k) - h(\hat{\mathbf{S}}(k|k-1))\}_i > 0$ under NLOS detection, we replace $\alpha^2\sigma_n^2$ by $\sigma_n^2 + \beta^2[\{\widetilde{\mathbf{d}}(k) - h(\hat{\mathbf{S}}(k|k-1))\}_i]^2$ in the equation above, where β is a scaling factor (e.g. set equal to 1 in our simulations for simplifications). The underlying idea is that NLOS outliers would require a gradual response in the filter, depending on how far they are from the LOS-based measurement predictions, without altering too much the gain corrective power. Accordingly, multiple observation noise levels are admitted on a potentially continuous scale depending on the quality of each link, instead of applying hard decisions and binary levels like in [2, 10].

2.3 Biased EKF with NLOS Detection Scheme

The bias only applies to NLOS condition. To detect such conditions, we use the idea of [2] that relies on the assumption that the non-Gaussian biases are mostly generated during the NLOS conditions. We can then detect the LOS/NLOS transitions by monitoring marginal innovation terms. Thus, the resulted scheme that joints the illustrated biases mitigation methods and the NLOS detection scheme could be represented as follow:

$$\begin{cases} \mathbf{D}(k) = \widetilde{\mathbf{d}}(k) - h(\hat{\mathbf{S}}(k|k-1)) \\ \textbf{if } (\{\mathbf{D}(k)\}_i > \{\mathbf{\Delta}(k)\}_i \ \&\ \{\mathbf{D}(k)\}_i > 0) \\ \quad \hat{\sigma}_{ii}^2(k) = \sigma_n^2 + \beta^2[\{\mathbf{D}(k)\}_i]^2 \\ \textbf{end} \end{cases},$$

where $\{\mathbf{\Delta}(k)\}_i$ is the corresponding selective scaling factor for detecting the channel transition. An optimal setting of $\{\mathbf{\Delta}(k)\}_i$ is critical. Hereafter, similarly to [2], we propose to choose the threshold at a value where approximately 95% of the expected gaussian innovation terms $\{\mathbf{D}(k)\}_i$ only caused by gaussian bias noise occurrences would not generate any detection event, i.e. with:

$$\{\mathbf{\Delta}(k)\}_i = 2\sqrt{\{\mathbf{\Sigma}(k) + \mathbf{H}(k).\mathbf{M}(k|k-1).\mathbf{H}^T(k)\}_{ii}}$$

3. SIMULATIONS AND RESULTS

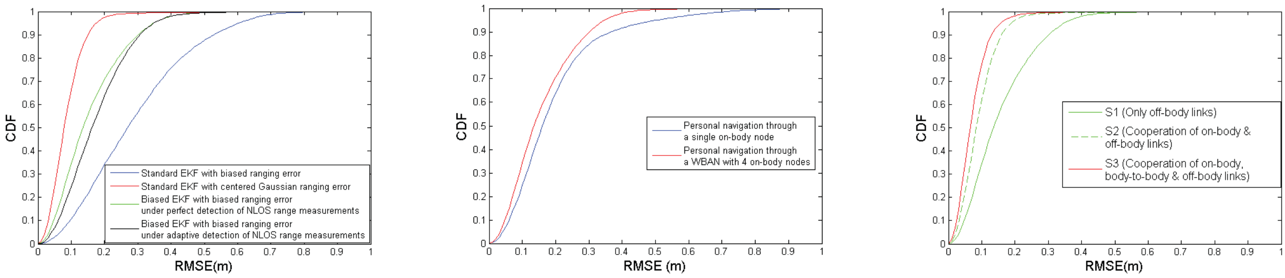
We evaluate our algorithm by simulating a group of 3 persons equipped with 4 sensors that move randomly in a $20\,m \times 20\,m \times 4\,m$ 3D room. The room is equipped with 4 anchors at an altitude of 2 m. Each run lasts $112\,sec$, during which each person, i.e. the centroid of each BAN, moves according to a *Random Gauss Position Markov* process [1] at the constant speed of $1\,m/sec$. Body movements are modeled by a biomechanical cylindrical-based model. At each timestamp, the the measurement noise and bias are computed for each pair of devices based on their relative positions. We consider that on-body nodes communicate using IR-UWB in the $4GHz$ band with a bandwidth of $500MHz$. Let us denote by $\widetilde{d}_{ij}(k)$ and $d_{ij}(k)$ the measured and real distances between devices i and j at time step k respectively. $n_{ij}(k)$ represents a centered Gaussian random variable with standard deviation σ_n and $b_{ij}(k)$ is a bias term due to the absence of direct path while estimating TOA. Following the observations in [4], we add we add a random ranging error equal to $\widetilde{d}_{ij}(k) = d_{ij}(k) + n_{ij}(k)$ if the link is in LOS condition and to $\widetilde{d}_{ij}(k) = d_{ij}(k) + n_{ij}(k) + b_{ij}(k)$ if the link is in NLOS condition. Simplifying further the model, our simulations are carried out using a constant σ_n equal to $10\,cm$, independently of the instantaneous signal to noise ratio, but still in the range of the values observed and characterized in [4] based on real measurements. $b_{ij}(k)$ is a random positive bias, added only in NLOS conditions, which follows a uniform distribution in the interval $[0, 10]cm$. Moreover $b_{ij}(k)$ is assumed constant over one walk cycle in first approximation (i.e. $b_{ij}(k) = b_{ij}, \forall k$), which complies to the observations in [4]. For body-to-body and off-body links, we assume a similar ranging error behavior with different noise parameters that comply to [1, 9]. All parameters are reported in Table 1.

	LOS	NLOS
on-body links	σ_n=0.1 m $b_{ij}(k) = 0$	σ_n=0.1 m $b_{ij}(k) \in$ [0, 0.1] m
off-body and body-to-body links	σ_n=0.3 m $b_{ij}(k) = 0$	σ_n=0.5 m $b_{ij}(k) \in$ [1, 2] m

Table 1: Ranging error model parameters

Each estimated body position is updated on average every $30\,ms$. We apply the aforementioned biased and cooperative EKF tracking algorithm, including adaptive observation noise covariance terms and a 6- or variable state vector $\mathbf{S}(k)$ depending if we consider body-to-body cooperation or not, respectively. We empirically and a priori determine the state-space noise covariance matrix $\mathbf{Q}$, relying on the variation of the true simulated on-body locations over a long period of time. In details, we apply the state-space equation onto these real positions, aggregate the noise residuals over each state component (i.e. computing $\mathbf{u}(k) = \mathbf{S}(k) - \mathbf{A}\mathbf{S}(k-1), \forall k$) over a long period (still with the same time step of 30 ms) and finally compute the variance over each state component in $\mathbf{S}$. If we denote by $diag(\gamma_1, \ldots, \gamma_n)$ designates diagonal matrix whose diagonal elements are equal to the γ_i, the state-space noise covariance matrix can be expressed as: $\mathbf{Q} = \mathbf{I}_n \otimes diag(0.004, 0.002, 10^{-4}, 4.3, 2.25, 0.1253)$.

Fig. 1(a) represents the empirical CDF of the RMSE of the estimated on-body nodes' centroids, averaged over 100 independent walk cycles. The figure compares 4 non-cooperative algorithms relying uniquely on off-body links: the blue curve represents a standard EKF, with no NLOS ranging error mitigation. The red curve is a genius-aided EKF using systematically debiased range measurements for reference. The green curve represents the biased EKF fed by biased observations but implementing NLOS mitigation through covariance scaling and assuming a perfect detection of the NLOS conditions. The black curve corresponds to addition of adaptive detection scheme of the NLOS links. The mitigation of the NLOS ranging errors clearly outperforms the standard EKF under a priori knowledge and adaptive detection of the channel conditions. Moreover, the gain resulting from the adaptive detection scheme is significant and close to the gain resulting from perfect knowledge of the channel condition. The median RMSE reaches 16.5 cm, largely compatible with most indoor navigation applications. Figure 1(b) compares



(a) Locating a single user ; off-body links only

(b) Single node vs. centroid of a 4-nodes WBAN ; off-body links only

(c) Cooperative algorithms : all types of links

Figure 1: Compared CDFs of the positioning Root Mean Square Error for various algorithms

the performance achieved by localizing only a single node in the WBAN, placed on the chest, vs. computing the centroid of a 4-nodes WBAN, each node being localized individually. These figures show the interest of spatial diversity and measurement redundancy: localizing multiple nodes leads to a better accuracy (median error at CDF=50 %) and is more robust (worst case error at CDF=90 %). Figure 1(c) shows the improvement that results from cooperation by comparing three scenarios. Scenario S1 is non-cooperative: nodes only utilize off-body measurements to position themselves. In scenario S2, they also use on-body links and they further add body-to-body links in scenario S3. The median RMSE to drop to 8.5 cm when considering on-body links, but adding body-to-body links does not yield a significant improvement.

4. CONCLUSION

This paper proposes and evaluates the use of a biased EKF to mitigate NLOS ranging errors caused by body shadowing, combined to an NLOS detection mechanism in WBANs. We show through simulation that detecting and mitigating these ranging errors greatly improves the localization precision that approaches the accuracy achieved by a scheme perfectly aware of the channel conditions. We also compare the non-cooperative strategy that computes each WBAN position with the sole help of infrastructure anchors with cooperative schemes that also use off-body and body-to-body links. Cooperative schemes provide spatial diversity and redundancy that improves the accuracy up to a certain limit. Other results, not included in this article, show that selecting the most relevant links based, for instance, on the packet error rates, allows further improvement and future work will consist in designing an intelligent link selection mechanism.

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