NLoS Mitigation for Cooperative Localization using Bayesian Techniques

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Abstract

The use of self-localizing, nodes in wireless networks is becoming necessary for modern military and civilian applications. A scenario of particular interest is short to medium range localization in GPS-denied environments and various techniques have been proposed to tackle the problem. This paper proposes an NLoS mitigation method to be used in conjunction with Bayesian self-localization techniques in Ultra-Wide Band (UWB) wireless networks. The method extracts useful information from NLoS measurements, which is especially useful, in situations with a lot of multipath noise and little LoS direct communication between nodes.

I. Introduction

Location awareness has become an important feature in both civilian and military modern wireless networks. As a result the ability for mobile ad-hoc devices to self-localize in arbitrary and potentially hostile environments is currently a hot research topic. The current de facto technology for localization is the Global Positioning System (GPS), unfortunately requires direct LoS transmission between devices and the satellites it uses, which limits its ability in closed environments, like heavily canopied forests, caves, urban canyons, underground and the inside of buildings. An alternative suitable for the GPS-denied environments is the use of Ultra-Wide Band (UWB) wireless networks, e.g. [1]. By taking advantage of the fine delay resolution properties of UWB signals, reliable and precise distance measurements can be derived, even in dense multipath environments,[2]. With the use of UWB signals the positioning problem can thus be defined as follows. A wireless networks consists of a number of nodes. Some of the nodes, called anchors, have precise estimates of their position. The rest of the nodes, called agents, are then trying to self-localize using information provided by the anchors. Cooperative Localization makes use of two distinct types of information. The first is metrics derived the physical properties of the signals transmitted between nodes and anchors. The fine delay resolution of UWB makes Time of Arrival (TOA) the most suitable choice [3]. The second type of information is the message of the transmission itself. Inside it, nodes share information of their position estimate. This way the information from the anchors diffuses from node to node all over the network, allowing more agents to self-localize. Various algorithms have been proposed which tackle the problem. Algorithms can be categorized as centralized, e.g. [4], and distributed, e.g. [5]. In the latter case, a number of algorithms that use Bayesian techniques, e.g. [6],[7] agents have been investigated. The UWB indoor channel has also been widely investigated, e.g. [8],[9]. Despite the many existing algorithms, the issues of NLOS propagation have not been yet well addressed, even though in the aforementioned scenarios large NLoS propagation can degrade localization accuracy significantly. An NLoS mitigation algorithm has been proposed in [6] but is based on a iterative deterministic method. In this paper, we address the issue of NLoS mitigation, when using a bayesian framework in cooperative localization. In section 2 we formulate the problem and provide the foundations of the bayesian approach to the localization problem. In section 3 we describe the proposed NLoS mitigation method. Simulation results are provided in section 4. Finally in section 5, some conclusions are derived.

II. Problem Formulation

Consider a 2D square network with an area size of $(X \times Y)m^2$, consisting of $M \geq 2$ anchors with known locations and $N >> M$ agents, whose aim is to self-localize. The true location of the nodes are denoted by $\Theta = [\theta_1 \ldots \theta_{M+N}]$, where $\theta_i = [x_i, y_i]^T$ is the coordinate of node $i \in \{N+M\}$, and $(\cdot)^T$ is the matrix transpose operation. Let R_{max} be the maximum range of communication between two nodes. Then two nodes i and j will be neighbours if $\parallel \theta_i - \theta_j \parallel \leq R_{max}$ and all nodes j within range belong in the neighbourhood S_i of node i. Two neighbouring nodes will communicate and obtain a noisy range estimate r_{ij} of their true distance. We assume that range estimates are symmetric, i.e. $r_{ij} = r_{ji} \forall i, j$. Agents are trying to make an estimate $\hat{\theta}_i = [\hat{x}_i, \hat{y}_i] \forall i \in N$, of their true location $\theta_i, \forall i \in N$.

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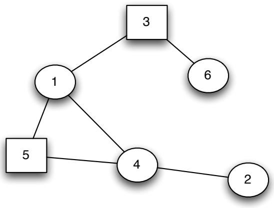

Fig. 1. An example of a network where circles are agents, squares are anchors and branches (or edges) correspond to communication between them.

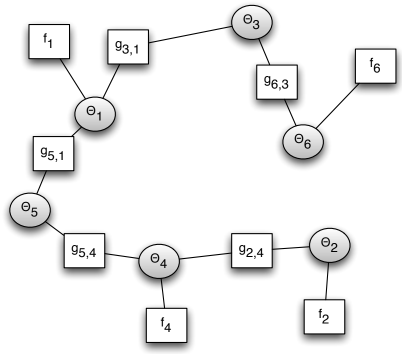

Fig. 2. A factor graph example of the network in Figure 1.

We represent this as a graphical model. The wireless nodes are represented by the set $\mathcal{V}$ of vertices of the graphical model. If they are within communication range then there is an edge $e_{ji} \in \mathcal{E}$, connecting nodes i and j. The set of all nodes j with edges e_{ji} to node i is the neighborhood S_i. A simple network example with nodes and anchors can be seen in Figure 1.

The belief probability density function (pdf) node i possesses regarding its state is denoted as $p_i(\theta_i)$. At each timeslot nodes broadcast their belief to their neighbors and vice versa. The prior belief for agents can be a non informative uniform pdf over the grid, while for anchors their pdfs are reduced to dirac delta functions pinpointing to their exact coordinates. From the signal received each node can measure a corresponding distance estimate. For example node i receiving a message from node j will calculate a noisy distance estimate:

$$r_{ji} = \|x_i - x_j\| + v_{ji}, \tag{1}$$

where v_{ji} is a random noise factor and follows a Gaussian $\mathcal{N}(\mu_{ij}, s_{ij}^2)$ with variance $s_{ij}^2 = K_e \|x_i - x_j\|^{\beta_{ij}}$ and mean $\mu_{ij} = 0$ for LoS and $\mu_{ij} = b_{ij}$ in the case of NLoS as proposed in [10]. It has been shown in [11] that the NLoS bias $b_{ij}$is much larger than s_{ij}^2 and is uniformly distributed between $[b_{min}, b_{max}]$. K_e is a proportionality constant capturing the combined physical layer and receiver effect, and β_{ij} denotes the path loss exponent. The derivation of K_e can be found in [2]. We define the mean network- average (RMS) localization error, in order to compare different localization scenarios and methods, as follows:

$$\Omega = \sqrt{(1/n) \sum_{i=1}^{N} \mathbb{E}\{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2\}} \tag{2}$$

Let $p(r_{ji}|\theta_i, \theta_j)$ be the likelihood of measuring r_{ji} given the believed states $p_i(\theta_i)$ and $p_j(\theta_j)$ of nodes i and j, respectively. The joint pdf describing this probabilistic model is given by

$$p(\Theta, \mathcal{R}) = p(\mathcal{R}|\Theta)p(\Theta) = \prod_{i,j \in \mathcal{E}} p(r_{ji}|\theta_i, \theta_j) \prod_{\theta_i \in \mathcal{V}} p_i(\theta_i). \tag{3}$$

The joint pdf (3) can be represented using the factor graph shown in Figure 2, with the local factors being:

$$f_i(\theta_i) = p_i(\theta_i), \tag{4}$$

$$g_{j,i}(\theta_j, \theta_i) = p(r_{j,i}|\theta_i, \theta_j). \tag{5}$$

For each node there is a variable node, representing the node's position. We connect it to a factor node f_i corresponding to its prior state belief, and also to $g_{j,i}$ factor nodes for each neighbor it has. Our objective is for each node i to calculate the maximum posterior (MAP) of $p(\theta_i|\mathbf{r}_i)$. This can be done by using a message passing algorithm in the factor graph of (3). Due to the noisy measurements of r_{ji} the message passing algorithm will have to be iterated a number of times until all nodes have converged to a solution. At each iteration we define the estimated state belief of node i as $p_i^t(\theta_i)$, where t is the iteration/timeslot index. Using Baysian theory, we have

$$p^t(\theta_i|\mathbf{r}_i) \propto p_i^{t-1}(\theta_i) \prod_{j \in S_i} p^t(r_{ji}|\theta_i) \propto p_i^{t-1}(\theta_i) \prod_{j \in S_i} \int p^t(r_{ji}|\theta_i, \theta_j) p_j^{t-1}(\theta_j) d\theta_j. \tag{6}$$

All the above pdfs can be locally estimated at node i except the belief pdfs of its neighbors $p_j(\theta_j)$. At each timeslot node i receives $p_j(\theta_j), \forall j \in S_i$ and measures a distance metric r_{ji} for each j. Based on these node i calculates the message:

$$m_{j \to i} = p_j(\theta_i) = \int p^t(r_{ij}|\theta_i, \theta_j) p_j^{t-1}(\theta_j) d\theta_j = \underbrace{g_{j,i} \times f_j \times \theta_j}_{\text{factor graph nodes}}. \tag{7}$$

The message $m_{j\to i}$ can be thought of as the belief pdf of the state of node i based on the information provided by node j. Then, it combines its own belief with the belief calculated from all its neighbors in order to update its state estimate. As such, using (7), (6) can be rewritten as

$$p^t(\theta_i|\mathbf{r}_i) \propto f_i^{t-1} \prod_{j\in S_i} m_{j\to i}^t. \tag{8}$$

This continues until all nodes have self localized. This message passing analysis leads naturally to a distributed cooperative system because each node only requires to do local calculations concerning its corresponding neighborhood.

III. Proposed NLoS Mitigation Method

A. Non Parametric Belief Propagation

We cannot tackle the localization problem by solving (7) and (8) analytically because of the large computational cost involved. We assume that a non parametric belief propagation (NPBP) approximation technique is used. For more information the reader is referred to [12], [13], [14]. In summary, each message is represented by a sample based density estimate as a mixture of Gaussians. This means that by using L weighted samples we can approximate $p_i(\theta_i)$ as

$$p_i(\theta_i) \simeq \sum_{l=1}^{L} w_i \mathcal{N}(\theta_i; \mu_i^l, \Sigma_i), \tag{9}$$

where $\mathcal{N}(\theta;\mu,\Sigma)$ denotes a normalized Gaussian density with mean μ and covariance Σ evaluated at θ. Similarly, we can approximate the message (7):

$$m_{j\to i}(\theta_i) = p_j(\theta_i) \simeq \sum_{l=1}^{L} w_{ji} \mathcal{N}(\theta_i; \mu_{ji}^l, \Sigma_{ji}). \tag{10}$$

The NPBP method can be summed up in the following steps:

1) Draw samples of the marginal estimate pdfs;
2) Use samples to approximate the outgoing message;
3) use MAP to estimate the agent location.

The bayesian technique even thought quite powerful, has not been investigated in the case of high NLoS communication. In this scenario, performance degradation may be high, so in the next section we develop a NLoS mitigation technique extending the bayesian approach, to tackle this. Even thought we consider the use of NPBP, any other message passing technique could be used, such as particle filtering methods [15], [16], or Monte-Carlo methods [17].

B. NLoS Mitigation

We assume that there is some a priori knowledge of the NLoS condition of the environment in the scenario. That means that we have some rought information of the positive bias and the channel characteristics. Various measurement campaigns have been made for UWB channel data in typical indoors environments. e.g. [8],[18],[19]. By using hypothesis testing based on the the multipath channel statistics such as the kurtosis, the mean excess delay spread and the root mean square delay spread, as proposed in [6], it is possible to distinguish up to 90% LoS/NLoS realizations in most channel models. Using this NLoS identification scheme, we determine whether a range estimate is NLoS or LoS. If it is LoS it is used in the calculation of (8). If it is NLoS we further examine whether the current solution is within the current ranging circle or not. If the current solution lies outside, the message is used normally. If not then it will not contribute more to the convergence of a solution and thus it is dropped. We can analyze the neighborhood of node i S_i as follows:

$$S_i = S_i^L \cup S_i^N \tag{11}$$

where S_i^L and S_i^N are the sets of the LoS and NLoS neighbors of node i respectively. The set of nodes who will contribute to (8),i.e. the useful collection of neighbors, will be the following:

$$S_i^C = S_i^L \cup \left\{ j \mid j \in S_i^N, \parallel \hat{\theta}_i - \hat{\theta}_j \parallel \geq r_{ij} \right\} \tag{12}$$

As the messages received from the neighbors are actually approximations of the pdf's and especially in the early iterations of the algorithm there will be a large number of equiprobable points the use of $\hat{\theta}_i$ and $\hat{\theta}_j$ eliminates a huge number of possible states of nodes i and j respectively. In order to overcome this we propose the following. Sample K samples from $p_i(\theta_i)$ and $p_j(\theta_j)$ in order to get two sets of states θ_i^K and θ_j^K, for each node. Then form two convex set for the respective samples and choose the two samples which are further away as position estimates for nodes i and j. This can be easily achieved by using the maxdist algorithm, developed in [20]. The maxdist algorithm uses a rotating calipers technique to estimate the maximum distance between two convex hulls. Simply the algorithm takes advantage of the knowledge that the NLoS bias is much larger than the noise variance. With that in mind the distance measurement is compared with the maximum belief distance of the two nodes. If the belief distance is smaller than the measured distance, then the algorithm considers it is better not to use it as there is unknown positive bias and the constraint in (12) is already satisfied. This way only NLoS measurements which will contribute constructively are used.

IV. SIMULATION RESULTS

In this section we present simulation results, i.e. the RMS error defined in (2), of the proposed NLoS mitigation techniques. The results are then compared to the ones found in [6]. The results are averaged after 20 monte carlo simulations in the following scenario. We consider a grid $100 \times 100\text{m}^2$ with $R_{max} = 15$m. There are 200 agents and 20 anchors. The proportionality factor $K_e = 0.000625$. The path loss exponint is $\beta_{LoS} = 2$ for the LoS estimate and $\beta_{NLoS} = 3$ for the NLoS estimate. The NLoS bias is chosen uniformly from $[26\% R_{max}, 53\% R_{max}]$. for the sake of comparison a pure LoS scenario is also considered that clearly shows the superiority of the bayesian approach compared to the non-bayesian IPPM method proposed in [6]. The results are summarized in table I. NPBP uses no NLoS mitigation while NLoS NPBP does.

% of NLoS nodes	NPBP Ω	NLoS NPBP Ω	IPPM method Ω from [6]
0%	0.1m	0.1m	1.8m
20%	1.9m	1.3m	2.2m
40%	2.8m	2.0m	3.5m
60%	4.3m	3.12m	4.8m
80%	4.5m	3.6m	4.9m

TABLE I

COMPARISON OF Ω FOR VARIOUS NLOS SCENARIOS

The first thing to notice is that in the 0% NLoS scenario the bayesian approach vastly outperforms the deterministic IPPM method. Secondly even though there is deterioration as the NLoS % increases the mitigation algorithm improves consistently the localization accuracy, even in the case of very high NLoS.

V. CONCLUSIONS

We proposed a NLoS mitigation method based on the assumption of NLoS identification by hypothesis testing in UWB signals. The method extends the bayesian framework to the localization problem for the NLoS case and helps even in the case of very large NLoS node percentage.

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