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A loosely coupled cooperative localization augmentation to improve human geolocation in indoor environments

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***Abstract*— This paper reports on the use of a cooperative localization augmentation to increase the localization accuracy of human agents in an opportunistic fashion by processing inter-agent relative measurements. The main challenge in the decentralized cooperative localization algorithm design is how to account for the strong correlations, which the relative measurement updates create between the state estimates of the agents, with a reasonable communication cost. To keep track of the correlations agents need to communicate with each other through some form of a network-wide communication topology, which is hard to maintain for human agent localization applications. In this paper, we discuss a cooperative localization method that, instead of maintaining the correlations, accounts for them in an implicit manner by using conservative upper-bound estimates on the joint correlation matrix of the agents. This provably consistent loosely coupled cooperative localization method requires only the two agents involved in a relative range measurement to communicate with each other. Our results include the use of this algorithm for human agent localization via UWB ranging sensors. We demonstrate our results in simulation and experiments.**

Keywords—cooperative localization; human agent; coupling; communication; UWB ranging

I. INTRODUCTION

Location is a vital dimension of situation awareness for any mobile agent, including humans. Human tracking and geo-localization are in high demand in applications such as monitoring patients in hospitals and senior citizens in nursing homes, detecting miners in underground mines, tracking soldiers in battlefield and locating firefighters [1-2]. For indoor applications Global Positioning System (GPS) fails to provide accurate localization information due to obstructed line of sight to satellites and weak signal strength. To compensate for lack of GPS, robotic community has relied on fixed feature-based Simultaneous Localization and Mapping (SLAM) algorithms [3]. SLAM allows autonomous agents to create a map of the environment and localize themselves in that map. Such a solution, which uses vision for detecting features in the environment, is not necessarily effective for geo-localization and tracking of human agents in a global frame, when the

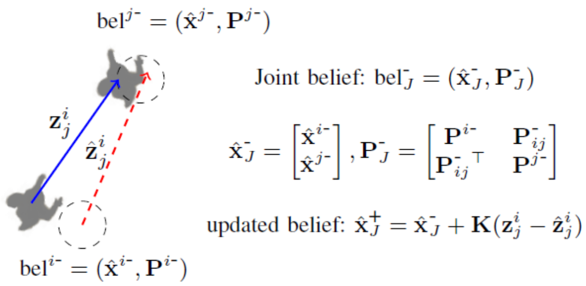

Fig. 1. Components of a relative measurement update process in cooperative localization. z^i_j is the real relative measurement (in this paper taken by an UWB ranging sensor), $\hat{z}^i_j$ is the estimated measurement, $\mathrm{bel}^{l-} = (\hat{x}^{l-}, \mathbf{P}^{l-})$ is the belief of agent $l \in \{i, j\}$ about its location prior to the relative measurement update, and $\mathrm{bel}^{l+} = (\hat{x}^{l+}, \mathbf{P}^{l+})$ is the belief of agent $l \in \{i, j\}$ after the relative measurement update.

environment is not fixed (e.g., fireground), the lighting is poor (underground) or the features are not revisited.

Popular solutions for human agent localization are (a) pedestrian dead reckoning (PDR) and (b) wireless indoor localization. In PDR, acceleration and angular velocity measurements via foot-mounted inertial measurement unit (IMU) sensors are used to propagate the equations of motion of human agents to localize them. However, navigation based solely on inertial sensors is subject to unbounded growth of position error over time. To reduce the growth rate of the error, the Zero Velocity Update (ZUPTing) approach is introduced, which uses human legged locomotion and detection of the steps to re-calibrate inertial sensors during the rest phases of the foot [4]. Despite its help in improving the accuracy of the PDR methods, ZUPTing does not fully bound the error. In recent years, wireless signal assisted indoor localization techniques have also emerged to improve the localization accuracy. These techniques typically utilize pre-installed devices (beacons) with known locations [5]. That is, they use time-of-arrival (TOA) and received-signal strength (RSS) measurements to obtain relative distance of human agents from the pre-installed beacons and use this relative range measurement and the known location of the beacons to improve localization accuracy of the agents. Even

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though these solutions are proven effective, they are not suitable for every application, especially for those that take place in a priori inaccessible areas and also in disaster stricken areas, e.g. firegrounds. For such applications, a technique that can have promising prospect is cooperative localization (c.f. [6] for an overview of CL approaches).

In CL, mobile agents in a team improve their local pose estimates using inter-agent relative measurement feedbacks (see Fig. 1). Despite offering the appealing advantage of an infrastructure-free localization in GPS and land-marked challenged environments, integration of CL algorithms in real world applications, especially in uncoordinated smart mobile applications such as human agent localization, has been challenging. In this paper, we explore a CL algorithm for a team of human agents.

The main challenge in design of a decentralized CL algorithm arises from the strong correlations that relative measurement updates create among the pose estimates of the participating agents. The correlation reflects itself in coupling terms that appear in the estimation equations of the agents. Similar to any estimation filter, the correlation terms cannot be ignored, because it will cause the rumor propagation phenomenon that can lead to overconfidence and even to estimate divergence as reported in [7]. To maintain the correlation terms, agents need to communicate with each other on a persistent manner at each time-step of the algorithm. Decentralized solutions that use decomposition techniques to decouple the propagation and update equation of the joint CL via various estimation filters such as extended Kalman filter or unscented Kalman filter have been proposed in the literature [6,8-10]. Despite reducing the communication incidences, these approaches still require some form of inter-agent connectivity among the team members. In applications involving human agents, especially for first responders and firefighters, maintaining multi-agent connectivity is challenging, if not impossible.

To remove network-wide connectivity conditions, literature (see e.g. [7,11-13]) has proposed methods that instead of maintaining the prior agent-to-agent correlations, they account for it in an implicit manner using Covariance Intersection fusion (CIF) method (for CIF methods c.f. [14-15]). In CIF two or more tracks from same process in the absence of correlation information are fused together in an implicit manner. In CL, however, we are updating the local pose estimates of two agents (two different processes) by joint processing of the relative inter-agent measurement feedbacks. Consequently, CL techniques that use CIF approach require each agent to keep a copy of the state estimate of the entire team locally, see e.g., [7]. To avoid this requirement, [11-13] propose algorithms in which the agent taking a relative pose (relative position and relative orientation) measurement uses this measurement and its current pose estimate to obtain and broadcast a pose and the associated error covariance of its landmark agent (the landmark agent is the agent the relative measurement is taken from). Then, the landmark agent uses the CIF method to fuse the newly acquired pose estimate with its own current estimate to increase its estimation accuracy. The downside of these algorithms is their crucial dependence on

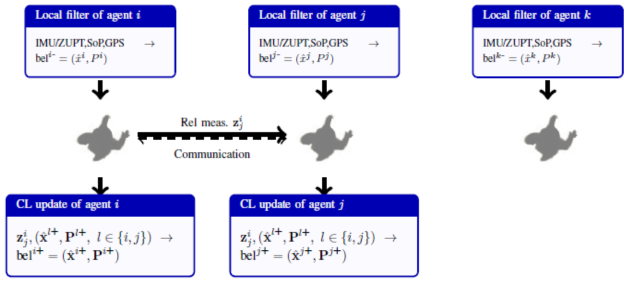

Fig. 2. Cooperative localization as an augmentation system gets activated whenever there is a relative measurement between two agents. Other agents can carry out their localization using their own local filter, without any effect on them. Once the relative measurement update is concluded, CL augmentation service goes to sleep until the next relative measurement takes place. No form of network-wide connectivity is needed.

relative pose measurements. That is, they cannot be used if the relative measurement is range only, which is the form of the measurement normally we have for human agents.

In this paper, we investigate the effectiveness of our previously proposed CL algorithm [16] as an augmentation service to improve localization accuracy of human agents via Ultra-wideband (UWB) relative range measurements. Our CL algorithm of interest uses an upper bound on the joint covariance matrix of the agents to account for the unknown inter-agent cross-covariance terms. This bound is reminiscent of the bound used in the CIF method, however, our method is different as it takes a direct approach to process relative measurement feedbacks, without requiring to reconstruct a state estimate from the relative pose measurement. Consequently, no assumption on the type of the inter-agent relative measurements is needed and this algorithm can be used for relative range measurement updates via an UWB ranging sensor. The framework we study consists of (a) a local filter for each agent that uses an IMU system for dead reckoning and also can process occasional absolute measurements to improve localization accuracy of the agent (b) a CL augmentation that gets activated when there is a relative measurement between two agents. In our setting the coupling between CL and the local filter is loose, in a sense that when a relative measurement update is completed, the CL filter goes to sleep until the next relative measurement takes place, (see Fig. 2). As such no restrictive network-wide connectivity is needed to implement our CL algorithm. Therefore, one can use our CL algorithm as an augmentation service on top of any existing localization filter to increase self-localization accuracy of a human agent through opportunistic collaboration with other agents. This augmentation is agnostic to the type of the local localization filter as well as to the type of the relative measurement sensor on-board of the mobile agents. Lastly, this augmentation system can be integrated in the existing systems with minimum overhead. To demonstrate our loosely coupled CL augmentation's effectiveness, we built a human agent localization device capable of on-board computation, communication and UWB ranging. We use several experiments and simulations via this portable localization device to gain insight on effectiveness of our CL augmentation. Our results point to promising prospects.

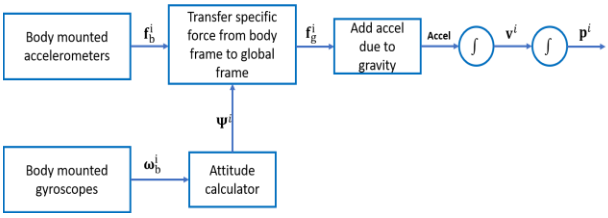

Fig. 3. The mechanization of strapdown inertial navigation system.

II. A LOOSELY COUPLED COOPERATIVE LOCALIZATION AUGMENTATION SYSTEM

A. Local Filter

We consider an indoor CL method based on UWB ranging for an infrastructure-free human agent localization. We consider an operation where human agents are equipped with a portable localization device with computation and communication capabilities. We assume that each agent has a PDR system powered by a body mounted IMU. Let the state of each agent be $x^i \triangleq [p^i, v^i, \varphi^i]^T$, which includes, respectively, position, velocity and attitude that defines the body orientation. The self-motion measurement obtained from an IMU unit is $u^i \triangleq [f_b^i, w_b^i]^T$ where f_b^i is the specific force measured by the accelerometers and w_b^i is the angular velocity of the body measured by the gyroscopes. The mechanization of the inertial navigation system (INS) is shown in Fig. 3. The motion of each agent is independent from others and is described by $x^i(t+1) = f(x^i(t), u^i(t) + \upsilon_u^i) + \upsilon_x^i$, where the u^i is the self-motion measurement command obtained from IMU measurements. Here, υ_u^i is the self-motion measurement noise and υ_x^i is the process noise. The noises are assumed to be uncorrelated zero-mean white Gaussian with covariance matrices given by $E[\upsilon_u^i(t)\upsilon_u^i(t)^T] = Q_u^i(t) > 0$ and $E[\upsilon_x^i(t)\upsilon_x^i(t)^T] = Q_x^i(t) > 0$.

Each agent uses an INS to obtain an estimate of its own state $\hat{x}^{i-}(t) \in \mathbb{R}^{n^i}$ and corresponding error covariance matrix $\mathbf{P}^{i-}(t) > 0$ at each time step $t \in \mathbb{Z}^+$. This state estimate can be enhanced via other means such as ZUPTing, and occasional access to signals of opportunity (SOP) or GPS. In what follows, we use $\mathrm{bel}^{i-}(t) = (\hat{x}^{i-}(t), \mathbf{P}^{i-}(t))$ as the belief of agent *i* at time *t* prior to a relative measurement update. Because of inherent noises in the self-motion measurements, process noises and also unreliable access to SoP and GPS, relying only on the local filter to obtain pose estimates can result in poor estimation accuracy. To bound the error and improve the estimation accuracy of the agents, processing of occasional inter-agent relative measurements taken by body-mounted UWB ranging sensors is used.

B. Relative measurement for cooperative localization

Suppose each agent has an exteroceptive sensor with limited sensing zone to detect, uniquely, the other agents in the team and to take relative measurements with respect to them. In this paper, we use relative range obtained via an UWB ranging sensor. Let the relative measurement taken by agent *i* from agent *j* at time *t* be denoted by $i \xrightarrow{t} j$ and described by

Algorithm 1 Cooperative localization augmentation for agent i

1: **Input**: $\mathrm{bel}^i(t) = (\hat{\mathbf{x}}^i(t), \mathbf{P}^i(t)), \mathbf{M}$
2: **Output**: $\mathrm{bel}^i(t+1) = (\hat{\mathbf{x}}^i(t+1), \mathbf{P}^i(t+1))$

3: **if** $\mathbf{M}$ is a self-motion measurement (or control input) **then**:
4: $\quad \mathrm{bel}^i(t+1) \leftarrow \mathrm{predictBelief}(\mathrm{bel}^i(t), \mathbf{M})$
5: **if** $\mathbf{M}$ is an absolute measurement **then**:
6: $\quad \mathrm{bel}^i(t+1) \leftarrow \mathrm{abscorrectBelief}(\mathrm{bel}^i(t), \mathbf{M})$
7: **if** $\mathbf{M}$ is a relative measurement to agent j **then**:
8: $\quad$ request from agent j: $\mathrm{bel}^j(t)$
9: $\quad (\mathrm{bel}^i(t+1), \mathrm{bel}^j(t+1)) \leftarrow \mathrm{relcorrectBelief}(\mathrm{bel}^i(t), \mathrm{bel}^j(t), \mathbf{M})$
10: $\quad$ send to agent j: $\mathrm{bel}^j(t+1)$

$$\mathbf{z}_j^i = \mathrm{h}(x^i(t), x^j(t)) + \upsilon^i(t), \qquad \mathbf{z}_j^i \in \mathbb{R}^{n_{rz}^i}, \tag{1}$$

e.g., for relative range in a two-dimensional space, we have $\mathrm{h}(x^i(t), x^j(t)) = \sqrt{(x^i - x^j)^2 + (y^i - y^j)^2}$. We assume that the sensor measurements are mutually independent and synchronized. The measurement noise υ^i is assumed to be white and Gaussian with $E[\upsilon^i(t)\upsilon^i(t)^T] = \mathbf{R}^i > 0$, and $E[\upsilon^i(t)\upsilon^i(l)^T] = 0$ for $k \neq l$. When at any time step *t* agent *i* takes relative measurement from agent *j*, we take a sequential updating approach (c.f. [17]) to process this relative measurement to correct the belief $\mathrm{bel}^{l-}(t) = (\hat{x}^{l-}(t), \mathbf{P}^{l-}(t))$ of the local filter of agents $l \in \{i, j\}$. We use the superscript $^-$ and $^+$ to indicate, respectively, beliefs before and after relative measurement update. As mentioned, the inherent noises accumulate as the beliefs propagate based only on the self-motion measurements taken by the IMU along with unreliable access to SoP or absolute measurement via GPS under indoor environment, which result in poor localization accuracy. To bound the error and improve the localization accuracy, relative range measurements can be used to update the local beliefs. After a relative measurement update a correlation is generated among the state-estimate of the agents. Naively ignoring the correlations will lead to inconsistent estimate while keeping track of the correlations require all-to-all communication at all times. It is expensive and hard to satisfy the connectivity requirement for all-to-all communication under indoor environments. Therefore the challenge of designing relative measurement update is how to account for the correlations without all-to-all communication to make sure the estimate is consistent.

C. A loosely coupled cooperative localization augmentation

Our proposed cooperative localization framework is described in Algorithm 1. In this framework, functions predictBelief denotes the self-motion measurement based localization function of the local filter of agent *i* while abscorrectBelief denotes the component due to occasional access to, for example, GPS and as a result absolute measurement update. Function relcorrectBelief denotes the consistent relative measurement update method below. This function consists of the novel relative measurement update procedure that we introduced in our previous work [16], and described below. In what follows, to simplify notation, we drop variables' time index when timing information is clear from the context.

Suppose each agent $l \in \{i, j\}$ has a consistent but correlated local belief $\mathrm{bel}^{l-}(t) = (\hat{x}^{l-}(t), \mathbf{P}^{l-}(t))$. Let $\mathbf{z}^i_j(t)$ be the relative range measurement taken by agent *i* from agent *j* at time *t*. Based on the measurement model given in (1), the first-order expansion of $\mathrm{h}^i_j(x^i, x^j)$ about the $\hat{x}^{i-}$ and $\hat{x}^{j-}$ be

$$\begin{aligned}&\mathrm{h}^i_j(x^i, x^j)\\&= \mathrm{h}^i_j(\hat{x}^{i-}, \hat{x}^{j-}) + \mathbf{H}^i_i(x^i - \hat{x}^{i-}) + \mathbf{H}^i_j(x^j - \hat{x}^{j-}),\end{aligned} \tag{2}$$

where $\mathbf{H}^i_i = \partial \mathrm{h}^i_j(\hat{x}^{i-}, \hat{x}^{j-}) / \partial x^i$ and $\mathbf{H}^i_j = \partial \mathrm{h}^i_j(\hat{x}^{i-}, \hat{x}^{j-}) / \partial x^j$.

Agent *i* wants to update its belief using this relative measurement. Agent *i* knows the relative measurement $\mathbf{z}^i_j(t)$, its associated linearized measurement model ($\mathbf{H}^i_i$ and $\mathbf{H}^i_j$), the measurement covariance matrix $\mathbf{R}^i$, and its own local belief. Assume that agent *i* obtains the local belief of agent *j* at time *t* prior to the measurement update (agent *j* sends its belief via communication). Then, the updated belief $\mathrm{bel}^{i+}(t) = (\hat{x}^{i+}(t), \mathbf{P}^{i+}(t))$ of agent *i* is given by the corresponding components of the joint update

$$x^+_J(t) = x^-_J(t) + \mathbf{K}(\mathbf{z}^i_j(t) - \hat{\mathbf{z}}^i_j(t)),$$

$$\begin{aligned}\mathbf{P}^+_J(t) &= \begin{bmatrix} \mathbf{P}^{i+}(t) & \mathbf{P}^+_{ij}(t) \\ \mathbf{P}^+_{ij}(t)^T & \mathbf{P}^{j+}(t) \end{bmatrix}\\ &= (\mathbf{I} - \mathbf{K}\mathbf{H}) \begin{bmatrix} \mathbf{P}^{i-}(t) & \mathbf{P}^-_{ij}(t) \\ \mathbf{P}^-_{ij}(t)^T & \mathbf{P}^{j-}(t) \end{bmatrix} (\mathbf{I} - \mathbf{K}\mathbf{H})^T\\ &\quad + \mathbf{K}\mathbf{R}^i\mathbf{K}^T,\end{aligned}$$

where

$$\mathbf{H} = [\mathbf{H}^i_i(t), \mathbf{H}^i_j(t)]. \tag{3}$$

The update gain can be obtained from $\mathbf{K} = \mathrm{argmin}\,\mathrm{Tr}(\mathbf{P}^+_J)$. If there is no relative measurement between agents in the past, then $\mathbf{P}^-_{ij} = 0$. But it is evident in (3), after a relative measurement update, $\mathbf{P}^+_{ij}$ is non-zero. To avoid the necessity to maintain this correlation, which incurs a huge communication cost on the agents, the authors in their previous work [15] have proposed to account for the cross covariance matrix in an implicit manner by taking advantage of a known matrix inequality fact (c.f. [18]) that guarantees

$$\begin{aligned}\bar{\mathbf{P}}^-_J(t) &= \begin{bmatrix} 1/\omega\,\mathbf{P}^{i-}(t) & 0 \\ 0 & 1/1-\omega\,\mathbf{P}^{j-}(t) \end{bmatrix}\\ &\geq \begin{bmatrix} \mathbf{P}^{i-}(t) & \mathbf{P}^-_{ij}(t) \\ \mathbf{P}^-_{ij}(t)^T & \mathbf{P}^{j-}(t) \end{bmatrix}, \quad \forall \omega \in [0,1],\end{aligned} \tag{4}$$

for any unknown value of $\mathbf{P}^-_{ij}$. Given this observation the cooperative localization augmentation that we use (function relcorrectBelief) is described as follows

$$x^+_J(t) = x^-_J(t) + \mathbf{K}(\omega)(\mathbf{z}^i_j(t) - \hat{\mathbf{z}}^i_j(t)), \tag{5a}$$

$$\begin{aligned}\mathbf{P}^+_J(t) = (\mathbf{I} - \mathbf{K}\mathbf{H}) &\underbrace{\begin{bmatrix} 1/\omega\,\mathbf{P}^{i-}(t) & 0 \\ 0 & 1/(1-\omega)\mathbf{P}^{j-}(t) \end{bmatrix}}_{\bar{\mathbf{P}}^-_J}\\ &(\mathbf{I} - \mathbf{K}\mathbf{H})^T + \mathbf{K}\mathbf{R}^i\mathbf{K}^T.\end{aligned} \tag{5b}$$

The update gain is obtained from

$$\begin{aligned}&\mathbf{K}(\omega)\\ &= \mathrm{argmin}\,\mathrm{Tr}((\mathbf{I} - \mathbf{K}\mathbf{H})\bar{\mathbf{P}}^-_J(\mathbf{I} - \mathbf{K}\mathbf{H})^T + \mathbf{K}\mathbf{R}^i\mathbf{K}^T)\\ &= \begin{bmatrix} \mathbf{K}_i \\ \mathbf{K}_j \end{bmatrix} = \bar{\mathbf{P}}^-_J\mathbf{H}^T\mathbf{S}^{-1}_{ij}\\ &= \begin{bmatrix} 1/\omega\,\mathbf{P}^{i-}(t)\mathbf{H}^{iT}_i\mathbf{S}^{-1}_{ij} \\ 1/(1-\omega)\,\mathbf{P}^{j-}(t)\mathbf{H}^{i\,T}_j\mathbf{S}^{-1}_{ij} \end{bmatrix},\end{aligned} \tag{6}$$

where

$$\begin{aligned}\mathbf{S}_{ij} &= \mathbf{H}\bar{\mathbf{P}}^-_J\mathbf{H}^T + \mathbf{R}^i\\ &= 1/\omega\,\mathbf{H}^i_i\mathbf{P}^{i-}\mathbf{H}^{iT}_i + 1/(1-\omega)\,\mathbf{H}^i_j\mathbf{P}^{j-}\mathbf{H}^{i\,T}_j + \mathbf{R}^i\end{aligned} \tag{7}$$

The optimal value of $\omega \in [0,1]$ minimizes the total uncertainty of joint updated belief is given by

$$\omega^* = \underset{\omega\in[0,1]}{\mathrm{argmax}}\ \det(\mathbf{P}^{+\ -1}_J), \tag{8}$$

which can be cast in an equivalent convex optimization problem form

$$\begin{aligned}\omega^* &= \underset{\omega\in[0,1]}{\mathrm{argmin}}\ \text{-logdet}(\mathbf{P}^{+\ -1}_J)\\ &= \underset{\omega\in[0,1]}{\mathrm{argmin}}\ \text{-logdet}(\bar{\mathbf{P}}^{-\ -1}_J + \mathbf{H}^T\mathbf{R}^{i\ -1}\mathbf{H}),\end{aligned} \tag{9}$$

The updated belief of agent *i* is then the corresponding component of $(x^+_J, \mathbf{P}^+_J)$ evaluated at ω^*. As shown in [16] this estimate is consistent in the first order approximate sense, i.e., $\mathbf{P}^{i+} \geq \mathrm{E}[(\mathrm{x}^{i+}\text{-}\mathrm{x}^i)(\mathrm{x}^{i+}\text{-}\mathrm{x}^i)^T]$. Agent *i* can send the components of $(x^+_J, \mathbf{P}^+_J)$ that corresponds to agent *j* to that agent, so that agent *j* can benefit also from the relative measurement update. This is the approach that is described in Algorithm 1 and we use in our experiments. Another option for agent *j* is to obtain its own range measurement from processing the UWB ranging signal and proceed with similar calculations in the update equations (5)-(9) to obtain its updated state estimate locally.

Notice here that the update equations (5)-(9) of this relative measurement update procedure are only loosely coupled with the local filter's equations. By loosely, what we mean is that the relative measurement update procedure only needs the local beliefs generated by the local filters at the time of taking the relative measurement. Once the relative measurement update is done, agents can proceed with their local filter localization until the next relative measurement takes place. As such one can look at our cooperative localization scheme as an augmentation service, which agents can take advantage of to opportunistically improve their localization accuracy with least amount of communication cost.

III. UWB SYSTEM

In our proposed CL algorithm, the assumption is that each agent in the team is capable of sensing and communicating with others. Relative range measurements are used as a feedback to update the prior belief produced by agent's local filter (via INS and occasional absolute measurements) and prior belief is communicated between the two agents involved in the relative measurement. In indoor human agent localization problems, especially in first-responder environments, indoor or covered

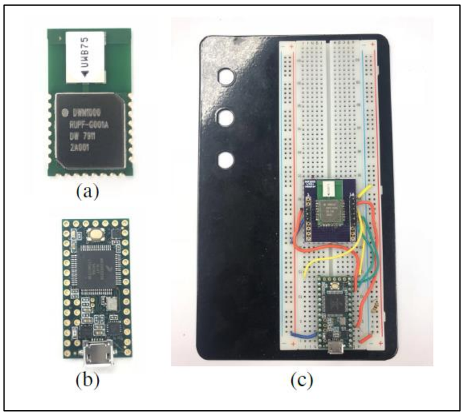

Fig. 4. UWB ranging sensor: (a) DWM1000 Module, (b) Teensy 3.2, (c) our UWB ranging sensor and communication module.

outdoor environments are considered as dense multipath and non-line-of-sight conditions. For such environments traditional interference of radio signals. Recently, UWB radio has gained a lot of attention. UWB is a radio technology with a wide bandwidth. The short impulse of UWB signal makes it less susceptible to interfere with each other and with other coexisting radio signals such as WIFI and Bluetooth in complicated applications. Because of its wide bandwidth, another approach is to split a very wide band into sub-bands which will also avoid interference. In addition, the low power emission of UWB signal makes it energy-efficient. Hence, UWB is a promising technology that can be used effectively as ranging sensor and communication module for challenging human agent localization problems such as firefighter localization.

A. UWB device

In our experiments, we use DWM1000 developed by DecaWave as our both relative ranging sensor and communication module. We have used a Teensy 3.2 micro-controller as data acquisition interface. The ranging and communication software is mounted on this micro-controller. Fig. 4 shows the prototype of the ranging sensor that we have built in our lab.

B. Time-of-arrival based UWB ranging

The common UWB ranging is based on time-of-arrival (TOA) algorithms, which measure the propagation time of an impulse that travels from transmitter to the receiver. Then, the

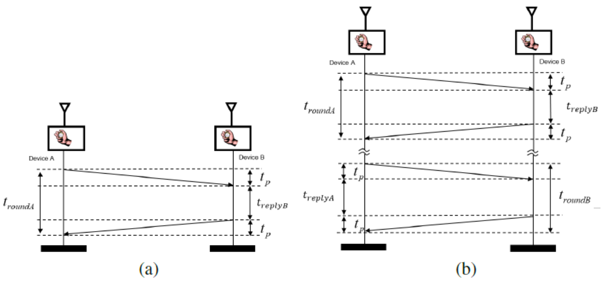

Fig. 5. Time-of-flight based ranging algorithms: (a) single-sided two-way ranging, and (b) symmetric double-sided two-way ranging.

distance will be known because the speed of propagation of radio signal in the air is a known constant. In practice, the time is derived from the difference of the two time-stamps when the signal is sent and received, which are based on the local clock of transmitter and receiver, respectively. This requires clock synchronization of each sensor node to achieve high ranging accuracy, which can be problematic. To eliminate the error caused by lack of synchronization, two-way ranging (TWR) as in Fig. 5(a) is used ([19]). In TWR, the TOA is given by

$$t_p = (t_{roundA} - t_{replyB})/2. \tag{10}$$

Here round time is used instead of absolute time stamps so that the requirement of clock synchronization is relaxed. However, frequency offsets of crystal oscillators, which provides clock signal for electronic devices, can still result in measurement errors. If the frequency offset of device A and B are denoted as e_A and e_B respectively, the resultant TOA error in fact is given by

$$\tilde{t}_p = \hat{t}_p - t_p = t_{replyB}(e_A - e_B)/2. \tag{11}$$

The frequency offset of crystal oscillators is normally represented in parts per million (ppm). Even small frequency offsets can lead to non-negligible ranging errors because of the high speed of radio signal propagation. For instance, a 1 ppm frequency with 1 ms reply time will lead to 15 centimeters ranging error. Therefore, mitigation of the ranging error caused by crystal oscillator frequency offset is important for UWB ranging based localization. The symmetric double-sided TWR [20] is shown to mitigate the error significantly. In symmetric double-sided TWR, radio signal is sent from one node to another back and forth twice as Fig. 5(b). The TOA for this method is

$$t_p = (t_{roundA} - t_{replyA} + t_{roundB} - t_{replyB})/4, \tag{12}$$

and the corresponding TOA error caused by frequency offset e_A and e_B will become

$$\begin{aligned} \tilde{t}_p &= \hat{t}_p - t_p \\ &\approx t_p(e_A - e_B)/2 + (t_{replyB} - t_{replyA})(e_A - e_B)/4, \end{aligned} \tag{13}$$

which can be significantly reduced by setting $t_{replyA} = t_{replyB}$ comparing with single-sided TWR since the second term in the error will be close to zero and t_p which is the propagation time between transceivers in the first term is much smaller than the reply time.

C. UWB ranging tests and results

The performance of the two ranging algorithms described above was tested using our sensors in the Engineering Gateway Building of UC Irvine under indoor line-of-sight condition. Test cases are described using the actual distance between a transmitter and a receiver node for the following two cases of true ranges:

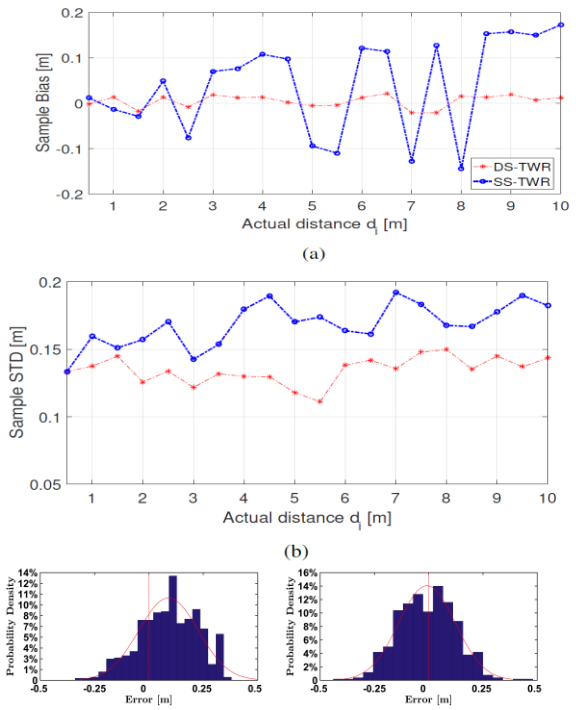

Fig. 6. Test results of set 1 ranging accuracy: (a) bias, (b) standard deviation for each case (blue plot is for single-sided TWR and red plot is for double-sided TWR), and (c) histograms of ranging error corresponding to Case_{14}^{1} (left is for single-sided TWR and right is for double-sided TWR

$$\text{Case}_i^1 = \{d_i\}, \quad d_i \in \{0.5\text{m}, 1\text{m}, ..., 10\text{m}\}$$
$$\text{Case}_i^2 = \{d_i\}, \quad d_i \in \{1\text{m}, 3\text{m}, ..., 50\text{m}\}$$

To guarantee the validity of the measurement results, over 500 samples are obtained for each measurement point. The results for first case study is shown Fig. 6. As seen in Fig. 6(a) andFig.6 (b) symmetric double-sided two-way ranging (DS-TWR) ranging method producing a better measurement model with considerably smaller bias in the measurements. The plots in Fig.6 (c) are the histograms of the collected samples for one of our cases. These histograms point to the Gaussian nature of the measurement noises. Fig. 7(a) and Fig. 7(b) show the bias ad the standard deviation of the DS-TWR ranging measurement for case 2 (distance from 1m up to 50m, which is about the maximum ranging capability of our current UWB sensors). As these plot shows, the performance of the DS-TWR ranging is reliable up to around 25m. The ranging performance can be improved by increasing the number of the two way signal exchanges. However, this increase comes with the increase in the energy consumption of the UWB sensors.

D. UWB communication

As mentioned previously, to process a relative measurement, the agents involved need to exchange their local beliefs with each other. Considering the environments firefighters working in, UWB is the technology that has the potential to provide a

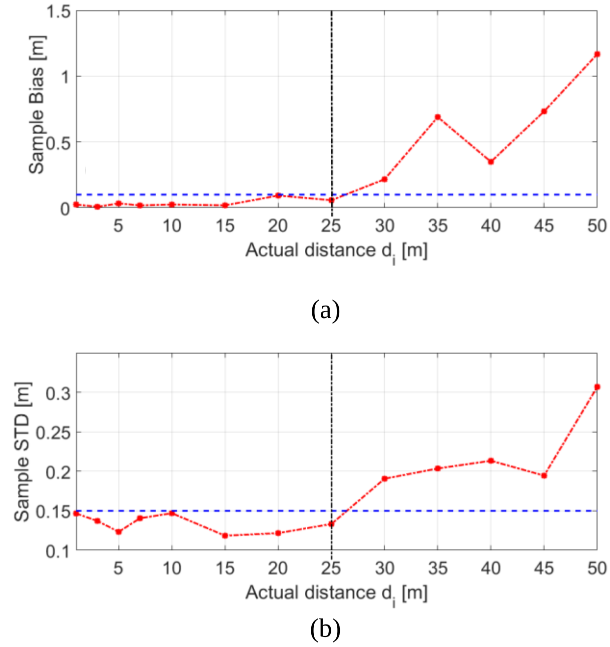

Fig. 7. The bias and the standard deviation in the DS-TWR ranging model of the test case 2.

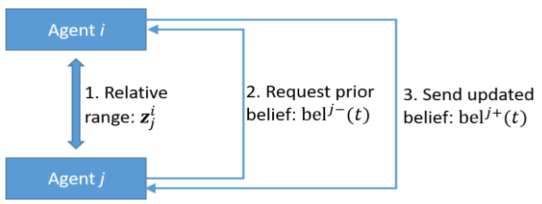

Fig. 8. UWB ranging and communication in proposed cooperative localization algorithm.

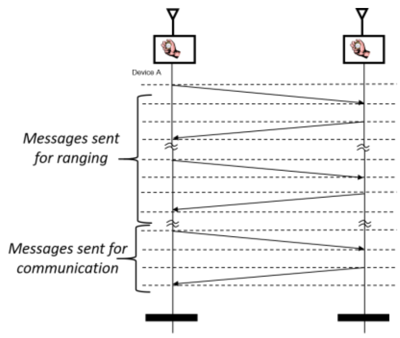

Fig. 9. UWB communication framework: symmetric double-sided TWR followed by communication between two agents.

robust communication. The DWM1000 transceiver is capable of communication at a maximum data transmission rate of 6.8 Mbps. During symmetric double-sided TWR, the message containing corresponding time stamps are transmitted four time between two agents to get the relative range measurement. As in Fig. 7, the agent takes relative measurement need to acquire the prior belief of the other one in order to update the prior beliefs in our proposed cooperative localization algorithm. Once the

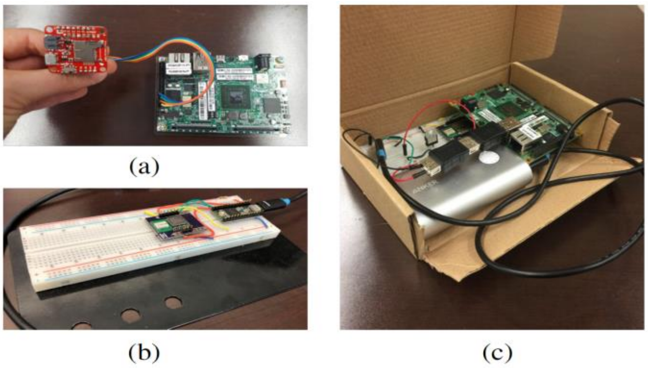

Fig. 10. Initial prototype of a stand-alone portable localization device: (a) a single board computer with IMU (b) UWB ranging sensor (c) the portable localization device.

prior beliefs are updated, the updated belief will be sent back. In Fig. 8, ranging process is followed by two more times of message transmission and each message contains the corresponding prior belief and updated belief that are shared. To realize robust communication, the maximum data size for each message has to been large enough to contain all the data exchanged. For DWM1000, data size is up to 127 coded octets based on IEEE standard and could be extended up to 1023 coded octets which is more than enough. Real-time implementation of UWB communication has been achieved using the developed devices as in Fig. 4.

IV. DEMONSTRATIONS

In this section, we demonstrate the effectiveness of the loosely coupled cooperative localization algorithm described in previous sections in simulation and experiments. To test the performance of the proposed CL augmentation service based on UWB relative ranging measurements and communications, an indoor experiment via two human agents was conducted in one of the hallways of the Engineering Gateway Building at UC Irvine, see Fig. 9. Each agent carries a portable hand-held localization unit that is shown in Fig. 8. This unit consists of an INFORCE 6410PLUS single board computer powered by a portable battery, a commercial IMU (SparkFun 9DoF Razor IMU) and our UWB ranging/communication sensor shown in Fig. 4. The computations are carried out on the single board computer and communication between agents are done via the UWB sensor. In this paper, our focus is on demonstrating our loosely coupled cooperative localization augmentation's effectiveness in improving state estimates obtained by a local filter. Once we validated our algorithm, we will test it on a system that uses foot-mounted IMU system along with ZUPTing.

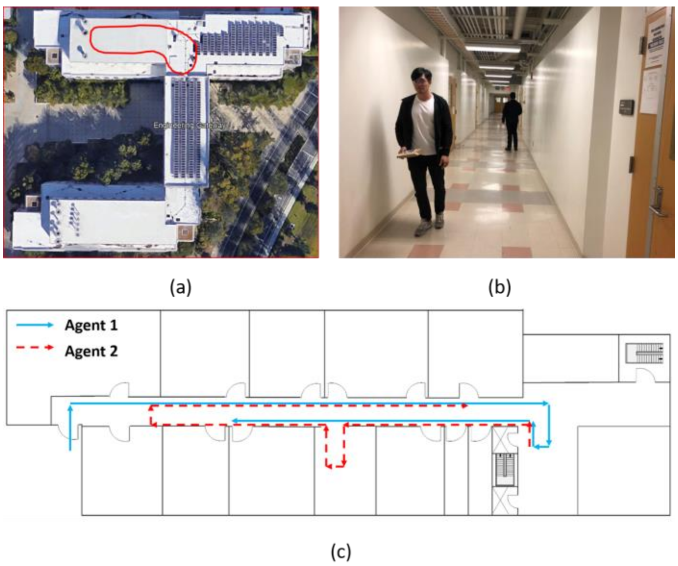

Fig. 11. Experimental setup with human agents: (a) Engineering Gateway Building at UC Irvine (from Google Earth Pro), (b) experiment scenario, and (c) planned trajectory in the hallway.

The experimental test is shown in Fig. 11 for two agents. The results corresponding to agent 1 are shown on the top and for agent 2 in the bottom. The true trajectory of each agent is shown in black with the starting point marked via the black $\times$. INS only localization is shown by the dashed blue lines. The relative measurement update times are marked by circles and numbered according to their occurrence. The best benefit from CL happens when one of the agents has better localization accuracy. To emulate a situation in which agent 1 has a higher localization accuracy, we have conducted 5 absolute measurement updates with respect to a beacon with a known location at occasions that are marked with the green squares on the trajectories of agent 1. As we can see by use of our loosely coupled CL augmentation agents can improve their localization accuracy. This benefit is more pronounced for agent 2, which gets a considerable localization improvement by implementing CL with respect to agent 1 that has a better localization accuracy due to 5 absolute measurement update occasions (marked by green squares). A simulation results corresponding to a case with higher accuracy IMU is shown in Fig. 12. In this simulation we can see far more benefits from CL updates. In our future work, we will consider foot-mounted IMU systems with ZUPTing which deliver better localization accuracy for local filters.

V. CONCLUSION

In this paper, we studied the effectiveness of our cooperative

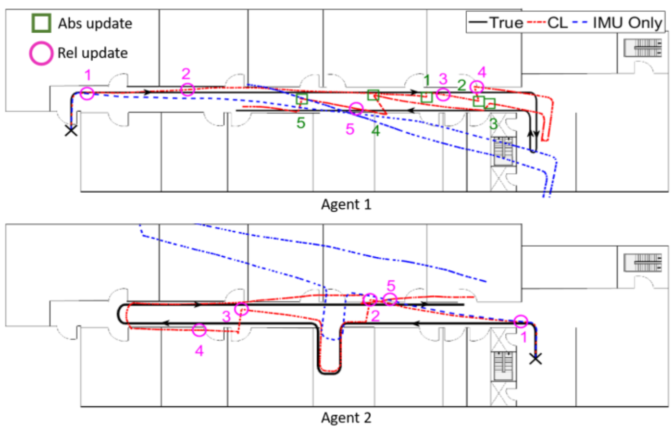

Fig. 12. The estimated trajectories based on our experiment. The results corresponding to agent 1 are shown on the top and for agent 2 in the bottom.

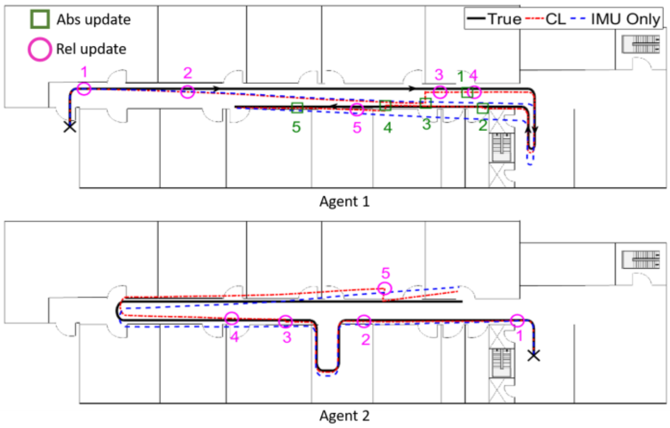

Fig. 13. The estimated trajectories from a simulation study in which we use a higher grade IMU unit. The results corresponding to agent 1 are shown on the top and for agent 2 in the bottom.

localization algorithm in [16] for human agent localization via inter-agent UWB relative ranging. This algorithm serves as an augmentation service that gets activated whenever there is a relative measurement between two agents. Once the relative measurement is done the augmentation goes to sleep until the next relative measurement. Since this algorithm does not require any form of network wide connectivity it can serve as an effective method to increase localization accuracy of human agents via opportunistic relative measurement updates with least amount of communication and computation overhead.

Our experiments show that indeed our cooperative localization can result in improving the agents accuracy. In this paper our focus was on proof of concept and validation aspect of our cooperative localization augmentation service. Our future work focuses on implementing our algorithm over local filters with foot-mounted IMU systems with ZUPTing capability. We will focus also on non-line-of-sight UWB measurement modeling and its utilization in CL updates.

Nevertheless, our concluding remark from our experiments is that a local filter plus CL augmentation is not enough to achieve high accuracy localization. In operational scenarios, it makes sense to assume that from time to time one of the agents can obtain high localization accuracy via opportunistic GPS access or measurements with respect to beacons mounted in outside the building. In such cases, the other agents in the team can increase their localization accuracy by taking relative measurements from that agent.

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References

[1] K. Pahlavan, X. Li, and J. P. Makela, "Indoor geolocation science and technology," IEEE Communication Magazine, vol. 40, pp. 112-118, 2002.

[2] K. Pahlavan, P. Krishnamurthy, and Y. Geng, "Localization challenges for the emergence of the smart world," IEEE Access, vol. 3, pp. 3058-3067, 2015.

[3] G. Dissanayake, P. Newman, H. F. Durrant-Whyte, S. Clark, and M. Csorba, "A solution to the simultaneous localization and map building (SLAM) problem," IEEE Transaction on Robotics and Automation, vol. 17, no. 3, pp. 229-241, 2001.

[4] O. Bebek, M. A. Suster, S. Rajgopal, M. J. Fu, X. Huang, M. C. avusoglu, D. J. Young, M. Mehregany, A. J. van den Bogert, and C. H. Mastrangelo, "Personal navigation via high-resolution gait-corrected inertial measurement units," IEEE Transaction on Instrumentation and Measurement, vol. 59, no. 11, pp. 3018-3027, 2010.

[5] A. Haeberlen, E. Flannery, A. M. Ladd, A. Rudys, D. S. Wallach, and L. E. Kavraki, "Practical robust localization over large-scale 802.11 wireless networks," in MobiCom, 2004.

[6] S. S. Kia, S. Rounds, and S. Martínez, "Cooperative localization for mobile agents: a recursive decentralized algorithm based on Kalman filter decoupling," IEEE Control Systems Magazine, vol. 36, no. 2, pp. 86–101, 2016.

[7] P. O. Arambel, C. Rago, and R. K. Mehra, "Covariance intersection algorithm for distributed spacecraft state estimation," in American Control Conference, (Arlington, VA), pp. 4398–4403, 2001.

[8] S. I. Roumeliotis and G. A. Bekey, "Distributed multirobot localization," IEEE Transactions on Robotics and Automation, vol. 18, no. 5, pp. 781–795, 2002.

[9] S. S. Kia, J. Hechtbauer, D. Gogokhiya, and S. Martínez, "Server assisted distributed cooperative localization over unreliable communication links," IEEE Transactions on Robotics, Vol. 34, no. 9, 2018.

[10] Vu Dinh and S. S. Kia, "A Server-Client Based Distributed Processing for an Unscented Kalman Filter for Cooperative Localization", IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (San Diego, CA), 2015.

[11] L. C. Carrillo-Arce, E. D. Nerurkar, J. L. Gordillo, and S. I. Roumeliotis, "Decentralized multi-robot cooperative localization using covariance intersection," in IEEE/RSJ Int. Conf. on Intelligent Robots & Systems, (Tokyo, Japan), pp. 1412–1417, 2013.

[12] H. Li and F. Nashashibi, "Cooperative multi-vehicle localization using split covariance intersection filter," in IEEE Intelligent Vehicle Symposium, (Spain), pp. 211–216, 2012.

[13] D. Marinescu, N. O'Hara, and V. Cahill, "Data incest in cooperative localisation with the common past-invariant ensemble kalman filter," in IEEE Int. Conf. on Information Fusion, (Istanbul, Turkey), pp. 68–76, 2013.

[14] S. J. Julier and J. K. Uhlmann, "A non-divergent estimation algorithm in the presence of unknown correlations," in American Control Conference, vol. 4, pp. 2369–2373, Jun 1997.

[15] S. J. Julier and J. K. Uhlmann, Handbook of Data Fusion. CRC Press, 2001.

[16] J. Zhu and S. S. Kia, "A loosely coupled decentralized cooperative navigation for team of mobile agents," in Proceedings of the International Technical Meeting of The Institute of Navigation, (Monterey, CA), pp. 782–804, 2017.

[17] Y. Bar-Shalom, P. K. Willett, and X. Tian, Tracking and Data Fusion, a Handbook of Algorithms. Storts, CT, USA: YBS Publishing, 2011.

[18] R. A. Horn and C. R. Johnson, Topics in Matrix Analysis. Cambridge: Cambridge University Press, 1991.

[19] IEEE Computer Society, IEEE Std 802.15.4a-2007, August 2007.

[20] Z. Sahinoglu and S. Gezici, "Ranging in the IEEE 802. 15. 4a standard", Wireless and Microwave Technology Conference, 2006.