DiPLoc: Direct Signal Domain Particle Filtering for Network Localization

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***Abstract*—We envisage a very high mobile terminal (MT) density for future wireless networks which requires ubiquitous high-definition network self-localization ability. Traditional network localization contains two steps: ranging and localization. The coherence between the two steps is not fully exploited. We propose a direct signal domain particle filter for network self-localization (DiPLoc). The key objective is to obtain the location information directly from the received signal samples, i.e. the waveform, avoiding hard decision in the intermediate step and the ranging model approximation. The complexity of the proposed DiPLoc is similar to the two-step approach. Both of the numerical and experimental results show that, the DiPLoc outperforms the traditional two-step approaches especially when the network is dense.**

I. INTRODUCTION

Ubiquitous localization in a wireless network is essential for a wide range of applications, from situation awareness of mass-market devices such as vehicular collision avoidance, mobile crowd sensing and smart city [1], [2], to professional multi-agent collaborations such as robotic swarm exploration, disaster management and security applications [3]. In open areas, localization is enabled through the global navigation satellite systems (GNSS). In GNSS-denied areas, such as urban canyon and public indoor, the terrestrial radio networks, e.g. 3GPP-LTE and DVB-T, are exploited to augment localization. However, the accuracy of both satellite and terrestrial localization is limited by the number of visible anchors (GNSS satellites, base stations and access points) and the complex propagation channel condition.

Due to the emergence of direct communication applications, such as car-to-car communication, smart city and internet of things, we envisage ubiquitous mesh networks with very high mobile terminal (MT) density for future wireless networks. In these networks, MTs directly communicate to the neighbors via short range and low power radio links, also known as device-to-device (D2D) links. It has been verified, for example in the WINNER 2 channel model [4], that for the typical scenario of network localization applications, the probability of having non-line-of-sight (NLOS) links is exponentially decreasing along with the distance between the transmitter and the receiver. The massive LOS links offer new opportunities for network localization. Through cooperation, an MT can estimate its own location relative to the neighbors. This relative location information can be either fed directly to some applications, e.g. collision avoidance, or fused with other sensors to obtain more precise absolute location information. A multi-agent application for the network self-localization is illustrated in Fig. 1. $\mathbf{p}_u$ is the MT position to estimate, $d_{u,\nu}$ is the true distance between node u and node ν, $z_{u,\nu}$ is the generic relative observation between node u and node ν which contain the position information.

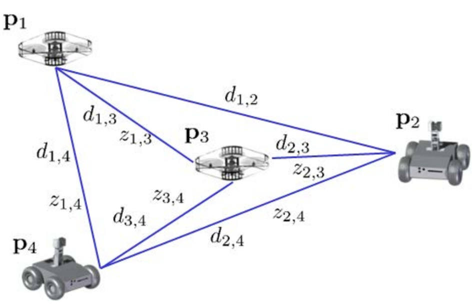

Figure 1. A multi-agent application for the network self-localization

Though intensive research has been conducted on network localization, e.g. in [5], [6], [7], [1] , the potential of these networks is not fully explored. One of the main reasons is that most research considers localization as a two-step problem: distance estimation (ranging) and location estimation (localization). Each step is optimized separately. In the first step, the distance of each link is estimated by the receiver from the received signal samples. For time-based localization, a delayed replica of the reference signal is generated at the receiver side and compared with the received signal in order to find the most likely propagation delay. In practice, it is normally achieved by calculating the cross-correlation and finding the maximum peak of the correlation function [8]. For a multipath distorted channel, a first peak detection has to be applied additionally to prevent obtaining a peak from the multipath [9]. Alternatively, a super-resolution algorithm, e.g. space-alternating generalized expectation-maximization (SAGE) algorithm, can be apply to outperform the peak detection-based algorithms [10]. The super-resolution algorithm jointly estimates the multipath components. The first detected path is considered as the geometry line-of sight (GLOS) path and is used for the distance estimate.

In the second step, a non-linear estimator uses the distance estimates of multiple links as the 'measurements' and solves the location equations. In order to fuse the estimates from multiple links, the error distribution of the distance estimate need to be modeled intermediately. In practice, a weighting scheme is normally applied, e.g. in the weighted least square algorithm. In this case, a Gaussian model is assumed for the ranging error. For example, based on the estimated signal-to-noise ratio (SNR), the Cramér-Rao bound (CRB) or the Ziv-Zakai bound (ZZB) can be calculated to lower bound the variance of distance estimate and used as the weight for each link. However, even with the weighting scheme, the coherence between the two steps is not fully exploited. A wrong correlation peak could be acquired in the first step due to the distortion by the noise or multipath. Consequently, a large error in the location estimate may occur. [11] proposed a high-dimension likelihood parameter fitting to reduce the error from the intermediate step. However, these algorithms require a training data set and are computationally costly. Recent research has been conducted to further investigate the coherence between ranging and localization for non-cooperative localization. A non-parametric algorithm, mostly a particle filter, is applied directly on the signal domain, e.g. in [12] and [13] for GNSS-based localization and in [14] for terrestrial localization. However, for a multipath scenario, the non-parametric maximum a-posterior (MAP) estimator becomes computational intractable, due to the high dimensional state space.

In this paper, we extend the direct signal domain localization into a D2D network with massive low power and short distance links. The raw received signal samples is taken as the measurements to derive the joint likelihood function of the location estimate with single channel tap assumption. Based on the derived likelihood function, we propose a direct signal domain particle filtering algorithm for network localization (DiPLoc). The key motivation is to obtain the location information directly from the received signal samples, avoiding the ranging model approximation. Particles are randomly initiated for each MT within the position a-priori information. Each particle is considered as a location hypothesis and generates delayed replicas of the reference signal according to its distances to the neighbors. In the update stage, the weight of particle is calculated directly from the inner-products of the replicas and the received signals. The proposed DiPLoc is not an MAP estimator for a multipath scenario. However, it takes every peaks of the correlation function as soft hypotheses and prevents making hard decision in the intermediate step. The massive links jointly support the right hypothesis and reject the wrong ones with high probability. In the DiPLoc, multiple links are inherently weighted by the overall likelihood. Therefore, the DiPLoc preserves as much information as possible from the signal domain to the location domain. More importantly, the cross-correlation can be seen as a group of inner-products between the received signal and the signal replicas with a shifting delay window. From this viewpoint, each particle hypothesis in the DiPLoc can be considered as a realization of the shifted window. Therefore, the complexity of the DiPLoc is comparable to a simple cross-correlation-based estimator.

We verify our proposed DiPLoc with both numerical and experimental results. For the numerical simulation, the moving network scenario (D2) of the WINNER 2 channel model is applied. We investigate the non-cooperative and the anchor-free network localization with different numbers of nodes. In the non-cooperative case, a single MT locates itself in an anchor network. In the anchor-free case, none of the nodes in the network knows its location, and they estimate the relative geometry of the network in a distributed fashion. We compare the two-step algorithms: correlation-based and super-resolution-based with the single-step DiPLoc. In both cases, the DiPLoc outperforms the two-step approaches when the number of neighbors increases. For the experimental results, we conduct a measurement campaign with a dynamic meshed network and exploit the measurement data for anchor-free localization. First we compare the distance estimate through cross-correlation with the CRB and the ZZB. We find out that even though the ZZB is a relatively tight bound, it cannot substitute the ranging variance in practice due to the multipath, bias, inaccurate SNR estimate and outliers. We further compare the ZZB-aided traditional particle filter and the DiPLoc. The DiPLoc significantly outperforms the traditional particle filter and achieves the accuracy below one meter for most of the time. With the theoretical analysis, the numerical simulation and the experimental results, we can conclude that the DiPLoc we propose is more suitable for network localization, in particular for dense networks.

II. Framework of Network Localization and Tracking with OFDM Signal

A. Problem Formulation

We consider a network with $B+M$ nodes (set: $\mathbb{K}$), including B BSs (set: $\mathbb{B}$) and M MTs (set: $\mathbb{M}$). A node ν is considered as the neighbor of MT u if MT u can communicate and make ranging measurement with it. The neighboring node set of MT u at step k is defined as $\mathbb{K}_u^{(k)}$. The neighboring MT and BS set of MT u at step k are defined respectively as $\mathbb{M}_u^{(k)} = \mathbb{M} \bigcap \mathbb{K}_u^{(k)}$ and $\mathbb{B}_u^{(k)} = \mathbb{B} \bigcap \mathbb{K}_u^{(k)}$. The position of a node u at step k is defined as

$$\mathbf{p}_u^{(k)} = \left[x_u^{(k)}, y_u^{(k)}\right]^T, \qquad u \in \mathbb{K}. \tag{1}$$

The node position and the velocity at step k are described by a state space model. A BS is assumed to be stationary with a known position, i.e.:

$$\mathbf{x}_b^{(k)} = \left[x_b, y_b, 0, 0\right]^T, \qquad b \in \mathbb{B}. \tag{2}$$

MT is dynamic:

$$\mathbf{x}_u^{(k)} = \left[x_u^{(k)}, y_u^{(k)}, \dot{x}_u^{(k)}, \dot{y}_u^{(k)}\right]^T, \qquad u \in \mathbb{M}. \tag{3}$$

The state transition of MT u from step $k-\delta_u$ to step k is described as a linear stochastic process:

$$\mathbf{x}_u^{(k)} = \mathbf{A}(\delta_u)\mathbf{x}_u^{(k-\delta_u)} + \boldsymbol{\epsilon}_u^{(k-\delta_u)}, \tag{4}$$

where $\boldsymbol{\epsilon}_u^{(k-\delta_u)} \sim \mathcal{N}\left(0, \mathbf{Q}(\delta_u)\right)$ is the transition noise,

$$\mathbf{A}(\delta_u) = \begin{pmatrix} 1 & 0 & \delta_u T_0 & 0 \\ 0 & 1 & 0 & \delta_u T_0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \tag{5}$$

$$\mathbf{Q}(\delta_u) = \sigma_{\epsilon_u}^2 \begin{pmatrix} \frac{(\delta_u T_0)^3}{3} & 0 & \frac{(\delta_u T_0)^2}{2} & 0 \\ 0 & \frac{(\delta_u T_0)^3}{3} & 0 & \frac{(\delta_u T_0)^2}{2} \\ \frac{(\delta_u T_0)^2}{2} & 0 & \delta_u T_0 & 0 \\ 0 & \frac{(\delta_u T_0)^2}{2} & 0 & \delta_u T_0 \end{pmatrix}, \tag{6}$$

T_0 is the time between a single step and $\sigma_{\epsilon_u}^2$ is the variance of the continuous acceleration which can be determined based on the application. We assume in general the state updates of all the MTs are asynchronous and the number of steps from the last updates to the step k are:

$$\boldsymbol{\delta} = [\cdots, \delta_u, \cdots]^T, \qquad \forall u \in \mathbb{M} \tag{7}$$

MT u requests radio-based measurements from a generic neighbor ν, which contains the relative position information of both nodes

$$\mathbf{z}_{u,\nu}^{(k)} = \mathbf{h}_{u,\nu}^{(k)} \left(\mathbf{x}_u^{(k)}, \mathbf{x}_\nu^{(k)}, \boldsymbol{\omega}_{u,\nu}^{(k)} \right) \quad \nu \in \mathbb{K}_u^{(k)} \tag{8}$$

The $\mathbf{h}_{u,\nu}^{(k)}$ is the observation function which depends on the measurement method and $\boldsymbol{\omega}_{u,\nu}^{(k)}$ is the observation noise.

We define the following notations of variable $\mathbf{v}$ (can be scalar, vector or matrix):

1. $\mathbf{v}_{\mathbb{V}}$ is the collection of variables of nodes $u, \forall u \in \mathbb{V}$.

2. $\mathbf{v}^{(\mathbf{k}-\boldsymbol{\delta})}$ is the collection of variables of all the MTs at the individual last updating time $k - \delta_u, \forall u \in \mathbb{M}$.

3. $\mathbf{v}(\boldsymbol{\delta})$ is the collection of delay-dependent variables for all the MTs with the individual delay $\delta_u, \forall u \in \mathbb{M}$.

4. $\mathbf{v}^{(a:b)}$ is the variable collection from step a to step b. For simplicity, we omit the subscript $\mathbb{M}$ when a variable is a collection of all the MTs without any ambiguity. With the notation above, the global state of all the MTs is defined as

$$\mathbf{x}^{(k)} = \left[\cdots, \left(\mathbf{x}_u^{(k)} \right)^T, \cdots \right]^T, \qquad \forall u \in \mathbb{M}. \tag{9}$$

The transition function of all MTs is:

$$\mathbf{x}^{(k)} = \mathbf{A}(\boldsymbol{\delta}) \mathbf{x}^{(\mathbf{k}-\boldsymbol{\delta})} + \boldsymbol{\nu}^{(\mathbf{k}-\boldsymbol{\delta})} \tag{10}$$

$$\boldsymbol{\nu}^{(\mathbf{k}-\boldsymbol{\delta})} \sim \mathcal{N}\left(0, \mathbf{Q}(\boldsymbol{\delta})\right). \tag{11}$$

The global observation vector is:

$$\mathbf{z}^{(k)} = \mathbf{h}^{(k)} \left(\mathbf{x}^{(k)}, \boldsymbol{\omega}^{(k)} \right). \tag{12}$$

The localization problem can be solved independently at each step by a maximum likelihood (ML) estimator, i.e.

$$\hat{\mathbf{x}}^{(k)} = \arg\max_{\mathbf{x}^{(k)}} p\left(\mathbf{z}^{(k)} | \mathbf{x}^{(k)} \right), \tag{13}$$

or by a Bayesian tracking filter, i.e.

$$\hat{\mathbf{x}}^{(k)} = \arg\operatorname*{opt}_{\mathbf{x}^{(k)}} f_{\text{opt}} \left(p\left(\mathbf{x}^{(k)} | \mathbf{z}^{(1:k)} \right) \right). \tag{14}$$

The optimization function f_{opt} can be calculating the mean (minimum mean square error (MMSE)) or the mode (maximum a-posterior (MAP)) of the posterior filtered density $p\left(\mathbf{x}^{(k)}|\mathbf{z}^{(1:k)}\right)$. By applying the Bayes' rule, the posterior filtered density can be rewritten in a recursive fashion:

$$\begin{aligned} & p\left(\mathbf{x}^{(k)} | \mathbf{z}^{(1:k)} \right) \\ & \propto p\left(\mathbf{z}^{(k)} | \mathbf{x}^{(k)} \right) p\left(\mathbf{x}^{(k)} | \mathbf{x}^{(\mathbf{k}-\boldsymbol{\delta})} \right) p\left(\mathbf{x}^{(\mathbf{k}-\boldsymbol{\delta})} | \mathbf{z}^{(1:\mathbf{k}-\boldsymbol{\delta})} \right). \end{aligned} \tag{15}$$

The three components in the right side of (15) are: the a-priori for state prediction:

$$p\left(\mathbf{x}^{(k)} | \mathbf{x}^{(\mathbf{k}-\boldsymbol{\delta})} \right); \tag{16}$$

the likelihood for state update:

$$p\left(\mathbf{z}^{(k)} | \mathbf{x}^{(k)} \right); \tag{17}$$

and the last-step posterior for sequential calculation:

$$p\left(\mathbf{x}^{(\mathbf{k}-\boldsymbol{\delta})} | \mathbf{z}^{(1:\mathbf{k}-\boldsymbol{\delta})} \right). \tag{18}$$

As assumed in (4), the state transition of each agent is independent, i.e.

$$p\left(\mathbf{x}^{(k)} | \mathbf{x}^{(\mathbf{k}-\boldsymbol{\delta})} \right) = \prod_{u \in \mathbb{M}} p\left(\mathbf{x}_u^{(k)} | \mathbf{x}_u^{(k-\delta_u)} \right). \tag{19}$$

Therefore the prediction step of a distributed Bayesian estimator can be easily implemented. In contrast, a marginalization is required in the update step due to the cooperation between MTs:

$$\begin{aligned} & p\left(\mathbf{z}^{(k)} | \mathbf{x}^{(k)} \right) = \prod_{u \in \mathbb{M}} p\left(\mathbf{z}_u^{(k)} | \mathbf{x}_u^{(k)} \right) \\ & = \prod_{u \in \mathbb{M}} p\left(\mathbf{z}_{\mathbb{B}_u}^{(k)} | \mathbf{x}_u^{(k)} \right) \int p\left(\mathbf{z}_{\mathbb{M}_u}^{(k)} | \mathbf{x}_u^{(k)}, \mathbf{x}_{\mathbb{M}_u}^{(k)} \right) p\left(\mathbf{x}_{\mathbb{M}_u}^{(k)} | \mathbf{x}_u^{(k)} \right) d\mathbf{x}_{\mathbb{M}_u}^{(k)}. \end{aligned} \tag{20}$$

The marginalization brings a high complexity into a distributed Bayesian estimator. Research has been conducted to solve it.

In this work we focus on the conditional likelihood $p\left(\mathbf{z}_u^{(k)}|\mathbf{x}_u^{(k)}, \mathbf{x}_{\mathbb{K}_u}^{(k)}\right)$ derived directly from the waveform.

B. OFDM Waveform for Localization

We assume the localization signal is modulated with OFDM technique because of the flexibility for resource allocation and the inter-subcarrier interference-free property. In general, the ranging signal can apply other modulation scheme as well. For a single link ν, an OFDM signal is transmitted from a node ν and received by an MT u. The transmitted OFDM symbol is expressed as:

$$s_\nu(t) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} S_n e^{j2\pi f_{sc} n t} \tag{21}$$

f_{sc} is the subcarrier spacing, n is the subcarrier index, N is the number of subcariers, and S_n is the information symbol carried by each subcarrier. The received signal can be modeled as a noisy discrete copy of the $s(t)$ with a propagation delay τ_ν and a complex path gain α_ν, i.e.:

$$r_\nu(iT) = \alpha_\nu s_\nu(iT - \tau_\nu) + w(iT), \tag{22}$$

$w(iT) \sim \mathcal{CN}\left(0, \sigma^2/2\right)$ is the thermal noise for each sample from the receiver's frontend. T is the sampling period. We assume the signal propagating with the speed of light c_0, i.e.

$$\tau_\nu = \|\mathbf{p}_u^{(k)} - \mathbf{p}_\nu^{(k)}\| / c_0. \tag{23}$$

Hence the received waveform contains information of the euclidian distance between the transmitter and the receiver. Therefore, the MT u can use the received waveform as the observation to estimate its position. It is worth to mention that for the propagation time based ranging, the clock offsets from different MTs can lead to a bias. However, it can be eliminated with multiple-way time measurements, e.g. the round-trip delay estimate we applied in [15]. We will discuss in detail about extracting the position information from the waveform in Section III and IV. Although the phase of the waveform might contain some information about the relative velocity, i.e. the Doppler shift, we do not further exploit this information in this paper. Therefore, the waveform observation only directly contributes to the relative position. The velocity is indirectly filtered out by the transition function.

III. TWO-STEP NETWORK LOCALIZATION

Most state-of-the-art localization algorithms contain two steps: ranging, i.e. distance estimation from the waveform; and localization, i.e. position estimation with the pre-estimated distance. For the ranging step, an ML estimator is normally applied:

$$\begin{aligned}\hat{d}_\nu &= \arg\max_{d_\nu} p\left(r_\nu | d_\nu\right) \\ &= \arg\min_{d_\nu} \sum_{i=0}^{N-1} \left| r_\nu(iT) - \alpha_\nu s_\nu(iT - d_\nu/c_0)\right|^2 \\ &= \arg\max_{d_\nu} \Re\{\alpha_\nu^* \sum_{n=0}^{N-1} e^{j2\pi n f_{sc} d_\nu/c_0} R_n S_n^*\}. \qquad (24)\end{aligned}$$

R_n is the received single on subcarrier n. We further define

$$f(d) \triangleq \sum_{n=0}^{N-1} e^{j2\pi n f_{sc} d/c_0} R_n S_n^*. \qquad (25)$$

For the non-coherent case, i.e. the phase of α_ν is unknown, (24) can be modified with

$$\hat{d}_\nu = \arg\max_{d_\nu} \left| f(d_\nu) \right|. \qquad (26)$$

(26) is the cross-correlation between received and transmitted signal and in practice obtained by the signal acquisition and sub-sample refinement. The distance estimate is associated with the strongest peak of the cross-correlation function . For a multipath distorted channel, a first peak detection has to be applied additionally to prevent obtaining a peak from the multipath. Alternatively, a super-resolution algorithm, e.g. space-alternating generalized expectation-maximization (SAGE), algorithm can be apply to outperform the peak detection-based algorithms. The super-resolution algorithm jointly estimates the multiple paths. The first detected path is considered as the geometry line-of sight (GLOS) path and used for the distance estimate. Once the MT u collects sufficient distance estimates from its neighbors, it takes these estimates as the observation, i.e. the $\mathbf{z}_i^{(k)}$ in (20), and runs an ML position estimator with approximated observation models:

$$\tilde{\mathbf{p}}_u = \arg\max_{\mathbf{p}_u} \prod_{\nu \in \mathbb{K}_u} \tilde{p}\left(\hat{d}_\nu | \mathbf{p}_u, \mathbf{p}_\nu\right). \qquad (27)$$

The observation likelihood is usually modeled with Gaussian distribution

$$\tilde{p}\left(\hat{d}_\nu | \mathbf{p}_u, \mathbf{p}_\nu\right) \sim \mathcal{N}\left(\|\mathbf{p}_u - \mathbf{p}_\nu\|, \sigma_\nu^2\right). \qquad (28)$$

σ_ν^2 is the auxiliary parameter and can be approximated from measurement set or derived from some estimation bounds, e.g. Cramér-Rao bound (CRB) or the Ziv-Zakai bound (ZZB) [16]. A block diagram of the two-step localization can be found in Fig. 2.

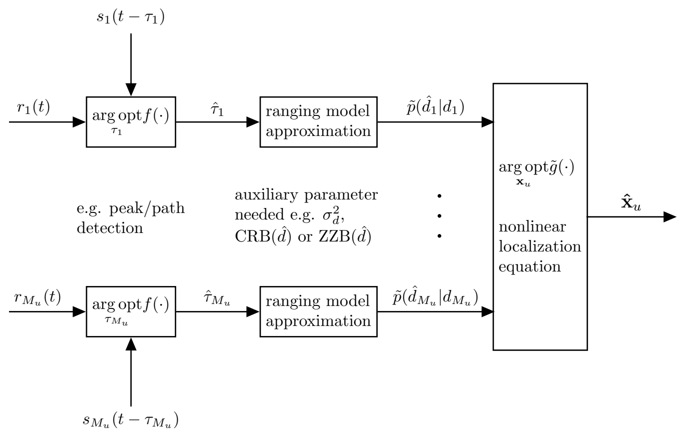

Figure 2. Block diagram of the update step in two-step localization

However, with the parametric likelihood model, the coherence between the two steps is not fully exploited. A wrong correlation peak could be acquired in the first step due to the low signal-to-noise ratio, distortion from the noise and the multipath. Consequently, a large error in the location estimate is not avoidable. Recent research attempts to acquire high-definition localization by high-dimension likelihood parameter fitting. However, these algorithms require a training data set and are computationally costly.

IV. DIPLOC: DIRECT SIGNAL DOMAIN PARTICLE FILTERING FOR NETWORK LOCALIZATION

Instead of exploiting the distance estimate we propose to directly use the raw received signal samples, i.e. the waveform, as the 'observation'. The key objective is to obtain the location information directly from the received signal samples, avoiding the ranging model approximation. The distributed particle filter fits to this objective naturally.

Particles are drawn for each MT from the position a-priori density function. As we discussed previously, the prediction step of a distributed particle filter is easy to implement. Here, we focus on the update step. In the update stage, each particle is considered as a location hypothesis and generates delayed replicas of the reference signal according to its distances to the neighbor's position or position hypothesis. The weight of each particle is calculated directly from the inner-products of the replicas and the received signals. The inner products can be also taken from the pre-calculated correlation function. We refer to this approach as the direct signal domain particle filtering for network self-localization (DiPLoc). Comparing with the traditional two steps localization, the DiPLoc takes every peaks of the correlation function as soft hypotheses and prevents making hard decision in the intermediate step. The likelihood of the position of MT u given received signals $r_{\mathbb{K}_u}$ from all neighbors $\nu \in \mathbb{K}_u$ with the single channel tap assumption is

$$
\begin{aligned}
p(r_{\mathbb{K}_u} \mid \mathbf{p}_u, \mathbf{p}_{\mathbb{K}_u}) &= \prod_{\nu \in \mathbb{K}_u} p(r_\nu \mid \mathbf{p}_u, \mathbf{p}_\nu) \\
&\propto \exp\left(\sum_{\nu \in \mathbb{K}_u} \frac{|R_\nu|}{|S_\nu|} 2\Re\{e^{-j\Delta\phi_\nu} f(\|\mathbf{p}_\nu - \mathbf{p}_u\|)\} - 2|R_\nu|^2 \right)^{\frac{1}{\sigma^2}}
\end{aligned} \tag{29}
$$

where $|R_\nu|$ and $|S_\nu|$ can be interpreted as the magnitude of received and transmitted signal respectively. For a non-coherent estimator, the likelihood is approximated as

$$
\begin{aligned}
& p(r_{\mathbb{K}_u} \mid \mathbf{p}_u, \mathbf{p}_{\mathbb{K}_u}) \\
&\propto \exp\left(\sum_{\nu \in \mathbb{K}_u} \frac{|R_\nu|}{|S_\nu|} \sqrt{2}\, |f(\|\mathbf{p}_\nu - \mathbf{p}_u\|)| - 2|R_\nu|^2 \right)^{\frac{1}{\sigma^2}},
\end{aligned} \tag{30}
$$

Each MT runs a particle filter locally to approximate its marginal posterior filtered density

$$
p\left(\mathbf{x}_u^{(k)} | \mathbf{z}^{(1:k)}\right) \approx \sum_{p=1}^{P_u} w_{u,p}^{(k)} \delta(\mathbf{x}_u^{(k)} - \mathbf{x}_{u,p}^{(k)}). \tag{31}
$$

For a distributed particle filter, similar to the belief propagation algorithm, MTs have to exchange their particle clouds (belief) with multiple inner iterations in a single update step [6]. The optimal number of iterations L depends on the topology of the network. We look into the weight updating scheme for the p^{th} particle of MT u at step k. The initial weight for inner iteration is set to the value from last step contributed with the current observation from the BSs

$$
w_{u,p}^{(k,1)} = w_{u,p}^{(k-1)} \prod_{b \in \mathbb{B}_u} p\left(r_b \mid \mathbf{p}_{u,p}^{(k)}\right) \tag{32}
$$

$$
w_{u,p}^{(k,1)} = \frac{w_{u,p}^{(k,1)}}{\sum_{r=1}^{P_\nu} w_{u,r}^{(k,1)}} \tag{33}
$$

At the iteration l

$$
w_{u,p}^{(k,l)} = w_{u,p}^{(k,l-1)} \prod_{\nu \in \mathbb{M}_u} \sum_{q=1}^{P_\nu} w_{\nu,q}^{(k,l-1)} p\left(r_\nu \mid \mathbf{p}_{u,p}^{(k)}, \mathbf{p}_{\nu,q}^{(k)}\right) \tag{34}
$$

$$
w_{u,p}^{(k,l)} = \frac{w_{u,p}^{(k,l)}}{\sum_{r=1}^{P_\nu} w_{u,r}^{(k,l)}} \tag{35}
$$

After iteration L, $w_{u,p}^{(k)} = w_{u,p}^{(k,L)}$. The iterative calculation of DiPLoc algorithm from step $k-1$ to k is shown in Algorithm 1.

Algorithm 1 DiPLoc algorithm from step $k-1$ to k

for inner iteration $l = 1$ to L **do**
  for MT $u = 1$ to M **in parallel do**
    receive particles from neighbor $\forall \nu \in \mathbb{M}_u$
    for particle $p = 1$ to P_u **in parallel do**
      if $l = 1$ **then**
        $\hat{\mathbf{x}}_{u,p}^{(k-1)} \rightarrow \bar{\mathbf{x}}_{u,p}^{(k)}$ Eq. (4)
        $w_{u,p}^{(k-1)} \rightarrow w_{u,p}^{(k,1)}$ Eq. (32), (33)
      else
        $w_{u,p}^{(k,l-1)} \rightarrow w_{u,p}^{(k,l)}$ Eq. (34), (35)
      end if
    end for
    resample if needed
    broadcast particles
  end for
end for

A block diagram of the update step of the DiPLoc can be found in Fig. 3.

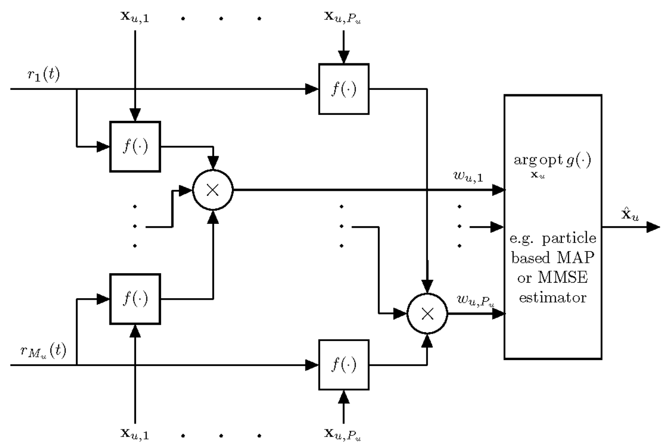

Figure 3. Block diagram of the update step in DiPLoc

The massive links jointly support the true hypothesis and reject the wrong ones with high probability. In the DiPLoc, multiple links are inherently weighted by the overall likelihood. Therefore, the DiPLoc preserves as much information as possible from the signal domain to the location domain. More importantly, the cross-correlation can be seen as a group of inner-products between the received signal and the signal replicas with a shifting delay window. From this viewpoint, each particle hypothesis in the DiPLoc can be considered as a realization of the shifted window. Therefore, the complexity of the DiPLoc is comparable to a simple cross-correlation-based estimator.

V. Results

A. Numerical Results

We run numerical simulations with the multipath environment generated from the WINNER 2 channel model [4] to verify our proposed DiPLoc algorithm. We first test the DiPLoc in non-cooperative network localization case from with different number of nodes. Only one of the nodes is an MT, the rest nodes are the BSs. DiPLoc is compared with

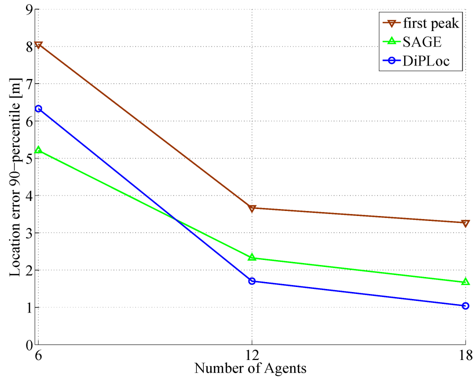

Figure 4. Non-cooperative network localization: different number of total nodes. DiPLoc is compared with two-step algorithm: first correlation peak detection

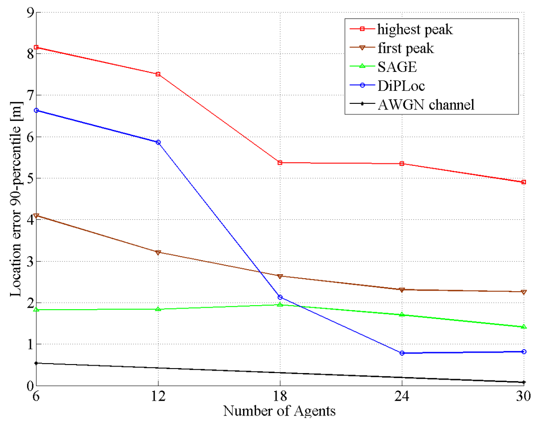

Figure 5. Anchor-free network localization: different number of total nodes. DiPLoc is compared with two-step algorithms: strongest/first correlation peak detection and super-resolution algorithm (SAGE). the AWGN case is used as a benchmark.

two different two-step algorithms: correlation-based first peak detection and SAGE-based first path detection algorithm. The 90-percentile of the position error is depicted in Fig.4. We can see that when number of nodes increases, the DiPLoc starts outperforming the two-step algorithms. The reason is that for massive links, the multipath effect is more likely to be averaged out and the link quality evaluation becomes more important. We also test the anchor-free case, i.e. all of the nodes are MTs. They try to estimate their relative position in the network. DiPLoc is again compared with two step algorithms: strongest/first peak detection, and SAGE-based. An estimator in AWGN scenario is also tested as the benchmark. In order to assess the relative positioning performance, the estimated network position is aligned back to the ground truth. The error 90-percentiles are shown in Fig.5. Similarly to the non-cooperative case, DiPLoc outperforms the others in a massive link scenario.

B. Experimental Results

We also conduct a measurement campaign and use the measurement data to verify our DiPLoc algorithm. The system parameters is similar to [17]. In the measurement, fully meshed six nodes, five stationary nodes and one moving node, makes radio-based measurements in a round-trip delay manner in

Figure 6. Measurement campaign: fully meshed six nodes: five stationary nodes and one moving node. The ground truth of the moving node is obtained from the tachymeter. Distance of each node pair is measured with the round-trip delay.

order to eliminate the impact of the asynchronous clocks. All the links are pre-calibrated in the lab with cables to compensate the processing time. None of the nodes knows its position, hence an anchor-free scenario. The ground truth of the nodes is obtained from the tachymeter. Two different distributed particle filter is tested, namely two-step strongest peak detection and the DiPLoc. For the two-step algorithm, ZZB is used to evaluate the performance of each link. The moving/stationary information is not available for the nodes. Fig.6 shows the setup of the experiment. Fig.7 the absolute distance estimate error obtained from the strongest correlation peak detection the CRB and the ZZB based on the estimated SNR. The error from multipath, bias and outliers is visible in the plot which leads to the ranging error diverging from the bounds. In Fig. 8 the estimated trajectory from the DiPLoc (green) is compared with the ground truth trajectory (magenta). Optimal coordinate system alignment is applied for the comparison since it is an anchor-free scenario. In Fig.9 the root-mean-square error of the DiPLoc is compared with the traditional particle filter which utilizes the ZZB as the auxiliary parameter. We can find that the ZZB-aided particle filter does not converge and the DiPLoc converges to the true trajectory in a few steps. With the result from both numerical simulation and the experimental measurement, we can conclude that the DiPLoc algorithm we proposed is more suitable for network self-localization, especially when the network is dense.

VI. Conclusion

In this paper, we investigate the network localization problem. We envisage a very high MT density for future wireless networks which requires ubiquitous high-definition network self-localization ability. Traditional network localization contains two steps: ranging and localization. The estimated inter-node distance as the observation for the localization step. The coherence between the two steps is not fully exploited. We propose to use directly the raw received signal samples, i.e. the waveform, as the 'observation'. The key objective is to obtain the location information directly from the received signal samples, avoiding the ranging model approximation. We

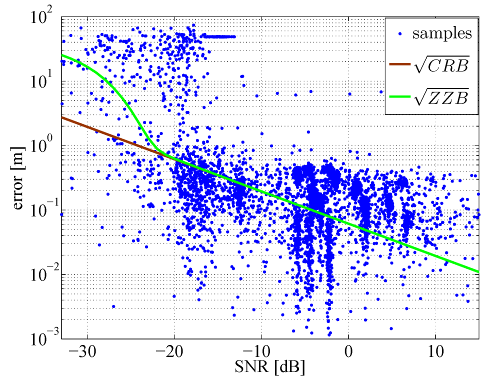

Figure 7. Distance estimate error (obtained from the strongest correlation peak detection) is compared with the CRB and the ZZB. The error from multipath, bias and outliers is visible which leads to the ranging error diverging from the bounds.

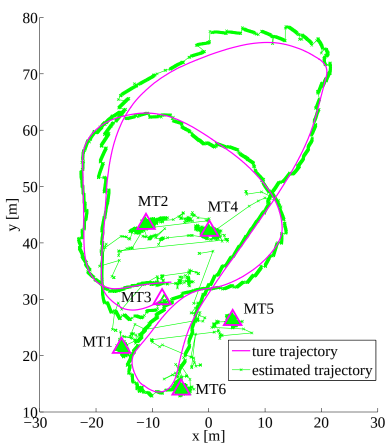

Figure 8. The estimated trajectory from the DiPLoc (green) is compared with the ground truth trajectory (magenta). Optimal coordinate system alignment is apply for the comparison since it is anchor-free scenario.

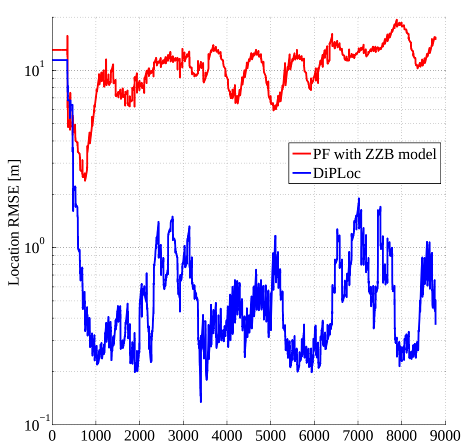

Figure 9. Root-mean-square error of network localization: DiPLoc is compared with the ZZB-aided traditional particle filter

design a direct signal domain particle filter for network self-localization (DiPLoc). The DiPLoc takes every peaks of the correlation function as soft hypotheses and prevents making hard decision in the intermediate step. More importantly, the cross-correlation can be seen as a group of inner-products between the received signal and the signal replicas with a shifting delay window. From this viewpoint, each particle hypothesis in the DiPLoc can be considered as a realization of the shifted window. The inner products can be also taken from the pre-calculated correlation function. Therefore, the complexity of the DiPLoc is comparable to a simple cross-correlation-based estimator. Both the numerical and experimental result shows the DiPLoc outperforms the traditional two-step approach especially when the network is dense. Considering the low complexity and the high estimation accuracy, we can conclude that the DiPLoc is a promising algorithm for self-localization of the future network.

References

[1] M. Caceres, F. Penna, H. Wymeersch, and R. Garello, "Hybrid gnss-terrestrial cooperative positioning via distributed belief propagation," in *GLOBECOM 2010, 2010 IEEE Global Telecommunications Conference*, dec. 2010, pp. 1 –5.

[2] S. Zhang, R. Raulefs, A. Dammann, and S. Sand, "System-level performance analysis for bayesian cooperative positioning: From global to local," Oct. 2013.

[3] S. Zhang and R. Raulefs, "Multi-agent flocking with noisy anchor-free localization," in *Wireless Communications Systems (ISWCS), 2014 11th International Symposium on*. IEEE, 2014, pp. 927–933.

[4] "WINNER II Deliverable D1.1.2: WINNER II Channel Models," Sep. 2007. [Online]. Available: http://www.ist-winner.org/deliverables.html

[5] H. Wymeersch, U. Ferner, and M. Z. Win, "Cooperative bayesian self-tracking for wireless networks," *Communications Letters, IEEE*, vol. 12, no. 7, pp. 505–507, 2008.

[6] H. Wymeersch, J. Lien, and M. Win, "Cooperative Localization in Wireless Networks," *Proceedings of the IEEE*, vol. 97, no. 2, pp. 427 –450, feb. 2009.

[7] Y. Shen, H. Wymeersch, and M. Win, "Fundamental limits of wideband localization - part ii: Cooperative networks," *Information Theory, IEEE Transactions on*, vol. 56, no. 10, pp. 4981 –5000, oct. 2010.

[8] S. Sand, A. Dammann, and C. Mensing, *Positioning in Wireless Communications Systems*, 1st ed. Wiley Publishing, 2014.

[9] C. Gentner, S. Sand, and A. Dammann, "OFDM Indoor Positioning based on TDOAs: Performance Analysis and Experimental Results," in *Localization and GNSS (ICL-GNSS), 2012 International Conference on*. IEEE, 2012, pp. 1–7.

[10] J. Fessler, A. O. Hero *et al.*, "Space-alternating generalized expectation-maximization algorithm," *Signal Processing, IEEE Transactions on*, vol. 42, no. 10, pp. 2664–2677, 1994.

[11] T. Van Nguyen, Y. Jeong, H. Shin, and M. Win, "Machine learning for wideband localization," *Selected Areas in Communications, IEEE Journal on*, vol. 33, no. 7, pp. 1357–1380, July 2015.

[12] B. Krach, *Sensor Fusion by Bayesian Filtering for Seamless Pedestrian Navigation*. Der Andere Verlag, 2010.

[13] P. Closas and C. Fernandez-Prades, "Bayesian nonlinear filters for direct position estimation," in *Aerospace Conference, 2010 IEEE*, March 2010, pp. 1–12.

[14] X. Yin, T. Pedersen, P. Blattnig, A. Jaquier, and B. Fleury, "A single-stage target tracking algorithm for multistatic DVB-T passive radar systems," in *Digital Signal Processing Workshop and 5th IEEE Signal Processing Education Workshop, 2009. DSP/SPE 2009. IEEE 13th*, Jan 2009, pp. 518–523.

[15] S. Zhang, S. Sand, R. Raulefs, and E. Staudinger, "Self-Organized Hybrid Channel Access Method for an Interleaved RTD-based Swarm Navigation System."

[16] D. Dardari, A. Conti, U. Ferner, A. Giorgetti, and M. Win, "Ranging with ultrawide bandwidth signals in multipath environments," *Proceedings of the IEEE*, vol. 97, no. 2, pp. 404–426, Feb. 2009.

[17] S. Zhang, E. Staudinger, S. Sand, R. Raulefs, and A. Dammann, "Anchor-free localization using round-trip delay measurements for martian swarm exploration," in *Position, Location and Navigation Symposium-PLANS 2014, 2014 IEEE/ION*. IEEE, 2014, pp. 1130–1139.