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Compressive Sensing Based Device-Free Multi-Target Localization Using Quantized Measurement

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ABSTRACT Device-free localization (DFL), requiring no extra devices equipped with a target, is an important field of research on the Internet of Thing (IoT). Energy efficiency issue is essential for the development of the IoT, but seldom of the existing papers are focus on it. So we investigate this issue with quantized data of only several bits under the compressive sensing (CS) framework, which can both reduce the required wireless link number and the bit number in the DFL scheme. First, through exploiting the discrete property of CS theory, we calculate the discrete measurement probability bypass computing the complex or uncalculated measurement probability density function (pdf), which can well represent the measurement distribution characteristic. Second, we design a unique quantization scheme for each wireless link according to their measurement probability and build a novel DFL model by analyzing the quantization error. Third, a new DF-QVBI algorithm is proposed to recover the target location, which can make great use of the quantization error. Finally, numerical simulations show the superiority and robustness of the proposed method.

INDEX TERMS Multi-target localization, device free, compressive sensing, quantization, variational EM algorithm, energy efficiency.

I. INTRODUCTION

Nowadays, Internet of Thing (IoT) [1] has been widely applied in people's daily lives, especially in remote sensing, smart home and so on [2]. Many papers are involved into the researches of the target activity recognition, gesture identification and so on [3], [4], which are all based on the exact target localization techniques. As to improve the service performance in IoT, localization issue is one of the most essential techniques. Traditional localization methods has been widely applied in IoT such as Global Positioning System (GPS) and so on [5], which requires relating devices being attached with targets. However, targets in certain cases are non-cooperative or can not be equipped with devices, making the device-based localization scheme valid. For example, in the military field, the hostile target certainly do not want to be detected and always try to escape from detecting; in the emergency rescue, the human trapped can not be equipped with any devices beforehand; in the smart house, the elderly is not willing to wear any devices to help detect the falling which may influence their daily lives and so on [6]. Above all, Device-free Localization (DFL) scheme that requires no extra devices to be attached to target has become a topic of great concern [7].

DFL scheme can directly utilize the wireless signals, ubiquitous in our daily life, to obtain target location. Once the targets existing into the detected domain, their surrounding wireless signal will be influenced in a predictable way and then we can use the changeable signal to estimate the locations [8]. DFL is firstly proposed in Paper [9], which gives a primary introduction of the DFL framework. Paper [10] achieves the multiple target localization by exploiting the property of the WLAN signal. And paper [11] can simultaneously achieve the target counting and localization. In order to improve the localization accuracy, more localization information should be gathered, undoubtedly requiring a large number of wireless kinks. So paper [12] applies the Compressive Sensing (CS) [13] theory in DFL scheme, greatly reducing the

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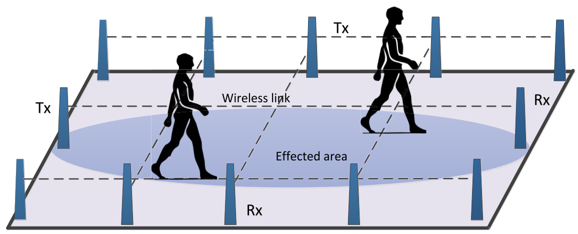

FIGURE 1. The illustration of the DFL scene.

required wireless links. As is shown in the Fig. 1, where each pair of transceiver/receiver consists of a single wireless link to measure the changed RSS. In order to save human effort involved into the dictionary building, paper [14] proposes a dictionary transition approach which can utilize only a few samples to recover the complete dictionary. Paper [15] considers a dictionary refinement approach to approximate the RSS changes and achieve a good performance. Paper [16] consider the elderly consideration issue and proposed a fall detection scheme in smart home.

All the above algorithms make great contributions into DFL, but seldom of the them take consideration of the energy efficiency issue. Wireless signal is produced and propagated continuously but the devices are digital-based, undoubtedly resulting into a quantization error. Once the available bits inside the devices are large enough to represent the received signal, the quantization error can be ignored. But the transceivers/receivers are all battery-powered, more bits will unquestionably leading to more energy consumption. In order to save energy and resource, there are only several bits can be used in some applications, which involves into the quantization issue. Coming to this, quantization is a significant technique which should be exploited in DFL to save energy.

In fact, quantization problem has been widely considered in the recent researches. Many papers research the quantization issue in the theory field to improve the quantization performance. Some researchers consider this issue in the field of CS theory and propose Quantized Compressive Sensing (QCS) [17], [18], which provide a novel idea for other researches. In addition, 1-bit CS is more and more popular in recent year, which can be regarded as a special kind of quantization scheme [19], [20]. Paper [21] considers the quantization problem in the device-based localization area, which can achieve the target location only use several bits. However, this progress requires knowing of the measurement probability density function (pdf) and assumes the same quantization scheme for all the sensors, which can not be applied widely. Paper [22] researches the DFL with several bits which is based on the binary localization model in DFL. When coming to other occupations, several bits will not be enough.

Above all, we consider the energy efficiency problem in DFL using quantized data in this paper. As for quantization scheme, measurement pdf is always utilized to design the quantizer which strongly influence the localization performance. However, on one hand, the measurement pdf sometimes are too complex to be calculated. On the other hand, the measurement pdf can not be calculated especially in the experiment-based DFL whose measurements are gathered by testing. Considering the issues, we exploit the discrete property of the CS-based DFL and propose a discrete approach to calculate the measurement probability instead of pdf. Then the new algorithms DF-QVBI is proposed to recover the location by analyzing quantization error, which can use both fewer wireless links and bits to promise accurate localization. The main contributions of the proposed algorithm are as follows:

- The energy efficiency issue is exploited in the DFL scheme in this paper, and only several bits are required to achieve the target location by our proposed algorithm.
- We calculate the discrete measurement probability by exploiting the CS-based DFL framework which avoids to calculate the complex measurement pdf. And a unique and optimal quantizer is designed for each wireless link, which can take good advantage of the measurement.
- In order to make good use of the quantization error, its pdf is approximated as a liner function within each quantization interval. And then we build a new CS-based DFL model considering the quantization error.
- Under the new DFL model, a novel algorithm called DF-QVBI approach based on the quantization error is proposed, which owns a better localization performance.

The rest paper is organized as follows. Section 2 presents some related works. Section 3 shows the quantization scheme and analyzes the quantization error. The new DFL model and the designed algorithm DF-QVBI are both shown in details in section 4. Numerical simulations are set in the section 5 and section 6 gives the conclusion of the paper.

II. RELATED WORK

A. DEVICE FREE LOCALIZATION PRINCIPLE

Compared with the traditional device-based localization, DFL estimates target location without requiring any transceivers equipped with targets. As for DFL, although targets do not produce the signal, they affect the wireless signal in a predictable way which could be used to localize target. As a result, we calculate the signal changes instead of the received signal in the device-based localization to localize. The most popular signals used in DFL are image information [23], infrared signal [24], RSS signal [25] and so on. Image information need a larger samplings and may involve into the privacy security. And when coming to the smog and dark sense, the image information may valid. The infrared signal based DFL always requires the devices owning the ability of measuring the infrared signal, greatly limiting its development because this kind of devices are not widely applied. Among these kinds of signals, Received Signal Strength (RSS) been especially appreciated for the following advantages:

- Wireless signal is ubiquitous, which has been widely applied almost anywhere.

- RSS value is convenient to be obtained and almost all the devices can record the RSS information.
- RSS acts well even in the smog and dark situation where the other signals are valid.

To calculate the RSS changes by the entering target, $R_0(m)$ and $R_1(m)$ are utilized to represent the RSS when there is no target and several targets located within the detecting area for wireless link m, respectively. Then the RSS changes $R(m)$ of wireless link m caused by targets are as:

$$R(m) = R_0(m) - R_1(m). \tag{1}$$

There are mainly two techniques to calculate $R(m)$, one is the experiment-based and the other is the model-based. The experiment-based approach gathers the RSS changes through practically measure, making the measurement pdf can not be calculated. Although this type of approach can suit the certain environment well, it may be a waste of human labor and the gathered information can not be directly applied in other circumstance. The model-based approach can approximate the signal changes by theoretical analysis, which can be applied in many situations without collecting the signal practically. The most utilized models are binary model [26], elliptical model [27], saddle surface model [28] and so on. Binary model is simple which can only determine whether the objective is in the affected area of wireless links or not. Target would be regard within the area when the RSS changes above a certain threshold. Elliptical model designs the effected area as an elliptical and RSS changes are only related to the distance between the target and the wireless link. As for saddle surface model, it also considers the distance between the target and transceiver/receiver when compared with the Elliptical model. Here in the paper, saddle surface model is applied to more exactly approximate the RSS changes.

$$R(m) = \left(\frac{1-c_m}{(0.5d_m)^2}\left(p_{mn}^x\right)^2 - c_m\left(\frac{p_{mn}^y}{\lambda_m}\right)^2 + c_m\right)E_m,$$
$$s.t. \frac{\left(p_{mn}^x\right)^2}{(0.5d_m)^2} + \left(\frac{p_{mn}^y}{\lambda_m}\right)^2 \leq 1, \tag{2}$$

where E_m and $c_m \in (0, 1)$ are the maximum RSS changes and a constant to normalize the RSS changes of LOS path of the midpoint for link m. $\left(p_{mn}^x, p_{mn}^y\right)$ is the relative coordinates of target n in the coordinate system constituted by link m, where the X axis is the ligature between transceiver and receiver. In addition, d_m and $2\lambda_m$ are the length and the width of ellipse of wireless link m.

B. CS-BASED DFL MODEL

In this section, we mainly introduce the CS-based localization framework. According to the CS theory which operates the discrete signal, we divide the location area into N grids and each target is assumed to be randomly located at the grid point. Once the grid number that target located at is determined, the target coordinates will be obtained by the relationship between the grid point and the real coordinate. M $(M \ll N)$ wireless links, making up by couples of transceivers and receivers, are uniformly deployed in the area to gather the localization information. Then the RSS changes recorded by M wireless links are as:

$$\mathbf{y} = \mathbf{Dx} + \mathbf{n}. \tag{3}$$

1) SENSING MATRIX D

the element D_{mn} shows the relationship between the target location at the grid point n and the RSS changes received by wireless link m. As introduced in the above subsection, it can be calculated by experiments or model.

2) LOCATION VECTOR x

$\mathbf{x}$ denotes the target location, when there is single target located at grid n, $x_n = 1$; otherwise $x_n = 0$. $\|\mathbf{x}\|_0 = K$ represents the target number all around the detecting area.

3) MEASUREMENT VECTOR y

y_m is the RSS changes of wireless link m caused by all the K targets entering into the location domain.

4) MEASUREMENT NOISE n

$\mathbf{n}$ is used to approximate the environment noise.

Remark: Notice that the shadowing effect is not simply the sum of the single one for multiple targets especially who distort the same wireless link. So, the above equation may be a little inappropriate in such case and now it is still an open problem. Fortunately, the detecting area of the wireless link is limited, making the RSS changes is independent as the targets distort different wireless links. And in practice, the assumption that any two targets are located sparsely is easy to satisfy. Above all, most of the current DFL approaches assume that different targets affect the measurements in an independent way [7], [15], [25]and when multiple targets distort a same link they are considered as one target. Following these most widely abroad paper, we take the same operation here.

III. QUANTIZATION SCHEME

A. ANALYSIS OF THE QUANTIZATION SCHEME

Most of the algorithms assume that the measurement is exactly precise which can be represented by unlimited bits. However, this type of operation becomes valid where the devices with lower performance, limited communication bandwidth, restricted battery power and so on, especially in the national defense and wildlife protection where only several bits are available. So the quantization is essential. Here in the CS-based DFL, the quantization can be represented as:

$$\mathbf{z} = Q(\mathbf{y}), \tag{4}$$

where $\mathbf{z}$ is the quantized values represented by the receivers, Q is the defined quantization function which is essential to the quantization performance.

Quantization performance is mainly influenced by the quantization bits number and the quantization scheme. More bits, more accurate the quantization result. The available bits are always set before the devices deployed. So, in order to

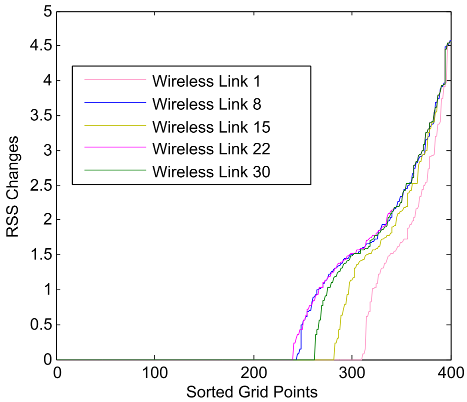

FIGURE 2. The possible measurement values for different wireless links.

ensure an accurate localization, the quantization principle should be well designed.

At first, weather to choose the scalar quantization [29] or vector quantization [30] should be considered. Scalar quantization scheme operates the data independently while the vector quantization considers all the data together. In DFL, every wireless link disposes the received signal itself and then transmits the localization information to the data center without communicating with others, making the scalar quantization more suitable.

Next, how to quantize the data for each wireless link is greatly essential. Uniform method quantizes the measurement by dividing it into L quantization levels with the same interval length. However, the measurement distribution is always nonuniform, making this type of quantization cause a higher error. Nonuniform quantization is emerged, which takes the measurement distribution into consideration and can well solve the issue. But the measurement pdf is difficult or unable to be estimated as stated above in some cases. So, how to apply the nonuniform quantizing scheme without the knowing of measurement pdf is required to be solved.

B. DESIGN OF THE QUANTIZER

To design the optimal quantizer for each wireless link, we exploit the CS-based DFL property and propose a novel quantization approach using discrete method without calculating measurement pdf. In CS-based DFL, targets are assumed exactly at the grid points but not everywhere in the detecting area, providing a naturally discrete property. Measurement values, caused by the target entering into the detecting area, will undoubtedly hold a discrete property. This characteristic renders us to exploit the property of the discrete value.

Following the idea, we assume that targets, independent with each other, are randomly located at the grid points with equal probability $1/N$. And target in different grid point will cause the relative measurement with the probability of $1/N$. In fact, the dictionary built in the off-line step can be utilized to approximate the measurement value of single target. That is to say the possible measurement is just the element of the relating rows of sensing dictionary. As is shown in Fig.2, the possible measurement values of the several wireless links are selected, where we can find that each wireless link process different possible measurement values, rendering a unique quantizer for each wireless link. And then we analyze the measurement values to compute the measurement probability.

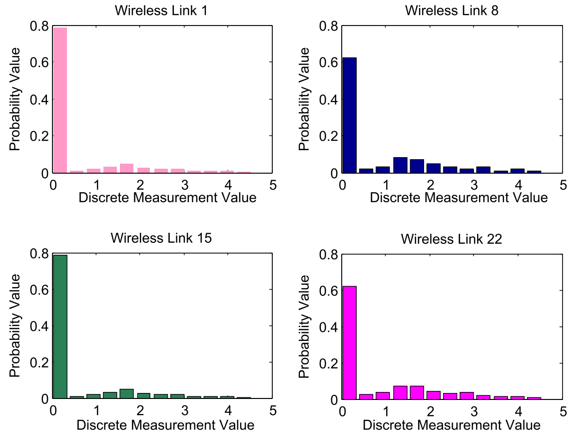

FIGURE 3. The discrete measurement probability values for different wireless links.

To approximate the measurement distribution, we divide the domain into N_T intervals and calculate the relating probability values where the middle point of each interval is assumed as the discrete measurement value. The detail has been shown in Fig.3. When there is single target, the discrete measurement probability of wireless link m is $p(y_m = r_i)$

$$p(y_m = r_i) = \frac{Num(A(m,:) \in R_i)}{N}, \quad (r \in \chi), \tag{5}$$

where r_i is the assumed measurement values in interval i and $Num(A(m,:) \in R_i)$ means the number of elements of $m-th$ row of the dictionary within the $i-th$ interval. χ is the set of the discrete measurement values. For multiple targets independent with each other, the measurement probability is:

$$p(y_m = r) = \sum_{r_1 \in \chi} \cdots \sum_{r_{K-1} \in \chi} \frac{p\left(y_m^1 = r_1\right) \cdots p\left(y_m^{K-1} = r_{K-1}\right)}{p\left(y_m^K = r - r_1 \cdots r_{K-1}\right)}. \tag{6}$$

After obtain the measurement probability, the distribution of the measurement can be approximately learned. Accordingly, we design the quantizer with L levels considering the nonuniform distribution as follows:

$$z_m = \begin{cases} c_1, b_0 < y_m \le b_1 \\ c_i, b_{i-1} < y_m \le b_i \\ \cdots \\ c_L, b_{L-1} < y_m \le b_L, \end{cases} \tag{7}$$

where $(b_{i-1}, b_i]$ is the $i-th$ interval bound and c_i is the code value which divides the region into two equal probability part. And considering maximum entry concept of the information theory, we design the quantizer where in each interval the sum of the probability is $1/L$:

$$\sum_{r_i \in (b_{i-1}, b_i]} p(y_m = r_i) = 1/L. \tag{8}$$

Then each wireless link can operate the continuous signal into quantized code automatically according to the designed quantizer.

C. ANALYSIS OF QUANTIZER ERROR

To analyze quantization error, we build the CS-based DFL model considering the quantization error as follows:

$$\mathbf{z} = \mathbf{y} + \mathbf{e} = \mathbf{D}\mathbf{x} + \mathbf{n} + \mathbf{e}, \tag{9}$$

where $\mathbf{z}$ is the quantized data represented by several bits and $\mathbf{e}$ is the relative quantization error.

Once the original signal y_m sensed by wireless link m, it will be quantized as $z_m = Q(y_m)$ according to the quantized principle inside the wireless link using Eq. 7. If the quantized measurement is achieved as $c_i \,(i = 1, 2 \cdots L)$, the quantization error probability will be computed as:

$$p(e_m = \varepsilon) = p(y_m = c_i - \varepsilon), \quad (\varepsilon \in [e_{ml}, e_{mu})), \tag{10}$$

in which ε is the quantization error within the interval $[e_{ml}, e_{mu})$ and $e_{ml} = c_i - b_i$, $e_{mu} = c_i - b_{i-1}$.

For each quantization z_m, its quantization error is in a certain interval, providing a chance to approximately calculate the continuous pdf referencing to discrete probability values. Usually, these two types of probabilities hold certain relationship. Larger the value of the discrete probability, larger the value of the pdf. Here in each quantization error interval, a liner function is utilized to approximate the quantization error pdf:

$$p(e_m | t_m, h_m) = \frac{t_m e_m + h_m}{C}, \quad (e_m \in [e_{ml}, e_{mu})), \tag{11}$$

where

$$C = \frac{(p(e_u) + p(e_l))(e_u - e_i)}{2}, \tag{12}$$

$$t_m = \frac{p(e_u) - p(e_l)}{C \cdot (e_u - e_i)}, \tag{13}$$

$$h_m = \frac{p(e_u) - t_m e_u}{C}, \tag{14}$$

where e_u and e_l are the maximum and the minimum value of the quantization error within certain interval, respectively. C used here to normalize probability because of the requirement that the whole integration of pdf should be 1. Then the quantization scheme is summarized as follow:

Algorithm 1 The Algorithm of Quantization Scheme

Require: $\boldsymbol{D}$

1: Obtain the possible measurement values using $\boldsymbol{D}$.
2: Calculate the measurement probability using (5) or (6).
3: Design the quantizer for each wireless link using (7).
4: Quantize the localization signal according to the designed quantizer.
5: Calculate the relating quantization error probability using (10).
6: Approximate quantization error using (11)-(14).

IV. RECONSTRUCTION ALGORITHM USING QUANTIZED INFORMATION

In order to recover the target location using the quantized information, we proposed a new algorithm named Quantized Variational Bayesian Inference algorithm for Device-Free localization (DF-QVBI). The proposed algorithm is mainly based on the idea of the variational Bayesian inference [31], whose recovery accuracy is guaranteed by an advanced probabilistic distribution imposed on the random variables. Under the variational Bayesian inference framework, each of the variables is assumed a probabilistic model to promise an accurate reconstruction. We build the DF-QVBI under the same framework, and the illustration of the relationship between variables are shown in Fig.4.

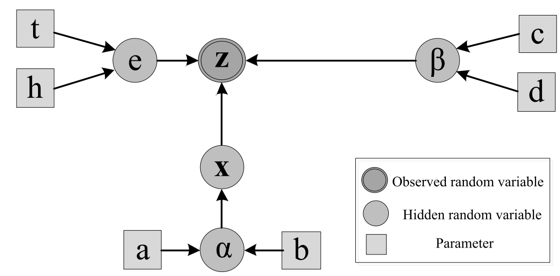

FIGURE 4. Graphical model of variables for the proposed DFL scheme.

A. LOCATION VECTOR x

to exploit the sparsity of the location vector, a two-layer hierarchical prior distribution is imposed on the location vector. Compared with the stationary Gaussian distribution, this nonstationary one assumes a variable variance which can provide more flexibility to exploit the characteristics of location vector. Of the first layer:

$$\begin{aligned} p(\mathbf{x}|\boldsymbol{\alpha}) &= \prod_{i=1}^{N} N\left(x_i | 0, \alpha_i^{-1}\right) \\ &= \frac{1}{(2\pi)^{N/2}|\mathbf{A}|^{-1/2}} \exp\left(-\frac{1}{2}\mathbf{x}^T\mathbf{A}\mathbf{x}\right), \end{aligned} \tag{15}$$

in which $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \cdots, \alpha_N]$ and α_i^{-1} is the variation of x_i. In addition, $\mathbf{A} = diag(\alpha_1, \alpha_2, \cdots, \alpha_N)$ is the inverse of the covariance. However, such a model includes the variations as much as the observations, making it unable to be worked out. As a result, a Gamma prior distribution is imposed on $\boldsymbol{\alpha}$:

$$\begin{aligned} p(\boldsymbol{\alpha}; a, b) &= \prod_{i=1}^{N} Gamma(\alpha_i | a, b) \\ &= \prod_{i=1}^{N} \frac{1}{\int_0^\infty u^{a-1} e^{-u} du} b^a {\alpha_i}^{a-1} e^{-b\alpha_i}, \end{aligned} \tag{16}$$

where a and b are parameters to determine $\boldsymbol{\alpha}$.

B. MEASUREMENT NOISE n

in order to approximate the most widely applied noise, the Gaussian distribution is imposed on the measurement noise:

$$p(\mathbf{n}) = N\left(\mathbf{n}|\, 0, \beta^{-1}\mathbf{I}\right), \tag{17}$$

where β and $\mathbf{I}$ are the inverse of the variance and the unite matrix, respectively. To make the noise be more available in the varying environment, a Gamma distribution is assumed for the noise inverse variance β:

$$p(\beta; c, d) = \prod_{i=1}^{N} Gamma(\beta|\, c, d), \tag{18}$$

where c and d are parameters according to β.

C. QUANTIZATION ERROR e

for this type of error, we have discussed in the above section. In each quantization error interval, its quantization error pdf has been approximated as an liner function according to Eq.(11).

According to Bayesian algorithms, the distribution $p(\mathbf{x}, \boldsymbol{\alpha}, \beta, \mathbf{e}|\, \mathbf{z})$ should be calculated when construct the location vector. From the above analysis, location vector $\mathbf{x}$, measurement noise $\mathbf{n}$ and quantization error $\mathbf{e}$ are all apparently independent, so as their depending parameters. Then the above distribution can be represented as:

$$p(\mathbf{x}, \boldsymbol{\alpha}, \beta, \mathbf{e}|\, \mathbf{z}) = \frac{p(\mathbf{z}|\, \mathbf{x}, \beta, \mathbf{e})\, p(\mathbf{x}|\, \boldsymbol{\alpha})\, p(\boldsymbol{\alpha})\, p(\beta)\, p(\mathbf{e})}{p(\mathbf{z})}, \tag{19}$$

where according to Eq.(17):

$$p(\mathbf{z}|\, \mathbf{x}, \beta, \mathbf{e}) = \left(2\pi\beta^{-1}\right)^{-M/2} \exp\left(-\frac{\beta}{2}\|\mathbf{z}-\mathbf{Dx}-\mathbf{e}\|_2^2\right), \tag{20}$$

where we can see that all the distributions in the numerator can be easily calculated but for the distribution of the measurement in the denominator $p(\mathbf{z})$:

$$p(\mathbf{z}) = \int p(\mathbf{z}|\, \mathbf{x}, \beta, \mathbf{e})\, p(\mathbf{x}|\, \boldsymbol{\alpha})\, p(\boldsymbol{\alpha})\, p(\beta)\, p(\mathbf{e})\, d\mathbf{x} d\boldsymbol{\alpha} d\beta d\mathbf{e}, \tag{21}$$

which cannot be analytically calculated.

Thus the variational inference is applied, imposing the posterior independence among the location vector $\mathbf{x}$, variance parameters $\mathbf{n}$ and $\mathbf{e}$:

$$\begin{aligned} p(\mathbf{x}, \boldsymbol{\alpha}, \beta, \mathbf{e}|\, \mathbf{z}; a, b, c, d, \mathbf{t}, \mathbf{h}) \\ \approx q(\mathbf{x}, \boldsymbol{\alpha}, \beta, \mathbf{e}) = q(\mathbf{x})\, q(\boldsymbol{\alpha})\, q(\beta)\, q(\mathbf{e}). \end{aligned} \tag{22}$$

To calculate the posterior, we recall the defined prior probability distribution for the variables and the variational Bayesian inference theory. Accordingly, the posterior distribution of $\mathbf{x}$, $\boldsymbol{\alpha}$, β and $\mathbf{e}$ are updated as follows.

For the location vector $\mathbf{x}$, we have the following result:

$$\begin{aligned} \ln q(\mathbf{x}) &= \langle \ln p(\mathbf{z}, \mathbf{x}, \boldsymbol{\alpha}, \beta, \mathbf{e}) \rangle_{q(\boldsymbol{\alpha})q(\beta)q(\mathbf{e})} + C \\ &= \langle \ln p(\mathbf{z}|\, \mathbf{x}, \beta, \mathbf{e})\, p(\mathbf{x}|\, \boldsymbol{\alpha}) \rangle_{q(\boldsymbol{\alpha})q(\beta)q(\mathbf{e})} + C \\ &= \left\langle -\frac{\beta}{2}(\mathbf{z} - \mathbf{Dx} - \mathbf{e})^T (\mathbf{z} - \mathbf{Dx} - \mathbf{e}) - \frac{1}{2}\mathbf{x}^T\mathbf{Ax} \right\rangle + C \\ &= -\frac{\langle\beta\rangle}{2}\left(\mathbf{x}^T\mathbf{D}^T\mathbf{Dx} - 2\mathbf{x}^T\mathbf{D}^T\mathbf{z} + 2\mathbf{x}^T\mathbf{D}^T\langle\mathbf{e}\rangle\right) \\ &\quad - \frac{1}{2}\mathbf{x}^T\langle\mathbf{A}\rangle\mathbf{x} + C \\ &= -\frac{1}{2}\mathbf{x}^T\left(\langle\beta\rangle\mathbf{D}^T\mathbf{D} + \langle\mathbf{A}\rangle\right)\mathbf{x} - \mathbf{x}^T\langle\beta\rangle\mathbf{D}^T(\mathbf{z} - \langle\mathbf{e}\rangle) + C \\ &= -\frac{1}{2}\mathbf{x}^T\Sigma^{-1}\mathbf{x}^{-1} - \mathbf{x}^T\Sigma^{-1}\mu + C, \end{aligned} \tag{23}$$

where it is apparent that $q(\mathbf{x})$ obeys Gaussian distribution with $q(\mathbf{x}) \sim N(\mathbf{x}|\, \boldsymbol{\mu}, \Sigma)$ and its mean $\boldsymbol{\mu}$ and covariance matrix Σ are calculated as follows:

$$\boldsymbol{\mu} = \langle\beta\rangle\, \Sigma\mathbf{D}^T(\mathbf{z} + \langle\mathbf{e}\rangle). \tag{24}$$

$$\Sigma = \left(\langle\beta\rangle\, \mathbf{D}^T\mathbf{D} + \langle\mathbf{A}\rangle\right)^{-1}. \tag{25}$$

Considering that the inversion for matrix is a high complex operation, which can increase the calculate complexity of the above equations. So, we transfer the Eq.(25) into the following form:

$$\Sigma = \langle\mathbf{A}\rangle^{-1} - \langle\mathbf{A}\rangle^{-1}\mathbf{D}^T\mathbf{E}^{-1}\mathbf{D}\langle\mathbf{A}\rangle^{-1}, \tag{26}$$

where $\langle\mathbf{A}\rangle$ is a diagonal matrix whose inversion is easy to obtain. And for $\mathbf{E} = \langle\beta\rangle^{-1}\mathbf{I} + \mathbf{D}^T\langle\mathbf{A}\rangle^{-1}\mathbf{D}$, it is $M \times M$ dimensions ($M \ll N$), greatly reducing the complexity form $O\left(N^3\right)$ to $O\left(M^3\right)$.

Then by assuming that the $q(\boldsymbol{\alpha})$ is only depend on $\boldsymbol{\alpha}$, we have the following equation:

$$\begin{aligned} \ln q(\boldsymbol{\alpha}) &= \langle \ln p(\mathbf{z}, \mathbf{x}, \boldsymbol{\alpha}, \beta, \mathbf{e}) \rangle_{q(\mathbf{x})q(\beta)q(\mathbf{e})} + C \\ &= \langle p(\mathbf{x}|\, \boldsymbol{\alpha})\, p(\boldsymbol{\alpha}) \rangle_{q(\mathbf{x})} + C \\ &= \frac{1}{2}\sum_{m=1}^{M} \ln\alpha_m - \frac{1}{2}\sum_{m=1}^{M}\alpha_m\left\langle x_m^2\right\rangle \\ &\quad + \left(a - \frac{1}{2}\right)\sum_{m=1}^{M}\ln\alpha_m - \sum_{m=1}^{M} b\alpha_m + C \\ &= (a-1)\sum_{m=1}^{M}\ln\alpha_m - \sum_{m=1}^{M}\left(b + \frac{1}{2}\left\langle x_m^2\right\rangle\right)\alpha_m + C \\ &= (\widehat{a}-1)\sum_{m=1}^{M}\ln\alpha_m - \sum_{m=1}^{M}\widehat{b}\alpha_m + C, \end{aligned} \tag{27}$$

which informs that the above distribution is the product of M independent Gamma distribution:

$$q(\boldsymbol{\alpha}) = \prod_{i=1}^{N} Gamma\left(\alpha_i|\, \widehat{a}, \widehat{b}\right), \tag{28}$$

where the relative parameters are given as follows:

$$\widehat{a} = a + \frac{1}{2}. \tag{29}$$

$$\widehat{b}_m = b + \frac{1}{2}\left\langle x_m^2 \right\rangle. \tag{30}$$

For $q(\beta)$ according to the measurement noise $\mathbf{n}$, its posterior distribution is as follows:

$$\begin{aligned}
\ln q(\beta) &= \langle \ln p(\mathbf{z}, \mathbf{x}, \boldsymbol{\alpha}, \beta, \mathbf{e}) \rangle_{q(\mathbf{x})q(\boldsymbol{\alpha})q(\mathbf{e})} + C \\
&= \langle \ln p(\mathbf{z}|\, \mathbf{x}, \beta, \mathbf{e})\, p(\beta) \rangle_{q(\mathbf{x})q(\boldsymbol{\alpha})q(\mathbf{e})} + C \\
&= \frac{M}{2}\ln\beta - \left\langle \frac{\beta}{2}(\mathbf{z}-\mathbf{Dx}-\mathbf{e})^T(\mathbf{z}-\mathbf{Dx}-\mathbf{e}) \right\rangle \\
&\quad + (c-1)\ln\beta - d\beta + C \\
&= \left(c + \frac{M}{2} - 1\right)\ln\beta \\
&\quad - \begin{pmatrix} d + \frac{1}{2}\left(\|\mathbf{z}-\mathbf{D}\mu\|_2^2\right) + tr\left(\mathbf{D}\Sigma\mathbf{D}^T\right) \\ -2\langle\mathbf{e}\rangle^T(\mathbf{z}-\mathbf{D}\boldsymbol{\mu}) + \left\langle \mathbf{e}^T\mathbf{e} \right\rangle \end{pmatrix}\beta \\
&= (\widehat{c}-1)\, ln\beta - \widehat{d}\beta + C,
\end{aligned} \tag{31}$$

where it is obvious that $q(\beta)$ follows a Gamma distribution with the defined parameters as follows:

$$\widehat{c} = c + \frac{M}{2}. \tag{32}$$

$$\begin{aligned}
\widehat{d} &= d + \frac{1}{2}\left(\|\mathbf{z}-\mathbf{D}\boldsymbol{\mu}\|_2^2\right) + tr\left(\mathbf{D}\Sigma\mathbf{D}^T\right) \\
&\quad - 2\langle\mathbf{e}\rangle^T(\mathbf{z}-\mathbf{D}\boldsymbol{\mu}) + \left\langle \mathbf{e}^T\mathbf{e} \right\rangle.
\end{aligned} \tag{33}$$

And then, we update the posterior distribution of quantization error $q(\mathbf{e})$ as follows:

$$\begin{aligned}
\ln q(\mathbf{e}) &= \langle \ln p(\mathbf{z}, \mathbf{x}, \boldsymbol{\alpha}, \beta, \mathbf{e}) \rangle_{q(\mathbf{x})q(\boldsymbol{\alpha})q(\beta)} + C \\
&= \langle \ln p(\mathbf{z}|\, \mathbf{x}, \beta, \mathbf{e})\, p(\mathbf{e}) \rangle_{q(\mathbf{x})q(\boldsymbol{\alpha})q(\beta)} + C \\
&= \left\langle \ln\left[exp\left(-\frac{\beta}{2}\|\mathbf{z}-\mathbf{Dx}-\mathbf{e}\|_2^2\right) p(\mathbf{e}) \right] \right\rangle + C \\
&= \ln\left[exp\left(-\frac{\langle\beta\rangle}{2}\begin{pmatrix} \|\mathbf{e}-(\mathbf{z}-\mathbf{D}\boldsymbol{\mu})\|_2^2 \\ +tr\left(\mathbf{D}\Sigma\mathbf{D}^T\right) \end{pmatrix}\right) p(\mathbf{e}) \right] + C,
\end{aligned} \tag{34}$$

where we can conclude that the posterior of the quantization error $q(\mathbf{e})$ is the product of a Gaussian distribution and its prior distribution. For the Gaussian distribution, its relative parameters are as follows:

$$\widehat{\boldsymbol{\mu}} = \mathbf{z} - \mathbf{D}\boldsymbol{\mu}, \tag{35}$$

$$\widehat{\sigma}^2 = \langle\beta\rangle^{-1}, \tag{36}$$

where $\widehat{\boldsymbol{\mu}}$ and $\widehat{\sigma}^2$ are the mean and the variance, respectively.

As stated above, the quantization error e_m for wireless link m has been approximated as a liner distribution, making the posterior distribution $q(e_m)$ be the product of the truncated Gaussian distribution and the liner function. According to the paper [32], the first and the second moment for quantization error are given as follows:

$$\langle e_m \rangle = \frac{t_m\xi_2 + h_m\xi_1}{t_m\xi_1 + h_m}, \tag{37}$$

$$\left\langle e_m^2 \right\rangle = \frac{t_m\xi_3 + h_m\xi_2}{t_m\xi_1 + h_m}, \tag{38}$$

in which the ξ_i $(i = 1, 2, 3)$ is calculated as follows:

$$\xi_i = \sum_{j=0}^{i} \binom{i}{j} \widehat{\sigma}^j \widehat{\mu}_m^{i-j} P_j, \tag{39}$$

where $g(\gamma_m)$ is a standard normal distribution pdf and $G(\gamma_m)$ is its distribution function and P_j can be calculated as :

$$\begin{cases} P_0 = 1 \\ P_1 = -\dfrac{g(\gamma_m) - g(\chi_m)}{G(\gamma_m) - G(\chi_m)} \\ P_j = -\dfrac{\gamma_m^{j-1} g(\gamma_m) - \chi_m^{j-1} g(\chi_m)}{G(\gamma_m) - G(\chi_m)} + (j-1)P_{j-2}, \end{cases} \tag{40}$$

in which

$$\gamma_m = \frac{(e_{ml} - \widehat{\mu}_m)}{\widehat{\sigma}}$$

$$\chi_m = \frac{(e_{mu} - \widehat{\mu}_m)}{\widehat{\sigma}}. \tag{41}$$

Above all, the update for all the variables has been given. Then, the DF-QVBI algorithm is summarized in algorithm 2:

Algorithm 2 The Algorithm of DF-QVBI

Require: $\mathbf{D}$, $p(\mathbf{e})$,$\boldsymbol{t}$, $k_{\max}$, $\tau_{\max}$, δ.
Ensure:
1: Compute $p(\mathbf{e})$ according to algorithm 1.
2: Initialize the relative parameters.
3: Compute $\langle\mathbf{e}\rangle^{(0)}$ and $\left\langle\mathbf{e}^T\mathbf{e}\right\rangle^{(0)}$ according to (11)-(14).
4: Set Iteration number $\tau = 1$.
5: **while** $\tau < \tau_{\max}$ and $\Delta r > \delta$ **do**
6: Update $\boldsymbol{\alpha}^{(\tau)}$ using (28)-(30).
7: Update $\beta^{(\tau)}$ using (31)-(33).
8: Update $\langle\mathbf{e}\rangle^{(\tau)}$ and $\left\langle\mathbf{e}^T\mathbf{e}\right\rangle^{(\tau)}$ using (37)-(41).
9: Update $\mathbf{x}^{(\tau)}$ using (23),(24),(26).
10: Compute the reduction using $\Delta\tau = \left\|\boldsymbol{\alpha}^{(\tau)} - \boldsymbol{\alpha}^{(\tau-1)}\right\|_2 / \left\|\boldsymbol{\alpha}^{(\tau)}\right\|_2$;
11: Update the Iteration number $\tau = \tau + 1$.
12: **end while**
13: Output the current distribution mean of $\boldsymbol{x}$ as the estimate.

Coming to initializing the relative parameters, we set $a = b = c = d = 10^{-6}$ to promise a good result according to the variational Bayesian inference algorithm. Additionally, $\Delta\tau = 10^4$, $\delta = 10^{-4}$ and the maximum iteration $\tau_{\max} = 500$.

V. NUMERICAL SIMULATIONS

In this section, we test our proposed DFL scheme by simulations. The DFL detecting area with size $14m \times 14m$ are divided into $N = 196$ point grids. To sense the signal changes, $M = 32$ wireless links are uniformly deployed as is shown in Fig.1 and K targets are randomly distributed at the grid points. In order to model the signal changes caused by target appearing, the saddle surface DFL model is applied.

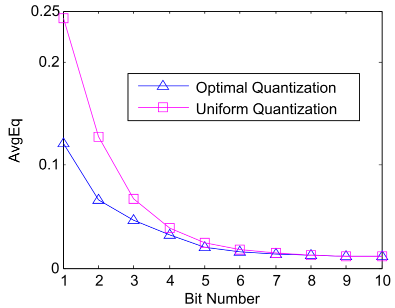

FIGURE 5. Average quantization error via different quantization schemes.

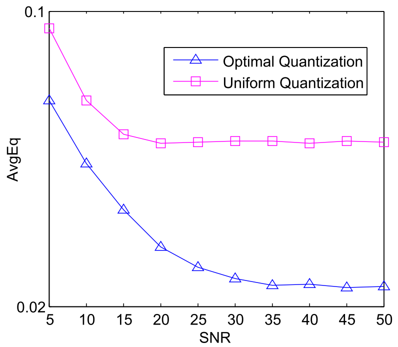

FIGURE 6. Average quantization error via different noise.

Additionally, in order to test the performance of the proposed recovery algorithm, the most widely applied CS recovery algorithms are utilized, such as Basis Pursuit (BP) [33], Greed Matching Pursuit (GMP) [34], Orthogonal Matching Pursuit (OMP) [35], Bayesian Compressive Sensing (BCS) [36].

In this paper, we design a discrete approach to approximate the measurement distribution instead of computing the complex or incomputable pdf. As to test the quantization scheme, the uniform quantization is utilized to be an compare. Here the average quantization error for the location vector is represented by $AvgEq$, which is given as follows:

$$AvgEq = \frac{1}{S \cdot N} \sum_{i=1}^{S} \left\| \mathbf{x}^i - \widehat{\mathbf{x}}^i \right\|_1, \tag{42}$$

where S and i are the total simulation number and the current simulation number. $\mathbf{x}$ and $\widehat{\mathbf{x}}$ are the real location vector and the estimated location vector with N dimensions, respectively.

At first, we test the quantization performance by comparing the average quantization error via different quantization schemes. As is shown in the Fig.5, the quantization error decreased with the increasing of the bit number for both the quantization schemes. In details, the proposed quantization scheme always holds better quantization performance. And we notice that as the bit number goes up to 7 bits, the error is almost the same for both the quantization scheme. This result is reasonable for that more quantization levels makes the quantization more approximal to the real values.

Then, in order to test the robustness of the quantization scheme, we compare the two schemes with $K = 2$ and $3bits$ by varying the SNR. We can see from the Fig.6 that both schemes can obtain convergence when the SNR is above $35dB$. However, the proposed optimal quantization scheme always performs better no matter how the noise changes.

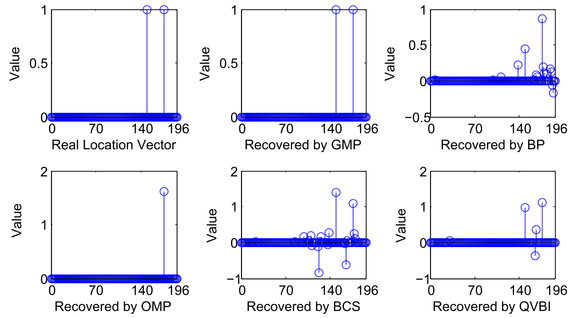

FIGURE 7. The illustration of the recovered location vectors by different algorithms.

A. LOCALIZATION PERFORMANCE

In fact, our proposed algorithm is utilized to obtain localization. So, the average localization error $AvgEl$ is applied to measure the localization performance, which is given as:

$$AvgEl = \sum_{i=1}^{S} \sum_{k=1}^{K} \frac{1}{K \cdot S} \sqrt{\left(x_k^i - \hat{x}_k^i\right)^2 + \left(y_k^i - \hat{y}_k^i\right)^2}, \tag{43}$$

where (x, y) and $(\widehat{x}, \widehat{y})$ are the real and the estimated target location, respectively. S and K are the total simulation number and the target number. In order to testify the localization performance, we perform the following simulations.

First, we compare the different location vectors recovered by the existing CS recovery algorithms. Set target number $K = 2$ and $M = 32$ respectively, the result is shown in the Fig.7. We can see that the recovered location vectors are different, compressible or sparse, for the different recovery theory. The GMP and OMP are absolutely sparse, making the target locations are exactly the relative grid points of the non-zero elements. And for BP, BCS and DF-QVBI which are the compressible vector, only K largest elements are chosen to determine the target location. So although the recovered vectors by GMP and OMP may has the most similar style to the original location vector, they may not obtain the better localization performance.

Secondly, we illustrate the localization result of different recovery algorithms in Fig.8. We can see that all most all the algorithms can localize the targets, however, the OMP algorithm has a lower recovery accuracy. We should note that this figure is just the result of one simulation. So, we perform more simulations to test the localization accuracy.

Thirdly, the robustness of the proposed algorithms are tested via different noise. As is shown in Fig.9, the localization error decreased as the SNR varies from $5dB$ to $40dB$. The OMP algorithm always has the highest localization error while the newly proposed DF-QVBI holds the most lower

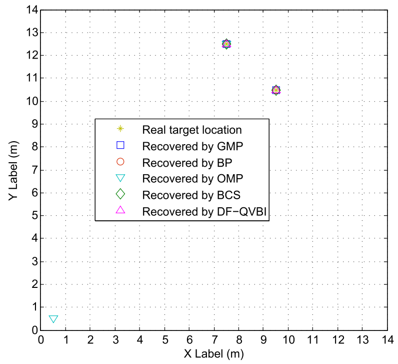

FIGURE 8. The localization result by different algorithms.

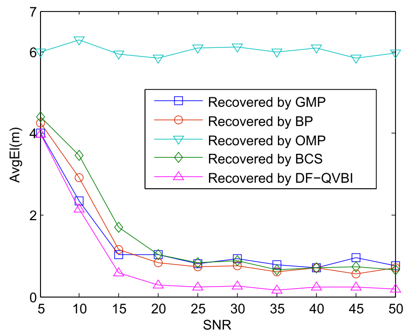

FIGURE 9. The localization performance of different recovery algorithms via different SNR.

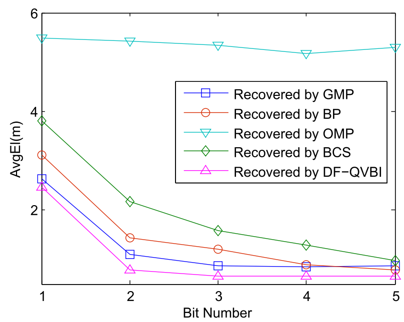

FIGURE 10. The localization performance of different recovery algorithms via different bit number.

localization error. The simulations shows that the DF-QVBI has better performance to defence the noise.

Then in order to test the effect of the quantization length for the localization, the length is varied from $L = 2^1$ to $L = 2^8$. Fig.10 shows the localization error via different bit number and algorithms. With the increasing of the quantization length, all algorithm can obtain lower quantization error. And once the quantization length reaches $L = 5$, the localization error obtains convergency. Compared with other algorithms, our proposed DF-QVBI can achieve the best localization accuracy.

At last, we both test the quantization performance and the localization performance via different algorithms and different bit number. As is shown in the Fig.11, on one hand,

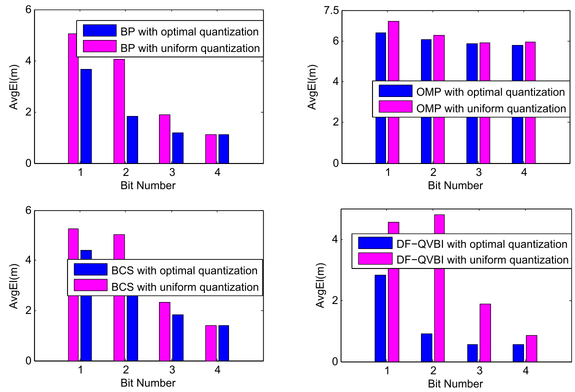

FIGURE 11. The localization error via different algorithms and different bit number.

the *AvgEl* for the optimal quantization scheme is always lower than the uniform quantization scheme according to the same recovery algorithm. On the other hand, we can see that our proposed algorithm DF-QVBI has better localization performance when compared with other recovery algorithms using the same quantization scheme. All in all, our proposed DF-QVBI always performs better when compared with other algorithms.

VI. CONCLUSION

In this paper, We studied the CS-based DFL utilizing the quantized information, extending the application of the DFL especially in the energy and resource constrained scene. Firstly, through exploiting the discrete property of CS theory, we calculate the discrete measurement probability bypass computing the complex or uncalculated measurement pdf. Secondly, we design the optimal quantizer for each wireless link according to the calculated measurement probability. Thirdly, the quantization error pdf in each interval is approximated as a liner function and considered in the new CS-based DFL model. Then, a novel algorithm DF-QVBI is proposed to reconstruct the location vector. Finally, simulations show that the proposed scheme outperforms the state-of-the-art CS-based DFL algorithms.

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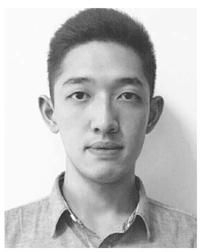

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