Distributed, Robust Acoustic Source Localization in a Wireless Sensor Network

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***Abstract*—A distributed, robust source location estimation method using acoustic signatures in a wireless sensor network (WSN) is presented. A contaminated Gaussian (CG) noise model is proposed to characterize the impulsive, non-Gaussian nature of acoustic background noise observed in some real-world WSNs. A bi-square M-estimate approach then is applied to provide robust estimation of acoustic source locations in the presence of outlier. Moreover, a Consensus based Distributed Robust Acoustic Source Localization (C-DRASL) algorithm is proposed. With C-DRASL, individual sensor nodes will solve for the bi-square M-estimate of the source location locally using a lightweight Iterative Nonlinear Reweighted Least Square (INRLS) algorithm. These local estimates then will be exchanged among nearest neighboring nodes via one-hop wireless channels. Finally, at each node, a robust consensus algorithm will aggregate the local estimates of neighboring nodes iteratively and converge to a unified global estimate on the source location. The effectiveness and robustness of C-DRASL are clearly demonstrated through extensive simulation results.**

***Index Terms*—Acoustic energy, M-estimate, source localization, network consensus, wireless sensor networks.**

I. Introduction

ACOUSTIC source (uncooperative) localization using energy signature is an important signal processing task in wireless sensor network (WSN) applications [1]. By assuming that the background observation noise at individual sensors are identically, independently distributed (i.i.d.) Gaussian noise, a maximum-likelihood estimation (MLE) method has been proposed [2] to solve the source localization problem. Several variants including non-linear least square (LS) methods have also been proposed subsequently [3]–[6].

However, observations of background acoustic noise in real-world WSNs do not always fit the Gaussian model well. When a WSN is operating in a hazardous outdoor environment its sensor observations are likely to be corrupted by impulsive (non-Gaussian) noises, namely outliers, due to sensor failures, attacks or interferences of unrelated acoustic sources, etc. Such outliers are found to be detrimental to existing acoustic source localization algorithms [7]–[9].

One solution to deal with this problem is to eradicate outliers in sensor observations before applying location estimation algorithms [7], [8]. However, without precise knowledge of the statistical properties of the outliers, legitimate acoustic signatures may inadvertently be rejected due to the so-called "masking effect" [10]. Another approach is to incorporate *robust statistics* [10] estimation methods that discount large fitting errors due to outliers during the estimation process. Along this direction, several methods have been proposed for time-of-arrival (TOA) based source localization against outliers caused by non-line-of-sight (NLOS) propagation [9], [11]. In [12], a robust maximum likelihood method is introduced for energy based acoustic source localization. With outlier-corrupted sensor observations, a bi-square M-estimation computed at the fusion center yields much more accurate location estimates than obtained using conventional LS or MLE based methods. Note that acoustic source localization using other signal modalities, e.g., DOA [13], can also experience degradations due to outliers. Since the acoustic signal signatures used are different, the causes of outliers as well as localization approaches are also different.

A key design constraint of WSN applications is the limited on-board energy reserve. In particular, long range wireless transmission should be avoided to conserve energy. Instead, distributed (decentralized) processing that leverages local data transmission and processing to reduce the payload of wireless transmission has become a widely accepted approach of WSN information processing. Rabbat *et al.* [14] introduced a Distributed Incremental Gradient (DIG) optimization method for sensor networks which can be applied to energy based acoustic source localization and tracking [15]. The POCS (projection onto convex sets) based method [3] has also been implemented in a distributed fashion, which is closely related to the DIG method. Earlier, the centralized bi-square M-estimation method [12] has been extended to a Decentralized Robust Acoustic Source Localization (DRASL) algorithm [16]. With DRASL, sensors forward a local robust estimate of the source locations, instead of raw data, to a centralized fusion center where the global source location estimation is computed.

The consensus algorithm [17] is a widely studied distributed algorithm in WSNs. It requires only local communications and simple computation. Li *et al.* [18] consider the problem of robust consensus algorithm design in the presence of outliers and proposed a generalized consensus algorithm for robust convex cost functions. However, the optimizing objective functions in practical localization problems are hardly convex even the ro-

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bust cost functions are convex. This property will be elaborated in Sections II and III.

Individual sensors also have very limited resources for computation and storage. In [19], a sequential M-estimator is proposed whose computation, storage, and communication costs may grow dramatically as the number of sensors increases. To reduce computation cost, light-weight robust regression algorithms, such as Iterative Reweighted Least Square (IRLS) [10], may be applied.

In this work, potential causes of non-Gaussian background noise are analyzed and a *contaminated Gaussian* model is introduced to model some non-Gaussian disturbances. With this model, a bi-square M-estimate [20] based robust estimation formulation for energy-based WSN acoustic source localization is developed. Criteria for selecting the robust cost function are suggested; and an empirical approach for threshold selection of the robust cost function based on the outlier probability is introduced. Moreover, a Consensus based Distributed Robust Acoustic Source Localization (C-DRASL) algorithm is proposed so that raw sensor data need not be transmitted through costly wireless channels and only local communications and computations are used to achieve unified global result. Taking advantage of the locally broadcasting feature of omni-directional antenna, individual sensor nodes will compute a local estimate of source locations based on its own data and data broadcast from its immediate neighbors. The local estimation is computed using a light-weight Iterative Nonlinear Reweighted Least Square (INRLS) algorithm. The locally estimated source locations then will be shared among one-hop neighboring nodes and fused by the robust consensus algorithm to obtain the global source location estimate on each node.

The significance of this work consists of two aspects:

1) Use real-world experimental data to justify the validity of using a CG distribution to model the heavy tail distribution in the presence of outliers in the background noise energy model.
2) The development of a novel distributed C-DRASL algorithm to provide robust estimation of source location in the presence of impulsive noise.

The remaining of this paper is organized as follows. In Section II, the contaminated Gaussian model for acoustic energy observations is elaborated and justified by real-world data. Section III develops the M-estimate based robust localization method where selection of ρ-functions and its threshold are discussed. Section IV introduces the Consensus Based Distributed Robust Acoustic Source Localization (C-DRASL) algorithm. Simulations and results are shown in Section V. Section VI concludes the paper.

II. Models

A. Attenuation Model for Acoustic Energy Observations With Gaussian Noise

Assume that N sensors are randomly deployed in a 2-D sensing field at known locations $\{l_i; 1 \leq i \leq N\}$. At kth time instant, a source at location $\tau(k)$ is emitting an acoustic signal with a constant energy level S (measured at 1-unit distance). At the ith sensor, the jth $(1 \leq j \leq M)$ energy of the received signal can be expressed as [2]

$$y_{i,j}(k) = f(x_i, \theta(k)) + e_{i,j} \tag{1}$$

where

$$f(x_i, \theta(k)) = \frac{g_i S}{\|l_i - \tau(k)\|^2} \tag{2}$$

is the energy of received source signal at the ith sensor, g_i is the sensor gain, and $\|\cdot\|$ is the Euclidian distance. In the above equations, $x_i = \{l_i, g_i\}$ are the known parameters of the ith sensor and $\theta(k) = \{S, \tau_x(k), \tau_y(k)\}$ are unknown variables which may be estimated using MLE or nonlinear LS methods [2]–[4]. For notational brevity, the time index k in (1) and (2) will be dropped in the remaining discussions of this paper.

The additive noise process $e_{i,j} \sim \mathrm{N}(\mu_i, \sigma_i^2)$ is assumed to be a wide-sense stationary *Gaussian* random process whose mean value μ_i (>0) and standard deviation σ_i can be estimated empirically from data samples.

B. Contaminated Gaussian Noise Model for Acoustic Energy Observations

The use of a Gaussian distribution to model the acoustic energy of background noise $e_{i,j}$ could become inadequate under the following situations:

a) Natural causes, such as wind gust, animal movement, thunder, hail storm, etc. are all potential sources for producing high intensity acoustic energy burst in the background.
b) When the WSN is deployed a hostile environments, sensors may be sabotaged and acoustic interferences may be imposed to compromise the performance of the WSN.
c) Equipment failures in individual sensor nodes may also manifest themselves as impulsive outlier background noise.

Acoustic background noise interferences due to the above causes seldom persist continuously. Instead, they are often intermittent in time. Yet they often exert large, impulsive amount of acoustic energy into the acoustic observations.

While there are a few ad hoc remedies proposed to deal with the previously mentioned outlier interferences [21]–[23], these existing approaches focus on coping with the negative impacts of these interferences rather than aggressively mitigating the damage. In this work, a *contaminated Gaussian* model of the form

$$F = (1 - \varepsilon)G + \varepsilon H \tag{3}$$

is proposed to characterize the properties of these abnormal observations (outliers). In (3), ε $(0 \leq \varepsilon \leq 1)$ is the prior probability of outlier occurrence (outlier probability), and $G = N(f(x_i, \theta) + \mu_i, \sigma_i^2)$ is a Gaussian probability density function (PDF). Since energy is non-negative, one has $f(x_i, \theta) + \mu_i > \sigma_i > 0$. Note that G is identical with the attenuation model with the Gaussian noise in (1). On the other hand, H is an asymmetric

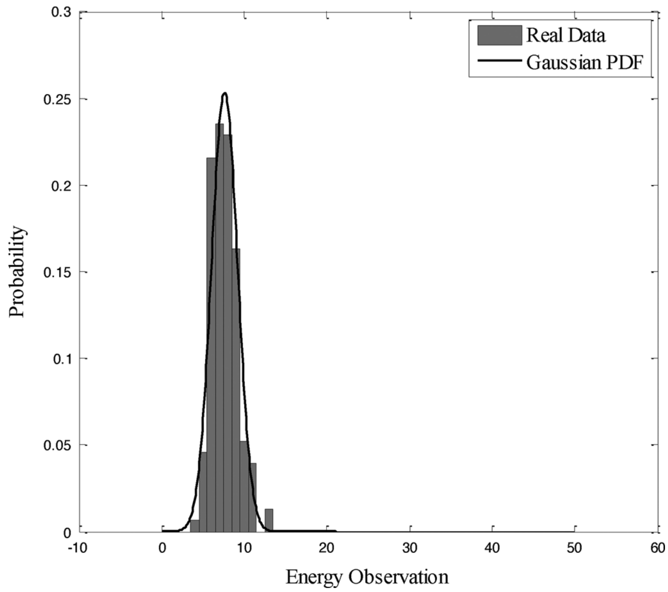


Fig. 1. Distribution of acoustic energy observations collected in the anechoic chamber. For the Gaussian PDF, $N(\hat{\varphi}, \hat{\omega}^2)$, parameters are estimated by the mean and standard deviation of the observations, i.e., $\hat{\varphi} = 7.61, \hat{\omega} = 1.58$.

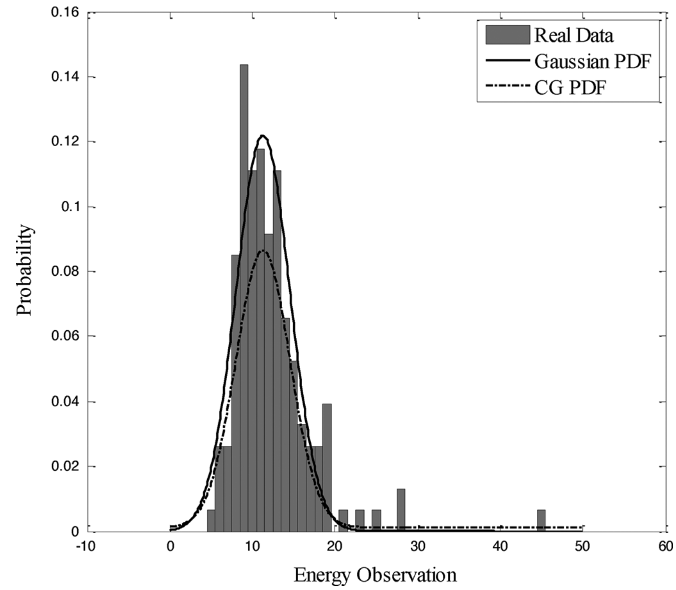


Fig. 2. Distribution of acoustic energy observations collected in the campus parking lot. For the Gaussian PDF, $\mathrm{N}(\hat{\varphi}, \hat{\omega}^2)$, parameters are estimated by the median and normalized median absolute deviation (page 33 in [10]) of the observations, i.e., $\hat{\varphi} = 11.27, \hat{\omega} = 3.27$. The contaminated Gaussian (CG) PDF has the form $(1 - 0.3)\mathrm{N}(\hat{\varphi}, \hat{\omega}^2) + 0.3\mathrm{U}(0, 255)$.

probabilistic distribution having much larger dispersion than G. In practice, one may assume H is a uniform distribution

$$U(0, \Gamma) = \begin{cases} 1/(\Gamma + 1) & 0 \leq e_{i,j} \leq \Gamma; \\ 0 & \text{otherwise} \end{cases}$$

where Γ may be the dynamic range of the data samples. For example, $\Gamma = 65\,535$ for 16-bit unsigned integers.

The CG model belongs to a heavy-tail distribution class. Other heavy tail distributions include the Cauchy distribution and the t-distribution. The CG model provides a flexible representation to model how the non-Gaussian portion (H) mixing with the Gaussian noise portion (G) of the distribution. Thus, it is uniquely suitable for modeling the impulsive outliers in the background noise.

C. Experimental Validation

To validate the CG noise models, experiments are conducted to acquire acoustic sensor background noise in two different environments, a sound proof anechoic chamber and a parking lot, in the absence of a source signal $(f(x_i, \theta) = 0)$. The acoustic noise is collected using the microphone on a MTS310 sensor board connected to a MICAz node [24]. It is transferred directly into the hard-drive of a laptop and hence is free from wireless channel loss. The data type of the acoustic samples is 8-bit unsigned integer and the sampling rate is 512 Hz. A total of 15 360 acoustic samples are taken over a time interval of 30 s. One energy reading is calculated over every 100 samples [2].

The histograms of the acoustic energy measured in the two different environments are plotted in Figs. 1 and 2, respectively. The energy distribution of the acoustic background noise in the anechoic chamber (Fig. 1) closely follows a traditional Gaussian distribution. On the other hand, as shown in Fig. 2, the acoustic background noise sampled in a campus parking lot may be contaminated by a few loud samples which form a (one-sided) *heavy tail* of the distribution. For such an operating environment, traditional Gaussian distribution would be inadequate. Instead, the acoustic noise energy distribution in Fig. 2 may be better fitted using this CG model:

$$(1 - 0.3)\mathrm{N}(\hat{\varphi}, \hat{\omega}^2) + 0.3\mathrm{U}(0, 255).$$

Note that whether a CG model is suitable for a particular environment depends on specific operating conditions of the WSN. In practical applications, it would be prudent to carefully analyze the potential scenario of WSN operations and make exploratory empirical observations before deciding which noise energy model (Gaussian or CG) to use.

III. M-Estimate Based Robust Acoustic Source Localization in WSN

A. Robust M-Estimate of the Acoustic Source Location

An M-estimator, as proposed by Huber [25], is a generalized ML estimator that seeks to minimize a class of *robust* cost functions. Acoustic energy readings at individual sensor nodes will be aggregated in a centralized fusion center. At the fusion center, the M-estimate of unknown acoustic source parameters $\theta = (S, \tau)$ may be obtained by minimizing

$$L_M(\hat{\theta}) = \sum_{i=1}^{N} \sum_{j=1}^{M} \rho\left(\frac{r_{i,j}(\theta)}{\sigma_i}\right) \tag{4}$$

where $r_{i,j}(\theta) = y_{i,j} - f(x_i, \theta) - \mu_i$. Note that the conventional MLE is a special case of the M-estimate with $\rho(a) = a^2$. Being a nonlinear cost function, (4) may be solved using iterative optimization procedures such as the Newton method.

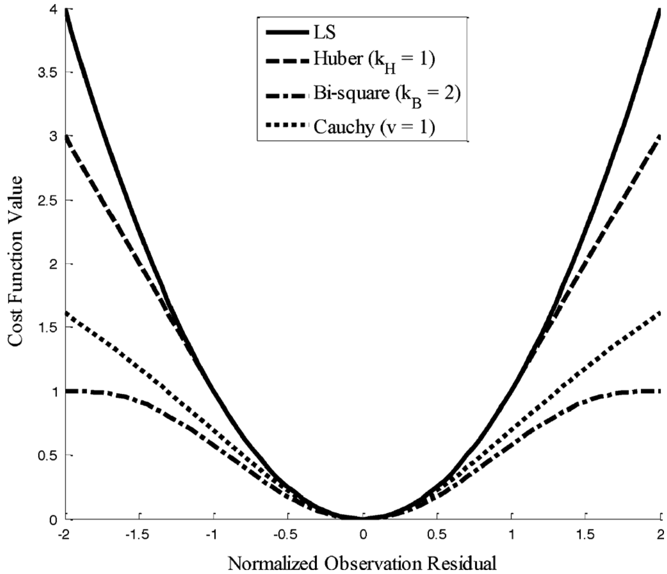


Fig. 3. Plots of different robust cost functions, i.e., $\rho(\cdot)$.

B. Selection of the Robust Cost Function

The robust cost function $\rho(\cdot)$ in (4) should be chosen to provide a balanced estimator with desirable robustness and efficiency. It should yield comparable performance as conventional MLE when the background noise is Gaussian; yet minimizing performance degradation when the observations are corrupted with outliers.

To choose $\rho(\cdot)$, three popular candidates are considered: the *Huber function* [10], the *Bi-square function*, and the *Negative log-likelihood of the Cauchy distribution* [9]. A plot of these three functions, together with the least square (LS) function against the normalized observation residue $r_{i,j}(\theta)/\sigma_i$ is depicted in Fig. 3.

Note that as the magnitude of the residue $r_{i,j}(\theta)$ increases, the traditional LS method is likely to be dominated by those large errors, causing significant performance degradation. The three robust cost functions (Huber, bi-square, and Cauchy), on the other hand, discount the outlier and hence exhibit more robust estimates. Among them, the bi-square method is most aggressive in discounting larger magnitudes of $r_{i,j}(\theta)$ as outliers. In this paper, we will focus on the bi-square function. Specifically, the bi-square robust function can be described as

$$\rho_B(a) = \begin{cases} 1-(1-(a/k_B)^2)^3 & \text{if } |a| \le k_B \\ 1 & \text{if } |a| > k_B \end{cases} \tag{5}$$

where the parameter k_B is usually determined empirically.

C. Selection of k_B for the Bi-Square Cost Functions

The threshold parameter of a robust cost function must be carefully chosen to ensure good performance of an M-estimator. Existing methods include the 3-sigma rule [10], and outlier rejection confidence level [26]. These methods use a fixed threshold for all possible values of the outlier probability ε in (3). In this section, an empirical approach will be developed that leads to a more accurate, variable threshold of k_B that is a function of ε.

TABLE I
SIMULATION RESULTS OF BEST k_B FOR DIFFERENT ε

ε	0	0.1	0.2	0.3	0.4	0.49
Best k_B	8	8	7	5	5	5
RMSE	3.13	3.38	3.58	4.11	4.80	6.42

The experiments are conducted based on the following scenario: in a 100 m × 100 m 2D sensing field, a single acoustic source at a random position emits an acoustic signal with intensity $S = 50\,000$ (measured at 1 m distance). A total of 16 sensor nodes are randomly deployed over the sensing field. Each sensor has a unity gain $(g_i = 1)$ and collects one measurement per time interval $(M = 1)$. The background contaminated Gaussian noise has a Gaussian noise component with $\mu_i = \mu = 10$ and $\sigma_i = \sigma = 3$ for $1 \le i \le 16$. The non-Gaussian component H is a uniform distribution over an interval [0, 65 535].

For each simulation, ε varies between 0 and 0.49 while k_B assumes integer values in the range of [2] and [15]. A total of 1000 trials are conducted. The best k_B value giving the smallest RMSE of the source's position estimate for each setting of ε is listed in Table I. Note that when ε increases, the optimal threshold tends to decrease. That is to say, when non-Gaussian components increase, the robust estimator needs to be more aggressive in discounting larger value of residues. In a practical application, ε may be estimated first. Then the choice of k_B can be deduced using Table I.

Potential influences of the nominal distribution variance σ and the node density on threshold selection are also investigated. Simulation results are plotted in Figs. 4 and 5, respectively. From these figures, it is shown that these factors have little impact on the selection of k_B.

IV. CONSENSUS BASED DISTRIBUTED ROBUST ACOUSTIC SOURCE LOCALIZATION ALGORITHM IN WSN

A. WSN Distributed Computing and C-DRASL

The distributed sensing nature of WSNs invites opportunities of *in-network processing* ([27] and references therein) with which partial results are computed and updated in local intermediate nodes while being routed toward the final destination. Since partial results are more concise then raw data, less data will need to be transmitted wirelessly, promising significant energy savings than a centralized operation where raw data are transmitted.

In this work, a C-DRASL algorithm is proposed. With C-DRASL, a sensor node broadcasts its energy observations or partial results to its nearest neighbor nodes (nodes within one-hop distance). Reciprocally, each sensor node will also receive broadcast data or partial results from its neighbors. Based on the local data and those from its neighbors, an initial local robust estimate of source locations will be computed using a light-weight INRLS algorithm described in Section IV-B. Then the partial location estimates will be aggregated using an iterative robust consensus algorithm [18]. Eventually, source location estimates at every node will converge to a global estimate in a way similar to the statistical bootstrapping [28]. More

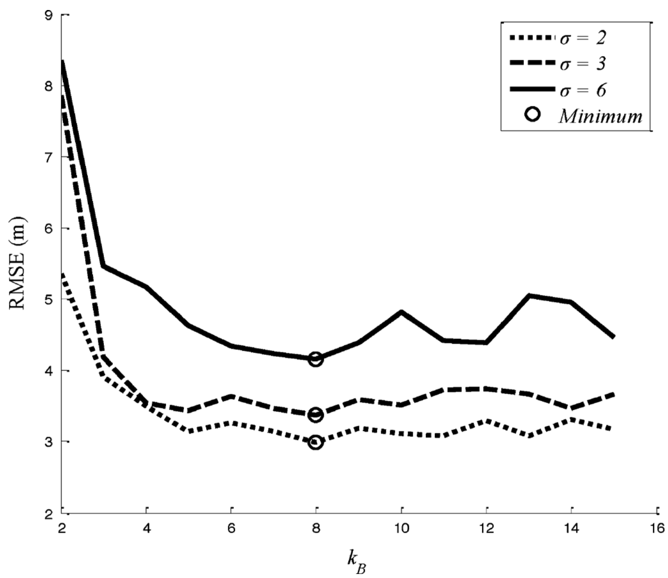


Fig. 4. RMSE of estimates on the source's location with different $\mathrm{k_B}$ under different nominal distribution variances. $\varepsilon = 0.1$ and $N = 16$.

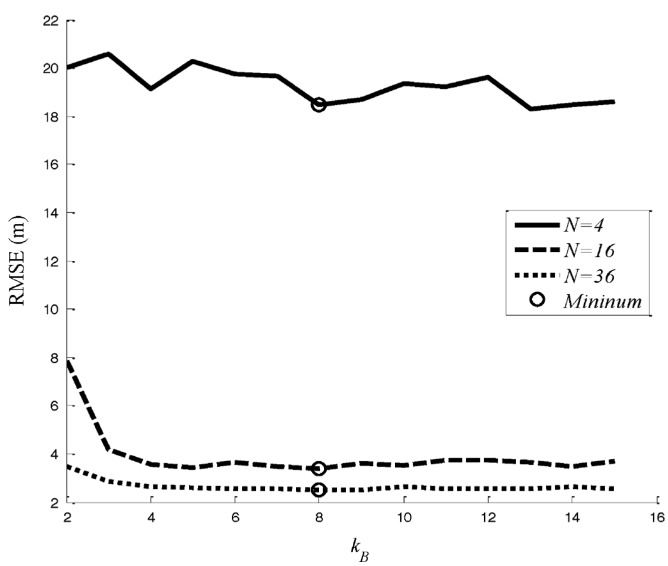


Fig. 5. RMSE of estimates on the source's location with different k_B under different node densities. $\varepsilon = 0.1$ and $\sigma = 3$.

specifically, the C-DRASL algorithm consists of following steps.

a) The ith sensor node broadcasts its energy observation $y_i = \{y_{i,j}, j = 1 \ldots M\}$ to all neighboring nodes $k \in \Omega(i)$, where $\Omega(i)$ is the set of node indices of one-hop neighboring nodes of sensor i (within the communication range d_c). It also receives the broadcasts from its neighbors $\{y_{i'}; i' \in \Omega(i)\}$

b) The ith sensor node computes a local estimate $\hat{\theta}_i$ based on $\{y_{i'}; i' \in \Omega(i)\} \cup \{y_i\}$ using the INRLS algorithm.

c) The ith sensor node broadcasts its local location estimates $\hat{\theta}_i$ to its one-hop neighboring nodes $i' \in \Omega(i)$ and use the robust consensus algorithm to update the local estimates until convergence.

C-DRASL is a fully distributed version of the DRASL algorithm reported earlier [16]. In DRASL, the global estimate is computed in a centralized fusion center while in C-DRASL, every node will maintain a locally updated version of the global location estimate until convergence. C-DRASL is developed under the assumption that sensor nodes may freely exchange data/partial results via local broadcasting to their one-hop neighbors. This distributed processing scheme promises scalability, fault-tolerance, and saves energy.

B. Iterative Nonlinear Reweighted Least Square

For linear regression tasks, an IRLS [10] has been proposed as a light-weight computing algorithm for solving a M-estimation problem. For the local estimation procedure of C-DRASL, it is generalized here to solve a nonlinear optimization problem with the objective function described in (4). Setting $\nabla_\theta L_M(\hat{\theta}) = 0$, one has

$$\begin{aligned} 0 &= \sum_{i=1}^{N} \sum_{j=1}^{M} \nabla_\theta \rho \left(\frac{r_{i,j}(\theta)}{\sigma_i} \right) \\ &= \sum_{i=1}^{N} \sum_{j=1}^{M} \varphi \left(\frac{r_{i,j}(\theta)}{\sigma_i} \right) \cdot \nabla_\theta \left(\frac{r_{i,j}(\theta)}{\sigma_i} \right) \end{aligned}$$

where $r_{i,j}(\theta) = y_{i,j} - f(x_i, \theta) - \mu_i$ and $\varphi(a) = \partial\rho(a)/\partial a$. Note that $\rho(a) \approx a^2$ as $|a| \to 0$. Thus, it is reasonable to represent $\varphi(a)/a \approx w(a)$ as $|a| \to 0$ where $w(a)$ approaches a constant. Hence, the above expression may be rewritten as

$$\sum_{i=1}^{N} \sum_{j=1}^{M} w \left(\frac{r_{i,j}(\theta)}{\sigma_i} \right) \cdot \left[\frac{r_{i,j}(\theta)}{\sigma_i} \right] \cdot \nabla_\theta f(x_i, \theta) = 0.$$

If one ignores the dependence of θ by $w(r_{i,j}(\theta)/\sigma_i)$ and denotes

$$w_{i,j} \approx w(r_{i,j}(\theta)/\sigma_i),$$

then one may approximate the above expression as the gradient of a weighted least square cost function:

$$\begin{aligned} &\nabla_\theta \left\{ \sum_{i=1}^{N} \sum_{j=1}^{M} w_{i,j} \cdot (r_{i,j}(\theta))^2 \right\} \\ &\qquad \approx \sum_{i=1}^{N} \sum_{j=1}^{M} w \left(\frac{r_{i,j}(\theta)}{\sigma_i} \right) \cdot \left(\frac{r_{i,j}(\theta)}{\sigma_i} \right) \cdot \nabla_\theta f(x_{i,j}, \theta). \end{aligned}$$

Finally, θ may be solved from an approximated cost function

$$\min_\theta \sum_{i=1}^{N} \sum_{j=1}^{M} w_{i,j} \left(y_{i,j} - f(x_i, \theta) - \mu_i \right)^2. \tag{6}$$

An iterative quazi-Newton procedure may be applied. Specifically, in the mth iteration,

$$\hat{\theta}_{i,m} = \hat{\theta}_{i,m-1} + \Delta_m \tag{7}$$

where Δ_m is obtained by solving following *normal equation*:

$$J_m^T W_m J_m \cdot \Delta_m = J_m^T W_m (Y - \bar{f}(X, \hat{\theta}_{i,m-1}) - \bar{\mu}) \quad (8)$$

and the augmented vectors of parameters within sensor i's neighborhood $\Omega(i)$ are $\mathrm{Y}, \mathrm{X}, \bar{\mu}$, and $\bar{f}(X,\theta)$, which consists of the column-vector blocks $\bar{y}_{i'}, \bar{x}_{i'}, \bar{\mu}_{i'}$ and $\bar{f}(X,\theta)$, respectively, for all $i' \in \Omega(i)$. Meanwhile, $\bar{y}_{i'} = [y_{i',1}, \ldots, y_{i',M}]^T$, $\bar{x}_{i'} = x_{i'} \cdot I_{M\times 1}, \bar{f}(x_{i'}, \theta) = f(x_{i'}, \theta) \cdot I_{M\times 1}$ and $I_{M\times 1}$ is the M by 1 matrix with all ones. J_m is the Jacobian matrix of $\bar{f}(X,\theta)$ subject to $\hat{\theta}_{i,m-1} = \{\hat{S}_{m-1}\hat{\tau}_{x,m-1}, \hat{\tau}_{y,m-1}\}$. In particular, the ith column block of J_m is

$$\begin{aligned}[J_m]_i &= I_{M\times 1} \cdot \left[\left. \frac{\partial \bar{f}(X,\theta)}{\partial \theta} \right|_{\theta=\hat{\theta}_{i,m-1}} \right] \\ &= I_{M\times 1} \cdot \frac{g_i}{(\hat{\tau}_{x,m-1} - r_{xi})^2 + (\hat{\tau}_{y,m-1} - r_{yi})^2} \\ &\quad \times \begin{bmatrix} 1 \\ -2\hat{S}_{m-1}(\hat{\tau}_{x,m-1} - r_{xi}) \\ -2\hat{S}_{m-1}(\hat{\tau}_{y,m-1} - r_{yi}) \end{bmatrix}^T . \end{aligned} \quad (9)$$

However, the weight matrix $W = \mathrm{diag}(\bar{w}_1, \ldots, \bar{w}_N)$ is, in fact, a function of θ and $\bar{w}_i = \mathrm{diag}(w_{i,1}, \ldots, w_{i,M})$. Thus, the weight matrix should be updated as new estimate of θ are computed as follows:

$$w_{i,j}^{(m)} = w(r_{i,j}(\hat{\theta}_{i,m-1})/\sigma_i). \quad (10)$$

The above equations constitute the core steps of the INRLS algorithm. The termination condition can be either the difference of the estimates between successive iterations is below a preset threshold or the iteration number exceeds a bound.

The convergence of INRLS can be proved in a manner similar to that given in [10, Sec. 9.1] for the linear regression problems, provided the following conditions are met:

a) the objective function in (4) is a single-modal differentiable function about θ;
b) $w(r_{i,j}(\theta)/\sigma_i)$ is non-negative and non-increasing about the absolute value of the residual $r_{i,j}(\theta)$;
c) $f(x_i, \theta)$ is differentiable about θ and the Jacobian matrix J_m has full column rank.

Among these conditions, b) can be easily verified for the bi-square function. However, a) and c) may not always be valid. a) is only valid in the near vicinity of the true θ value. Therefore, the initialization of the estimate should be in the vicinity of the true solution. In our algorithm, if no prior information of the source location is available, each sensor i will choose the geometrical center of the node positions in its neighborhood $\Omega(i)$ as the initial estimate value. From (9), condition c) might be invalid when the $(m-1)$th estimate is on the same straight line with all the sensors in $\Omega(i)$. This is a rare ill-condition and may be ignored for randomly deployed sensors.

C. The Robust Average Consensus Algorithm in C-DRASL

The robust average consensus algorithm in C-DRASL that minimizes the sum of robust cost functions of local estimates updates the estimates on each node in the following form [18]:

$$\hat{\theta}_i(\eta+1) = \arg\min_{\theta} \left\{ \rho_c(\theta) + \beta_i(\eta)\theta + \sum_{i' \in \Omega(i)} c(\eta)[\theta - 0.5(\hat{\theta}_{i'}(\eta) + \hat{\theta}_i(\eta))]^2 \right\} \quad (11)$$

$$\beta_i(\eta+1) = \beta_i(\eta) + c(\eta) \sum_{i' \in \Omega(i)} (\hat{\theta}_i(\eta+1) - \hat{\theta}_{i'}(\eta+1)) \quad (12)$$

where the iteration index is η and $\{c(\eta) > 0\}$ is a non-decreasing step size. β_i is the auxiliary state of the Lagrange multipliers and $\beta_i(0) = 0$ for $1 \le i \le N$. In this case, the robust cost function $\rho_c(\theta)$ needs to be a convex function, such as absolute function $\rho_c(\theta) = |\theta|$ that enforces the consensus final estimate is the *median* of local estimates.

V. Simulations

A. Localizing a Static Source

Over a 100 m $\times$ 100 m 2D sensing field, a single acoustic source (e.g., a gunshot) at a random position is emitting an acoustic signal with a constant intensity such that the energy emitted over 0.1 s, measured at 1 m away from the source is 50 000.

Assume N sensors are randomly deployed. Each sensor node is equipped with a microphone that samples acoustic signal at a sampling rate of 2 KHz. The sensor gain is assumed to be unity ($g_i = 1$). At each sensor node, the background noise is a contaminated Gaussian noise process consisting of a Gaussian noise component $\mu_i = 10$, and $\sigma_i = 3$ for $1 \le i \le N$; and a non-Gaussian component with a uniform distribution over [0, 65 535]. Energy of the sampled acoustic signal over an interval of 0.1 second will be computed and forwarded to a fusion center such that $M = 1$. The wireless transmission error and delay are ignored in this simulation.

Centralized Robust Acoustic Source Localization: In this section, the performance of bi-square M-estimate based acoustic source localization algorithm on a central fusion center will be compared with LS estimator with outlier-corrupted energy observations. Since our purpose is to estimate the source location, the source energy S, which may be utilized in source recognition, is not listed in simulation results. However, as observed in the simulations, the estimation performance of S is consistent with that of the location parameters.

For comparison purpose, source localization is solved by an exhaustive search over a grid size of 5 m $\times$ 5 m $\times$ 2000. The first two refer to the 2D coordinates; and the third is the number of equal partitions of the source energy in the range of [40 000, 60 000]. A total of 1000 trials of Monte Carlo simulations are conducted. When the number of sensor is $N = 16$, the mean and covariance matrices of localization errors with different outlier probabilities ε are summarized in Table II. Note that both the LS and bi-square estimates yield unbiased location estimates. However, the variances of the LS estimates are significantly increased when ε increases.

In Table III, the mean square errors of source locations as a function of node densities with $\varepsilon = 0.2$ are listed. The bi-square

TABLE II
MEAN AND COVARIANCE MATRICES OF THE LOCATION ESTIMATION ERROR UNDER DIFFERENT OUTLIER PROBABILITIES

	$\varepsilon = 0$	$\varepsilon = 0.1$	$\varepsilon = 0.3$
LS	$[0.06\ \ -0.04]$ $\begin{bmatrix}4.73 & 0.16\\ 0.16 & 5.54\end{bmatrix}$	$[-1.47\ \ -1.58]$ $\begin{bmatrix}1250.6 & 54.42\\ 54.42 & 1384.1\end{bmatrix}$	$[-0.18\ \ 0.17]$ $\begin{bmatrix}1619.1 & -64.32\\ -64.32 & 1627.8\end{bmatrix}$
bi-square	$[0.02\ \ 0.02]$ $\begin{bmatrix}5.33 & -0.28\\ -0.28 & 5.55\end{bmatrix}$	$[0.04\ \ -0.05]$ $\begin{bmatrix}5.98 & 0.44\\ 0.44 & 5.63\end{bmatrix}$	$[0.15\ \ -0.02]$ $\begin{bmatrix}7.11 & -0.67\\ -0.67 & 11.29\end{bmatrix}$

TABLE III
MEAN AND COVARIANCE MATRICES OF THE LOCATION ESTIMATION ERROR WITH DIFFERENT NODE NUMBERS

	N=10	N=16	N=25
LS	$[0.75\ \ 2.93]$ $\begin{bmatrix}1580.5 & -54.56\\ -54.56 & 1592.3\end{bmatrix}$	$[3.15\ \ 5.97]$ $\begin{bmatrix}1750.9 & -71.18\\ -71.18 & 1677.3\end{bmatrix}$	$[0.33\ \ 5.32]$ $\begin{bmatrix}1627.8 & 9.50\\ 9.50 & 1769.2\end{bmatrix}$
bi-square	$[0.03\ \ -0.03]$ $\begin{bmatrix}7.55 & -0.27\\ -0.27 & 7.35\end{bmatrix}$	$[0.01\ \ -0.01]$ $\begin{bmatrix}1.85 & 0.00\\ 0.00 & 1.53\end{bmatrix}$	$[-0.02\ \ -0.02]$ $\begin{bmatrix}0.27 & -0.05\\ -0.05 & 0.22\end{bmatrix}$

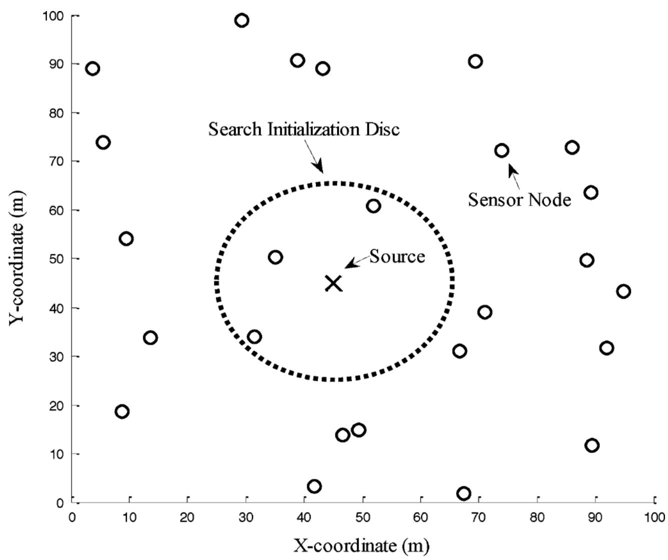


Fig. 6. Scenario settings for convergence simulations.

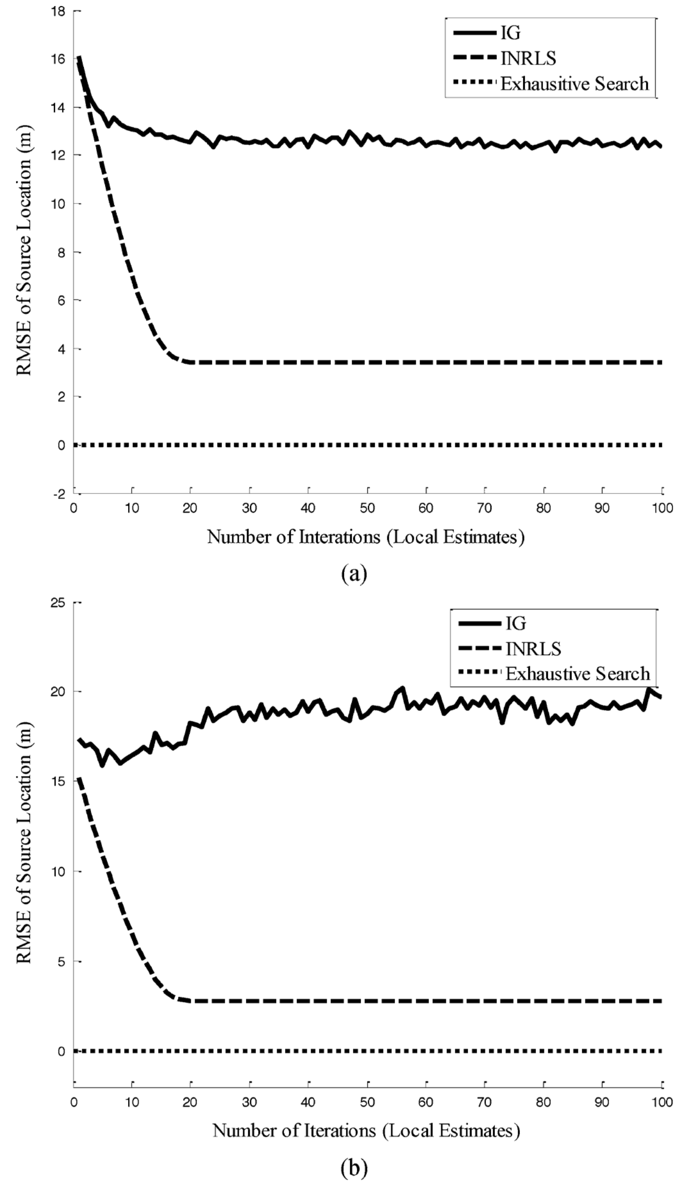


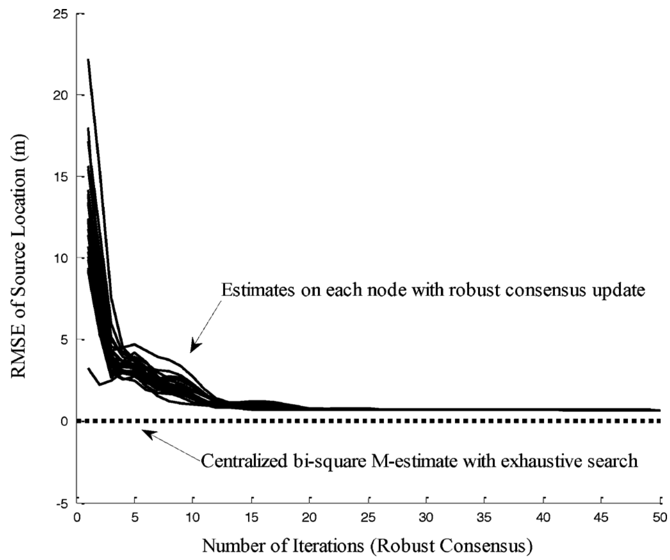
Fig. 7. Source location RMSE of IG and INRLS. (a) $\varepsilon = 0$ and (b) $\varepsilon = 0.2$.

estimates are uniformly better than LS estimates. As number of nodes increases, bi-square estimation renders smaller variance but LS is still highly influenced by outliers.

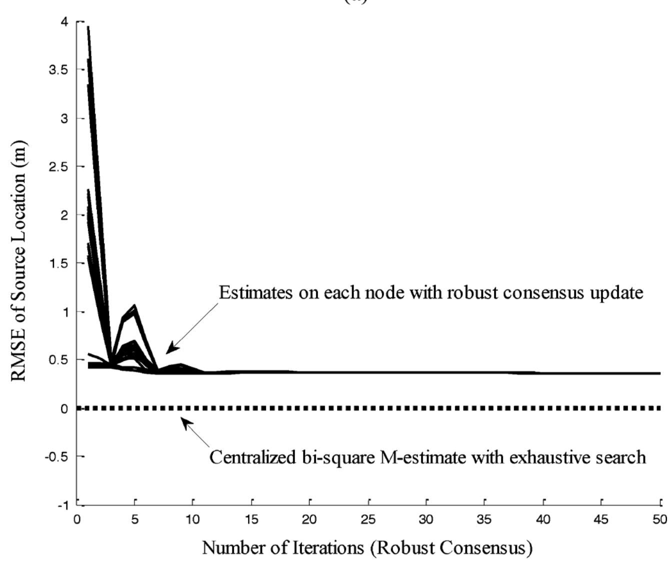
Convergence of Local Estimation and Consensus Algorithms: In the next simulations, the convergence performance of C-DRASL is compared with the DIG method [14]. The simulation settings are identical to those specified in Section V-A, except that the single source and 25 nodes are deployed in the sensing field as shown in Fig. 6. The nodes are connected by one-hop links and the communication range d_c is varied.

In C-DRASL, to first obtain the local estimates, each node applies the INRLS algorithm to solve the robust cost functions which are non-convex and non-linear. Hence its convergence is most of interest. Here, by setting the communication range of each node to be infinity $(d_c = \inf)$, INRLS and IG methods are conducted as a centralized solver on each node and their convergence performance are compared. For the IG method [14], the step size is 0.01 and Huber function is applied and its threshold is $k_H = 0.86$. The bi-square robust cost function, in which the threshold k_B is selected according to Table I, is chosen for INRLS. For the comparison purpose, initial location estimates of both algorithms are set to be an identical uniformly-random value in a 20 m radius disc to the true source location [45, 45] ("Search Initialization Disc" in Fig. 6) and the initial energy estimate is the same with true value. New observations are randomly drawn for each trial according to (3) with different ε in each simulation of 100 trials.

Two typical snapshots of the RMS location estimation errors of both methods are depicted in Fig. 7. In Fig. 7(a), both IG and INRLS converge to the near vicinity of the true value when the outlier probability ε is zero while INRLS has a smoother and more stable convergence. When ε increases, IG tends to diverge or converge to local optima as shown in Fig. 7(b) due to the ineffectiveness of Huber function under large outliers. However, in both cases, INRLS converges to more accurate results which are very close to those of the exhaustive search. Therefore, INRLS is more robust when large outliers are present and also more efficient when no outlier appears.



(a)



(b)

Fig. 8. RMSE convergence of local estimates on 25 nodes in the robust consensus algorithm. (a) $d_c = 50$ m and (b) $d_c = \mathrm{inf}$.

Moreover, in the next simulations, with the same scenario settings as shown in Fig. 6, we examine the convergence of robust consensus algorithm with different node communication range settings. The robust consensus algorithm in C-DRASL is to let each node get the median of all local estimates as the final global estimate of the source location.

After 100 trials, the localization RMSE convergence curves of the nodes in the robust consensus algorithm are plotted in Fig. 8. In the simulations, the communication range is set to ensure that the network topology graph is connected such that the convergence conditions are met. When the communication range is 50 m, as shown in Fig. 8(a), after around 25 iterations, the estimates on each node converge to a unified global result which is the median of all original local estimates. In Fig. 8(b), when the communication range is infinite, the estimates on local nodes are converging much faster. Note that the robust consensus algorithm renders very close RMSE results to that of the centralized method with exhaustive search and as communication range increases, they get even closer.

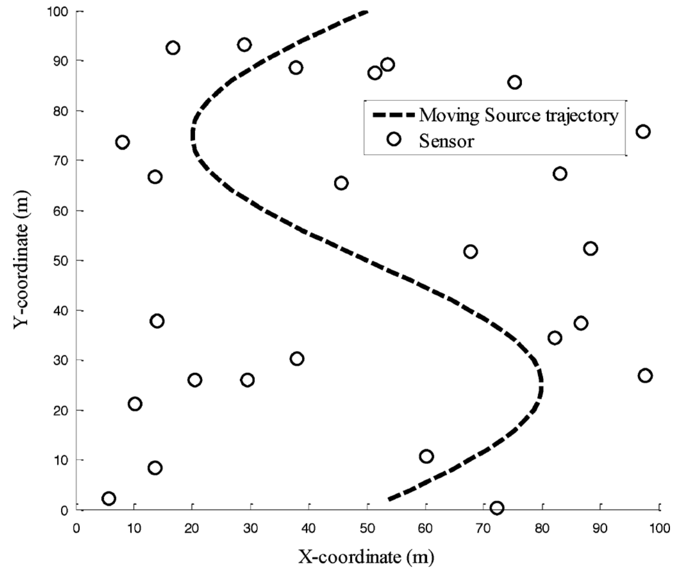


Fig. 9. True source trajectory with one realization of randomly deployed 25 sensors.

B. Localizing a Moving Source

A second scenario considers a moving source navigating in a sensing field over a period of 50 seconds at a speed between 2 and 3 m/s. The trajectory of source movement is depicted as dashed line in Fig. 9. Both the DIG and C-DRASL methods will be applied to solve for source locations every second. During this 1-s time step, $M\ (= 10)$ energy readings will be estimated, each over a period of 0.1 s. The sensing field configuration and other parameters are identical to the first experiment.

To better compare the performance difference of these two methods, the dynamic equation describe the motion will not be exploited. Instead, the last estimated source locations will be used as initial source location estimate of the present time step. As for the first second, the initial source location is chosen randomly with a disk region of 20 m radius from the true source location. The initial estimate on source energy S is a random value in [40 000, 60 000].

The DIG algorithm is terminated if either the iteration count exceeds 100 or the incremental update magnitude is smaller than 0.001. For C-DRASL, both the INRLS and he robust consensus algorithm has an upper limit of 30 iterations. The centralized bi-square preforms an exhaustive search over the entire sensing field. Each cell on the search grid is 2 m × 2 m, and the original energy estimate is set equal to the real value. A total of 100 trials are performed for each simulation with new sensor locations drawn randomly in each trial. The Averaged Root Mean Square Error (ARMSE) [29], which is the RMSEs averaged among all estimates on individual nodes, is used as the performance criterion for C-DRASL and DIG.

With different ε but fixed $N = 25$ and $d_c = 50$ m, the localization RMSE/ARMSE of different algorithms averaged over time is summarized in Table IV. It is shown that the ARMSE of C-DRASL is consistently smaller than that of DIG and very close to the RMSE of centralized method. C-DRASL has better normal efficiency when $\varepsilon = 0$ and is more robust to the perturbations caused by outliers when $\varepsilon > 0$.

TABLE IV
LOCALIZATION PERFORMANCE OF DIFFERENT ALGORITHMS

ε	DIG (ARMSE)	C-DRASL (ARMSE)	Centralized Method (RMSE)
0	1.96	0.48	0.66
0.1	3.59	0.84	0.81
0.2	2.76	0.62	0.78
0.3	2.79	0.77	0.61
0.4	6.00	0.98	0.77

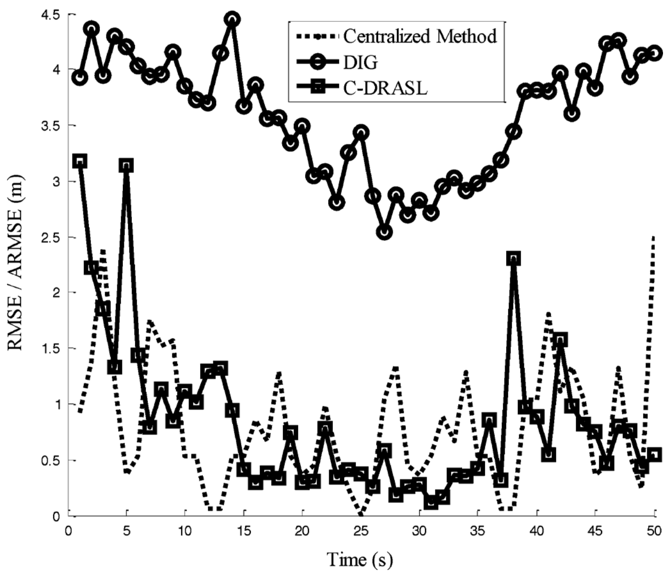


Fig. 10. The localization RMSE/ARMSE of DIG, C-DRSAL and centralized method along time when $N = 25$, $\varepsilon = 0.1$, and $d_c = 50$.

TABLE V
COMMUNICATION COST AND LOCALIZATION PERFORMANCE OF DIFFERENT DISTRIBUTED ALGORITHMS

N	DIG		C-DRASL		Centralized Method	
	packet #	ARMSE	packet #	ARMSE	packet #	RMSE
15	1111	2.81	600	5.51	1161	0.86
25	1261	2.76	1000	0.62	2500	0.78
35	1441	2.18	1400	0.46	4141	0.55
50	2149	1.87	2000	0.13	7971	0.60

A sample plot of the RMSE/ARMSE over the course of a 50-s simulation run is depicted in Fig. 10. Clearly, the performance of C-DRASL is on par with that of the centralized method while the DIG trailing behind consistently. The estimation error is larger at the beginning and the end of the experiment because the source locations are closer to the border of the sensing field and the SNRs on most sensor nodes are lower.

With different node number N but fixed outlier probability $\varepsilon = 0.2$ and communication range $d_c = 50$ m, the communication cost, measured by the number of packets (packet #) transmitted and the RMSE/ARMSE of C-DRASL, DIG and the centralized method are listed in Table V. All values are averaged over time. It shows that at a lower energy cost (fewer packet number), C-DRASL outperforms DIG in localization ARMSE. DIG needs more packet transmission because the massive packet circulation in its iterative optimization mechanism. To achieve better performance, a smaller footstep is needed that makes DIG converge slower and more circulations are required. Note that the packet number of centralized method is calculated from an energy consumption lower bound in [14] while those of DIG and C-DRASL are data from simulations.

TABLE VI
LOCALIZATION PERFORMANCE OF C-DRASL WITH DIFFERENT COMMUNICATION RANGE

d_c	C-DRASL	
	ARMSE	packet #
35	3.84	1500
50	0.62	1500
65	0.51	1500
∞	0.32	1500

Finally, the impact of the communication range d_c on the performance of C-DRASL is investigated. With different communication range but fixed outlier probability $\varepsilon = 0.2$ and node number $N = 25$, Table VI shows the localization performance and energy cost of C-DRASL. All values are averaged over time. When the communication range decreases, there is a higher probability that the network would be unconnected and the convergence rate also becomes lower such that the consensus of the nodes is not reached. Therefore, a longer communication range is preferred, at a higher cost of energy consumption for C-DRASL to have more accurate localization results. Note that DIG is not affected by the variation of communication range because it requires a fixed route among all nodes ordered by the detection protocol.

VI. CONCLUSION

Both centralized and distributed robust acoustic source localization algorithms are presented in the paper. By modeling real world sensor background noise as a contaminated Gaussian model, robust M-estimate formulation is derived. An empirical method for dynamically choosing the threshold of robust cost functions according to the outlier probability is provided. Using a distributed in-network processing framework, a C-DRASL algorithm is also proposed. Simulation results validate the superior efficiency and robustness of these proposed algorithms compared to traditional centralized least square or MLE approaches and the DIG distributed optimization method. Future works may include robust target detection and tracking methods for outliers in WSN.

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