RSS-based Cooperative Localization and Transmit Power(s) Estimation using Mixed SDP-SOCP

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Abstract—Received signal strength (RSS)-based localization techniques are widely used to estimate the location of wireless sensor nodes as they utilize minimum bandwidth and do not require additional hardware. However, these techniques typically assume that the nodes’ transmit power is known, despite the fact that changes in transmit power, influenced by factors such as antenna orientation and battery level, can significantly impact localization performance. To address this issue, we propose an RSS-based cooperative localization technique that jointly estimates the location and transmit power of the nodes and will refer to it as FCUP (Fast Cooperative localization technique with Unknown transmit Power). The maximum likelihood (ML) estimator for joint estimation of location and transmit power is non-convex, discontinuous, and computationally challenging to solve. So, we reformulate the optimization problem into a mixed semidefinite second-order cone program (SDP-SOCP) using the Taylor expansion, epigraph method, and semidefinite relaxation. FCUP takes advantage of the high accuracy of SDP and the low complexity of SOCP. FCUP is compared to the existing techniques to demonstrate its superior performance based on localization accuracy, computational complexity, and execution time.

Index Terms—Received signal strength (RSS), cooperative localization, semidefinite programming (SDP), transmit power

I. INTRODUCTION

WIRELESS sensor networks (WSNs) have become a lot more effective over time and are now widely used for supply chain management, environment monitoring, animal tracking, and smart home management. In WSNs, it is vital to know the position of the nodes, and it is not feasible to equip all the nodes with global positioning systems (GPS) as they are expensive and consume a significant amount of power. Thus, the nodes whose locations are unknown (referred as target nodes) localize themselves with the help of nodes whose locations are known (referred as anchor nodes) using various localization techniques [1]. Most of the localization techniques [2] assume the complete knowledge of the nodes’ transmit power. However, the transmit power of the nodes varies over time as it depends on several factors [3] [4], i) battery level of the node, ii) orientation of the antennae, and iii) environmental conditions. Numerous localization techniques [5] estimate locations based on the pairwise distance between nodes. Variations in the transmit powers will affect the pairwise distances, which will considerably impact the performance of the techniques. So, it is essential to estimate the transmit power of the nodes along with their locations. Thus, in this work, we propose a cooperative localization technique that jointly estimates the location and transmit powers of the nodes.

In RSS-based localization techniques, the maximum likelihood (ML) estimator derived from the pairwise RSS measurements is solved to estimate the location of the nodes. However, the ML cannot be solved using standard optimization techniques as it has multiple discontinuities and is non-convex. Researchers have used various techniques like convex relaxation [6], conic relaxation [7], and multidimensional scaling to convert the ML into tractable forms. Semidefinite relaxation (SDP)-based techniques are extensively used due to their high accuracy and guaranteed convergence [8].

Current methods [8], [4], [3] that jointly estimate a node’s location and transmit power are implemented in non-cooperative manners, i.e. the techniques only use RSS measurements of the target-anchor links. Hu et al. [8] proposed a localization technique based on blind RSS measurements and considered both known and unknown transmit power scenarios. They solved the blind RSS measurements-based linear models using SDP. In [4] authors proposed RSS-based localization techniques by considering unknown model parameters (transmit power of the nodes and pathloss exponent) and uncertainties in sensor position. They used Taylor series approximation and semidefinite relaxation to determine nodes’ location and transmit power. Shi et al. [3] developed a localization technique based on least squares relative error (LSRE) estimation. They converted the log-normal RSS model into a multiplicative model and reformulated it into a convex optimization problem using semidefinite relaxation. The above mentioned techniques have high execution times as they are implemented in non-cooperative manners, and an SDP has to be solved for each node of the network (refer Table I(a) for more details). Thus, these SDP-based non-cooperative techniques do not scale well for large networks.

Researchers also proposed localization methods that are independent of transmit powers by using differential RSS (RSSD) measurements [9]. Yang et al. [9] proposed an RSSD-based non-cooperative localization technique by reformulating the ML into a robust weighted least squares (WLS) problem and solved it using semidefinite relaxation. The RSSD-based techniques can not be implemented in a cooperative manner (making it non suitable for large networks) and are incapable of estimating the nodes’ transmit power.

Tomic et al. [6] introduced a novel least square (LS) estimator to approximate the non-convex ML objective func-
tion of the RSS-based cooperative localization (measurements from target-anchor and target-target links are considered). The authors convexified the LS estimator and solved two mixed SDP-SOCP problems to estimate the locations and transmit powers of the nodes. In the first step, an SDP is used to estimate the location and transmission power of the target nodes. Then using the estimated location, the transmit power of the nodes are recalculated. Finally, a second SDP is solved to obtain an improved location estimate of the nodes by using the predicted transmit powers. However, they assumed all the nodes to transmit at the same power level.

In contrast to previous methods, our proposed localization technique FCUP (Fast Cooperative localization technique with Unknown transmit Power) estimates both the location and transmit power in cooperative localization scenario (i.e. it uses RSS measurements from both anchor and target nodes) while maintaining a low computational complexity and CPU runtime. We assumed all the nodes to transmit at different power levels. The key contribution of our work is summarized below: a) we reformulate the non-convex ML problem into a tractable mixed SDP-SOCP problem by using Taylor series approximation, semidefinite relaxation, and epigraph method. FCUP benefits from the high accuracy of SDP and the low computational complexity of SOCP; b) we derive the Cramer-Rao lower bound on the root mean square error in estimating location and transmit power of the target nodes; and c) we carry out extensive simulations to demonstrate the superior performance of FCUP as compared to the state-of-the-art techniques based on estimation accuracy of location and transmit power, and computational complexity.

II. JOINT ESTIMATION OF LOCATION AND TRANSMIT POWER IN COOPERATIVE LOCALIZATION

A. Channel Model

Assume a two-dimensional sensor network consists of \( M \) target nodes and \( N \) anchor nodes. The target and anchor nodes are indexed using the sets \( T = \{1, \ldots, M\} \) and \( A = \{1, \ldots, N\} \), respectively. Let the location of \( i^{\text{th}} \) anchor node and \( j^{\text{th}} \) target node be denoted by \( a_i = [a_{i1}, a_{i2}]^\top \) and \( t_j = [x_j, y_j]^\top \), respectively. The set of neighboring target and anchor nodes of \( t_j \) be represented by \( T_j = \{i | i < j, i \in T, \|t_j - t_i\| \leq R_c\} \) and \( A_j = \{i | i \in A \text{ and } \|t_j - a_i\| \leq R_c\} \), respectively, where \( R_c \) is the communication range of the node.

The fading of the wireless channel is modeled using the log-normal distribution [10],

\[
P_{ij} = P_j - 10\beta \log_{10} \frac{d_{ij}}{d_0} + n_{ij}, j \in T, i \in A \cup T_j,
\]

where \( P_{ij} \) (dBm) is the received power at the \( i^{\text{th}} \) target/anchor node, \( d_{ij} \) is the Euclidean distance between \( t_j \) and \( a_i \), \( \beta \) is the path loss exponent. \( P_j \) (dBm) is the received power when \( \|t_j - a_i\| = d_0 \) or \( \|t_j - t_i\| = d_0 \), and we will refer \( P_j \) as the transmit power of \( t_j \). In this work, we consider \( d_0 = 1 \) m. \( n_{ij} \) is the measurement noise, and it follows a zero-mean Gaussian distribution with variance \( \sigma_n^2 = \sigma^2 \). In this paper, without loss of generality, we assume that \( n_{ij} \) is independent and identically distributed, and \( \sigma^2 = \sigma^2 \).

B. Proposed SDP-SOCP Based Method: FCUP

The ML estimator corresponding to the measurement model (1) is obtained by solving

\[
\min_{\mathbf{q}, \mathbf{p}} \sum_{j \in T} \sum_{i \in A \cup T_j} (P_{ij} - P_j + 10\beta \log_{10} d_{ij})^2, \tag{2}
\]

where \( \mathbf{q} = [t_{1j}^\top, \ldots, t_{Mj}^\top]^\top \) and \( \mathbf{p} = [P_1, \ldots, P_M]^\top \). The objective function of (2) is discontinuous\(^1\) and non-convex, and solving (2) using standard optimization algorithms may lead to local optima. To remove the discontinuity, we reformulate (1) by rearranging the logarithmic term and using the first-order Taylor series expansion (considering noise to be sufficiently small):

\[
10\pi \sigma^2 d_{ij}^2 = 10\pi \sigma^2 10 \log 10 \left( 1 + \frac{\ln 10}{5\beta} n_{ij} \right) = 10 \pi \sigma^2 + \tilde{n}_{ij}, \tag{3}
\]

where \( \tilde{n}_{ij} \sim \mathcal{N}(0, \sigma^2) \) and \( \kappa_j = \frac{\ln 10}{5\beta} \pi \sigma^2 \). The ML estimator correspond to (3) is

\[
\min_{\mathbf{q}, \mathbf{p}} \sum_{j \in T} \sum_{i \in A_j \cup T_j} \frac{1}{\kappa_j} (10 \pi \sigma^2 d_{ij}^2 - 10 \pi \sigma^2)^2. \tag{4}
\]

However, the objective function of (4) has a non-removable discontinuity at \( \kappa_j = 0 \). Also, the problem suffers from numerical stability at low transmit power scenarios as \( \kappa_j^2 \) becomes very small. To address this issue we drop the factor \( \frac{1}{\kappa_j} \) and reformulate (4) as a constrained optimization problem

\[
\min_{\gamma_{ij}, r_j} \sum_{j \in T} \sum_{i \in A_j \cup T_j} \frac{(10 \pi \sigma^2 d_{ij}^2 - r_j)^2}{\gamma_{ij}} \tag{5a}
\]

s.t.

\[
\gamma_{ij} = \|t_j - a_i\|^2, \forall j \in T, i \in A_j \tag{5b}
\]

\[
\gamma_{ij} = \|t_j - t_i\|^2, \forall j \in T, i \in T_j \tag{5c}
\]

where \( \gamma_{ij} = d_{ij}^2 \) and \( r_j = 10 \pi \sigma^2 \). The objective function (5a) is convex and using Lemma III.1 of [11] it can be shown that if \( (\hat{\mathbf{q}}, \hat{\mathbf{p}}) \) is an optimal solution of (5) then it is also an optimal solution of (4).

In Fig. 1, the objective function of (2) and (5) is plotted as a function of \( t_j \) and \( P_j \). A 1-dimensional network is considered, which consists of a target node (located at \( 0 \)) and five anchor nodes (located at \( -18 \), \( 3 \), \( 7 \), \( 12 \) and \( 18 \)). The transmit power of the node is set to \( 0 \) dBm. The noise level and path loss coefficient are set to \( 1 \) dB and 4, respectively. The step size of the mesh grid is \( 0.2 \) m and \( 0.05 \) dBm for \( t_j \) and \( P_j \), respectively. Fig. 1(a) shows the

Fig. 1. Illustration of the objective functions as a function of target node’s location and transmit power.

\(^1\)The objective function of (2) has “infinite discontinuity” at \( t_j = a_i \) and \( t_j = t_i \).
global minimum of (2) to be located at (-0.20,-0.25), and there are other local minimums and saddle points. On the other hand, as depicted in Fig. 1(b), the objective function of (5) is continuous and has a global minimum at (-0.20,-0.35).

However, due to the equality constraints, the optimization problem (5) is still non-convex. To address this issue, we reformulate (5) using auxiliary variable Q.

\[
\begin{align*}
\text{minimize} & \quad \sum_{j \in T} \sum_{i \in A_j \cup T_j} (10 \gamma_{ij} - r_j)^2 \\
\text{s.t.} & \quad \gamma_{ij} = tr( E_j Q E_j^T) - 2a_i^T E_j q + |a_i|^2, \\
& \quad \forall j \in T, i \in A_j \\
& \quad \gamma_{ij} = tr( E_j Q E_j^T) - 2E_j E_i E_i^T + E_i E_i^T, \\
& \quad \forall j \in T, i \in T_j \\
& \quad Q = qq^T, \\
& \quad \text{rank}(Q) = 1.
\end{align*}
\]

Now, (9) is reformulated in to a SDP-SOCP problem by converting the constraint (9b) to a second order cone by using an auxiliary variable \( \lambda = [\lambda_1^T, \ldots, \lambda_M^T]^T \), \((\lambda_k = [\ldots, \lambda_{ij}, \ldots]^T, i \in A_k \cup T_k, \forall k \in T)\), and expressing the constraint (9c) as a LMI:

\[
\begin{align*}
\text{minimize} & \quad \gamma_{ij,r_j,q,Q,\mu,\lambda} \mu \\
\text{s.t.} & \quad \|2\lambda^T, \mu - 1\| \leq \mu + 1 \\
& \quad \text{diag}(\ldots, \lambda_{ij} - 10 \frac{\rho_{ij}}{\Delta} \gamma_{ij} + r_j, \ldots, \\
& \quad \ldots, -\lambda_{ij} + 10 \frac{\rho_{ij}}{\Delta} \gamma_{ij} - r_j, \ldots) \geq 0 \\
& \quad j \in T, i \in A_j \cup T_j \\
& \quad (6b), (6c), (7b)
\end{align*}
\]

Problem (10) can be solved efficiently using CVX [14] and we will refer to it as FCUP (Fast Cooperative localization technique with Unknown transmit Power). FCUP and (7) have similar accuracy, but FCUP has lower complexity and fewer constraints (for more details, refer Table I(b)). Let the solution of (10) be denoted by \( \{\gamma_{ij}, r_j, q^*, Q^*, \mu^*, \lambda^*\} \) and the estimated location and transmit power of \( t_j \) are obtained using \( \hat{t}_j = q^* [2j - 1 : 2j] \), \( \hat{P}_j = 5\beta \log r_j \).

III. CRAMER-RAO LOWER BOUND (CRLB)

CRLB is used as a benchmark as it provides a lower bound on the performance of an estimator. Let the unknown parameters be represented by \( \theta = [q^T, P^T]^T = [x_1, y_1, \ldots, x_M, y_M, P_1, \ldots, P_M]^T \). The RSS measurements corresponding to the wireless links are given by \( P_{ij} = P_j, j \in T, i \in A_j \cup T_j \). The log-likelihood of \( P^* \) is obtained using (1) and is expressed as \( \ln p(P^*; \theta) = \frac{-\ln (2\pi \sigma^2)}{2} - \frac{1}{2} K + \sum_{i=1}^{M} (P_{ij} - P_j + 10 \log_{10} d_{ij})^2 \\
\]

where \( K = \sum_{j \in T} (|A_j| + |T_j|) \) is the total number of wireless links. The Fisher information matrix (FIM) [15] corresponding to \( \theta \) is given by \( F(\theta) \) and the elements of \( F(\theta) \) are provided in Section I of the supplementary material. The root mean square error (RMSE) of the estimator \( \hat{\theta} = [q^T, P^T]^T \) satisfies

\[
\begin{align*}
\epsilon_t & = \sqrt{\frac{1}{M} \sum_{j=1}^{M} \|t_j - \hat{t}_j\|^2} \geq \sqrt{\frac{1}{M} \text{tr}(F^{-1})_{1:2M}} \\
\epsilon_p & = \sqrt{\frac{1}{M} \sum_{j=1}^{M} \|P_j - \hat{P}_j\|^2} \geq \sqrt{\frac{1}{M} \text{tr}(F^{-1})_{2M+1:3M}}
\end{align*}
\]

Therefore, CRLB \( _t \) = \( \frac{1}{M} \text{tr}(F^{-1})_{1:2M} \) and CRLB \( _p \) = \( \frac{1}{M} \text{tr}(F^{-1})_{2M+1:3M} \) are the lower bounds on the RMSE of target nodes’ location and transmit power.

IV. NUMERICAL RESULTS

In this section, we compare the performance of FCUP with the existing localization techniques (LLS [16], MCRS [17], RWLS-AE [18], UT-SD/SOCP [19], SDP-Tomic [6], and SOCP-U [20]). We used the CVX toolbox [14] to solve...
Fig. 2. Performance of the localization techniques for estimating location and transmit power as a function of noise level in N/W1 and N/W2.

Fig. 3. Performance of the localization techniques for estimating location and transmit power as a function of the number of anchor nodes in N/W3.

The NRMSE of location estimate in N/W1 as a function of \(\sigma\).

The NRMSE of transmit power estimate in N/W1 as a function of \(\sigma\).

The NRMSE of location estimate in N/W2 as a function of \(\sigma\).

The NRMSE of transmit power estimate in N/W2 as a function of \(\sigma\).

A. Performance Analysis

1) Effect of the Noise Level: The study evaluates the localization techniques’ performance in the presence of noise using two networks (N/W1 and N/W2), both of which comprise five anchor nodes and ten target nodes. In N/W1, all the target nodes are present inside the convex hull of the anchor nodes, and in N/W2, some of the target nodes are located outside the convex hull of the anchors. The communication range \(R_c\) of the node is set to 110 m. Fig. 2 shows the performance of the localization techniques as a function of noise level \(\sigma\). In Fig. 2(a) and Fig. 2(c), we present the NRMSE in estimating the location of the target nodes. FCUP and UT-SD/SOCP exhibit superior performance compared to other techniques when \(\sigma\) is less than 5 dB. However, UT-SD/SOCP’s performance degrades significantly beyond \(\sigma > 5\) dB, and it has a higher complexity as well (discussed in Section IV-B). For high noise level scenarios, the cooperative techniques (FCUP, MCRS, and RWLS-AE) outperform the non-cooperative techniques (LLS, MCRS, and RWLS-AE) as they leverage more information from the target-target links.

In Fig. 2(b) and Fig. 2(d), we present the performance of the localization techniques in estimating the transmit power of the nodes. Based on the observations, it can be concluded that FCUP, MCRS, and RWLS-AE have similar performance and are superior to other techniques. On the other hand, SDP-Tomic and SOCP-U fail to accurately estimate the transmit power.
power of target nodes because they assume all nodes transmit at the same power. This is true for all studies reported in this paper regarding estimating transmit power (refer Fig. 3(b), Fig. 4(b), and Fig. 5(b)). For both networks, the performance of FCUP is closest to the CRLB and CRLB (for most of the scenarios) in estimating location and transmit power, respectively.

2) Effect of the Number of Anchors: This study examines the effectiveness of different localization techniques as the number of anchor nodes (N) in N/W3 is increased from 5 to 20. Fig. 3 displays the NRMSE for estimating the location and transmit power of the target nodes. In this study, the value of $R_c$ and $\sigma$ is set to 110 m and 4 dB, respectively. In Fig. 3(a), it can be observed that FCUP and UT-SD/SCOP perform better than other methods, especially when the number of anchor nodes is small, as they utilize both the anchor-target links and the target-target links. Additionally, FCUP and MCRS techniques demonstrate comparable performance and outperform existing techniques in estimating transmit power, as shown in Fig. 3(b). Fig. 3 demonstrates that the localization techniques exhibit marginal improvement when $N > 10$. This is because the information obtained from additional anchor nodes is not significant enough beyond a certain threshold, rendering them redundant.

3) Effect of the Number of Targets: Fig. 4 shows the performance of the localization techniques as the number of target nodes is increased from 5 to 20 in N/W4. In this study, the value of $R_c$ and $\sigma$ is set to 70 m and 4 dB, respectively. The non-cooperative techniques (LLS, MCRS, and RWLS-AE) were not included in our study due to their requirement of at least four anchor nodes to be connected to each target node for location and power estimation. With the increase in the number of target nodes in a network, it becomes difficult to ensure this condition. Fig. 4 illustrates that the cooperative localization techniques’ performance improves as the number of target nodes increases. This enhancement is due to the increased number of RSS readings available as a result of the additional target-target links. In the context of estimating the location and transmit power of target nodes, FCUP and UT-SD/SCOP outperform SDP-Tomic and SOCP-U (refer Fig. 4(a)). Specifically, FCUP performs better in estimating transmit power than the other methods (refer Fig. 4(b)). However, it is worth noting that UT-SD/SCOP assumes complete knowledge of the transmit power and requires solving fewer unknown variables than FCUP.

4) Effect of the Communication Range: In Fig. 5, we study the effect of communication range on the performance of the localization techniques. We used N/W2 in this study and varied $R_c$ from 50 m to 110 m. The value of $\sigma$ is set to 4 dB. Similar to Section IV-A3, our analysis does not incorporate non-cooperative techniques. In Fig. 5, when $R_c$ is increased the performance improves because the target nodes are able to connect with more nearby anchor and target nodes. However, beyond a certain value of $R_c$, the network becomes almost fully connected, and there is no further improvement. Figure 5(a) shows that both FCUP and UT-SD/SCOP achieve comparable performance and surpass SDP-Tomic and SOCP-U in estimating the location of the target nodes. Additionally, Figure 5(b) reveals that FCUP outperforms the existing methods and is closest to the CRLB.

A detailed study regarding the bias of the estimators is given in Section III of the supplementary document. Additionally, Section IV of the supplementary document presents the performance of FCUP in a three-dimensional setting.
TABLE I
COMPLEXITY OF THE LOCALIZATION TECHNIQUES (NC: NON-COOPERATIVE; C: COOPERATIVE).

<table>
<thead>
<tr>
<th>Algo.</th>
<th>Year</th>
<th>NC: UDCP</th>
<th>C: RWLS-AE</th>
<th>Dim. of SDP variables</th>
<th>Dim. of SOCP variables</th>
<th>Complexity</th>
<th>CPU Runtime</th>
</tr>
</thead>
<tbody>
<tr>
<td>LLS</td>
<td>2018</td>
<td>NC</td>
<td>RWLS-AE</td>
<td>12</td>
<td>12</td>
<td>O(N^3)</td>
<td>0.34</td>
</tr>
<tr>
<td>MCRS</td>
<td>2020</td>
<td>NC</td>
<td>SDP-Tomic</td>
<td>4</td>
<td>4</td>
<td>O(M^3)</td>
<td>2.47</td>
</tr>
<tr>
<td>RWLS-AE</td>
<td>2022</td>
<td>NC</td>
<td>SOCP-U</td>
<td>12</td>
<td>12</td>
<td>O(N^2 M)</td>
<td>20.73</td>
</tr>
<tr>
<td>SDP-Tomic</td>
<td>2018</td>
<td>C</td>
<td>FCUP</td>
<td>12</td>
<td>12</td>
<td>O(N^2 M)</td>
<td>2.47</td>
</tr>
<tr>
<td>SOCP-U</td>
<td>2014</td>
<td>C</td>
<td>FCUP</td>
<td>12</td>
<td>12</td>
<td>O(N^2 M)</td>
<td>20.73</td>
</tr>
</tbody>
</table>

(b) Number of Optimization Variables and their Dimensions

<table>
<thead>
<tr>
<th>CVX parameters</th>
<th>UT-SD/SOCP</th>
<th>SDP-Tomic</th>
<th>SOCP-U</th>
<th>FCUP</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of variables</td>
<td>224</td>
<td>178</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>No. of equality constraints</td>
<td>33</td>
<td>120</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>Dim. of SDP variables</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>Dim. of SOCP variables</td>
<td>120</td>
<td>120</td>
<td>120</td>
<td>120</td>
</tr>
</tbody>
</table>

B. Complexity Analysis

We evaluate the complexities of the algorithms based on CPU runtime, size and dimension of the optimization variables, and the number of floating-point operations. Worst-case complexities are calculated using a fully connected N/W1 and N/W2 (refer Table I(a)). All the algorithms are implemented in MATLAB R2021a with the processor Intel(R) Xeon(R) W-2245 CPU @ 3.90GHz and 64GB RAM. In Table I(a), K and k represent the number of RSS measurements and the number of required iterations. One can observe that LLS demonstrates the least complexity, yet it suffers from notably inferior estimation accuracy (refer Fig. 2 and Fig. 3). Although MCRS has low CPU runtime, it is an evolution-based technique, and its convergence is not guaranteed. UT-SD/SOCP has limited scalability as it solves two SDPs and also uses an iterative local search method for estimation. Its computational complexity depends on the number of iterations (l) the local search method requires to converge. RWLS-AE has high computational complexity (O(N^6.5)) and CPU runtime (∼ 20x slower than FCUP) because it estimates the location and the transmit power of each node individually and iteratively. FCUP has a computational complexity of ∼O(M^6.5) whereas the computational complexity of SDP-Tomic and SOCP-U are ∼2O(M^6.5) as they solve two SDP problems. Furthermore, FCUP has lower complexity than (7) as it uses a mixed SDP-SOCP algorithm, and SOCP has significantly lower complexity with respect to SDP. FCUP is ∼1.95× and ∼8.4× faster than SDP-Tomic and SOCP-U, respectively.

Table I(b) displays the number of optimization variables (their dimensions) and equality constraints required by CVX to solve the SDP problems. FCUP has less number of variables and equality constraints compared to SDP-Tomic and SOCP-U, which validates FCUP’s low CPU runtime. Also, the dimension of the SDP variable in FCUP (which solves (10)) is 14x lower than (7), which justifies the importance of converting the SDP problem into a mixed SDP-SOCP problem.

V. CONCLUSION

In this article, we proposed an RSS-based cooperative localization algorithm that jointly estimates the target nodes’ location and transmit powers. We used the Taylor expansion, semidefinite relaxation, and the epigraph method to reformulate the original ML estimator into a mixed SDP/SCOP problem. We leverage the high accuracy of the SDP and the low complexity of SOCP. In the future, we will explore scenarios where malicious nodes disrupt the localization process. We will aim to develop a robust and secure cooperative localization technique.

REFERENCES