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Title: Target Localization Using Approximate Maximum Likelihood for MIMO Radar Systems

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Huaping Liu

This thesis deals with target localization using multiple-input multiple-output (MIMO) radars. In the field of communications, navigation, radar, and sensing networks, one of the common and most sophisticated problems is target localization. We develop a target localization scheme in distributed MIMO radar systems using bistatic range measurements. The localization approach consists of two phases. First, measurements are divided into multiple groups based on the various transmitter and receiver elements. For each group, an approximate maximum likelihood (AML) estimator is proposed to estimate the location of a target. Then, the estimation results from these different groups are combined to form the final estimate. The performance of the proposed algorithm is validated by simulation and is shown to reach the Cramér-Rao lower bound (CRLB) in a range of measurement noise levels. The main advantage of the proposed algorithm is that it achieves a higher accuracy than existing schemes for locating a target position in high-noise conditions.

Target Localization Using Approximate Maximum Likelihood for MIMO Radar Systems

by

Abdulellah Almalki

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Chapter 1: Introduction

Radio detection and ranging system (radar) is considered the backbone of the field of communication and navigation [1]. Due to its significance in the military and air traffic control, it has an active research area for many decades. Several advancements have been made in the design of radar systems, which has led to several variants of radars. One such arrangement, which has become a hot area, is multiple-input multiple-output (MIMO) radar.

This chapter will provide a basic review of radar and some of its concepts. Then, analyze MIMO radar fundamentals and design and its categories, including the field of signal processing in MIMO radars. At the end of this chapter, the thesis outline will be presented.

1.1 MIMO Radar Background and Motivation

Radar has become a continued area of research in recent times. In 1904, spark gap transmitter and receiver were developed by Christian Hansmeyer [2]. This technology became the first radar with limited capabilities. The major development in the field of radar technology was a patent by Robert Watson in 1935 [3]. This radar has all the properties that exist in a working system. Due to its significance in the military and air traffic control, it has become an active area of research for researchers.

A device that uses electromagnetic waves for the detection of location and coordinates of a target is known as radio localization [4–9]. In radar systems, as illustrated in Figure 1.1, it is evident that electromagnetic signals are transmitted in the atmosphere using a transmitter, and the receiver collects the waves that reflect from the target. When this signal is collected at the receiver, the system gives information about the targets coordinates. The targets distance is calculated using the time it takes the electromagnetic wave to complete a round trip between the radar and the target.

The motivation for this thesis work stems from the drawback faced by some localization schemes in distributed MIMO radar systems when it comes to locating the position

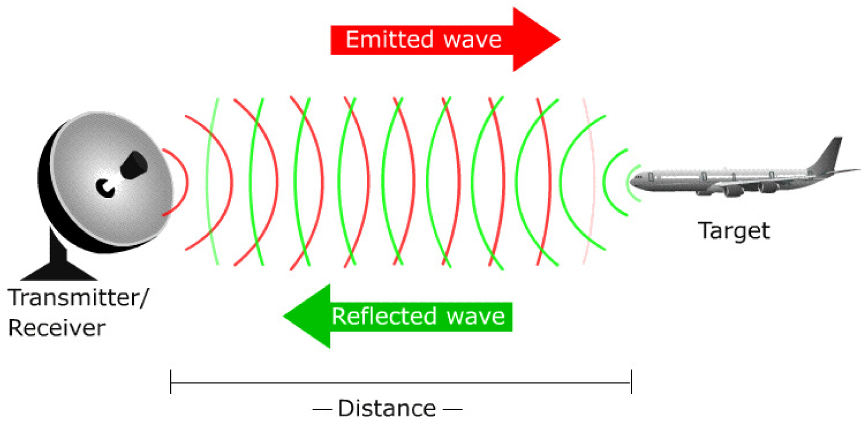

Figure 1.1: Working of radar systems.

of a target with high-noise condition, which leads to undesired outcomes. To address this issue, we have developed an efficient MIMO radar position estimator, which performs better than other existing schemes especially in high-noise conditions.

1.2 MIMO Radar

In the previous two decades MIMO technologies have been widely used in wireless communication systems to achieve diversity and/or spatial multiplexing gains [10–12]. In the field of communication, navigation, radar, and sensing network, one of the common and most sophisticated problems is target localization. In this thesis, we are mainly interested in target localization using MIMO radars. In MIMO radar systems, target localization has generated significant interests in both academia and industry. Compared to its counterparts, MIMO radar has the advantage of using an array of transmitters for transmitting waveform and uses multiple receivers to receive an array of reflected signals at the receiver end, making it more accurate to find the target location.

The information gathered from these antennas is used for accurate and precise detection and location of the target compared to a conventional radar system. Figure 1.2 describes the basic design and functionality of MIMO radars.

From Figure 1.2, it is evident that an array of transmitters is used to detect and localize the target in MIMO radar design. The reflected signals from the target are

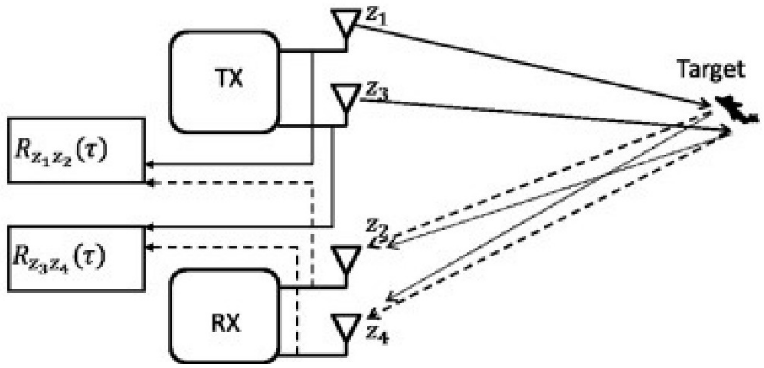

Figure 1.2: Basic MIMO radar design.

scattered in different directions and received at the array of the radar receivers. This enables our radar system to locate the desired target accurately [13].

MIMO radars can be categorized into two types; one of them is known as the co-located antennas radar (CAR) while the other is called widely separated antennas radar (WSAR) [14]. Waveform diversity is used by the co-located antennas radar, whereas spatial diversity is associated with the radar with widely separated antennas. Each of the above-mentioned category has advantages over their phase array counterparts.

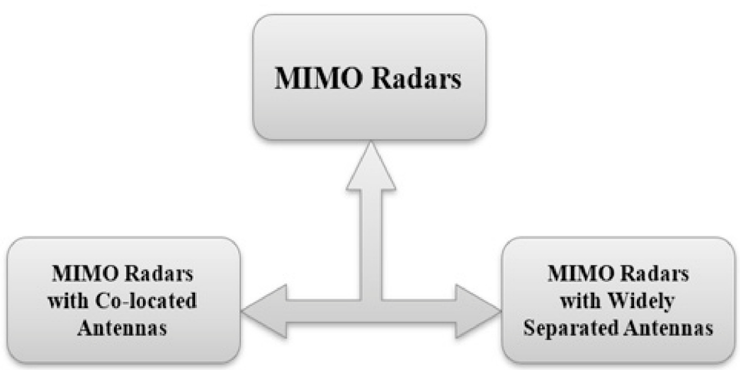

Figure 1.3: Types of MIMO radars.

1.2.1 MIMO radar with co-located antennas

Radars with co-located antennas are considered a substitute for the conventional reconnaissance radar system. These radars scan the space sequentially by using its narrow antenna beams. Even though they are capable of providing large power for illumination of the target, they are not considered suitable for application in a wide-range area for surveillance purposes [15].

There are some disadvantages associated with MIMO radars with co-located antennas. Since they use their narrow beam for transmission, they are not capable of tackling close and fast-moving targets, as they require a large amount of time to scan the whole area. This makes their revisit time period large, which is not suitable for fast-moving targets.

The other major drawback of this system is the fixed time surveillance. This means that only a few reflected waves from the target can be collected, which are not enough for rejection of noise and other unwanted signals.

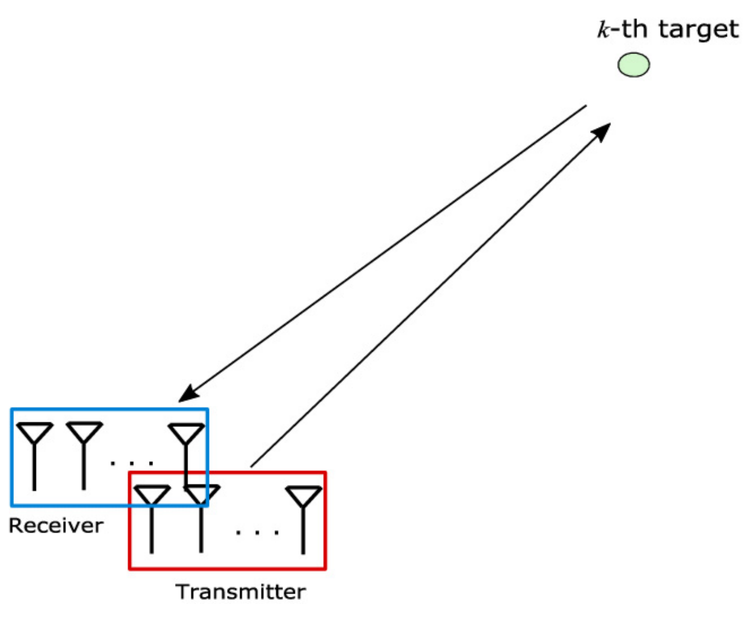

Figure 1.4: Configuration of lo-located MIMO radar.

1.2.2 MIMO radar with widely separated antennas

MIMO radar with distributed antennas [16] is the counterpart of MIMO with co-located antennas. As far as the model is concerned, radars with these types of antennas use the concept of spatial diversity. Basically, in radars with distributed antennas, we try to mitigate the variations at the receivers input, which has an analogy of signal fading mitigation in the field of communication systems [17].

Signal variation at the receiver end is unavoidable when there is a difference between the size of the target and the wavelength of the illuminated signals (fluctuation increases with greater target size). This will directly result in the deterioration of detection performance of the radar system. In literature, to overcome this problem, MIMO radars with distributed antennas are used. If a large distance is maintained between antennas, this results in non-correlation of signal variation at the receivers input. But this signal variation mitigation is achieved at the expense of energy loss of the signal. To overcome this, several methods are employed using radars with distributed-type antennas that are discussed below.

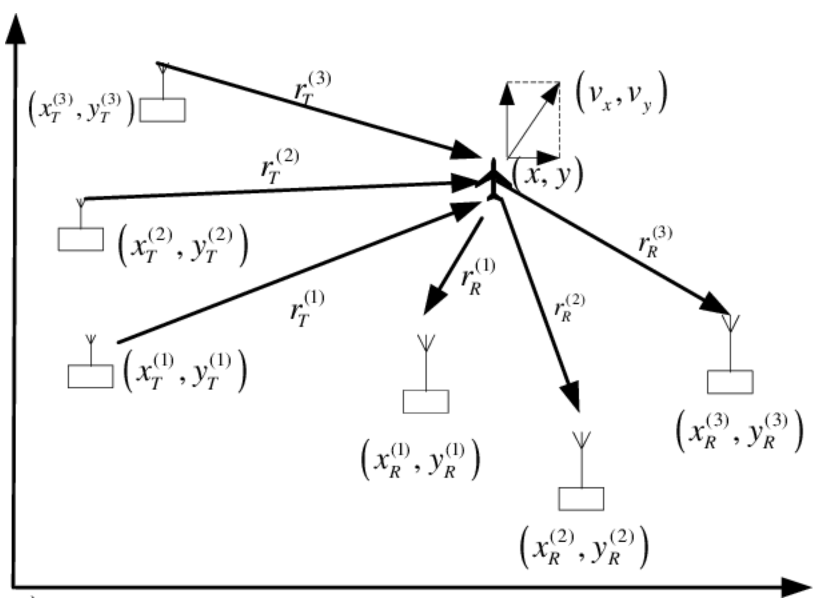

Figure 1.5: Configuration of MIMO radar with distributed antennas.

It has been noted that this problem of energy loss can be solved by smoothening the signal variations, which has high detection probabilities. One of the methods of smoothening the variations is to use incoherent processing of signals that have uncorrelated variations of the signals from the target. Frequency diversity is one of the ways to solve this problem using illuminating signals. Spatial diversity is another method that is associated with receiving and transmitting antennas, which helps us to approach our target from all locations [18, 19]. This method is employed using the statistical MIMO radars.

1.3 Signal Processing in Distributed MIMO Radar Systems

The MIMO radars with widely separated antennas are divided into two types: one of them is known as coherent MIMO radar, whereas the other is known as non-coherent MIMO radar [16].

1.3.1 Coherent and non-coherent signal processing

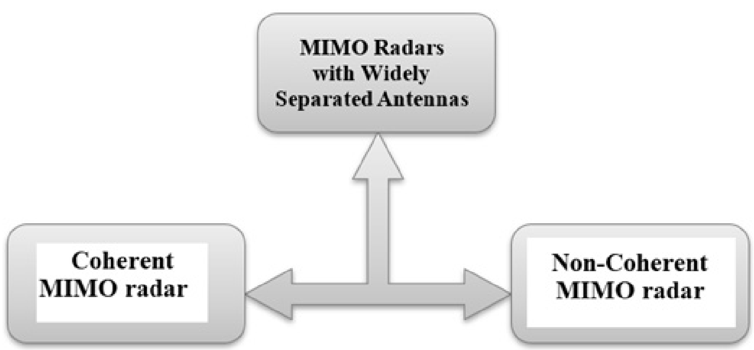

Figure 1.6: Processing techniques for MIMO radars with distributed antennas.

It was previously mentioned that antenna elements at the receiving and transmitting ends may be arranged as co-located or widely spaced when dealing with MIMO radars. One thing that is common with both approaches is increasing the degree of freedom (DOF) by selecting the transmitter signals independently [20]. This radar property makes target localization and tracking relatively easy compared to conventional radars.

The collocated antennas are focused towards the target because these types of radars lack angle diversity. Hence, in this case, coherent processing is considered suitable, whereas in the case of widely spaced antennas, we approach the target from all directions. Different radar cross-section (RCS) are displayed by target, hence in this case, non-coherent processing is suitable [19, 21].

It can be seen that for MIMO radars, both coherent and no-coherent processing techniques have their own pros and cons. Researchers have addressed target localization problem for MIMO radars using coherent processing techniques [18]. In this work, the authors have shown several benefits of the above-mentioned technique. One of them has to do with phase alignment of the transmitter and receiver antennas. This is not possible in the case of a non-coherent process, but the non-coherent processing approach has the benefit of being less complex than its counterpart. The coherent processing approach has a better mean-square error (MSE) performance compared to the non-coherent approach [22].

Non-coherent MIMO radars do not need phase synchronization between antennas present at the receiving and transmitting ends. Figure 1.7 describes the configuration of non-coherent MIMO radars.

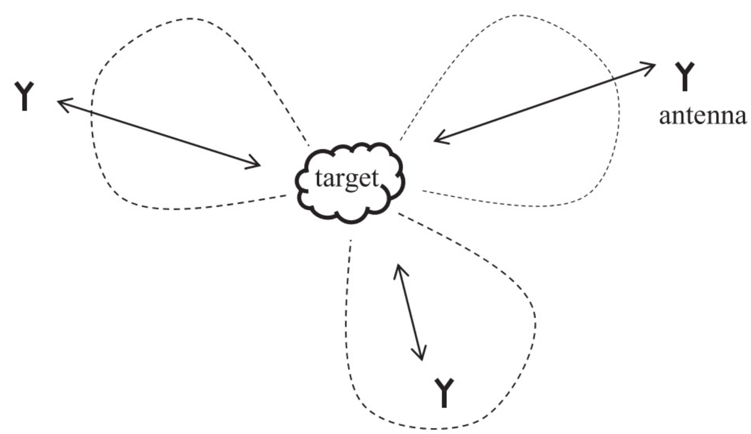

Figure 1.7: Non-coherent MIMO radar configuration.

Coherent MIMO radars require phase synchronization between the antennas present at the receiving and transmitting ends [18]. Figure 1.8 below describes the configuration of coherent MIMO radars.

In this work, our concern is to achieve high localization resolution with the MIMO radar system. The the Cramér-Rao lower bound (CRLB) will be used as the benchmark performance for assessing the performances of various estimators in the simulation results.

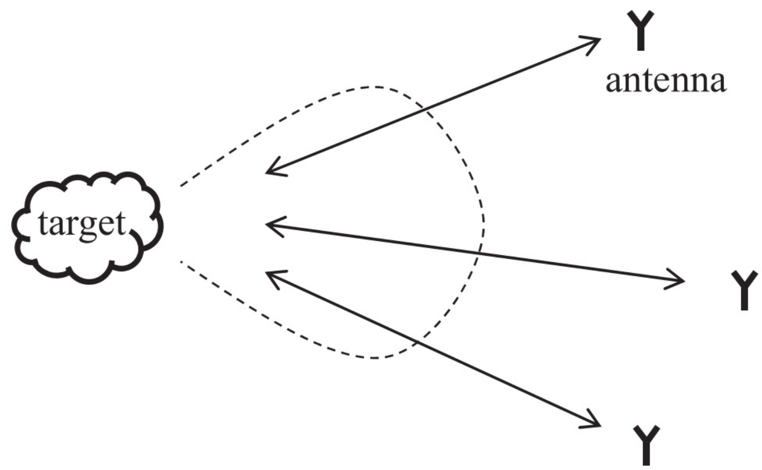

Figure 1.8: Coherent MIMO radar configuration.

1.4 Thesis Outline

This thesis presents an efficient localization scheme for estimating the target position using MIMO radar. Using the bistatic range measurements, the proposed scheme can provide a desirable accuracy when it comes to estimating the target position at high-noise levels. The performance of the proposed scheme has been provided and compared with other algorithm schemes that are in the related work section.

Chapter 1 discussed the introduction of radar basics in general. Then it presented MIMO radar design and the different types of MIMO radars. Signal processing in MIMO was explained. The last section of the chapter discussed the motivation for this work.

Chapter 2 describes the background review in MIMO radar, including localization forms for estimating the target position for both direct and indirect forms. Then it described the related works used in simulation comparison.

In Chapter 3, the bistatic range measurement model and theoretical derivation are described and the proposed localization algorithm is analysed. The goal of the thesis is to provide an estimator for locating a target using MIMO radar that will work better than existing schemes especially in high levels of noise.

Chapter 4 shows the simulation results and provides several numerical simulations to present the performance of the proposed algorithm, including comparison with other related works. The performance is evaluated by the root mean-square errors (RMSEs).

Chapter 5 summarizes the work on the proposed new localization method in MIMO radar. The conclusion discusses the developed algorithm and future work.

Chapter 2: MIMO Radar Localization Background Review and Related Work

2.1 Introduction

There are many existing localization techniques, for example, the conventional time-based techniques, such as time-of-arrival (TOA) and time-difference-of-arrival (TDOA) [5–9]. The accuracy of timing-based systems strongly depends on the bandwidth of the radio signals used. For example, with ultrawideband signaling [30–39] the accuracy would be very high, at the expenses of a high system complexity.

Target localization is one of the important applications associated with MIMO radars. This is considered a challenging problem because the relationship between the measured variables and the desired location of the target is nonlinear. When used for localization, MIMO radar could overcome some of the disadvantages of traditional time-based systems by exploiting the multiple antenna elements. We can categorize this problem using MIMO radars with wide stationary antennas into two forms: direct target localization and indirect target localization [23]

2.2 Target Localization Forms in MIMO Radars

2.2.1 Direct form for target localization

In this method, the coordinates of the targets are directly estimated using the reflected signal received at the receiver. The advantage of using this scheme is the lower MSE for the estimation of the signal. However, one of the major drawbacks of this method is that it cannot provide the closed form solution for the above-mentioned problem. Also, in order to achieve the optimum result from the direct method, the required computational cost is relatively higher than its counterpart due to the multi-dimensional grid search [18, 23, 25]. The examples of this method include sparse recovery method and the maximum likelihood (ML) [26, 27] method.

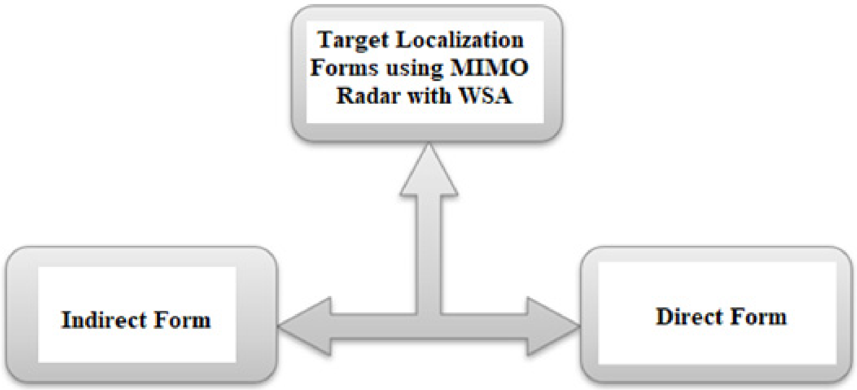

Figure 2.1: Target localization forms in MIMO radars.

2.2.2 Indirect form for target localization

The indirect form of localization using MIMO radar is a two-step approach for estimating the position of the target. These steps are the process of obtaining the measurement and the estimation of the target position based on the measurements [24, 28]

The first step is related to the information about the time delay. In this process, we estimate (by using received data) the signal traveling time from the transmitter to the target and then back to the receiver end [29]. The second step is to obtain the estimates for the bistatic range from the product of the signal traveling speed with the delays for creating the elliptic equation set [29]. This set of equations is then used to determine the position of the target.

Using this method requires that we use a time delay for the target location. Coherent or non-coherent processing is used to estimate the time delay. Hence, data compression can be achieved by using the indirect method, which results in the reduction of complexity.

One of the other advantages of MIMO radar using this approach is the reduction in the cost of communications; i.e., the indirect approach needs to send only two receiver parameters in every localization interval to the central node. As a result, it can be implemented easily compared to its counterpart.

In this work, we adopt the indirect method for MIMO radars with widely separated antennas.

2.2.3 Bistatic range estimation

In the past few years, using MIMO radars with distributed antennas for target localization has been a popular topic. These radars are used in applications like target tracking and surveillance. MIMO radars with distributed antennas have multiple pairs of receivers and transmitters, and these provide an independent and distinct parameter of position. These target localization parameters are divided into different types: bistatic range, arrival angle, and Doppler shift [40, 41]. This research is oriented towards the use of bistatic range-based techniques, which are considered accurate and less complex for most scenarios.

2.3 Related Work

Many researchers have worked on target localization, which has become an important problem for MIMO radars with distributed antennas. This work focuses on localization using MIMO radar that employs the indirect form and assumes that the information on the bistatic range has been estimated. We are interested in developing the localization algorithm from the bistatic measurements. The following section is a brief discussion of the works that have been done on this topic.

2.3.1 Target localization using least squares method for MIMO radar

The research work in [28] focuses on using MIMO radars that have widely distributed antennas for target localization. In this method, the authors have established the linear mathematical relationship between the transmitter, receiver data and the unknown coordinates of the target. Then by using the least squares (LS) technique, the estimation of the target was obtained. Basically, the least squares method, along with the given time delays, was used by the authors to develop an algorithm, which is in closed form with no requirement of initial guess. The comparison of this algorithm with the proposed one is provided in the simulation section.

2.3.2 Target localization using two-stage weighted least squares method for MIMO radar

In [42], the authors devised a method for estimating the speed and location of the unknown target. The authors investigated the MIMO radar with distributed antennas for non-coherent arrangement. The essence of this method is to use Doppler shift (DS) measurement and time delay (TD) data.

Based on the different transmission and receiving elements, the DS and TD data are then divided into different groups. In the next step, each data group is examined by applying two times BLUE algorithm. Consequently, the authors obtained different approximations for the speed and location of the target. These estimates are independent and by merging these estimates, the final estimate for the position and speed of the target is obtained. This method is also in closed-form with no requirement of initial guess. Comparing with the CRLB-approaching estimators, it is found that this method improves the performance when it is implemented in the indirect form and there is a small noise.

Chapter 3: Target Localization Using Approximate Maximum Likelihood in MIMO Radar Systems

3.1 Introduction

As discussed in the previous section, target localization using least squares method [28] and Two-Stage Weighted Least Square (2SWLS) Method [42] for MIMO Radar has a disadvantage, which is that the accuracy of estimating a target position in high-noise levels is not desirable. Our idea is similar to the one in [42], by grouping and combiningbut we used the approximate maximum likelihood (AML) approach [43].

Based on the values obtained by the bistatic range, we developed an algorithm that acts as the localization estimator, which is inspired by the work done on AML [43, 44].

This algorithm starts with the conventional maximum likelihood function. This function is then converted into a partial linear equation with respect to the variable of the target location, which is unknown. The coefficients of these equations also rely on the values of the unknown parameters. After that, the AML algorithm uses the initial value of the target location to solve the partial linear equation. This solution gives us the new location of the target and the coefficients are updated afterwards. This process is repeated several times. Afterwards, the cost function of ML is updated, in addition to the location of the target. The solution is the minimum of the whole process.

The following notations are used in this thesis. Bold uppercase and bold lower-case letters denote matrices and vectors respectively. $\|\cdot\|$ represents the l_2 norm. The notation $[\cdot]^T$ represents the transposition operator and $E[\cdot]$ represents the expectation operator. A diagonal matrix is represented by diag$[\cdot]$, and $d(n)$ is the nth element of $\mathbf{d}$. $\mathbf{A}(n,:)$ is the MATLAB expression, i.e., the nth row of matrix $\mathbf{A}$.

3.2 Measurement Model

Consider a widely distributed incoherent MIMO radar system with M transmitting radars and N receiving radars. The mth, $m = 1, 2, \cdots, M$, transmitter is located at coordinate

$$t_m = [x_m^t, y_m^t]^T,$$

the nth, $n = 1, 2, \cdots, N$, receiver is located at coordinate

$$\mathbf{r}_n = [x_n^r, y_n^r]^T,$$

and a single target is located at position

$$\mathbf{u} = [x, y]^T.$$

The development is in the two-dimensional (2-D) plane;

The measurement of the bistatic range $R_{m,n}$ for the pair of the mth transmitter and the nth receiver is given by

$$R_{m,n} = \|\mathbf{u} - \mathbf{t}_m\| + \|\mathbf{u} - \mathbf{r}_n\| + e_{m,n} \tag{3.1}$$

where $e_{m,n}$ is the additive bistatic range measurement noise.

3.3 Localization Algorithm

Next we develop an efficient estimator method for estimating the target position by using the measurements of the bistatic range. The method comprises two steps. The first step is to divide the measurements into M groups based on the various transmitters or receivers (we use the transmitter as an example). Thus, the mth group includes $[R_{m,1}, \cdots, R_{m,N}]$. Next, for each measuring group, the approximate maximum likelihood (AML) estimator is used to calculate the target position. After processing for all the M groups of measurements, we then obtain M estimates, which are independent of each other. In the end, by combining these M estimates, a more precise estimate can be obtained. First, we present the ML estimator for the mth group of measurements.

Let the vector of mth group measurement be

$$\begin{aligned} \mathbf{R}_m &= [R_{m,1}, \cdots, R_{m,N}]^T \\ &= \mathbf{R}_m = \mathbf{d}_m + \mathbf{e}_m \end{aligned} \tag{3.2}$$

where

$$\mathbf{d}_m = [\|\mathbf{u}-\mathbf{t}_m\| + \|\mathbf{u}-\mathbf{r}_1\|, \cdots, \|\mathbf{u}-\mathbf{t}_m\| + \|\mathbf{u}-\mathbf{r}_N\|]^T$$

is the vector of the mth group true bistatic range, and

$$\mathbf{e}_m = [e_{m,1}, \cdots, e_{m,N}]^T \tag{3.3}$$

is the vector of the mth group additive measurement errors. The elements of $\mathbf{e}_m$ are independent and identically distributed (i.i.d.), zero mean Gaussian variables with covariance matrix

$$\mathbf{Q}_m = E[\mathbf{e}_m \mathbf{e}_m^T] = \mathrm{diag}[\sigma^2, \cdots, \sigma^2].$$

Then the probability density function (pdf) of $\mathbf{R}_m$ given $\mathbf{u}$ is

$$f(\mathbf{R}_m \mid \mathbf{u}) = (2\pi)^{-\frac{N}{2}} (\det(\mathbf{Q}_m))^{-\frac{1}{2}} \exp\left(-\frac{J_m}{2}\right) \tag{3.4}$$

where

$$J_m = (\mathbf{R}_m - \mathbf{d}_m)^T \mathbf{Q}_m^{-1} (\mathbf{R}_m - \mathbf{d}_m). \tag{3.5}$$

The ML estimate is the $\mathbf{u}$ that minimizes J_m.

Setting the gradient of J_m with respect to $\mathbf{u}$ to zero gives

$$\left[\frac{\partial \mathbf{d}_m}{\partial \mathbf{u}}\right]^T \mathbf{Q}_m^{-1}(\mathbf{R}_m - \mathbf{d}_m)) = \mathbf{0} \tag{3.6}$$

where

$$\frac{\partial \mathbf{d}_m}{\partial \mathbf{u}}(n,:) = \frac{(\mathbf{u}-\mathbf{t}_m)^T}{\|\mathbf{u}-\mathbf{t}_m\|} + \frac{(\mathbf{u}-\mathbf{r}_n)^T}{\|\mathbf{u}-\mathbf{r}_n\|}, n = 1, \cdots, N. \tag{3.7}$$

Now substituting

$$R_m(n) - d_m(n) = \frac{(R_{m,n} - \|\mathbf{u} - \mathbf{t}_m\|)^2 - \|\mathbf{u} - \mathbf{r}_n\|^2}{(R_{m,n} - \|\mathbf{u} - \mathbf{t}_m\|) + \|\mathbf{u} - \mathbf{r}_n\|}$$

$$= \frac{R_{m,n}^2 - \|\mathbf{r}_n\|^2 + \|\mathbf{t}_m\|^2 - 2R_{m,n}\|\mathbf{u} - \mathbf{t}_m\| + 2\mathbf{u}^T(\mathbf{r}_n - \mathbf{t}_m)}{(R_{m,n} - \|\mathbf{u} - \mathbf{t}_m\|) + \|\mathbf{u} - \mathbf{r}_n\|} \tag{3.8}$$

into (3.6) yields

$$\mathbf{\Phi}_m \boldsymbol{a}_m = 0 \tag{3.9}$$

where

$$\mathbf{\Phi}_m = \left[\frac{\partial \mathbf{d}_m}{\partial \mathbf{u}}\right]^T \mathbf{Q}_m^{-1} \mathbf{\Lambda}_m, \tag{3.10}$$

$$\mathbf{\Lambda}_m = \operatorname{diag}\left[\frac{1}{R_{m,1} - \|\mathbf{u} - \mathbf{t}_m\| + \|\mathbf{u} - \mathbf{r}_1\|}, \ \cdots, \frac{1}{R_{m,N} - \|\mathbf{u} - \mathbf{t}_m\| + \|\mathbf{u} - \mathbf{r}_N\|}\right], \tag{3.11}$$

$$\boldsymbol{a}_m = 2\mathbf{D}_m \mathbf{u} - \mathbf{v}_m, \tag{3.12}$$

$$\mathbf{D}_m = \begin{bmatrix} (\mathbf{r}_1 - \mathbf{t}_m)^T \\ \vdots \\ (\mathbf{r}_N - \mathbf{t}_m)^T \end{bmatrix}, \tag{3.13}$$

$$\mathbf{v}_m = \mathbf{h}_m + \mu_m \mathbf{f}_m, \tag{3.14}$$

$$\mu_m = \|\mathbf{u} - \mathbf{t}_m\|, \tag{3.15}$$

$$\mathbf{h}_m = \begin{bmatrix} -R_{m,1}^2 + \|\mathbf{r}_1\|^2 - \|\mathbf{t}_m\|^2 \\ \vdots \\ -R_{m,N}^2 + \|\mathbf{r}_N\|^2 - \|\mathbf{t}_m\|^2 \end{bmatrix}, \tag{3.16}$$

and

$$\mathbf{f}_m = [2R_{m,1}, \cdots, 2R_{m,N}]^T. \tag{3.17}$$

Note that (3.9) can be written as

$$2\mathbf{\Phi}_m \mathbf{D}_m \mathbf{u} = \mathbf{\Phi}_m \mathbf{v}_m. \tag{3.18}$$

However, in the expression of $\mathbf{\Phi}_m$ there exists the unknown $\mathbf{u}$. Thus, we need an initial estimate of $\mathbf{u}$. The initial estimation is calculated from

$$R_{m,n} - \|\mathbf{u} - \mathbf{t}_m\| = \|\mathbf{u} - \mathbf{r}_n\|, n = 1, \cdots, N. \tag{3.19}$$

Squaring both sides and rearranging it, we can obtain

$$2\mathbf{u}^T(\mathbf{r}_n - \mathbf{t}_m) = -R_{m,n}^2 + \|\mathbf{r}_n\|^2 - \|\mathbf{t}_m\|^2 + 2R_{m,n}\|\mathbf{t}_m\|. \tag{3.20}$$

And we can form

$$2\mathbf{D}_m \mathbf{u} = \mathbf{h}_m + \mu_m \mathbf{f}_m \tag{3.21}$$

whose weighted LS is

$$\mathbf{u} = \frac{1}{2}\left(\mathbf{D}_m^T \mathbf{Q}_m^{-1} \mathbf{D}_m\right)^{-1} \mathbf{D}_m^T \mathbf{Q}_m^{-1}\left(\mathbf{h}_m + \mu_m \mathbf{f}_m\right). \tag{3.22}$$

This solution gives $\mathbf{u}$ in terms of μ_m. Substituting this $\mathbf{u}$ into (3.15) produces a quadratic form in μ_m. Next, a root selection routine, chooses the correct roots as follows. If only one root is positive, it is the value that replaces μ_m in the LS solution of (3.22). If both roots are positive, it selects the one that gives the smaller J_m in (3.5). If both roots are negative or imaginary, it takes the absolute values of the real parts. The AML takes the $\mathbf{u}$ from the first step to calculate $\mathbf{\Phi}_m$, and then, from (3.18)

$$\mathbf{u} = \frac{1}{2}(\mathbf{\Phi}_m \mathbf{D}_m)^{-1}\mathbf{\Phi}_m(\mathbf{h}_m + \mu_m \mathbf{f}_m). \tag{3.23}$$

Again, $\mathbf{u}$ is in terms of μ_m, and following the procedure after (3.22) gives the updated values of $\mathbf{u}$. Repeating (3.23) with the new values of $\mathbf{u}$ by q (=5 in simulations) times produces q values of J_m, from which the AML selects the minimum.

We can get M estimates $\hat{\mathbf{u}}_m, m = 1, 2, \cdots, M$, from the first procedure, which are independent of each other. Thus, the final estimate is a weighted fusion of the M estimates [42]

$$\hat{\mathbf{u}} = \left(\sum_{m=1}^{M} \mathrm{cov}(\hat{\mathbf{u}}_m)^{-1}\right)^{-1} \sum_{m=1}^{M} \left(\mathrm{cov}(\hat{\mathbf{u}}_m)^{-1}\hat{\mathbf{u}}_m\right) \tag{3.24}$$

where $\mathrm{cov}(\hat{\mathbf{u}}_m)$ is equivalent to the CRLB of $\mathbf{u}$ under the mth group estimation [43]

$$\mathrm{cov}(\hat{\mathbf{u}}_m) = (\mathbf{P}_m^T \mathbf{Q}_m^{-1} \mathbf{P}_m)^{-1} \tag{3.25}$$

Instead of the unknown $\mathbf{u}$, we use $\hat{\mathbf{u}}_m$ for calculating the CRLB of $\mathbf{u}$, where

$$\mathbf{P}_m = \begin{bmatrix} \frac{(\hat{\mathbf{u}}_m - \mathbf{t}_m)^T}{\|\hat{\mathbf{u}}_m - \mathbf{t}_m\|} + \frac{(\hat{\mathbf{u}}_m - \mathbf{r}_1)^T}{\|\hat{\mathbf{u}}_m - \mathbf{r}_1\|} \\ \vdots \\ \frac{(\hat{\mathbf{u}}_m - \mathbf{t}_m)^T}{\|\hat{\mathbf{u}}_m - \mathbf{t}_m\|} + \frac{(\hat{\mathbf{u}}_m - \mathbf{r}_N)^T}{\|\hat{\mathbf{u}}_m - \mathbf{r}_N\|} \end{bmatrix}. \tag{3.26}$$

3.4 Contribution

We developed a target localization scheme in distributed MIMO radar systems using bistatic range measurements. The localization approach consists of two phases. First, the measurements are divided into multiple groups based on the various transmitter and receiver elements. For each group, an approximate maximum likelihood (AML) estimator is proposed to estimate the location of the target. Then, the estimation results from these different groups are combined to form the final estimate. The performance of the proposed algorithm is validated by simulation and is shown to reach the CRLB in a range of measurement noise levels. The main advantage of the proposed algorithm is that it provides a higher accuracy for locating a target position in high-noise conditions than existing schemes.

Chapter 4: Simulation and Result

4.1 Introduction

To prove that the proposed method improves higher estimation accuracy of the target position than existing algorithms in high-noise level using MIMO radar, the performance is evaluated by the root mean square errors (RMSEs) and compared with the least squares method [28] and the two-stage weighted least squares method (2SWLS) [42]. The proposed scheme was tested in different scenarios. One of the scenario is changing the target positions in space. For this scenario, the proposed method produces a better performance than the other two methods. The second scenario involves decreasing the number of transmitters and receivers of the radar system. Again, the proposed method produces a better performance compared to both LS and 2SWLS. The simulation was done in Matlab. The next section shows the simulation results between these methods. We shall refer to the method in [42] as the Group-2SWLS and refer to the proposed algorithm as Group-AML.

4.2 Design and Simulations

In this section, we provide several numerical simulations to show the performance of the proposed Group-AML algorithm, and then compare with the results of Group-2SWLS [42] and least squares [28]. The performance is evaluated by the root-mean square errors, which is defined by

$$RMSE(\mathbf{u}) = \sqrt{\frac{\sum_{j=1}^{K} \|\hat{\mathbf{u}}_j - \mathbf{u}\|^2}{K}} \tag{4.1}$$

where K is the number of Monte Carlo runs and $\hat{\mathbf{u}}$ is the estimate of the source position.

Assume a distributed MIMO radar system with four transmitters and four receivers placed as in Fig. 4.1, and one target can be located in any position.

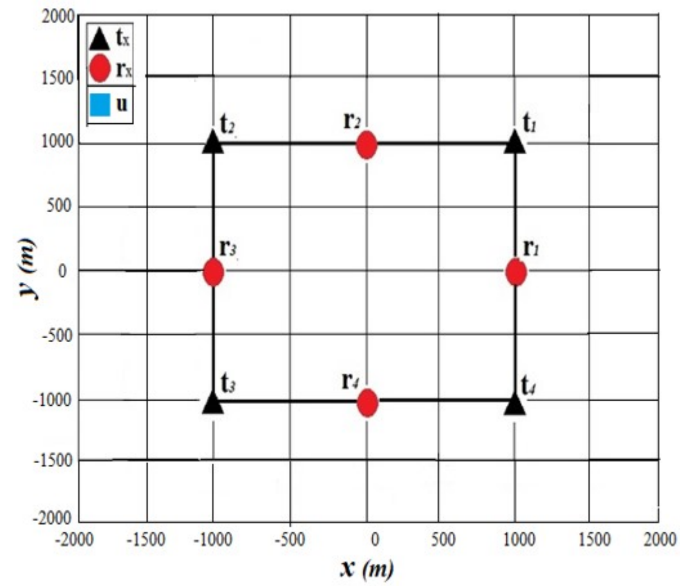

Figure 4.1: Position of transmitters and receivers.

transmitters	$[x_m^t, y_m^t]^T m$	receivers	$[x_n^r, y_n^r]^T m$
$\mathbf{t}_1$	$[1000, 1000]^T m$	$\mathbf{r}_1$	$[1000, 0]^T m$
$\mathbf{t}_2$	$[-1000, 1000]^T m$	$\mathbf{r}_2$	$[0, 1000]^T m$
$\mathbf{t}_3$	$[-1000, -1000]^T m$	$\mathbf{r}_3$	$[-1000, 0]^T m$
$\mathbf{t}_4$	$[1000, -1000]^T m$	$\mathbf{r}_4$	$[0, -1000]^T m$

Table 4.1: Transmitters and receivers location.

The bistatic range measurement noise $e_{m,n}$ is an independent and identically distributed (i.i.d.) Gaussian variable with zero-mean and variance σ^2. 5000 Monte Carlo realizations were done in each simulation. The unit of the x-axis, dBm, is defined as $10log_{10}(\sigma(m))$. The y-axis is expressed as $10log_{10}(RMSE)$

Now, let us assume that a target is located inside the square region of transmitters and receivers.

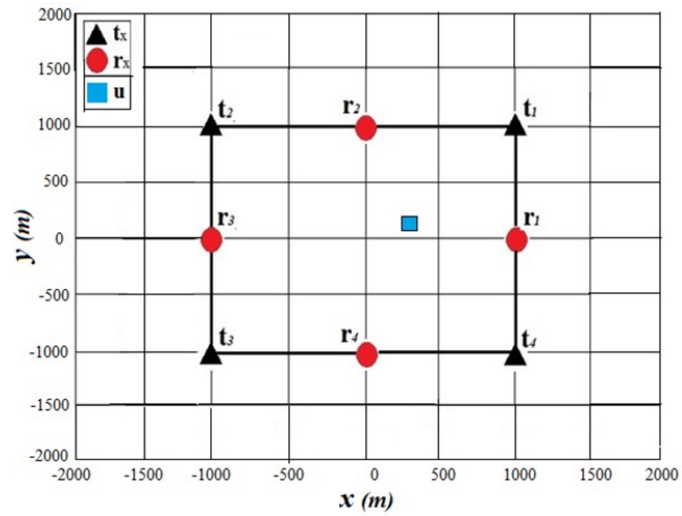

Figure 4.2: $\mathbf{u} = [300, 200]^T m$.

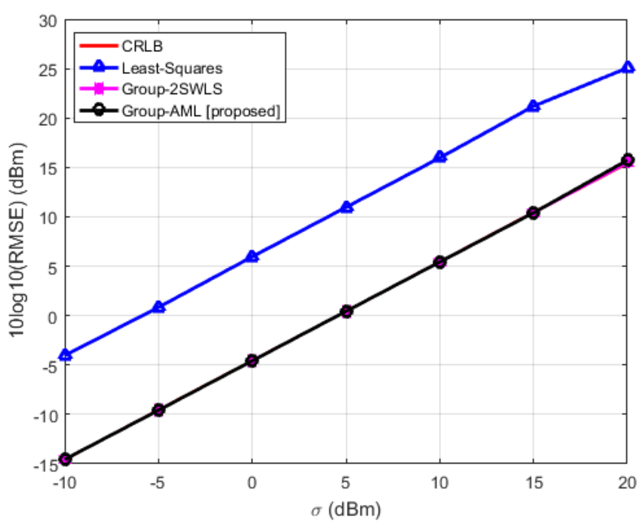

Figure 4.3: RMSE vs. σ, $\mathbf{u} = [300, 200]^T m$.

The comparison is between Group-AML with least-squares, and Group-2SWLS evaluated by the root-mean square errors. In Fig. 4.3, the target is located at $\mathbf{u} = [300, 200]^T m$. As we can see from the figure, the LS algorithm proposed by Dianat [28] has a poor performance and is above the Cramér-Rao lower bound, which is about 10dB. On the other side, we can see that both the Group-2SWLS algorithm proposed by Du [42] and Group-AML can reach the CRLB in this localization geometry.

Now, let us assume that is target located outside the square region of transmitters and receivers.

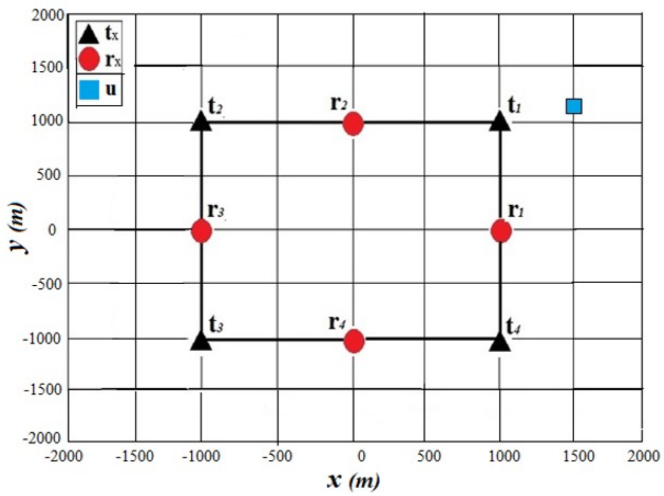

Figure 4.4: $\mathbf{u} = [1500, 1100]^T m$.

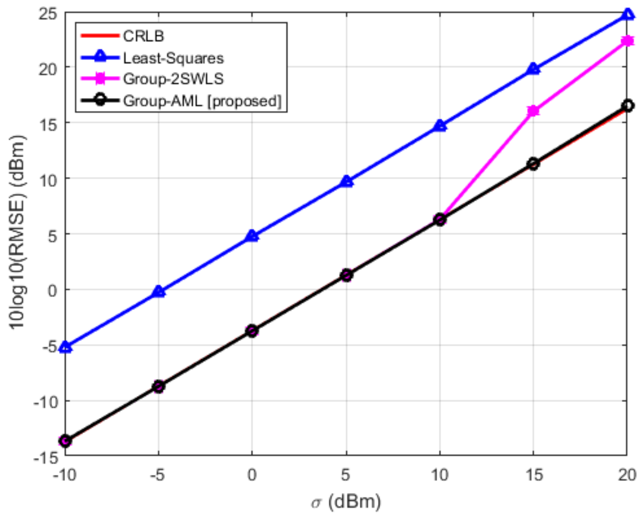

Figure 4.5: RMSE vs. σ, $\mathbf{u} = [1500, 1100]^T m$.

The comparison is between the algorithms when the target is located at $\mathbf{u} = [1500, 1100]^T m$. From Fig. 4.5, we can see that the LS algorithm is above the CRLB by about 8dB, where the Group-2SWLS algorithm deviates from the CRLB when σ is greater than 10 dBm, while the proposed Group-AML can reach the CRLB when σ is smaller than 20 dBm.

Let us assume that target is in the region of the transmitters and receivers.

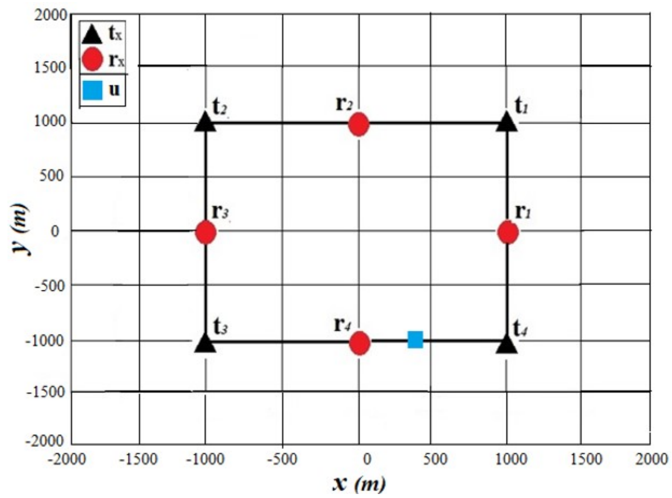

Figure 4.6: $\mathbf{u} = [400, -1000]^T m$.

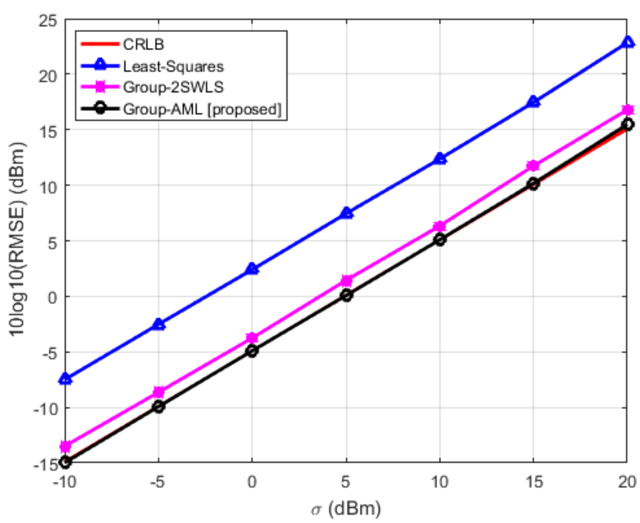

Figure 4.7: RMSE vs. σ, $\mathbf{u} = [400, -1000]^T m$.

The comparison between the algorithms when the target is located at $\mathbf{u} = [400, -1000]^T m$. From Fig. 4.7, we can see that both the LS and Group-2SWLS algorithms are above the CRLB. The proposed Group-AML can reach the CRLB in the tested noise levels.

Now, a target can be located uniformly and randomly as in Fig. 4.9.

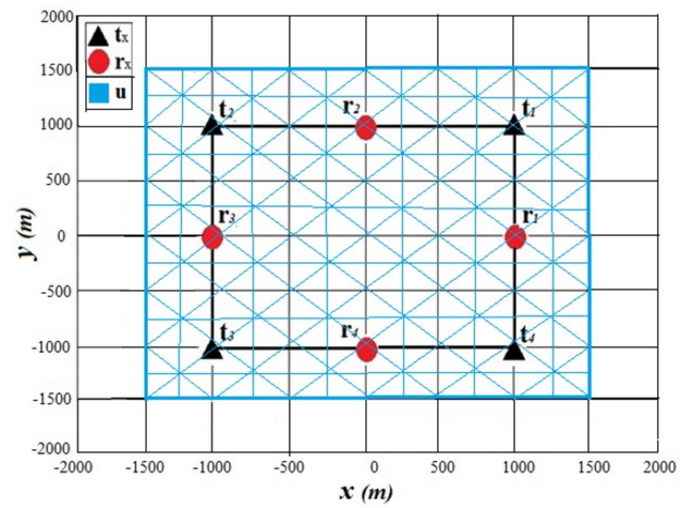

Figure 4.8: $\mathbf{u} = [-1500, 1500]^T m \times [-1500, 1500]^T m$.

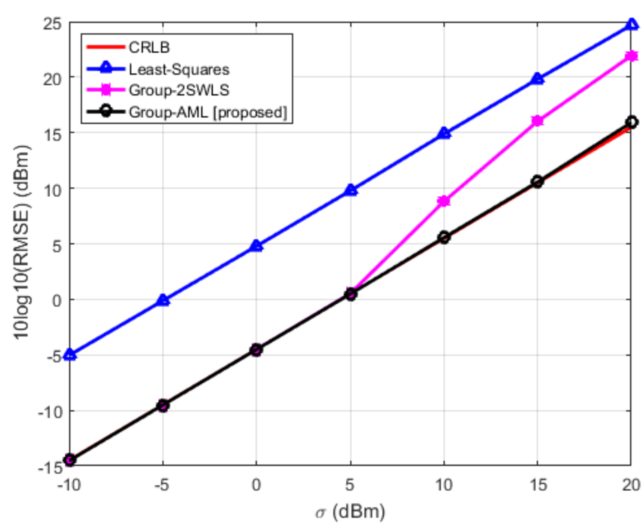

Figure 4.9: RMSE vs. σ, $\mathbf{u}$ is uniformly and randomly located in a square region: $[-1500, 1500]^T m \times [-1500, 1500]^T m$.

The comparison is between the algorithms when the target is uniformly and randomly located in a square region. From Fig. 4.9, we can see that when σ is smaller than 5 dBm, the Group-2SWLS algorithm can reach the CRLB, which agrees with the study in [42]. The method can achieve the CRLB at sufficiently small noise conditions, but when the noise level starts to increase, the performance of this algorithm becomes accurate. The proposed Group-AML can attain the CRLB when σ is smaller than 20 dBm.

4.2.1 The effect of decreasing the number of t_x and r_x

In general, decreasing the number of antennas in MIMO will affect the performance of locating a target position and make it less accurate. Now, Let us compare the proposed method with the least squares and Group-2SWLS algorithms in terms of reducing the number of transmitters and receivers. Assume a distributed MIMO radar system with three transmitters and three receivers as shown in Fig. 4.10.

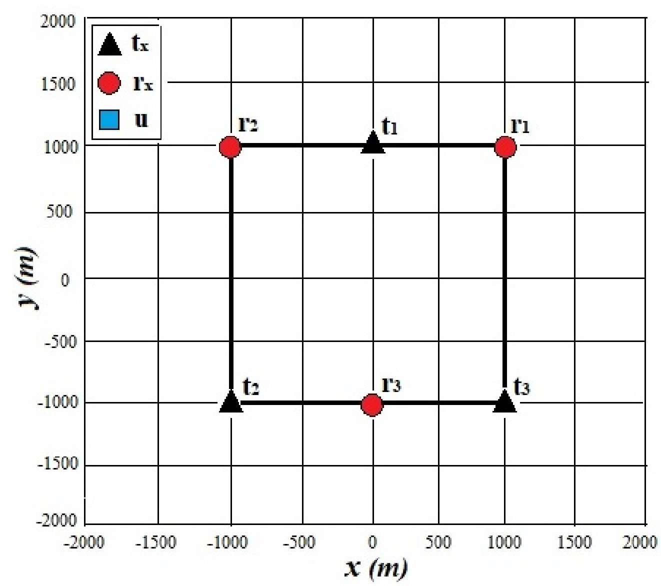

Figure 4.10: Position of three transmitters and receivers.

Now, let us assume that a target is located inside the square region of the transmitters and receivers.

transmitters	$[x_m^t, y_m^t]^T m$	receivers	$[x_n^r, y_n^r]^T m$
$\mathbf{t}_1$	$[0, 1000]^T m$	$\mathbf{r}_1$	$[1000, 1000]^T m$
$\mathbf{t}_2$	$[-1000, -1000]^T m$	$\mathbf{r}_2$	$[1000, -1000]^T m$
$\mathbf{t}_3$	$[1000, -1000]^T m$	$\mathbf{r}_3$	$[0, -1000]^T m$

Table 4.2: Transmitters and receivers location after decreasing the number of antennas.

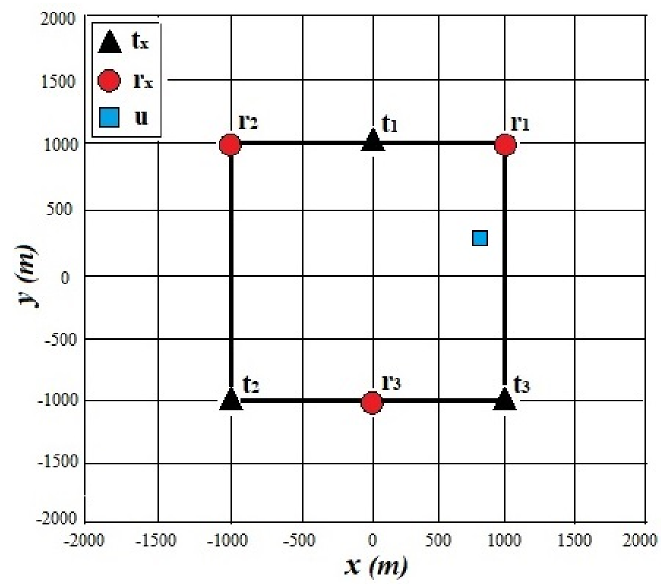

Figure 4.11: $\mathbf{u} = [800, 300]^T m$.

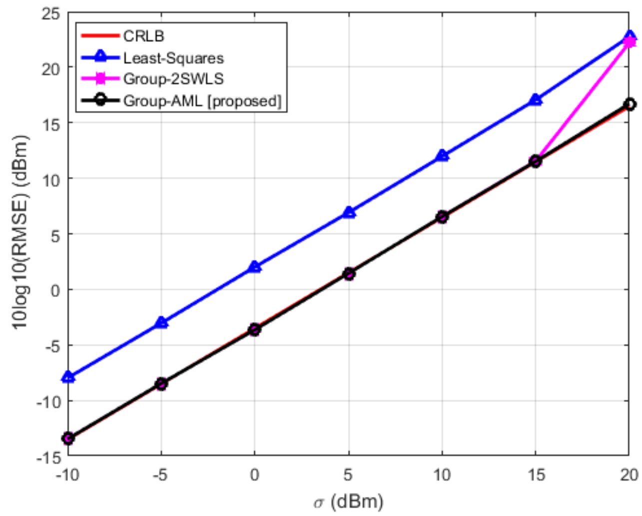

Figure 4.12: RMSE vs. σ, $\mathbf{u} = [800, 300]^T m$.

In Fig. 4.12, the target is located at $\mathbf{u} = [800, 300]^T m$. As we can see from the figure, the LS algorithm has a poor performance, which is away from the Cramér-Rao lower bound by about 10 dB. On the other hand, the Group-2SWLS starts top CRLB when σ reaches 15 dBm, where Group-AML can reach the CRLB in this localization geometry.

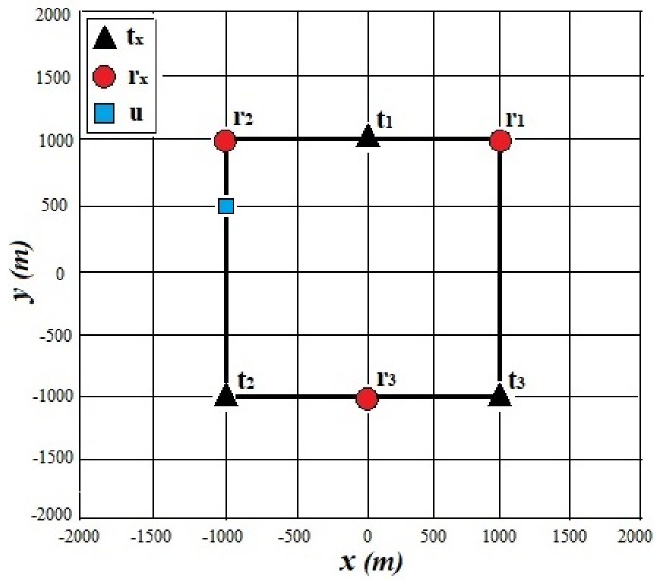

Figure 4.13: $\mathbf{u} = [-1000, 500]^T m$.

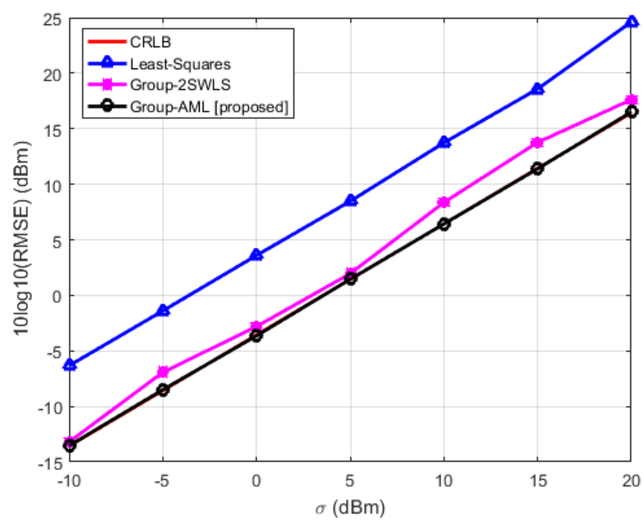

Figure 4.14: RMSE vs. σ, $\mathbf{u} = [-1000, 500]^T m$.

The comparison is between the algorithms when the target is located at $\mathbf{u} = [-1000, 500]^T m$.

From Fig. 4.14, we can see that both LS and Group-2SWLS algorithms are above the CRLB. The proposed Group-AML can reach the CRLB in the tested noise levels.

Now, let us assume that a target is located outside the square region of the transmitters and receivers.

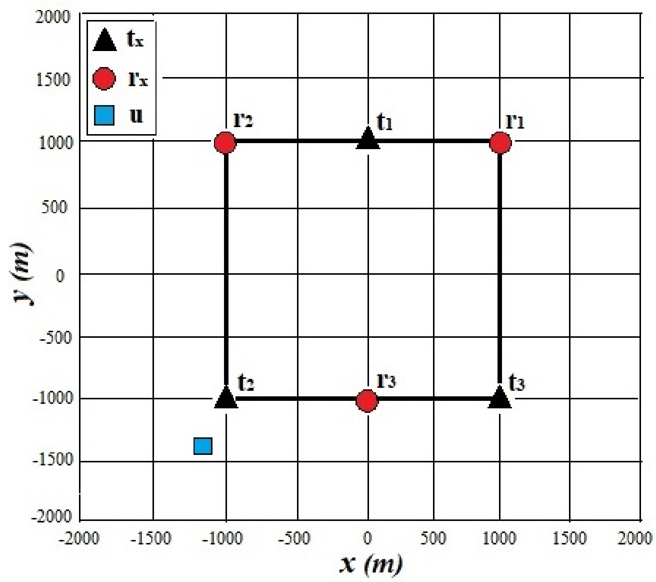

Figure 4.15: $\mathbf{u} = [-1200, -1400]^T m$.

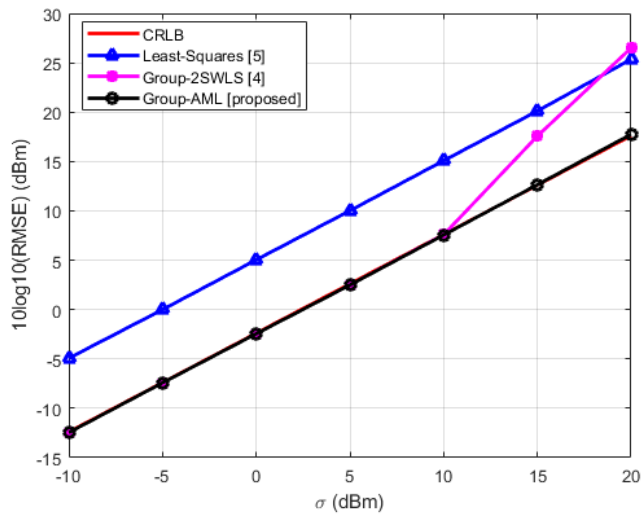

Figure 4.16: RMSE vs. σ, $\mathbf{u} = [-1200, -1400]^T m$.

The comparison is between the algorithms when the target is located at $\mathbf{u} = [-1200, -1400]^T m$. From Fig. 4.16, we can see that least squares method has low accuracy performance. Group-2SWLS performed well in low noise level and reached CRLB in change when σ reaches 10 dBm. After this point, the performance of Group-2SWLS starts to degrade while the proposed Group-AML can reach the CRLB.

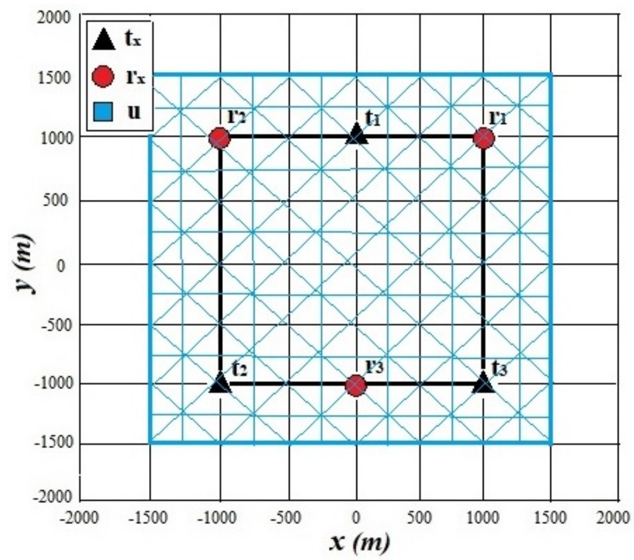

Figure 4.17: $\mathbf{u} = [-1500, 1500]^T m \times [-1500, 1500]^T m$.

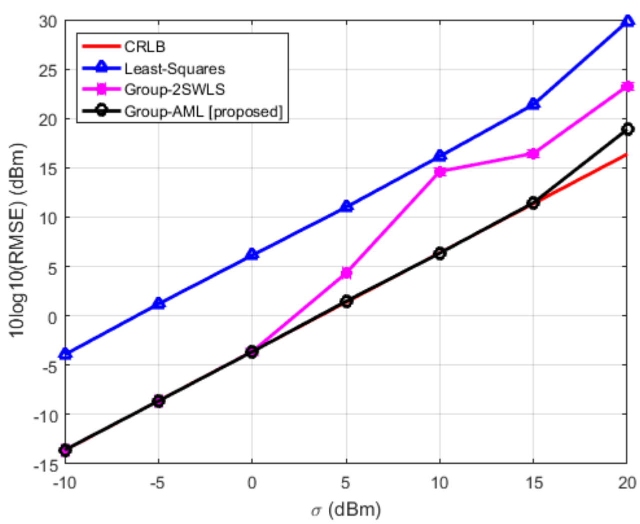

Figure 4.18: RMSE vs. σ, $\mathbf{u}$ is uniformly and randomly located in a square region: $[-1500, 1500]^T m \times [-1500, 1500]^T m$.

Next, the comparison is between the algorithms when the target is uniformly and randomly located in a square region. From Fig. 4.18, we can see that Least Squares is away from CRLB. When σ is 0 dBm, the Group-2SWLS algorithm starts to go above the CRLB, and when σ reaches 10 dBm, the algorithm is affected by the high-noise level, which is the result of this method's inability to locate the target precisely. The proposed Group-AML can attain the CRLB when σ is smaller than 15 dBm.

4.2.2 The effect of increasing the number of t_x and r_x

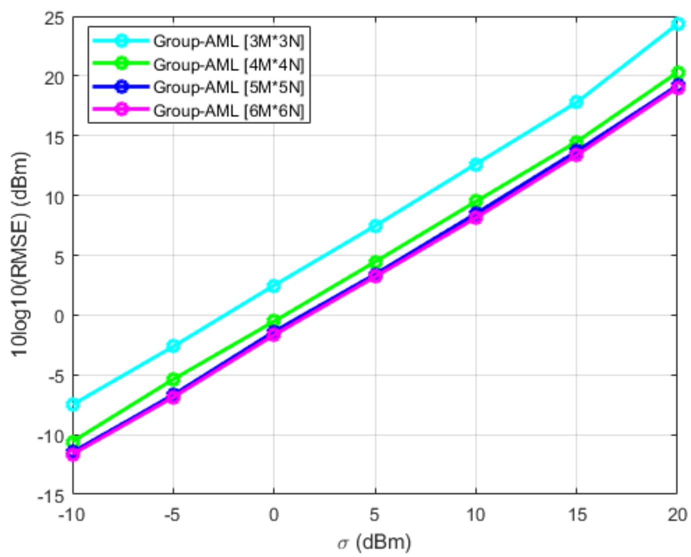

Figure 4.19: RMSE vs. σ, $\mathbf{u}$ is uniformly and randomly located in a square region: $[-5000, 5000]^T m \times [-5000, 5000]^T m$.

As we can see from the figure above, we assumed a target $\mathbf{u}$ is uniformly and randomly located in a square region: $[-5000, 5000]^T m \times [-5000, 5000]^T m$. The performance with respect to locating the position of a target by increasing the number of transmitters and receivers improved.

Chapter 5: Conclusion and Future Work

In order to improve the performance of locating a target position in MIMO radar in high-noise levels, a new approximate ML estimator for target location in non-coherent MIMO radar system using bistatic range measurement has been developed. These measurements are divided into several groups based on the different receivers or transmitters and then the AML estimator is applied on each group. The AML only requires a quadratic root selection routine over the unknown parameter. By using the proposed algorithm estimator in MIMO radar, the accuracy of detecting a target position in high-noise level conditions is validated by simulations. It is shown that it achieves the CRLB in a range of reasonable measurement noise levels.

This thesis focused on improving the localization accuracy in high-noise level condition in MIMO radar. A follow-up work could involve building multiple receivers and transmitters outdoor in the real world and testing the algorithm in a noisy environment. One of the advantages we discovered during testing of the developed algorithm under different scenarios is that decreasing the number of transmitters and receivers does not have a significant effect on the performance, which reduces the expenses. This needs to be verified by carrying out a real-world test with all the interferences from different signals.

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