Position Location of Mobile Terminal in Wireless MIMO Communication Systems

Ji Li, Jean Conan, and Samuel Pierre

Abstract: **A promising approach to improve the performance of mobile location system is the use of antenna arrays in both transmitter and receiver sides. Using advanced array signal processing techniques, such multiple-input multiple-output (MIMO) communication systems can offer more mobile location information by exploiting the spatial properties of the multipath channel. In this paper, we propose a novel approach to determine the position of mobile terminal based on estimated multipath signal parameters using only one base station in MIMO communication systems. This approach intends to minimize the error occurring from the estimation of multiple paths and gives an optimal estimation of the position of mobile terminal by simultaneously calculating a set of nonlinear location equations. This solution breaks the bottleneck of conventional mobile location systems which have to require multilateration of at least three base stations.**

Index Terms: **Least squares, mobile location, multipath, multiple-input multiple-output (MIMO), Taylor series.**

I. INTRODUCTION

Wireless communication has enjoyed explosive growth over the past decade. With the increasing need for location-based service and applications, mobile positioning will be one of the most exciting features of the next generation wireless systems. With this technique, a mobile device can either gather the information about its position or can be localized from elsewhere [1].

One of the most important applications of mobile positioning is personal safety, such as in the emergency localization (E-911 service); automatic location identification (ALI) will be a system requirement for wireless operators in the near future. Mobile location systems can also be used by advanced user hand-off schemes, and potentially many user services for which a global positioning system (GPS) is impractical. Other applications are automatic billing and fraud detection for cellular providers, accident reporting, law enforcement, cargo tracking, and intelligent transportation systems [2], [3].

MIMO technology is the most promising candidate for next generation wireless communication systems. With multiple transmit and multiple receive antennas, it can achieve higher data rate, without increasing the total transmission power or bandwidth, compared to the single antenna counterpart [4]. However, how to implement the location of mobile device in MIMO system remains an open area of research. As the existing location methods are mainly based on multi-lateration techniques, a particular mobile location technique needs to be developed to fully take advantage of MIMO channel characteristics.

In a wireless MIMO communication system, with both transmit and receive side use multiple antennas, the spatial characteristics of multipath in MIMO communication system can be exploited. It is then possible to estimate channel parameters such as angle of arrival (AOA), angle of departure (AOD), and delay of arrival (DOA) in a multipath environment by using adaptive array signal processing techniques [5], [6].

In this work, by using estimated MIMO channel parameters in a multipath environment, we propose a novel approach to calculate the position of mobile terminals, involving an iterative nonlinear least squares (LS) solution. We demonstrate its viability in mobile and sensor position location with numerical experiments. To our knowledge, no similar results for the mobile location technique for MIMO communication systems are available in previously published works.

The paper is organized as follows. In Section II, we give an overview of wireless position location systems. In Section III, we briefly describe the MIMO communication system under consideration of mobile location. Section IV proposes the hybrid DOA/AOA/AOD location method for MIMO systems. In Section V, the analysis of the proposed location method is given, and the Cramer-Rao lower bound (CRLB) is derived. The performance of the proposed method is evaluated via computer simulation in Section VI. Conclusions are given in Section VII.

II. OVERVIEW OF WIRELESS POSITION LOCATION SYSTEMS

Wireless position location (PL) systems focus on providing geographic information system (GIS) and spatial information via mobile and base units. However, in traditional PL system, the accuracy is limited by the possible directivity of the measure aperture or array, as well as by multipath fading and shadowing.

A. Classification of Wireless PL System

Location enabled technologies that have been proposed to date fall into three broad categories: Network-based, handset-based, and hybrid in nature.

A.1 Handset-Based Technologies

Handset-based technologies use the radio navigation system provided by the satellites of the U.S. government-operated GPS. GPS-based technology utilizes an embedded GPS receiver in the handset to triangulate its position from at least three GPS satellites. GPS-based technology is well suited for many outdoor local positioning tasks. However, GPS has its shortcomings in dense urban areas and inside buildings. Unfortunately, this

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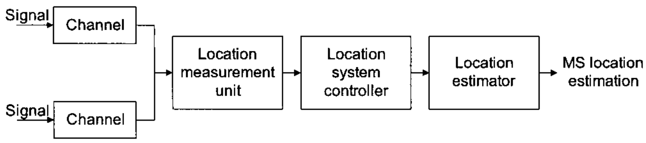

Fig. 1. The block diagram of a wireless PL system.

is exactly the area where heavy, strongly-growing local wireless data transfer takes place. Moreover, it has other drawbacks such as increased cost, size, and power consumption of mobile devices. Because of the drawbacks of non-network-based technologies, cellular carriers generally favor the use of a network-based approach, provided the necessary infrastructure is not prohibitively expensive.

A.2 Network-Based Technologies

Network-based technologies use the cellular network to determine the location of the mobile devices. The network-based location technologies are based on the parameters of the transmission such as signal propagation time and angle of arrival. These technologies typically require considerable expenditure on the network infrastructure but do not require any modifications on the handset.

A.3 Hybrid Technologies

Network-assisted GPS hybrid technologies are expected to deliver the accuracy of GPS and overcome the drawbacks of GPS associated with its line-of-sight requirement, and power consumption by shifting significant processing load from the device to the network.

In cellular systems, PL technology typically use base stations (BSs) or other devices to measure radio signals from the mobile station (MS). The general structure of a wireless PL system is illustrated in Fig. 1. Each part of this structure will be investigated in detail in following sections.

B. Location Measurement and Principles

The location measurement unit measures the parameters need for location estimation from the received signal corrupted with additive noise, multipath, and/or non-line-of-sight (NLOS) errors. Classical parameters include signal strength, direction of arrival, and propagation time or delay of received signal. The measurement principle of radio position systems can be classified into two broad categories: Direction finding (DF) and range based systems. DF systems estimate the position of a mobile source by measuring the AOA of the source's signal, using parameter estimation methods of array signal processing. Range based PL systems may be categorized as received signal strength (RSS) systems since they are mainly based on propagation-loss equations, and propagation-time based systems. The second type of systems can be further divided into three different subclasses: Time of arrival (TOA), round trip time of flight (RTOF), and time difference of arrival (TDOA) [7]. The detailed measurement principle will be present in the following section.

B.1 Direction Finding Systems

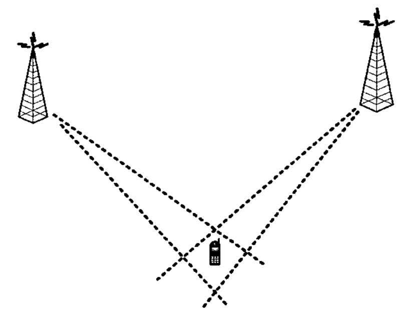

Fig. 2. AOA-based wireless location.

Direction finding systems use antenna array at the base station to determine the direction from which the mobile's signal arrives. The AOA measurement restricts the location of the source along a line in the estimated AOA. When multiple AOA measurements are made simultaneously by multiple base stations, a triangulation method may be used to form a location estimate of the source at the intersection of these lines-of-bearing (LOB). Signal AOA information, measured at BSs with an antenna array, can be used for positioning purpose as in Fig. 2. MS is at the intersection of several direction lines corresponding to AOA measurements.

Numerous techniques have been developed to determine the AOA of signals incident on an antenna array [8], [9]. These methods typically are based on the phase difference of the signal at adjacent elements in the antenna array since this phase difference is proportional to the angle of arrival of the incoming signal.

B.2 Range-Based Systems

B.2.a RSS-Based Wireless Location Systems. RSS are based on propagation-loss equations. The free space transmission loss for instance is proportional to $1/r^2$ (r is the propagation distance). The major advantage of RSS systems is the fact that most modern radio modules already provide a *received signal strength indicator* (RSSI). Also the BER can be used to estimate the signal attenuation. However, for RSS based location systems, high accuracy is difficult to obtain. In a multipath propagation environment, variations in the RSS can be 30–40 dB over distances on the order of an half wavelength. The power control mechanism employed in cellular systems will impose another difficulty in estimating the location via RSS measurements [10].

B.2.b Propagation Time-Based Wireless Location Systems. Due to their physical restraints, AOA and RSS systems only deliver moderate position accuracy, whereas the propagation time-based measurements can achieve higher accuracy and does not require complex antenna arrays. The perhaps most intuitive and accurate approach for local position measurement is to measure the RTOF of the signal traveling from the transmitter to the measuring unit and back. Obviously, the time-of-flight can then be used to calculate the distance. In TOA systems, the one-way propagation time is measured and the distance between measuring unit and signal transmitter is calculated. However, there're two main drawbacks of these two approaches: The transmitted signal must be labeled with a time stamp in order for the receiver

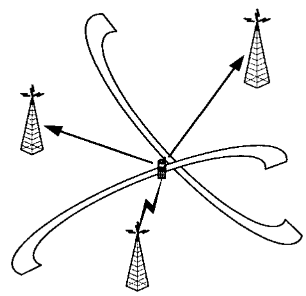

Fig. 3. TDOA-based wireless location.

to discern that the signal has traveled, and precise time synchronization of all involved fixed measuring units and mobile units is required. Therefore, TDOA method is a more practical means of location for commercial systems. The TDOA system determines the MS position based on trilateration technique, as shown in Fig. 3. In TDOA systems, the time-difference of arrival of the signals received in several pairs of measuring units is evaluated. The benefit of TDOA systems is that it is only necessary to synchronize the measuring units. This synchronization is done using a backbone network or a reference transponder in a known position.

C. Location System Controller

Depending on the location scheme used, the location measurement unit passes measured information such as AOA, TOA, or TDOA to the location system controller. The location system controller gathers all the information and selects the measurements to be used in the location estimator. The error statistics of each measurement is a major concern for choosing the measurements. The decision to select or reject a measurement can be based on a number of factors.

C.1 NLOS Error Mitigation

Extensive research on NLOS mitigation techniques have been carried out in the past, as evidenced by the literature [11]–[13]. Most of these techniques assume that NLOS corrupted measurements only consist of a small portion of the total measurements.

C.2 Hearability

Hearability is the ability of receiving signals from a sufficient number of BSs simultaneously at a sufficient power level, and it is evaluated by the number of BSs that an MS can detect or hear. The higher the value, the better is the hearability [14].

D. Location Estimator and Algorithms

The location estimator takes the measurement from the location system controller, and estimate the MS location. A straightforward approach uses a geometric interpretation to calculate the intersection of lines for AOA, circles for TOA, and hyperbolas for TDOA. This approach, however, becomes difficult if the lines or curves do not intersect at a point due to measurement errors.

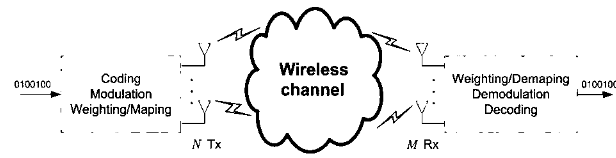

Fig. 4. Diagram of a MIMO wireless transmission system.

The traditional techniques for position location such as direction finding and ranging are based on trilateration/multilateration system [15]. Trilateration/multilateration PL systems utilize measurements from three or more BSs to estimate the 2-dimensional (2D) location of the mobile transmitter. In a trilateration hyperbolic ranging PL system, two range-difference measurements produced from three base stations can provide the position of the mobile target, additional measurements from more BSs can be used to reduce the ambiguities due to multipath, signal degradation, and noise [16], [17]. To improve positioning accuracy, it is better to use as much information as possible. Hybrid solutions are proposed by simply combining TDOA and AOA measurements [15], [18].

III. POSITION-LOCATION IN MIMO SYSTEMS

A. Introduction to MIMO Communication Systems

MIMO wireless systems can be viewed as an extension of the so-called smart antennas. Such a system is illustrated in Fig. 4. MIMO systems use multiple transmit and receive antennas to exploit the spatial properties of the multipath channel, thus offer a new dimension to enable enhanced communication performance. The idea behind MIMO is that the signals on the transmit (Tx) antennas at one end and the receive (Rx) antennas at the other end are "combined" in such a way that the quality (BER) or the data rate (bps) of the communication for each MIMO user will be improved. Such an advantage can be used to increase both the network's quality of service and the operator's revenues significantly. A key feature of MIMO systems is the ability to turn multipath propagation, traditionally a pitfall of wireless transmission, into a benefit for the user.

B. The MIMO Propagation Channel Model

The MIMO channel models can be divided into the non-physical and physical models. The non-physical models are based on the channel statistical characteristics using non-physical parameters. In general, the non-physical models are easy to simulate and provide accurate channel characterization for the situations under which they were identified. On the other hand they give limited insight to the propagation characteristics of the MIMO channels and depend on the measurement equipment, e.g., the bandwidth, the configuration and aperture of the arrays, the heights and response of transmit and receive antennas in the measurements. The influence of the channel and measurement equipment on the model can not be separated. Another category are the physical models. In general, these models choose some crucial physical parameters to describe the MIMO propagation channels. Some typical parameters include AOA, AOD,

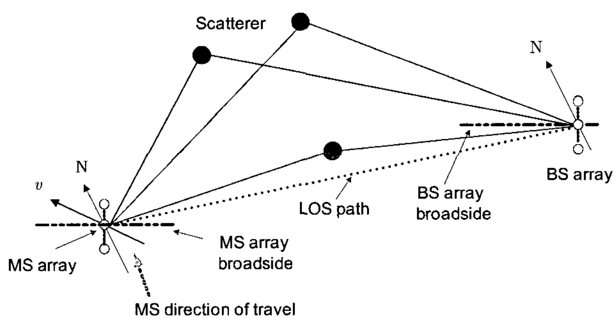

Fig. 5. A specular MIMO multipath propagation channel model.

and DOA.

In order to jointly estimate multipath channel parameters, we shall consider the following conditions on the mobile radio propagation scenario:

- The MIMO multipath environment is modeled by a discrete number of rays, each parameterized by a delay, complex amplitude (path gain), angle of arrival and angle of departure.
- The source signals are digital sequences that are linearly modulated by known pulse shape functions.
- The parameters such as AOD, AOA, and DOA are not changing significantly from each time slot to the next. It implies that the channel has quasi-static property.
- The source signals are transmitted and received by a narrowband phased array.
- The data transmitted by the antennas is sampled at or above the Nyquist rate.

In this work, we consider a simplified 3GPP MIMO channel model [19] which is a specular multipath propagation channel model illustrated as Fig. 5. In this model, we assume there is only one path that goes through each scatterer. Each path has its own AOD, AOA, and the delay between each pair of paths can also be measured.

C. Parameter Estimation for MIMO Systems

Parameter estimation has received a significant amount of attention over the last several decades, because of its widespread applications and the difficulty of obtaining the optimum estimator [20]. The estimation of parameters such as DOA, AOA, etc., for a known signal is the central function for PL systems [21]–[23]. The conventional wireless communication system can only estimate the DOA or AOA of the received signal in order to perform position location method through trilateration or multilateration of more than two BSs. The existing methods for estimating the AOA or DOA of the received signal in a wireless communication system are based on transmitting a known signal, such as a pulse, and performing correlation or parametric estimations separately [8], [9]. Unfortunately, in many cases, the received signal is composed of multiple reflections having different AOAs and DOAs, which cause the signal to overlap in either the time or space domain. Thus, the classical methods for estimating the AOA and DOA are no longer optimal in such situations [10], [24], [25].

In smart antenna systems, the joint estimation of the AOA and DOA of the received signal is possible through some advanced array signal processing techniques. In [26] and [27], joint angle and delay estimation (JADE) algorithms for smart antenna systems have been proposed for more robust estimation. In a multipath environment, the direction of received signals and associated delays of the path do not change quickly, so that it possible to estimate these parameters by extending the classical methods to the joint space and time domain. However, multiple base stations are still required in this case except with high-speed moving MS.

In wireless MIMO systems, it is possible to estimate more channel parameters in a multipath environment using adaptive array signal processing techniques. The estimation methods for multipath signal parameters such as AOA, AOD, and DOA have been proposed in [5] and [6]. With additional AOD information in MIMO system, it motivates us to estimate the position of mobile terminal from signals of multipath. If we estimate the TDOA between the first path and other paths, along with the estimation the AOD and AOA for each path, a set of nonlinear equations whose solution gives the 2D coordinates of the source can be defined. As mentioned earlier, solving the set of nonlinear equation can be performed by linearization. Therefore, we expect to develop a novel hybrid TDOA/AOA/AOD method which is extended from Taylor series [16] and TSLS [17] solutions to give an optimum position of mobile terminal using single BS.

D. The Benefit to PL in MIMO Systems

With the joint parameters estimation of AOA/AOD/DOA, the MIMO techniques will bring the following benefits to PL methods:

- If the received signal arrived in same direction, the conventional estimation algorithm can not distinguish their difference, but with joint estimation, the two signals with same direction can be separated by their delays.
- Unlike the traditional methods, the joint estimation method can work in cases when the number of paths exceeds the number of antennas. Thus, it can resolve more multipath than the number of array elements.
- Since more parameters (AOA, AOD, and DOA) can be exploited in MIMO channel, it is possible to locate the position of mobile terminals using only one BS in MIMO communication systems.
- The location estimation seems also possible at MS side which is not realistic in traditional communication system.

IV. THE PROPOSED HYBRID TDOA/AOA/AOD LOCATION METHOD FOR MIMO SYSTEM

A. System Model for Position-Location

The location estimation model for MIMO multipath propagation channel is illustrated in Fig. 6. The proposed algorithm intends to minimize the error occurring from the estimation of multiple paths and give an optimal estimation of the MS position by simultaneously calculating a set of nonlinear position equations.

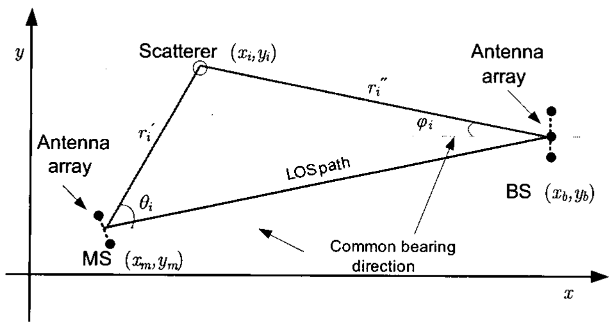

Fig. 6. Illustration of the ith scattered path with respect to transmit and receive antenna array.

A.1 Line-of-Sight Scenario

If we have a line-of-sight path available, the position of mobile station can be calculated easily, then we will have

$$\begin{aligned} &\theta_i' = \theta_i - \theta_1,\ \phi_i' = \phi_i - \phi_1 \\ &r_i' = \frac{r_1 \sin\phi_i'}{\sin(\theta_i' + \phi_i')},\ r_i'' = \frac{r_1 \sin\theta_i'}{\sin(\theta_i' + \phi_i')} \\ &r_i = r_i' + r_i'' \end{aligned} \tag{1}$$

where θ_i and ϕ_i are the angles of departure and arrival for the ith path from the mobile station to the base station, respectively. The angles θ_1 and ϕ_1 are respectively the AOD and AOA for LOS propagation path. As depicted in Fig. 6, r_i is the total length of the ith path, while r_i' and r_i'' are the lengths of the segments forming the ith path, and r_1 is the LOS distance between MS and BS, respectively.

Thus, we could have the LOS distance between MS and BS

$$r_1 = r_{i,1} \Big/ \left(\frac{\sin\theta_i' + \sin\phi_i'}{\sin(\theta_i' + \phi_i')} - 1 \right) \tag{2}$$

where $r_{i,1} = r_i' + r_i'' - r_1$ is the realtive distance between ith path and LOS path. And the position of MS will be

$$\begin{aligned} x_m &= x_b - r_1 \cos\theta_1 \\ y_m &= y_b - r_1 \sin\theta_1. \end{aligned} \tag{3}$$

In this case, we found there is only one BS station required to give an estimation of the position of MS, because the multiple antennas or antenna array at MS site provide more information for location position. The conventional trilateration method using multiple BSs is not necessary for MIMO system.

A.2 Non-Line-of-Sight Scenario

However, in practice, the LOS is not always available or can not be distinguished easily. Moreover, the measurements of DOA, AOA, and AOD always contain errors due to the hostile wireless propagation environment. As illustrated in Fig. 6, let (x_b, y_b), (x_m, y_m), and (x_i, y_i) denote the true position of respectively the BS, the MS and the ith scatterers. The values of (x_m, y_m) and (x_i, y_i) are not known in practice and must be estimated.

From Fig. 6, it is straightforward to obtain θ_i and ϕ_i as a function of the mobile station and the scatterers

$$\begin{aligned} \theta_i(x_m, y_m, x_i, y_i) &= \arctan\left(\frac{y_i - y_m}{x_i - x_m}\right) \\ \phi_i(x_m, y_m, x_i, y_i) &= \arctan\left(\frac{y_i - y_b}{x_i - x_b}\right) \end{aligned} \tag{4}$$

for $i = 1, \cdots, N$, where N is the total number of paths. Similarly, with c defined as the signal propagation speed, the TDOA can be computed

$$\tau_i(x_m, y_m, x_i, y_i) = (r_i - r_1)/c,\quad i = 2, \cdots, N \tag{5}$$

where $r_i = r_i' + r_i''$ with

$$\begin{aligned} r_i' &= \sqrt{(x_i - x_m)^2 + (y_i - y_m)^2} \\ r_i'' &= \sqrt{(x_i - x_b)^2 + (y_i - y_b)^2}. \end{aligned} \tag{6}$$

The objective is to determine the unknown position (x_m, y_m) from the exact position (x_b, y_b) and uncertain measurements of $\hat{\theta}_i$, $\hat{\phi}_i$, and $\hat{\tau}_i$ (the time delay between paths are known). These assumptions are realistic as several methods have been recently proposed to measure θ_i, ϕ_i, and τ_i in MIMO communications [5], [6].

Statistically, the measurement contain errors

$$\begin{aligned} \hat{\tau}_i &= \tau_i(x_m, y_m, x_i, y_i) + n_{\tau_i} \\ \hat{\theta}_i &= \theta_i(x_m, y_m, x_i, y_i) + n_{\theta_i} \\ \hat{\phi}_i &= \phi_i(x_m, y_m, x_i, y_i) + n_{\phi_i} \end{aligned} \tag{7}$$

where $i = 1, \cdots, N$ for $\hat{\theta}_i$ and $\hat{\phi}_i$, $i = 2, \cdots, N$ for $\hat{\tau}_i$. n_{τ_i}, n_{θ_i}, and n_{ϕ_i} are the measurement errors of TDOA, AOA, and AOD, respectively.

When the number of path $N \geq 4$, then we have $(3N-1)$ measurements and $(2N+2)$ unknown parameters, and the system is over-determined. It is then possible to apply the least-squares method to this nonlinear estimation problem.

B. A Generic Nonlinear Location Estimation Method

The process of location estimation is computing a value for an unknown state vector from a related measurement vector. The value or estimate will in general be in error because of measurement noise and "model" errors. In most estimation problems, knowledge of the probability density function of the state parameter to be estimated was always required prior to the measurement parameter. However, this information is not available in many practical cases. The state parameter to be estimated may not even be a random variable. One approach to such problems is to interpret the lack of knowledge concerning the *a priori* probability density function of the parameter in the sense that the density function is implicitly assumed to be uniform (or approximately so over a very wide range).

However, it is often desirable to use an estimation concept free of such assumptions. The well known maximum likelihood estimate of a parameter is that value which will make a given measurement most likely, i.e., the parameter value which causes the conditional probability density induced on the measurements to have its greatest maximum at the given measurements.

More precisely, let $\mathbf{x}$ be the state vector to be estimated (in general an n-vector). Let $z(i), 1 \leq i \leq k$, be a sequence of measurements (here we assume each $z(i)$ is scalar) which are generated by the functional relationship

$$z(i) = h_i[\mathbf{x}, v(i)],\ i = 1, \cdots, k \tag{8}$$

where each $v(i)$ is representing measurement noise or other random interference which tends to make it possible to infer the true value of $\mathbf{x}$ from the observation $z(i)$. Assuming now that the conditional probability density $p[z(1), \cdots, z(k)|\mathbf{x}]$ is known, or has been derived from (8) and the statistics of $v(i)$, we may define the "likelihood function"

$$l(\mathbf{x}) \doteq p[z(1), \cdots, z(k)|\mathbf{x}] \tag{9}$$

where the conditional probability density $p[z(1), \cdots, z(k)|\mathbf{x}]$ is now assumed to have been evaluated at a given received measurement sequence, $z(1), \cdots, z(k)$.

The *maximum likelihood* (ML) estimate of $\mathbf{x}$, denoted by $\hat{\mathbf{x}}$, is now the value of $\mathbf{x}$ which maximizes $l(\mathbf{x})$ which was the conditional probability density $p[z(1), \cdots, z(k)|\mathbf{x}]$ evaluated for the given received measurements.

Let the observation noise $v(i)$ in (8) be additive and represent a zero-mean independent gaussian random sequence. Then, we have

$$z(i) = f_i(\mathbf{x}) + v(i)\ i = 1, \cdots, k \tag{10}$$

and

$$\begin{aligned} E[v(i)] &= 0 \\ E[v(i)v(j)^T] &= \mathbf{Q}(j, i)\Delta(j - i) \end{aligned} \tag{11}$$

where $\mathbf{Q}(j, i)$ is a sequence of known covariance matrices, each covariance matrix representing the covariance among the components of $v(i)$.

It is desired to determine the maximum likelihood estimate of the parameter $\mathbf{x}$. the likelihood function, i.e., the conditional probability of $z(1), \cdots, z(k)$ given $\mathbf{x}$ is given by

$$l(\mathbf{x}) = C \exp -\frac{1}{2}\sum_{i=0}^{k}[z(i) - f_i(\mathbf{x})]^T \mathbf{Q}^{-1}(i, i)[z(i) - f_i(\mathbf{x})] \tag{12}$$

where C (which involves factors of $\sqrt{2\pi}$ and $|\mathbf{Q}(i, i)|$) is a constant independent of $\mathbf{x}$. From the form of (12), we see that maximizing $l(\mathbf{x})$ leads to minimizing the quadratic function

$$\min_{\mathbf{x}} \sum_{i=1}^{k}[z(i) - f_i(\mathbf{x})]^T \mathbf{Q}^{-1}(i, i)[z(i) - f_i(\mathbf{x})]. \tag{13}$$

Let

$$\mathbf{z} = \begin{pmatrix} z_1 \\ \vdots \\ z_k \end{pmatrix},\ \mathbf{f}(\mathbf{x}) = \begin{pmatrix} f_1(\mathbf{x}) \\ \vdots \\ f_k(\mathbf{x}) \end{pmatrix},\ \text{and } \mathbf{v} = \begin{pmatrix} v_1 \\ \vdots \\ v_k \end{pmatrix}. \tag{14}$$

We get the following expression in matrix form:

$$\mathbf{z} = \mathbf{f}(\mathbf{x}) + \mathbf{v}. \tag{15}$$

If $\mathbf{f}(\mathbf{x})$ is a linear function, $\mathbf{f}(\mathbf{x}) = \mathbf{G}\mathbf{x}$, where $\mathbf{G}$ is a constant matrix. The operation specified by (13) define the method of weighted least squares for estimating the parameter $\mathbf{x}$ when the observation consists of a discrete sequence. If $\mathbf{Q}(i, i)$ was identity matrices, then we would have the ordinary least squares problem. In the ordinary LS problem, we simply choose $l(\hat{\mathbf{x}})$ such that the expected observation (i.e., $z(i) = f_i(\mathbf{x})$ which ignores the noise $v(i)$) comes as close as possible to the actual measurement in LS sense of (13). Thus, when the measurement errors are small, the ML estimator gives an LS solution

$$\hat{\mathbf{x}} = (\mathbf{G^T Q^{-1} G})^{-1}\mathbf{G^T Q^{-1} z}. \tag{16}$$

It was shown above that the method of ML and LS yield the same results in the special case of additive white gaussian noise. Notice that a stochastic optimization problem characterized by ML estimation is in fact replaced by a deterministic optimization problem defined by (13).

For a nonlinear $\mathbf{f}(\mathbf{x})$, we have to linearize it in order to determine a reasonably simple estimator. The most straightforward linearization approach is to use the Taylor Series expansion. Consider a nonlinear state/measurement model in (15), we have measurement $\mathbf{z}$ and want to estimate $\mathbf{x}$. In addition, the k-dimension vector function $\mathbf{f}(\cdot)$ is assumed to be defined and "well-behaved" in particular, the first derivatives of $\mathbf{f}(\cdot)$ components with respect to $\mathbf{x}$ exists. Let $\mathbf{x}^*$ be an arbitrary estimate of the true state vector $\mathbf{x}$, then a weighted sum of squares of measurement residual J is defined by

$$J \doteq [\mathbf{z} - \mathbf{f}(\mathbf{x}^*)]^T \mathbf{Q}^{-1}[\mathbf{z} - \mathbf{f}(\mathbf{x}^*)]. \tag{17}$$

The objective of this nonlinear least squares estimation problem can be described as follows: For the measurement/state model of (15) and for the residual performance index given by (17) with $\mathbf{Q}^{-1}$, find that estimator $\mathbf{x}^*$ for which J in (17) is minimized.

The solution to this nonlinear problem will be an iterative one using perturbations. More specifically, the global properties of $\mathbf{f}(\cdot)$ will not be involved—it will be assumed that an initial guess (usually $\mathbf{x}_0$) for the required minimizing value in the problem is in a convergent neighborhood of this minimizing value. Thus, we define

$$\hat{\mathbf{x}}_{k+1} \doteq \hat{\mathbf{x}}_k + \delta_k,\ k = 0, 1, \cdots \tag{18}$$

as an iterative sequence for optimal estimate $\hat{\mathbf{x}}$:

$$\hat{\mathbf{x}} = \lim_{k \longrightarrow \infty} \hat{\mathbf{x}}_k. \tag{19}$$

Criteria for stopping the iteration in a finite number of steps will be introduced. For a general $(k + 1)$th step in the iteration, the value of the performance index J in (17) is

$$J(\hat{\mathbf{x}}_{k+1}) \doteq [\mathbf{z} - \mathbf{f}(\hat{\mathbf{x}}_{k+1})]^T \mathbf{Q}^{-1}[\mathbf{z} - \mathbf{f}(\hat{\mathbf{x}}_{k+1})]. \tag{20}$$

Combining (18) and (20) gives a perturbation equation in the performance index; i.e., the performance index value changes from $J(\hat{\mathbf{x}}_k)$ to $J(\hat{\mathbf{x}}_{k+1})$ if the estimator value is changed from $\hat{\mathbf{x}}_k$ to $\hat{\mathbf{x}}_{k+1}$. A perturbation of $J(\hat{\mathbf{x}}_{k+1}) - J(\hat{\mathbf{x}}_k)$ results from a perturbation of $\hat{\mathbf{x}}_{k+1} - \hat{\mathbf{x}}_k = \delta_k$. These are related by combining the equations

$$J(\hat{\mathbf{x}}_{k+1}) \doteq [\mathbf{z} - \mathbf{f}(\hat{\mathbf{x}}_k + \delta_k)]^T \mathbf{Q}^{-1} [\mathbf{z} - \mathbf{f}(\hat{\mathbf{x}}_k + \delta_k)]. \quad (21)$$

Now, we use linear perturbations by retaining only the first-order terms in an expansion for $\mathbf{f}(\cdot)$

$$\mathbf{f}(\hat{\mathbf{x}}_k + \delta_k) \simeq \mathbf{f}(\hat{\mathbf{x}}_k) + \frac{\partial \mathbf{f}}{\partial \mathbf{x}} |_{\mathbf{x}=\hat{\mathbf{x}}_k} \delta_k. \quad (22)$$

We then take that

$$\mathbf{f}(\hat{\mathbf{x}}_k + \delta_k) \simeq \mathbf{f}(\hat{\mathbf{x}}_k) + \mathbf{A}_k \delta_k \quad (23)$$

where the $m \times n$ matrix $\mathbf{A}_k$ is defined by

$$\mathbf{A}_k \doteq \frac{\partial \mathbf{f}}{\partial \mathbf{x}} |_{\mathbf{x}=\hat{\mathbf{x}}_k}. \quad (24)$$

Solving (21) gives the sought-after iterative solution algorithm for the nonlinear least squares problem

$$\hat{\mathbf{x}}_{k+1} = \hat{\mathbf{x}}_k + (\mathbf{A}_k^T \mathbf{Q}^{-1} \mathbf{A}_k)^{-1} \mathbf{A}_k^T \mathbf{Q}^{-1} [\mathbf{z} - \mathbf{f}(\hat{\mathbf{x}}_k)]. \quad (25)$$

In a practical application of the iterative algorithm, the iteration would be stopped after a finite number of steps and $\delta_\mathbf{k}$ would not in general be zero. An error is thus introduced into the estimate and is held to acceptable levels with iteration-stopping criteria discussed in conjunction with applications of iterative least squares in the text.

C. Solution to Hybrid TDOA/AOA/AOD Location Equations

In this section, we derive a location estimator to solve the nonlinear TDOA/AOA/AOD equations for the MS location. Let $\mathbf{x} = [x_m, y_m, x_1, y_1, \cdots, x_N, y_N]^T$ denote true positions of mobile station and scatterers, and we define $\mathbf{f}$ the $(3N-1)$ column vector valued function according to (4) and (5):

$$\mathbf{f}(\mathbf{x}) = \begin{pmatrix} \tau_i(x_m, y_m, x_i, y_i) \\ \vdots \\ \theta_i(x_m, y_m, x_i, y_i) \\ \vdots \\ \phi_i(x_m, y_m, x_i, y_i) \end{pmatrix}. \quad (26)$$

The estimation model of the unknown $(2N+2)$ column vector $\mathbf{x}$ in the presence of additive Gaussian noise is

$$\mathbf{z} = \mathbf{f}(\mathbf{x}) + \mathbf{n} \quad (27)$$

where $\mathbf{z} = [\hat{\tau}_i \cdots \hat{\theta}_i \cdots \hat{\phi}_i]^T$ are $(3N-1)$ measurement values [18]. And the measurement noise $\mathbf{n} = [n_{\tau_i} \cdots n_{\theta_i} \cdots n_{\phi_i}]^T$ is assumed to be a multivariate random vector with a $(3N-1) \times (3N-1)$ positive covariance matrix

$$\mathbf{Q} = E[(\mathbf{n} - E[\mathbf{n}])(\mathbf{n} - E[\mathbf{n}])^T]. \quad (28)$$

If the covariance matrix $\mathbf{Q}$ has zero mean, it can be further expressed as

$$\mathbf{Q} = \begin{pmatrix} \mathbf{Q}_t & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{Q}_d & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{Q}_a \end{pmatrix} \quad (29)$$

where $\mathbf{Q}_t$ is the covariance matrix for TDOA measurement errors, $\mathbf{Q}_d$ and $\mathbf{Q}_a$ are the covariance matrix for AOD and AOA measurement errors, respectively.

As shown in (24), we could have the gradient matrix [25]

$$\mathbf{A}_k = \begin{pmatrix} \frac{\partial f_1(\mathbf{x})}{\partial x_1} & \cdots & \frac{\partial f_1(\mathbf{x})}{\partial x_{2N+2}} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_{3N-1}(\mathbf{x})}{\partial x_1} & \cdots & \frac{\partial f_{3N-1}(\mathbf{x})}{\partial x_{2N+2}} \end{pmatrix} \quad (30)$$

where the gradient matrix $\mathbf{A}_k$ is a $(3N-1) \times (2N+2)$ matrix.

Assume $\mathbf{A}_k^T \mathbf{Q}^{-1} \mathbf{A}_k$ is nonsingular, similar to (25), the iterative nonlinear LS solution of the location estimator gives the estimated $\mathbf{x}$ for $(k+1)$th iteration

$$\hat{\mathbf{x}}_{k+1} = \mathbf{x}_k + (\mathbf{A}_k^T \mathbf{Q}^{-1} \mathbf{A}_k)^{-1} \mathbf{A}_k^T \mathbf{Q}^{-1} [\mathbf{z} - \mathbf{f}(\mathbf{x}_k)]. \quad (31)$$

Therefore, given a set of measured multipath signal parameters, such as TDOA between each pair of path, and AOD and AOA for each path, along with a previous estimate of the mobile's location and angles of departure and arrival of multipath signals, it is possible to determine values of $\delta_k = \mathbf{x}_{k+1} - \mathbf{x}_k$, to update the estimated position of MS and scatterers to more closely approximate the actual value. This process is repeated until the value of δ_k becomes smaller than a desired threshold, indicating convergence.

Now, let's summarize the procedure to obtain $\hat{\mathbf{x}}$ from (31) for the proposed method as follows:

1. Choose $\mathbf{x}_0$, initial guesstimate.
2. Linearize $\mathbf{f}$ about $\mathbf{x}_0$ and obtain $\mathbf{A}_k$ matrix.
3. Compute residuals $[\mathbf{z} - \mathbf{f}(\mathbf{x}_k)]$ and then compute the $\hat{\mathbf{x}}$.
4. Check for the orthogonality condition:
$$\mathbf{A}_k^T [\mathbf{z} - \mathbf{f}(\mathbf{x})] |_{\mathbf{x}=\hat{\mathbf{x}}} = 0.$$
5. If the above condition is not satisfied, then replace and repeat the procedure.
6. Terminate the iterations when the orthogonality condition is at least approximately satisfied.

V. ANALYSIS OF THE PROPOSED LOCATION METHOD FOR MIMO SYSTEMS

Suppose there are $N(\geq 4)$ multiple paths available between BS and MS with 2D array layout for determining the MS position, we have a set of over-determined nonlinear location equations. Because of measurement errors, the solution is not unique.

A. Cramer-Rao Lower Bound (CRLB)

The CRLB provides a lower bound on the variance of any unbiased parameter estimators. Hence, it is of interest to compare the proposed estimator with the optimum.

The CRLB of the mobile location problem is derived in the Appendix. It is given by

$$\Phi = \left(\frac{\partial \mathbf{f}^T(\mathbf{x})}{\partial \mathbf{x}} \mathbf{Q}^{-1} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}\right)^{-1} \quad (32)$$

where $\partial \mathbf{f}(\mathbf{x})/\partial \mathbf{x}$ is found to be the true value of $\mathbf{A}_k$ in (30).

B. Advantages of Proposed MIMO PL Method

The proposed hybrid TDOA/AOA/AOD location method for MIMO communication system exploits the spatial properties of the multipath channel, and then it can resolve more signal parameters than traditional PL methods. It has the following advantages:

1. No time synchronization required: All the propagation time-based PL systems require precise time synchronization of all involved measuring units. For the proposed method, since only one base station is involved in the position location, the time synchronization is straightforward.
2. No multilateration: Most position location approaches require measurements at multiple receiving stations. This requirement is counter to the cellular network design that assigns one base station to serve a given user. Our new method uses single base station to perform position location in wireless MIMO communication systems.
3. No LOS signal required: Most PL systems require LOS communication links. However, such direct links do not always exit in reality because of the intrinsic complexity of mobile channels. In this work, the proposed method can not only work perfectly without LOS signal, but also find the LOS signal.
4. Less network traffic for PL system: Since only one base station is required for location estimation, it will generate less location update information in the whole PL system. Thus, the overall network traffic related to PL can be reduced. Moreover, PL information collection by the network is facilitated.

VI. SIMULATIONS AND RESULTS

The performance of the proposed mobile location method for MIMO communication system is investigated by computer simulations. The geometric scatterers arrangement in Fig. 7 is used as an example which is a simplified MIMO channel propagation model based on 3GPP standard [19]. In this model, we assume that the signal follow N paths and that along the ith path, the signal is only scattered by only one obstacle at the planar location (x_i, y_i). For the two dimensional array MS and BS layout, we have BS much higher than MS and most scatterers. For simplicity, we assume that the signals and noises are Gaussian random process. The TDOA covariance matrix $\mathbf{Q}_t$ is similar to [17] which has TDOA variance σ_t^2 for diagonal elements and $0.5\sigma_t^2$ for all other elements. The TDOA estimates are simulated by adding to the actual TDOA's correlated Gaussian random noises with covariance matrix given by $\mathbf{Q}_t$. The AOD covariance matrix $\mathbf{Q}_d$ and the AOA covariance matrix $\mathbf{Q}_a$ have AOD variance σ_d^2 and AOA variance σ_a^2 as their diagonal elements, respectively.

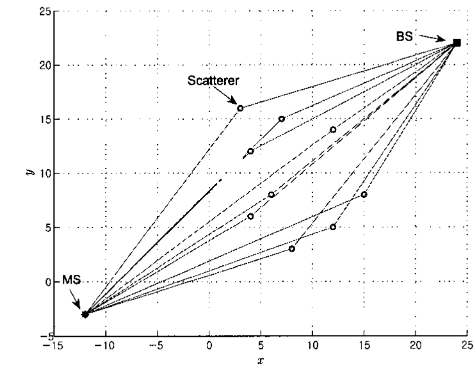

Fig. 7. Geometry arrangement of scatters between MS and BS.

Table 1. Positions of all scatterers.

N	1	2	3	4	5	6	7	8	9	10
x	7	3	15	4	12	8	12	4	3	6
y	15	16	8	6	14	3	5	12	3	8

The Taylor series estimator is used to derive the MS location. The measured AOD and AOA information are used as initial guess of AOD and AOA, and location error (about 5 percent of distance between MS and BS) is added to true MS location as initial guess of MS position. Simulations show that at most five iterations are required for Taylor series solutions to converge. A validity test at each step is implemented. We compute $\det[\mathbf{A}_k^T \mathbf{Q}^{-1} \mathbf{A}_k]$ and reject the input data or the position guess if this number is too small. To detect the failure of convergence, we compute the trace of $(\mathbf{A}_k^T \mathbf{Q}^{-1} \mathbf{A}_k)^{-1}$ at the end of each iteration, and after five steps or so, start to compare it with that of the previous step. If the ratio is not much less than unity, the process is not converging. The squared error of MS location estimation is derived at the end of iteration, as a useful check on the validity of the solution. The *mean square error* (MSE) is obtained from the average of 10,000 independent runs. For each simulation run, the noise corrupted measurements are used where the noises are generated according to the standard deviation of TDOA, AOA, and AOD. The iterative computation time of each simulation run is less than 0.01 second.

The position of all scatterers are given in Table 1 with MS at position $(-12, -3)$, and BS at position $(24, 22)$. The distance unit is 100m in this work. The squared error, MSE and CRLB values use the same unit.

In Fig. 8, the squared location error estimations are compared as the number of scatterers increases from 4 to 10. The TDOA noise standard deviation is set to be $\sqrt{0.0005}/c$, whereas the AOD and AOA noise standard deviation is 0.3 degree and 0.1 degree, respectively. It is clear that the proposed method performs better with more scatterers since there are more location equations than unknown parameters. For example, if $N = 4$, we have 11 location equations and 10 parameters to estimate; however, as $N = 10$, we have 29 location equations and 22 parameters to estimate. Thus, the performance improvement introduced by additional scatterers is significant.

Table 2 compares the MSE errors with the CRLB. The first two diagonal elements from (32) are used to compute the CRLB

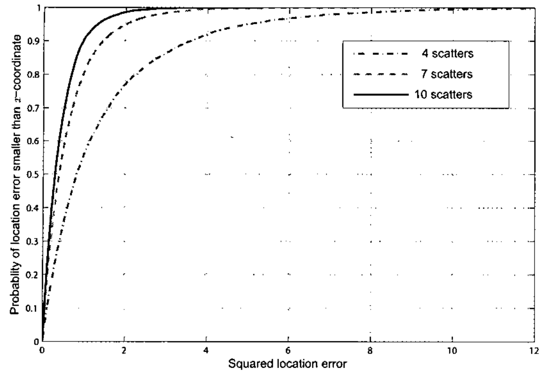

Fig. 8. Squared location error with different scatterers' geometry arrangement.

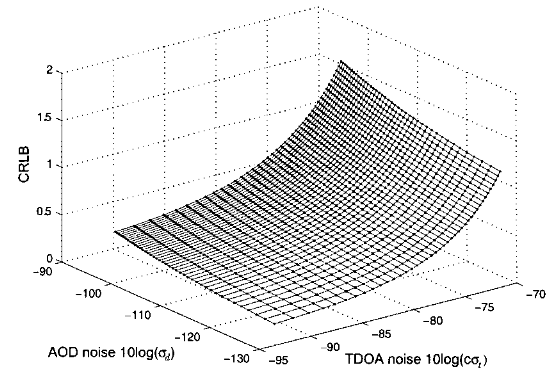

Fig. 10. CRLB with different TDOA and AOD noise measurement.

Table 2. Comparison of MSE error with CRLB.

Multipaths	MSE	CRLB
$N = 4$	1.4479	1.1869
$N = 5$	0.9775	0.8781
$N = 6$	0.7254	0.6147
$N = 7$	0.6214	0.5319
$N = 8$	0.6082	0.5247
$N = 9$	0.4667	0.4398
$N = 10$	0.4319	0.4100

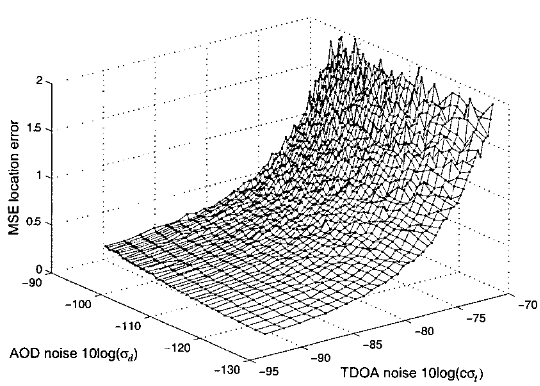

Fig. 9. MSE with different TDOA and AOD noise measurement.

for MS location estimation. The standard deviation of TDOA, AOA, and AOD are the same as Fig. 8. From the results, we can see that the position of MS can be estimated with high accuracy, and MSE error estimation of the proposed method approaches CRLB very closely.

In Fig. 9, we show a 3D illustration of the MSE estimation with different TDOA and AOD noise measurement, whereas the AOA noise standard deviation is set to be 0.1 degree. The simulation results show that the maximum value of MSE is lower than 2. Similarly, we show a 3D illustration of the CRLB in Fig. 10.

VII. CONCLUSIONS

For conventional mobile location methods, multi-lateration of several BSs is required to give location estimation. In this work, we proposed a novel mobile location estimation method for MIMO communication systems. The advantage of MIMO systems is to use multiple antennas at both sides, thus multipath will be utilized to enhance overall performance of wireless communication. Moreover, it is also possible to estimate more parameters of multipath signals such as AOA, AOD, and TDOA.

Using measured multipath signal parameters in MIMO systems, such as AOD and AOA for each path, as well as TDOA between each pair of path, an over-determined system can be established with a set of nonlinear location equations. The proposed hybrid TDOA/AOA/AOD location method utilizes Taylor series linearization to give a iterative nonlinear LS solution. With an initial guess of the mobile's position, the least-squared difference between true MS position and previous estimation of MS position will be minimized. This process is repeated iteratively until the difference under a desired threshold. The performance of the proposed method has been evaluated through computer simulation. The Cramer-Rao lower bound is also derived.

This method is able to determine the position of the mobile station so as to minimize the measurement noise by using single base station. It would be a revolution for PL problems by takeing full advantage of the power of MIMO communication system for multipath dispersion.

APPENDIX: CRAMER-RAO LOWER BOUND

The CRLB is a lower bound on the variance of any unbiased estimator. We now derive the CRLB for the proposed MIMO Hybrid TDOA/AOA/AOD method. The vector of TDOA/AOA/AOD measurements $\mathbf{z}$ in (15) is asymptotically zero mean Gaussian with covariance matrix given by $\mathbf{Q}$, the conditional probability density function is

$$P(\mathbf{z}|\mathbf{x}) = \frac{\exp\left\{-\frac{1}{2}(\mathbf{z}-\mathbf{f}(\mathbf{x}))^T\mathbf{Q}^{-1}(\mathbf{z}-\mathbf{f}(\mathbf{x}))\right\}}{(2\pi)^{k/2}|\mathbf{Q}|^{1/2}}. \quad (33)$$

If the MIMO hybrid measurement errors are small so that the bias square is insignificant compared with the variance, the CRLB of $\mathbf{x}$ is given by [6]

$$\mathbf{\Phi} = \left\{E\left[\left(\frac{\partial}{\partial \mathbf{x}}\ln P(\mathbf{z}|\mathbf{x})\right)\left(\frac{\partial}{\partial \mathbf{x}}\ln P(\mathbf{z}|\mathbf{x})\right)^T\right]\right\}^{-1}. \quad (34)$$

From vector calculus, if $\mathbf{z}$ is a $K \times 1$ vector and A is a $K \times K$ symmetric matrix, then

$$\frac{d}{d\mathbf{z}}(\mathbf{z}^T\mathbf{A}\mathbf{z}) = 2\mathbf{A}\mathbf{z}. \tag{35}$$

Thus, the partial derivative of $\ln P(\mathbf{z}|\mathbf{x})$ with respect to $\mathbf{x}$ is

$$\frac{\partial}{\partial \mathbf{x}} \ln P(\mathbf{z}|\mathbf{x}) = -\frac{\partial \mathbf{f}^T(\mathbf{x})}{\partial \mathbf{x}} \mathbf{Q}^{-1}(\mathbf{z} - \mathbf{f}(\mathbf{x})). \tag{36}$$

Hence,

$$\mathbf{\Phi} = \left(\frac{\partial \mathbf{f}^{\mathbf{T}}(\mathbf{x})}{\partial \mathbf{x}} \mathbf{Q}^{-1} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} \right)^{-\mathbf{1}} \tag{37}$$

where $\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}$ is found to be the true value of $\mathbf{A}_k$ in (30).

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