Enhanced Tracking Performance with Signal Amplitude Information of Sensor Networks*

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Abstract -

Automatic multi-target tracking in a binary sensor network needs to solve the simultaneous multiple sources localization problem. The virtual measurement (VM) approach [1] provides a way to solve this problem via the integrated sensing processing (ISP). In the VM approach, a set of activated sensor detections are mapped into a set of virtual measurements as if they were observed by a large sensor. The set of VMs are then used for multi-target tracking. A drawback of this method is that some VMs may have larger variances when sensor nodes are sparsely distributed, which can yield considerably large estimation error. In this paper, we present a method to reduce the uncertainty of VMs using relative signal amplitude information at the cost of communicating more bits from activated sensors to base station. Instead of assigning a VM, we estimate the target source position using relative signal amplitude information which is also known as received signal strength (RSS) and is assumed to be available to the base station. This position is then treated as an alternative VM used by a LMIPDA tracker. Simulation results shown that an improved tracking accuracy can be obtained compared to the case where the standard VMs are used.

Keywords: Multi-target tracking, Integrated Sensing and Processing, Virtual Measurement, Signal amplitude information, Localization.

1 Introduction

Advanced applications for networks of small low-cost sensors like motes have evoked increasingly interest to scientific researchers in recent years. A typical problem is the automatic target tracking in the distributed sensor networks [2].

We consider a centralized tracking problem, where the entire surveillance region is covered by passive sensor nodes whose locations and sensing ranges are known to the base station (or dominant sensor node) which performs target tracking and exchange information with other networks. The sensor nodes are constrained by power, sensing and processing capabilities and are usually deployed in a significant number. It is often appropriate to model them as simple binary sensors, i.e., the output of a sensor has a binary outcome, e.g., target present or target absent, so as to avoid expensive signal processing and save communication bandwidth [3, 4, 5]. A sensor is activated if a moving target is entering its sensing range. At each data sampling time, the activated sensors signal base station via wireless communications and the base station estimate the target states.

Automatic multi-target tracking in this environment needs to solve the simultaneous multiple sources localization problem based on (active) sensor detections [6, 7]. This is apparent in the context of classical target tracking, where large sensors are considered [2]. However, for binary sensors, it is not trivial to solve the problem via available techniques of either signal processing [8] or stochastic filtering [9, 10]. The primary difficulty is the development of an appropriate integrated sensing and processing (ISP) technique which can recover target location information from highly compressed sensor data.

A number of approaches in this context have been proposed, see for references in [3, 4, 5, 1]. Most of them, except [1], naturally choose the particle filtering technique as the backbone of their ISP. It is not clear whether they can handle multiple target tracking problem. In addition, the computational complexity may become an issue for the low-cost sensors. The virtual measurement (VM) approach proposed in [1], convert the problem into a classical multi-target tracking framework, where computationally efficient algorithms are available. At each scan a set of activated sensor detections are mapped into a set of virtual measurements as if they were observed by a large sensor. The set of VMs is then feeded into a classical multi-target tracker (MTT) for automatic multi-target tracking. A drawback of this method is that some VMs may have large variances when sensor nodes are sparse distributed, which may cause large estimation errors.

In this paper, we present a method for reducing uncertainties of VMs via sensor received signal amplitude information and therefore, improve tracking accuracy under the framework of VM approach. To this end, we assume that additional bits can be transmitted be-

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\[ w_n \]

They are distributed to cover the area of interest by

\[ N \]

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signal amplitude information is discussed in Section

\[ 4 \]

the localization of a single target source via detected

\[ 5 \text{ problem of multi-target tracking in a binary sensor net-} \]

between sensors and base station. This was motivated by

the following observations:

- The detected RSS is readily available at sensors
  as for many type of small sensors (such as acoustic
  sensors) the binary detection outcomes are ob-
  tained by the thresholding operation on the re-
  ceived signal. Figure 1 illustrates an example,
  where sensors \( s_1, s_2 \) and \( s_3 \) are activated though
  all sensors received signal from the target.

- It is relatively simple to localize a single target
  source (rather than multiple target sources) us-
  ing RSS received from multiple sensors, while the
  VM approach offers such a framework (even when
  multiple target sources are present).

The rest of the paper is organized as follows. The
problem of multi-target tracking in a binary sensor
network and the VM approach are described in Section 2,
the localization of a single target source via detected
signal amplitude information is discussed in Section 3,
where a modified VM-AM algorithm is proposed,
Section 4 presents simulation results and discussions.
Finally, conclusion is addressed in Section 5.

2 Problem and VM approach

Let a binary sensor network have a set of \( N \) sensors
(motes) and a base station. The sensors have their
sensing ranges \( R_i \) at locations \( r_i \), \( i = 1, 2, \ldots, N \).
They are distributed to cover the area of interest by
joint or non-joint sensing field where \( n \) targets of states
\( x_j \sim [\text{position}, \text{velocity}, \cdot \cdot \cdot ] \), \( j = 1, 2, \ldots, n \) may
be present. The \( j \)th target trajectory may be modeled as
a Markov process,

\[ x_{k+1}^j = f(k, x_k^j, w_k^j) + w_k^j \quad j = 1, 2, \ldots, n \]  

(1)

where \( f \) is the state transition function, \( u \) is an input
parameter for target dynamics and \( w \) is process noise.

Target detection of the \( i \)th of \( N \) sensors is a binary
output based on the model

\[ z_k^i = h(k, ||x_k^i - r_i||) + v_k^i, \quad \forall j = 1, 2, \ldots, n \]  

(2)

where \( v_k^i \) is a noise term to account for uncertainties
associated with sensor location, target location, sens-
- ing range and the environment of sensor field, etc. In
particular,

\[ z_k^i = \begin{cases} 1, \text{ with } 0 \leq P_D \leq 1, & \text{if } ||x_k^i - r_i|| \leq R_i \\ 0, & \text{otherwise} \end{cases} \]  

(3)

where \( \forall j = 1, 2, \ldots, n \). If the output of the \( i \)th
sensor equals to one, we say that the \( i \)th sensor is ac-
- tivated. At each time \( k \), base station will collect sensor
detection outputs \( Z_k = \{ z_k^1, z_k^2, \ldots \} \) from all activated

sensors.

The problem is to estimate those target states using
all available prior information and sensor detections up
to time \( k \) collected by the base station, i.e., find the
conditional posterior densities

\[ p(x_k|Z_k, Z_{k-1}, \cdots), \forall j = 1, 2, \ldots, n \]  

(4)

In [1], a virtual measurement space \( Y \), which is a
mapping of the target state space \( X \), is defined, such
that, for any set of sensor detections \( Z_k \), a unique set
of \( Y_k \subseteq Y \) can be found and the solution to (4) is
converted to

\[ p(x_k^i|Y_k, Y_{k-1}, \cdots), \forall j = 1, 2, \ldots, n \]  

(5)

which can be solved using conventional algorithms of
multi-target tracking in clutter [11, 10, 9, 7].

Figure 2: Distinct sensing regions of the sensor net-
work are characterized using random variables – vir-
tual measurements.

As illustrated in Figure 2, the surveillance region
covered by a binary sensor network comprises of a set
of distinct sensing regions (DSR). In general, the more
DSRs the network has, the more target information
can be acquired through sensor detection. In the VM
approach, these DSRs are characterized using a set of
random variables, called virtual measurements. The
mean of each VM is the center of the corresponding DSR and its variance is approximated by the maximum spans of the DSR in each axis direction. The set of VMs construct the $\gamma$ space.

One of the remarkable points in the VM approach is that a DSR (see Figure 2), characterized by a VM, describes the resolution of “an equivalent sensor”, which is the function of sensor distribution. In other words, at most a single target source can be detected in a DSR. Clearly, a better approximation for a VM can yield a more accurate “sensor observation” and thus a smaller state estimate error. Next we discuss the use of RSS received from activated sensors to reduce the uncertainty of a VM within a DSR.

3 Signal Amplitude Information

The VM approach [1] promises a framework for the presence of multiple target sources where we can simply deal with the problem of localizing a single target source given it is in a specific area covered by a set of sensors. Following the VM approach, we use signal amplitude information to narrow down the location of a possible target source (a virtual measurement) and obtain a better statistics of the VM for the MTT and thereby an improved tracking performance.

3.1 Signal Amplitude Model

According to [12], the amplitude of an electronic signal received by the $i$th out of $N$ sensors follows an isotropic signal power attenuation model

$$a_i^2 = \frac{P_0}{1 + \alpha r_i^n} \quad i = 1, 2, \cdots, N \quad (6)$$

where $\alpha$ is an adjustable constant and $n$ is the signal decay exponent which takes values between 2 and 3, $r$ is the relative distance between the target detected and the sensor. Denoted by $x_k$ the target state at time $k$, and $H$ a transition matrix, the relative distance may be expressed as

$$r_i = ||H x_k - y_i^0||$$

where $y_i^0$ is the location vector of the $i$th sensor. $P_0$ in (6) is the reference power, i.e., the signal power received from the target at zero distance $r_i = 0$.

The sensor observed signal amplitude may be fluctuating due to the presence of uncertainties in the process of sensor detection, which include the contributions of 1) signal from other objects; 2) quantization errors and thermal-noise; 3) environment etc. Taking these factors into account, we approximate the signal amplitude actually observed by the $i$th sensor as

$$A_i = a_i + v_{i,k} \quad (7)$$

where $v_{i,k} \sim N(0, \sigma_v^2)$ is zero-mean Gaussian noise with known variance $\sigma_v^2$. We use the signal to noise ratio (SNR) to measure the quality (uncertainty) of the signal received by a sensor, which is defined as

$$\text{SNR} = 10 \log_{10} \left( \frac{A_i^2}{\sigma_i^2} \right), \quad i = 1, 2, \cdots, N \quad (8)$$

where $A_i^2$ is the average signal power observed by the $i$th sensor, $\sigma_i^2$ is the average noise power observed by the sensor.

Equation (6) is isotropic. This implies that in 2D case, we need RSS signal received from three or more separated sensors for target localization when only one target source is present. In the presence of RSS noise, the localization results in a random variable. We will replace the related VM using this random variable if it is of less uncertainty. In the case of 2 sensors, it is still possible to reduce the uncertainty of the original VM by using RSS information. We discuss this further below.

3.2 Two Sensors Detection

Assume that a target at location $T_p = [x, y]^T$ is simultaneously observed by 2 sensors at locations $S_1 = [x_1, y_1]^T$ and $S_2 = [x_2, y_2]^T$, with signal amplitudes $A_1$ and $A_2$ respectively. Sensor reference power ($P_0$ in (6)) is identical to all sensors. Using Equation (6), we can obtain

$$A_1^2 + A_1^2 \alpha r_1^n - A_2^2 - A_2^2 \alpha r_2^n = 0 \quad (9)$$

where the relative distances are given by

$$r_i = ||T_p - S_i|| \quad i = 1, 2.$$

Figure 3: Example of target location curves in 2 sensor detection case parameterized by the signal amplitude ratio ($A_1/A_2$).

In the absence of RSS noise, Equation (9) defines a curve (rather than a point), on which a target source will yield a constant amplitude ratio of signals received by both sensors. Figure 3 depicts possible locations of the target source at different signal amplitude ratios. The curve will become curve band when RSS noise is present.
Clearly, the signal amplitude information from only 2 sensors is not enough to localize a 2D target source of \((x, y)\). However, in the framework of the VM approach, we can use this information to narrow down the uncertainty of a VM in the direction in line between sensors. In particular, we assume that the mean of a VM lies on the line between these 2 sensors within its DSR (instead of being the center of the DSR as in the VM approach). The mean of the VM can then be determined via Equation (9). We approximate the variance of the modified VM as the same (i.e., the “worst” case) variance as in the VM approach.

3.3 Three Sensors Detection

Similar to equation (9), the target location \(T_p = [x, y]_\text{opt}\) can be isolated from the signal amplitudes detected by 3 sensors by solving the following equations:

\[
\begin{align*}
A_1^2 + A_1^2 \alpha r_1^2 & - A_2^2 - A_2^2 \alpha r_2^2 = 0 \\
A_1^2 + A_1^2 \alpha r_1^2 & - A_3^2 - A_3^2 \alpha r_3^2 = 0
\end{align*}
\] (10)

where \(r_i = ||T_p - S_i|| \quad i = 1, 2, 3\).

The equations (10) determine the point (in 2D case) at which a target source will activate sensors \(s_1, s_2\) and \(s_3\) with the signal of amplitudes of \(A_1, A_2\) and \(A_3\) observed by these sensors respectively. In practice, the solution of (10) can be obtained by using a root-finding algorithm (such as Newton iteration). Note that, however, undesired solutions may be obtained. Figure 4 shows a no solution case, Figure 5 shows a two solutions case and Figure 6 shows a single solution case. In addition, the processing complexity can step up when multiple target sources are presented.

In the framework of the VM approach, each DSR is covered by an independently activated sensor group (IASG) and each IASG is assumed to be triggered by a single target source. It turns out that within the VM framework, the signal amplitude information becomes useful for reducing the ambiguity of a VM. Because 1) only a single target source is involved, 2) given that the target is in a DSR enclosed by 3 or more sensors you can always find the correct solution from Equation (10). This situation is depicted in Figure 6 for noiseless case. If an IASG has more than 3 sensors, we may pick the signal amplitude information from any three of these sensors (in 2D case) to solve Equation (10).

In the presence of RSS noise as in (7), the localization process will result in a random variable. This random variable is treated as an alternative VM (which, for clarification, is denoted as VM-AM) associated with a DSR. Since it is difficult to obtain the closed form of the solution of the nonlinear equation (10), we adopt the technique of unscented transformation presented in [13] to find the mean and variance of the VM-AM.

Let \(A = [A_1, A_2, A_3]'\) be the RSS of the target detected by three sensors of locations \(S = [S_1, S_2, S_3]'\); and \(v = [v_1, v_2, v_3]'\) be a Gaussian zeros mean ran-
dom vector with variance $V = \text{diag}\{\sigma_1^2, \sigma_2^2, \sigma_3^2\}$, where $\sigma_i$, $i = 1, 2, 3$ is the standard deviation of $v_i$. For convenience, we denote the solution of (10) as

$$T_p = f(A, S, \alpha) \quad (11)$$

For each set of RSS detections $A$, a set of $2N_A$ sigma points is calculated [13].

$$A^i = \bar{A} + (\sqrt{N_A}V)_i,$$

$$W^i = \frac{1}{2N_A},$$

$$A_i + N_A = \bar{A} - (\sqrt{N_A}V)_i,$$

$$W_i + N_A = \frac{1}{2N_A} \quad (12)$$

where $N_A = 3$ is the dimension of the vector $A$, $(\sqrt{N_A}V)_i$ denotes the $i$th column of the variance matrix $V$, $W^i$ is the weight associated with the $i$th point $A^i$. $\bar{A}$ is the mean of $A$. For small noise term $v_i$, $i = 1, 2, 3$ in (7) (compared to $A_i$), we may approximate $\bar{A} \approx A$.

Given the above set of sigma points, the VM-AM (denoted as $T_p$) associated with these three sensor detections $A$ can be calculated as follows.

$$T_p = \frac{2N_A}{\sum_{i=1}^{2N_A} W^i T_p} \quad (13)$$

$$\Sigma T_p = \frac{2N_A}{\sum_{i=1}^{2N_A} W^i (T_p - \bar{T}_p)(T_p - \bar{T}_p)^T} \quad (14)$$

where the transformed sigma points $T_p^i$, $i = 1, 2, \cdots, 2N_A$ can be obtained using (11). $\Sigma T_p$ is the approximated variance of the VM-AM.

Figure 7 illustrated the “observed” target distribution via 3 binary sensors from 100 Monte Carlo runs. The target is located at the geometric center of the locations of sensors 1, 2, 3 and the red dots are locations of the target calculated using (11) based on the RSS of SNR = 14 dB received from these 3 sensors. The green circle is the contour of $3 - \sigma$ variance calculated via unscented transformation. We assume that the sensing ranges $R_i$ of these 3 sensors are identical.

**Observations:**

1. The variance of VM-AM calculated via unscented transformation (green circle) does not depend on sensing range $R_i$, while the variance of VM does.

2. If $R = 10$, the overlapping area of 3 sensors which corresponds to the DSR in red thin curve abc is comparable to the distribution of the observed target (i.e., the corresponding VM).

3. However, if $R = 20$ (corresponding to blue dash curve ABC) the uncertainty of the associated VM is much larger than that calculated via signal amplitudes.

Figure 7 indicates that the gains on the accuracy of VM could be significant by using signal amplitude information. Furthermore, when RSS involves more that three sensor detections, we may repeat the trilateration localization for each 3 sensors and obtain even accurate VM-AM via averaging.

### 3.4 VM-AM algorithm

As detailed in [1], the standard VM approach consists of following 2 processes:

1. Network Initialization — obtain VM space.

2. Target Tracking — on line estimation of the states of all targets in the area covered by the sensor network based on the collection of binary sensor detections. At each epoch, on receiving data, the algorithm performs following 2 tasks:

   (a) Identify IASGs, and assign VMs accordingly;

   (b) Conventional multi-target tracking in clutter using the assigned VMs.

In order to utilize signal amplitude information, we have developed a modified VM assignment, called the VM-AM algorithm for assigning VMs in the target tracking process. The process of the modified VM assignment is illustrated in Figure 8, where we assume that the signal amplitude information is available from each activated sensor at the base station at each time. For each identified IASG that contains more than one sensor, an alternative VM (i.e., VM-AM) is computed using signal amplitude information in addition to the originally associated VM. The MTT tracker will then use the VM with smaller uncertainty.

The concept of VM-AM is same as VM, except that both the mean and variance of the VM are calculated via signal amplitude information.

### 4 Simulation Result

With detection signal amplitude information available, we evaluate the proposed method via the scenario used in [1]. As shown in Figure 9, a sensor network comprises of 100 sensors which are uniformly distributed.
Sensors have identical sensing range of 10 meters. A base station (or dominant sensor node) receives signals including signal amplitude information from activated sensors at each data sampling time. The collected data is then processed and a set of VM are assigned to a MTT which is implemented based on the linear multi-target integrated probabilistic data association (LMIPDA) algorithm [14, 15]. In the context of mote tracking, this algorithm has offered following advantages:

- Lower computational complexity (linear to number of targets)
- Probabilistic target confidence measure which can be conveniently used for track assessment in the multi-target tracker.

Target motion is described by

$$x_{k+1} = Fx_k + Gw(k)$$

and the state of target can be “observed” according to

$$y_k = Hx_k + v_k$$

where \(x_k\) is the target state, a vector with four components that includes target position and velocity in a 2D Cartesian coordinate system at time \(k\), \(y_k\) is the VM assigned at time \(k\), \(F\), \(H\) and \(G\) are known transition matrices given by

$$F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \quad G = \begin{bmatrix} T^2/2 & 0 \\ 0 & T \\ 0 & T^2/2 \\ 0 & T \end{bmatrix},$$

with \(T = 1\) (sec) being the sampling period. As in [6], the system process noise and observation noise are assumed to be Gaussian, i.e., \(w_k \sim \mathcal{N}(0, Q_k)\) and \(v_k \sim \mathcal{N}(0, S_k)\), \(Q_k = GG^Tq^2\), \(q = 0.5\) and \(S_k\) is determined by VM assigned at \(k\). In [1], the variance of a VM is approximated by a diagonal matrix \(\text{diag}(\sigma_x^2, \sigma_y^2)\), where \(\sigma_x\) and \(\sigma_y\) are the maximum spans of the corresponding DSR areas of the VM in \(x\) and \(y\) directions respectively.

Sensor received signal amplitude from the target was generated based on Equations (6) \((\alpha = 1, n = 2)\) and (7). The Gaussian noise term in (7) was chosen such that the sensor observed SNR are 3 dB and 7 dB respectively.

As we mentioned, the variance of a VM-AM may be approximately obtained via Monte Carlo simulation with given SNR and noise level. However, in our simulation, we used the “worst case”– variance of the standard VM instead. An identical detection probability \(P_D = 0.9\) for all sensors is assumed. Simulation results are summarized over 1000 Monte Carlo runs (no track loss), where Table 4 presents the average VM assignment performance over 50 scans, Figures 10 and 11 show the comparison of root-mean-squared (RMS) errors between the estimated target state and the ground truth, where three cases were considered: 1) SNR = 7 dB, 2) SNR = 3 dB, 3) original VM assignment without taking signal amplitude into account.

<table>
<thead>
<tr>
<th>Table 4: VM Statistics (over 1000 runs)</th>
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<tbody>
<tr>
<td>Average No. of VMs assigned/50 Scans</td>
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<tr>
<td>Average No. of VMs assigned/Per Scan</td>
</tr>
<tr>
<td>VMs assigned from 1 sensor detection</td>
</tr>
<tr>
<td>VMs assigned from 2 sensor detections</td>
</tr>
<tr>
<td>VMs assigned from &gt; 2 sensor detections</td>
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Result Discussion:

1. An improved tracking performance can be obtained when SNR level is above 3 dB as seen in Figures 10 and 11, especially, when the signal SNR is high (e.g. 7dB).
2. In this particular scenario, more than half of VMs are generated based on a single sensor detection as indicated in Table 4. Since only a small percentage of VMs were due to 2 or more than 2 sensor detections and assigned using VM-AM (method), the influence of the proposed method to the tracking accuracy was not as significant as we expected even with high SNR.

3. In the simulation, we assumed that the noise term in (7) is independent of the sensor sensing boundary noise. In fact, the two noises are correlated, that is, a lower SNR corresponds to a shorter sensing range with the larger uncertainty. In other words, the simulation results suggest that the proposed method can improve the tracking performance compared to the standard VM approach when high SNR is available.

5 Conclusion

In this paper, we proposed a method which uses the detected signal amplitude information to improve the accuracy of VMs and thus the tracking performance in the framework of the VM approach. The detected RSS received by 2 or more sensors in an IASG is used to recalculate the statistics (mean and variance) of the corresponding VM.

Simulation results demonstrate that an improved tracking performance over the standard VM approach can be achieved by taking signal amplitude information into account when detected signal of higher SNR is available. The proposed method is particularly useful when sensors of the network have large sensing ranges and sparse placement.

References


