A Hybrid Data Fusion Based Cooperative Localization Approach for Cellular Networks

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***Abstract*—One of the major challenges of Cellular network based localization techniques is lack of hearability between mobile terminals (MTs) and base stations (BSs), thus the number of available anchors is limited. In order to solve the hearability problem, previous work assume some of the MTs have their location information via Global Positioning System (GPS). These located MT can be utilized to find the location of an un-located MT without GPS receiver. However, its performance is still limited by the number of available located MTs for cooperation. This paper consider a practical scenario that hearability is only possible between a MT and its home BS. Only one located MT together with the home BS are utilized to find the location of the un-located MT. A hybrid cooperative localization approach is proposed to combine time-of-arrival and received signal strength based fingerprinting techniques. It is shown in simulations that the proposed hybrid approach outperform the stand-alone time-of-arrival techniques or received signal strength based fingerprinting techniques in the considered scenario. It is also found that the proposed approach offer better accuracy with larger distance between the located MT and the home BS.**

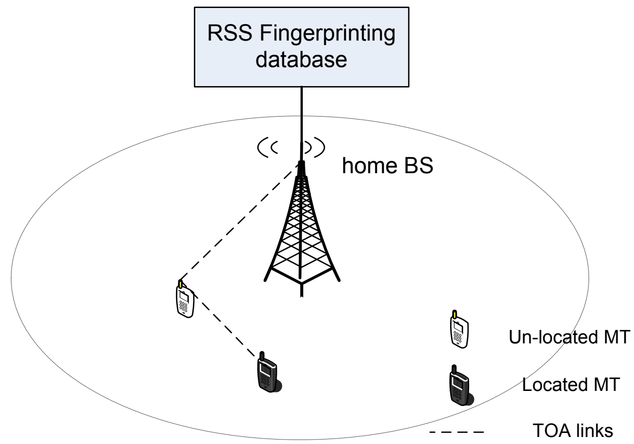

Fig. 1. Considered Scenario

I. Introduction

Cellular network based localization techniques have recently received increasing interests in both localization and communication community, e.g., [1]-[7]. This is not only because of the request made by Federal Communication Commission (FCC) about the accurate localization of the mobile terminals (MTs), but many other applications about the location information such as location sensitive billing, fleet management, mobile yellow pages, etc. [8]. Previous approaches includes time-of-arrival (TOA) [1], time-difference-of-arrival (TDOA) [2], angle-of-arrival (AOA) [9], received signal strength (RSS) techniques [3], and fingerprinting based approaches [10]. Various signal characteristics, including RSS and multipath delay can be utilized for fingerprinting based localization [10].

The location estimation is based on training sequences sent by MTs or BSs. Usually, the BSs serve as reference nodes (i.e. anchors) for localization. TOA and TDOA approaches generally require at least three BSs for localization. AOA approaches, on the other hand, require only a minimum of two BSs. If the number of available BSs is less than the minimum requirement, ambiguities of location estimation exist and a large estimation error may be introduced. Hybrid techniques, which utilize combinations of the available parameters, have also been proposed, e.g., [9]-[11]. These approaches are especially useful in hearability-restricted conditions, where power control is employed [12].

Cooperative localization is also a suitable approach in hearability-restricted conditions. Previous work about cooperative localization for cellular networks are proposed in [12]-[14]. For example, the work in [14] employs Global Positioning System (GPS) enable MTs (i.e. located MTs) to serve as anchors. Then, at least three located MTs can find the location of an un-located MT. In this case, even if no BS is involved in localization, localization of the un-located MT is possible. However, cooperative localization is still limited by the number of available located MTs for cooperation, especially when the density of MTs is low.

This paper consider a hearability-restricted scenario, which is depicted in Fig. 1. In this scenario, hearability is only possible between an un-located MT and its home BS, which can serves as an anchor. This scenario reflect a practical case, where the un-located MT is located nearing the home BS. In this case, the hearability may not be possible between a MT and its inter-cell BSs due to interference. Since the number of available MTs may also be limited in some practical case, we also assume only one located MT is available to help the un-located MT to find its location.

In the considered scenario, TOA techniques is employed to estimate the distance between the un-located MT and the home BS (or the located MT). The reason we consider TOA based distance estimation is that it offer more accurate distance estimation than RSS based techniques [15]. Moreover, an

RSS fingerprinting database is connected to the home BS, which can estimate the location of the un-located MT if the corresponding RSS information is obtained.

Since there are totally only two anchors available, ambiguity of location estimation exists for TOA approaches. The ambiguities also exist using the RSS based fingerprinting approach. These ambiguities are caused by the same RSS measurement for difference location of the un-located MT. Since ambiguities exist for both the TOA approach and RSS based fingerprinting approach in this scenario, the localization accuracy degrades significantly. In order to remove the ambiguities and improve the localization accuracy, a hybrid data fusion based approach is proposed to fuse the estimates obtained from both of the two approaches. The simulation results show that the proposed approach can offer much more accurate location estimation than TOA approaches or RSS based fingerprinting approach in the considered scenario. Moreover, the proposed approach offer better accuracy with larger distance between the located MT and the home BS.

II. System Model

As depicted in Fig. 1, an un-located MT has only two anchors, including the home BS and the located MT. Training sequences are sent between the un-located MT and the home BS (or the located MT) for TOA estimation. Training sequences for RSS-based fingerprinting approach are sent between the un-located MT and its home BS. Different training signal is sent with different time or frequency to avoid collision. All the estimated TOA and RSS are collected at the home BS for centralized processing. Denote $\mathbf{a} \triangleq (a_x, a_y)$ as the true 2-D location of the located MT, $\mathbf{u} \triangleq (u_x, u_y)$ as the true location of the un-located MT. Without loss of generality, the location of the home BS is set as $\mathbf{o} = (0, 0)$.

A. Modeling of TOA based distance estimation errors

For simplicity, clock synchronization between the un-located MT and the home BS (or located MT) is assumed for the TOA estimation. In practice, however, the TOA estimation can be implemented by using the Two-way Time Transfer or the Double Token Exchange techniques, where the strict clock synchronization is not necessary [16]. The TOA based distance estimates can be modeled as

$$\hat{d}_{bs} = d_{bs} + e_{bs} + b_{bs} \tag{1}$$

$$\hat{d}_{mt} = d_{mt} + e_{mt} + b_{mt} \tag{2}$$

where d_{bs} denotes the ture distance between the un-located MT and the home BS, d_{mt} the ture distance between the un-located MT and the located MT. $\hat{d}_{bs}$ and $\hat{d}_{mt}$ the corresponding estimates, respectively. e_{bs} and e_{mt} the Gaussian noise of $\hat{d}_{bs}$ and $\hat{d}_{mt}$. b_{bs} and b_{mt} the non-line-of-sight (NLOS) error of $\hat{d}_{bs}$ and $\hat{d}_{mt}$. b_{bs} and b_{mt} follow exponential distribution [13] and has p.d.f

$$p(b) = \begin{cases} \lambda e^{-\lambda b}, b \geq 0 \\ 0, b < 0 \end{cases} \tag{3}$$

where b denotes NLOS error, $\mathbb{E}(b) = \frac{1}{\lambda}$.

B. Modeling of the location estimates of the located MT

Since the location of the located MT is obtained using GPS signals, this location information is imperfect. Denote $\hat{\mathbf{a}} \triangleq (\hat{a}_x, \hat{a}_y)$ as the estimated location using GPS. The estimated location is modeled as

$$\hat{a}_x = a_x + e_x \tag{4}$$

$$\hat{a}_y = a_y + e_y \tag{5}$$

where e_x and e_y denotes the error of location estimation from GPS signals and modeled as independent Gaussian random variables with variance ω_{gps}^2.

C. Modeling of the location estimates using RSS fingerprinting approach

Since the RSS fingerprints are collected at only one BS, there are ambiguities of location estimation. Then the location estimates vector can be written as $\mathbf{S} = [\mathbf{s}_0, \mathbf{s}_1, \ldots, \mathbf{s}_M]$, one of which is the true location estimate and the others are the ambiguities, M the number of ambiguities. $\mathbf{s}_j = (s_{jx}, s_{jy}), j \in [0, M]$.

$$s_{0x} = u_x + n_x \tag{6}$$

$$s_{0y} = u_y + n_y \tag{7}$$

n_x and n_y the error of location estimation from fingerprinting approaches and modeled as independent Gaussian random variables with variance ω_{rss}^2.

III. Proposed Algorithm

In this section, localization algorithm is proposed to hybrid the estimates from TOA approaches and RSS-based fingerprinting approach.

Denotes the location estimates provided by TOA approach as $\mathbf{G} \triangleq [\mathbf{g}_0, \mathbf{g}_1]$, one of which is the true estimate and the other one the ambiguity. $\mathbf{g}_i = (g_{ix}, g_{iy}), i \in [0, 1]$. $\mathbf{G}$ can by calculated by finding the intersections of two circles, one of which has center $\mathbf{o}$ and radius $\hat{d}_{bs}$, the other one has center $\hat{\mathbf{a}}$ and radius $\hat{d}_{mt}$. $\mathbf{G}$ can be calculated using the following equations with respect to x and y

$$\begin{cases} x^2 + y^2 = \hat{d}_{bs}^2 \\ (x - \hat{a}_x)^2 + (y - \hat{a}_y)^2 = \hat{d}_{mt}^2 \end{cases} \tag{8}$$

Use the first equation in (14) to subtract the second one to get x, then plug x into the first equation in (14) yields

$$Ay^2 + By + C = 0 \tag{9}$$

where $A = 1 + \left(\frac{\hat{a}_y}{\hat{a}_x}\right)^2$, $B = -2D\frac{\hat{a}_y}{\hat{a}_x}$, $C = D^2 - \hat{d}_{bs}^2$, $D = \frac{\hat{d}_{bs}^2 - \hat{d}_{mt}^2 + \hat{a}_x^2 + \hat{a}_y^2}{2\hat{a}_x^2}$. In order to have two different solutions for (9), the following equation should be satisfied.

$$B^2 - 4AC > 0 \tag{10}$$

Then the two intersessions are obtained as

$$\begin{cases} \mathbf{g}_0 = \left(D + \frac{\hat{a}_y}{\hat{a}_x}\frac{B - \sqrt{B^2 - 4AC}}{2A}, \frac{-B + \sqrt{B^2 - 4AC}}{2A}\right) \\ \mathbf{g}_1 = \left(D + \frac{\hat{a}_y}{\hat{a}_x}\frac{B + \sqrt{B^2 - 4AC}}{2A}, \frac{-B - \sqrt{B^2 - 4AC}}{2A}\right) \end{cases} \tag{11}$$

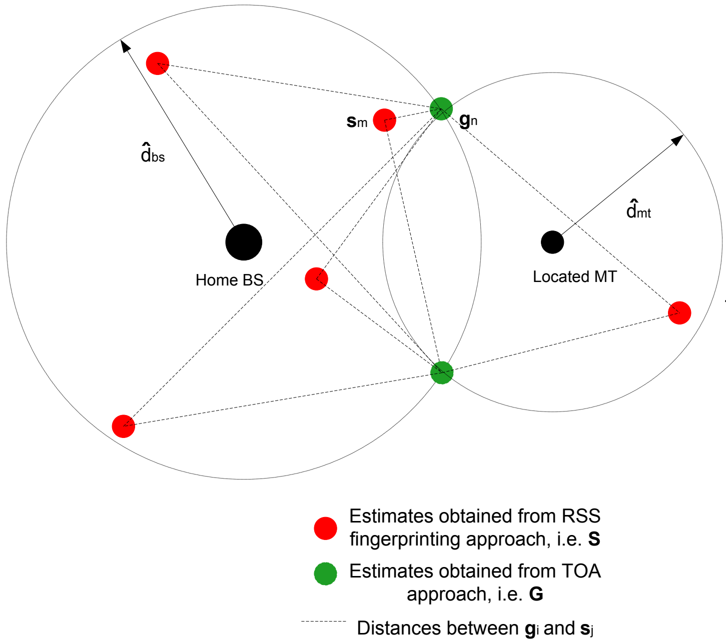

Fig. 2. Proposed Hybrid Algorithm

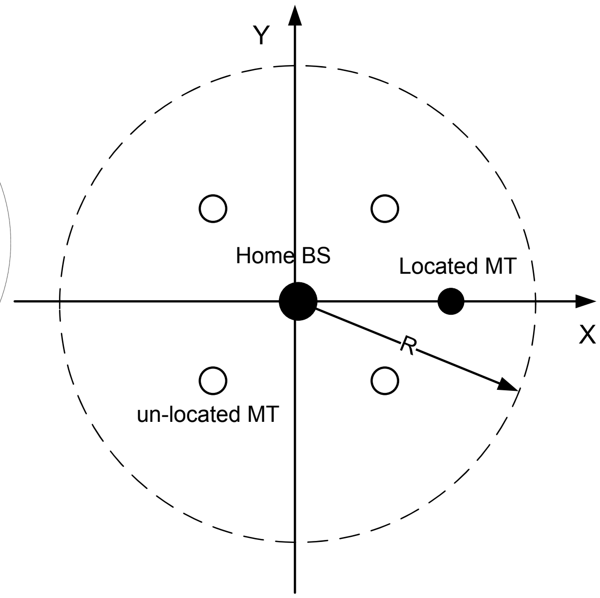

Fig. 3. Model for simulations

Otherwise, if (10) is not satisfied, the two intersections are defined as

$$\mathbf{g}_0 = \mathbf{g}_1 = \left(\frac{\hat{a}_x}{2}, \frac{\hat{a}_y}{2}\right) \tag{12}$$

The ambiguities usually introduce large errors. And the true estimates are usually closer to the true location compared with the ambiguities. Based on the above fact, the proposed hybrid algorithm is depicted in Fig. 2. Firstly, the estimate pair $\mathbf{g}_i$ and $\mathbf{s}_j$ with the shortest euclidean distance is found, the other pairs are treated as ambiguities and removed. Then, the final estimate is the averaged of the estimate pair. The algorithm is written as follows,

$$(n, m) = \text{argmin}_{i,j} \|\mathbf{g}_i - \mathbf{s}_j\|, \tag{13}$$

Then the final location estimate is $\hat{\mathbf{u}} = (\hat{u}_x, \hat{u}_y)$, where

$$\begin{cases} \hat{u}_x = \frac{g_{nx}+s_{mx}}{2} \\ \hat{u}_y = \frac{g_{ny}+s_{my}}{2} \end{cases} \tag{14}$$

The disadvantage of this algorithm is that an ambiguity pair may have very small distance, in this case, the ambiguity removal fail. However, the probability of this case to happen is very small.

IV. Simulation Results and Discussions

Simulations is performed to evaluate the proposed algorithm in this section. The model for simulations is depicted in Fig. 3. Without loss of generality, the line linking home BS and the located MT is set as X axis. Thus, $a_y = 0$. The location of the un-located MT is uniformly distributed within the the circle with radius R. The ambiguities of RSS based fingerprinting approach are also uniformly distributed within the circle. For simplicity, the variances of the two TOA based distance estimation are assumed to have the same value σ^2. The NLOS error of the two distance estimates are assumed to have the same exponential p.d.f with parameter λ. Monte Carlo simulation is carried out to evaluate the location error, which is defined as $\mathbb{E}(\|\hat{\mathbf{u}} - \mathbf{u}\|)$ ($\mathbb{E}$ denotes expectation). The accuracy of the proposed approach is compared with the stand-alone TOA approach and RSS based fingerprinting approach. For the two stand-alone approaches, the final estimate is randomly chosen from $\mathbf{G}$ and $\mathbf{S}$, respectively.

Since the accuracy of these approaches depend on various parameters, including σ, λ, ω_{rss}, ω_{gps}, a_x, r, M. The effect of different parameters on accuracy are evaluated by simulations and the results are shown in Fig. 4 to 9. The parameters for simulations is shown in Tab. I. Fig. 4 to 7 shows that with different value of σ, λ, ω_{rss}, ω_{gps}, the proposed hybrid approach significantly outperform stand-alone TOA approach and RSS based fingerprinting approach. The reason is the proposed approach remove the ambiguities introduced by stand-alone approaches. Fig. 8 shows that when M is small enough, the proposed algorithm can not offer better accuracy than the stand-alone RSS based fingerprinting approach. However, the proposed algorithm still outperform the TOA approach. The reason is that there is limited number of ambiguities from RSS-based fingerprinting approach need to be removed, however, the proposed approach still can remove the ambiguities from TOA approach. Fig. 9 shows that when the located MT is far enough from the home BS, the proposed approach outperform the two stand-alone approaches. A larger distance between the located MT and the home BS leads to better accuracy of the proposed approach.

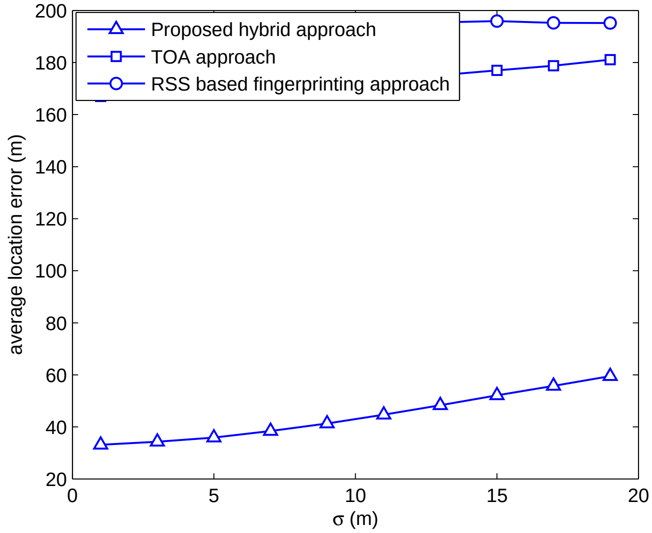

Fig. 4. Effect of σ on accuracy

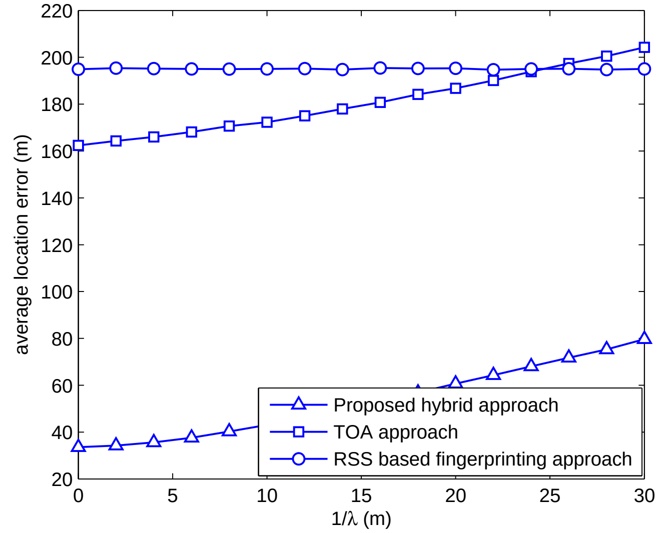

Fig. 5. Effect of λ on accuracy

TABLE I
PARAMETERS FOR SIMULATIONS

σ	10 (m)
λ	0.1
ω_{rss}	20 (m)
ω_{gps}	5 (m)
M	4 (m)
a_x	150 (m)
R	300 (m)

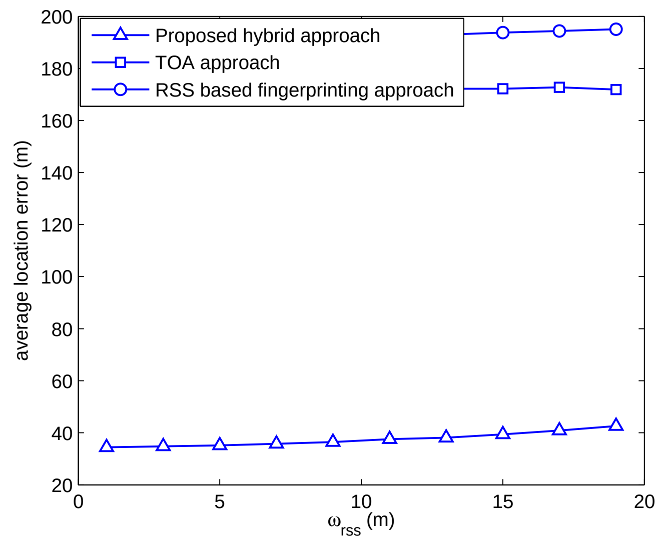

Fig. 6. Effect of ω_{rss}^2 on accuracy

V. CONCLUSIONS

In this paper, we consider a practical scenario that hearability is only possible between a MT and its home BS. In addition, located MTs can be utilized to find the location of an un-located MT without GPS receiver. In the considered scenario, only one located MT together with the home BS are utilized to find the location of the un-located MT. TOA techniques is employed to estimate the distance between the un-located MT and the home BS (or the located MT). In addition, an RSS fingerprinting database is connected to the home BS, which can estimate the location of the un-located MT if the corresponding RSS information is obtained. A hybrid cooperative localization approach was proposed to combine time-of-arrival and received signal strength based fingerprinting techniques. It was shown in simulations that the proposed hybrid approach outperform the stand-alone time-of-arrival techniques or received signal strength based fingerprinting techniques in the considered scenario. It was also found that the proposed approach offer better accuracy with larger distance between the located MT and the home BS.

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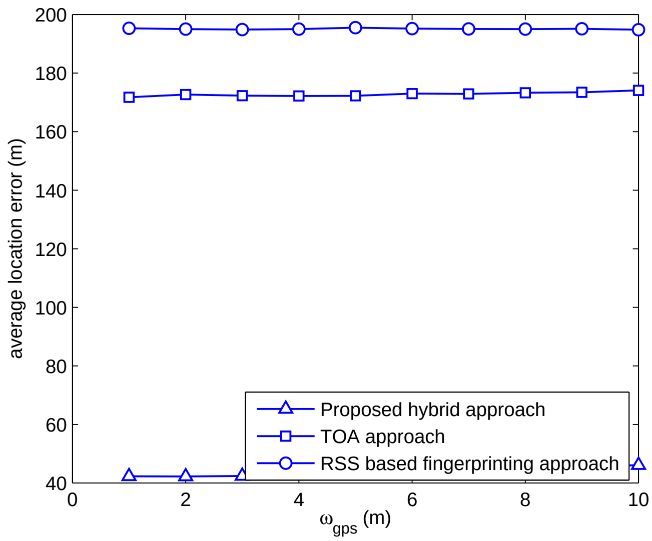

Fig. 7. Effect of ω_{gps}^2 on accuracy

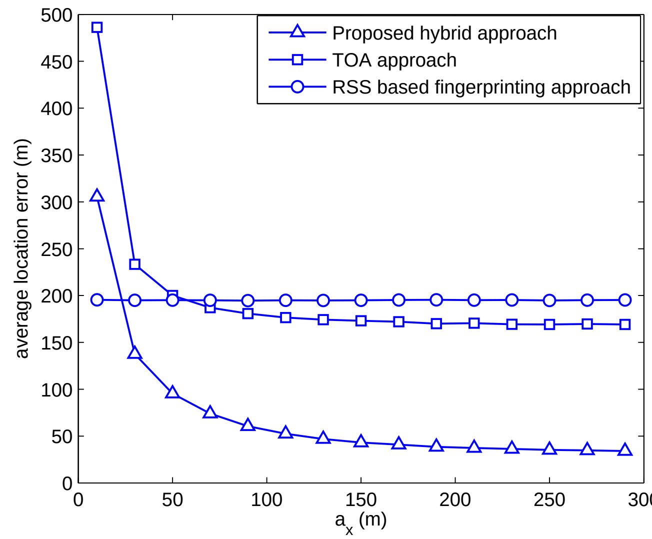

Fig. 9. Effect of a_x on accuracy

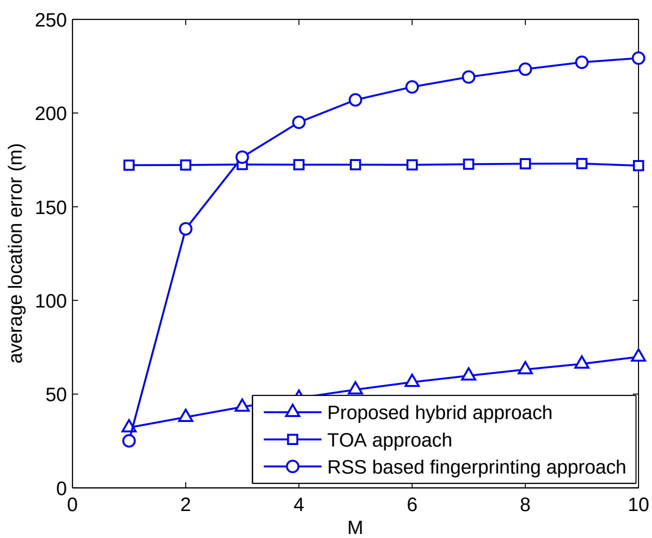

Fig. 8. Effect of M on accuracy

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