EURASIP Journal on
Wireless Communications and Networking
a SpringerOpen Journal

RESEARCH Open Access

Energy-efficient mobile tracking in heterogeneous networks using node selection

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Abstract

Range-based positioning is capable of achieving better accuracy in heterogeneous networks, where mobile nodes enabled with multiple radio access technologies are allowed to deploy not only the faraway access points but also high spatial density peer nodes as anchor nodes. However, due to peer node energy supply constraint and network capacity constraint, an efficient cooperation strategy is required. In this paper, we propose a cooperation method to track the position of a moving target with high accuracy and reduce the energy consumption and signaling overhead via node selection. It is demonstrated by simulation that in a specific practical scenario, the proposed method is capable of reducing the signaling overhead by about 34% to within 0.5-m degradation of accuracy compared to exhaustive cooperation. We also evaluate the achievable performance averaged over randomly located node configurations and compare the proposed scheme with the mostly used nearest-node selection algorithm in terms of accuracy and cost.

Keywords: Heterogeneous network; Anchor selection; Accuracy indicator

1 Introduction

Indoor localization via wireless signals is increasingly becoming a prominent feature for intelligent services and applications. Range-based positioning first estimates the Euclidian distance between the target node and several position-known anchor nodes via received signal strength (RSS), time of arrival (ToA), or other distance-dependent signal metrics and then derives the target node coordinates by exploiting the geometrical relationship between distances and coordinates. In the context of noncooperative homogeneous network, the number of anchor nodes such as Wi-Fi access points are small and far away from each other, which limits the localization accuracy.

In the context of heterogeneous network, a multi-Radio Access Technology (RAT) aided mobile device is capable of communicating not only with the access points (APs) but also with peer nodes such as fixed ZigBee/Bluetooth sensors or other mobile nodes if cooperation is supported. The spatial density of peer nodes is typically much higher than APs, so by exploiting these nodes as anchor nodes, we could significantly decrease the distance estimation error and improve the range-based positioning accuracy. However, peer nodes are energy-constrained. Unlike the APs, they are not supposed to be always in transmission mode broadcasting their coordinates. In order to cooperate with peer nodes, training sequences and extra packets are required for distance estimation and location information exchange, which results in signaling overhead and energy consumption. Hence, an efficient cooperation strategy is required so as to achieve the required positioning accuracy and to minimize the resultant energy consumption and traffic overhead.

In this paper, we investigate a heterogeneous network containing fixed location-known Wi-Fi APs covering the area of interest and sufficient number of connected multimodal (Wi-Fi and ZigBee) peer nodes. The goal is to estimate the position of a moving node with required accuracy. We propose a cooperation method to reduce the signaling overhead via anchor node selection. The main idea is to select a subset of anchor nodes for location estimation. As the mobile moves, the selected subset remains the same until the required accuracy drops to within a minimum threshold, at which point the reselection process is triggered. Compared to exhaustive cooperation, the proposed method is capable of reducing 34% signaling overhead to within 0.5-m degradation of accuracy in a specific practical scenario. We also evaluate the achievable performance averaged over randomly located node configurations and compare the proposed scheme with the mostly used

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nearest-node selection algorithm [1] in terms of accuracy and cost.

The rest of the paper is organized as follows: in the next section, we present the state of the art solutions in anchor selection. In Section 3, we propose our target scenario. The proposed method is detailed in Section 4. Simulation results and discussion are given in Section 5, and finally, Section 6 concludes the paper.

Notation: we use unhighlighted letters for scalar variables, highlighted lowercase letters for vectors, and highlighted uppercase letters for matrix. $(\ )^T$ and $(\ )^{-1}$ represent matrix transportation and inversing. E ( ) and var ( ) represent the expectation and variance of a random variable. Variables with a hat $\hat{(.)}$ represent estimated values directly from estimators or from computations using estimated values. Variables without a hat represent the true value.

2 Related work

The accuracy of positioning algorithm is influenced by both measurement noise and relative node geometry [2,3]. The Geometric Dilution of Position (GDOP) [4] captures the relative node geometry aspect, while the Cramer-Rao Lower Bound (CRLB) captures both aspects. They are often used as positioning accuracy indicators [5,6]. Besides positioning accuracy, some works [7-9] apply concepts from coalitional games and utility functions and select anchor nodes according to a cost function jointly considering power consumption and localization performance.

Most of the previous works related to anchor node selection are in the context of homogeneous network, especially sensor network [3,8-11]. Anchor node selection in heterogeneous network is less addressed [5,6]. The authors in [7] considered iterative cooperative localization among static nodes having imperfect position information. The algorithm in [5] includes both transmit and receive censoring. Transmit censoring prevents broadcast of unreliable position estimates, while receive censoring discards inadequate links for position estimation. All censoring decisions are distributed and based on a modified CRLB. In [6], unreliable links are consecutively discarded based on CRLB analysis. A comparison of different selection criteria, namely CRLB and GDOP, and analysis of their correlation with localization error in both cooperative and noncooperative scenarios have been given in [12]. Here, the mobile scenario has been studied, so the selection criteria are used for predicting the best set of anchor nodes.

An important aspect in localization is energy saving. The use of coalitional games has been proposed in [8] with the purpose of determining which nodes can stay in sleep mode while only a subset participates in the positioning algorithm. In [1], experiments were performed to increase the energy efficiency of a localization system in wireless sensor networks. The idea is to use the closest anchor nodes, and the remaining ones stay in semi-active state. Besides radio localization, there are also works that consider multimedia (camera) sensors for energy aware target tracking [13].

Compared to previous works, this paper investigates mobile tracking in a heterogeneous network with the following novel contributions:

1. The proposed method exploits the knowledge of indoor layout to improve the RSS-based distance estimation accuracy.
2. We propose a new positioning accuracy indicator for linear weighted least square (LWLS) estimator and demonstrate that it outperforms the estimated CRLB positioning accuracy indicator.

3 Target scenario

The target indoor scenario is illustrated in Figure 1, which shows a heterogeneous network containing three types of nodes: Wi-Fi APs, peer nodes, and mobiles. Peer nodes and mobiles are equipped with both Wi-Fi and ZigBee modules. APs and peer nodes both know their positions, which are served as anchor nodes. However, they are different in two aspects: (1) APs are spatially separated, covering long distance, while peer nodes are densely packed with short-distance coverage; (2) APs periodically broadcast its position information, while peer nodes do not due to power supply constraints. We are interested in the scenario having dense nodes so that the moving multi-RAT mobile is always able to communicate with APs and more than three peer nodes.

For the target mobile, we denote the set of reachable APs as N_{AP}, the set of reachable peer nodes as N_{P}, the set of potential anchor nodes for selection as $N_{\mathrm{A}} \subseteq (N_{\mathrm{AP}} \cup N_{\mathrm{P}})$ and their locations as $\mathbf{x}_n = [x_n, y_n]^T (n \in N_{\mathrm{A}})$ in two-dimensional space. We assumed that there is at least one AP ($|N_{\mathrm{AP}}| \geq 1$) and at least three reachable peer nodes ($|N_{\mathrm{P}}| \geq 3$). The AP associated with the target node is called connected AP. The target node position is denoted as $\mathbf{x} = [x, y]^T$. The distance between the nth anchor and the target node is denoted as $d_n = \sqrt{(x_n - x)^2 + (y_n - y)^2}$. The estimated distance using ranging technical such as RSS/TOA is denoted as $\hat{d}_n$ with mean value $E\left(\hat{d}_n\right)$ and variance $\mathrm{var}\left(\hat{d}_n\right)$. The estimated target location is denoted as $\hat{\mathbf{x}} = [\hat{x}, \hat{y}]^T$. We employed root mean squared error (RMSE) to represent the positioning accuracy, which is formulated as

$$\mathrm{RMSE} = \sqrt{\mathrm{tr}(\mathbf{C}_{\hat{\mathbf{x}}})} = \sqrt{E\left((\hat{x} - x)^2 + (\hat{y} - y)^2\right)} \qquad (1)$$

The notation $\mathbf{C}_{\hat{\mathbf{X}}}$ represents the covariance matrix of estimated vector $\hat{\mathbf{x}}$. The required accuracy is denoted as

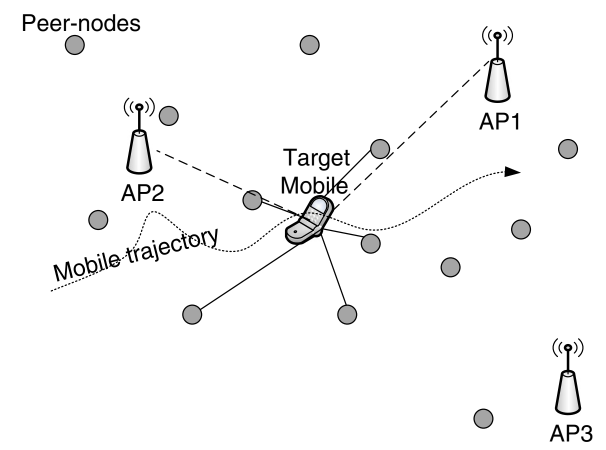

Figure 1 Heterogeneous network. It contains location-known access points, peer nodes serving as anchor nodes, and one multi-RAT target mobile moving according to a certain trajectory.

$\mathrm{RMSE}_{\mathrm{req}}$ (in meters). Our goal is to select a subset of nodes $N_S(N_S \subseteq N_A)$ having a fixed cardinality $|N_S|$ such that (1) the required accuracy can be achieved or approached as close as possible and (2) the remaining unselected anchors could remain silent so as to save energy consumption and reduce traffic overhead.

4 Proposed method

4.1 General description

The proposed method is illustrated in Figure 2. At the beginning ($t = 0$), the target mobile node transmits training sequence at its highest transmit power and seeks for assistance from all reachable peer nodes. Peer nodes measure the related signal parameters such as RSS/ToA and transmit measurement results to connected AP. (If peer nodes cannot communicate with the AP, the measurement results are sent via the target node). Upon receiving the measurements, the connected AP performs distance estimation and then chooses the best set of anchors, N_S, over all possible combinations which is expected to achieve the smallest RMSE. The estimation result $\hat{\mathbf{x}}$ and the chosen set N_S are transmitted to the target node.

As the target node moves on, it periodically transmits training sequences and seeks assistance from those selected peer nodes. Upon receiving the measurements, the connected AP will estimate the achievable RMSE using the selected set of anchors. If the required accuracy is satisfied, the estimation result $\hat{\mathbf{x}}$ using this chosen set N_S is transmitted to the target node. Otherwise, a reselection process is triggered, and a new set of N_S anchors providing the best accuracy will be chosen.

In addition, the indoor layout map is assumed to be available at the AP, which will be used to improve the RSS-based distance estimation by exploiting the knowledge of location-dependent channel parameters such as path loss, shadowing, and line-of-sight (LoS)/non-line-of-sight (NLoS) conditions. The coordinates of all anchor nodes are also recorded and updated at the AP to avoid the overhead traffic caused by exchanging location information between peer nodes and target nodes.

4.2 Positioning accuracy indicator

The pseudocode of the proposed method is summarized in Algorithm 1. The key aspect is positioning accuracy estimation. In this section, we will detail two positioning accuracy indicators: estimated CRLB denoted as $\widehat{\mathrm{CRLB}}$

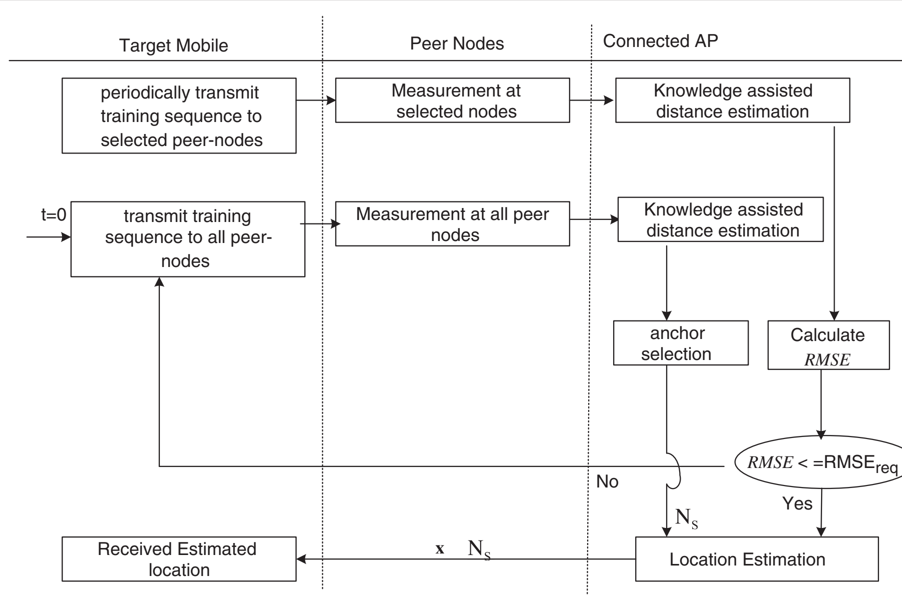

Figure 2 Illustration of the proposed method.

and estimated RMSE for LWLS estimator denoted as $\widehat{\mathrm{RMSE}}_{\mathrm{LWLS}}$. In the next section, we will compare these two indicators in terms of their correlation with the true RMSE.

Algorithm 1 Algorithm cooperative scheme with anchor selection at the time (*t*), given the previous selected anchor set $N_S^{(t-1)}$

If $t > 0$ **and** $\widehat{\mathrm{RMSE}}(N_{\mathrm{S}}^{(t-1)}) \le \mathrm{RMSE}_{\mathrm{req}}$

$N_{\mathrm{S}}^{(t)} = N_{\mathrm{S}}^{(t-1)}$

else

$N_{\mathrm{A}} = N_{\mathrm{AP}} \bigcup N_{\mathrm{P}}$

$S = \{N_{\mathrm{S}}\},\ |S| = C_{|N_{\mathrm{A}}|}^{|N_{\mathrm{S}}|}$,

For $i = 1:\ |S|$

Calculate $\widehat{\mathrm{RMSE}}(S_i)$

End for

$N_{\mathrm{S}}^{(t)} = \arg\min\limits_{S_i} \widehat{\mathrm{RMSE}}(S_i)$

End if

$\hat{\mathbf{x}}(t) = f\left(N_{\mathrm{S}}^{(t)}\right);\ t = t + 1;$

4.2.1 Estimated CRLB ($\widehat{\mathrm{CRLB}}$)

The goal of range-based positioning is to estimate target coordinates $\mathbf{x}$ based on the observation of distance vector $\hat{\mathbf{d}}$. In estimation theory, CRLB is defined as the lower bound on variance of any unbiased estimator, which is formulated as

$$\mathrm{RMSE} = \sqrt{\mathrm{tr}\left(\mathbf{C}_{\hat{\mathbf{x}}}\right)} \ge \sqrt{\mathrm{CRLB}}. \tag{2}$$

Supposed that the log-likelihood function of coordinates $\mathbf{x}$ given the distance vector $\hat{\mathbf{d}}$ is equal to the natural logarithm of the probability density function of $\hat{\mathbf{d}}$ given $\mathbf{x}$, formulated as $\ell\,(\mathbf{x}|\hat{\mathbf{d}}) = \ln\left(p(\hat{\mathbf{d}}|\mathbf{x})\right)$, the CRLB is calculated as

$$\mathrm{CRLB} = \frac{1}{\mathrm{tr}(\mathbf{F}(\mathbf{x}))},\quad \mathbf{F}(\mathbf{x}) = -E\left(\frac{\partial^2 \ell\left(\mathbf{x}|\hat{\mathbf{d}}\right)}{\partial \mathbf{x}^2}\right). \tag{3}$$

The Fisher information matrix $\mathbf{F}(\mathbf{x})$ is a function of the second derivation of the likelihood function. If $\mathbf{F}(\mathbf{x})$ contains any unknown parameters, they are replaced by their estimated values, and the resultant bound is called estimated CRLB, which is denoted as $\widehat{\mathrm{CRLB}}$ For example, the CRLB of RSS-based ranging in a two-dimensional space derived in [12,14] is a function of the true distances d_n, which are in practice unknown. Hence, it is only feasible to calculate the estimated $\widehat{\mathrm{CRLB}}$ using $\hat{d}_n$.

4.2.2 RMSE for linear weighted least square estimator

If the LWLS estimator is used, we can have a closed-form expression of $\hat{\mathbf{x}}$ as

$$\hat{\mathbf{x}} = \left(\mathbf{A}^T \mathbf{C}_{\hat{\mathbf{b}}}^{-1} \mathbf{A}\right)^{-1} \mathbf{A}^T \mathbf{C}_{\hat{\mathbf{b}}}^{-1} \hat{\mathbf{b}}. \tag{4}$$

Matrix $\mathbf{A}$ is a function of anchor coordinates $\mathbf{X}_n$, vector $\hat{\mathbf{b}}$ is a function of distance estimates $\hat{d}_n$ as well as anchor coordinates $\mathbf{X}_n$, and $\mathbf{C}_{\hat{\mathbf{b}}}^{-1}$ is the inverse of covariance matrix of $\hat{\mathbf{b}}$. Hence, the covariance matrix $\mathbf{C}_{\hat{\mathbf{x}}}$ also has a close-form expression as

$$\mathbf{C}_{\hat{\mathbf{x}}} = \left(\mathbf{A}^T \mathbf{C}_{\hat{\mathbf{b}}}^{-1} \mathbf{A}\right)^{-1}. \tag{5}$$

In the case when $\mathbf{C}_{\hat{\mathbf{b}}}^{-1}$ is a function of (unknown) true distances d_n, the estimated version $\widehat{\mathbf{C}_{\hat{\mathbf{b}}}^{-1}}$ using $\hat{d}_n$ is employed. We derive the location accuracy indicator formulated as

$$\widehat{\mathrm{RMSE}}_{LWLS} = \sqrt{\left[\left(\mathbf{A}^T \widehat{\mathbf{C}_{\hat{\mathbf{b}}}^{-1}} \mathbf{A}\right)^{-1}\right]_{1,1} + \left[\left(\mathbf{A}^T \widehat{\mathbf{C}_{\hat{\mathbf{b}}}^{-1}} \mathbf{A}\right)^{-1}\right]_{2,2}} \tag{6}$$

5 Simulation results and analysis

Although the proposed method is not constrained by ranging techniques, RSS-based distance estimation is used in our simulation for its universal applicability and ease of implementation. Using the unbiased distance estimator, the estimated distance squared for the nth anchor can be formulated as [15]

$$\widehat{d_n^2} = e^{-\frac{2r_n}{\alpha} - \frac{2\lambda_n^2}{\alpha^2}} \tag{7}$$

It has zero mean and a variance of $\mathrm{var}\left(\widehat{d_n^2}\right) = d_n^4\left(e^{\frac{4\lambda_n^2}{\alpha}} - 1\right)$. In detail, $r_n = \ln(P_{n,r}) - \ln(X_n) - \ln(P_{n,t})$, $\lambda_n^2 = 0.01\ln(10)^2\sigma^2$, and $P_{n,y}$ and $P_{n,t}$ represent time-averaged received and transmitted signal strength from the nth anchor; α is the path loss exponent, and X_n denotes the summation of all other losses (e.g., wall penetration loss). X_n is assumed to be perfectly compensated using the knowledge of layout map. We express the location accuracy indicators described in Section 4 as follows. Using the unbiased RSS-based distance estimator, the estimated CRLB is formulated as

$$\widehat{\mathrm{CRLB}}_{\mathrm{RSS}} = \sqrt{\frac{1}{b}\frac{\sum_{n=1}^{N}\widehat{d_n^{-2}}}{\sum_{n=1}^{N-1}\sum_{m=n+1}^{N}\left(\frac{\widehat{d_{t\perp n,m}}\,d_{n,m}}{\widehat{d_n^2}\,d_{n,m}^2}\right)^2}}, \tag{8}$$

where $d_{n,m}$ is the distance between the nth and mth anchors, and the term $\widehat{d_{t\perp n,m}}$ is the estimated shortest distance from the target to the segment connecting the nth and mth anchors. The term b accounts for channel conditions and is calculated as $b = \frac{10\alpha}{\sigma \ln 10}$.

Using the best linear unbiased estimator proposed in [15], the estimated RMSE is formulated as Equation 6 using

$$\mathbf{A} = \begin{pmatrix} -2x_1 & -2y_1 & 1 \\ -2x_2 & -2y_2 & 1 \\ \vdots & \vdots & \vdots \\ -2x_n & -2y_n & 1 \end{pmatrix},$$

$$\widehat{\mathbf{C}_{\mathbf{b}}^{-1}} = \begin{pmatrix} \widehat{\mathrm{var}\left(\widehat{d_1^2}\right)} & & 0 \\ & \ddots & \\ 0 & & \widehat{\mathrm{var}\left(\widehat{d_n^2}\right)} \end{pmatrix}^{-1} \tag{9}$$

In the rest of this section, we describe the simulation for (a) the specific scenario from Figure 3 and (b) generalized scenarios with randomly distributed anchors and averaged performances over 10 different constellations. We generated the setups in MATLAB (Mathworks, Inc., Natick, MA, USA) and then determined the channel conditions based on the WINNER tool.

5.1 A specific scenario

We consider a practical scenario illustrated in Figure 3, which consists of one Wi-Fi AP and seven peer nodes. The target moves from the corridor to a room. Along the movement trajectory, propagation conditions between the target and the other nodes change (LoS or NLoS) as modeled by the WINNER II channel [16].

The target node moves at the speed of 1 m/s. We trace the location of the target node every 1 s ($T_s = 1$ s), which results in 38 footprints. The WINNER model [16] for indoor scenario at a carrier frequency of 2.4 GHz is used to simulate the channel between AP/peer nodes and target node. The path loss parameter α is set to $\alpha_{\mathrm{LoS}} = 1.85$ and $\alpha_{\mathrm{NLoS}} = 3.68$. The variance of zero-mean log-normal shadowing σ^2 is set to $\sigma^2_{\mathrm{LoS}} = 2\ dB$ and $\sigma^2_{\mathrm{NLoS}} = 5\ dB$, respectively. The true location RMSE is averaged over 1,000 independent shadowing samples. Setting $|N_s|$ and $\mathrm{RMSE}_{\mathrm{req}}$ in different values, we simulate the following four schemes:

- Scheme 1. $|N_S| = |N_{AP}| + |N_P|$, $\mathrm{RMSE}_{\mathrm{req}} = 0$. This is equivalent to exhaustive cooperation, where all reachable APs and peer nodes are used for location estimation at every sampling time.

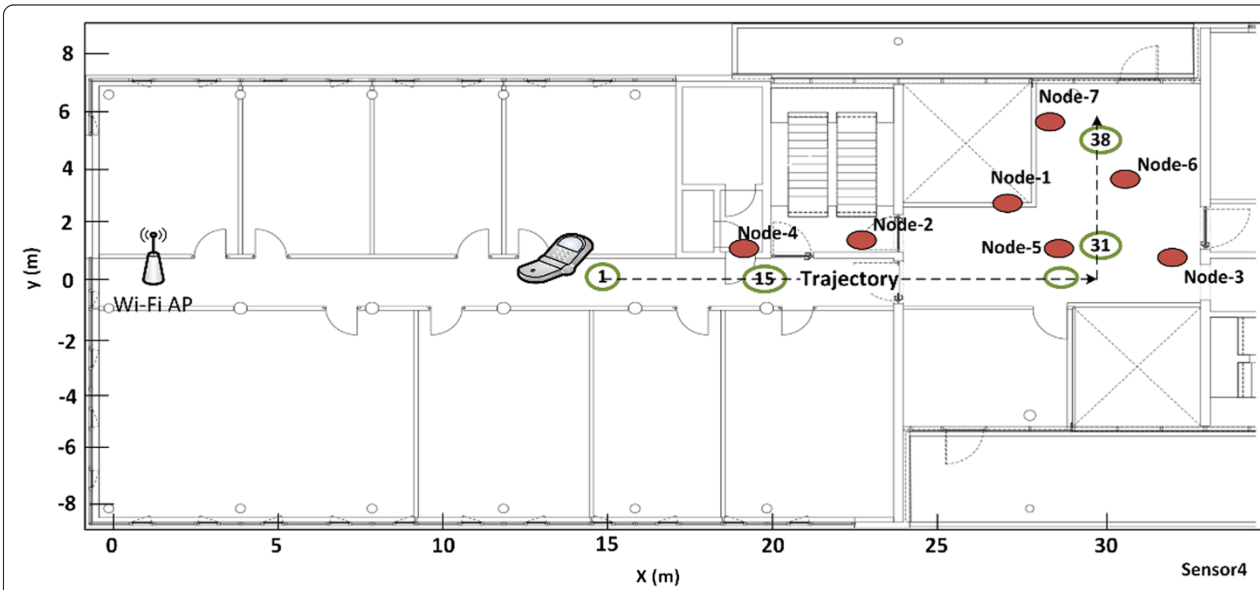

Figure 3 Simulation scenario. It consists of one Wi-Fi access point, seven peer nodes, and one target mobile node moving from the corridor to a room.

- Scheme 2. $|N_S| = 3$, $\mathrm{RMSE}_{\mathrm{req}} = 0$, using $\widehat{\mathrm{CRLB}}_{\mathrm{RSS}}$ in Equation 8 as indicator and LWLS/ML location estimator.
- Scheme 3. $|N_S| = 3$, $\mathrm{RMSE}_{\mathrm{req}} = 0$, using $\widehat{\mathrm{RMSE}}_{\mathrm{LWLS}}$ in Equations 6 and 9 as indicator and LWLS location estimator.
- Scheme 4. $|N_S| = 3$, $\mathrm{RMSE}_{\mathrm{req}} = 1$ and 2, using $\widehat{\mathrm{RMSE}}_{\mathrm{LWLS}}$ in Equations 6 and 9 as indicator and LWLS location estimator.

5.1.1 Location accuracy indicator comparison

Using the parameters set for Scheme 2, three out of eight anchors, which provide the lowest value of $\widehat{\mathrm{CRLB}}_{\mathrm{RSS}}$, are chosen at each sampling time. The true RMSEs using the LWLS estimator and maximum likelihood (ML) estimator are compared to the indicated value $\widehat{\mathrm{CRLB}}_{\mathrm{RSS}}$ in Figure 4. The ML estimator is the optimal RSS-based position estimator; however, it is computationally very demanding, and we use it for benchmark purposes. It is demonstrated that from the 15 sample onward, where the anchor nodes are dense and distributed in variable directions, the indicated RMSE using $\widehat{\mathrm{CRLB}}_{\mathrm{RSS}}$ has a good correlation with the true RMSE using the ML estimator but is much lower than the true RMSE using the LWLS estimator. In the first few samples, the $\widehat{\mathrm{CRLB}}$ values are low, but the true RMSE using either linear or ML estimators are very high. The reason is that the closest three anchors are not in line with the target but almost collinear with each other. In this situation, the assumption $\ell\ (\mathbf{x}|\hat{\mathbf{d}}) = \ln\left(p(\hat{\mathbf{d}}|\mathbf{x})\right)$ does not hold anymore. In fact, given $\hat{\mathbf{d}}$, the log-likelihood function of $\mathbf{x}$ achieves two peak values: one at the true location, and the other at the mirror location symmetric to the approximate line connecting these to the near collinear anchors. Hence, $\widehat{\mathrm{CRLB}}$ gives false accuracy estimation. It chooses the close, but near collinear anchors, which results in high positioning error.

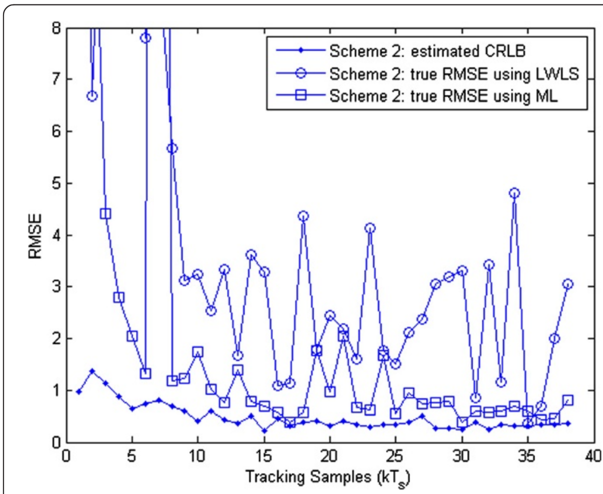

Figure 4 Comparison of the CRLB indicators and the true RMSE when using Scheme 2.

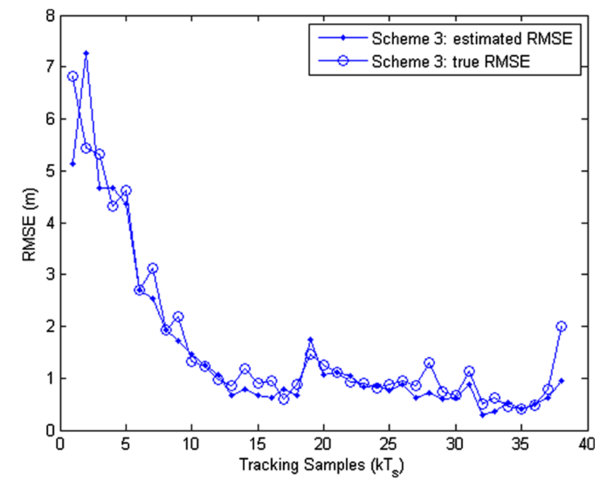

Figure 5 Comparison between indicator $\widehat{\mathrm{RMSE}}_{\mathrm{LWLS}}$ and the true RMSE when using Scheme 3.

Using similar parameters, Figure 5 compares the indicator $\hat{\mathrm{RMSE}}_{LWLS}$ and the true RMSE. Again, three out of eight anchors, which provide the lowest value of $\widehat{\mathrm{RMSE}}_{\mathrm{LWLS}}$, are chosen at each sampling time. The results show that the indicated RMSE using $\widehat{\mathrm{RMSE}}_{\mathrm{LWLS}}$ has a good correlation with the true RMSE using the LWLS estimator at all samples. Near collinear anchors are avoided during the first few samples.

Based on these two figures, we could conclude that $\widehat{\mathrm{RMSE}}_{\mathrm{LWLS}}$ is a better RMSE indicator than $\widehat{\mathrm{CRLB}}$, which can avoid choosing near collinear anchors, and provides

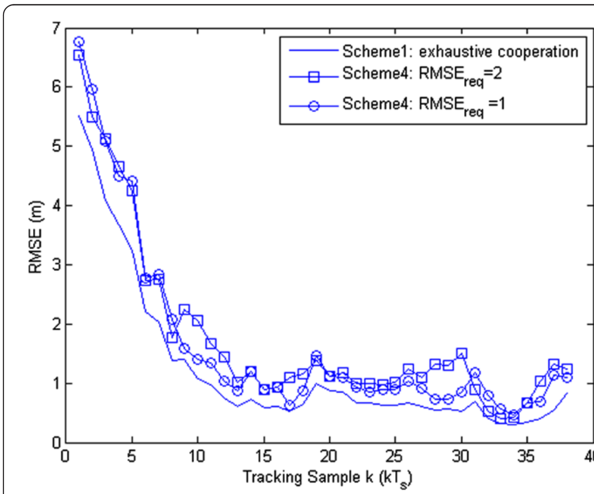

Figure 6 Comparison of achievable accuracy RMSE between exhaustive cooperation (Scheme 1) and the proposed method (Scheme 4).

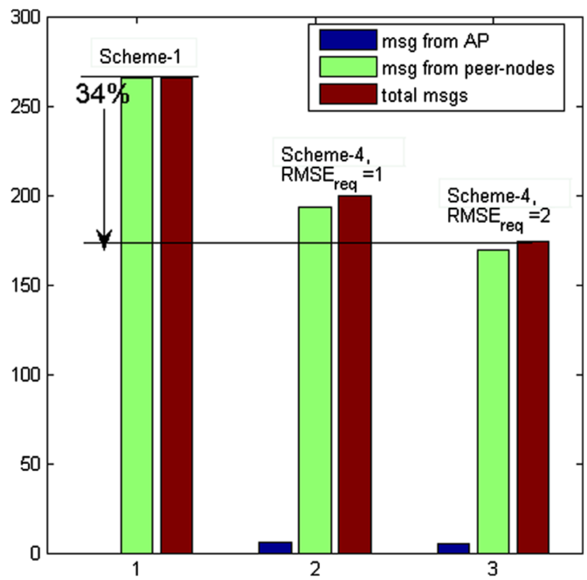

Figure 7 Comparison of traffic overhead between exhaustive cooperation (Scheme 1) and the proposed method (Scheme 4).

a more accurate estimation of the achievable RMSE LWLS estimator deployed. Hence, we will use the $\widehat{\mathrm{RMSE}}_{\mathrm{LWLS}}$ indicator and LWLS estimator to evaluate the proposed method.

5.1.2 Exhaustive cooperation versus the proposed method

We simulate the proposed method and compare its RMSE to those using exhaustive cooperation. The parameters are summarized in Scheme 4 and Scheme 1, respectively. As shown in Figure 6, the degradation of accuracy is negligible. When using the proposed method with $\mathrm{RMSE}_{\mathrm{req}} = 2$, the average RMSE is about 0.53 m higher than exhaustive cooperation. However, the total traffic overhead reduction is about 34% as shown in Figure 7. More explicitly, the proposed method does not always require a message from all anchors (in green). It only occasionally requires additional control packets from the AP (in blue) to invoke the reselection process. Compared to exhaustive cooperation, the overall transmit overhead over 38 samples is reduced by 34% using the proposed method. The energy used to spend on this traffic overhead is saved.

5.2 Generalized scenario

In order to extend the validity of the results presented for the specific scenario from Figure 3, we evaluated the proposed method in more generalized scenarios. We consider a mobile moving across a 25-m × 10-m room. The number of anchors in the room is 20, where one of them is the access point ($|N_{\mathrm{AP}}| = 1$) and the remaining ones are peer nodes ($|N_{\mathrm{P}}| = 19$). We generated 10 setups having anchor nodes randomly distributed over the room, while the target node follows the same trajectory from the bottom left to the upper right. The averaged performance that sat 30 sampled locations along the trajectory is evaluated.

Again, the WINNER model for indoor scenario at a carrier frequency of 2.4 GHz are used with the path loss

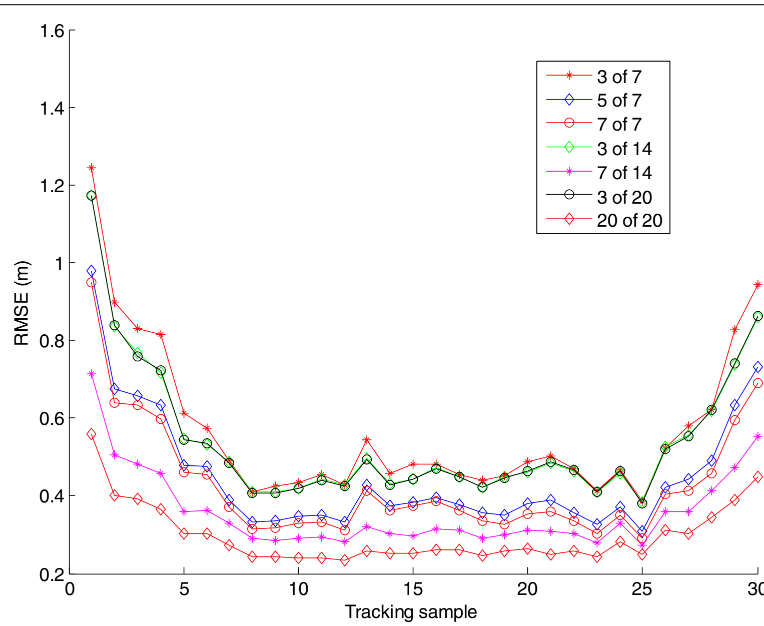

Figure 8 Comparison of different combinations of $|N_S|$ and $|N_A|$ using the proposed algorithm (averaged localization accuracy).

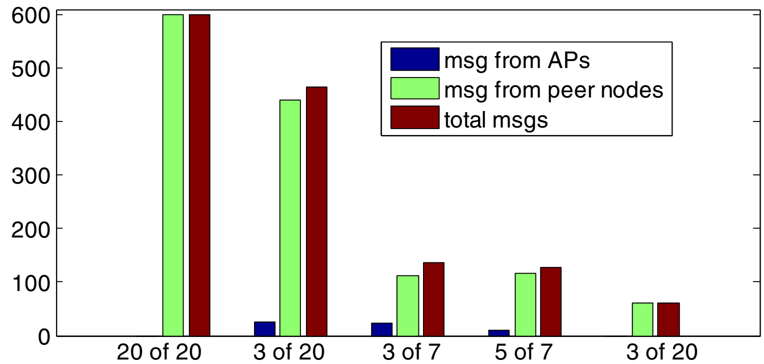

Figure 9 Averaged traffic overhead. Using (1) the proposed algorithm with different combination of $|N_S|$ and $|N_A|$ and (2) the nearest-three-node selection algorithm in [1].

parameter α set to $\alpha_{LoS} = 1.85$ and $\alpha_{NLoS} = 3.68$. The variance of zero-mean log-normal shadowing σ^2 is set to $\sigma^2_{LoS} = 2\ dB$ and $\sigma^2_{NLoS} = 5\ dB$, respectively. The true location RMSE is averaged over 1,000 independent shadowing samples. We simulate the following two schemes:

- Proposed algorithm: using $\widehat{\mathrm{RMSE}}_{\mathrm{LWLS}}$ in Equations 6 and 9 as indicator and LWLS location estimator, $\mathrm{RMSE}_{\mathrm{req}} = 0.6$ m, and various combinations of $|N_S|$ and $|N_A|$ $(|N_S|, |N_A|) = \{(3,7), (3,14), (3,20), (5,7), (7,7), (7,14), (20,20)\}$.
- Nearest-three-node selection algorithm used in [1].

5.2.1 Comparison of different combination of $|N_S|$ and $|N_A|$

The averaged localization accuracy using the proposed algorithm with different combinations of $|N_S|$ and $|N_A|$ are shown in Figure 8. First of all, the required accuracy, $\mathrm{RMSE}_{\mathrm{req}} = 0.6$ m, is achieved for all settings from track sample 5 to 27, when the target moves in the central area of the room surrounded with sufficient number of anchor nodes. By contrast, when the target moves in the edge of the room corresponding to samples 1 to 5 and 27 to 30, the accuracy requirement is only always achieved if $(|N_S|, |N_A|) = (20,20)$. It is because at edge areas, the number of reachable anchors is limit and they are not 360° spread. Also, as expected, the accuracy improves by increasing the number of selected nodes $|N_S|$ or the cardinality of potential selection set $|N_A|$. However, the performances using the three selected nodes out of 7, 14, and 20 are very similar. The accuracy is significantly improved when both $|N_S|$ and $|N_A|$ are increased such as (5,7) and (7,14).

Figure 9 illustrates the traffic overhead accumulated from 30 tracking samples and averaged over 10 different setups. The traffic overhead consists of one message from $|N_S|$ selected nodes at each tracking sample, one message from AP, and $|N_A| - |N_S|$ messages from peer nodes at some tracking sample when reselection is activated. Figure 8 shows that selecting five nodes of seven candidates achieve the smallest traffic overhead, while selecting three nodes results in higher traffic overhead because it triggers more often reselection.

Deploying the parameters stated in [17], we compare the energy consumption in Table 1. More explicitly, we assume that each message lasts for 1 ms and adopt the typical value of 32 mW (15 dBm) as transmit power of peer nodes and 63 mW (18 dBm) as transmit power of APs [17]. The total energy required for transmitting the averaged traffic shown in Figure 9 is calculated, assuming that each message lasts 1 ms. Again, it demonstrates that the (5,7) combination achieves the smallest energy consumption.

5.2.2 Nearest-nodes algorithm versus the proposed method

As a benchmark, we used the approach of choosing the three closest nodes, as in [1], which is popular because of its simplicity. Although it has the lowest signaling overhead and power consumption as shown in Figure 9 and Table 1, we can see from Figure 10 that the accuracy requirement is much worse compared to the proposed algorithm. The main reason for this is that by choosing simply three nodes with the strongest RSSI, we run the

Table 1 Energy consumption for overhead messages

Case	Proposed algorithm with different combination of $|N_S|$ and $|N_A|$				Nearest-three nodes
	20 of 20	3 of 20	3 of 7	5 of 7	
Energy (mJ)	19.2	16.315	5.903	3.661	1.92

Using (1) the proposed algorithm with different combination of $|N_S|$ and $|N_A|$ and the nearest-three-node selection algorithm in [16].

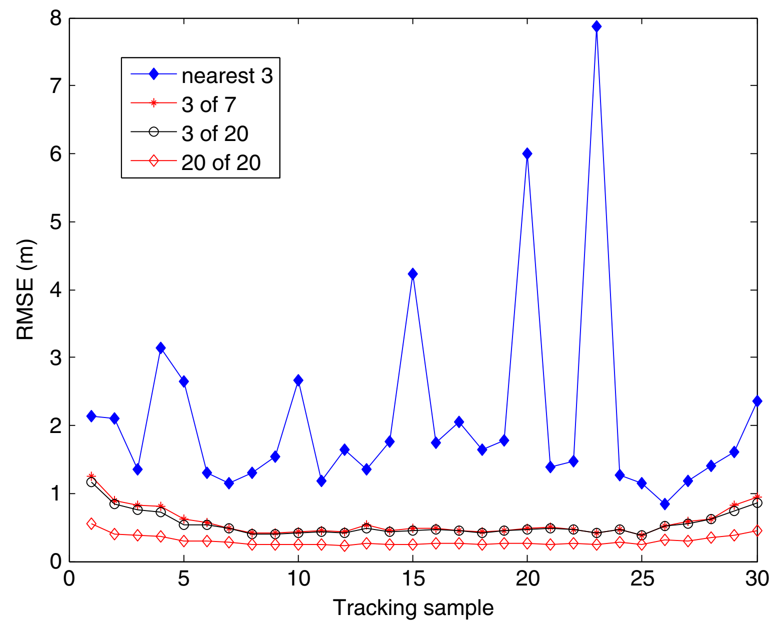

Figure 10 Comparison of the nearest-three-node selection algorithm to the proposed algorithm in terms of averaged localization accuracy.

risk to choose three collinear nodes, or almost collinear, which is an ill-conditioned scenario and yields large errors. This prenominal has been overlooked in [1], where anchor nodes are regularly placed. It is a reasonable assumption in sensor network as considered in [1] but no longer valid in our heterogeneous network.

Finally, we summarize our analysis in terms of performance trade-offs in Table 2. In this sense, 'cost' is related to communication overhead, energy consumption, search complexity, and computational complexity. For accuracy metrics, we used the mean RMSE. For the communication overhead metric, we use the number of messages which are exchanged in the anchor selection process. The search complexity is the number of possible search space size, and the computational complexity arises from matrix inversions that have to be performed in WLS localization algorithm. The proposed algorithm provides the flexibility of achieving different trade-offs by manipulating the value of $|N_S|$ and $|N_A|$.

6 Conclusions

In this paper, we proposed a cooperation method for range-based positioning in a heterogeneous network via node selection in order to reduce communication and energy cost. Inactive nodes do not waste energy while collecting, processing, and communicating measurements. We analyzed a specific scenario and generalized one that corresponds to realistic indoor environments. We presented an extensive study of different setups in order to determine the best trade-off between desired accuracy and cost. In our future work, we aim at obtaining experimental results of the proposed method. Another extension will be to consider more practical scenarios and to investigate moving peer nodes and

Table 2 Analysis of performance trade-offs

Performance metric		Mean RMSE (m)	Communication overhead (packet number)	Size of search space	Computational complexity (size of A in Equation 4)
The nearest-three nodes		2.109	60	1	3×3
Proposed algorithm	20 of 20	0.2975	600	1	20×20
	3 of 20	0.5424	465	1,140	3×3
	3 of 7	0.5716	136	21	3×3
	5 of 7	0.4501	128	35	5×5

imperfect prior knowledge of anchor locations. These virtual anchors are the result of error propagation in the localization procedure.

Competing interests
The authors declare that they have no competing interests.

Acknowledgements
The research leading to these results was partly funded from the European Community's Seventh Framework Programme [FP7/2007-2013] under grant agreement n° 264759 [GREENET], n° 248894 [WHERE2], and funding from FEDER through Programa Operacional Factores de Competitividade – COMPETE and from National funds from FCT (Portugal) – Fundação para a Ciência e a Tecnologia under the project PTDC/EEA-TEL/119228/2010 – SMARTVISION. Senka Hadzic would like to acknowledge the support of the FCT - Portugal through the scholarship SFRH/BD/61023/2009.

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Received: 23 July 2013 Accepted: 8 December 2013
Published: 4 January 2014

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doi:10.1186/1687-1499-2014-2
Cite this article as: Hadzic *et al.*: **Energy-efficient mobile tracking in heterogeneous networks using node selection.** *EURASIP Journal on Wireless Communications and Networking* 2014 **2014**:2.