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ORIGINAL ARTICLE

Neural network based mobile phone localization using Bluetooth connectivity

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Abstract Location information is useful for mobile phones. There exists a dilemma between the relatively high price of GPS devices and the dependence of location information acquisition on GPS for most phones in current stage. To tackle this problem, in this paper, we investigate the position inference of phones without GPS according to Bluetooth connectivity and positions of beacon phones. With the position of GPS-equipped phones as beacons and with the Bluetooth connections between neighbor phones as constraints, we formulate the problem as an optimization problem defined on the Bluetooth network. The solution to this optimization problem is not unique. Heuristic information is employed to improve the performance of the result in the feasible set. Recurrent neural networks are developed to solve the problem distributively in real time. The convergence of the neural network and the solution feasibility to the defined problem are both theoretically proven. The hardware implementation of the proposed neural network is also explored in this paper. Simulations and comparisons with different application backgrounds are considered. The results demonstrate the effectiveness of the proposed method.

Keywords Feasible solution neural network · Solution improvement neural network · Mobile phone · Localization · Bluetooth connectivity

1 Introduction

Location information is necessary for a variety of mobile phone–based applications [1]. For most commercial mobile phones, the localization capability is enabled by the embededness of GPS devices. Two drawbacks exist for the GPS-enabled localization of mobile phones in current stage: first, GPS fails in environments without GPS signal coverage, such as tunnels, underground subway stations, etc. Second, the cost of GPS devices is relatively high and is not available for most low-cost mobile phones. For most phones, the Bluetooth devices are available, and we investigate in this paper a localization strategy based on the Bluetooth in hardware and neural networks in algorithm.

Bluetooth is originally designed for exchanging data with a low-power consumption over short distances. There are three different transceiver modes for Bluetooth, namely class 1, class 2 and class 3 transceivers, in which the maximum communication range is 100, 10, and 5 m, respectively. Actually, the maximum range of the Bluetooth communication also provides useful distance information. For example, the fact that the phone A connects to the phone B implies that their distance is within the maximum communication range. Actually, with merely the proximity information provided by Bluetooth and positions of some beacon phones with GPS, we are able to localize the mobile phone without GPS with certain accuracy.

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In contrast to existing base station– based localization strategy [2–5], which requires a dense deployment of base stations, the proposed approach in this paper thoroughly reduces the number of beacons. Also, compared to the work only using inequalities to model the problem [6], this work applies heuristic information to the problem and receives better performance.

Different from static networks, such as wireless sensor networks (WSNs), the Bluetooth network constructed by phones is essentially a dynamic one due to the mobility of phone users. Therefore, the localization algorithm is necessary to be time efficient in order to complete the calculation before the switching of the network topology. Inspired by the great success of recurrent neural network on realtime signal processing [7], robotics [8, 9], online optimization and [10], we design a recurrent neural network to tackle the problem in real time.

The remainder of this paper is organized as follows. In Sect. 2, we formulate the problem as an optimization problem. In Sect. 3, two neural networks are proposed to solve the two subproblems decomposed from the original optimization problem. In Sect. 4, the convergence of the neural network is analyzed and it is proven to be convergent to a feasible solution of the problem. In Sect. 5, the hardware implementation of the neural network model is explored. In Sect. 6, two applications are given, and simulations are performed to demonstrate the effectiveness of our method. Section 7 concludes this paper.

2 Problem formulation

For the convenience of problem formulation, we first define beacon phones and blind phones as follows:

Definition 1 Beacon phone: the mobile phone with a GPS device.

Definition 2 Blind phone: the mobile phone without GPS.

Both beacon phone and blind phone referred in this approach are assumed to be equipped with Bluetooth devices. Figure 1 sketches the connectivity topology of a phone network consisting of beacon phones and blind phones. In the network, the positions of beacon phones are obtained by GPS. Each Bluetooth connection link gives a constraint to the positions of mobile phones asides the link. In equation, we have

$$(x_i - x_j)^T (x_i - x_j) \leq R^2 \quad \text{for } j \in \mathbb{N}(i) \tag{1a}$$

$$x_k = \bar{x}_k \quad \text{for } k \in \mathbb{B} \tag{1b}$$

where x_i, x_j represents the position of the ith and the jth mobile phone, respectively, R is the maximum communication range of the Bluetooth device, $\mathbb{N}(i)$ denotes the jth mobile phone's neighbor set, which includes all mobile phones connected to it via Bluetooth, $\mathbb{B}$ is the beacon phone set, $\bar{x}_k$ is the GPS measured position of the beacon phone labeled the kth.

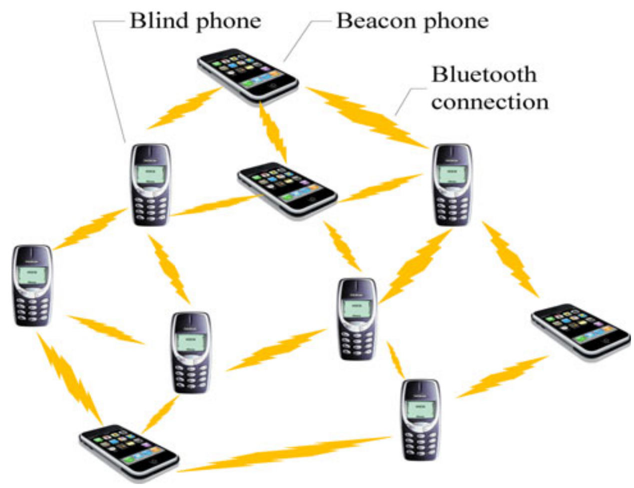


Fig. 1 Connectivity topology of the Bluetooth-aided mobile phone localization system

Note that there is no explicit objective function but inequality and equality constraints in problem (1a, 1b). The solution to this problem is generally not unique. Every feasible solution of (1a, 1b) corresponds to a possible distribution of mobile phones with the given Bluetooth connectivity restriction. Actually, among all the feasible solutions, the one with an uniform distribution of phones in space is more likely to happen than other feasible solutions as it corresponds to a maximum entropy estimation of the spatial distribution in the feasible solution set [11]. Therefore, we impose the following extra objective function to enforce this tendency,

$$\text{minimize} \quad \sum_{i=1}^{n} \sum_{j \in \mathbb{N}(i)} (x_i - x_j)^T (x_i - x_j) \tag{2a}$$

$$\text{subject to} \quad (x_i - x_j)^T (x_i - x_j) \leq R^2 \quad \text{for } j \in \mathbb{N}(i) \tag{2b}$$

$$x_k = \bar{x}_k \quad \text{for } k \in \mathbb{B} \tag{2c}$$

Note that minimizing $\sum_{i=1}^{n} \sum_{j \in \mathbb{N}(i)} (x_i - x_j)^T (x_i - x_j)$ tends to increase the difference between x_i and x_j for all i and $j \in \mathbb{N}(i)$ in the feasible solution set defined by (2b) and (2c). It is noteworthy that the constraints in (2a, 2b, 2c) are convex, and the objective function is also convex. Conventionally, a constrained optimization problem can be approximated with an unconstrained one by introducing an extra penalty term, which represents the effect of the constraints, to the objective function. To avoid the violation of the inequality constraints (2b) and on the other hand to enhance the tendency to uniformly spatial distribution within the feasible region defined by the inequality constraints, we relax the problem (2a, 2b, 2c) into the following two cascaded optimization problems,

- Feasible solution problem,

$$(x_i - x_j)^T (x_i - x_j) \leq (R - \delta)^2 \quad \text{for } i \in \mathbb{N}(i) \tag{3a}$$

$$x_k = \bar{x}_k \quad \text{for } k \in \mathbb{B} \tag{3b}$$

  where x_i is randomly initialized for $i \notin \mathbb{B}$. δ is a positive constant with $0 < \delta \ll R$. The small value δ is used to ensure the solution strictly in the open set formed by (1a, 1b). Problem (3a, 3b) is a convex problem with only inequality constraints. Denoting x_i' the solution of x_i obtained by solving (3a, 3b), the second optimization problem, which improves the estimated value of the decision variables progressively, is expressed as follows,
- Solution Improvement problem,

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^{n} \sum_{j \in \mathbb{N}(i)} (x_i - x_j)^T (x_i - x_j) \\ & - c_0 \sum_{i=1}^{n} \sum_{j \in \mathbb{N}(i)} \log\left(R^2 - (x_i - x_j)^T (x_i - x_j)\right) \end{aligned} \tag{4a}$$

$$x_k = \bar{x}_k \quad \text{for } k \in \mathbb{B} \tag{4b}$$

where $c_0 > 0$ is a coefficient. Note that the first term in (4a) contributes to the equal distribution of phones in space. For the ith phone, the corresponding term involving x_i writes $2\sum_{j \in \mathbb{N}(i)} (x_i - x_j)^T (x_i - x_j)$. The minimization of $2\sum_{j \in \mathbb{N}(i)} (x_i - x_j)^T (x_i - x_j)$ in terms of x_i tends to adapt x_i to the center formed by all x_j for $j \in \mathbb{N}(i)$. It is discovered that this type of terms plays an important role in the flocking of birds [12] and is used in the formation control of mobile sensor networks [13]. The second term in (4a) is essentially a barrier term and approaches to infinitely large when the solution tends to violate the inequality constraints given in (1a, 1b). This term works to restrict the solution in the feasible set.

3 The model

In this section, we present our neural network models to solve the feasible solution problem (3a, 3b) and the solution improvement problem (4a, 4b).

3.1 Feasible solution neural network

The solution of the feasible solution problem (3a, 3b), which has no explicit objective function, is identical to the solution of the following optimization problem,

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^{n} \sum_{j \in \mathbb{N}(i)} w_{ij} \max\{(x_i - x_j)^T (x_i - x_j) \\ & - (R - \delta)^2, 0\} \\ \text{subject to} \quad & x_k = \bar{x}_k \quad \text{for } k \in \mathbb{B} \end{aligned} \tag{5}$$

where n denotes the number of all mobile phones, $w_{ij} > 0$ is the weight of the connection between the ith and the jth phone. Note that the optimization problem (5) is nonsmooth due to the presence of the function $\max(\cdot)$. The following recurrent neural network [6], with the switching criteria augmented negative gradient evolution, finds a feasible solution of the optimization problem (5),

$$\begin{aligned} \dot{x}_i &= -\epsilon_1 \sum_{j \in \mathbb{N}(i)} w_{ij} I_{ij} (x_i - x_j) \\ x_k &= \bar{x}_k \quad \text{for } k \in \mathbb{B} \end{aligned} \tag{6}$$

where x_i is the position estimation of the blind mobile phone labeled i ($x_i \in \mathbb{R}^2$ in 2-dimensional space), $\epsilon_1 > 0$ is a scaling factor, w_{ij} is a positive weight, and I_{ij} is an indicator function defined as follows:

$$I_{ij} = \begin{cases} 1 & \text{if } (x_i - x_j)^T (x_i - x_j) - (R - \delta)^2 > 0 \\ 0 & \text{if } (x_i - x_j)^T (x_i - x_j) - (R - \delta)^2 \leq 0 \end{cases} \tag{7}$$

3.2 Solution improvement neural network

The solution improvement problem (4a, 4b) is an unconstrained optimization problem defined on a network. We use the following gradient-based recurrent neural network to solve it:

$$\begin{aligned} \dot{x}_i &= -\epsilon_2 \sum_{j \in \mathbb{N}(i)} \left(1 + \frac{c_0}{R^2 - (x_i - x_j)^T (x_i - x_j)}\right) (x_i - x_j) \\ x_k &= \bar{x}_k \quad \text{for } k \in \mathbb{B} \quad x_i(0) = x_i' \end{aligned} \tag{8}$$

where x_i is the position estimation of the blind mobile phone labeled i ($x_i \in \mathbb{R}^2$ in 2-dimensional space), x_i' is the ultimate output of the feasible solution neural network (6), that is, the solution of x_i obtained by solving (5). The expression $x_i(0) = x_i'$ means that x_i is initialized with x_i'. $\varepsilon_2 > 0$ is a scaling factor and $c_0 > 0$ is a positive constant.

Remark 1 The recurrent neural network (8) is a distributed one since the update of x_i in (8) only depends on x_j for $j \in \mathbb{N}(i)$, that is, the position estimations of the neighbor phones. Therefore, communication only happens between neighbor phones with direct Bluetooth connections. No routing or cross-hop communication is required for the implementation of the neural network. This structure of the neural network thoroughly reduces the communication burden and makes the neural network scalable to a network with a large number of phones involved.

Remark 2 The solution improvement neural network (8) is initialized with the output of the feasible solution neural network (6) cascaded to it, and the ultimate output of the solution improvement neural network is used as the location estimation of the phones.

4 Convergence analysis

As the ultimate output of the solution improvement neural network (8) is used as the location estimation of the phones; in this section, we investigate the convergence of the neural network (8) and the solution feasibility to the constraints (1a). Before stating the main result, we first give the following lemma:

Lemma 1 [6] *The feasible solution neural network* (6), *with* $\epsilon_1 > 0$, $w_{ij} > 0$ *for all possible i and j, asymptotically converges to a feasible solution* x_i' *(for all i in the blind mobile phone set) of problem* (3a, 3b).

With this lemma, we are able to prove the following main result:

Theorem 1 *The solution improvement neural network* (8) *with* $\epsilon_2 > 0$, $c_0 > 0$, *initialized with* x_i', *which is the ultimate output of the feasible solution neural network* (6), *stays in the open set constructed by* (1a, 1b).

Proof We construct the following function to analyze the dynamic of the recurrent neural network (8):

$$V = \sum_{i=1}^{n}\sum_{j\in\mathbb{N}(i)}(x_i - x_j)^T(x_i - x_j) - c_0\sum_{i=1}^{n}\sum_{j\in\mathbb{N}(i)}\log\left(R^2 - (x_i - x_j)^T(x_i - x_j)\right) \tag{9}$$

The time derivative of V along the trajectory of the solution improvement neural network (8) has the following form:

$$\begin{aligned}\dot{V} =& 2\sum_{i=1}^{n}\sum_{j\in\mathbb{N}(i)}(x_i - x_j)^T(\dot{x}_i - \dot{x}_j) \\ &+ 2c_0\sum_{i=1}^{n}\sum_{j\in\mathbb{N}(i)}\frac{(x_i - x_j)^T(\dot{x}_i - \dot{x}_j)}{R^2 - (x_i - x_j)^T(x_i - x_j)} \\ =& 2\sum_{i=1}^{n}\sum_{j\in\mathbb{N}(i)}\left(1 + \frac{c_0}{R^2 - (x_i - x_j)^T(x_i - x_j)}\right)(x_i - x_j)^T(\dot{x}_i - \dot{x}_j) \\ =& 2\sum_{i=1}^{n}\sum_{j\in\mathbb{N}(i)}\left(1 + \frac{c_0}{R^2 - (x_i - x_j)^T(x_i - x_j)}\right)(x_i - x_j)^T\dot{x}_i \\ &- 2\sum_{i=1}^{n}\sum_{j\in\mathbb{N}(i)}\left(1 + \frac{c_0}{R^2 - (x_i - x_j)^T(x_i - x_j)}\right)(x_i - x_j)^T\dot{x}_j\end{aligned} \tag{10}$$

We have $2\sum_{i=1}^{n}\sum_{j\in\mathbb{N}(i)}\left(1+\frac{c_0}{R^2-(x_i-x_j)^T(x_i-x_j)}\right)(x_i-x_j)^T\dot{x}_j = 2\sum_{j=1}^{n}\sum_{i\in\mathbb{N}(j)}\left(1+\frac{c_0}{R^2-(x_i-x_j)^T(x_i-x_j)}\right)(x_i-x_j)^T\dot{x}_j$ by noticing that the summation in this term in nature happens among all neighboring links. Therefore, the expression (10) further yields,

$$\begin{aligned}\dot{V} =& 2\sum_{i=1}^{n}\dot{x}_i^T\sum_{j\in\mathbb{N}(i)}\left(1 + \frac{c_0}{R^2 - (x_i - x_j)^T(x_i - x_j)}\right)(x_i - x_j) \\ &- 2\sum_{j=1}^{n}\dot{x}_j^T\sum_{i\in\mathbb{N}(j)}\left(1 + \frac{c_0}{R^2 - (x_i - x_j)^T(x_i - x_j)}\right)(x_i - x_j) \\ =& -2\epsilon_2\sum_{i=1}^{n}\left\|\sum_{j\in\mathbb{N}(i)}\left(1 + \frac{c_0}{R^2 - (x_i - x_j)^T(x_i - x_j)}\right)(x_i - x_j)\right\|^2 \\ &- 2\epsilon_2\sum_{j=1}^{n}\left\|\sum_{i\in\mathbb{N}(j)}\left(1 + \frac{c_0}{R^2 - (x_i - x_j)^T(x_i - x_j)}\right)(x_i - x_j)\right\|^2 \\ =& -4\epsilon_2\sum_{i=1}^{n}\left\|\sum_{j\in\mathbb{N}(i)}\left(1 + \frac{c_0}{R^2 - (x_i - x_j)^T(x_i - x_j)}\right)(x_i - x_j)\right\|^2 \\ \leq& 0\end{aligned} \tag{11}$$

Note the relation that $\sum_{j=1}^{n}\left\|\sum_{i\in\mathbb{N}(j)}\left(1+\frac{c_0}{R^2-(x_i-}\ x_j)^T(x_i - x_j))(x_i-x_j)\right\|^2 = \sum_{i=1}^{n}\left\|\sum_{j\in\mathbb{N}(i)}\left(1+\frac{c_0}{R^2-(x_i-x_j)^T(x_i-}\ x_j))(x_i - x_j)\right\|^2$, which is obtained by switching the notation i and j inside, is utilized in the above derivation. As $\dot{V} \leq 0$, we conclude that $V(t) \leq V_0 = V(0)$ for $t \geq 0$. Since the solution improvement neural network is initialized with x_i' (the ultimate output of the feasible solution neural network) for all i, the value of V_0 therefore is a function of x_i' for all i with finite value. According to Lemma 1, we have

$$(x_i' - x_j')^T(x_i' - x_j') \leq (R - \delta)^2 < R^2 \quad \text{for } i \in \mathbb{N}(i) \tag{12}$$

meaning that the initial value of the state variables is in the open set constructed by (1a, 1b). Also note that the function V approaches infinitely large when $(x_i - x_j)^T(x_i - x_j)$ approaches R from below for $j \in \mathbb{N}(i)$, which implies that $(x_i - x_j)^T(x_i - x_j) < R^2$ holds all the time for $j \in \mathbb{N}(i)$ after initialized with such an inequality satisfied. Otherwise, if there exists time t_1, at which $(x_i(t_1) - x_j(t_1))^T(x_i(t_1) - x_j(t_1)) > R^2$, then there must be a time $0 < t_2 < t_1$ with the equality relation $(x_i(t_2) - x_j(t_2))^T(x_i(t_2) - x_j(t_2)) = R^2$ according to the intermediate value theorem. However, $(x_i(t_2) - x_j(t_2))^T(x_i(t_2) - x_j(t_2)) = R^2$ results in the infinitely large value of $V(t_2)$, which contradicts the fact $V(t_2) \leq V_0$. This contradiction in turn validates the claim $(x_i - x_j)^T(x_i - x_j) < R^2$ holds all the time for $j \in \mathbb{N}(i)$ after initialization. This completes the proof. □

5 Hardware implementation of the neural network

The proposed neural network can either be implemented on microprocessors in series for the update of position estimation by discretizing the dynamic equations or be implemented in analog circuits in parallel. In this section, we study the parallel implementation of the proposed model. Particularly, we focus on the analog circuit implementation of the solution improvement neural network.

In the solution improvement neural network (8), the state variable x_i is associated with the mobile phone labeled i, which is in correspondence with the ith neuron in the network. Each neuron in the network only interacts with its neighbor, and all the neurons together perform the localization task collaboratively. Different from conventional iterative methods, which may only be implementable in series, the proposed neural network can be implemented in analog circuits and accordingly processes signals in parallel and solve the problem in real time. In the network, summators, multipliers, dividers, and integrators are employed for the implementation of neurons in the network. As an example, the hardware implementation of the neural module associated with the blind mobile phone labeled j, with $j1, j2, \ldots, jk$ denoting the neighbor phones (either blind phones or beacon phones), is shown in Fig. 2. The neuron gets inputs from its neighbor phones and outputs its own position estimation. Equipped with such an analog implementation of neurons, mobile phones are able to localize themselves with proximity information provided by the Bluetooth devices.

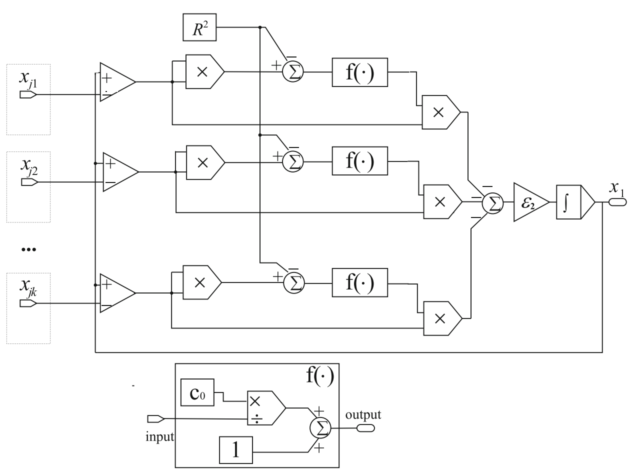


Fig. 2 Analog circuit architecture of the jth neuron in the proposed neural network, where the *lower figure* shows the implementation of the function $f(\cdot), j1, j2, \ldots, jk$ denote the neighbor phones of the jth one

6 Simulations

In this section, two application-oriented simulations are performed to show the effectiveness of the proposed method.

6.1 Localization in tunnels

The Zhujiang Tunnel (as shown in Fig. 3) is a highway tunnel under the Pearl River in Guangzhou, China, with a total length of 1,238.5 m and a traffic of 10,000 vehicles per day on average. GPS signal is not available in the tunnel, and therefore, drivers are not able to localize the vehicle inside. The Bluetooth-aided mobile phone localization strategy provides an option for rough localization of vehicles. As the tunnel can be simplified into a straight line (see Fig. 3), the problem therefore is a one-dimensional localization problem, and we perform simulation experiment to validate the effectiveness of the proposed strategy for this particular application.

Suppose there are 20 vehicles and their positions are randomly distributed along the tunnel direction in the simulation and there are only two beacon phones, each of these locates at an end of the tunnel. The Bluetooth devices work in class 3 transceiver mode with a maximum range of 100 m. For simulation convenience, we set the coordinates of the two beacon phones at 0 and 1,238.5 m, respectively. The values of x_i for all i are randomly initialized. In the simulation, the neural network parameters are chosen as $\epsilon_1 = 10^5$, $\epsilon_2 = 20 \times 10^5$, $c_0 = 5$, $\delta = 5$ and $w_{ij} = 1$ for all possible pairs of i and j. Figure 4 depicts the estimation results obtained by the feasible solution neural network and the results obtained by the solution improvement neural

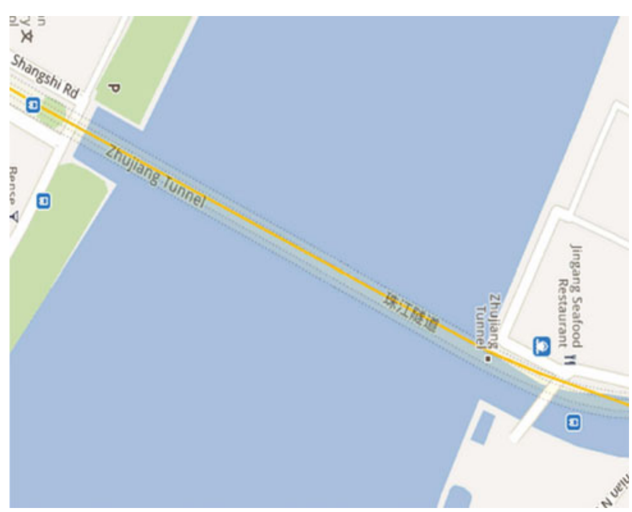


Fig. 3 The Zhujiang Tunnel under the Pearl River in Guangzhou, China

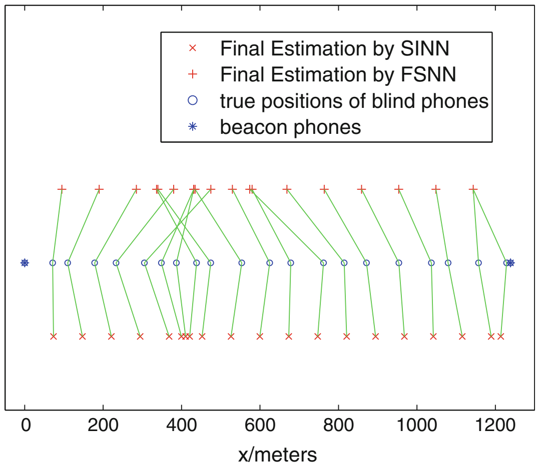


Fig. 4 The estimated positions by the solution improvement neural network (abbreviated as *SINN* in the figure) versus the estimated positions by the feasible solution neural network (abbreviated as *FSNN* in the figure) for the example in tunnel environments

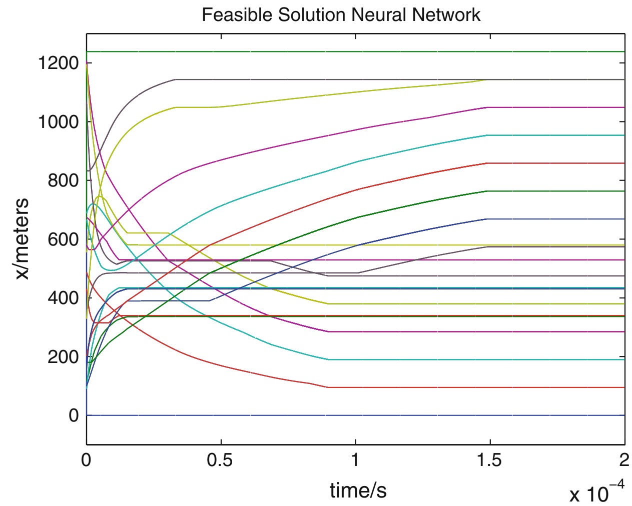


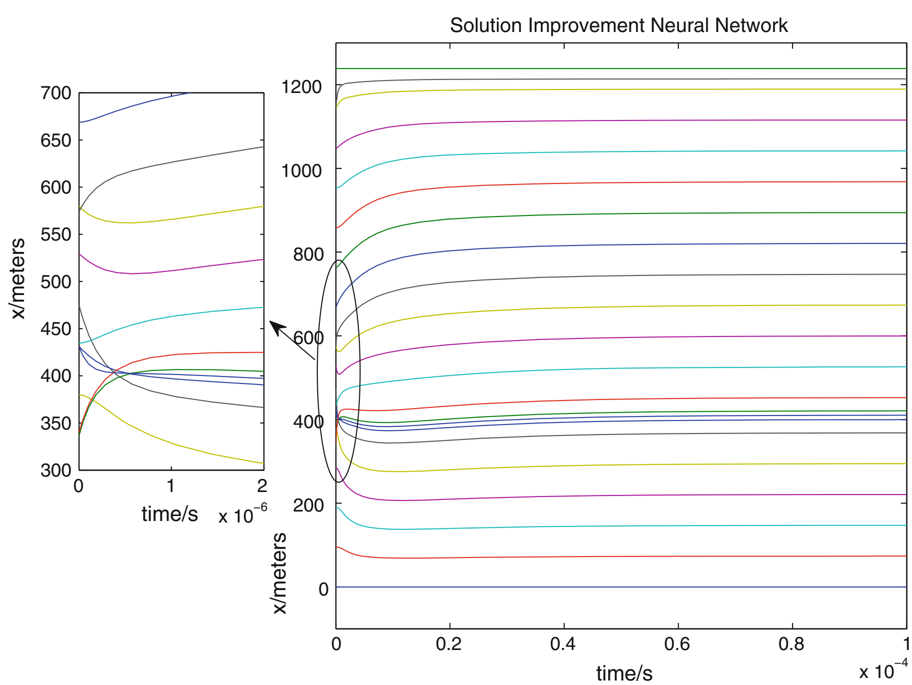
Fig. 5 The output of the feasible solution neural network for the example in tunnel environments

network. From Fig. 4, we can see that both the feasible solution neural network and the solution improvement neural network generate solutions satisfying the constraint that neighboring phones are within the range of Bluetooth connections. The transient of position estimations by the feasible solution neural network and the transient of position estimations by the solution improvement neural network are plotted in Figs. 5 and 6, respectively. Compared with the feasible solution neural network, the results obtained by the solution improvement neural network are more evenly distributed along the tunnel direction. It is noteworthy that there exists interlacing between the true positions and the estimated positions by the feasible solution neural network, while the solution improvement neural network tends to unlace them, and the estimated position by the solution improvement neural network is closer to the true position than the solution obtained by the feasible solution neural network as can be observed in Fig. 4.

6.2 Localization in supermarkets

In this section, we explore the Bluetooth-aided localization problem in supermarkets. In the simulation, the whole floor of the supermarket is assumed to be a 60 $\times$ 60 square

Fig. 6 The output of the solution improvement neural network for the example in tunnel environments



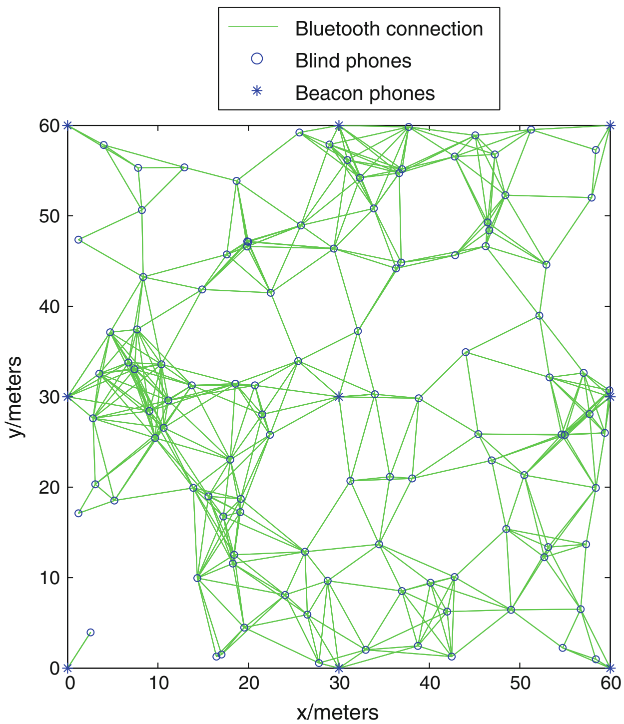


Fig. 7 True positions of phone network and the Bluetooth connection topology in the simulation example in supermarket environments

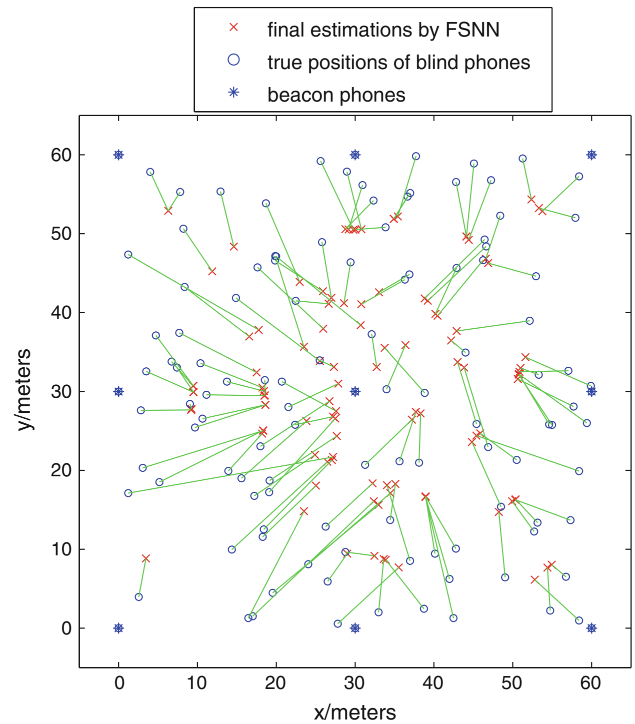


Fig. 8 The estimated positions by the feasible solution neural network (abbreviated as *FSNN* in the figure) in the simulation example in supermarket environments

meters area, and 110 customers with blind phones distribute in this area randomly, and 9 beacon phones are deployed along the perimeter and at the center, with relative coordinates [0, 0], [30, 0], [60, 0], [60, 30], [60, 60], [30, 60], [0, 60], [0, 30], [30, 30] respectively, as shown in Fig. 7. The Bluetooth devices work in class 2 mode and have an maximum range of $R = 10$ m. The scaling factors are chosen as $\epsilon_1 = \epsilon_2 = 10^5$, the parameter $\delta = 0.5$, the connection weight w_{ij} equals 5 for connections with a beacon phones and 1 otherwise for the neural network, and the weighting parameter c_0 is chosen as 1. Figures 8 and 9 show the estimated positions of blind phones using the final output of the feasible solution neural network and the solution improvement neural network, respectively. In the figures, the green line connects the real position and the estimated one and therefore its length measures the estimation error. By comparing the two figures, we can see that the total length of the green lines in Fig. 9 is clearly shorter than that in Fig. 8, which implies the solution improvement neural network indeed improves the estimation. It is noteworthy that the feasible solution neural network converges to a solution in the feasible solution set, which in general includes infinite number of feasible solutions, all feasible solutions are possibly being the solution. In Fig. 8, we can see the blind phone locating in the lower left gets an estimation located even further away from the lower left beacon phone under the condition that this blind phone

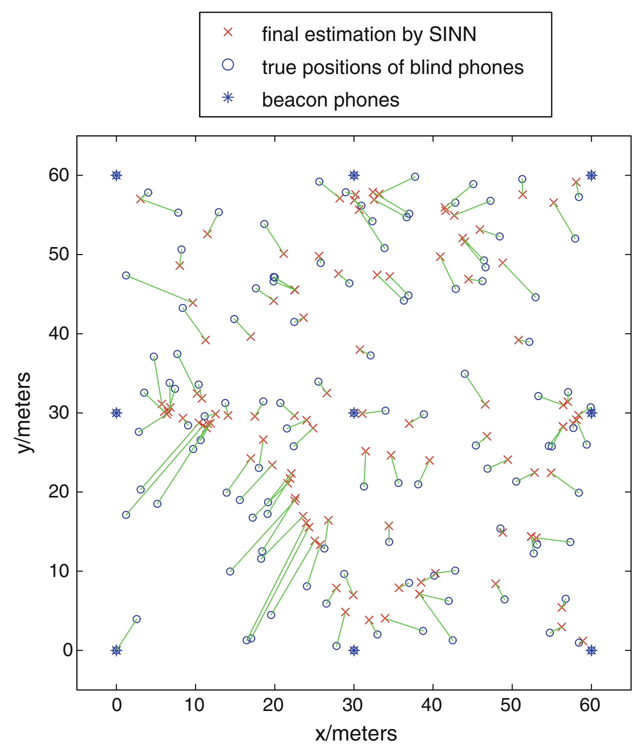


Fig. 9 The estimated positions by the solution improvement neural network (abbreviated as *SINN* in the figure) in the simulation example in supermarket environments

only has a single neighbor, which is the lower left beacon phone (see Fig. 7). In such a scenario with a single phone as the neighbor, it is more reasonable to make the estimation that the position of the neighboring beacon phone is the estimated position. Actually, this is definitely the estimation made by the solution improvement network as shown in Fig. 9, which shows that the lower left blind phone connects to the lower left beacon phone with a green line (the corresponding red cross indicating the associate estimated position is covered by the star sign indicating the beacon phone in the figure). The time histories of the feasible solution neural network and the solution improvement neural network along both x-axis and y-axis are plotted in Figs. 10, 11, 12 and 13. It can be observed that the outputs converge for both the feasible solution

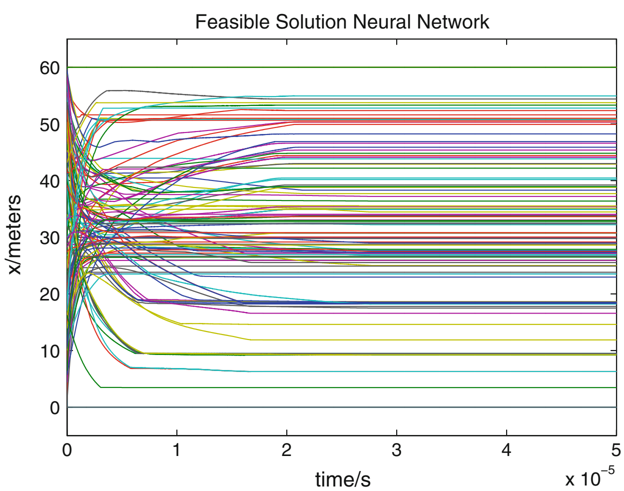


Fig. 10 The x-directional output of the feasible solution neural network in the simulation example in supermarket environments

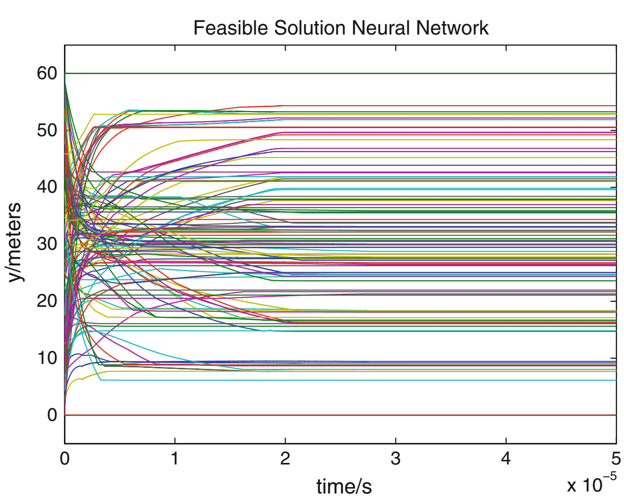


Fig. 11 The y-directional output of the feasible solution neural network in the simulation example in supermarket environments

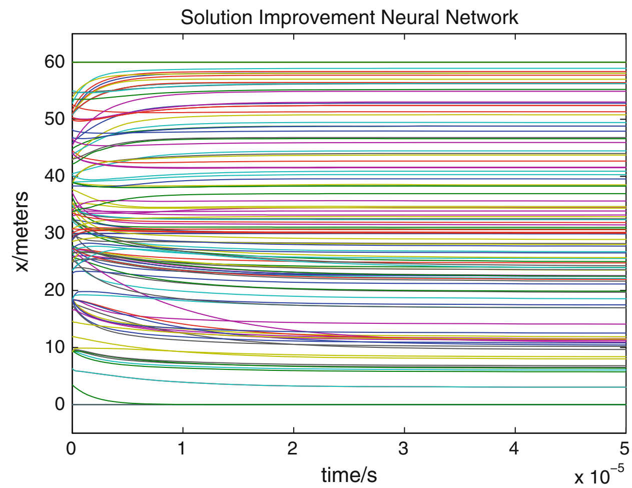


Fig. 12 The x-directional output of the solution improvement neural network in the simulation example in supermarket environments

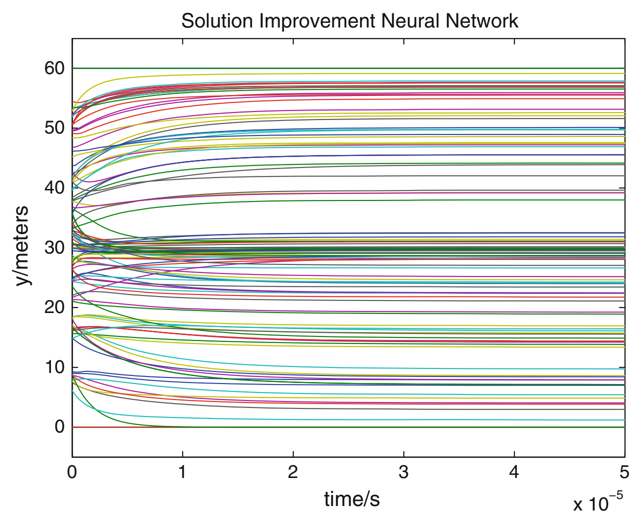


Fig. 13 The y-directional output of the solution improvement neural network in the simulation example in supermarket environments

neural network and the solution improvement neural network.

7 Conclusions

In this paper, we proposed a recurrent neural network–based method for Bluetooth-aided mobile phone rough localization. The problem is decomposed into subproblems, namely the feasible solution problem and the solution improvement problem. Correspondingly, a feasible solution neural network and a solution improvement neural network are proposed to solve the two problems, respectively. The convergence of the proposed neural network and the feasibility of the neural solution are proven in theory. The architecture of the circuit implementation of the neural network is given. Finally, application-oriented simulations are performed to demonstrate effectiveness of the method.

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