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Research on a reference signal optimisation algorithm for indoor Bluetooth positioning

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Abstract

GPS has a sharp performance decline in terms of accuracy indoors due to the complex building structure. A combined algorithm, targeting at received signal strength indication (RSSI) calibration optimisation, depending on deep neural network training via input vector Γ and the target output vector Ψ , termed reference signal optimisation algorithm (RSOA) is proposed to improve the positioning accuracy in the indoor Bluetooth positioning networks. Experimental results show that the relative error of the proposed RSOA between the estimated results and the measured ones can reach as low as 0.2%, and the absolute errors can be reduced to 0.13 m at most within 10 m.

Keywords: Bluetooth, deep learning, Gaussian filter, indoor positioning, supervised learning

1 Introduction

With the rapid increasing demand for data and multimedia services, especially in complex indoor environments such as airports, supermarkets and halls, location information of the mobile terminal or its holders indoors becomes much more important [1].

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Nevertheless, the performance of a traditional GPS system deteriorates dramatically, and it is not able to satisfy the requirements for indoor positioning services nowadays due to the influence of building structures [2]. As a consequence, several alternative indoor positioning mechanisms such as Wi-Fi-based, Bluetooth-based and UWB-based methods have been proposed both in the industry sector and academia in recent decades.

The first well-known positioning system can be dated back to the active badge location system provided in 1992 by Want et al. [3], relying on infrared ray (IR) technology [3,4]. Five years later, Ward et al. [4] introduced an active bat system, termed as the Bat Ultrasonic Location System, with an accuracy of around 3 cm in three dimensions. In 2013, Apple Inc. released the iBeacon positioning system, especially for indoor positioning, whose accuracy reaches 2–3 m [5]. In 2014, Gu et al. [6] presented an indoor localisation algorithm based on RFID, gaining a higher accuracy compared to the previous adaptive K-nearest neighbour algorithm and error self-correction algorithm. In 2015, Yang et al. [7] put forward a Wi-Fi-based positioning system to provide a much high accuracy in 20/40 MHz bandwidth Wi-Fi applications by considering the bottleneck in time of arrival (ToA) and angle of arrival (AoA) algorithms. In 2017, Pola et al. [8] proposed an OFDM-oriented approach using direct signal delay estimation. In the same year, Sultana et al. [9] introduced a new tracking system which was equipped with an innovative additional device to combine cellular devices, information and communications technologies (ICTs), indoor and outdoor positioning systems and server software methods to provide the guide service for customers.

Besides hardware systems, some optimisation algorithms have been suggested simultaneously. Chen et al. [10] proposed an improved Wi-Fi indoor positioning method using improved unscented Kalman filter and particle swarm optimisation (PSO), resulting in a decrease in the mean error to the extent of 26.72% compared with the unlicensed Kalman filter method. A cluster-based distance estimation calculation method, termed PLE, was provided by Riri et al. [11] to better understand the attenuation coefficient of a wireless channel. Zhiyong et al. [12] developed a coarse-time navigation system with the receiver autonomous integrity monitoring (RAIM) algorithm to deal with the performance deterioration of the previous global navigation satellite system caused by signal attenuation, non-line-of-sight propagation, multipath propagation and cross-correlation effects. Xujian et al. [13] optimised the traditional location fingerprint algorithm by adopting weighted fuzzy matching algorithms and Kalman filters from the perspective of average error. In 2018, Hongkai et al. [14] introduced a novel lifelong learning approach to enable efficient and real-time visual positioning, achieving sub-metre positioning accuracy. Other algorithms are also proposed in the literature [15,16].

Despite the soundness of the various approaches elucidated above, the indoor position system is far from real-world application. Generally speaking, Wi-Fi can be distinguished from the other approaches by its aspect of wide deployment but suffers from a huge amount of energy consumption [17]. The methods based on RFID have the advantages of high accuracy, anti-interference and disadvantage of compatibility. Bluetooth is a low-cost solution in a wireless position system but is limited by its accuracy to the environment indoors.

Factors such as indoor layout, material structure and building scale result in signal reflection, diffraction, refraction and scattering [18]. As a consequence, the received signal strength indication (RSSI) at the receiver varies. A combination of Gaussian filter and supervised learning mechanisms [19], depending on deep learning, is introduced in this paper to optimise reference signal strength adaptively, aiming at enhancing the positioning accuracy of the Bluetooth-based indoor positioning system [20].

The difference characterising this paper in comparison with other similar works in the literature is that we have supervised learning and optimisation of the environmental factors, which allows us to improve the accuracy of the distance calculation based on the free propagation model of the electromagnetic field.

2 A reference signal optimisation algorithm for Bluetooth

2.1 Gaussian filtering algorithm

The distance in Bluetooth positioning system can be obtained, depending on the free space propagation model, by using the following formula:

$$d = 10^{\frac{-RSSI + A + \xi}{10n}} \quad (1)$$

where $RSSI$, A and n denote the measured signal strength, reference signal strength and attenuation coefficient, respectively, and ξ represents the Gaussian random variable with zero mean.

Even the measured signal strength at the same point at different time periods is quite different due to the non-linear time-varying characteristics of wireless channels. One way to alleviate the noise, in practice, is to pass the sampling RSSI values via a Gaussian filter, after which RSSI measurements are averaged or further processed.

Assuming that RSSIs obey the Gaussian distribution (μ, σ^2) at any point in a relatively small space, the probability density function at d_0 is given as follows:

$$P(RSSI_{d_0}) = \frac{1}{\sqrt{\frac{2\pi}{k-1} \sum_{i=1}^k (RSSI_{d_0,i} - \frac{1}{k} \sum_{i=1}^k RSSI_{d_0,i})^2}} e^{-\frac{(RSSI_{d_0} - \frac{1}{k} \sum_{i=1}^k RSSI_{d_0,i})^2}{\frac{2}{k-1} \sum_{i=1}^k (RSSI_{d_0,i} - \frac{1}{k} \sum_{i=1}^k RSSI_{d_0,i})^2}} \quad (2)$$

where $RSSI_{d_0,i}$ denotes the i th measured signal strength of the total k signal strength at d_0 .

Let

$$\varphi(RSSI_{d_0}) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{RSSI_{d_0}} e^{-\frac{\xi^2}{2}} d\xi \quad (3)$$

$$F(RSSI_{d_0}) = \int_{-\infty}^{RSSI_{d_0}} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\xi-\mu)^2}{2\sigma^2}} d\xi \quad (4)$$

and the probability in the interval $\mu - \sigma \leq RSSI_{d_0} \leq \mu + \sigma$ equals

$$P(\mu - \sigma \leq RSSI_{d_0} < \mu + \sigma) = F(\mu + \sigma) - F(\mu - \sigma) = 2\varphi(1) = 0.6828 \quad (5)$$

As mentioned above, the mathematic average method may lead to large errors, even after the Gaussian filter alone, when the sampling space is not big enough due to disturbance brought by measurements with large probability. Therefore, we insist that those RSSI measurements after the Gaussian filter be further processed via the supervised learning algorithm, relying on the deep learning method rather than simply averaging.

2.2 Supervised and unsupervised learning

Assuming that the number of the probability density function of RSSI equals k and all the samples obey the Gaussian distributions, we surmise that the probability density function of RSSI is given by the following equation:

$$P(RSSI_d; \mu, \sigma) = \sum_{i=1}^k \alpha_i \phi(RSSI_d; \mu_i, \sigma_i) \quad (6)$$

where μ_i and σ_i denote the μ and σ of the i^{th} sample of the k measurements, respectively, and α_i represents the weight of the i^{th} Gaussian component.

We define binary hidden variable γ_{ji} , which denotes whether the j^{th} RSSI at d comes from the i^{th} Gaussian component. The expectation of γ_{ji} , termed expectation-step (E-step), can be obtained as follows:

$$E(\gamma_{ji}; \text{RSSI}_d, \mu_i, \sigma_i) = P(\gamma_{ji} = 1; \text{RSSI}_d, \mu_i, \sigma_i) = \frac{\alpha_i \mathcal{N}(\text{RSSI}_{d,j}; \mu_i, \sigma_i)}{\sum_{i=1}^k \alpha_i \mathcal{N}(\text{RSSI}_{d,j}; \mu_i, \sigma_i)} \quad (7)$$

where $\mathcal{N}(\text{RSSI}_{d,j}; \mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{(\text{RSSI}_{d,j} - \mu_i)^2}{2\sigma_i^2}}$ is the posterior probability of $\text{RSSI}_{d,j}$. The log-likelihood function of all $\text{RSSI}_{d,j}$ is given by the following equation:

$$\sum_{j=1}^N \sum_{i=1}^k (\gamma_{ji} \log \alpha_i + \gamma_{ji} \log \mathcal{N}(\text{RSSI}_{d,j}; \mu_i, \sigma_i)) \quad (8)$$

where $\log \mathcal{N}(\text{RSSI}_{d,j}; \mu_i, \sigma_i) = -\frac{1}{2} \log(2\pi) - \log \sigma_i - \frac{(\text{RSSI}_{d,j} - \mu_i)^2}{2\sigma_i^2}$.

We take the partial derivatives of μ_i and σ_i of Eq. (8), respectively, and let them both be equal to 0; then, we have

$$\frac{\partial}{\partial \mu_i} \left(\sum_{j=1}^N \sum_{i=1}^k (\gamma_{ji} \log \alpha_i + \gamma_{ji} \log \mathcal{N}(\text{RSSI}_{d,j}; \mu_i, \sigma_i)) \right) = \sum_{j=1}^N \left(-\gamma_{ji} \frac{(\text{RSSI}_{d,j} - \mu_i)}{\sigma_i^2} \right) = 0 \quad (9)$$

$$\frac{\partial}{\partial \sigma_i} \left(\sum_{j=1}^N \sum_{i=1}^k (\gamma_{ji} \log \alpha_i + \gamma_{ji} \log \mathcal{N}(\text{RSSI}_{d,j}; \mu_i, \sigma_i)) \right) = \sum_{j=1}^N \left(-\gamma_{ji} \frac{1}{\sigma_i} + \gamma_{ji} \frac{(\text{RSSI}_{d,j} - \mu_i)^2}{\sigma_i^3} \right) = 0 \quad (10)$$

Assuming γ_{ji} to be a value already known, then we obtain the following:

$$\mu_i = \frac{\sum_{j=1}^N \gamma_{ji} \text{RSSI}_j}{\sum_{j=1}^N \gamma_{ji}} \quad (11)$$

$$\sigma_i^2 = \frac{\sum_{j=1}^N \gamma_{ji} (\text{RSSI}_{d,j} - \mu_i)^2}{\sum_{j=1}^N \gamma_{ji}} \quad (12)$$

Taking the partial derivative of α_i of Eq. (9) and using the Lagrange multiplier method along with the constraint condition of α_i , we obtain the following equation:

$$\begin{cases} \sum_{i=1}^k \alpha_i = 1 \\ \alpha_i = \left(\sum_{j=1}^N \gamma_{ji} \right) / (-\lambda) \end{cases} \quad (13)$$

Summing from 1 to k at both sides of Eq. (13), termed maximisation step (M-step), finally, we can get the following:

$$\alpha_i = \frac{\sum_{j=1}^N \gamma_{ji}}{N} \quad (14)$$

For programming, initially we choose μ_i , σ_i and α_i randomly. For every d , i and j , we repeat E-step and M-step until they converge. The unreasonable outliers can thus be filtered out by defining the threshold of the locally

weighed logarithmic likelihood. Then, the threshold of the probability determines which distribution the RSSI belongs to, with the value of k based on the reality.

We select l target nodes at the same height and let the distance between the transmitting node and the target nodes be $d_1, d_2, d_3, \dots, d_l$, respectively. We assume that the attenuation coefficient n has been determined with experiments or experience. For every RSSI measured at every node, the following equation is obtained:

$$A_{d_k,i} = -|RSSI_{d_k,i}| + 10nlgd_k \quad (15)$$

where $k = 1, 2, \dots, l, I = 1, 2, \dots, m$, $RSSI_{d_k,i}$ denotes the i^{th} RSSI measurement at d_k and $A_{d_k,i}$ represents the reference signal strength affected by noise at every point.

The input vector $\mathbf{\Gamma}$ and the target output vector $\mathbf{\Psi}$ are given as follows:

$$\mathbf{\Gamma} = (|RSSI_{d_1,1}|, |RSSI_{d_1,2}|, \dots, |RSSI_{d_1,m}|, |RSSI_{d_2,1}|, \dots, |RSSI_{d_k,i}|, \dots, |RSSI_{d_l,m}|)^T \quad (16)$$

$$\mathbf{\Psi} = (A_{d_1,1}, A_{d_1,2}, \dots, A_{d_1,m}, A_{d_2,1}, \dots, A_{d_k,i}, \dots, A_{d_l,m})^T \quad (17)$$

We feed the input and the target output vector into the deep neural network for training and we can generate the model. The most possible reference signal strength A will be obtained according to the RSSI inputs without the model.

3 Experiment settings and result analysis

3.1 Experiment settings

Table 1 illustrates the basic settings in our experiments. As given, the transmission power of the Bluetooth device is 1 mW by default. Samples are collected every 0.1 m, starting from 0.2 m to 10.0 m, and each of them contains 200 RSSI values, among which 100 measurements are dedicated for Gaussian filter and supervised learning, and another 100 samples are designed for testament of the effects of the reference signal optimisation algorithm (RSOA) that are measured at the rate of once a second.

The sampling number can be obtained via $(10 - 0.2 \text{ m}) * 200 / 0.1 \text{ m} = 19600$.

Fig. 1 Experiment site.

Figure 1 outlines the experiment scenario in a living room. As seen, there are some furniture and plants in the room. One sender and one receiver are also observed.

Table 1 Experiment settings

Parameters	Settings
Transmission power of Bluetooth device (mW)	1
Sampling rate (/s)	1
Interval of sampling distance (m)	0.1
Maximum sampling distance (m)	10
The number of samples	19600
The height of the nodes (m)	0.7

3.2 Result analysis and discussion

3.2.1 Optimisation via the Gaussian filter

Figure 2 demonstrates the effect of a Gaussian filter. As observed in Figure 2a, original samples collected at the height of 0.7 m have dynamic fluctuation due to the interference caused by the obstacles when the distance is less than 3 m, while the distribution of other samples is relatively stable. Meanwhile, many outliers whose RSSI values deviate significantly from normal levels are likely to be noise. As the distance increases, the impact of non-linear characteristics of wireless channels becomes much more obvious due to the signal attenuation and multipath transmission effect.

The number of samples declines to 17512 after Gaussian filter, as given in Eq. (5). As seen, most of the outliers have been removed, and the impact of non-linear characteristics has been reduced to some extent.

Fig. 2 Comparison of samples before and after Gaussian filter.

Figure 3 shows the errors, in term of metres and percentage respectively, between the estimated position and pre-defined position, before and after Gaussian filter obtained via Eq. (1) and Eq. (5) by setting attenuation coefficient n fixed according to our experiment settings. Note that the errors in Figure 3a are obtained by setting reference signal strength A and attenuation coefficient n as fixed values that are equal to -53.13 and 1.8 , respectively.

As seen, the absolute errors become larger with the increase of distance, and the relative errors fluctuate dynamically in general. Specifically, the errors fluctuate around 1 m or 20% in relative when the distance is within 3 m, although it surges to 140% in relative occasionally. When the distance reaches 3 m, there is an abrupt fluctuation where the error reaches 4 m or 120% correspondingly. The absolute errors remain under 1 m beginning from 4 m to 5.2 m. Nevertheless, when the distance increases to 5.3 m, the absolute errors boom from

5.3 m to 6 m, and the relative errors even climb up to 150%, after which the absolute errors tend to be stable at about 50%, with only one fluctuation occurring at 7.2 m. As the distance continues to grow to 8 m, the relative errors begin to decrease gradually. Some of the relative errors drop to about 15%, but the fluctuations increased. The relative errors reach about 70% at the distance of 9.4–9.9 m. non-linear characteristics has been reduced to some extent.

Fig. 3 Effect of Gaussian filter.

3.2.2 Optimisation via supervised learning

Figure 4 shows the errors, using supervised learning method without Gaussian filter, in terms of metres and percentages for the estimated position, before and after the supervised algorithm, obtained via Eq. (1), Eq. (16) and Eq. (17).

Fig. 4 Errors after supervised learning.

As outlined in Figure 4a, the absolute errors rise initially, peak at 5 m and start to decline until the distance increases to 10 m in general. The relative errors display a gradual decrease trend as seen in Figure 4b.

Specially, the absolute errors stay below 2 m with one exception, and the relative errors range from 25% to 40% with several exceptions when the distance is within 3 m. As the distance increases to about 3.5 m,

the errors climb dynamically, topping at 5 m or 130%, after which the errors plummet to 1.5 m or 20% on average. Nevertheless, the errors rise sharply again up to 3.8 m or 65% in relative when distance continues to grow to about 5 m due to the interference from the outliers imposed on the training process. The errors decrease gradually with the increase of distance until it reaches 10 m.

3.2.3 Optimisation via Gaussian filter and supervised learning (RSOA)

By using the RSOA algorithm, the performance is ascertained in terms of errors between prediction, as given in Figure 5. In general, the absolute errors increase and decrease alternatively before rising stably at 7 m as given in Figure 5a. As depicted in Figure 5b, contrary to fluctuation of absolute errors, relative errors show a constant decrease within 7 m. In contrast, both the absolute errors and the relative errors display a steady increase beyond 7 m.

Fig. 5 Errors before and after the RSOA. RSOA, reference signal optimisation algorithm.

Specially, the absolute errors are marginal within 3 m and between 6 m and 7 m. They are doubled as the distance increases to 6 m. The absolute errors continue to grow beyond 7 m. When the distance increases to 3.8 m, the relative errors rise up to 80% but decline to 18% at once as the distance exceeds 4 m. The relative errors decrease soon and remain stable at about 6% when the distance is between 6 m and 8 m. The errors increase slowly, nevertheless, and did not exceed 23% as the distance approaches 10 m.

In comparison with Figures 3a and 4a, the absolute errors have similar performance when the distance stays below 6 m. Nevertheless, the absolute errors fluctuate, drop and rise in Figures 3a, 4a and 5a, respectively. The relative errors in Figures 3b, 4b and 5b display similarly as the distance keeps below 6 m, whereas errors in Figures 3b and 4b manifest differently compared to Figure 5b.

3.3 Convergence

Figure 6 shows the descent of the loss function in the training process, where the blue line and the orange line represent the loss of the training set and the validation set, respectively. As seen, the loss converges and remains stable until the end at both figures. Therefore, the proposed RSOA model is regarded to be rational for prediction. Meanwhile, the training process after the Gaussian filter converges much faster and more steadily, obviously so in comparison with those without Gaussian filter that experience several bounces and fluctuations around 40 epochs. Although the loss rate of the Gaussian-filtered training process had dropped to 3% by the 40th period, it rebounded a little to 5% by the 75th period and remained convergent at 2.7%. In conclusion, the training process can be optimised via the Gaussian filter.

Fig. 6 Training process of RSOA. RSOA, reference signal optimisation algorithm.

4 Conclusion

A combined reference signal strength optimisation algorithm, termed RSOA, relying on the Gaussian filter and supervised learning, is proposed in this paper to enhance the performance of the indoor positioning system based on Bluetooth. The efficiency of the RSOA, in terms of error, is validated via extensive experiments.

Specifically, the errors can be reduced by 20–40%, peaking at about 103%, in most circumstances via the Gaussian filter. Moreover, the convergence of the supervised learning can be improved after the Gaussian filter. The samples collected beyond 8 m interfere with the training process whose samples are collected between 5 m and 8 m, resulting in extreme jitter. Despite little improvement as the distance increases to 10 m, it ensures that the overall errors remain at a low level. For the evaluation of the RSOA, the absolute and relative errors can be reduced to 2 m or 30%, respectively, on average within 4 m. When the distance grows from 5 m to 8 m, the improvement in absolute errors is in the range of 1.5–7 m, which indicates that a much more accurate and convincing prediction has been made possible. As the distance reaches 10 m, the supervised learning algorithm has better stability, compared to the traditional averaging method that leads to polarised error levels.

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