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An Indoor User Location Estimation Method in Wireless Sensor Networks

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Abstract: Aiming at improving both performances including accuracy and real time on the application of Wireless Sensor Networks (WSN) user location estimation, a localization approach that employs Gauss Mixture Model (GMM) to analyze received signal strength is proposed in this study. This approach consists of an offline training phase and a real time localization phase. In the offline phase the signals came from many training locations were recorded and the GMM parameters were calculated and in the real time phase this GMM was employed to match the received signal strength patterns against the training patterns. The signal strengths were modeled by GMM can improve model precision in the training phase and further increased accuracy of location estimation in the localization phase. Experiment results demonstrated that the proposed method had better performances on both accuracy and real time of WSN user localization.

Key words: Wireless sensor networks, received signal strength indicator, Gauss mixture model, location estimation

INTRODUCTION

The recent work in the area of user location estimation falls into the following broad categories (Hightower and Borriello, 2001): (1) wide-area mobile cellular networks, (2) Global Positioning System (GPS) and (3) Wireless Local Area Network (WLAN). Comparing to WLAN, in spite of such limitations as low computation ability and power capability, Wireless Sensor Networks (WSN) has some special advantages on the application of user location estimation, for example, low cost, good robustness and facile deployment, etc. Especially, with advance of software and hardware and continual occurrence of improved sensor nodes with more competent sensor, computation, communication and energy resources, WSN user location estimation based on RF especial Received Signal Strength Indication (RSSI) gained more and more attention recently (Deng and Huang, 2011, Lorincz and Welsh, 2005). Among these methods based RSSI, Roos *et al.* (2002) regarded the user location estimation as a problem of a machine learning method. A Single Variable Gauss Model (SVGM) was accepted by Roos to model the RSSI distribution. This method need not extra hardware and can be employed in various conditions. But the localization accuracy of this method is still low while employing less APs, if increasing AP, its real time performance will become worse. For the sake of improving the localization accuracy while the number of APs keeps invariable, Youssef *et al.* (2005) presented a multivariable gauss model (MVGM) to model RSSI distribution. Experiment results demonstrated that the MVGM method excelled SDGM method in localization accuracy (Youssef *et al.*, 2005). Whereas, employing multivariable Gauss probability to model RSSI distribution obviously increased computation workloads.

In order to improve localization accuracy and real time performance simultaneously in WSN, another RSSI localization method is introduced in this study. A Gauss Mixture Model (GMM) is employed to model RSSI distribution in the training phases, which tries to enhance accuracy of the RSSI model in the training phase and further increase accuracy of location estimation in the localization phase, with a lower computation workload in the localization phase, which can enhance the real time performance. Experiment results demonstrated that the proposed method had better effects on both accuracy and real time of WSN user localization.

GAUSS MIXTURE MODEL AND EM ALGORITHM

GMM is an extension of single variable Gauss probability density function, GMM can smoothly simulate various density distributions with arbitrary shapes, GMM is often utilized by voice recognition system, image recognition system (Youssef *et al.*, 2005), etc.

Let X denote a set of N RSSI values, $X = \{x_1, x_1, \ldots x_N\}$, for s single sample x_i of X, gives the density function of Gauss mixture distribution as:

$$P(x_i|\Theta_j) = \sum_{j=1}^{M} \rho_j g(x_i|\mu_j, \Sigma_j) = \sum_{j=1}^{M} \frac{\rho_j}{\sqrt{2\pi|\Sigma|}} \exp[-\frac{1}{2}(x_i - \mu_j)\Sigma_j^{-1}(x_i - \mu_j)^T](i = 1, 2, \ldots, N; j = 1, 2, \ldots, M) \quad (1)$$

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where, Θ ($\Theta = \{\rho_1, \rho_2,...,\rho_k, \mu_1, \mu_2,...\mu_k, \Sigma_1, \Sigma_2,...\Sigma_k\}$) is ($I = 1, 2,...N; j = 1, 2,...,M$) the parameter set of all mixture components, Θ ($\Theta_j = \{\rho_j, \mu_j, \Sigma_j\}$) denotes the parameter set of the jth Gauss distribution: ρ_j is a mixture weighted factor that described the prior probability of the jth mixture component μ_j and Σ_j are the mean and variance of the jth Gauss distribution, respectively, $C_j = (\mu_j, \Sigma_j)$, $p(x|\Theta) = \prod^{N}_{j=1} p(x_i|\Theta_j)$, the maximum likehood estimation $\bar{\Theta}$ of parameter set Θ can be expressed as:

$$\bar{\Theta} = \underset{\Theta}{\arg\max}\, p(X|\Theta) = \underset{\Theta}{\arg\max}\left[\prod_{i=1}^{N} p(x_i|\Theta_j)\right] = \underset{\Theta}{\arg\max}\left[\prod_{i=1}^{N}\sum_{j=1}^{M} \rho g(x_i|C_j)\right] \quad (2)$$

An EM algorithm can employed to solve Eq. 2, which consists of the follow four steps.

- **Initialization:** Let there are *m* Gauss components, denotes the initial parameter set as $\Theta^0_j = \{\rho^0_j, \mu^0_j, \Sigma^0_j\}$ ($j = 1, 2,\dots, M$), where ρ^0_j is the initial weight value, which expresses the occurrence probability of the jth component:

$$\rho^0_j = \frac{1}{M}$$

Take the centroids calculated by some clustering algorithms such as K-Means as the values of the parameter μ^0_j, Σ^0_j is a covariance matrix:

$$\Sigma^0_j = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu^0_j)(x_i - \mu^0_j)^T$$

(2) **E-Step:** Let a mathematics symbol $E(z_{ij})$ denote $p(C_j|x_i)$, $E(z_{ij})$ can be considered as the posterior probability of the following event: if the observed RSSI value are x_i, x_i were generated by the jth Gauss density function. The probability $E(z_{ij})$ can be expressed as:

$$E(z_{ij}) = p(C_j|x_i) = \frac{p(C_j)p(x_i|C_j)}{p(x_i)} = \frac{p(C_j)p(x_i|C_j)}{\sum_{j=1}^{M} p(C_j)p(x_i|C_j)} = \frac{\rho_j p(x_i|C_j)}{\sum_{j=1}^{M} \rho_j p(x_i|C_j)} \quad (3)$$

Then, Eq. 4 can be obtained from Eq. 3:

$$E(z_{ij}) = \frac{\rho^t_j p(x_i|C^t_j)}{\sum_{j=1}^{M} \rho^t_j p(x_i|C^t_j)} \quad (4)$$

(3) **M-Step:** Solving the parameter set Θ^{t+1}_j by introducing the results of E-Step to (5)-(7):

$$\rho^{t+1}_j = \frac{1}{N}\sum_{i=1}^{N} E(z_{ij}) \quad (5)$$

$$\mu^{t+1}_j = \frac{1}{N\rho^{t+1}_j}\sum_{i=1}^{N} E(z_{ij})x_i \quad (6)$$

$$\Sigma^{t+1}_j = \frac{1}{N\rho^{t+1}_j}\sum_{i=1}^{N} E(z_{ij})\left[(x_i - \mu^{t+1}_j)(x_i - \mu^{t+1}_j)^T\right] \quad (7)$$

(4) If the calculated Θ^{t+1}_j accord with the convergence conditions expressed by Eq. 8, stop the iterative computing, or else, go to E-Step, where ε is a less threshold. (we set it as 10^{-5} in our experiments):

$$\left\|\Theta^{t+1}_j - \Theta^t_j\right\| < \varepsilon \text{ or } \sum_{j=1}^{M}\left\|\Theta^{t+1}_j - \Theta^t_j\right\| < \varepsilon \quad (8)$$

LOCALIZATION METHOD

The localization process is actual a RSSI pattern matching process, which consists of the following two phases. (1) Off-line training phase. Firstly, select some training locations in the area covered by WSN, for each training location, plentiful detecting signals are sent with an invariable power; some APs receive these signals and build the RSSI example data set for each training location. Then, each AP implements a probability analysis employing GMM on the collected RSSI example data set and finally builds a RSSI probability distribution database. The record format of such database is $<AP^{(i)}, x_t^{(j)}, \Theta_t^{(j)}>$, where $AP^{(i)}$ means this record belongs to the ith AP, $x_t^{(j)}$ denotes location of the jth training location recorded by the ith AP and $\Theta_t^{(j)}$ denotes the GMM parameters of the jth training location trained by the ith AP. (2) Localization phase. While locating a mobile user, the user emits detecting signals, let the RSSI mode received by each AP is $<x^{(1)}, x^{(2)}, ...x^{(p)}>$, where P is the number of AP whose RSSI met a threshold, then the probability that the user may occur at certain training locations is calculated according to the GMM parameters, take the location with maximal probability as the user location estimate, the estimated location $X^{(i)}$ of the ith AP is expressed it as:

$$X^{(i)} = \underset{x_t^{(j)}}{\arg\max}\, p(x^{(i)}|\Theta_t^{(j)}) \quad (9)$$

Take the location with the maximum probability among all APs as the final localization result X, expressed it as:

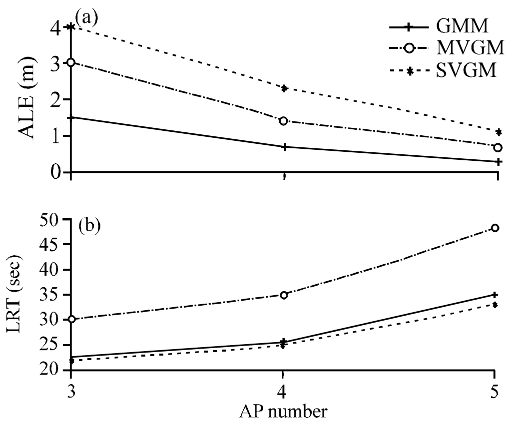

Fig. 1(a-b): Comparison of three methods on (a) ALE and (b) LRT

$$X = \underset{x_t^{(j)}}{\operatorname{argmax}} \{\max\{p(x^{(i)} \mid \Theta_t^{(j)})\}\} \qquad (10)$$

EXPERIENCE EVALUATION

The test area consisted of a typical one-floor office with an area of 400 m^2 (20×20 m), where WSN consisted of about 13 Crossbow MicaZ nodes equipped GPS. Some portable computers were employed to be APs and implemented the TinyOS adc.h and ADCGETDATA function to collect RSSI. The programs were designed with WinAVR GCC studio. A group of experiments were performed to evaluate our method.

Average Localization Error (ALE) and Localization Respond Time (LRT) evaluation on three localization techniques including SVGD, MVGD and GMM. A series of experiments were performed where we took various parameter combinations to evaluate ALE and LRT for three methods, experiment results are shown as Fig. 1.

From Fig. 1, it can be seen that (1) ALE of GMM method is lowest among three methods and (2) as the number of AP increases, ALE decreases, whereas, LRT increases in all methods and (3) LRT of SVGD exceeds a little than GMM, considering the tradeoffs between localization accuracy and real time performance, it can been concluded that the GMM technique exceeds other two techniques.

CONCLUSION

Instead of taking the physical properties of the signal propagation into account directly, the WSN user location estimation problem is researched in a machine learning framework, where GMM was employed to match the received signal pattern against the training patterns. On the basis of this matching model, an approach of WSN user localization that consists of an offline training phase and a real time localization phase is presented in this paper. Experiment results show that the ALE of the proposed method can be below 1 m. Nevertheless, the real-time performance is bad relatively when the user moves rapidly and the stabilization also need be enhanced, which exhibited by the instability of the ALE. So, the proposed method should be improved further to enhance the real time performance and stabilization in the future work.

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