Iterative Bayesian-based Localization Mechanism with Mixture Distribution

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Abstract—We evaluated the performance of a RSS-based positioning system that uses an iterative Bayesian network with mixture distribution. It showed a better performance than the previous Bayesian network literature.

I. INTRODUCTION

In wireless networks, the location information of connected devices became an important asset to improve the security and overall system performance. In fact, the operation of such networks is improved by allocating resources based on the knowledge of the devices positions. Particularly, indoor deployment scenarios are more susceptible to channel variations and thus need more elaborated techniques which can continuously learn, while accounting for additional processing and signaling exchange. In this regard, Authors in [1], [2] use Bayesian networks and Received Signal Strength Index (RSSI) to estimate a device position without employing offline learning. Herein, we extend the formulation in [3] by introducing a new mixture-based iterative method which provides considerable gains in terms of Root Mean Square Error (RMSE) when compared to the previous literature.

II. SYSTEM MODEL

A. Bayesian network

Bayesian network is an approach that uses directed graphical model to make inferences about desired random variables (RVs) [4]. We use the Bayesian network to describe the interdependence of the RVs in a statistical model. First, we make some assumptions of the probability distribution of the RVs based on our prior knowledge, hereafter represented by prior distributions. With the assumptions and the Bayesian network we need an algorithm to estimate the RVs. We decided to use a Markov Chain Monte Carlo (MCMC) approach called No-U-Turn Sampler to go through the graph and find the estimation of the random variables. In a Bayesian network approach, the RVs are assumed to be conditionally independent of nodes that are not you parents [4]. As presented next,

\[
f(V) = \prod_{v \in V} f(v|\text{pa}(v)),
\]

where \(V\) is the set of all RVs on the graph and \(\text{pa}(v)\) is the set of all the parents of the RV \(v\). The Bayes’ theorem allows us update our prior belief about the RVs based on observed data of the RVs as follows [5],

\[
f(H|D) = \frac{f(D|H)f(H)}{f(D)},
\]

where \(D\) is the observed data and \(H\) is our prior belief. In this work, we use the MCMC sampler to estimate the position of the target as the posterior distribution \(f(H|D)\) in (2).

B. Deployment Scenario and Localization Mechanism

The test scenario is composed by four anchor nodes at the vertices of a square warehouse with side of 100 meters. We consider line of sight and log-distance shadowed path loss. The access points measure the RSSI and send the information to a server where the algorithm performs the estimation of the target position. The prior distributions for the Bayesian network in Fig. 1 are provided in the following [2],

\[
(X,Y) \sim [\text{Uniform}(0,L)],
\]

\[
D_i \sim \sqrt{(X-x_i)^2+(Y-y_i)^2},
\]

\[
\mu_i \sim \rho_0 + \eta_i \log(D_i),
\]

\[
\rho_0 \sim \text{Normal}(0,100),
\]

\[
\eta_i \sim \text{Normal}(0,100),
\]

\[
\sigma^2 \sim \text{HalfNormal}(10),
\]

where \((X,Y)\) are the target’s coordinates, \(D_i\) is the distance of the target to the \(i\)th access point, \(\rho_0\) is the transmission power, \(\mu_i\) is the received power, \(\eta_i\) is the coefficient of path loss, and \(\sigma^2\) is the standard deviation associated to the \(i\)th access point measurement. The distributions in (3) represent our initial assumptions for the first iteration using the Bayesian network. Thereafter, each subsequent posterior distributions are used as the prior for the next iteration.
III. Iterative Method

At each new iteration, we update the Bayesian network with new observed data. Here, the prior distribution of each such iteration is a mixture of the posterior of the last iteration with parameters \((\mu, \sigma)\) and a Gaussian distribution specified by \((\mu, 2\sigma)\). The mixture distribution approach was made to give more freedom to the algorithm to explore the sampling space. The mixture distribution is given by \([5]\),

\[
f(x) = \sum_{i=1}^{n} w_i P_i(x),
\]

where \(w_i\) is the weight of the respective PDF \(P_i(x)\).

IV. Performance Analysis

In this section, we use the MCMC sampler to evaluate the performance of the proposed Bayesian-based solution in terms of the RMSE. The weights applied were 0.2, 0.5 and 0.8 to the Gaussian distribution. The simulation carried out had an exhaustive campaign to be able to assess the performance. Each simulation run had 20 iterations with new 250 RSSI measurements in each one of them. The actual target position is \((20, 80)\), anchors independently acquire the RSSI measurements, and the MCMC-based NUTs algorithm \([6]\) is used to estimate that position. The measurements are sent to a server at the edge of the network, and the algorithm is used to find the estimation of the target’s position.

The Fig. 2 shows the improvements of the estimation through the iterations. The mean gets closer to the real location and the uncertainty is reduced.

The Fig. 3 shows the RMSE for the different weights analyzed in this work. We have a best performance when the Gaussian has a bigger weight because the algorithm can explore more the sampling space. In the prior work \([3]\), the mixture of distribution technique was not used, and the Gaussian distribution was used as prior distribution, so we can consider that the Gaussian had weight 1. However, we have a better performance using weight 0.8 than 1 for the Gaussian distribution, it means that the posterior distribution has important information that affects the estimation made by the system and it should not be discarded. The estimation of the simulation using the weights 0.2 and 0.5 had poorer performance when compared to the weights 0.8 and 1.

V. Conclusions and Final Remarks

The iterative method with mixture distribution improve the performance of the system. However, the performance changes substantially with the weight given to the mixtures.

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References