Indoor Location Estimation based on IEEE 802.15.7 Visible Light Communication and Decision Trees

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***Abstract*— Indoor positioning estimation has become an attractive research topic due to the growing interest in location-aware services. Many research works have been proposed on solving this problem by using wireless networks. Nevertheless, there is still much work needed to achieve high accuracy levels. In the last years, the emergence of visible light communication brings a brand new approach to high accuracy indoor positioning. Among its advantages, this new technology is immune to electromagnetic interference and also allows knowing the received optical power accurately. In this paper, we propose a fingerprinting indoor location estimation methodology based on decision trees. Along with the method, we also share some experimental results using the received signal strength obtained from an IEEE 802.15.7 simulator developed by our research group. Results are encouraging. The tested model (classifier) yielded a 93% accuracy, with an average error distance for misclassified instances of 37 centimeters.**

Keywords-Indoor Location; Visible Light Communication; Decision Trees; Received Signal Strength.

I. INTRODUCTION

Indoor localization has gained considerable attention over the past decade due to the emergence of numerous location-aware services. These new services have made it possible to use applications capable of sensing their location and dynamically adjusting their settings and functions [1]. Many indoor localization approaches based on globally deployed radiofrequency systems, such as WLAN, Bluetooth and UWB, have been proposed, mainly because of their low cost and mature standardization state. Nevertheless, they usually deliver an accuracy of up to two meters because multipath propagation [2]. Visible light communication (VLC) is experiencing a growing interest due to improvements in solid state lighting and a high demand for wireless communications. VLC can offer a higher positioning accuracy [3] mainly because of two reasons: this kind of networks is not affected by electromagnetic interferences and the received optical power is more stable than radio signals and can be accurately known. For example, authors in [4] proposed a system with a positioning error about 10 centimeters using a location code and a spatial power distribution map where RSS measurements are gathered every 5 centimeters.

Indoor positioning techniques for VLC are mainly classified into two groups based on geometric properties: lateration and angulation [5]. Lateration techniques estimate the target location by measuring distances from the receiver to multiple LEDs base stations with known coordinates. The distances can be estimated involving the time of arrival (TOA), time difference of arrival (TDOA) and the received signal strength (RSS). On the other hand, with angulation techniques or angle of arrival (AOA) the target location is estimated by measuring angles to multiple base stations. Nevertheless, these techniques often require additional hardware, time synchronization between emitter and receiver, knowing every base station coordinates and extra computation. Thus, fingerprinting techniques combined with VLC can be an alternative to the aforementioned techniques because they estimate positioning by matching online measured data with pre-measured location-related data, such as RSS. Hence, only RSS information is needed and extra sensors are unnecessary. In fact, fingerprinting is one of the most commonly used techniques for RF indoor location [6]. Localization based on fingerprinting is usually carried out in two phases. The first phase (offline phase) consists on the sampling of RSS measurements for every emitter and each reference location (VLC receiver). During the second phase (online phase), the particular receiver position is estimated by feeding new measurements to the positioning model built with previously acquired samples. Most research differs in the latter phase. In this paper, we propose an indoor location estimation method based on an ensemble model of decision trees. We present some preliminary results showing the achieved high accuracy and low computational complexity.

On the other hand, in 2011, Institute of Electrical and Electronic Engineers (IEEE) published the IEEE 802.15.7 standard, which defines Physical (PHY) and Medium Access Control (MAC) layers for short-range wireless optical communications using visible light [7]. Within the last few years, many studies on VLC based positioning have been published. Nevertheless, to the best of our knowledge, to this date there is no any published indoor positioning research using this standard. This paper is the first work to use decision trees in IEEE 802.15.7 VLC networks for indoor location estimation.

With the present work, our contribution is the following: we propose an ensemble model of decision trees based indoor

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positioning methodology together with some promising results. Furthermore, we make use of the IEEE 802.15.7 standard on VLC to obtain RSS values, which may be a useful piece of information for other researchers and practitioners at this stage of (un)deployment of such standard.

The rest of the paper is organized as follows. In Section 2, we describe our simulator that implements the IEEE 802.15.7 standard. Next, in Section 3, we describe the ensemble model of decision trees used for VLC indoor location estimation. In Section 4, we describe the two phases of our indoor positioning method based on an ensemble model of decision trees. In Section 5, we show some experimental results that demonstrate the high accuracy of our approach. Finally, we sum up the conclusions and we present the future work.

II. SIMULATION MODEL BASED ON IEEE 802.15.7

We built our IEEE 802.15.7 simulator using OMNET++ simulation framework from the model developed by [8], designed for sensor networks based on IEEE 802.15.4 standard. We can do that due to the similarities that exist between both standards IEEE 802.15.7 and IEEE 802.15.4.

OMNeT++ provides built-in support tools for recording and analysis and visualization of simulation results. Several data can be chosen for simulation results, such as throughput, delay, packet loss and RSS.

The developed simulation model has been designed with the following premises:

- IEEE 802.15.7 star topology has been chosen, due to its importance and wide range of applications.
- For the MAC layer, we opted to use the superframe structure, since it allows the use of both contention (CAP) and no contention (CFP) access methods. In addition, the use of the superframe enables devices to enter the energy save state during the idle period.
- A VPAN identifier is assigned to each emitter in order to identify each coordinator (LED lamp).

Next subsections describe the most important features in our simulator, for a better comprehension of the presented results.

A. *Optical channel model*

The transmission medium is modeled as free space without obstacles. We chose the directed line of sight (LOS) link configuration to model the optical signal propagation, requiring a LOS between each device and the coordinator. We have considered only the direct component of the received signal to calculate the received power, despising the possible influence of reflections. According to the results presented in [9], at least 90% of total received optical power is direct light in VLC when using a receiver field of view (FOV) of 60 degrees. Therefore, to ensure the validity of our implemented model, we have configured all optical receivers using a 60 degrees FOV value.

TABLE I. PHY LAYER PARAMETERS

Parameter	Value
Transmission rate	1.25 Mbps
Optical clock rate	3.75 MHz
Coordinator optical transmission power	15 W
Half Power Angle $\theta_{1/2}$	60º
Field of Vision (FOV)	60º
Photo detector area (A)	10 mm^2
Photo detector responsivity (R)	0.54 A/W
Optical concentrator gain (G)	15
Optical filter transmission coefficient (T)	1

The adopted optical channel model facilitates reaching high transmission speeds, since the effects of multipath distortion on the optical signal are not considered. Considering only the direct component of the signal has the additional benefit of improving the efficiency of the implemented simulation model. The computational load required to run simulations of scenarios with multiple nodes including the functionality of different layers of the architecture is reduced significantly.

B. *PHY layer simulation parameters*

Table 1 shows the main configuration parameters of PHY layer used in all simulation scenarios. We selected the PHY II operating mode, intended for both indoor and outdoor environments, using MCS-ID number 16, since support for the minimum clock and data rates for a given PHY is mandatory. Because of the optical channel model used, transmitters' directivity is characterized by its half power angle, $\theta_{1/2}$ while receivers' directivity is defined by its FOV. According to [9], both parameters are assigned a value of 60 degrees, to ensure validity of the implemented channel model, since the calculation of received optical power takes in account only the direct component of the signal. In order to simplify the calculation process of the model, the values used for the concentrator gain (G) and the transmission coefficient of the optical filter (T) are set up as constant values, so they do not depend on the angle of incidence ψ.

The rest of the values selected to characterize VLC transmitters and receivers are commonly used values in literature, similar to those used in [10][11].

III. ENSEMBLE MODEL OF DECISION TREES

Indoor positioning has been a very active research area where several data mining techniques have proved useful to extract knowledge from raw data [12][13]. To solve this problem, we propose a general approach based on decision trees classifications.

Decision trees build classification models in the form of a tree structure. In general, they can handle both categorical and numerical data. A decision tree has internal nodes and leaf nodes. An internal node includes a condition or function of any feature of the dataset, which breaks down the dataset into

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several subsets, corresponding to two or more branches. Each leaf is assigned to one class representing the classification decision. For instance, in the location problem, the received optical power from luminaries is used in the internal node conditions, and the locations or reference points are used in the leaf nodes. Samples are classified by navigating from the root of the tree down to a leaf, according to the outcome of the condition or function along the path [14].

On the other hand, ensemble models are methods that combine the capabilities of multiple models to achieve better prediction accuracy than any of the individual model could do on its own. Ensemble methods generate multiple base models, and the final prediction is produced as the result of a combination of them, in some appropriate manner, from the prediction of each base model. For instance, the output of each base model is weighted. The success of the ensemble model is based on the ability of generating a set of base models that make errors that are as uncorrelated as possible.

In our indoor localization method, we use a weak classifier based on the C4.5 algorithm [15] to generate a decision tree as a base model. Then, the adaptive boosting (AdaBoost) algorithm [16] is used to build an ensemble model based on previous base models, that is a location estimation model formed by multiple weighted decision trees. In a previous work, we demonstrated that this combination of machine learning techniques provides excellent results for indoor localization [17].

IV. INDOOR LOCALIZATION METHOD

In this Section, we describe our positioning method based on an ensemble model of decision trees, and it is divided into two phases. The first phase is the training phase (offline phase). Coordinators send beacon frames and RSS samples are collected at reference locations (receivers) to build a dataset. From this dataset, the ensemble model is built. The second stage is the test phase (online phase) where a receiver infers its position by using the online RSS observations.

A. Training phase

In this phase, we aim at building an ensemble model of decision trees using the RSS measurements dataset as training set. Several simulations are carried out at each reference location to calculate different values of RSS. Each simulation is performed with a random orientation vector of each receiver to obtain different values. RSS data are denoted by $\varphi_{i,j}(\tau)$ and indicate the τ-th RSS value measured from i-th coordinator at the j-th receiver. The database can be represented by ψ as in (1):

$$\omega = \begin{pmatrix} \varphi_{1,1}[\tau] & \cdots & \varphi_{1,R}[\tau] \\ \vdots & \ddots & \vdots \\ \varphi_{A,1}[\tau] & \cdots & \varphi_{A,R}[\tau] \end{pmatrix} \quad (1)$$

where A is the number of coordinators, R is the number of receivers or reference locations, $\tau = 1, ..., N$ is the index of RSS samples and N is the number of RSS samples at each reference location.

After that, once that RSS dataset of the environment is compiled, an ensemble model of decision trees is built using boosting technique.

B. Test phase

In this phase, a dataset formed by a RSS sample from each coordinator is taken as input of ensemble model of decision trees to infer the current location. Using similar notations, the online measurements can be represented as in (2):

$$\omega_r = \begin{pmatrix} \varphi_{1,r} \\ \vdots \\ \varphi_{A,r} \end{pmatrix} \quad (2)$$

where the location r is unknown.

V. EXPERIMENTAL RESULTS

Our method was tested in a simulation environment that models a 4 by 4 by 3 meters room. As shown in Fig. 1, the environment consists of 16 coordinators or LED lamps (red triangles) configured as 4 x 4 grids placed 1 meter apart from each other on the ceiling. On the lower part, we set up 100 receivers (blue circles) in a 10 x 10 grid configuration, with a 36 cm separation from each other. In order to consider different distances between receivers and coordinators, the receivers plane is set up at three different heights: 75, 100 and 125 centimeters from the floor. Receivers orientation was randomly produced for each simulation as follows: they are pointing out to the ceiling with an initial orientation vector [0,0,1] and a random (-0.2,0.2) offset is applied to each axis in each simulation. Thus, each receiver has a different orientation in each simulation.

Eleven simulations were performed on each three vertical layers. One RSS measurement was estimated at each receiver and simulation. This leads to 3.300 RSS measurements. From this dataset, training and test dataset were random split, picking the same proportion of samples at each class

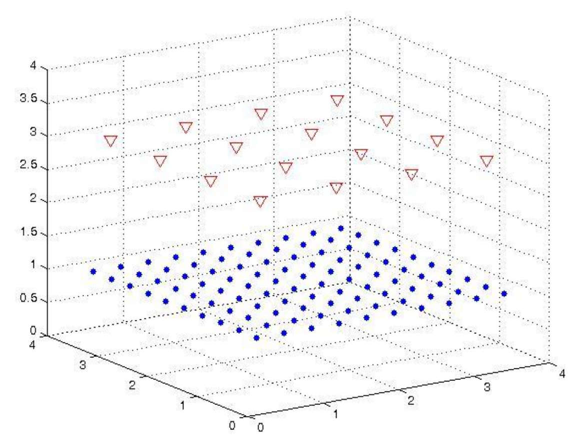

Figure 1. Network scenario with 16 coordinators and 100 receivers.

(stratified split). In order to test the robustness of the method, different training size datasets were used, from 50% to 90% of the whole dataset. The simulation parameters are provided in Table 1.

Fig. 2 shows the received optical power (lux) at 1 meter from the floor with sixteen coordinators. As it can be seen there is enough lighting to receive the beacon frame in every reference location.

For each training dataset, an ensemble model based on decision trees was generated using Weka tool in an Intel i7 2.2 GHz/8GB non-dedicated Windows machine. The classification trees were created by the C4.5 algorithm (implemented in Weka by the classifier class: *weka.classifiers.trees.J48*). The boosting method used was the metalearning AdaBoostM1 algorithm implemented by the Weka classifier class *weka.classifiers.meta.AdaBoostM1* with number of iterations equal to 10. For the validity of simulation results, all experiments were run based on 10-fold cross validation.

Experiments were focused to determine the location method accuracy. The error is the expected distance from the misclassified instance and the real location. The error is calculated by the Euclidean distance between these points, and the arithmetic mean was computed from the results of the experiments. Being a classification problem, an error simply means that a receiver was estimated to be in a wrong positioning cell, in the receivers grid.

Table II shows experimental results in terms of correctly classified instance percentage and average error distance for each training dataset size. As expected, the elapsed time to build each model increases with the training dataset size. Nevertheless, this not meaningful, because the maximum time is about thirty seconds and it must take into account that the model is generated only once, in the offline phase. On the other hand, using only five samples at each receiver for training (50% training dataset size) the model has an accuracy about 88% and an average error distance of 4.7 cm. Nevertheless, an average error distance of 39.4 cm is reached if misclassified instances are only considered. Obviously, better results are achieved by increasing training dataset size, however, the accuracy is only improved about a 5% from 50% to 90% dataset size, and the average error distance of misclassified instances improves about 2.4 cm. Fig. 3 shows the cumulative distribution function (CDF) for 90% training dataset size. As it can be seen, most of instances are correctly classified and it is about 93%. Fig. 4 shows the CDF of misclassified instances for 90% training dataset size. As it can be seen, the maximum error distance is about 50 cm. Furthermore, 86% of misclassified instances have an error distance less than 37 cm, that is, most of misclassified locations are the nearest neighbours (receivers) of exact locations.

TABLE II. EXPERIMENTAL RESULTS

Training Dataset Size (%)	**Time to build Model (s)**	**Correctly Classified Instances (%)**	**Average Error Distance ± std (cm)**	**Average Error Distance ± std (cm) of Misclassified Instances**
50	20.96	88.55	4.7 ± 0.131	39.4 ± 0.075
60	23.26	89.66	4.5 ± 0.124	37.75 ± 0.051
70	26.65	90.44	3.8 ± 0.113	37.4 ± 0.045
80	31.8	92.16	3.3 ± 0.109	37.08 ± 0.069
90	32.73	93.33	2.8 ± 0.099	37.02 ± 0.058

VI. CONCLUSIONS

In this paper, we have demonstrated that decision trees provide a high accuracy for indoor location estimation in VLC networks. This is mainly because the visible light is less susceptible to multipath effects making the propagation and

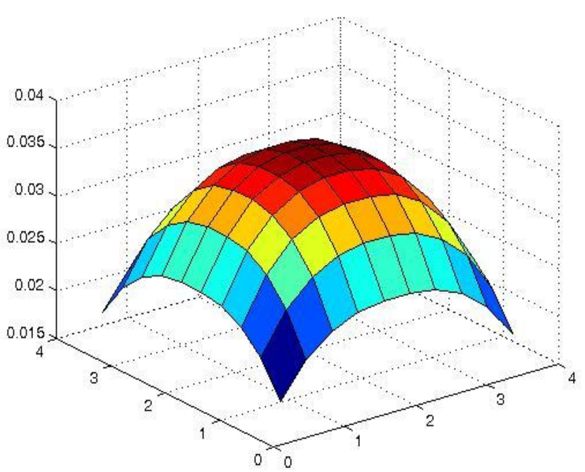

Figure 2. Distribution of the received optical power at 1 meter from the floor.

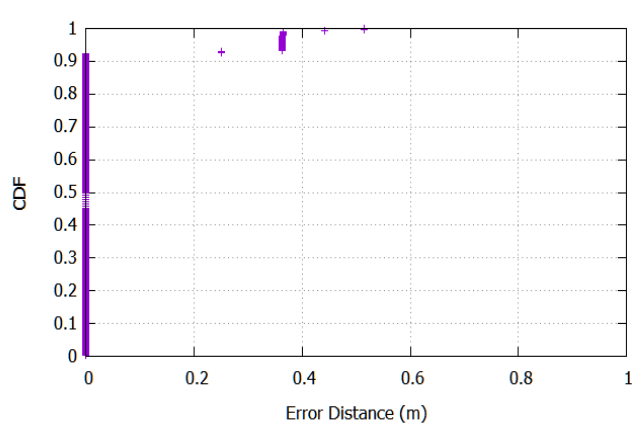

Figure 3. CDF of performance for 90% training dataset size.

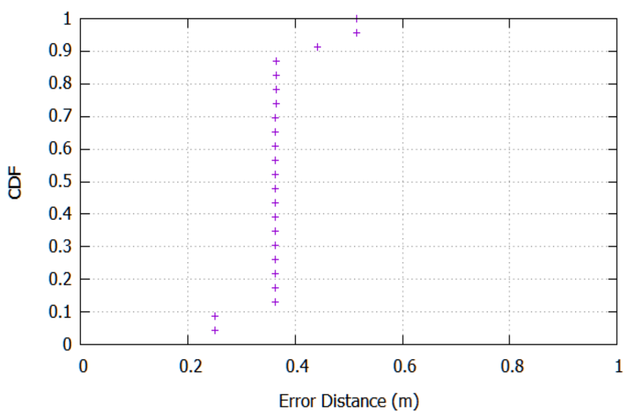

Figure 4. Misclassified instances CDF of performance for 90% training dataset size.

the received optical power more predictable. With regard to accuracy, about 93% of instances are correctly classified and average error of 2.8 cm. Furthermore, the ensemble model of decision trees achieves an average error distance of misclassified instances of 37 cm, taking account that the receivers are placed in a grid with a 36 cm separation from each other. On the other hand, the accuracy of the ensemble model improves with the training dataset size, and its effect on the elapsed time to get the model is not meaningful.

Since the average error distance of misclassified instances cannot be less than the distance among receivers when decision trees are used, in our ongoing work, we are planning to use other techniques of data mining, such as regression, to reduce the error distance.

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