Visible Light Positioning: A Machine Learning Approach

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***Abstract*—Visible light positioning (VLP) systems have experienced substantial revolutionary progress over the past year because they can offer great positioning accuracy without needing any additional infrastructure, as conventional radio-frequency (RF)-based systems. Received signal strength (RSS)-based VLP systems are a promising approach to many indoor positioning estimation problems, but still suffer from difficulty in providing high accuracy and reliability. A potential solution to these challenges is to combine VLP systems, and machine learning (ML) approaches to enhance the position prediction accuracy in two-dimensional (2-D) spaces, or more complex problems. In this paper, we propose a ML approach to accurately predict the 2-D indoor position of a mobile receiver (eg. an automated guided vehicles-AGV), based on the measured RSS values of 4 photodiodes (PDs) forming a star architecture. We examine and evaluate the performance of different ML learners applied to the above-described problem. The proposed ML and Neural Network (NN) methods exhibit great accuracy results in predicting the 2-D coordinates of a PD-based receiver.**

I. Introduction

Visible light communication (VLC) technology is progressing rapidly, thus the accurate estimation of indoor positioning seems to be essential. Estimating a user's location has emerged as a crucial need for wireless augmented and virtual reality applications [1]. Traditional indoor positioning techniques, include Wireless Local Area Network (WLAN), Ultra Wideband Technology (UWB) and Bluetooth are not only susceptible to electromagnetic signal interference, but also require additional infrastructure. Thus, VLP system using RSS technique can be a promising candidate for solving indoor positioning needs, as it is easy to implement, interference-free and cost effective [1], [2]. (RSS)-based VLP systems still struggle to provide high accuracy, due to signal wave disturbances as well as noise in the environment [3]. To improve the system's accuracy and reliability, ML algorithms have been introduced as a possible solution. ML techniques, such as weighted k-nearest neighbor (WKNN) and artificial neural network (ANN), have been introduced to predict the indoor position in wireless-based VLP systems but in the literature there are not many applications for multiple PDs in VPL systems [4].

In [2] a VLP design containing one PD and a light emitting diode (LED) is introduced and a hybrid ML approach is used for the indoor positioning estimation. A Random Forest(RF) approach is used for the classification stage, whereas a density-based spatial clustering of applications with noise (DBSCAN) is combined with an extreme learning machine (ELM) learner for the position stage of the approach. The proposed hybrid algorithm achieves significant reduce to the maximum and averaged positioning errors. In [5] authors propose a hybrid approach, combining a kernel ridge regression machine learning (KRRML) learner and second-order linear regression machine learning (LRML) algorithm, for an RRS-based VLP system, in which the data have been pre-processed using a sigmoid function. The proposed approach achieves average 2cm positioning error in horizontal and vertical directions.

In our previous work [1], we examined the impact that the locations of the Lambertian LEDs have on the positioning performance solely and we performed single objective optimization using evolutionary algorithms. In this paper, we propose a ML approach to accurately predict the 2-D indoor position of a mobile receiver (eg. an automated guided vehicles-AGV), based on the measured RSS values of PDs forming a star architecture. We examine and evaluate the performance of different ML learners applied to the above-described problem.

The remainder of the paper is organized as follows: Section II depicts the formulation of the VLP system and the proposed positioning algorithms. Section III presents the ML models that are used for the positioning of the mobile receiver. In Section IV, simulation metrics and results are presented and analyzed. Finally, Section V contains conclusions and possible future work.

II. Formulation

We consider as in [1] a room of $5\,\mathrm{m}$ by $5\,\mathrm{m}$ at height and a typical VLP configuration, with four LEDs of order $m = 1$ placed in star topology. The 2D positioning accuracy is evaluated using a positioning error metric. The latter is calculated using the Euclidean distance between estimated and actual receiver position.

We consider the PD-based receiver to be untilted and has an active are $A_R = 13\,\mathrm{mm}^2$. The receiver is placed on $5\,\mathrm{m}$ by $5\,\mathrm{m}$ ground plane, which is $10\,\mathrm{cm}$ uniformly spaced. There are 4 LEDs that are located in $3\,\mathrm{m}$ high. We consider N_{LED} LEDs, LED$_j$ $(j = 1, 2, .., N_{LED})$ having coordinates $\mathbf{x_L} = (x_{L,j}, y_{L,j}, z_{L,j})$. These are intensity modulated to broadcast receiver-side demultiplexable beacon signals with unique frequencies [6]. The j-th LED emits a signal, which when received at the point of interest has a RSS value of received radiant power $P_{R,j}$. A localization technique uses the received signal strength (RSS) values related to the LED beacon transmission to estimate the position of the receiver $\hat{\mathbf{x}}$.

The Multilateration-based VLP works in two steps. First it converts the received radiant power values $P_{R,j}$ into a set of LED$_j$ - PD distances d_j by inverting the VLP channel model of [1]. Next the receiver position $\hat{\mathbf{x}}$ is calculated through minimisation of the linearised system relating $\{d_j\}$ to $\mathbf{x_L}$, by using least-squares approach [7], [8]. The computation of $\hat{\mathbf{x}}$ does not require the inclusion of all LEDs' $P_{R,j}$ (or d_j). The selection of a subset of K LEDs (in terms of descending $P_{R,j}/P_{t,j}$) with K $(K < N_{LED})$ could result to a more accurate $\hat{\mathbf{x}}$. The value of K is assumed to be set to 3 by default. More details about the localization algorithm can be found in [1].

III. Machine Learning Models

ML techniques offer various solution for indoor positioning and VLP challenges. In the following subsections, we present the basic characteristics of the ML algorithms in the multi-LED RSS based approach for the VLP position estimation [9].

A. Random Forest(RF)

The RF algorithm is an ensemble learning technique that builds the final model from many different individual decision trees. A class is being defined and selected from each decision tree and the most common class is used as the model's final prediction and RF can also be used for regression problems, like VLP. RF is commonly used in recent VLP application and can achieve great accuracy estimation of the indoor positions. [10]

B. Adaptive Boosting (AdaBoost)

Adaboost is a widely used algorithm for integrated learning challenges, and can be used in both classification and regression problems. The first step in Adaboost is to train a weak regressor. Next using a construction strategy Adaboost builds a stronger regressor. Adabbost can achieve great accuracy results in VLP systems.[11]

C. Gradient-boosted decision tree(GBDT)

GBDT is an ensemble algorithm that sums the predictions of a series of decision trees, as boosting method . At every step, GBDT manipulates the errors caused by the previously trained tree and the formulated decision tree is trained to minimize the residual between current prediction and true test value. GBDT can offer satisfactory results in terms of accuracy and efficiency in many different applications. [12].

D. Support Vector Regressor (SVR)

Support vector machine (SVM) is an algorithm that exploits any support vectors from the learning data-set to calculute an optimum margin from the classes and realize the best hyper-plane for the classification. SVR is a SVM-based approach, in which high and low mis-estimations are equally penalized, forming symmetrical loss function for the training of the model [13]

E. MLP

The MLP is a feedforward artificial neural network (ANN) with different layers: an input layer, a set of hidden layers, and an output layer. The nodes of each layers, are fully connected to one another and define the architecture of the MLP approach. The inputs and outputs of each neuron are mapped by an activation function. MLP is developed to mostly solve non-linearly input patterns. [4].

IV. Performance measures and results

A. Metrics

Suitable error measurement metrics can define the accuracy of the ML algorithms that are used for the position estimation. A comparison between the predicted positioning values and the real values of the test set is used for the error metrics. Suitable error measurement metrics in machine learning approaches are the Mean Absolute Error (MAE), the Root Mean Squared Error (RMSE) and the Mean Absolute Percent Error (MAPE). The formulas of the error measurement metrics are given below in equations (1)-(3):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{1}$$

$$RMSE = \sqrt{(\frac{1}{n})\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} |\frac{y_i - \hat{y}_i}{y_i}| x100\% \tag{3}$$

where n denotes the test set number of input records, y are the real measured data and $\hat{y}$ the predicted ones of the i-th data record. As the models use multiple output regression methods, other useful performance metrics are the Relative Root Mean Squared Error (RRMSE) and the average Relative Root Mean Squared Error (aRRMSE) [14]. Their definitions are given in the following equations :

$$RRMSE = \sqrt{(\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}} \tag{4}$$

$$aRRMSE = \frac{1}{t}\sqrt{(\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}} \qquad (5)$$

where $\bar{y}$ is the average of the true values for that target and t is the number of output variables.

B. ML Modeling

The main objective of this work is to achieve accurate predictions of the 2-D position of the receiver. This is accomplished by comparing the performance of different machine learning learners and by obtaining the best. A collection of 22500 position measurements, was prepared for each coordinate x and y of receiver position and RSS values were acquired for the 4 LEDs forming a star topology.

Modeling this kind of problem presents a first difficulty, the input values are four, while the target outputs are two. ML models require more inputs to compute this model with high accuracy. Thus, noise data augmentation was performed by inducing various noise levels to the measured RSS values from the four LEDs. The additive Gaussian noise level values applied to the measured RSS with different variances. Therefore, we obtained four measured and twelve pseudo RSS values (with induced noise level values were induced as training features in each of the ML models. Thus, the input parameters consist of the calculated and the RSS values with induced values as inputs and the 2-D position of the receiver as outputs. This results to a total number of sixteen input parameters. Additionally, the number of target output parameters is two (x and y coordinate of the receiver's indoor position).

The total collection of 2-D position and RSS values were divided into two data-sets, in a random manner: the training data-set, containing the 80% of the total data values and the remaining 20% defined the testing set, for the validation of every learner. A $k = 5$ k-fold cross-validation GridSearchCV was used for the hyperparameters tuning to tune in each ML model.

C. Numerical Results

In order to obtain the best suitable model for this case, we have trained different popular ML learners such as RF,SVR, AdaBoost, GTBD and MLP using Python language and evaluated them using suitable conventional error measurement metrics as shown in Table I and Table II, as well as multi-output regression error measurement metrics as shown in Table III.

We notice from Table I and Table II that SVR performs better than the other algorithms in terms of positioning errors in x as well as in y coordinates. The problem at hand is a multi-output regression problem and so, for Table III it is clear that SVR obtained the best results concerning the aRRMSE. The RF approach obtained the second best result, whereas GBTD and Adaboost results were pretty close but slightly worse than the previous models. The MLP approach is the less suitable for these problems, as it achieved the worst accuracy among the learners. The SVR method achieved small MAPE values for each of the 2-D position coordinates and with an aRRMSE value of 0.3811, is highly accurate. If aRRMSE approaches or its close to zero, then we have much better model performance [14]. The other approaches achieved aRRMSE values greater than 1 (the MLP value was > 2), so the SVR model is by far the most accurate and suitable for 2-D indoor position estimation of the receiver by using RSS values.

The graphical representations of the MAPE in each dimension and the aRRMSE of each model approach, are depicted as histograms in Figs 1-2 .

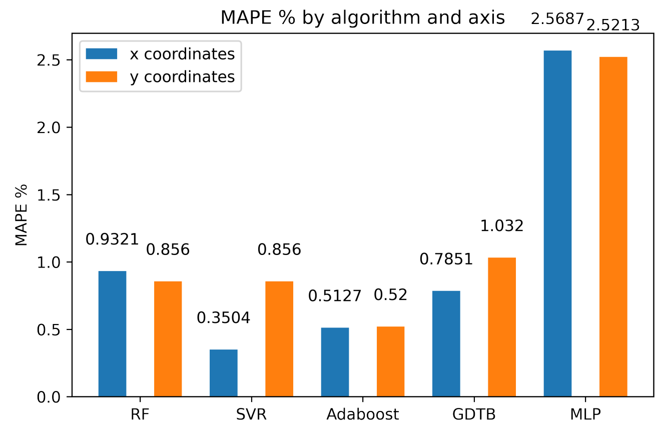

Fig. 1. MAPE for 2-D positioning.

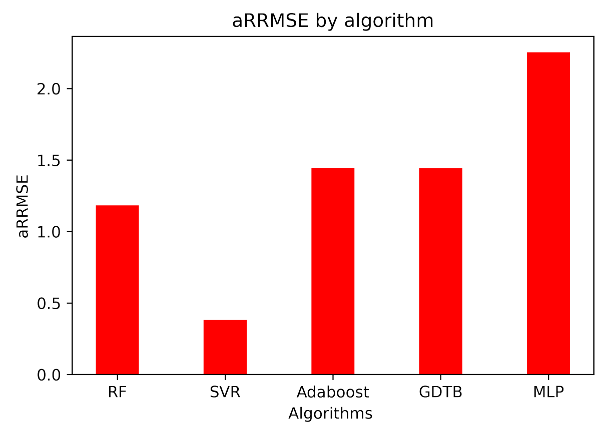

Fig. 2. aRRMSE for 2-D positioning.

TABLE I. ERROR MEASUREMENT METRICS FOR COORDINATES X

Algorithm	MAE	MSE	RMSE	MAPE %
RF	0.0078	0.0001	0.011	0.9321
SVR	0.003	0.000013	0.00372	0.3504
GBDT	0.009	0.00017	0.013	0.7851
Adaboost	0.0058	0.0002	0.014	0.5127
MLP	0.0157	0.00051	0.02256	2.5687

TABLE II. ERROR MEASUREMENT METRICS FOR COORDINATES Y

Algorithm	MAE	MSE	RMSE	MAPE %
RF	0.0086	0.00017	0.013	0.856
SVR	0.0086	0.00017	0.013	0.56
GBDT	0.0112	0.00097	0.0312	1.032
Adaboost	0.0061	0.00022	0.015	0.62
MLP	0.0166	0.00052	0.02281	2.5213

-4 present the correlation between the (real) measured values and the estimated values obtained by the SVR learner,

TABLE III. Error measurement metrics multi-output regression

Algorithm	RRMSE x	RRMSE y	Model's aRRMSE
RF	0.0043	0.0051	1.1831
SVR	0.0015	0.00155	0.3811
GBDT	0.0056	0.0059	1.44434
Adaboost	0.0057	0.0059	1.444
MLP	0.00903	0.0089	2.2526

for the x and y coordinates of the receiver respectively, The green dots represent the measurement values, while the line the fitting and accuracy of our model. The correlation shows a diminutive difference between real and predicted values, due to the small MAPE values for estimating the x and y coordinates for the 2-D positioning estimation.

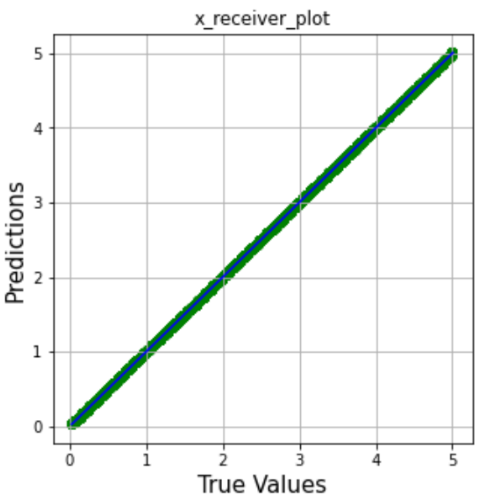

Fig. 3. Estimated versus real measurement x values.

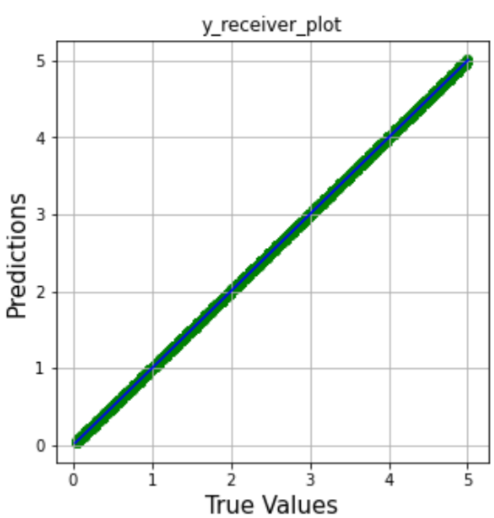

Fig. 4. Estimated versus real measurement y values.

V. Conclusion and Future Work

In this paper, a modeling methodology to predict the 2-D position of a mobile receiver in an indoor environment is proposed. First we generate data using a LED positioning algorithm These data are given as input to train various ML learners. To determine which ML model perform best in this situation, we compare their performances. The SVR approach delivered results with high accuracy, with the aRRMSE in the 2-D coordinates reaching the value of 0.3811. In conclusion, machine learning techniques can make accurate predictions of the 2-D indoor position of a mobile receiver. In our future work, we will expand and generalize the ML approach to model 3-D position, use different architectures (e.g. 4 square LEDs with a center LED), use more LEDs and possible tilt prediction for the mobile receiver in the star and square topologies.

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