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Indoor localization based on visible light communication and machine learning algorithms

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Abstract

An indoor localization system is proposed based on visible light communications, received signal strength, and machine learning algorithms. To acquire an accurate localization system, first, a dataset is collected. The dataset is then used with various machine learning algorithms for training purpose. Several evaluation metrics are used to estimate the robustness of the proposed system. Specifically, authors' evaluation parameters are based on training time, testing time, classification accuracy, area under curve, F1-score, precision, recall, logloss, and specificity. It turned out that the proposed system is featured with high accuracy. The authors are able to achieve 99.5% for area under curve, 99.4% for classification accuracy, precision, F1, and recall. The logloss and precision are 4% and 99.7%, respectively. Moreover, root mean square error is used as an additional performance evaluation averaged to 0.136 cm.

1. Introduction

Recently, the use of localization has increased rapidly due to its massive applications including surveillance, monitoring, and tracking [1]. Several traditional methodologies, such as time of arrival (TOA) and time difference of arrival (TDOA), have been used in localization [2]. Although these techniques can achieve high accuracy, they suffer from time synchronization requirement and high cost. Angle of arrival (AoA) has been acknowledged with high accuracy, but at the expense of complexity and high cost [3]. On the other hand, received signal strength (RSS) is characterized by simple construction, low cost, and good coverage, however, it suffers from low accuracy [1].

Generally, there are several indoor positioning technologies; for instance, ultra-wide band (UWB), Wi-Fi, radio-frequency identification (RFID), infrared, ultrasound, ZigBee, and fingerprint. These technologies are based on finding the actual target location by determining the relative position between the moving target and the fixed unit. Accordingly, there is a need for adding an infrared transmitter unit or access point (AP) which increases the cost of its management and maintenance [1]. On the other hand, visible light communication (VLC) is a promising technique in optical wireless communications and indoor positioning systems (IPSs). It can transmit high data rates without affecting human eyes. It can be distinguished from previous IPSs by being the most cost-effective due to high energy efficiency, secure technology, and wide bandwidth [4].

1.1. Application-based indoor localization

Nowadays, researchers are working on using the advantages of data mining and machine learning (ML) solutions in widespread applications. For instance, economic, health, scientific, engineering, and business sectors. In this subsection, the authors discuss some applications of indoor positioning services in real life.

1.1.1. Positioning and navigation in indoor enviroment

Current intensive scientific research has led to reducing the cost of external systems and various sensor devices that

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are related to different positioning systems. Many positioning technologies exist in large indoor places, e.g., airports, hotels, shopping malls, museums, convention, exhibition centres, etc. [5]. Indeed, this ensures the possibility of quick finding places of interest, entertainment places, and shops in malls. In addition, this helps passengers to easily find their destination in complex airport areas, as well as solve the problem of finding cars in large parking areas, etc.

1.1.2. Home isolation monitoring

With the spreading of COVID-19 pandemic around the world, home monitoring became an essential requirement [6]. Home monitoring ensures that patients are in home insolation or in a predefined virtual range. Of course, this reduces mixing between healthy and ill people.

1.1.3. Nursing personnel and tracking

In nursing homes, navigation services ensuring personal safety are considered an urgent need [7]. A real-time monitoring can be implemented using several localization technologies to ensure staff safety and prevent loss.

1.2. Related research

Achroufene *et al*. [8] have proposed a localization mechanism using the RSS technique and belief function theory. In order to make their model more realistic, non-Gaussian probability density functions have been used to reduce the inaccuracy of RSS measurements in an indoor wireless sensor network (WSN) [8]. In order to exploit the advantages of various technologies in localization, especially in indoor environments, Bluetooth low energy (BLE) technology has been studied in Ref. 9 where a radio frequency BLE signal has been utilized to construct RSS fingerprinting.

Furthermore, as the COVID-19 pandemic spreads, researchers are attempting to devise remote solutions for localization which do not require human presence, using current infrastructure as a starting point. Therefore, VLC is considered as one of the best choices. In Ref. 10, authors have proposed a real-time positioning system in an office. The suggested method uses the RSS-VLC technique based on a multilateration localization. Kalman filtering with averaging schemes in a VLC system has been proposed [11]. The authors have utilized a triangulation method as a localization technique. Both line-of-sight (LOS) and first-reflection non-LOS (NLOS) indoor environments have been considered in this paper. Lately, there have been several research efforts in using neural networks (NNs) and ML technologies for localization, especially in indoor environments. For instance, many studies have worked on improving the system performance through hybridizing ML with VLC [12].

In Ref. 13, underwater localization has been utilized in VLC and NN algorithms. This is based on changing several neurons numbers, activation function, and training algorithms. Accuracy of 98.7% was achieved using two neurons, an identity activation function, and limited-memory Broyden-Fletcher-Goldfarb-Shanno bound (L-BFGS-B) training algorithm.

A practical visible light positioning (VLP) system utilizing ML algorithms and repeated positioning cells was demonstrated by Chuang *et al*. [14]. The authors have concluded that the positioning accuracy obtained with their ML-VLP system is better than that of the RSS-VLP system in the 2D positioning. However, the latter is simpler.

In this context, the framework proposed by the authors is based on utilizing RSS as an inexpensive indoor localization methodology and improving its accuracy with the adoption of ML.

1.3. Aim of the paper

In this paper, an indoor localization system based on VLC technology, RSS, and ML models is proposed. At first, in order to obtain a dataset of received power values, a MATLAB program is developed to simulate indoor channel mode, transmitter, and photodetector. Authors' dataset consists of RSS values of 10 000 pixels, in a 5×5 m^2 room. Next, several ML algorithms are proposed to localize a target in a 2D positioning system. Here, the gathered RSS dataset is trained with the aid of the Orange data mining tool.

Specifically, in order to estimate the (x, y) Cartesian coordinates of a mobile device, a grid of dataset is trained with ML models. That means, the ML input is simply the received signal power and its output is an accurate predicted mobile device position. Further, several ML models are applied to obtain the optimum performance of the proposed framework. Specifically, NN, support vector machine (SVM), decision tree, logistic regression, k-nearest neighbours (k-NN), random forest (RF), adaptive boost (AdaBoost), naive Bayes (NB), and stochastic gradient descent (SGD) are ML models used by authors.

The proposed positioning system is featured by low complexity, high accuracy, and very small error in an acceptable time. This makes it a potential candidate for integration into mobile devices.

1.4. Paper organization

The remainder of this paper is organized as follows. In section 2, the channel model related to the dataset extraction is introduced. Section 3 is dedicated to illustrating the ML algorithm. In section 4, the data mining tool and the methodology of the proposed system are presented. Several evaluation methods are applied in section 5. Finally, concluding remarks are given in section 6.

2. Channel model

In this section, the authors' channel model is presented [15]. Since the LOS signals strengths are very large compared to that of NLOS signals [16], only LOS paths model is considered between transmitted light emitted diodes (LEDs) and photo detectors and that of NLOS is neglected. In addition, both shot and thermal noises are taken into consideration in the authors' studies.

The total received power P_r is determined by multiplying the transmitted power P_t with the DC channel gain for the LOS signal H_{LOS}^i:

$$P_r = \sum_{i=1}^{N} P_t H_{LOS}^i , \tag{1}$$

where N is the number of transmitters (LEDs), which is taken as 4, and H_{LOS}^i is the DC channel gain of LOS from the i^{th} transmitter, evaluated as follows. Figure 1 shows a light path from the LED to the receiver.

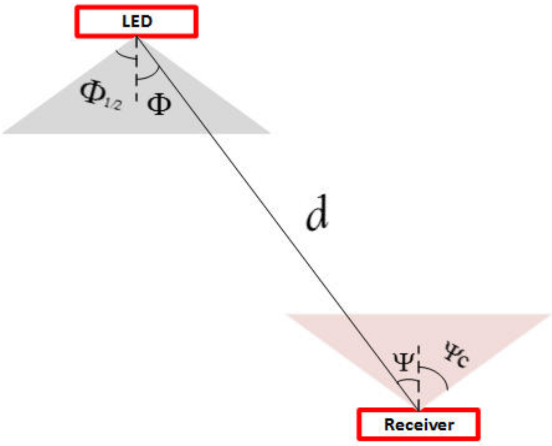

Fig. 1.. Transmission of light from the LED to the receiver.

Here, a Lambertian LED with the order m is utilized to transmit a light signal with an irradiance angle ϕ. The LED has $\phi_{\frac{1}{2}}$ as a semi-angle at half illuminance. The photo detector at a distance d from the LED is used to estimate the received power with an incident angle ψ. Of course, the incident angle value must not exceed the field of view ψ_c. Accordingly, it can be written:

$$H_{LOS}^{i} = \begin{cases} \dfrac{(m+1)A}{2\pi d_i^2} \cos^m(\phi_i) T_s(\psi) g(\psi) \cos\psi; & 0 < \psi < \psi_c, \\ 0; & \psi > \psi_c. \end{cases} \quad (2)$$

Here, A is the physical area of the detector, $T_s(.)$ is the gain of an optical filter assumed to be 1, and $g(.)$ is the gain of an optical concentrator evaluated according to:

$$g(\psi) = \begin{cases} \dfrac{n^2}{\sin^m \psi_c}; & 0 < \psi < \psi_c, \\ 0; & \psi > \psi_c, \end{cases} \quad (3)$$

where n is the refractive index of the optical concentrator [17]. It should be noticed that m is evaluated as:

$$m = -\frac{\ln(2)}{\ln\left(\cos \phi_{\frac{1}{2}}\right)}. \quad (4)$$

3. Machine learning algorithms

Machine learning is considered a vital branch of artificial intelligence (AI) and computer science depending on the use of data and algorithms to emulate the way humans learn to achieve improved accuracy. Depending on the learning style, it has been categorized into supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning [18]. In this study, several supervised learning algorithms are used as termed below.

3.1. Decision tree algorithm

Decision tree is an algorithm that is based on "if-then" statements [18]. It consists of two kinds of nodes. Decision nodes, which are responsible for choosing a decision from alternatives, and leaf nodes, which are final outputs. Its key advantage is being easy to read and interpret. However, its primary issue is instability, since a minor modification might cause a large change in the optimal decision tree structure.

3.2. Random forest algorithm

On the other hand, random forest (RF) algorithm is considered as multiple decision trees. It consists of two stages, creating trees and making decisions from this forest. The output of RF is simply the class selected by most trees. The major benefits of RF in decision tree techniques are high accuracy and less overfitting. However, since it is a mix of several decision trees, it necessitates a significant amount of computing time and power [18].

3.3. Neural network algorithm

A neural network (NN) is based on mimicry of human brain operations. It consists of three layers, an input layer, one or more hidden stages, and an output layer. A huge number of neurons are considered a processing unit which is responsible for processing the input data up to getting the final accurate output. These neurons are connected to each other, and each neuron is related to an activation function. Using NNs, complex and nonlinear datasets are classified very easily with no input restrictions as in other classification methods [18].

3.4. Support vector machine algorithm

A support vector machine (SVM) algorithm is based on finding the optimum boundaries between possible outputs. To acquire the optimal hyper-plane to classify the data, SVM performs some complex data transformation. The points that are utilized in boundary findings are called the support vector. It is worth mentioning that SVM separates itself from other ML methods by being an effective option in case of a high dimensional space. However, SVM is not suitable for large datasets. In addition, it does not perform well in the state of overlapping target classes [18].

3.5. k-nearest neighbours algorithm

A k-nearest neighbours (k-NN) algorithm is one of the simplest and straightforward lazy methods that is utilized for regression and classification. It classifies the dataset to a group of neighbours k. The classification is based on the distance between training and test data. Several distance functions are utilized; for instance, Euclidean distance, Manhattan distance, Chebyshev distance, Mahalanobis distance, Hamming distance, and Canberra distance. Orange tool (used in this paper) supports only Euclidean, Manhattan, Chebyshev, and Mahalanobis distance func- tions. Despite the fact that k-NN is classified as instance-based learning, it does not perform well with big datasets or data with high dimensionality [19].

3.6. Naive Bayes algorithm

An Naive Bayes (NB) algorithm is defined as a probabilistic classifier which is based on the Bayes theorem with the independence assumption between predictors. One of its main advantages is the easy and fast prediction of test data, as well as good performance in multiclass prediction. On the other hand, NB cannot obtain the relationship between the utilized features because of the independence assumption [20].

3.7. Adaptive boost algorithm

An adaptative boost (AdaBoost) is categorized as a boosting ensemble method in ML. It is based on the principle of the sequential growing of learners. Except for the first one, the update process is performed for each subsequent learner based on his previously grown learner. Furthermore, weights are reassigned to each instance with incorrectly classified instances with higher weights. Besides being fast, simple, and easy to program, AdaBoost differentiates for its flexibility in combining with any ML algorithm. However, it suffers from high sensitivity to noisy data [21].

3.8. Stochastic gradient descent algorithm

A stochastic gradient descent (SGD) is one of the optimization strategies which aims to minimize the loss function. Using a random subset of the data, SGD follows the direction of the steepest gradient estimation. The loss function is a measure of disagreement between model prediction and training data. Although efficient and easy to implement, SGD suffers from sensitivity to feature scaling [22].

3.9. Logistic regression algorithm

Logistic regression algorithm is used to predict the target variable probability. It is based on the logistic function. It is characterized by a simple implementation, interpretation, and efficiency in training. However, its major limitation is the assumption of linearity between the dependent variable and independent variables [23].

4. Orange data mining

As mentioned before, the Orange tool is utilized as authors' data mining. Orange is considered an open-source data mining tool that includes several toolboxes for data visualization and analysis. In addition, it includes several add-ons widgets to extend functionality [24]. In the following subsection, the authors' methodology in tackling the proposed system is discussed.

4.1. Methodology

Authors' methodology includes finding the optimum ML model that enables the superior target localization accuracy in an indoor environment. As mentioned before, the proposed methodology is divided into two stages. First, dataset is collected with the aid of MATLAB. Next, various ML algorithms are adopted for training the collected dataset with the aid of the Orange data mining toolbox.

In the technique proposed by the authors, the RSS dataset is estimated in a 2D area, located in an indoor environment of $5\times5\times5$ m^2. Specifically, four array LEDs are utilized as transmitters with a spacing of 1.5 m between them, as shown in Fig. 2. The dataset is determined at a height of 0.75 m. It consists of power estimations with a pixel size of 5×5 cm^2. Accordingly, the authors' trained dataset contains 10 000 values.

In order to acquire an accurate localization accuracy, the proposed system passes through several steps, as shown in Fig. 3.

4.1.1. First step

The first step is setting up the channel model for the indoor environment. As mentioned before, the received powers of LOS signals are estimated as authors' dataset in a 2D room. The simulation parameters used here are presented in Table 1. The corresponding received power distribution is shown in Fig. 4.

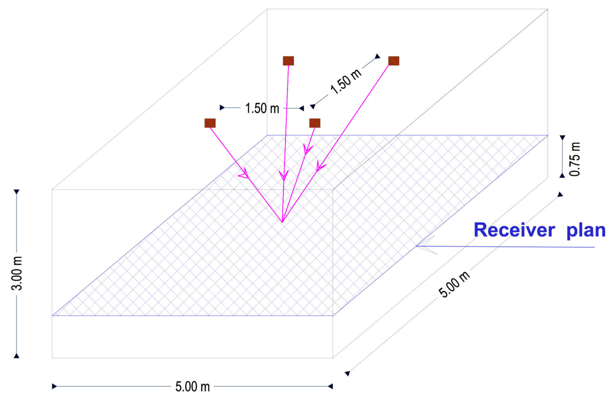

Fig. 2. Room dimensions and layout.

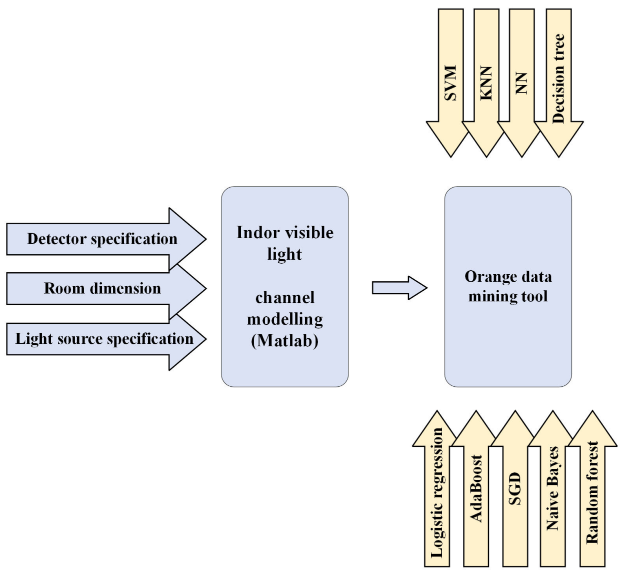

Fig. 3. Main steps of the proposed system.

Table 1.
Simulation parameters for VLC link.

	Parameters	Values
Room	Size	$5 \times 5 \times 3\ m^3$
Source	Semi-angle at half power	70
	Transmit power (per LED)	20 mW
	Number of LEDs per array	40 × 40
Receiver	Received plane above floor	0.75 m
	Active area	1 cm^2
	Half-angle FOV	70
Optical filter	Gain	1
Lens at PD	Refractive index	1.5

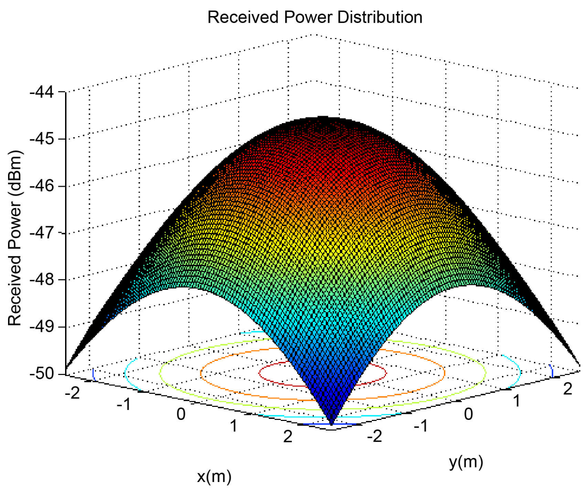

Fig. 4. Received power distribution.

4.1.2. *Second step*

Here, the acquired dataset is imported to the Orange data mining tool. In order to obtain the superior localization accuracy, a training phase is progressed through several ML methods as mentioned before. Figure 5 clarifies the steps of the proposed system in ML training utilizing the Orange toolbox. A pre-processing stage based on a principal component analysis (PCA) is performed after importing the dataset from MATLAB in order to reduce the dimensionality.

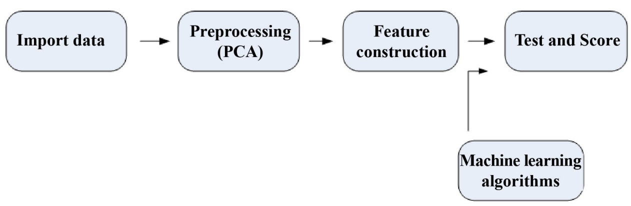

Fig. 5. Block diagram for the proposed ML system using Orange.

Authors' dataset consists of RSS values and their corresponding *x-y* plane values. A conversion method is used to convert the training data to single variable targets rather than multivariable objectives, as the latter is not supported by Orange. A feature constriction widget is utilized to create this conversion according to:

$$X_1 = x^2 + y^2. \tag{5}$$

That is, the authors' dataset is converted from points on the *x-y* plane to corresponding points on the line. Accordingly, the RSS dataset is utilized as the input of the ML leaning algorithms, while X_1 is their output.

4.1.3. *Third step*

Next, several ML models are used to train the dataset. Finally, in order to obtain the system performance, evaluation metrics are performed through test and score, as well as confusion matrix widgets. The parameters of each ML method are illustrated in Table 2. It is worth mentioning that the number of hidden layers, number of neurons, identity activation function, and L-BFGS-B training algorithm are chosen according to a recommendation with their superior performance as in Ref. 13. Moreover, the radial basis function (RBF) is the kernel function used in SVM.

Table 2.
Simulation parameters for ML methods used in the Orange toolbox.

Method	Parameters	Value
RF	Number of trees	10
	No. of splitting subsets smaller than	5
Decision tree	Min. number of instances per level	2
	No. of splitting subsets smaller than	6
k-NN	Number of neighbours	5
	Metric used	Euclidean
AdaBoost	Base estimator	Tree
	Number of estimators	50
	Learning rate	1
	Regression loss function	Linear
NN	Number of hidden layers	1
	Number of neurons	4
	Activation function	Identity
	Training algorithm	L-BFGS-B
	Max. number of iterations	1000
Logistic regression	Regularization type	Ridge (L2)
	Strength (C)	1
SGD	Loss function	Squared loss
	Regularization type	Ridge (L2)
	Regularization strength	0.00001
	Learning rate	Constant
	Initial learning rate	0.01
	Number of iterations	1000
	Tolerance	0.001
SVM	Cost	1
	Regression loss	0.01
	Kernel	RPF
	Tolerance	0.001
	Number of iterations	1000

4.1.4. Fourth step

In order to use all datasets for training and validation, stratified ten-fold cross-validation is applied as a sampling technique through using the test and score widget [25]. An average process is performed over the authors' results through a set of three classes. Discrete widgets are used to divide the dataset into three equal groups. The validation of the reliability of indoor localization applications through MLs is a critical issue, therefore, several validation metrics were adopted, in particular, training time, test time, classification accuracy (CA), area under curve (AUC), F1, recall, precision, logloss, and specificity [26, 27]. Furthermore, a confusion matrix is used to clarify both the number of instances and the proportions of prediction. Further, in order to evaluate the robustness of this system, the trials are repeated 100 times.

5. Results

In order to achieve the superb robustness of the proposed technique, various trials using several ML methods are performed. In this section, the results of these trials are presented.

5.1. Evaluation results

In this subsection, the performance of indoor localization for several ML methods is evaluated. The results of the evaluation metrics are illustrated in Table 3. The table shows that AUC of all algorithms performs equally with 0.995 except for AdaBoost that performs poorly around 0.667. Also, CA, F1, precision, and recall have the same behaviour with 0.994 for all algorithms. On the other hand, the results related to logloss vary from 0.04 to 0.781. It is also clear that decision tree, RF, NN, and NB achieve the superior performance, while AdaBoost achieves the worst performance. Further, specificity is around 0.997 for all the algorithms. It is also clear that the training time differs for all methods form 0.212 s for NB up to 2.937 s for AdaBoost, while test time values vary from 0.011 s to 1.665 s.

5.2. Model comparison

In this subsection a model comparison is conducted to obtain the superior ML method. The model comparison contains a pairwise comparison of models based on the metrics used. It is worth noting that to acquire the priority between two models, each value in the model comparison table represents the likelihood of choosing between two models. Furthermore, the obtained number represents the model likelihood for each row with respect to the corresponding value in the column.

5.2.1. Model comparison based on AUC

In this subsection, a model comparison is performed based on AUC and the results are presented in Table 4. AdaBoost has the worst probability than all models used

Table 3.
Results metrics using ML methods.

ML algorithm	Train time [s]	Test time [s]	AUC	CA	F1	Precision	Recall	LogLoss	Specificity
KNN	1.162	1..665	0.995	0.994	0.994	0.994	0.994	0.214	0.997
Decision tree	0.290	0.018	0.995	0.994	0.994	0.994	0.994	0.040	0.997
SVD	2.015	0.090	0.995	0.994	0.994	0.994	0.994	0.041	0.997
SGD	0.474	0.166	0.995	0.994	0.994	0.994	0.994	0.214	0.997
RF	0.195	0.091	0.995	0.994	0.994	0.994	0.994	0.040	0.997
NN	1.025	0.030	0.995	0.994	0.994	0.994	0.994	0.040	0.997
NB	0.212	0.011	0.995	0.9944	0.994	0.994	0.994	0.040	0.997
Logistic regression	0.495	0.080	0.995	0.994	0.994	0.994	0.994	0.041	0.997
AdaBoost	2.937	0.402	0.667	0.994	0.994	0.994	0.994	0.781	0.997

Table 4.
Model comparison based on AUC.

	k-NN	Decision tree	SVD	SGD	RF	NN	NB	Logistic regression	AdaBoost
KNN		0.029	0.158	0.500	0.002	0.045	0.029	0.029	1.000
Decision tree	0.971		0.951	0.971	0.254	0.746	0.500	0.500	1.000
SVD	0.842	0.049		0.842	0.034	0.078	0.049	0.049	1.000
SGD	0.500	0.029	0.158		0.002	0.045	0.029	0.029	1.000
RF	0.998	0.746	0.996	0.998		0.830	0.746	0.746	1.000
NN	0.955	0.254	0.922	0.955	0.170		0.254	0.254	1.000
NB	0.971	0.500	0.951	0.971	0.254	0.746		0.500	1.000
Logistic regression	0.971	0.500	0.951	0.971	0.254	0.746	0.500		1.000
AdaBoost	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

with almost zero probability. On the other side, by comparing other models with respect to each other, it can be concluded that k-NN performs with equal probability as that of SGD. However, it has a lower probability than all models used. However, the decision tree model is one of the superior models. Indeed, it performs equally with NB and logistic regression. The probability of the tree is better than other models except for the random forest model. Moreover, SVM has better probability scores than k-NN and SGD, while it performs poorly when compared to the rest.

In terms of the AUC model comparison, SGD is one of the worst models, except for having an identical probability as k-NN, as previously stated. Moreover, RF is having the superior probability of performance compared to all models used. NN has higher probability of performance than decision tree, SVM, and SGD, while less probability than others. In comparison to other models, NB and logistic regression have comparable likelihood of behaviour. In addition, they are identical to each other.

It can be concluded that, based on the AUC model comparison, RF has the highest probability of performance with respect to others.

5.3. *Confusion matrix*

As aforementioned, to show the number of instances and proportions of prediction, confusion matrices are used. Figure 6 shows the acquired confusion matrices. Particularly, the results in Fig. 6(a) illustrate the proportion of prediction over three classes. The prediction ratios are 99.5%, 99.0%, and 99.6%, respectively, for all models used. Figure 6(b) indicates the number of instances corresponding to acquired proportion prediction ratios.

		Predicted			
		< 2.65625	2.65625 - 5.28625	≥ 5.28625	∑
Actual	< 2.65625	99.6 %	0.4 %	0.0 %	3330
	2.65625 - 5.28625	0.4 %	99.0 %	0.5 %	3334
	≥ 5.28625	0.0 %	0.6 %	99.5 %	3336
	∑	3332	3336	3332	10000

(a)

		Predicted			
		< 2.65625	2.65625 - 5.28625	≥ 5.28625	∑
Actual	< 2.65625	3318	12	0	3330
	2.65625 - 5.28625	14	3304	16	3334
	≥ 5.28625	0	20	3316	3336
	∑	3332	3336	3332	10000

(b)

Fig. 6. Confusion matrices for ML: portion of prediction (a), number of instances (b).

5.4. *Results comparison*

In this subsection, a comparison is performed by utilizing two different evaluation metrics, namely, CA and root mean square error (RMSE).

5.4.1. CA

Here, CA is used as a comparison metric. It is used to evaluate the rate of correct classification. The results are listed in Table 5. It is clear that the authors' result is better than that in previous literature.

Table 5.
Results comparison based on CA.

Reference	Channel	Machine learning model	CA
[28]	Radio frequency	Convolutional neural networks	97.81%
[29]	Wi-Fi	Deep learning	95.95%
[30]	VLC	k-NN	99.33%
This work	VLC	RF	99.4%

5.4.2. RMSE

RMSE is an error metric that produces a cumulative error estimate. It is calculated as the square root of the arithmetic mean of the squares of the error in the dataset:

$$RMSE = \sqrt{\frac{1}{k}\sum_{j=1}^{k}[(\hat{x}_j - x_j)^2 + (\hat{y}_j - y_j)^2]}, \tag{6}$$

where $(\hat{x}_j, \hat{y}_j)$ and (x_j, y_j) refer to the estimated j^{th} and true locations, respectively, and k is the number of dataset points.

Authors' results are presented in Table 6. It is clear that the RMSE result outperforms that of other referred works. Authors would like to notify that the obtained RMSE is related to the random forest model that is concluded to have the superior probability of performance over other models. Therefore, the average RMSE value for 100 trials is 0.136 cm.

Table 6.
Results comparison based on RMSE.

Reference	Parameters	Localization technique	RMSE (cm)
[31]	LOS, $5 \times 5 \times 3$ m^3, $A = 1$ cm^2, $P_t = 1$ W, FOV $= 70°$	RSS + TDOA	5.81
[30]	LOS, NLOS, $5 \times 5 \times 3$ m^3, $A = 1$ cm^2, $P_t = 40$ W, FOV $= 60°$	Fingerprint	21.7
[32]	LOS, $5 \times 5 \times 3$ m^3, $A = 1$ cm^2, $P_t = 8.8$ W, FOV $= 60°$	RSS	4
This work	LOS, $5 \times 5 \times 3$ m^3, $A = 1$ cm^2, $P_t = 32$ W, FOV $= 70°$	RSS	0.1

It should be mentioned that the authors of Ref. 29 have supported both LOS and first reflection of NLOS in their calculations. Although they have achieved accuracy that is close to ours, their system suffers from high RMSE when compared to that of ours. In addition, according to Ref. 15, the rate value of reflected light is small (about 3.57%) when compared to direct light (about 95.16%).

The system proposed by the authors achieves high accuracy with low error, however, its performance is directly related to the calibration and performance of the photodetector.

6. Conclusions

In this paper, an indoor VLC localization system based on distinct ML models and RSS signals has been proposed. The main framework of the system has been constructed to gather the RSSs dataset values with the aid of MATLAB followed by training and analysis with the aid of the Orange data mining tool. While using several evaluation metrics, it has been observed that the optimum gained accuracy is 99.4% with a RF model at training and test times of 0.195 s and 0.091 s, respectively. Moreover, the average RMSE was shown to be 0.136 cm.

Accordingly, the system proposed by the authors is featured with high accuracy, low complexity, and small error distance at a very small training time. This makes it appropriate to be included in mobile devices that can be used in any environment.

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