UWB Localization Employing Supervised Learning Method

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***Abstract*—An indoor positioning system (IPS) is a technology employed to locate objects and people within a building scenario using signal processing or other sensory information. Ultra Wide Band (UWB) is a versatile wireless technology that can be employed as an IPS and has shown very good performances. UWB can be used in many scenarios and its effectiveness in through wall detection along with its excellent resolution for person localization is one of the best applications of IR-UWB. The main objective of this work is to propose a concept for intelligent radar systems employing UWB augmented by machine learning approaches to not only localize but understand the location of a person or target within a building. Although suitably developed UWB is excellent for obtaining localizing data it does not automatically understand what that location effectively means or where it is thus further methods are required to create meaningful data for end user appreciation. Learning from the huge amount of UWB signal data through Multi Class Support Vector Machine (MC-SVM) architecture enables a truly evolving scheme to both localize targets and identify them in a useful way. Statistical analysis of the experimental results supports the proposed algorithm.**

***Index Terms*—Indoor Positioning System (IPS), Localization, Ultra Wide Band (UWB), Principal Component Analysis (PCA), Multi Class Support Vector Machine (MC-SVM)**

I. Introduction

An IPS locates a targets position whether that is people, animals, objects etc. Applications are numerous, security, health, personal assistive living, home healthcare etc. Ultra Wide Band (UWB) radar has advantages over other existing technologies due to its high spatial resolution, safe Radio Frequencies (RF) levels (-44dBm/MHz) and its potential to penetrate through different materials or obstacles [1]. The proposed work focuses on identifying and naming the position of a user within a home environment through a supervised machine learning technique augmenting UWB radar system. Multi-Class Support Vector Machine (MC-SVM) is used as the supervised UWB signal learning algorithm in the proposed work. A brief description of the related work is included here from which motives the proposed work. Generally, in the case of UWB, identifying the position of a moving person is determined by monitoring the return UWB signals, and the positions are calculated using positioning methods [2], or moving persons are considered as radar blobs in radar images [3] [4]. Generally, localization observation is a complex procedure [5] [6]. Positioning or monitoring of a static person is also a difficult task because it involves detection and reliance on the periodical nature of breathing and heartbeat rates as well as differentiating them from clutter components. Recently, most of the localization techniques are based on respiratory motion [7] [8], but few works are based on cardiac-induced radar signatures [9]. Indoor-positioning systems using UWB signal for unmanned aerial vehicle (UAV) platforms to navigate through global navigation satellite system (GNSS) have been presented. Non-LOS rejection is implemented based on the ratio of the first path compared to the power of the cumulated channel impulse response [10]. UWB has also been presented for a high precision positioning system based on the time difference of arrival (TDOA) algorithm in a cluttered environment [11], assisted living potential and in the areas of energy reduction assistance [12] [13] [14] and [15].

To the best of our knowledge the proposed work is first work where an intelligent system can automatically identify the target location in building from a machine learning embedded IPS using radar signal. The detailed description of the proposed methodology, experimental set up and result analysis are described in the following sections.

II. Proposed Work

There are two stages in the proposed work, recognizing or predicting the pre-processed signal pattern, and recognizing or predicting the features extracted by Principal Component Analysis (PCA) using MC-SVM. The data process flow of the proposed architecture is presented in Fig. 1. Initially, the raw UWB signals containing the localization information are pre-processed to examine the leading part of the signals. This pre-processing stage is briefly described in Section III. Subsequently, each amplitude of the pre-processed UWB signals is considered as a feature value to train the MC-SVM, and outcomes are observed. Following this, each signal still contains too many amplitude values to be effectively fitted in a machine learning algorithm. Therefore, a well-known feature reduction method PCA [16] is applied to transform the high dimensional signal data into a low dimensional space which would help the MC-SVM to avoid the “curse of dimensionality” as well as reduce time complexity of the algorithm. PCA is briefly described in the following section. Subsequently MC-SVM is employed again to train the algorithm using low dimensional feature space and observe the performance improvement.

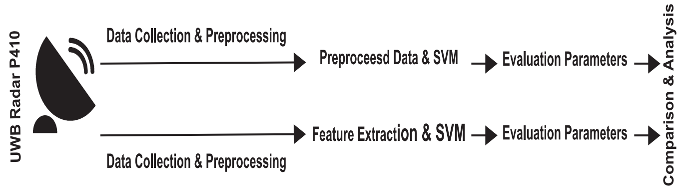

Fig. 1. Steps related to the proposed work

A. Orthogonal Transformation of UWB Signal

Large volumes of signal data are actually a bottleneck for any machine learning algorithm. Therefore, such dimensional loads could create more complexity when handling and analysing data. Thus, the well-known and thriving feature extraction procedure PCA is used as an intermediate step in the proposed machine learning work. It projects the entire pre-processed data into a different lower dimensional feature space through a linear transformation which helps to handle multi collinearity of data, "curse of dimensionality", and also the time complexity to increase the efficiency of the proposed work. PCA is preferred to other feature reduction techniques because of its low noise sensitivity, lower memory requirements, and its increased efficiency given the processes taking place in smaller dimensions. PCA identifies a small number of uncorrelated variables, known as "principal components" from the high dimensional pre-processed data and determines the maximum level of variance with fewest numbers of principal components. Let an UWB signal initially be s, whose amplitudes are $\{a_1, a_2, ..., a_{576}\}$, (576 is the number of prepossessed channels), then after applying PCA to the signal s, 288 key components are extracted from the signal which are a fewer number of variables compared to the original signal to avoid multicollinearity. Therefore, feature extracted signal is now, $\{f_1, f_2, ..., f_{288}\}$.

B. Crammer and Singer's MC-SVM

The proposed work considers the UWB localization data produced from the indoor scenario as a multi-class categorization case. Therefore the extracted features are labelled and fed into a Crammer and Singers MC-SVM, where a set of labelled training pattern is represented by $(x_1, y_1), ..., (x_l, y_l)$ of cardinality l, where $x_i \in R^d$ and $y_i \in 1, ..., k$, $w \in R^d$ is the weight vector, $C \in R_+$ is the regularization constant, and φ is mapping function which projects training pattern into a suitable feature space H that allows for nonlinear decision surfaces. Crammer and Singer [17] proposed a SVM with multi categorization ability by solving the quadratic optimization problem,

$$\begin{aligned} \min_{w_m \in H, \xi \in R^l} \quad & \frac{1}{2}\sum_{m=1}^{k} w_m^T w_m + C\sum_{i=1}^{l}\xi_i \\ subject\ to \quad & w_{y_i}^T\varphi(x_i) - w_t^T\varphi(x_i) \geq 1 - \delta_{y_i,t} - \xi_i \\ & i = 1, ..., l, t \in 1, ..., k \end{aligned} \tag{1}$$

where, $\delta_{i,j}$, j is the Kronecker delta, defined as 1 for $i = j$ and as 0 otherwise. The resultant decision function is defined as,

$$argmax_m f_m(x) = argmax_m w_m^T \varphi(x) \tag{2}$$

Note that the constraints $\xi_i \geq 0, i = 1, ..., l$, are implicitly indicated in the margin constraints of (1) when t equals y_i. In addition, (1) focuses on classification rule (2) without any bias terms. A nonzero bias term can be easily modelled by adding an additional constant feature to each x. Therefore, different categories of data are classified by solving this decision function and the results are analysed in the following section.

C. Statistical Measures of Performance

Performance rates of the proposed method are statistically analyzed. Well-established statistical metrics are used to evaluate the proposed localization algorithm: accuracy, sensitivity, specificity, positive predictive value, negative predictive value, area under the curve (AUC) of receiver operating characteristic (ROC) curve, and time taken for the simulation parameters are all measured.

III. Experimental Setup

The UWB localization experiment has been carried out on the ground floor area of a house located in Essex, UK. The floor plan is shown in Fig. 2 comprises four rooms: living room, kitchen, dining room, and bathroom. The single UWB device is fixed towards the back corner of the living room.

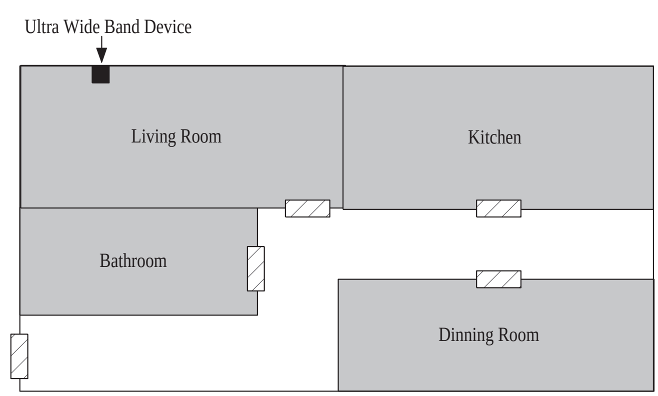

Fig. 2. Floor-Plan

The experimental set-up is the same set-up used in [15]. The commercial radar module, embedded with in-house developed software was connected to a Raspberry-Pi (RPi) which stored the time stamped radar data. The experiment was carried out in the house described and data analyzed later and compared to diary measurements made at the time to correlate findings. The module is sown in Fig. 3. It transmits RF from 3.1 GHz to 5.3 GHz, with center at 4.3 GHz, and follows Federal Communications Commission (FCC) restrictions.

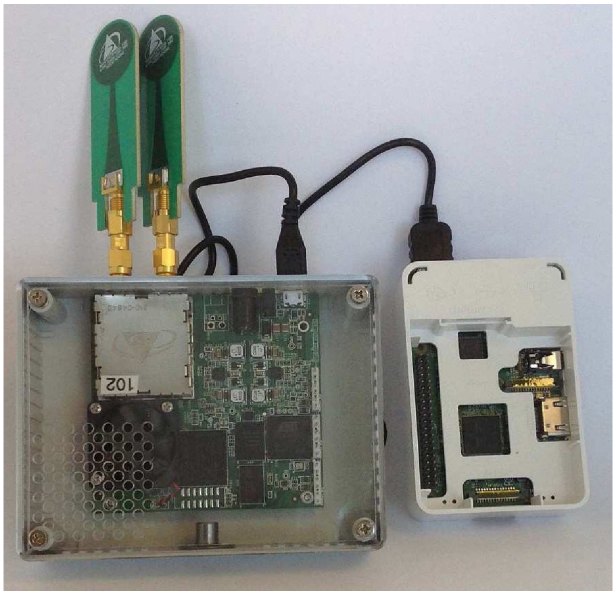

Fig. 3. P410Device

The raw data from four different rooms were accumulated over 30 minutes via a RPi connected to the radar module. The data is accumulated with the presence and absence of a single person where the rest of the environment is assumed static. Nine distinct possible situations are found during the data collection. Fig. 4 shows a typical signal sample when a person is present in kitchen.

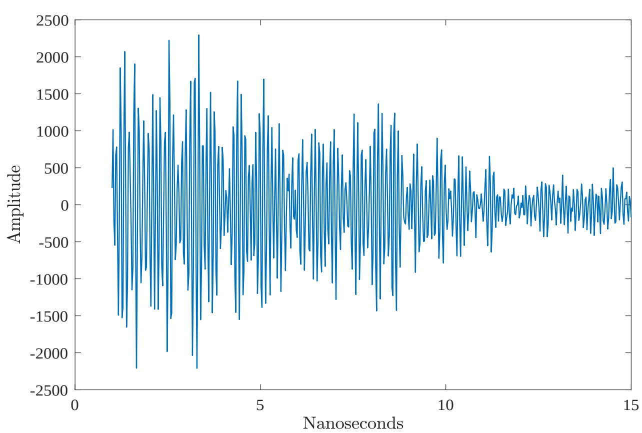

Fig. 4. A sample of UWB data is collected from kitchen in a particular time interval

A total of 7203 samples are collected during this experiment. All the samples comprise of 1152 data points in every 15 nanoseconds time interval. The consideration of all raw data points degrades the performance of the proposed method, due to the fixed range (10 meters) coverage of the device.

If the person is in the living room, this implies the person is in LOS of signal propagation within the first 1-5 meters distance from the radar. The signal strength weakens with distance due to the Free Space Path Loss (FSPL). Therefore, the major amplitude fluctuation can be found within this range. In the case of dining room, the person is in the LOS at 5-10 meters of distance from radar and distinct changes can be found in amplitude at that time. Therefore, all the signals data are pre-processed to focus on the leading edges of the signals based on the human position. For an instance of kitchen data, the second half (last 576 data points) of signal is considered as the leading edges, while the first half (first 576 data points) of signal is considered as important when the person is present in the living room. Therefore, the amplitudes of a pre-processed signals are $\{a_1, a_2, ..., a_{576}\}$ and extracted features are $\{f_1, f_2, ..., f_{288}\}$ using PCA (described in Section II) which fed into MC-SVM. This pre-processing step is needed to avoid the data redundancy and reduce time as well as computational complexity of the proposed work. It also resists MC-SVM from misleading and wrong prediction of the human position which helps to raise the accuracy of this experiment.

The experiment is carried out by Matlab R2016b tool in a Intel^R Core^{TM} i7 processor@ 3.60GHz based Windows 7 Enterprise 64 bit operating system and it has 7856 MB NVIDIA Graphics Processing Unit (GPU).

IV. Result Analysis

Two main phases are considered for the experiment. Firstly, the pre-processed data are learnt using MC-SVM to detect walls and localize targets. Secondly, the pre-processed data are simplified by selecting the key components using PCA, and then those reduced data are learnt through MC-SVM. In the first phase, pre-processed raw data with 576 data points are divided into training and testing data. To evaluate the model, data are divided into 10%, 20%, 30%, 40% for training, and 90%, 80%, 70%, 60% for testing purposes in the corresponding case. The testing results are listed in Table I with statistical evaluation parameters such as, correct rate, error rate, sensitivity, etc.

Statistical Measurements	10%	20%	30%	40%
Correct Rate	0.8804	0.8852	**0.8958**	0.8921
Error Rate	0.1196	0.1148	0.1042	0.1079
Sensitivity	0.9882	0.9805	0.9857	0.9875
Specificity	0.9928	0.9968	0.9957	0.9965
Positive Predictive Value	0.9653	0.9836	0.9792	0.9826
Negative Predictive Value	0.9976	0.9961	0.9971	0.9975
Area Under the curve	0.6982	0.7007	0.6995	0.7107
Time elapsed (in Seconds)	27.407	27.092	**24.962**	24.981

TABLE I
CLASSIFICATION RESULTS OVER PRE-PROCESSED DATA BY MC-SVM

Table I shows that the proposed predictive model provided the highest testing correction rate 0.8958 (is marked in bold) and lowest error rate 0.1042 in the 30% percent training data. Testing correction rate was increased from 0.8852 to 0.8958 for 10% to 30% training data. In the 40% training data case, the algorithm is being over-fitted due to the high dimensional data points, testing accuracy falls to 0.8921 and the error rate increases to 0.1079. The objective of the proposed method is to fit the model, so that it could make valid predictions on untrained or test data. Therefore, the performance of the proposed algorithm at 30% training data is considered as the performance of the model. Other evaluation parameters are also determined to support the robustness of the model. In this case (30% training and 70% testing data), sensitivity 0.9857 of the proposed IPS indicates the probability of correctly identifying the location of the person. Additionally specificity of 0.9957 tells the probability of the system to recognize the scenario accurately when there is no person present in a room. The Positive Predictive Value (PPV) 0.9792 signifies the probability that the system gives positive result about the person's location and truly there was the person, and also Negative Predictive Value (NPV) 0.9971 points out the probability that system says negative result (not in the room) about the person's location and it is true. The graphical illustration using ROC curve (shown in Fig. 5) is plotted to explore the prediction result of the algorithm. It is created by plotting True Positive Rate (TPR) (Sensitivity, recall) against False Positive Rate (FPR), where FPR is calculated using the expression (1 - Specificity). The AUC measures discrimination power of the classifier, i.e., the ability of the prediction to identify correctly the location of an occupant, which is almost equal for each amount of training data. It accommodates all of these parameter calculations, execution time for each case is determined, and 24.962 seconds elapsed to produce the highest correction rate 0.8958.

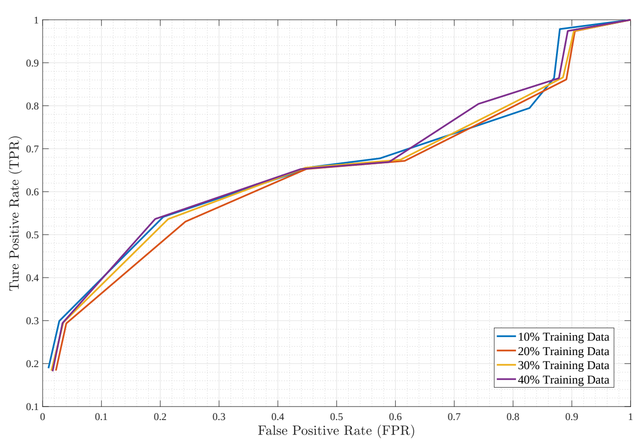

Fig. 5. ROC before feature extraction

In the second phase of the experiment, features are extracted from the initial set of pre-processed data and derived new key components (features) using PCA, which are informative and non-redundant, facilitated in subsequent learning steps. A simplified version of the signal shown in Fig. 4 is displayed in Fig. 6. The classification results for the reduced signal length method are presented in Table II. Only 288 derived feature values are considered for this phase, which is guided to achieve the maximal correction rate 0.9520 (marked in bold) within 0.6630 seconds.

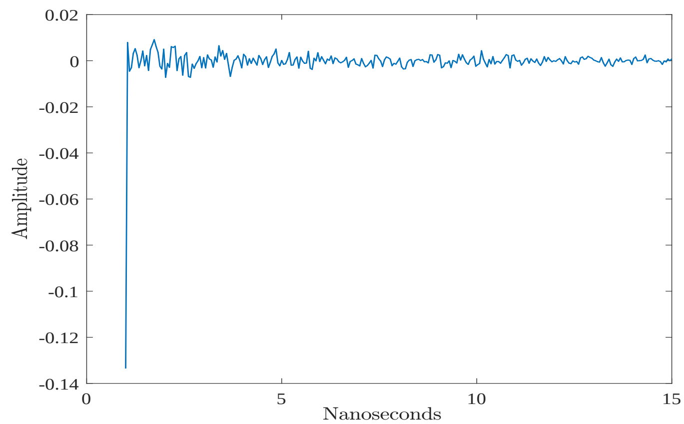

Fig. 6. The simplified sample of UWB data which is collected from kitchen in a particular time interval

Statistical Measurements	10%	20%	30%	40%
Correct Rate	**0.9520**	0.9518	0.9512	0.9509
Error Rate	0.0480	0.0482	0.0488	0.0491
Sensitivity	0.9991	0.9990	0.9989	1.0000
Specificity	0.9998	0.9998	0.9996	0.9995
Positive Predictive Value	0.9991	0.9990	0.9977	0.9976
Negative Predictive Value	0.9998	0.9998	0.9998	1.0000
Area Under the curve	0.7153	0.7242	0.7066	0.7076
Time elapsed (in Seconds)	**0.6630**	0.6891	0.7661	0.8297

TABLE II
CLASSIFICATION RESULTS OVER FEATURE EXTRACTED DATA USING PCA BY MC-SVM

Thus, a notable improvement of correction rate and time complexity is realized using a smaller number of training data, which is only 10% training data (=90% testing data) whereas, 30% training (as shown in Table I) data is required to achieve a maximal correction rate for pre-processed signal data. If the amount of training data is increased (e.g., to 20%, 30%, and 40%) then due to overfitting it loses its generalization power and ultimately makes poor predictions which is reflected in result table. Therefore, the correction rate of 10% training data is contemplated as the correction rate of the proposed localization method. In terms of other evaluation parameters, the performance refinement is also considerable.

As the sensitivity and specificity is slightly enhanced, therefore the change in AUC for ROC curve (displayed in Fig. 7) is modest.

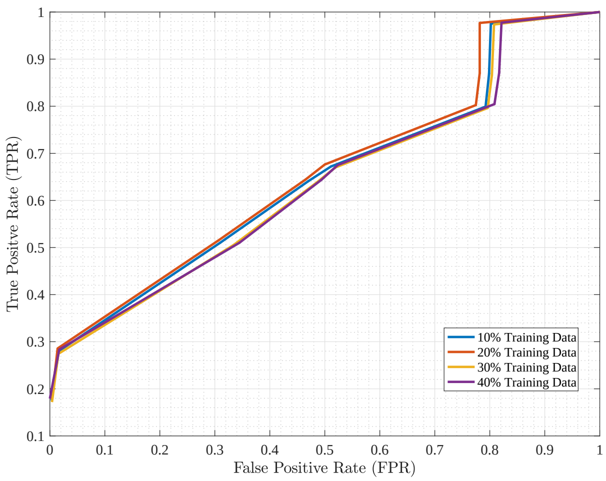

Fig. 7. ROC after feature extraction

This upgradation in TPR against FPR defines consequential development of the performance in localization accuracy (classification accuracy) of proposed method than any other localization method present in the current literature.

V. Conclusion

The proposed work and experimental results describe the ability of the machine learning algorithm method augmenting a UWB radar system to identify or recognize the position of a person within a building and correctly identify the specific room occupied. This work will be extended to a semi-supervised machine learning based human localization algorithm.

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