Classification of CommSense data using learning algorithms

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Abstract

In our previous work we have shown the design of a Communication based Sensing (CommSense) system. The current work presents analysis of the data captured by a CommSense system. Analysis is performed using Support Vector Machines (SVM) and a Multi-layer Perceptron (MLP) which are commonly used supervised learning algorithms. The predicted results are presented in the form of a confusion matrix and an analysis is presented showing the percentage of error in prediction.

1 Introduction

Implementation of radar systems for civilian applications has been an active area of research in the recent past. Out of the many different fields of interest the one of particular relevance to this paper is the field of commensal or passive radar [1–6]. Commensal radar[1] is a type of radar built to use the communication system transmitters in order to detect targets of interest, without affecting the performance of the original system. These transmitters, from the view point of radar systems, are known as "illuminators of opportunity". A special case of commensal radar is the passive bistatic radar [7–9] which uses wireless radio-frequency signals to determine the channel parameters.

Recently we have proposed a sensing system which uses the channel estimation process of a telecommunication system to sense the changes in the environment [10]. We call this system communication based sensing (CommSense) system. In this work we analyse the data captured by the CommSense system [11–13] using supervised learning algorithms. To validate the claim that it can sense the environment, an analysis is performed on the captured channel information using Support Vector Machines (SVM) [14–17] and a Multi-layer Perceptron (MLP) [18]. The results are discussed in this paper. Different categories of datasets are used here to classify the different scenarios including environmental conditions. In this work we have used the system to distinguish different weather conditions such as rain and humidity and for the detection of vehicles, such as trains and cars.

In our previous work we have shown implementation of a channel estimation algorithm in open source software defined radio platform [11]. The channel estimation technique was implemented to extract the real time channel information from a global system for mobile communication (GSM) [19] signals, which is then analysed using principal components analysis to show the definite clustering of the captured information [12]. The system was then built on a hand-held platform using a raspberry pi as the processing unit and BladeRF as the wireless receiver connected to power-banks as the power source [13].

The major novelties of the current work are as follows. We demonstrate that event detection and classification using a CommSense system based on GSM transmit signal from single base station is possible. In this we have used different classification algorithms as well. The machine learning algorithms we have used are SVM, a supervised learning model used for classification, and MLP, a feed-forward artificial neural network model that maps a set of inputs to a set of outputs. The results are presented and discussed.

The rest of the paper is organized as follows, In Section 2 the CommSense system is explained in brief. In Section 3 the details of SVM classifier and a MLP classifier are provided. The details of the experimental scenario if presented in Section 4, the data from which are then used in Section 5 to perform analysis. The results are analysed and a table portraying the simulation parameters used is presented here. Section 6 concludes the paper and provides scope for future work.

2 CommSense: A Short Review

A signal, when transmitted over a wireless channel gets reflected through all the obstacles in its path until it reaches the receiver. Figure 1 shows an overview of the system depicting the multipath signal. These multipath signals are affected by the specific parameters of a certain path. The idea of CommSense system is to extract this multipath information and trace back the channel it passed through, by a method

[1] The word commensal has been borrowed from biology in which this represents co-existence of two species out of which one is benefited and the other remains unaffected

called channel estimation. Since the CommSense system is designed in commensal mode, it uses the signal from the available base stations and performs channel estimation on it.

This system is based on GSM system, which is a wireless communication protocol. GSM signal consists of a known bit stream called training sequence in every frame to perform channel equalization. This increases the throughput of the system. CommSense captures the GSM broadcast signals and uses the training sequence to perform channel estimation and analysis. The system is built using open source hardware such as a raspberry pi and BladeRF as well as software such as GNU radio. GNU radio is an open source software platform to implement software defined radio as well as signal processing applications.

3 Classifier Models

This section provides an overview of SVM and MLP which are then used for classification of the CommSense datasets.

3.1 SVM Classifier

SVM is a supervised learning algorithm that takes a sample dataset and a predetermined kernel function as input, and generates a model for this sample. This model is then used to categorize the test dataset. The goal of SVM is to design a hyperplane or a set of hyperplanes in high-dimensional space that classifies all training vectors into different classes. Out of the multiple hyperplanes that can achieve the same task, the best choice will be the hyperplane that has the maximum separation from the nearest element of each class.

$$\min_{\alpha \in R^F} \frac{1}{2}||\alpha||_2^2 + C\sum_{i=1}^{n} l(y_i, f_\alpha(x_i)) \tag{1}$$

Let training data be represented as $D = \{(x_i, y_i)|i \in Z^+, 1 \leq i \leq n\}$, where $x_i \in R^d$ is training input points, $y_i \in \{1, -1\}$ are training labels, n is the size of the training data and d is the dimension of input data. In order to maximize the geometric margin between two classes and minimize the error, the soft-margin SVM can be represented as (1). Where α is normal vector to the hyperplane separating the classes, $l(.)$ is a loss function, C is a regularization parameter weighing the smoothness and errors and $f_\alpha(x_i) = \langle\phi(x_i), \alpha\rangle$. Where $\phi(x) : R^d \to R^F$ is a function mapping training data points from input space R^d to a new $F-$dimensional feature space R^F. For large F, the inner products of feature space can be calculated by a kernel function (2), such as Radial Basis Function (RBF) shown in (3). Where x is the training input points and y is the training label.

$$k(x, y) = \langle\phi(x), \phi(y)\rangle \tag{2}$$

$$k(x, y) = \exp(-||x - y||_2^2/\sigma^2) \tag{3}$$

The representation of SVM shown here is referred from [17].

3.2 MLP Classifier

The network topology of a MLP with a single hidden layer is shown in Figure 2. Here three layers are shown out of which the input and the output layers are visible to the users, whereas the hidden layer, as the name suggests, stays hidden. Each layer contains multiple nodes known as neurons. The nodes that are not a target of a connection are known as input neurons. Each neuron in the input layer takes one feature from the input dataset. These features then act as the input for the subsequent hidden layers and this continues until it gets to the output layer.

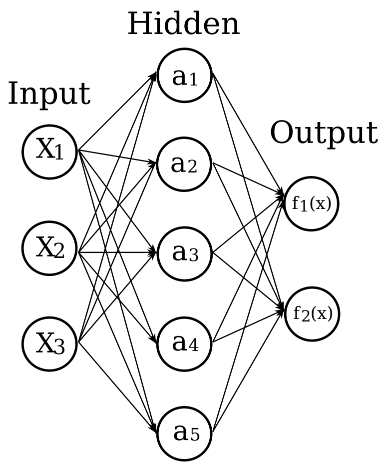


Fig. 2: One hidden layer MLP classifier

In Figure 2 $\{X_1, X_2, X_3\}$ are the features of the input dataset, which then becomes the input information for the hidden layer thereby generating a bias $\{a_1, a_2, a_3, a_4, a_5\}$. The bias of the hidden layer then acts as the input features of the output layer. During the training period the weights of each neuron is set by a method called backpropagation. This process is used to adjust the weights of the input at the output layer.

$$\Delta w = \eta dX \tag{4}$$

During training, the weights Δw are set to get a particular output as shown in (4). Here η is the learning rate that is usually less than 1, X is the input dataset and $d = Output_{predicted} - Output_{desired}$. The weight of each neuron is set individually by specific algorithms, such as gradient descent.

4 Experimental scenario

The different scenarios used to prove the claim of sensing the environment using CommSense system is given below.

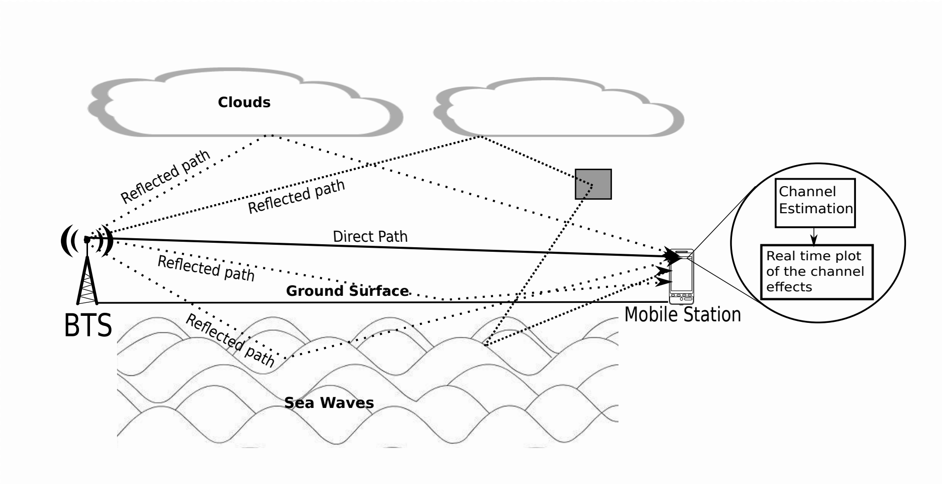


Fig. 1: System overview: Showing multipath signals from transmitter to receiver.

4.1 Environment

This scenario consists of four different environmental conditions named "Rain", "Medium Rain", "Humid No Rain" and "Hot Day". All the captures are taken with the receiver placed in the same location at different instances of time.

- Rain: This contains captures from a day when it was raining heavily outside.
- Medium Rain: This contains captures from the same day as "Rain" captures but later in the day when the intensity of rain was considerably low.
- Humid No Rain: This contains captures from the day after the "Rain" and "Medium Rain" captures. This day was very humid and the clouds were covering the region but there was no rain.
- Hot Day: This set of captures contains data from a very hot day without any humidity.

4.2 Vehicle Detection (Train-Car)

This scenario consists of four different situations with and without the presence of a train or a car. To obtain one particular dataset the presence or absence of one vehicle is focussed upon.

- With Train: This set of captures were taken at a train station with the receiver approximately $3\ \mathrm{m}$ from the train when the train was present in the platform.
- Without Train: This set of captures were taken just after the train left the station with the receiver at the same location as the "With Train" dataset. All other parameters were kept constant as far as possible.
- With Car: This set of capture was taken at an empty parking space with only one car in the direct vicinity of the receiver at about $3\ \mathrm{m}$ from the car. There were no other vehicles present around the receiver upto a distance of $100\ \mathrm{m}$ from the receiver. Although there was a highway at about $105\ \mathrm{m}$ from the receiver in one direction.
- Without Car: This set of captures were taken at the same day and location as the dataset "With Car", when the car was not in the $100\ \mathrm{m}$ radius of the receiver.

Multiple sets of each of the above mentioned scenarios are captured for $30\ \mathrm{s}$ each with a gap of $20\ \mathrm{s}$ between consecutive sets. Each $30\ \mathrm{s}$ dataset contains 4500×40 points. The analysis presented here is performed on two of these sets, using one set as training and the other set as testing. In the case of "Environment" 4000×40 points from set one of each condition is used as training data and 1000×40 from capture set two of each condition is used as test data, thereby a total training set of 16000×40 is used and test set of 4000×40 is used. In case of "Train-Car" scenario the training data is made of 4000×40 points of set one from each situation and the test data contains 4000×40 points from set two of each situation, in total making 16000×40 points for training and 16000×40 points for testing.

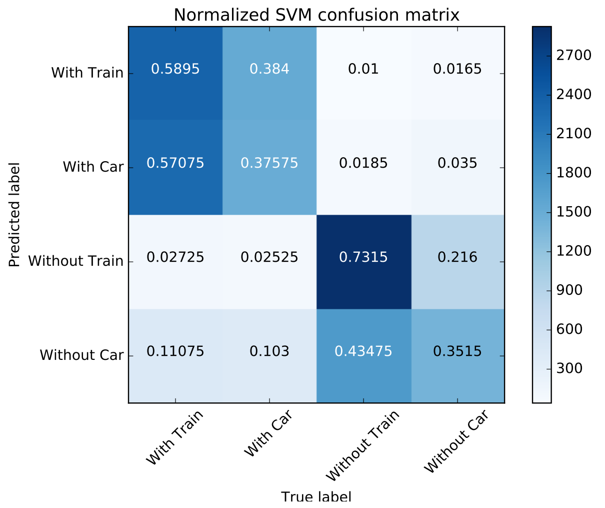
5 Analysis of data

The data analysed in this section is captured using CommSense system. The received signal is preprocessed to extract the channel impulse response as shown in [11]. The channel estimation algorithm implemented in the CommSense system extracts 40 multipath channel state information from each frame of received signal. With the assumption that each of the multipath channel state information consists of a specific feature it is defined that the captured dataset consists of 40 features per frame.

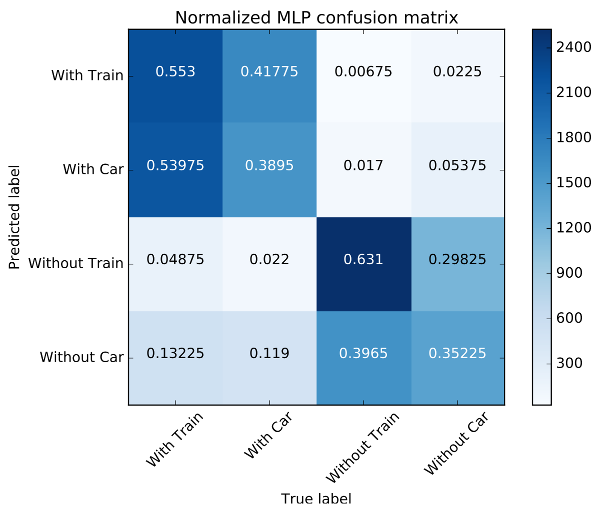
The captured data is passed through SVM and MLP classifiers and the results are presented here. The kernel used for

SVM classifier is RBF and the the MLP has two hidden layers containing 10 neurons each. In case of MLP the layers and its size is chosen after performing multiple tests with different configuration and the one showing optimum results are presented here. In the future more precise optimization methods should be chosen to find the hidden layer configuration.

Figure 3a and 3b contain the confusion matrices for classification between a presence and absence of a train or a car in the vicinity of the receiver. Figure 3a shows the normalized prediction of the datasets using a SVM classifier. Although the train and car cannot be distinguished from the confusion matrix a general separation between the presence and absence of a vehicle is visible. The prediction of train is better than the prediction of the car, mostly because the train is larger in size and reflects back stronger signal.



(a) SVM



(b) MLP

Fig. 3: Confusion matrix: Classification of Train-Car dataset.

Figure 3b shows the normalized prediction using a MLP classifier. The MLP classifier provides a slightly poor classification between the train and a car although even in this case the difference between a vehicle and no vehicle is clear. In both cases of Figure 3 the prediction percentage of a car is lower and mixed with the features of the train, as both the observed objects have metallic surfaces having common features.

Figures 4a and 4b contain the confusion matrices to classify different environmental conditions as mentioned above. Predictions from the SVM classifier is shown in Figure 4a and the predictions from the MLP classifier is shown in Figure 4b. The SVM classifier can clearly separate between rain and no rain conditions, there is some ambiguity between the medium rain and heavy rain conditions but that is expected as the water droplets have similar features. In case of MLP the prediction of hot day is mixed up with the prediction of humid no rain day. Although a similar prediction pattern is visible in SVM classification but the difference is almost double. It is observable that both the algorithms show ambiguity between the “Rain” and “Medium Rain” conditions which as explained above is due to the properties of water droplets. The scale on the right hand side of Figures 4 and 3 is to depict how many data points are predicted by the classifiers, the colour of the blocks represent the same in the plots.

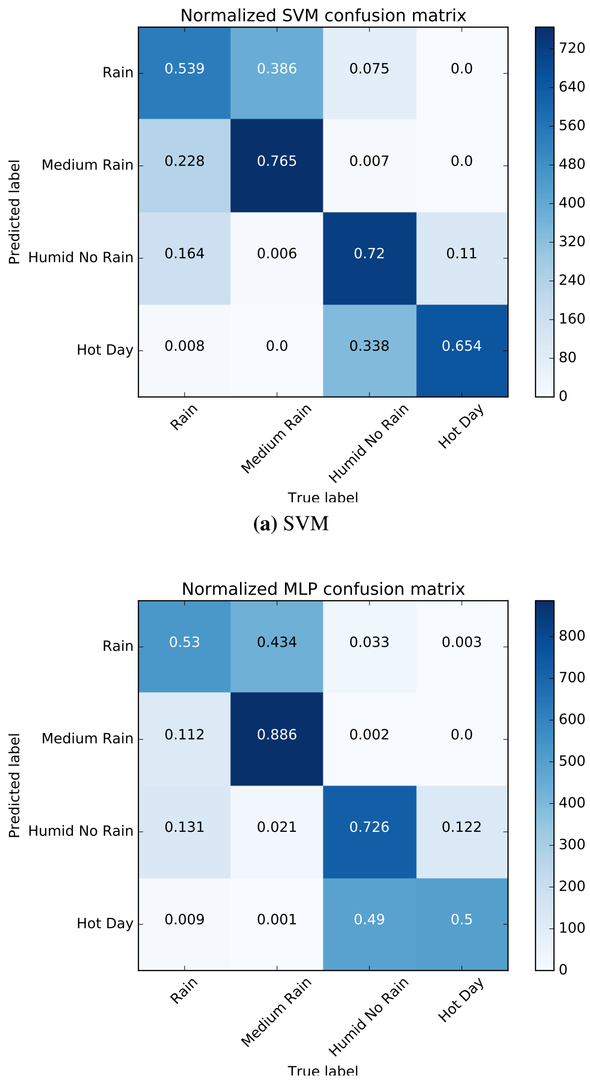
	Train-Car Dataset		**Environment Dataset**	
	SVM	**MLP**	**SVM**	**MLP**
Error Rate (in %)	48.79	51.86	33.05	33.95
kernel	RBF	-	RBF	-
hidden layer size	-	(10, 10)	-	(10, 10)

Table 1: Simulation parameters.

The confusion matrices show details of the prediction errors and Table 1 contains the simulation parameters used to perform the analysis presented in this paper and the error rate. The definition of error rate used here is, for a particular set of output prediction, how many does not match the true value. This is calculated by $error(\text{in }\%) = \frac{100}{N}\sum(predicted - true)$, where N is the total number of errors. The overall percentage of error in each of the algorithms for each scenarios is not good. This is because the algorithms are predicting certain aspects of the scenario such as in “Train-Car” scenario it can separate the situation of presence and absence of vehicles and in “Environment” scenario it can separate rain and no rain conditions better than the others.

6 Conclusion

Different datasets captured by the CommSense system is analysed and classified using the supervised learning algorithms, SVM and MLP. The results are presented in form of a confusion matrix and the matrices are discussed. The overall error rate in each analysis is presented and the reason for the differences are discussed also the reason for such high overall error percentage is discussed. The confusion



(a) SVM

(b) MLP

Fig. 4: Confusion matrix: Environmental parameters.

matrices show some ambiguous results which is due to the presence of similar reflective surfaces in each condition, but overall it proves the initial hypothesis of classifying different environmental conditions using the CommSense system. The error rate in detection of different environmental conditions is approximately 33% which is acceptable as this is the overall error and individual conditions provides better classification. The "Train-Car" dataset has a higher error rate even though the confusion matrix shows promising results. In the future different classification algorithms will be investigated to get better prediction accuracy in case of vehicles. More data needs to be captured at different environmental conditions and analysed to make accurate classifications with multi-class labels.

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