Optimized SVM Model for Vehicle Tracking and Positioning in GSM Network

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Abstract: Machine Learning is one of the major popular research topics of Artificial Intelligence and it pass on with the evolution of techniques and methods which enable the data processor to learn and execute activities. Support Vector Machine (SVM) is an isolated classifier which deals with both linear and nonlinear data from hyper plane with the help of Supervised Learning Approach. Whereas Statistical Learning Theory cannot procure location information in a Sentient Computing because of functional dependencies of geographic coordinates from RSSI but SVM can predict the location fingerprint with regression estimation and linear operator inversion and realize the actual risk minimization by structural risk minimization. SVM can also deliver a good learning outcome in the face of less sample volume. The basic idea of SVM is for linearly separable samples, to find the optimal classification hyperplane which can be described accurately and the samples are separated into two categories for the linearly non-separable problems; to transform the linear non-separable problems in the original space into the linearly separable problems in highdimensional feature space by a nonlinearly transformation for the given samples. SVM gives a very low error rate when used for classification. Here proposed a new SVM based approach for Vehicle Positioning and Tracking in GSM network.

IndexTerms **- Hyperplane; Location Fingerprint; Received Signal Strength Identity (RSSI); Statistical Learning; Support Vector Machine.**

I. INTRODUCTION

In 1992 Vapnik has introduced Support Vector Machine. This uses machine learning theory to maximize predictive accuracy and automatically avoiding over-fit to the data. A Support Vector Machine is a discriminative classifier formally defined by a separating hyper plane a labelled training data. The algorithm output san optimal hyper plane. Let's consider the following simple problem as shown in Fig.1. [13]. Where, a linearly separable set of 2D-points from one of two classes is shown. In this case it deals with lines and points in the Cartesian plane instead of hyper planes and vectors in a high dimensional space.

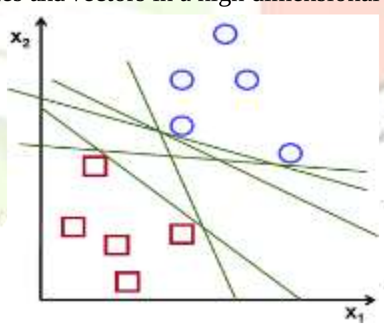

Fig. 1. Set of 2D points which is linearly separable belongs to one of two classes.

However the same concepts apply to jobs where the examples to classify lie in a space whose dimension is higher than two. In the above picture it is shown that there exist multiple lines that offer a solution to the problem. But one cannot say that any of them better than the others? So it has to define a criterion to estimate the worth of the stocks . A telephone circuitis defective if it gets too close to the points because it will be noise sensitive and it will not generalize correctly. It should be better to set the line passing as far as possible from all points [2].

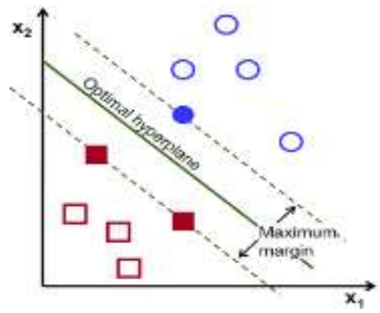

Fig. 2. The optimal separating hyper plane maximizes the margin of the training data.

Then, the operation of the SVM algorithm is based on finding the hyper plane that gives the largest minimum distance to the training examples as shown in Fig.2.[13]. This distance receives the important name of margin within SVMs theory. Hence the optimal separating hyper plane maximizes the margin of the training data.

1.1 Statistical Learning Theory

The statistical learning theory provides a framework for studying the problem of gaining knowledge, making decisions, making predictions, from a set of data [17]. It enables the choosing of the hyper plane space such a way that it closely represents the underlying function in the target space in statistical learning theory the problem of supervised learning is formulated as follows. System Admin can give a set of training data $\{x1,y1...x1,y1\}$ in R^nR sampled according to unknown probability distribution, $P(x,y)$ and a loss function $(y,f(x))$ that measures the error, for a given $x,f(x)$ is predicted rather than the actual value y Finding a function f that minimizes the expectation of the error on new data is the problem, equation 1 shows the function f which minimizes the expected error:

$$\int V(y, f(x))P(x,y)dxdy \qquad (1)$$

In statistical modelling there should be defined model of the hypothesis space, which is closest (with respect to some error measure) to the underlying purpose of the target space [12].

1.2 Theory of Learning and Generalization

Early machine learning algorithms aimed to learn representations of elementary functions. Hence, the goal of learning was to output a hypothesis that performed the correct classification of the training data and early learning algorithms were designed to detect such an accurate fit to the data [10]. The ability of a theory to correctly classify data not in the training set is known as its generalization. Another thing to observe is to find where making the best trade-off in trading complexity with the number of epochs; SVM performs better in term of not over generalization when the neural networks might end up over generalizing easily [15]. The illustration as shown in Fig. 3 brings to light more information about this.

Fig. 3. Number of Epochs Vs Complexity.

The paper continues to exist as follows: Section 2 deals with an overview of the related research regarding the SVM and its comparison, and Section 3 are about Model Generation of Proposed SVM with problem formation where as the conclusions is drawn in section 4..

II. RELATED WORK

The methods considered are k-Nearest Neighbour (k-NN), support vector machines (SVM), smallest vertex polygon (SMP), neural networks (NN), Bayes theorem (BT), and Markov Chains (MC). A common trait most finger printing methods share is that a small change in the layout of the environment or the position of emitter devices would require training the system. The NN and MC methods have a similar behaviour are discussed together. [10]

2.1 Performance of k-NN on Indoor Environments

The k-NN positioning method has a great accuracy at close range (2.4 mat 50m, 1.26 at 25m), but it quickly deteriorates when closing into the target. This is due to an innate problem of the k-NN algorithm similar readings (i.e. Close points) increase the probability of an estimation error .Even though the k-NN algorithm does not always compute position in the same way, it has a remarkable precision. A problem with k-NN is that greater granularity (more fingerprints) increases the computational needs and requires a greater training effort [15].

2.2 Performance of SVM on Indoor Environments

The SVM method has a high accuracy rate although hits precision can be affected by similar readings of signals coming from different points. However, the complexity of the operations required for the positioning estimations demands a powerful computing infrastructure. An advantage of this method is its scalability; it is able to support a large amount of simultaneous targets and can be easily adapted to position resources in 3-D environments, because of its multi dimensional approach [15].

2.3 Performance of SMP on Indoor Environments

SMP calculates target positions with the help of averages, which leads to a relatively high accuracy in most cases, but a high precision error rate [15]. This impacts SMP's score in boths calability and complexity, as with other finger printing methods.

2.4 Performance of NN on Indoor Environments

NN has great accuracy at close range as 2.94m at 50m and 1.39m at 25m [15]. A strongpoint of NN is that they have better performance than the methods when the training data base is very large, though it still requires a moderate amount of training and computing power to carry out acceptable estimation.

2.5 Performance of BT and MC on Indoor Environments

The BT and MC finger printing have greater accuracy at greater distances from the reference points, which decreases at closer distance [11]. But both methods work under probability assumptions and their complexity is relative to the size of the coverage area and amount of targets where sampling can be done at any time for the BT method, allowing the users to adjust marginal distributions of access points when a change in validates the current signal calibration. A drawback of the MC method is the enormous size of its state space, which grows with each new state update [11].

Sampled SVM is a new data modelling method for training SVMs. Where, it is shown that it is fast, scalable and parallelizable yielding approximate solutions to SVM training problems. Furthermore, the method may use any SVM training implementation. Comparing the eight core implementations of Sampled SVM and Cascade SVM demonstrates the algorithm to be faster across all four data sets. Additionally, training SVM sub problems in Sampled SVM is highly parallelizable. The main advantage of Sampled SVM over the Cascade SVM is the increase in the amount of work that is parallelizable. This advantage is particularly acute when the ratio of support vectors to data set size is large [10].

Table 1 . Comparison of finger printing positioning methods in indoor environment

Method	Accuracy	Precision	Scalability	Complexity	Cost
kNN	High	High	Medium	High	High
SVM	High	Medium	High	Medium	Medium
SPM	High	Medium	Medium	High	High
NN	High	High	High	Medium	High
BT	High	High	Medium	High	High
MC	High	High	Medium	High	High

III. MODEL GENERATION

The RSS levels (RSSI parameters) from cells are periodically measured at the Mobile Station in idle mode and could be transferred back to the network in the form of RI list report. The set of RSS values obtained at MS will be referred to as the reference inputs (RIs). Ideally, the MS should be served by the closest node of the network. That would invoke the highest probability that an MS is served by the cell with the strongest signal and the cell with the highest RSS value was used, once the positioning request is received, the serving location mobile centre (SLMC), based on the Cell-ID of the highest reported RSS value for each site, a specific positioning model is applied. The model inputs (MIs) are RSS values of a particular set of BSs. The RI list is then, in SLMC, matched with the MIs, which are specific for the area of a particular model [6]. The RI values that do not have corresponding MIs are discarded, whereas the missing MIs are entered with a threshold value of $-110dBm$. This threshold value is the minimal value of the RxLev parameter. On the other hand, the maximal value of the inputs was $-47dBm$, which is the maximal value of the RxLev parameter. The major phases in providing the location estimate are given in Fig.4.

Fig. 4. System Block Diagram

3.1 ProblemFormation

To develop and study SVM model with the help of kernel function for procuring location information in available GSM network which will be helpful in Vehicle tracking and positioning with minimum distance error means, to predict the location coordinates in the form of (x,y) of mobile vehicle in GSM network with greater accuracy [14].

1) Received Signal Strength (Received Power) is inversely proportional to square of distance from Base Station as shown in equation2.

$$P \propto 1/d^2 \tag{2}$$

2) Environmental characterization is considered with received power P_r where $P(d_0)$ is Power at distance from BS as in equation 3.

$$P_r = P\,(d_0) \div (d/d_0)^n \tag{3}$$

Where, 2.0 is the path loss component.

3) Received Power is calculated using the following formula 4.

$$P_r(d) = P_r(d_0) - 10 * n log(10)\,(d/d_0) \tag{4}$$

3.2 Proposed Algorithm

Algorithm1 Position Prediction

Require: RI List, Trained Data, SVM model

1. Positioning Request
2. MS calculates strongest signal strength and sends it to SLMC where, MS calculates signal strength for all nearest BS
3. SLMC calculates distance for all RSSI values using equations 2, 3 and 4
4. SLMC uses SVM model to optimize the coordinate set which satisfies all distance from given RI list
5. Prediction of the location (Display Position Coordinate)

3.2.1 Training Procedure of SVM

The SVM model should be trained by dataset.

1) Set up the training data
2) Set up SVMs parameters
    a) Type of SVM.
    b) Type of SVM kernel.
    c) Termination criteria of the algorithm.
3) Train the SVM
4) Regions classified by the SVM
5) Support vectors

For better performance of the system the kernel should be define or choose a kernel function carefully.

IV. CONCLUSION

Support Vector Machine, k-Nearest Neighbor, Neural Networks, Decision Tree, and many others are supervised learning algorithms, which are used to solve supervised learning problemsbut what makes SVM interesting, is the ability to classify complex problems having linearly non separable cases with nonlinear decision boundary and its ability to find the optimum nonlinear decision boundary. Using SVM system model will not get any arbitrary nonlinear decision boundary to separate the classes in the training data set. In fact, SVM algorithm will give the optimum linear separation in high dimensional feature space that will be the equivalent to the optimum non-linear decision boundary in the original data set. SVM has some major features such as convexity, duality, kernels, and sparseness used in Machine Learning. The Support Vector Machine algorithm displays a very low error rate when used for regression (spatial localization). The SVM based model could be designed such a way that it will procure location information in a GSM Network. Performance of SVM is fully depends on Kernel functions.

In future a technique for choosing and developing a Kernel Function and monolithic control system for predicating data from small training data sets has great scope.

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