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Travel Time Prediction using Support Vector Machine(SVM) and Weighted Moving Average(WMA)

Subrina Akter[1],Tanjil Huda[4]
Department of CSE
International Islamic University,
Chittagong, Bangladesh

Lutfun Nahar[2] Shamima Akter[3]
Department of CSE
University of Chittagong,
Chittagong, Bangladesh

***Abstract*— Travel Time forecasting in highway system has appeared a vital issue for delivering travellers exact guidance about choosing their route. In this paper, a new method for forecasting travel time from historical traffic data using SVM and WMA is depicted. The proposed work has been divided into two parts: First one is classifying Travel Time depending on the traffic condition or velocity class using Support Vector Machine(SVM) and Second one is predicting Travel Time using modified Weighted Moving Average(WMA) method with a modified equation where the WMA method will be applied on the support vectors whose are generated after classifying time using travel Multi class all versus all SVM. Considering the same historical traffic data, the outcomes of previous methods also compare with the outcome of propose method. In this case, previous methods include Successive Moving Average (SMA), Chain Average (CA), and Artificial Neural Network(ANN). The comparison result proofs the better performance of SVM and WMA method than the previous methods.**

Keywords*— *Intelligent Transportation System(ITS); Support Vector Machine(SVM);Weighted Moving Average(WMA); Successive Moving Average (SMA); Chain Average (CA); Artificial Neural Network(ANN); Travel Time Prediction.

I. INTRODUCTION

Travelling means movement from one geographical location to another geographical location by travellers. Since all time the condition of the road is not the same because of traffic flow or other reasons, so it is very important for the travellers to choose the correct path during traveling. If the travellers can know the available route and current condition about the road they can easily reach their destination. Therefore, Prediction of Travel Time is an important issue in the area of Intelligent Transport System(ITS). Intelligent Transport Systems(ITS) are highly developed applications, seek to provide novel services about various modes of transport and traffic administration and facilitate travellers to be up to date, more harmonized, and best use of transport networks. With the improvement of Advanced Travellers Information System (ATIS) travel time prediction is more and more important issue as it guide tourists delivering their desired route information[1].For tourist satisfaction, the consistent and exact prediction of travel time on street network has emerged a crucial role in any types of vivacious means guidance system[2].Furthermore, the significance of travel time forecasting is very useful to find out the shortest path in order to tour time. The features that are responsible for varying travel time are vehicle speed, traffic and weather condition and also incidence in roads[3]. Moreover, Travel time is also dependent on traffic flow because of busy time and free time[4]. That is, Time reliant feature of traffic flow is also significant. As a result, in this problem area research is very essential for delivering reliable travel time information to meet user's target [5,6,7,8,9].

Numerous algorithms and methods have been recommended in forecasting travel time including time series analysis along with techniques of data mining. Data mining is a computational process used to discover unique, incredible and valuable data from large dataset. To determine frequent incidences[10] (e.g., common pathways selected by tourists) and to seek out discrepancies [11] (e.g., irregularly hectic travel time) the contribution of common data mining techniques is very appreciable. In addition to, there are other data mining techniques available for forecasting travel time. For example, methods of classification[4] can be used for training historical traffic data and for calculating exact travel time for unknown data. Likewise, based on a class of similar data, travel time can be predicted by using clustering methods[12].This techniques used to cluster or bunch the same types of data into the same class. Last few years, a numerous procedures and algorithms have been developed[13,14,15] for forecasting travel time. For example, in KES 2008 a classification process, Naïve Baysian Classifier NBC[4] is recommended and KES 2009 introduced two other algorithms SMA and CA[16] for same task. Moving average was the conception of these algorithms and the outcomes of these methods were more perfect. MKC[12] which was a clustering algorithm proposed in KES 2010.It recovers the limitation of CA,SMA[16] and NBC[4]. Support vector machines (SVM) is widely applied on various study like document categorization and pattern recognitions. But financial market forecasting[17], assessment of power utilization [18], reformation of chaotic systems [19] and calculation of freeway traffic flow [20], are also under development using SVM. In this paper, an innovative method using SVM and WMA is applied to calculate travel time exactly and accurately and this method performs better than the previous methods. Analyzing experimental results, this method reveals satisfactory result in terms of cost and computational complexity. Furthermore, it eliminates unwanted fluctuations in the data set in comparing to conventional moving average method.

In this article at first some discussions about this area are demonstrated. Then our proposed method is discussed and examined and after this a comparison is made by MARE analysis. Finally, we conclude a fruitful conclusion.

II. BACKGROUND STUDY

Intelligent Transportation System is an important research area in predicting travel time. Many researches have been done in this are for forecasting travel time so that tourists can easily choose their desire route. Since last few years, a number of methods and algorithms have been established for calculating travel time exactly and accurately and these approaches revealed performance from different views. This section comprises related works about prediction of travel time. Artificial Neural Network (ANN) suggested by Park et al [21,22] used to predict freeway corridor travel time. But it could not predict the link travel time. For classification of traffic pattern contribution of Kohonen Self Organizing Feature Map (SOFM) and Fuzzy c-means is appreciable. Considering gaps in traffic data Lint et al[23,24] proposed a state-space neural network based method for predicting travel time exactly. Linear regression also performed better in travel time prediction which was proposed by Kwon et al[25]. Rice et al[26] developed a technique for calculating travel time. This time is required to pass through a given time in upcoming day. Comparison between the results (results of various travel time prediction methods) was made by Wu et al[27].In their paper they proposed Support vector regression (SVR) and used real highway traffic data. A switching model consisting of two linear predictors also used in travel time prediction proposed by Erick et al[28]. Considering the possible velocity level for any road segment, another method which was also scalable to road networks with random travel routes named NBC was suggested by Lee et al[4].This paper also used historical traffic data. Representing the knowledge as rules a Rule-based Bayesian classification(RBC)[29] also suggested. It was an extension of NBC.

Moving average was also another idea for travel time prediction and in this case Successive Moving Average (SMA) and Chain Average (CA)[16]- were originated. MKC method was successfully applied by Nath et al.[12] for calculating travel time. It was a clustering method where the data were grouped into a number of clusters and after this final travel time can be derived from the average of the mean of travel times of each cluster. The contribution of MKC in travel time prediction was very appreciable for addressing uncertain situations. In spite of these, existing systems still contain some significant problems. For example weighted moving average method use weight while moving average method does not use any weighted. The weighted moving average model weight recent historical data more heavily than older data when determining the average. In this paper, our contribution was to recover the limitations of earlier methods using our proposed SVM and WMA method.

III. PROPOSED METHOD

In this section a new method for forecasting travel time from historical traffic data using SVM and WMA is depicted. Support Vector Machine(SVM) gives a unique and optimal solution for any given data. Here the steps are depicted one by one.

A. *Step 1:*

1) *Original Data*

We have used real data set for this study which was collected by PNU (Pusan National University), trajectory data generator. This generator is based on real traffic situation in Pusan City, South Korea. They collected real data by using GPS sensor.

The sample historical traffic data is given below:

Vehicle ID	Road Id	Start Time (Sec)	End Time (Sec)	Time Difference (Sec)	Velocity Class	Time group	Distance (m)	Velocity (m/sec)
1	1464	8:0:0	8:0:3	3	B	8	45.946	15.315333
1	1539	8:0:3	8:0:11	8	VB	8	57.816	7.227
1	1547	8:0:50	8:1:6	16	VB	8	80.523	5.032688
3	646	8:5:4	8:5:15	11	VB	8	48.397	4.399727
3	698	8:5:15	8:5:29	14	VB	8	84.883	6.063072
3	693	8:5:29	8:5:40	11	VB	8	47.332	4.302909
5	1453	8:6:13	8:6:30	17	VB	8	127.479	7.498765
5	1458	8:6:30	8:6:38	8	VB	8	75.012	9.3765
5	1422	8:6:38	8:6:50	12	VB	8	64.999	5.416584
5	1360	8:6:50	8:6:58	8	VB	8	69.238	8.65475

TABLE I. SAMPLE HISTORICAL TRAFFIC DATA

In Table 1 there are nine columns. Each column indicates different feature of traffic data. Here a row has the remaining attributes like Vehicle ID, Road ID, and Start time, End Time, Time Group, Distance, Velocity, and Velocity Class. Vehicle Id indicates a specific Id for a vehicle. Road Id indicates vehicle starts from which Road and every road has a specific id. Two attributes Start Time and End Time indicate period during when a vehicle travels on a particular road segment.

2) Velocity Class:

Different velocity classes arise for vehicles at different time periods of a day. In a road network, the moving pattern of vehicles is varied according to the change of time in a day. Due to this, from historical traffic data we can found that they divided road segment velocity into three different. Let Velocity Class = {VB, B, F} be the set of velocity classes. The VB, B and F mean very busy, busy and free, respectively. The velocity classes are shown in Table 1.

No	Time
1	3
2	8
3	12
4	14
5	5
6	8
7	16
8	10
9	7
10	2

No	Class
1	B
2	VB
3	B
4	VB
5	B
6	VB
7	VB
8	VB
9	B
10	F

TABLE II. TIME AND VELOCITY CLASS USED AS ORIGINAL DATA

3) Time Difference:

Time difference indicates difference between Start Time and End time which is also time in second.

4) Distances:

Distance indicates distance between road segments.

Velocity:

5) Velocity :

Velocity indicates velocity or speed of vehicles on which Velocity Class also depends.

From this historical traffic data with nine different attributes or features I have used only two attributes or features for predicting travel time. These two attributes are Time Difference between start time and end time of a vehicle and another attribute is Velocity class. Because I have used Time Differences with Velocity Class for foretelling travel time and then imported data to Matlab.

B. Step 2:

After importing time and class to Matlab which converts Class into index vector because Class is a cell vector of strings; or a character matrix with each row representing a group label.

[G,GN]=grp2idx(Class) creates an index vector G from the grouping variable Class.

Class can be a categorical, numeric, or logical vector; a cell vector of strings; or a character matrix with each row representing a group label.

After converting into index vector, the result G is a vector taking integer values from 1 up to the number K of distinct groups and GN is a cell array of strings representing group labels. GN (G) reproduces Class.

In variable G we can see that there are three different digits 1, 2 and 3.

1 indicates Busy, 2 indicates Very Busy and 3 indicates Free class.

No	g
1	1
2	2
3	1
4	2
5	1
6	2
7	2
8	2
9	1
10	3

No	Gn
1	B
2	VB
3	F
4	..
5	..
6	..
7	..
8	..
9	..
10	..

TABLE III. VARIABLE G AND GN AFTER CONVERTING CLASS INTO INDEX VECTOR.

C. Step 3:

After preparing original data the next task is to splitting dataset for training and testing.

In dataset a training set is implemented to build up a model.Data points in the training set are excluded from testing set or validation set. On the other hand, testing set or validation set is used to validate the model built.

Usually a dataset is divided into a training set and validation set in each iteration.

D. Step 4:

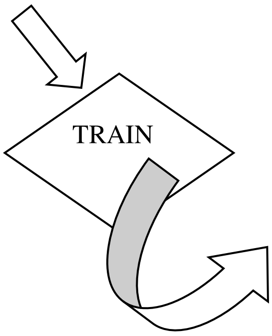
After training we will get a model and this model along with testing set will be used for classification using multi class SVM.

E. Step 5:

After Classification using Multiclass Support Vector Machine I have used support vectors from each binary classification and applied weighted moving average method (WMA) with a new equation.

No	Time
1	3
2	8
3	12
..	14
..	5
10	2

No	Class
1	B
2	VB
3	B
..	VB
..	B
10	F



No	SVM Model
1	<1x1 struct>
2	<1x1 struct>
3	<1x1 struct>

Fig. 1. Time and Velocity Class used as Training Data .

NO	SVM MODEL
1	<1 X 1 struct>
2	<1 X 1 struct>
3	<1 X 1 struct>

Field	Value	Minimum	Maximum
Support Vectors	<2059x1 double>	1	52
Alpha	<2059x1 double>	-0.1554	0.2806
Bias	-0.68867509	-0.6887	-0.6887
Kernel Function	@rbf_kernel		
Kernel Function Args	<1x1 cell>		
Group Names	<3654x1 double>	1	2
Support Vector Indices	<2059x1 double>	1	3651
Scale Data	[ ]		
Figure Handles	[ ]		

Field	Value	Minimum	Maximum
Support Vectors	<660x1 double>	1	26
Alpha	<660x1 double>	-0.4752	0.1267
Bias	0.720330939986315	0.7203	0.7203
Kernel Function	@rbf_kernel		
Kernel Function Args	<1x1 cell>		
Group Names	<1649x1 double>	1	3
Support Vector Indices	<660x1 double>	1	1645
Scale Data	[ ]		
Figure Handles	[ ]		

Field	Value	Minimum	Maximum
Support Vectors	<440x1 double>	1	52
Alpha	<440x1 double>	-0.7778	0.1148
Bias	0.779995289101020	0.7800	0.7800
Kernel Function	@rbf_kernel		
Kernel Function Args	<1x1 cell>		
Group Names	<2699x1 double>	2	3
Support Vector Indices	<440x1 double>	1	2683
Scale Data	[ ]		
Figure Handles	[ ]		

Fig. 2. Result of one verses one classificatio...

F. Weighted Moving average (WMA):

In this proposed methods we can predict travel time by analyzing the historical travel time data. As for example, a vehicle enters on a particular road segment at 10:00 AM and wants to predict travel time. For that reason, we need to accumulate all historical travel time data for that road segment during 10:00 AM. Let t = t1, t2, ...tn be the historical travel time data for any road segment where n is the total number of historical data within a given time interval. For travel time prediction problem, I pick as my sub-problems the problem of determining the time prediction of ti , ti+1,........$t\ j$ for $1 \leq i \leq j \leq n$. Let T[i, j] be the predicted time made by computing the time ti , ti+1,........$t\ j$; for the full problem, the predicted time to compute $t1$, $t2$,........tn would thus be T [1, n].

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Weighted moving average can be mathematically described by following formula:

Where, i=number of rows
j=number of columns
y+1 used for calculating serial number or weight

n=total no of historical data within a given time interval and

T(i,j)=the predicted time made by computing the time Ti,Ti+1…Tj

Example:

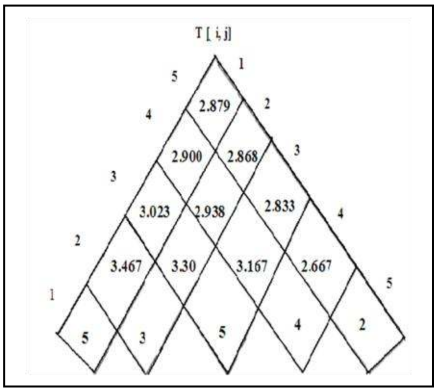
The T table is used for storing the value of T [i, j]. By using the equation of weighted moving average we can calculate the first value

$$T[1,2] = \frac{T[1,1]*1 + T[2,2]*2 + T[3,3]*3 + T[4,4]*4 + T[5,5]*5}{1+2+3+4+5}$$

=3.467

In this way the value in T[1,3] can be found by calculating weighted moving average of T[1, 2], T[2, 3], T[3,4] and T[4, 5] where weight for them will be 1, 2, 3 and 4 respectively.

T[i , j]					
Serial No (5×5)	*1*	*2*	*3*	*4*	*5*
1	5	3.4667	3.0233	2.90019	2.8790
2	0	3	3.3000	2.9389	2.8685
3	0	0	5	3.16667	2.8333
4	0	0	0	4	2.6667
5	0	0	0	0	2



	Serial No (1×5)	1
T[i,j]	1	5
	2	3
	3	5
	4	4
	5	2

Fig 3: Figure for proposed method(WMA)

Serial No (2059×2059)	2051	2052	2053	2054	2055
1	13.391	13.391	13.391	13.391	13.391
2	13.391	13.391	13.391	13.391	13.391
3	13.391	13.391	13.391	13.391	13.391
4	13.391	13.391	13.391	13.391	13.391
5	13.391	13.391	13.391	13.391	13.391
6	13.391	13.391	13.391	13.391	13.391
7	13.391	13.391	13.391	13.391	13.391
8	13.391	13.391	13.391	13.391	13.391
9	13.391	13.391	13.391	13.391	13.391
10	13.391	13.391	13.391	13.391	13.391

TABLE IV. PREDICTION OF TRAVEL TIME FOR BUSY AND VERY BUSY CLASS IS 13.

Serial No (660×660)	652	653	654	655	656
1	2.409	2.409	2.409	2.409	2.409
2	2.409	2.409	2.409	2.409	2.409
3	2.409	2.409	2.409	2.409	2.409
4	2.409	2.409	2.409	2.409	2.409
5	2.409	2.409	2.409	2.409	2.409
6	2.409	2.409	2.409	2.409	2.409
7	2.409	2.409	2.409	2.409	2.409
8	2.409	2.409	2.409	2.409	2.409
9	2.409	2.409	2.409	2.409	2.409
10	2.409	2.409	2.409	2.409	2.409

TABLE V. PREDICTION OF TRAVEL TIME FOR BUSY AND FREE CLASS IS 2.409

Serial No (440×440)	432	433	434	435	436
1	6.458	6.458	6.458	6.458	6.458
2	6.458	6.458	6.458	6.458	6.458
3	6.458	6.458	6.458	6.458	6.458
4	6.458	6.458	6.458	6.458	6.458
5	6.458	6.458	6.458	6.458	6.458
6	6.458	6.458	6.458	6.458	6.458
7	6.458	6.458	6.458	6.458	6.458
8	6.458	6.458	6.458	6.458	6.458
9	6.458	6.458	6.458	6.458	6.458
10	6.458	6.458	6.458	6.458	6.458

TABLE VI. PREDICTION OF TRAVEL TIME FOR VERY BUSY AND FREE CLASS IS 6.458

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Using the proposed method the value of T[1,5] will be the final predicted time. After using weighted moving average, the predicted travel time would be 2.879xl

So the average travel time is (13.391+2.409+6.458)/3=7.419sec.

III. RESULT ANALYSIS

$$T(i,j) = \begin{cases} \dfrac{\sum_{k=j-1,y=0}^{n,((n-j)+1)} T[y+i,k] * (y+1)}{\sum_{y=0}^{((n-j)+1)} (y+1)} & \text{if } i = j \\ & \text{if } j > i \end{cases}$$

A real data set collected by PNU (Pusan National University) path data generator is used here which is based on genuine traffic circumstances in Pusan City, South Korea. From this data, traffic pattern of Pusan city was extracted. The period of real traffic data covers both weekdays and weekends, and both busy hours and free hours. This should adequately reflect real traffic situations.167,669 paths are generated using this generator.

Every path may be calm with numerous road sections. Real traffic situations reflected by these data. For measuring algorithms efficiency and correct assessment, data is separated into two classes, namely training data and test data sets. 365 days and 30 days traffic data are used as training and testing dataset respectively. For fitting the model training data are used and for performance measure test data are used.

Mean Absolute Relative Error (MARE) which is a very well known method used to assess the overall error of tour time forecasting. The formula for calculating MARE is

$$MARE = \frac{1}{N}\sum_{t=1}^{N}\frac{|x(t) - x^{*'}(t)|}{x(t)}$$

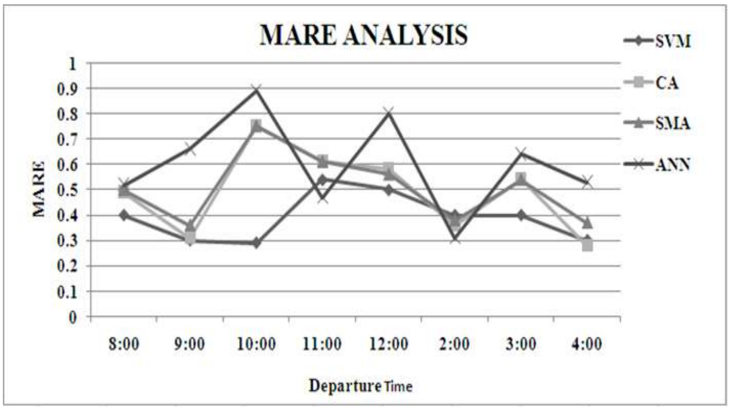
where, x(t)=Observation value,

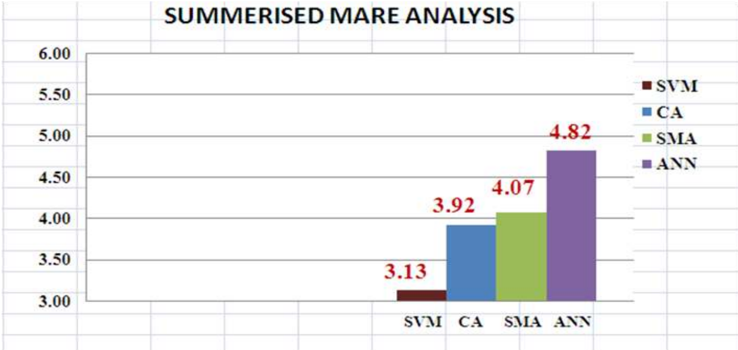
x*(t)=Predicted value

N=Total no. of samples.

In experimental estimation, the comparison is made with the propose method and the previous methods like and Artificial Neural Network (ANN), Chain Average (CA), Successive Moving Average (SMA). Calculation errors of all predictors from 8 AM to 5 PM (10 test cases are evaluated)are examined.

The line chart shown in Fig.4.1 illustrates relative performance of all travel time predictors.





From the overall point of view, proposed method performs much better than CA, SMA, and ANN method. In case of SVM & WMA method, it is shown that seven test cases exhibit errors less than or equal to 0.40. At 10.00 AM, 9.00 AM and 5.00 PM our method SVM &WMA predicted more accurately than others and datasets of those period included uncertain data. By contrary Support Vector Machine and Weighted Moving Average (SVM, WMA), Artificial Neural Network (ANN), Successive Moving Average (SMA) and Chain Average (CA) outperform our method in one, two and one cases respectively but that are slight differences. Summarized result of MARE for different travel time predictors are shown in Fig. 4.2.MARE of SVM &WMA, CA, SMA and ANN are 3.13, 3.92, 4.07 and 4.82 respectively. Thus, our proposed method reduces MARE from CA, SMA and ANN method by 19%, 23% and 40% respectively.

IV. CONCLUSION

This research explored mainly the use of support vector machine and weighted moving average method for travel time prediction of transportation automobiles under traffic environment. Before the SVM development, ANN spatial and temporal correspondence within tour times, running times and dwell times were investigated. The common variations in travel times, i.e. systematic and random variations have also been studied.

The research used GPS data which isn't quite a new data collection scheme in this area and an algorithm based on SVM and WMA has been developed for predicting the travel time of transit vehicles between any two road segments under consideration. As one might expect, the traffic conditions in developing countries are different with heterogeneity lack of lane discipline. Therefore, the prediction algorithm needs more care during development as compared to short-term travel time prediction that used homogeneous data in most previous reported studies on. The lack of historic data and permanent data collection schemes add to the difficulties.

This paper suggested two methods for predicting travel time by using real traffic data from Pusan National University (PNU) path generator. From the simulation result it has been showed that proposed methods provide a more precise prediction in most test cases. The appreciable part of modified WMA method is it uses weight whether the previous moving average methods do not. Moreover, SMA method is more precise than other methods. It provides accurate prediction, low cost due to simplicity and eliminates unwanted fluctuations in the data set.

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