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ENHANCED STOCHASTIC SEQUENCE TRANSLATION ALIGNMENT MODEL FOR TIME SERIES CLASSIFICATION

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Abstract

Lots of valuable information can be obtained by measuring time series data over times. It is hard to deal with variable-length sequences containing different rates of changes with noise and gaps. Finding out the similarity between two or more time series is the heart of many time series data mining applications.Time-series classification problems involves training a classifier on a set of instances, where each instance contains a well ordered set of real valued attributes and a class name. To perform time series classification effectively, an Enhanced Stochastic Sequence Translation Alignment (ESSTA) model is proposed which enjoys the benefits from two typical approaches widely used in sequence classification, such as alignment based and model based. The experimentation was performed with real time traffic data to classify the congestion levels in road traffic and found that the classification efficiency and performance are higher than the existing models taken for comparison.

Keywords: Time series classification, alignment based, model based, traffic congestion classification

1. Introduction

A time series is a series of data points, measured normally at consecutive points in time spaced at uniform time intervals i.e., a time series is a collection of data recorded periodically over time - weekly, monthly, quarterly, yearly and so on [14]. It has a natural sequential ordering [25]. Some of examples of time series are continuous evaluation of a person's heart beat rate, hourly recordings of air/room temperature, daily closing price of stock market, and monthly or yearly rainfall data and so on [24].

Time series classification is a field of machine learning that gained much attention during the recent decades[1]. Time series classification is defined as mapping of data into predefined classes labelled by human experts [30]. Hence it is referred to as a supervised learning method. Time-series classification problems is used in wide variety of fields such as data mining, statistics, signal processing, environmental sciences, computational biology, image processing, chemometrics, statistics, signal processing, pattern recognition, econometrics, mathematical finance, weather forecasting, earthquake prediction, electroencephalography, control engineering, automatic speech recognition, computer vision, bioinformatics, pattern recognition, artificial intelligence, astronomy, communications engineering, and basically in any domain of applied science and engineering which involves temporal measurements [2]. The high dimensionality, very high feature correlation, and the huge amounts of noises that characterize time series data are the major problems while dealing with time-series data [9] [33][4].

Time series analysis comprises methods for analyzing time series data in order to retrieve meaningful information and other characteristics of the data [21]. Time series analysis reveals the fact that data points taken over time may have an internal structure such as autocorrelation, trend or seasonal variation [3]. The time series analysis approach is clearly significant for wide variety of applications where unprecedented amounts of data are being generated and stored, and also for applications in industry (e.g., classifying anomalies on a production line) [32], finance (e.g., characterizing share price fluctuations) [5], business (e.g., detecting fraudulent credit card transactions) [18], surveillance (e.g., analyzing various sensor recordings) [6], astrophysics (e.g., analyze cosmic rays) [20], climate science(e.g., analyze air temperature) [7], Intelligent Traffic Monitoring Systems (e.g., analyzing the congestion levels of traffic) [16] and medicine (e.g., diagnosing heart beat recordings) [26] and so on. The ultimate aim of time series analysis are identifying patterns in correlated data, trends and seasonal variation [2][15], understanding and modeling the data [34], forecasting i.e, prediction of short-term trends from previous patterns [19], intervention analysis i.e, analyzing how does a single event change the entire time series [27], and quality control i.e, identifying deviations of a specified size indicating a problem [28].

2. Related Work

This section reviews some typical approaches widely used in sequence classification such as alignment based models and model based approaches.

The alignment based methods are used to estimate the distance or similarity measure between two sequences that are being time warped. In the alignment based methods, potentially non equal length sequences are aligned in time, usually in a non-parametric approach, with different time scales in measurement, different rates of changes, and noise or gaps [25]. Euclidean distance (ED) is a widely adopted alignment based model; but it requires the two series in comparison to be of equal length and has sensitivity to distortion in time [22]. In order to compare non equal length sequences Dynamic Time Warping (DTW) approach which is superior to ED is widely used [11]. The dynamic time warping has several variants like derivative DTW and band constrained DTW have been shown to be efficient for certain scenarios or data sets [17].

The model based approaches, on the other hand focus on modelling the class-specific representations, typically class conditional density models that can capture common patterns specific to each class. It often identifies dynamical or structural dependences among features in sequences [25].The model based methods constructs a model for the data within a cluster or class and classify new data according to the model that best fits it. The models used in model based classification can be broadly divided into two categories. They are statistical models and neural network models. The statistical models such as Gaussian, poisson, markov and hidden markov models, uses the probability distribution of the data [23]. Artificial neural networks (ANN) and recurrent neural networks are the widely used neural network models [29]. In machine learning and cognitive science, artificial neural networks (ANNs) are a cluster of statistical learning algorithms motivated by biological neural networks and are used to estimate or approximate functions that mainly depend on outsized number of inputs and are generally unknown. Artificial neural networks are usually represented as systems of interconnected *neurons* which send messages to all. The connections contain numeric weights that can be fine-tuned based on practice, resulting neural nets adaptive to inputs and capable of learning [31].

The alignment based approaches usually encompass difficulty in inducing certain structural assumptions or stochastic dependencies that exist in time series, which may cause potential performance degradation in classification. Another possible outcome is that the class prediction may be accompanied with label noise or outliers. In alignment based method class specific pattern or trend cant able to find out. It finds only the similarity measures of sequences that are time warped.The model based approaches like HMMs have the representational power and the ability to faithfully express sequences of a particular cluster. However, their performance is contingent on the goodness of the model structural assumption, which can be often very difficult to estimate in certain situations. In addition, failure to consider explicit alignment of time series may result in suboptimal solution. Furthermore, it can't able to perform the alignment of sequences that are time warped.

The huge number of time series application varying from medical diagnosis up to financial econometrics are there. Mining time series data can extract important patterns, such as similarities, trends, or periodicity. Since time-series data have a tendency to grow rapidly over time, they present several performance and efficiency issues to data mining algorithms. So in order to overcome the limitations of the time series data mining approaches typically used, an Enhanced Stochastic Sequence Translation Alignment Model (ESSTA) is proposed which enjoys the benefits by incorporating both alignment based and model based approaches.

3. ESSTA Classifier Architecture

The proposed ESSTA model for time series classification extracts benefits from both alignment based and model based approaches for sequence classification. By using alignment based approach it can able to calculate distance measures between unequal length time series data using direct comparison of aligned features. By using model based approach it can able to capture the class specific patterns or trends efficiently. The ESSTA uses the combined approach of dynamic time warping (DTW) [35], a popular alignment based approach for measuring similarity between two temporal sequences which may vary in time or speed and adaptive neuro fuzzy inference system(ANFIS) [12], a model based approach, which hybridizes an artificial neural network with a fuzzy inference system. The traffic dataset is obtained from a stationary camera and the image frames were labelled as low traffic, medium traffic and high traffic by training the classifier, forming a three way classification problem. The experimentation was carried out in MATLAB and classification of image frames into low traffic, medium traffic or high traffic are performed and evaluated. The system architecture of ESSTA depicts how the system flows on the working of its internal structure and is shown below in Figure 1.

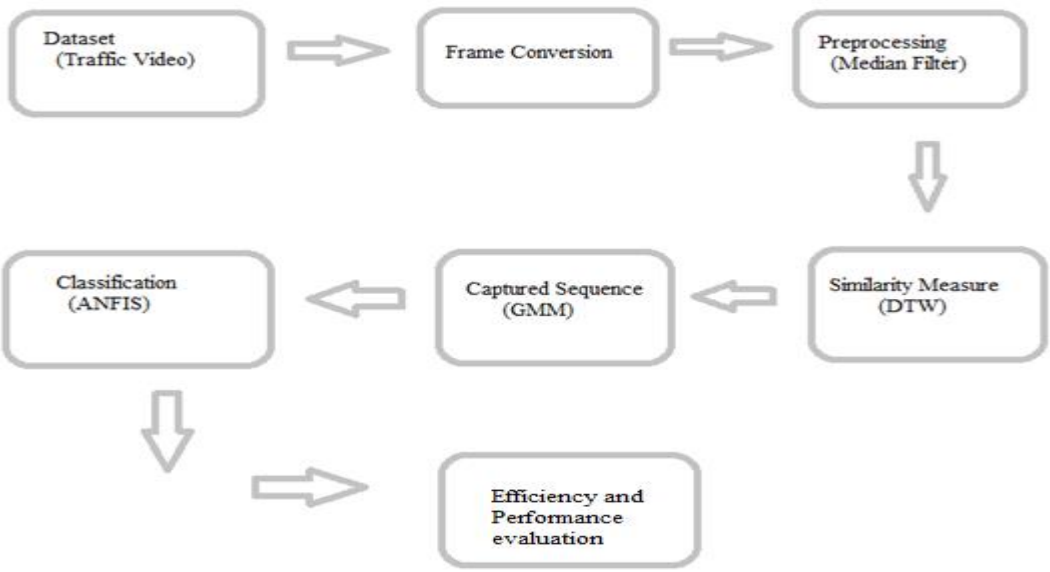

Figure 1: System Architecture

3.1 Frame Conversion

First the traffic video set is divided into number of frames. This will help to select a representative frame from the video and develop an algorithm on that frame. Then this algorithm can be applied to the processing of all the frames in the video.

3.2 Preprocessing

The noises in the image/frame reduce the quality of the frames. In order to improve the quality of the images and for eliminating unnecessary noises, preprocessing operations have to be performed. In ESSTA, Median filter is used for preprocessing [8]. The main advantage of using median filter is that it preserves edges while processing the images. It is particularly effective for removing impulsive noise. The median filter works by moving through pixel by pixel, replacing each value with the median value of the neighboring pixels. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.

3.3 Background Subtraction

In order to identify moving objects from a sequence of videos frames, background subtraction is applied. Background subtraction, also known as foreground detection, is a technique in the fields of image processing and computer vision wherein an image's foreground is extracted for further processing i.e., for object recognition etc. Generally an image's regions of significance are objects such as humans, cars, text and so on in its foreground. After the stage of image preprocessing, object localization is performed by using this technique. Here Gaussian mixture models are used for back ground extraction [8]. The GMM is a mixture of k Gaussian distributions that point the change of state of the corresponding pixels from one frame to another. The algorithm developed applies Gaussian mixtures to each frame and transforms images once colorful into binary images. For the corresponding pixels that undergo no state changes, the value 1 (black) is credited and for pixels that undergo severe changes in state, the value 0 (white) is credited. Thus, it is feasible producing the locations of all moving objects in the video.

3.4 Similarity Measurement

Dynamic time warping is used in ESSTA to find the similarity of the moving objects and also for the whole trajectory motion of the moving objects in the whole video in order to find out any anomalies in the moving path. In time series analysis, dynamic time warping (DTW) is an algorithm for measuring similarity between two temporal sequences which may vary in time or speed. The Dynamic time warping algorithm performs the similarity measurement by creating distance/cost matrix and calculates the value for each cell recursively by using the following Equation 1.

cell(i,j) = local_distance(i,j) + MIN(cell(i-1,j), cell(i-1,j-1), cell(i, j-1)). – Eqn 1

The value in the top right most cell, cell (m,n) gives the minimum distance between the two sequences. If cell(m,n) equals to zero, then two sequences are similar.

3.5 Classification

ANFIS is used to perform the classification of traffic congestion levels. Adaptive network based fuzzy inference system (ANFIS) is a neuro fuzzy technique where the blend is made between the neural network and the fuzzy inference system [13]. The ANFIS algorithm gives a method for the fuzzy modelling procedure to learn information about a particular data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data. The fuzzy logic considers the imprecision and uncertainty of the system that is being modelled, on the other hand the neural network provides it a sense of adaptability. By means of this hybrid method, formerly an initial fuzzy model along with its input variables are derived with the aid of the rules extracted from the input output data of the system that is being modelled. Subsequently the neural network is used to fine tune the rules of the initial fuzzy model to generate the final ANFIS model of the system. In this proposed work ANFIS is used as the backbone for the identification of traffic congestion levels.

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4. Implementation And Results

The experimentation was carried out in MATLAB by taking a real time traffic video data set. After reading the real time traffic video data set, the video is divided into 1470 frames (30 frames per second) and then performs pre-processing or filtering of images in order to improve the image quality. The Figure 2 and Figure 3 depict the snapshot of the selected traffic video and the frame conversion respectively. The method is based on the establishment of correspondences between regions and vehicles, as the vehicles move through the image sequence. This will help to select a representative frame from the video. In order to perform sequence capturing a particular frame wants to be selected. The Figure 4 depicts the captured frame for performing the background subtraction. After capturing a particular frame, background subtraction operation is performed to find out the moving objects in the frame [10]. Here to perform the background subtraction, Gaussian mixture model is used. After choosing a particular frame, Gaussian mixture algorithm is used to subtract the background from each frame and transforms images once colourful into binary images. For the corresponding pixels that undergo no state changes, the value 1 (black) is attributed and for pixels that undergo drastic changes in state, the value 0 (white) is attributed. Thus, it is possible generating the locations of all moving objects in the video. The Figure 5 depicts the captured sequence using the Gaussian mixture model. Dynamic time warping is used to find the similarity of the moving objects and also for the whole trajectory motion of the moving objects in the whole video in order to find out any anomalies in the moving path. The Figure 6 depicts the DTW result. The classification is performed using adaptive neuro fuzzy inference system algorithm. Here the attributes chosen is no of vehicles in a particular frame and three predefined classes low traffic, medium traffic and high traffic. Training of the classifier is performed by using these predefined classes and the evaluation of the unlabelled video frames i.e. test data is performed by using the trained classifier. The classifier is predefined in such a way that if the no of vehicles in a particular frame is less than 7, then it belongs to class "low traffic" and if the no of vehicles is between 7 and 14, then it belongs to class "medium traffic" and if the number of vehicles is equal to above 14, then it belongs to class "high traffic". The resulting system robustly identifies vehicles, rejecting background and tracks vehicles over a specific period of time and performs classification, by the combined approach of alignment based and model based techniques. The Figure 7 depicts the classification output using the ANFIS.

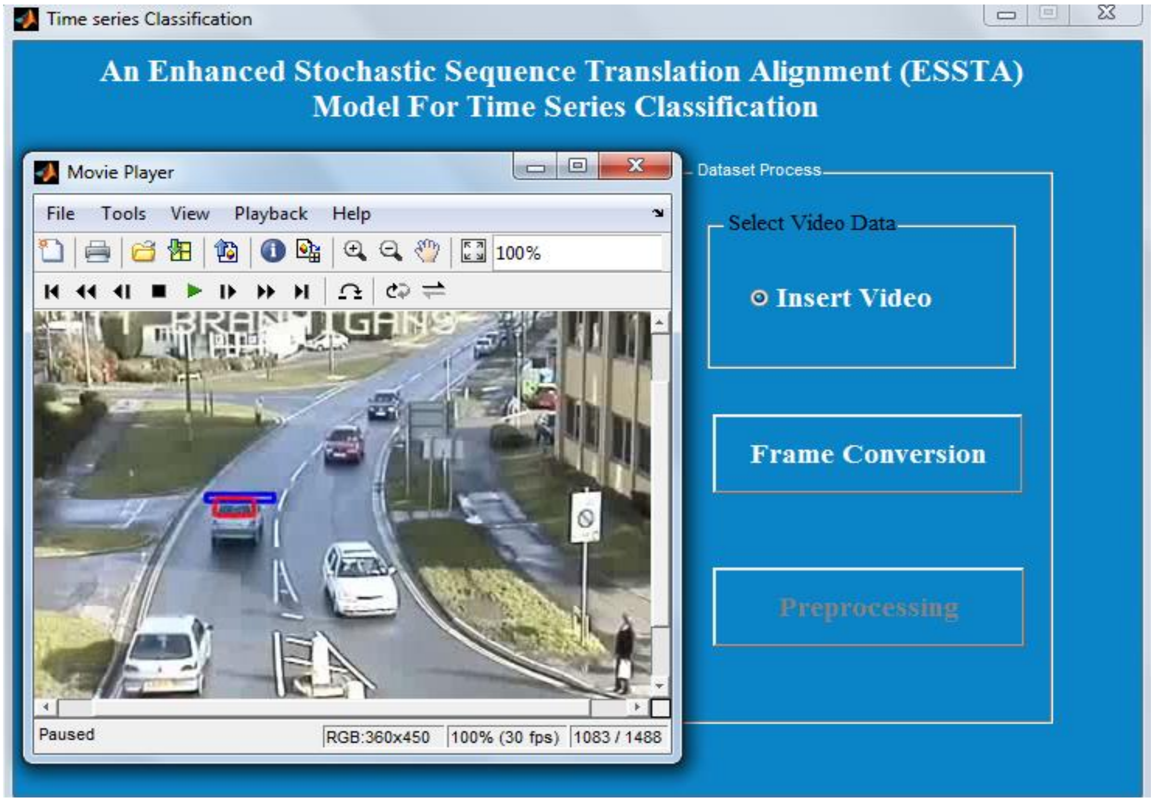

Figure 2: Snapshot of selected video

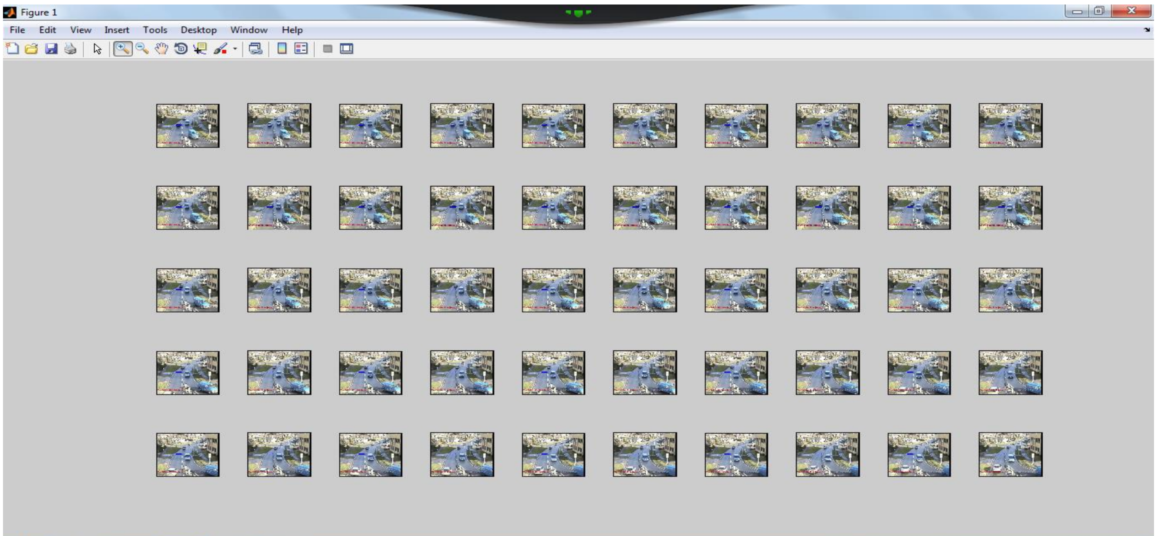

Figure 3: Frame conversion

Figure 4: Captured frame

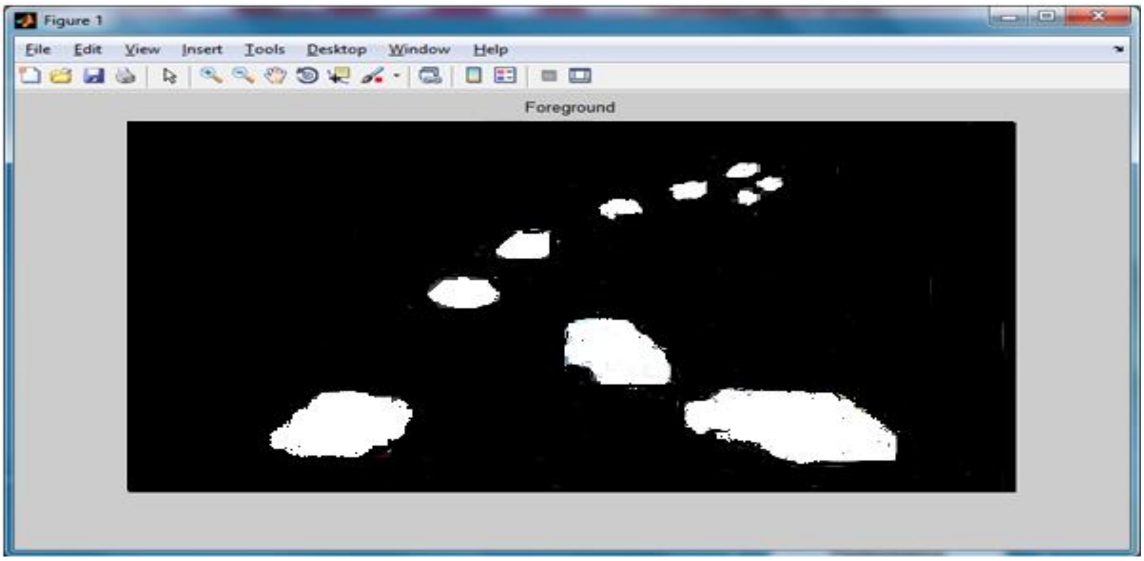

Figure 5: Captured sequence using GMM

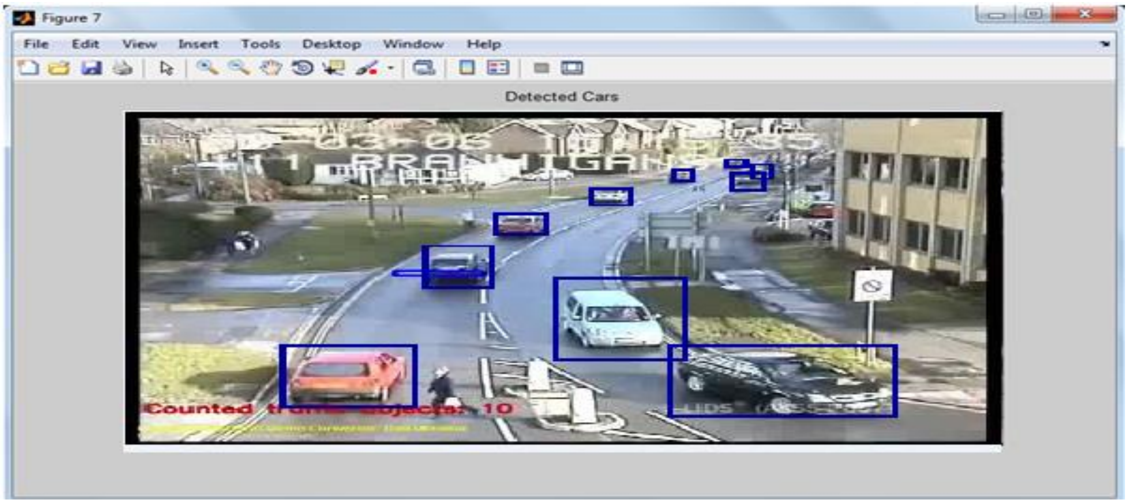

Figure 6: DTW result

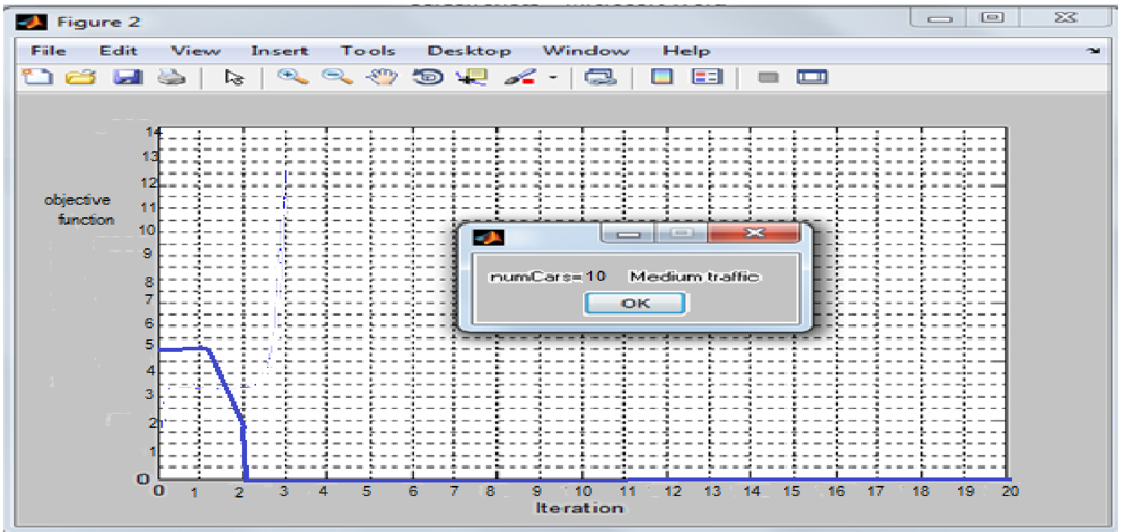

Figure 7: ANFIS classification output

In order to evaluate ESSTA model, two parameters efficiency and performance are taken into account. Efficiency is measured by estimating the total run time taken by the model to perform the classification and performance is measured in terms of accuracy.

4.1 Efficiency Evaluation

The ESSTA classifier classifies the frames in the traffic video data set into low traffic, medium traffic and high traffic congestion levels, forming a three way classification solution. In order to evaluate the efficiency, running time to train and test the ESSTA is calculated and compared with other models taken for consideration. The time taken for classifying the traffic data set is less when compared with other classification models taken for consideration. The experimental result demonstrates that the time taken for training the ESSTA classifier is about 21.34 seconds and for testing it takes 0.13 seconds. Total time taken to perform the classification is about is 21.47 seconds. The Figure 8 depicts the running time of ESSTA to perform the classification. The main advantage of the ESSTA model is that test prediction is faster than the existing approaches of time series classification models such as alignment based model (DTW) and model based approaches (HMM). The following Table1 and Figure 9 shows running time comparison of the ESSTA classifier with the widely used classifiers for time series classification such as HMM and DTW.

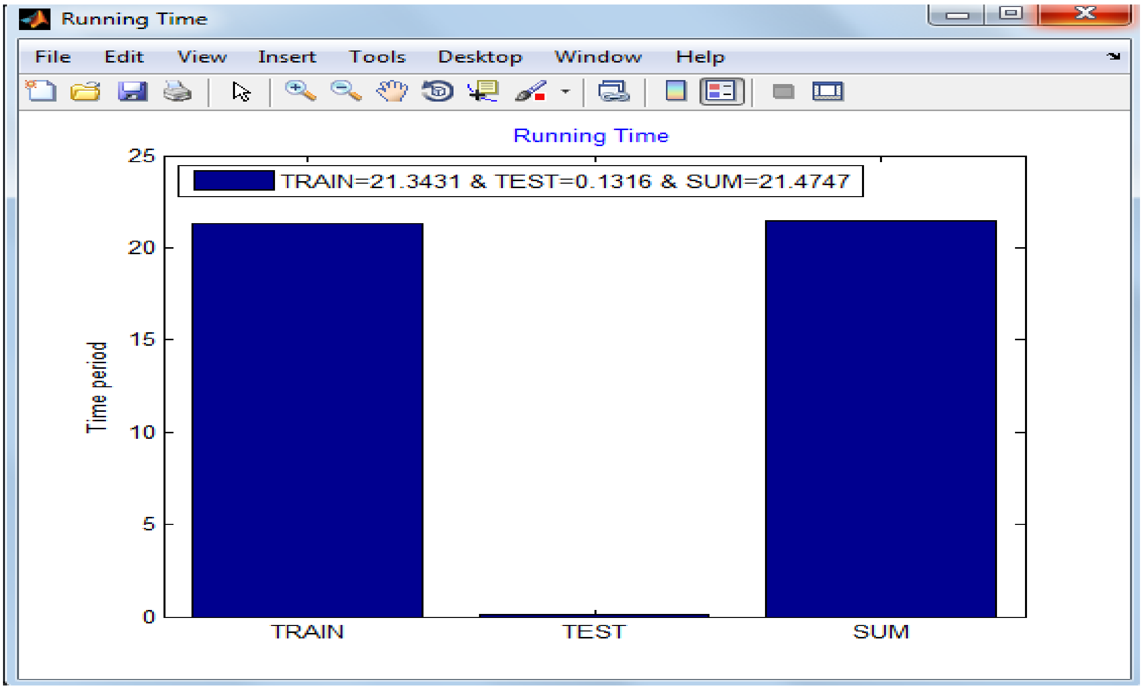

Figure 8: Running time

Phase	Run Time (seconds)		
	HMM	DTW	ESSTA
Train	22.12	N/A	21.34
Test	0.14	37.67	0.13
Total	22.26	37.67	21.47

Table 1: Comparison of time taken for classification for the various models taken for experimentation

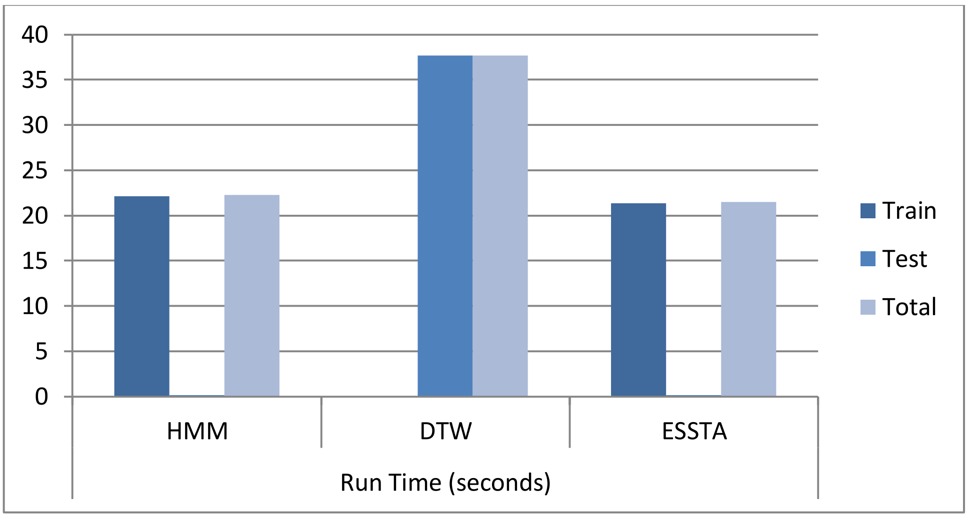

Figure 9: Comparison chart of run time (training, testing and total time taken) of various models taken for experimentation

4.2 Performance Evaluation

A confusion matrix or contingency table shows the number of correct and incorrect predictions made by the classification model compared to the actual outcomes (target value) in the data. The matrix is *N*x*N*, where *N* is the number of target values (classes). Performance of classification models is commonly evaluated using the data in the matrix. In ESSTA, in order to evaluate the performance first 300 frames were chosen of which first 120 frames are of low traffic frames, next 86 frames were of medium traffic and the remaining 94 frames were of high traffic. The confusion matrix of ESSTA time series classification model with three classes, low traffic, medium traffic and high traffic is given below in Table 2.

Confusion Matrix	Target			Precision	Accuracy
	low traffic	medium traffic	high traffic		
low traffic	112	6	2	93.33%	91.33%
medium traffic	2	80	4	93.02%	
high traffic	7	5	82	87.23%	

Table 2: Confusion matrix for ESSTA Classifier

The experimental result shows that accuracy percentage of ESSTA classifier is about 91.33%.Accuracy = (112+80+82)/300 = 0.9133.The precision of ESSTA classifier for low traffic, medium, traffic, heavy traffic congestion level classification is 93.33%, 93.02% and 87.23% respectively. Precision of low traffic congestion level = 112/120 = 0.9333.Precision of medium traffic congestion level = 80/86 = 0.9302. Precision of high traffic congestion level = 82/94 = 0.8723. The comparison of accuracy percentage of various models taken for experimentation is given below in Table 3 and in Figure 10.

Models	Accuracy
HMM	91.26%
DTW	91.06%
ESSTA	91.33%

Table 3: Comparison of accuracy in classification for the various models taken for experimentation

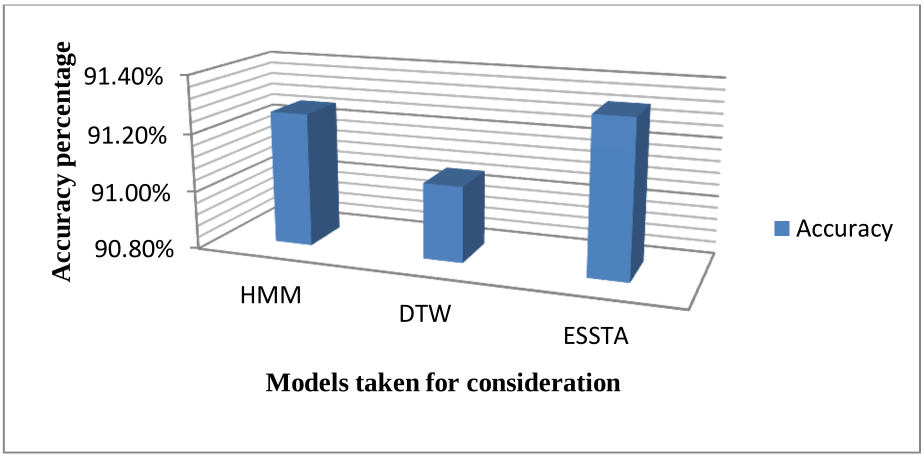

Figure 10: Comparison chart showing accuracy of various models taken for experimentation

The experimental result demonstrates that the efficiency and performance of ESSTA classifier is slightly higher than that of various models taken for experimentation.

5. Conclusion

An enhanced stochastic sequence translation alignment model for performing time series classification is developed by using traffic video dataset by using the combined approach of alignment based and model based techniques of sequence classification. The traffic congestion level classification framework developed here effectively classifies the traffic congestion levels into low traffic, medium traffic, and high traffic using ESSTA classifier. As the proposed ESSTA extracts the benefits from alignment based and model based approaches the efficiency and performance are higher than most of the widely used time series classification model and can be used as a proficient intelligent traffic monitoring system. Automatic traffic density estimation and vehicle classification through video processing is very important for traffic management especially in mega cities. In the context of heavy traffic congestion, a prior knowledge of the traffic details of the various routes could help choose an alternate route to avoid traffic delays. This model can also be used to provide advance warning to motorists of traffic jams, accidents and other emergency situations. Thus the proposed approach is useful for developing safe, smart and sustainable technology solutions. The system will also solve major problems of human effort and errors in traffic monitoring and time consumption in conducting survey and analysis of data. The project reduces the cost of traffic monitoring system and provides a complete automation of traffic monitoring system.

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A Brief Author biography

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