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A Novel Approach to Classification Capacity Urban and Rural Roads with Detection of Traffic Noise across Higher Density

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Abstract- A comprehensive methodology for modelling the heterogeneous traffic is presented in this article. Considering the no-lane discipline and the presence of various sizes of vehicles, several microscopic and macroscopic traffic variables are analyzed for their suitability in describing the heterogeneous traffic. Applicability in the modelling process and the feasibility in collecting field data are the important criteria used in deciding the suitable traffic variables. In place of occupancy, its variant termed as area occupancy was found to be suitable in describing the heterogeneous traffic. Vehicle size, mechanical characteristics, lateral distribution of vehicles and the lateral gaps maintained by them are found to be more suitable microscopic traffic variables. Data on these variables have been used in modifying the cell structure and the updating procedures of the KNN-based traffic flow model. A customized data collection technique has been used in collecting the field data on these variables. The modified KNN model with the relevant parameter values has been used in simulating the flow.

Keywords- Speed -flow relationship, undivided roads, Quality of service.

I. INTRODUCTION

Over the past decade, use of motorized vehicles has been significantly increased with rapid growth of urbanization in India. This robust increase in population has given a challenge for the development of modern society which has turned into a major concern in metropolitan cities in developing countries like India. At present, the world population crosses seven billion and population residing at urban areas are nearly half of seven billion counts which is expected to raise up to 60 % over worlds entire population by the end of 2025 [1].

Indian cities are well connected with urban roads and rural roads everywhere but, there exists poor transportation network/connectivity with negligible intra and intercity facilities [2]. Hence, traffic flow in heterogeneous conditions is highly complex and is difficult to predict the flow behaviour on urban roads.

Driver’s comfort, convenience, traffic volume, lane width, grade type, geometric design ravel delay and safety are the major concerns on Indian urban roads which are to be taken care. Monitoring traffic volume and level of service which represents quality transport has become indispensable [3].

In recent years, traffic congestion and decreasing level of service has become major issues in most of the metropolitan cities and results its impact on urban economy and its environment [1], [4,5], [6]. Good transportation facilities are needed to be provided as it plays a major role in growing India’s economy [7], [8] [9], [10].

From past studies, it was found that, obtained traffic volume plays a vital role in determining the existing conditions and even possible to predict the future traffic volume conditions [9], [11]. There are certain factors which are responsible for decreasing level of service and traffic congestion i.e., speed and travel time, traffic interruptions and restrictions. This downfall of level of service has become a serious threat as it creates difficulty for vehicle maneuvering. Similarly, traffic congestion also creates air pollution and noise pollution which is caused by the delays in traffic jams. This traffic congestion and poor level of service on Indian roads have huge impact on its economic growth [1], [9].

There are few commonly used methods like, Cluster Analysis, Genetic Algorithm, Fuzzy Set Theory and Neural Network etc., which are used to determine the Level of service of a particular road section. This paper aims to develop sound understanding of Level of Service (LOS) on urban and rural roads in Indian conditions from the previous studies conducted. The detailed information on various parameters that are used to define LOS are also reported and presented. The classifications of LOS grades along with its operating characteristics are also provided.

II. PROBLEM STATEMENT

Present study also aims to develop traffic flow model for corridor simulation. It comprises combination of two mid-blocks and two intersections. In first intersection turning movements are not incorporated and is included in second intersection. To represent multiple vehicle types, a multi cell representation was adopted. The position and speed of vehicles are assumed to be discrete in developed model. The speed of each vehicle changes in accordance with its interactions with other vehicles and is governed by pre-assigned (stochastic) rules.

Due to complexity involved in multi cell representation, cross traffic is eliminated and only through traffic is considered. The vision of this model is to incorporate traffic movement partially. The term partially is used here because the cross traffic and turning traffic is not taken in to consideration. Also model is aiming to check the feasibility of using CA for multi cell representation. Simulation result shows that the model performs reasonably well in predicting the travel time.

III. DETECTION OF TRAFFIC NOISE

Environmental noise is increasing year after year and be-coming a growing concern in urban and suburban areas, especially in large cities, since it does not only cause an-noyance to citizens, but also harmful effects on people. Most of them focus on health-related problems [1], being of particular worry the impact of noise on children [2], whose population group is especially vulnerable. Other investigations have also shown the effects of noise pollution in concentration sleep and stress [3].

Finally, it is worth mentioning that noise exposure does not only affect health, but can also affect social and economic aspects [4].

Among noise sources, road-traffic noise is one of the main noise pollutants in cities. According to the World Health Organization (WHO), at least one million healthy life years are lost every year from traffic-related noise in Western Europe [5].

For instance, it was recently stated that transportation noise alone accounts for 36% of the total burden of disease attributable to urban planning, an even higher percentage than the one caused by air pollution [6].

A major disadvantage of the Fourier Transform is it captures global frequency information, meaning frequencies that persist over an entire signal. This kind of signal decomposition may not serve all applications well, for example Electrocardiography (ECG) where signals have short intervals of characteristic oscillation. An alternative approach is the Wavelet Transform, which decomposes a function into a set of wavelets.

IV. PROPOSED METHODOLOGY

1. Capacity Classification Urban and Rural Roads:
In statistics, the *k*-nearest neighbor's algorithm (*k*-NN) is a non-parametric method proposed by Thomas Cover used for classification and regression. [1] In both cases, the input consists of the *k* closest training examples in the feature space. The output depends on whether *k*-NN is used for classification or regression:

- In k-NN classification, the output is a class membership. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.

- In k-NN regression, the output is the property value for the object. This value is the average of the values of k nearest neighbors.

K-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until function evaluation. Since this algorithm relies on distance for classification, normalizing the training data can improve its accuracy dramatically.[2][3]

Both for classification and regression, a useful technique can be to assign weights to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/*d*, where *d* is the distance to the neighbor.[4]

The neighbors are taken from a set of objects for which the class (for *k*-NN classification) or the object property value (for *k*-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.

The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples.

In the classification phase, *k* is a user-defined constant, and an unlabeled vector (a query or test point) is classified by assigning the label which is most frequent among the *k* training samples nearest to that query point. A commonly used distance metric for continuous variables is Euclidean distance. For discrete variables, such as for text classification, another metric can be used, such as the **overlap metric** (or Hamming distance). In the context of gene expression microarray data, for example, *k*-NN has been employed with correlation coefficients, such as Pearson and Spearman, as a metric.[5]

Often, the classification accuracy of *k*-NN can be improved significantly if the distance metric is learned with specialized algorithms such as Large Margin Nearest Neighbor or Neighbourhood components analysis.

A drawback of the basic "majority voting" classification occurs when the class distribution is skewed. That is, examples of a more frequent class tend to dominate the prediction of the new example, because they tend to be common among the *k* nearest neighbors due to their large number.[6] One way to overcome this problem is to weight the classification, taking into account the distance from the test point to each of its *k* nearest neighbors.

The class (or value, in regression problems) of each of the *k* nearest points is multiplied by a weight proportional to the inverse of the distance from that point to the test point. Another way to overcome skew is by abstraction in data representation. For example, in a self-organizing map (SOM), each node is a representative (a center) of a cluster of similar points, regardless of their density in the original training data. *K*-NN can then be applied to the SOM.

In *k*-NN regression, the *k*-NN algorithm [*citation needed*] is used for estimating continuous variables. One such algorithm uses a weighted average of the *k* nearest neighbors, weighted by the inverse of their distance.

This algorithm works as follows:
- Compute the Euclidean or Mahalanobis distance from the query example to the labeled examples.
- Order the labeled examples by increasing distance.
- Find a heuristically optimal number *k* of nearest neighbors, based on RMSE. This is done using cross validation.
- Calculate an inverse distance weighted average with the *k*-nearest multivariate neighbors.

V. RESULT AND ANALYSIS

1. Data Collection:

Accident data were obtained from the department of revenue (DOR) and were calculated by the total accidents recorded from 2021 December. It contains useful traffic information, such as crash location, severity, weather condition, and segment type, and the data were geo-coded into GIS databases by the PPACG (Pikes Peak Area Council of Governments).

Based on the GIS process of spatial join between whole road network and urban boundary, the road segments were classified into two categories: rural segments and urban segments. Before analyzing segment crashes, the crashes at intersections were separated from the databases. Thus, the 200-ft intersection buffers were first created, and the crashes within these intersection buffers were deleted from the segment crash analyses.

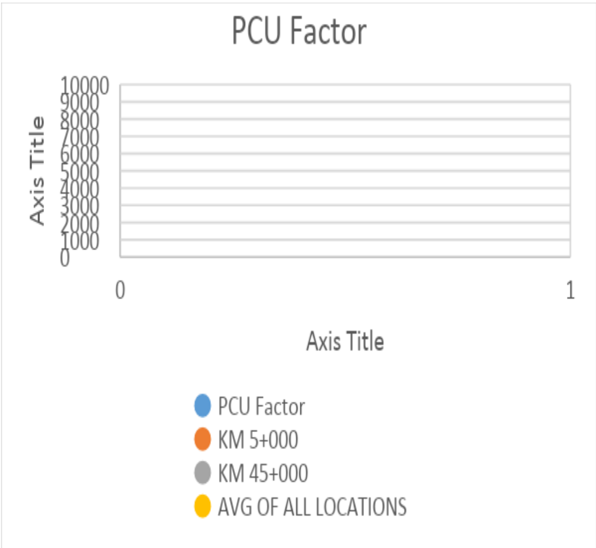

Fig 1. KNN classification Curve of Urban and Rural traffic density.

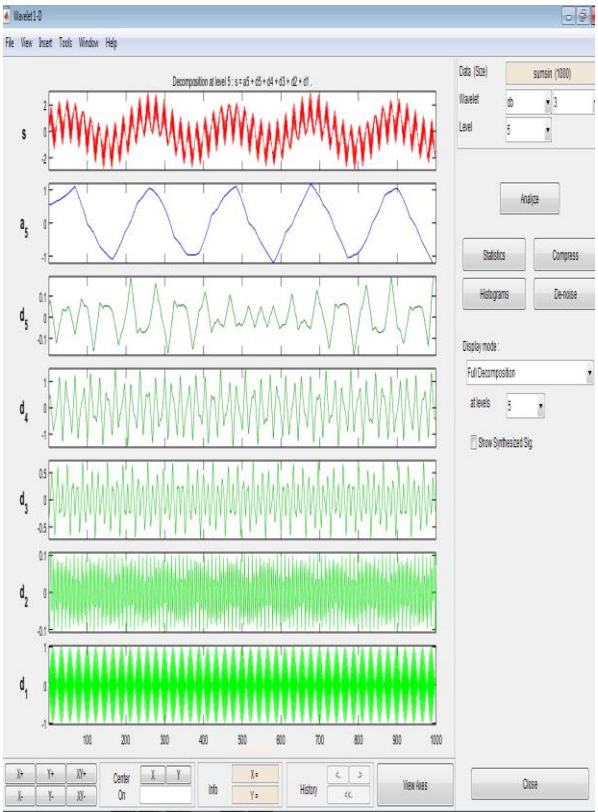

Fig 2. DWT noise signal analysis.

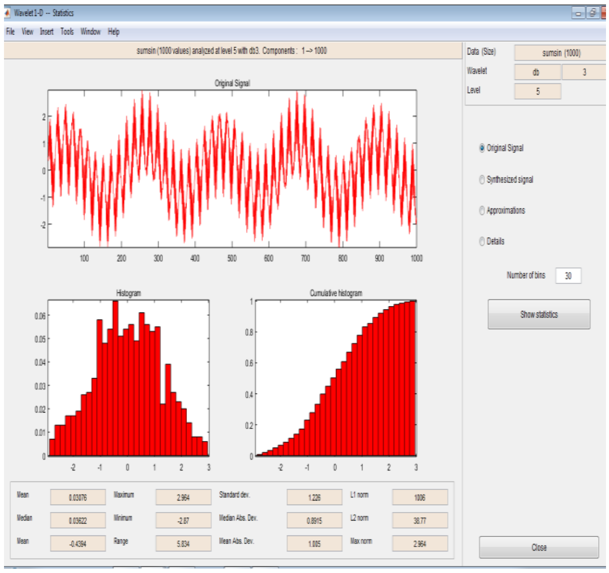

Fig 3. Noise reduction Histogram Curve.

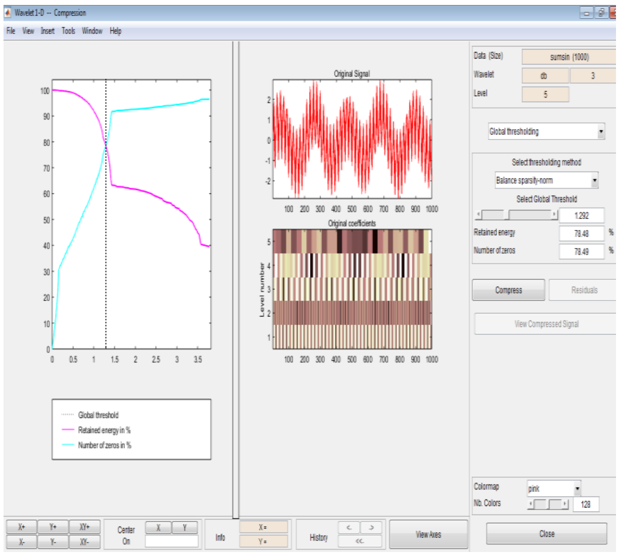

Fig 4. Signal Transformation.

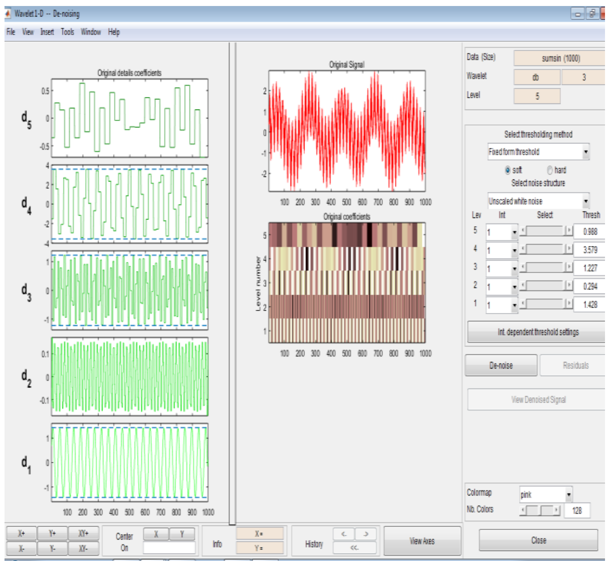

Fig 5. Signal denosing.

VI. CONCLUSION

Simulation models have been widely used to understand and predict traffic flow phenomena such as shock waves, queuing, and congestion. These models have also been applied in deriving flow characteristics like speed, density, and volume. Traditional car-following models use Newtonian laws of motion to describe traffic flow. Though such models are able to simulate traffic flow with high accuracy, they require large computational time making them unsuitable for real time applications.

Compared with more detailed models, the has the advantage that it has a very limited set of parameters to be adjusted. In this context, KNN has emerged as an efficient tool in modelling traffic flow. Several studies demonstrated the modelling simplicity and computational efficiency of KNN in traffic flow modelling.

Most of the KNN models developed so far concentrate on homogeneous traffic flow conditions, whereas a few studies have been reported on heterogeneous traffic flow modelling using KNN. They are still limited in their ability to represent heterogeneous traffic. Therefore, in this study an attempt is made to develop traffic flow model to simulate heterogeneous traffic using cellular automata. This study is limited to the development of a uni-directional traffic flow model at an urban mid-block section, urban intersection as well as an urban corridor traffic flow model.

VII. FUTURE SCOPE

The proposed models also have some limitations such as capability to handle only unidirectional flow. Geometric features like gradient, curve, and road characteristics have not been considered, and they are required to be compared at microscopic level with a large set of real microscopic traffic data.

The present work banks upon lots of IRC recommendations to identify different zones of speed reduction, sign placement etc., however the actual traffic condition may differ. This can be improved in future. The corridor model also has some limitations such as no cross traffic taken in to account and movement in only straight direction is considered. This can also be improved in future.

The present work can be extended for bi-directional traffic flow. The road characteristics and geometric features can be incorporated in the model.

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