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Research Article

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Detecting the Anomalies in Traffic Flow by Fisher Information Measure

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Abstract Traffic flow is one field where there is extensive strata of literature. Traffic flow has been shown to be often nonlinear, complex and noisy time series. Hence, statistical, nonlinear, and many other techniques have been employed. Here, Fisher Information Measure (FIM) is utilized to observe possible changes that are not quite obvious. The way FIM works makes it a useful tool in observing subtle changes in daily traffic flow. Authors are also aware that FIM is a parameter dependent tool, where a set of parameters affects the overall performance of a given analysis. The following study involves an optimization where over a series of trials an optimal set of parameters have been set and implemented. Two data sets have been selected. One set is 25000 data points long, covering a 24 hour-period. This location is a heavily used industrial zone where a constant flow of traffic is observed throughout the day. Another is rather a light suburban area with a daily 3000 vehicle observations approximately. FIM analyses of these two locations are made and presented. Results show that relatively fast but inconspicuous regime changes appear as spikes in FIM diagrams.

Keywords Vehicular traffic flow, Fisher information, anomaly detection, traffic flow characteristics

Introduction

Anomaly detection is a thought-provoking task and its evaluation in various complex systems could be based on entropy, and one of the research fields of it would be vehicles and traffic-led phenomena. Some of the recent related works in vehicular arena belong to e.g. [12] and [9]. Müter & Asaj [12] focus on the entropy-based attack detection for in-vehicle networks. The different attack scenarios are investigated in regard to in-vehicle networks and evaluated considering entropy. Marchetti et al. [9] also show the experimental evaluation of two attack scenarios, detecting the anomalies in CAN messages. In the other work, Stabili et al. [15] deal with the identification of malicious CAN messages in the CAN bus. The Hamming distance is taken into account by the proposed algorithm to identify anomalies in the sequence of the payloads. Such issues could be the one of the central points of the entropy-based anomaly detection in literature.

The anomalies could be indicated by FIM, and the computation of state probabilities and entropies are required for the employment of this information measure. Of the traffic flow variables, vehicular speed and traffic volume are two common datasets, and their analyses are investigated in the framework of entropy in numerous studies. For example, in a recent study [5], q-Gaussian pdf explicates the pattern of the highway speed counts. The study harmonizes the principles of generalized thermostatistics with the vehicle speed data. Another study [13] utilizes a stochastic optimization approach i.e. cross entropy method to find optimal parameter solutions of the considered traffic flow. In the investigation of the variability of drivers' car following behavior [16], the cross-entropy method is also performed to estimate the parameters. In the other study [6], the authors describe the driver behaviors during lane changing with respect to additive and nonadditive entropy frameworks. The traffic flow scenarios are proposed considering the short and long-range interactions. The comparative analyses for both entropy frameworks are provided.

As very well expected that the dynamic behavior of those complex systems e.g. traffic flow could involve changes, various counts in the observed variables, and this mostly corroborates the instabilities in traffic flow. In this paper, FIM analysis concentrates on those changes in vehicular speeds and detects the anomalies depending on the information level. Of the FIM and vehicular traffic flow literature, there is no vast number of studies. However, one recent paper [1] is related with the Fisher information and performance of public transportation systems. In the paper, the Fisher information is applied to realize the stability, order and regime shifts of the public transportation systems and the results are provided for the eight different patterns of the selected urbanized areas

2. Method

The anomalies in the traffic flow of industrial zone and light suburban zone are investigated by Fisher Information Measure for the first time in this study. Fisher Information algorithm is given as follows.

2.1, Fisher Information Measure Theory

In 1925, Fisher developed a new method to analyze nonlinear system anomalies and named it Fisher Information Measure (FIM) [2]. It has been used in complex signals and complex systems [10,11]. In the last couple of decades, this measure is used in quantum mechanics and atomic or molecular scale systems [8,14]. FIM is suitable to apply to EEG signals, and in [3] Frieden used it on human and turtle EEG's to observe epileptic seizures in their brains. One of the application of FIM is Fisher-Shannon Information plane. This is useful for non-stationary signal analyses. Martin et al. [11] showed in their work that FIM can be applicable for many nonlinear systems such as Lorentz model, Logistic map etc. The Fisher Information is additive and non-zero. This theory was first used in statistics [2] and it gained importance after it is used in information theory. In addition to that, Linnik [7] used Fisher Information to prove the central limit theorem.

If we summarize, FIM is very good anomaly detector in signal analyzing. Karabulut et al. [4], took an ECG signal from a human and they analyze the ECG signal with a FIM. ECG signal came from nonlinear dynamical system which is heart. Such systems can be deterministic as well as chaotic.

The entropy shows the uncertainty in signal but it could not be sensitive to time dependent changes. To identify the time varying changes in a system, it would be proper choice to use FIM in these systems. The implemented sliding window technique is a very useful algorithm. To analyze the signal, the model is composed as shown [4,10,11]:

$D = \{s(t_k), k=1,2,\ldots,K\}$

where s(t) is the instantaneous behavior of given signal.

To find the related probability, the minimum and maximum data points must be found such that [4,10,11]:

$S_0 = \min[D] = \min\{s(k), k=1,2,\ldots,K\}$,

$s_L = \max[D] = \max\{s(k), k=1,2,\ldots,K\}$, and

$s_0 < s_1 < s_2 < \ldots < s_L$

Here L is the number of disjoint amplitude intervals.

Now let define the set of disjoint intervals

$\{ I_l = [s_{l-1}, s_l), l = 1,2,\ldots,L\}$, and

$$D = \overline{\cup_{l=1}^{L} I_l} \quad (1)\ [4,10,11]$$

Then for the sliding window we need to identify its parameters which are w, number of data points in a window, and Δ, sliding factor of window. The sliding window function can be expressed with W such that:

$W(m;w,\Delta) = \{s(k), k = 1 + m\Delta, \ldots, w + m\Delta\}$,

$(m = 0, 1, 2, \ldots, M)$, [4,10,11]

The important point is the parameter selection for sliding window at first. The basic selection criteria is $w \le K$ and $(K - w)/\Delta \in \mathcal{N}$ and $M=(K-w)/\Delta$. However, it is not sufficient that these parameters will give the suitable or the best results. Karabulut et al. [4], shows that parameter selection for sliding window directly affects the FIM. Before the final step, the probability of the signal $s(k) \in W(m;w,\Delta)$ can be expressed as $P^m(I_l)$. In the light of these steps, FIM related with this probability [4,10,11]:

$$\wp(m) = \sum_l^L [P^m(I_{l+1}) - P^m(I_l)]^2 / P^m(I_l) \quad (2)$$

Which is also suitable for the continuous integration of FIM. In the next chapter the analysis will be shown and these analyses are done by applying this algorithm.

3. Analyses of Traffic Flow by FIM

It is seen that both time series analyses have generated fluctuating FIM graphs. The first FIM analysis of the industrial zone is 25000 data points long (Fig. 1). FIM analysis has basically generated two peaks both of which appeared in close proximity. If the vehicle speed graph is inspected, it is observed that the data ranges from quite low speeds up to 140 km/h values. This zone has all the vehicle types from multi-axle trailers to light sedans, explaining this rather curious variation. Again, an inspection of the speed graph reveals that the data logger device has cut off certain values top and bottom at certain locations. Authors made sure that this has no dramatic effect on the outcome, and the data is used as is.

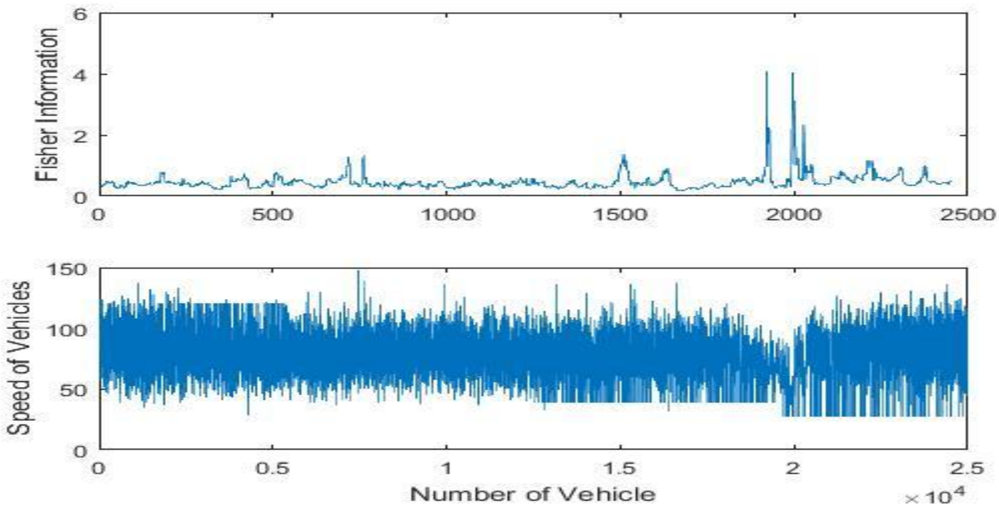

Figure 1: FIM result and industrial zone traffic data

The FIM analysis states that at the evening rush hour, there is a congestion in the flow. This slowing down and later speeding up is accentuated by two similar peaks in the FIM analysis. The first peak states that there is a congestion approaching, and hence a novelty is detected from the usual mean speeds. As for the latter peak, the reverse trend is detected, from the congested traffic to the free traffic flow. The reader should note the increasing variance after the congestion dissolves after 20000.

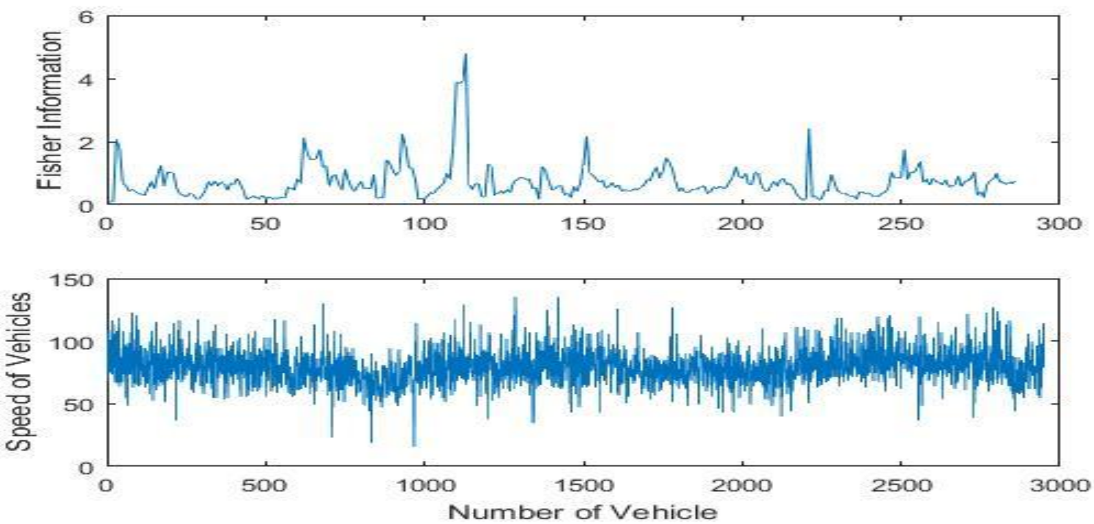

Figure 2: FIM results and light suburban area (Urla) data

In Urla location, vehicle speed series reveals a similar story (Fig. 2). But this time the relatively steady flow is now replaced by a series with fluctuating mean but with a constant variance. The speed is limited to and about 80 km/h with occasional drops and jumps. No cut-offs by the data logger helps better analyse the data. The only prominent peak in FIM is observed at around 1200th data point where a faint slowing of vehicles are observed. The occasional road controls are known to slow down the suburban traffic.

4. Conclusions

This study has dealt with an analysis of traffic time series of two different locations. As stated earlier, both series cover a time window of 24 hours, differing in density. The first series belonged to a dense industrial zone, active day-long. The latter was a suburban zone with much lighter traffic, albeit again active day-long. After a series of trials and much error, an optimal set of FIM parameters was determined and put to use.

FIM study of the traffic flow of the industrial zone has a relatively stable vehicle speed range. This range is observed to be in between from upper 20s to 140 km/h speeds. The occasional cut-off in the speed records, such as between data points 2500 and 5000, is logger device related, and its presence is ignored even though it has an effect on the eventual FIM values. This data shows a stable mean speed, as well as a stable variance up to data points 18000. The drops in speeds are due to an evening rush hour, where traffic experiences a compulsory slow down. It is observed that this slowing down has a pronounced peak in FIM plots.

Similarly, in Urla location, the largest peak in FIM again reflects a transient regime change in time series, which is not so prominent all by itself in the FIM analysis. Authors would like to emphasize that FIM is rather a good and effective tool in detecting less obvious changes that might be missed in the original time series.

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