Contemporary Engineering Sciences, Vol. 4, 2011, no. 1, 43 - 53

Analysis of Traffic Flow Variability on Two-Lane Highways

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Abstract

The main objective of this paper is to develop and test an approach for the spatio-temporal analysis of traffic flow variation on two lane highways. Traffic count devices located in several points of two lane highway links give the aggregate time series of data used in this approach, which is based on the Principal Components Analysis (PCA). The statistical analysis of main sources of temporal variation in traffic flow provides interesting insights about the properties and the characteristics of medium and long-term flow dynamics. This particular methodology was found to be capable of forecasting and identifying the location and the magnitude of traffic peak events in the network.

Keywords: Traffic flow, Principal component, Congestion

1 Introduction

Traffic flow forecasting is a common activity in daily traffic operations. In general, the problem of short-term traffic flow prediction is to determine the most likely traffic volume within the next time window (time windows vary from one minute to one hour). In particular, traffic flow forecasting techniques can support:
- the development of traffic control strategies in advanced traffic management systems;
- real-time driver's route guidance systems;
- adaptive ramp metering and signal control algorithms.

In a preliminary report on the structure of Intelligent Transportation Systems (ITS) [1], it was plainly underlined that the ability to make real-time predictions of traffic flows and link travel times for several minutes into the future, using real-time traffic data, is a major requirement for providing dynamic traffic control and guidance.

During the past years, various theoretical approaches have been adopted to develop traffic flow forecasting models within different time windows. Some of these models was based on time-series approach [7, 9], other on non-parametric estimation techniques [3, 14], regression models [2, 13], neural network approaches [12, 4, 6, 10, 18] and maximum likelihood formulation [8].
The increasing and easy availability of traffic flow information from archived data bank and other sources, such as inductive loop detectors, allows the development of data classification and processing techniques for the fast and efficient analysis and forecasting of network congestion. One of the main issue in facing such problems is the evaluation of the spatial and temporal variations in vehicular traffic flow. The knowledge of these variations is useful to develop a wide variety of applications. Such applications include: advanced systems that provide traffic information to travellers (ITS); the identification of wrong traffic forecasts and extreme peak events; the calibration and validation of traffic simulation models and the analysis of network capacity. Other important applications refer to the evaluation of traffic management and planning strategies, including traffic control and road pricing policies, and the assessment of their social and environmental impacts.
Nevertheless, existing applications of methods for measuring traffic variability are mainly focused on freeways and other uninterrupted flow facilities, and they typically refer to a short time window of analysis, varying from a few seconds to several hours. Moreover, the adoption of correction factors in order to measure daily or monthly traffic variations based on annual average daily traffic (AADT) estimation [15, 3], as obtained from traffic counts of medium-time period (usually of 24-hour period), cannot provide an exhaustive and clear investigation of the different sources contributing to the variability in traffic flow.
The investigation of traffic flow variability in road networks over long periods of analysis (several weeks or months) can provides interesting results in order to develop the potential of the above mentioned applications to reduce increasing congestion problems. Stathopoulos and Karlaftis [16] examined the spatio-temporal variations of traffic flow in a real urban network; Weijermars and van Berkum [17] presented an analysis of variance (ANOVA) of traffic flow along an arterial route during a series of weekdays.
This paper describes a methodology for the analysis of traffic flow time series observed over a period of one month from traffic counters located on a sample two lane highway links. The approach is developed under the assumption that some of these time series could be both temporally and spatially correlated, independently of any hypothesis about the distribution of traffic flows across the network. More specifically, the method of Principal Components Analysis (PCA) (originally conceived by Pearson, 1901, and independently developed by Hotelling, 1933; a good description of the method is given in Dunteman [5]), is applied in order to discern the complex phenomenon of medium and long-term traffic dynamics manifested in large-scale secondary road networks.
This goal is achieved by selecting common sources of temporal variability in traffic flow, which are obtained by calculating the eigenflows. An eigenflow is a particular time series that contains a common source of temporal variability in

traffic flow. Each complete traffic flow time series is so expressed as a weighted sum of eigenflows and the corresponding weights describe the magnitude to which each source of temporal variability affects the given traffic flow.
The paper is so organized: after an analytical description of PCA method and the illustration of the adopted dataset, is given a description of how PCA can be employed to measure the variability of individual traffic flows and of the implications of this measurement for traffic data reconstruction and traffic flow prediction.

2 Principal components analysis

The method of PCA is a statistical technique that provides the linear transformation of a dataset onto a new substantially smaller set of principal axes or components that represents most of the information present in the original set of variables. These new components are ordered by the amount of variation that they explain in the data. Therefore, the first principal component explains the maximum amount of variation that is possible to describe on a single axis. Each one of the remaining principal axes captures the amount of residual variation not explained by the preceding principal components. The PCA method is a powerful tool for analyzing the total traffic flow variability in a road network due to a large number of variability sources, by approximating it with a lower analysis space that maintains its original characteristics.
Let n be the number of traffic counters located on a subset of the total set of road links of a highway network, t be the number of successive periods in which the data are collected and stored, and γ be the number of time intervals in which each day is subdivided. The present study refers to realistic networks composed of many links servicing thousands of travellers. Such networks typically involve many traffic counters and the data are aggregated over small time intervals, such as 5, 10 and 15 minutes. Then, a matrix X can be defined, called observed flow matrix, with q rows and n columns, where $q=t*\gamma$. Therefore, each column i of matrix X denotes the i-th traffic flow time series, represented by the column vector x_i, and each row j denotes the particular time point in which traffic flows have been collected at interval j.
The calculation of the i-th principal component, p_i, is obtained through the spectral decomposition of the matrix X^TX, which quantify the covariance between different traffic flows time series, as follows:

$$X^T X p_i = \lambda_i p_i \qquad \text{with } i=1,\dots,n \tag{1}$$

where λ_i is the non-negative real scalar, known as the eigenvalue, corresponding to principal component p_i. By convention, the eigenvalues are arranged in order of magnitude, from large to small, so that $\lambda_1 \geq \lambda_1 \geq \ldots \geq \lambda_n$. By solving equation (1), the maximum variation of the observed flow matrix X is captured by the first principal component .Proceeding recursively, once the first i-1 principal components have been determined, the i-th principal component corresponds to

the maximum variation of the residual, that is the difference between the original data and the data contained onto the first i-1 principal axes.
The organization of the set of principal components $\{p_i\}_{i=1}^{n}$ in such an order, as columns, results in the principal matrix P, which has size $n \times n$. By definition, the columns of P matrix have unit norm, which means that the length of each column vector, as given by the square root of the sum of squares of all entry values, is equal to one.
Because the principal axes are arranged in order of contribution to the overall variation, the trend of time variation common to all flows along principal axis i can be represented through a column vector u_i with size q, referred to the eigenflow of the i-th principal axis, as follows:

$$u_i = \frac{Xp_i}{\rho_i} \qquad \text{with } i=1,\ldots,n \tag{2}$$

where $\rho_i = \sqrt{\lambda_i}$ is the singular value corresponding to the i-th principal axis. The magnitude of each singular values demonstrates the total variation assignable to each principal component and, substantially, the possibility to represent total traffic series using a smaller number of variables.
The eigenflow matrix U, which has size $q \times m$ contains the set of eigenflows $\{u_i\}_{i=1}^{n}$ in columns. Equation (2) shows that each traffic flow series x_i, normalized by the singular value σ_i, is a linear combination of the eigenflows, weighted by the associated principal component. In detail, the relationship among matrices X, U, and P can be formalized as follows:

$$\frac{x_i}{\rho_i} = U\left(P^T\right)_i \qquad \text{with } i=1,\ldots,n \tag{3}$$

where $\left(P^T\right)_i$ is the i-th row of matrix P. Under the assumption that only a small subset of $r < n$ eigenflows contributes to the explanation of temporal variability in traffic flow series, then, the matrix X that contains the measured flows can be approximated as follows:

$$X' \cong \sum_{i=1}^{r} \rho_i u_i p_i^T \qquad \text{with } i=1,\ldots,n \tag{4}$$

The reconstruction of matrix X through of a lower number of variables could simplify the interpretation of the medium and long-term dynamics of traffic flow in a transportation network.

3 Application

The traffic data used in this analysis are automatically collected using an

Automatic Vehicle Classification (AVC) system based on loop detectors at 50 key locations around 14 state highways in Emilia Romagna Region, in the north of Italy. These real-time data are recorded at the end of every 60-sec period and aggregated at time intervals of 15 minute. The traffic counting system provides an appropriate control system as to identify and exclude data from malfunctioning detectors. The dataset includes measurements corresponding to the month of may 2005. Each day covers 96 time intervals of the period spanning between 06:00 am and 20:00 pm. This gives a total number of 25,922 measurements.

Figure 1 shows an example of one eigenflow u_i and its corresponding principal axis p_i, as calculated with the principal components analysis of the recorded data. Fig. 1 in particular demonstrates the representation of a pattern of temporal variation common to all traffic flow time series through a specific eigenflow. Figure 2 shows the magnitude to which this temporal pattern is present in each recorded traffic flow, through the presence of the corresponding principal component. The eigenflow considered, for example, is most strongly present at traffic flow measurement point number 30, as shown in fig. 2. The immediately next strongest temporal trends are those corresponding to traffic flow at detector number 16 and traffic flow at detector number 28.

Basing on the previous definition of eigenflows and principal components, the negative sign of entries in some eigenflows means that the source of its temporal variation is negatively correlated with one or more of the registered traffic flow series. In the same way, the negative sign of a point in the corresponding principal component indicates the negative value of the covariance of the vehicular traffic flow measured at a specific recording point with the other traffic flows, such as for example the measurement point number 7 or number 23 (see fig. 2). That is, we can expect that an increase of the traffic flow rate at recording point number 7 or 23 would generate a reduction (with a magnitude less or more proportional) of the traffic flow rate in the other measurement points. This analysis can support the identification of different “critical” links in the road network, as well as “critical” time periods, wherein a particular or sudden traffic flow variation (under spatial or temporal point of view) has a likely strong impact on the aggregate network conditions and level of service.

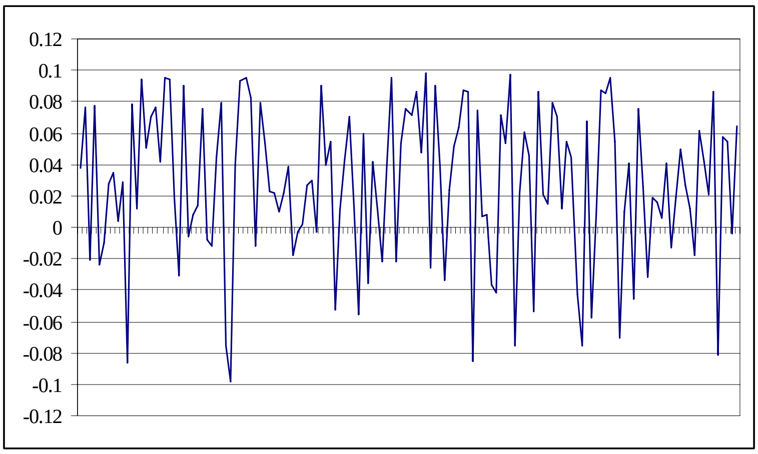

Fig. 1. Trend of an eigenflow during the observation period

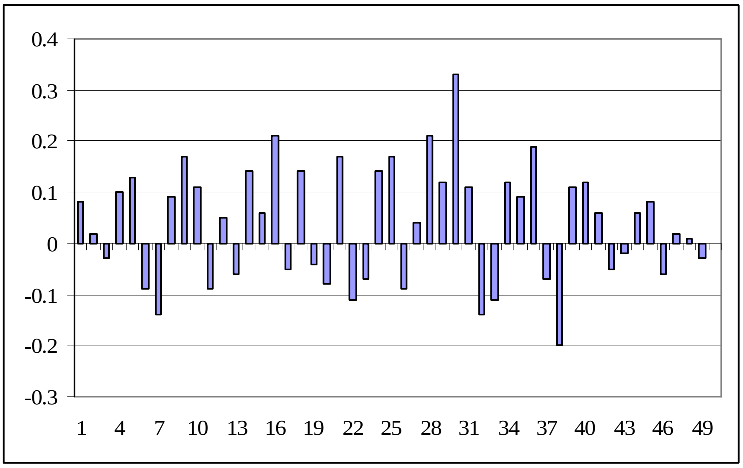

Fig. 2. Graphical representation of the principal components corresponding to the eigenflow considered in fig. 1

Based on the definition previously given, each eigenflow can be considered as a part of the overall dynamics scenario pertaining to each traffic flow phenomenon. Thus, the variability of single flows can be determined with respect to the number of eigenflows that are part of them. The number of significant eigenflows is related to the number of presences in the corresponding rows of the principal matrix *P* that are significantly different from zero.

We can consider a threshold value equal to $1/\sqrt{n}$ (this particular value has been often adopted in literature, see for example Lakhina et al., 2004 and Tsekeris et al., 2006). In this manner, the significant eigenflows are obtained counting how many elements in each row of matrix *P* exceed the threshold value (obviously considering the absolute value). This technique allows selecting the minimum number of significant eigenflows which can give a true reconstruction of each traffic flow pattern, based on equation (4).

The analysis of the number of significant eigenflows shows that no traffic flow distribution is composed of more than 25 significant eigenflows and it has been observed that about 50% of traffic flow series are composed of less than 5 significant eigenflows, and more than 65% of traffic flows are composed of less than 10 significant eigenflows. Figure 3 shows that the class containing up to 5 significant eigenflows is the most frequently among traffic flow distribution and the class containing 6 to 10 follows consequently. These results show that the temporal dynamics of most traffic flow scenarios can be described by a small number of sources of variability.

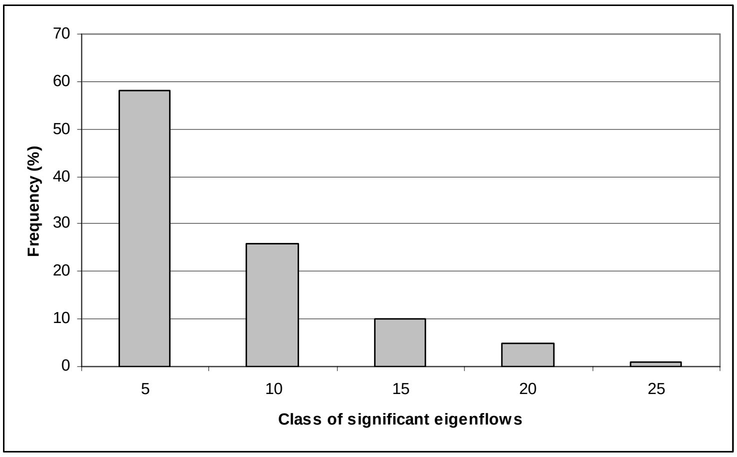

Fig. 3. Histogram of significant eigenflows

The scatterplot in fig. 4 shows the number of significant eigenflows related to the cumulate monthly average daily traffic flow rate registered in the different measurement stations. The results clearly show that there is a relationship between the traffic flow and the eigenflows (source of variability) that influence its manifestation. More in detail, the larger traffic flows appear to be explained by a large number (> 15) of significant eigenflows (see the region at the right-hand side of the scatterplot in fig. 4), in comparison to the smaller traffic flow series, which appear to be basically described by a small number (< 15) of significant eigenflows (see region at the left-hand side of the scatterplot in fig. 4). Consequently, we can affirm that the temporal variation of the larger flows gives the most significant contribution to the long-term dynamics of the network traffic in comparison to the variation of the other flows.

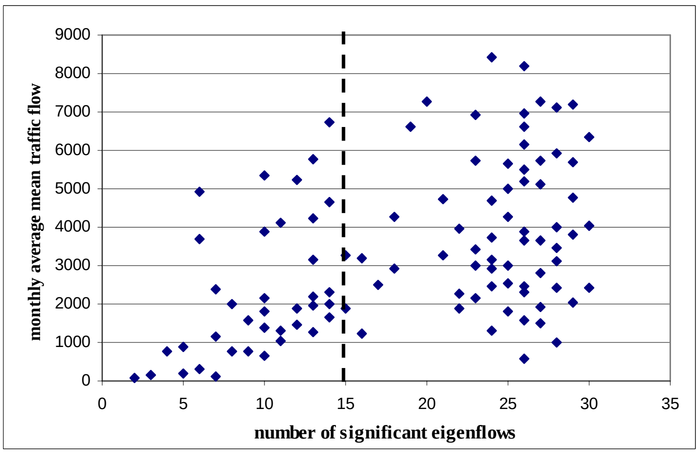

Fig. 4. Relationship between number of significant eigenflows and monthly average daily traffic

As previously illustrated in the paper, the singular values $\rho_i = \sqrt{\lambda_i}$ explain the overall variation ascribable to each principal component (and then to each source of variability). Therefore, the order of magnitude each singular value can provide a measure of the amount of variability in the global network traffic.

The potential capability to reconstruct traffic flows using a smaller number of variables is supported by the fact that only a few singular values can represent the largest portion of the overall variation in traffic distribution. The traffic flow series replicated adopting the whole set of significant eigenflows through equation (4) approximate the measured traffic flows without statistically significant differences at least at the 95% confidence level of the *t*-test statistic. This result indicates the accuracy of this methodology for the selection threshold values in order to determine the best number of significant eigenflows for the complete description of each traffic flow pattern. Furthermore, a generic traffic flow series at a given measurement point has been selected to be approximated by a series generated adopting a number of r=5 dimensions (see figure 5).

The graph shows that the temporal pattern of the simulated traffic flow follows the temporal distribution of the measured traffic flow. Finally, figure 6 shows the statistical analysis of the regression conducted on the calculated traffic flow versus the original measured traffic flow. The calculated flow generally slightly underestimates the measured flow, as it denotes the value of the slope of the linear trend line, which is quite lower than unity. This underestimation is stronger for traffic flows of lower size (<400 veh/h). The presence of extreme values especially in the flow range from 250 veic/h to 500 veh/h suggests that the most significant eigenflows, adopted in the calculation process, can better explain the temporal variation of smaller (< 250 veic/h) and larger (> 500 veh/h) traffic flows in comparison to the other eigenflows. On the other hand, the correlation coefficient between the two series of data shows that the calculated flow data can explain approximately 88% of the total variation contained in the original data.

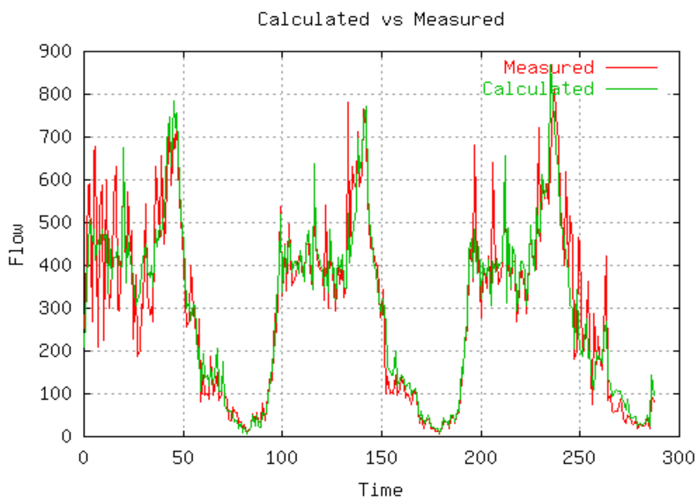

Fig. 5. Elaboration of a traffic flow profile adopting five principal components and comparison with measured traffic flow

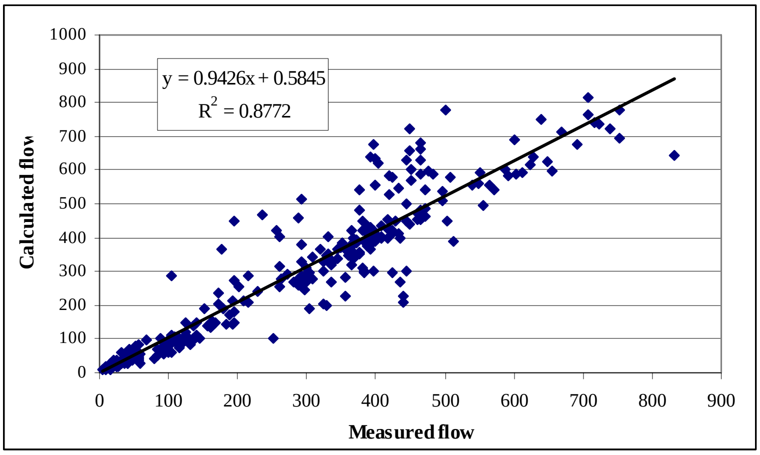

Fig. 6. Statistical comparison of calculated and measured traffic flow

The above results confirm the ability of the proposed model to identify a small set of common sources of variability in order to describe the complex temporal and spatial dynamics of traffic flow. In this way, this model facilitates the deeper understanding and a more likely interpretation of the key factors contributing to determine the medium and long-term evolution of the main characteristics of traffic flow on two lane highways network

4 Conclusions

This paper describes the analysis and interpretation of the variability in two lane highways traffic flow by analysing one-month traffic detector data recorded in some links of real two lane highways. It has been demonstrated that the method of principal components analysis (PCA) is able to provide a plausible and powerful tool for the analysis and identification of variability of traffic flow patterns. More specifically, the PCA method enables the identification of eigenflows, which identify common scenarios of temporal variability, according to their contribution to the aggregate traffic flow distribution. Despite the undeniable complexity and uncertainty in the phenomenology of urban traffic evolution, the main results of this study suggest that the spatial and temporal variation in traffic flow in a two lane highways network can be described - at least in its main characteristics - by only a small set of eigenflows.

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Received: August, 2010