Physica A 509 (2018) 989–997

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Speed estimation of traffic flow using multiple kernel support vector regression

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HIGHLIGHTS

- The proposed method improves the accuracy and robustness of the speed estimation.
- The proposed method can deal with some complicated cases, such as heterogeneous information or unnormalized data, large scale problems, etc.
- The proposed method can avoid the burden of choosing the appropriate kernel function and parameters.

ARTICLE INFO

Article history:
Received 14 March 2018
Received in revised form 31 May 2018
Available online xxxx

Keywords:
Speed
Estimation
Traffic flow
Multiple kernel learning
Support vector regression

ABSTRACT

Industrial loop detectors (ILDs) are the most common traffic detectors. In Shanghai, most of the ILDs are installed in a single loop way, which can detect various parameters, such as flow, saturation, and so on. However, they cannot detect the speed directly, which is one of the key inputs of intelligent transportation systems (ITS) for identifying the traffic state. Thus, this paper is dedicated to estimate speed accurately. It proposes a new algorithm that multiple kernel support vector regression (MKL-SVR) to complete this goal, which improves the accuracy and robustness of the speed estimation. Extensive experiments have been performed to evaluate the performances of MKL-SVR, compared with polynomial fitting, BP neural networks and SVR. All results indicate that the performances of MKL-SVR are the best and most robust.

1. Introduction

Traffic state identification is very important for traffic guidance and control, which is the main mission of Intelligent Transportation Systems (ITS) [1–5]. The speed is the key input of ITS for identifying the traffic state. At the intersections of the road networks of Shanghai, the single loop way is adopted to install the industrial loop detectors (ILDs), which can detect various parameters, such as flow, saturation, and so on. However, they cannot detect the speed directly. Thus, the speed have to be estimated accurately [6–8].

Data types and speed estimation methods are two key issues for speed estimation. In recent years, many types of traffic data has been generated for speed estimation, such as Global Position System (GPS) data, mobile phone data, camera video data, Industrial Loop Detector (ILD) data, and so on. GPS data is used to estimate the speed by Peng et al. [9], in which a Kalman Filter method is taken to estimate the speed. Shuliang Pan and Bo Jiang [10] use GPS data from different types of vehicles (i.e., taxis, buses, and logistic vehicles) to estimate average travel speed. Jinjun Tang, Fang Liu and Yajie Zou [11]

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https://doi.org/10.1016/j.physa.2018.06.082
0378-4371/

propose an Improved Fuzzy Neural Network to predict traffic speed and achieve good results. Mobile phone data is also used to estimate the speed by Gayathri et al. [12]. They introduce an algorithm which estimates the speed of a mobile phone by matching time-series signal strength data to a known signal strength trace from the same road. Puttipong Leakkaw and Sooksan Panichpapiboon [13] employ the mobile phone data generated by the accelerometer not the GPS to estimate the speed. Because they think that a GPS receiver consumes a lot of power, which can significantly shorten the battery life. Camera video data can be captured conveniently, which makes estimating the traffic flow parameters possible by computer vision technologies. Kazuki Osamura, Asako Yumoto, and Osafumi Nakayama [7] employ the video data and acceleration information of a drive recorder to estimate the speed. As most proposed methods cannot estimate the vehicle speed for multi-lane roads, Yang Yu et al. [14] propose a vehicle speed estimation method for multi-lane roads using camera video data. ILD data is most commonly used data [15,16]. Felix Rempe [17] et al. present a novel freeway traffic speed estimation method based on probe data is presented, which only requires velocity data from probes and does not depend on any additional data inputs. Yunteng Lao, Guohui Zhang and Jonathan Corey [18] use the single loop detector data (which is one kind of the ILD data) to estimate the speed and classify the vehicles. In their research, the Gaussian mixture model is employed for good performance. Lili Zhu and Sheng jin [19] adopt the single loop detector data to compute the typical effective vehicle length, and then to estimate the speed. For recognizing the effect of time interval on speed estimation, Jianhua Guo et al. [20] use the single loop detector data to complete this goal. The advantages of ILDs are: (1) they are very cheap; (2) the installation is quite simple; (3) they can avoid the interference of the environment successfully. In our paper, we will take the ILD data to estimate the speed accurately.

The methods of speed estimation are various a lot. As a technology of data fitting, polynomial fitting algorithm [21,22] is applied to speed estimation, which is one of the methods compared in our paper. BP neural networks have wide applications in classification and prediction problems, which are employed to estimate speed with GPS data, and satisfactory results are obtained [9,23]. But the structure and optimal parameters of the neural networks are difficult to obtain for good application results [24–27]. As a state-of-the-art technology, support vector regression (SVR) has a lot of advantages including good generalization ability and dealing with nonlinear problems well [28–31]. However, the kernel function and its parameters have profound impacts on the results of SVR, and it is difficult to find the optimal kernel function and its parameters [24,25,32]. In our research, multiple kernel support vector regression (MKL-SVR) algorithm is used to estimate the speed. An optimal combination consisted of basic kernels is adopted to construct MKL-SVR model. In this way, the trials that choosing the optimal kernel function and its parameters can be avoid conveniently. More importantly, MKL-SVR can deal with more complicated cases, e.g., unnormalized data, huge scale problems, etc. [33]. Extensive experiments have been performed to validate the performances of MKL-SVR. All results show that MKL-SVR has very robust performances, and its average performances are the best.

2. Methodology

This section will present the methodology of speed estimation using MKL-SVR. In this paper, standard SVR is abbreviated as SVR. As SVR is the foundation of MKL-SVR, it will be described firstly. SVR is widely used in solving various classification and prediction problems [30,31,34]. It can both cope with the linear and nonlinear regression problems. The main idea of SVR is that it transform the regression problem into a classification problem which can be solved with the support vector machine approach.

For speed estimation, suppose the training samples are given as:

$$S = \{(x_1, y_1), (x_2, y_2), \ldots, (x_i, y_i), \ldots, (x_l, y_l)\} \tag{1}$$

where $x_i \in R^n, y_i \in Y = R, i = 1, 2, \ldots, l$. x_i is the input of the training sample, which consists of the values of the traffic parameters, such as flow, occupancy, etc. y_i is the target value, which consists of the speed value. l is the number of the training samples. The goal for SVR problem is that when given an input x, SVR can find a function $f(x)$ to estimate the speed value y, precisely. The general form of the prediction function of SVR is

$$f(x) = \omega \cdot x + b \tag{2}$$

where ω is a coefficient vector, and b is a constant. The original problem [30] of SVR can be transformed to the optimization problem as follows:

$$\min_{\omega,b} \frac{1}{2}\|\omega\|^2 \tag{3}$$

$$s.t. \quad (\omega \cdot x_i) + b - y_i \le \varepsilon \quad i = 1, 2, \ldots, l \tag{4}$$

$$y_i - (\omega \cdot x_i) - b \le \varepsilon \quad i = 1, 2, \ldots, l \tag{5}$$

When slack variables ξ_i, ξ_i^* are introduced to cope with otherwise infeasible constraints of the optimization problem (3)–(5), the formulation stated in Ref. [34] is gotten.

$$\min_{\omega,b,\xi,\xi^*} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \tag{6}$$