Computers and Electrical Engineering 000 (2018) 1–9

Contents lists available at ScienceDirect

Computers and Electrical Engineering

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

Transmission power control of wireless sensor networks based on optimal connectivity☆

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ARTICLE INFO

Article history:
Received 30 May 2017
Revised 20 December 2017
Accepted 21 December 2017
Available online xxx

Keywords:
Satellite networks
Traffic prediction
Spatiotemporal correlation
Least square support vector machine

ABSTRACT

To develop a short-term traffic load prediction model for satellite networks, a prediction algorithm based on spatiotemporal correlation and least square support vector machine (STLS-SVM) is presented. The prediction model fully exploits the regularity and periodicity of satellite constellations and uses the lag correlation coefficients to determine which satellite pairs have the highest spatiotemporal correlation. Then, the traffic time sequences of the most highly correlated satellites are taken as input feature vectors for training the LS-SVM for short-term traffic prediction. A simulation test shows that the algorithm has higher network flow prediction accuracy and that using the spatiotemporal correlation improves the predictive performance.

1. Introduction

Satellite networks that provide seamless coverage have become indispensable components of the next-generation global communication infrastructure [1]. Various applications and traffic such as data, audio, video streaming, and multimedia are currently carried by satellite networks; consequently, the aggregated traffic has a huge volume and is complicated [2]. The design of a satellite traffic prediction model with cognitive characteristics enables the network to provide more reasonable bandwidth distribution, flow control, routing control, admission control, and error control, and it is an effective way to improve the quality of service.

There are currently many prediction algorithms such as the time sequence model [3], Kalman filtering model [4], and neural network model [5], and certain advances have been made. Neural network models are often applied to network traffic prediction because of their good capacity for nonlinear approximation and adaptive learning. However, neural networks are easily overfitted and suffer from local minima and the choice of network structure [6]. On the other hand, support vector machine (SVM) and least square support vector machine (LS-SVM) algorithms based on statistical learning theory can address some of the flaws of neural networks. They can find global minima and have many unique advantages for use with small samples [7–9].

In satellite networks, each satellite provides access to services for all users within its coverage area. The traffic load time sequence of a specific satellite is closely related to its ground track. Satellite networks are highly deterministic systems. Their satellites travel on fixed orbits. Because of the symmetry of satellite constellations, different satellites may have similar

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Associate Editor Dr. G. R. Gonzalez.

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https://doi.org/10.1016/j.compeleceng.2017.12.039

ground tracks. Moreover, the daily evolution of the terrestrial traffic intensity shows a strong daily periodicity [10]. It is not hard to imagine that the traffic load time sequences of different satellites may exhibit some spatiotemporal correlation.

In this paper, a prediction model based on spatiotemporal correlation and least square (STLS) SVM is proposed for predicting the short-term traffic load of satellite networks. First, the lag cross-correlation function [11] is used to select the satellites that have the highest spatiotemporal correlation with the target satellite and their corresponding time delay k. Then the traffic time sequences of these spatiotemporally correlated satellites are entered into the STLS-SVM as the input feature vector for short-term traffic prediction.

To the best of our knowledge, we are the first to apply the lag cross-correlation function to fully exploit the spatiotemporal correlation of satellite traffic time sequences and propose an STLS-SVM algorithm for short-term traffic prediction for satellite networks.

The remaining paper is described as follows: Section 2 describes the model of spatiotemporal correlation mining. The simulation results are discussed in the Section 3. The paper is then concluded.

2. Model description

2.1. Spatiotemporal correlation mining

The lag cross-correlation function [11] is a method to detect the lag correlations between data time sequences. Suppose that $\boldsymbol{X}$ is a discrete sequence of numbers $\{x_1, x_1, \ldots, x_n\}$; then the L-lag correlation function between two time sequences $\boldsymbol{X}$ and $\boldsymbol{Y}$ of equal length n is defined as

$$R(l) = \frac{\sum_{t=l+1}^{n}(xt-\bar{x})(yt-l-\bar{y})}{\sqrt{\sum_{t=l+1}^{n}(xt-\bar{x})^2}\sqrt{\sum_{t=1}^{n-l}(yt-\bar{y})^2}}$$
$$\bar{x} = \frac{1}{n-l}\sum_{t=l+1}^{n}xt, \quad y = \frac{1}{n-l}\sum_{t=1}^{n-l}yt, \tag{1}$$

where $R(l)$ denotes the L-lag cross-correlation coefficient when $\boldsymbol{X}$ is delayed by $l(l \geq 0)$. Further, $\bar{x}$ and $\bar{y}$ denote the means of $\boldsymbol{X}$ and $\boldsymbol{Y}$, respectively. For a lag l, we consider only the common part of $\boldsymbol{X}$ and the shifted $\boldsymbol{Y}$, that is, only the $n-l$ time ticks. Two sequences are strongly correlated when their correlation coefficient is close to 1 or −1. When the value is 0, the two sequences are not related at all. In our scheme, we seek strong correlations. Therefore, the absolute value of the correlation coefficient $|R(l)|$ is used in the measurement procedure.

2.2. Least square support vector machine (LS-SVM)

LS-SVM is an improved SVM algorithm that uses the quadratic loss function to replace the insensitive loss function in SVM. The SVM secondary optimisation procedure is changed to solving a linear equation by building a loss function, which improves the solving speed [12].

For the sample set $\{(\boldsymbol{x}_i, y_i), i=1,\ldots, n\}$, where $\boldsymbol{x}i \in R^d$ is an input vector, and y_i is the corresponding output, the input data $\boldsymbol{x}_i$ are transformed to a higher-dimensional feature space by $\boldsymbol{\phi}(\boldsymbol{x})$. The LS-SVM optimal classification plane function is

$$f(\boldsymbol{x}) = \boldsymbol{w}^T\varphi(\boldsymbol{x}) + b \tag{2}$$

where $\boldsymbol{w} \in R^d$ is the weight vector, and b is the offset.

According to the structural risk minimisation principle, LS-SVM determines the optimal weight vector and the offset by minimising the cost vector $\boldsymbol{J}$:

$$\min_{\boldsymbol{w},b,\boldsymbol{e}} \boldsymbol{J}(\boldsymbol{w},\boldsymbol{e}) = \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + \frac{C}{2}\sum_{i=1}^{n}e_i^2$$
$$s.t.$$
$$y_i = \boldsymbol{w}^T\varphi(\boldsymbol{x}) + b + e_i, i = 1, 2, \cdots, n \tag{3}$$

where C is the penalty parameter, and $ei \in R$ is the prediction error.

The constrained optimisation above is changed to an unconstrained dual space optimisation by introducing the Lagrange multiplier, and the Lagrange function is established:

$$L(\boldsymbol{w}, b, \boldsymbol{e}, \boldsymbol{\alpha}) = \boldsymbol{J}(\boldsymbol{w},\boldsymbol{e}) - \sum_{i=1}^{n}\alpha_i\left(\boldsymbol{w}^T\varphi(\boldsymbol{x}_i) + b + e_i - y_i\right) \tag{4}$$

where $\alpha_i \in R$ is the Lagrange multiplier.