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A Vehicle Detection Algorithm Based on Compressive Sensing and Background Subtraction

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Abstract

An efficient vehicle detection method is a necessity for the intelligent transportation system under the complicated traffic environment at present. To solve the problems of large computation and the poor real-time in traditional vehicle detecting methods, this article proposes a real-time vehicle detecting algorithm integrated compressive sensing (CS) theories and background subtraction method. In addition, this paper undertakes the reconstruction of foreground image of vehicle based on the orthogonal matching pursuit (OMP) algorithm. Proved by the experimental result, the proposed vehicle detection algorithm could produce higher precision detection, smaller calculation and higher-quality reconstructed image compared to the traditional ones.

Keywords: CS (compressive sensing); background subtraction; image reconstruction; OMP (orthogonal matching pursuit)

1. Introduction

The urban traffic has been developing rapidly. However, traffic accidents and road congestions have emerged along with an increasing number [1] which result in enormous casualties and economic losses.

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Intelligent transportation system has attracted plenty of researchers. As one of the essential steps, vehicle detection [1] is extremely significant for video intelligent traffic monitoring system.

The common methods for moving vehicle detection contain: optical flow [2], frame subtraction [3], and background subtraction [4]. For optical flow algorithm, it is of greatly large calculation and without of the real-time monitoring function. In view of the frame subtraction, it is hardly to get the complete vehicle information and the vehicle at low speed can not be detected. The background subtraction used in this article is the more popular algorithm at present [5-6]. At the earliest, Wren proposed the running-Gaussian-average background subtraction algorithm [7]. He believed that each pixel of the background image was independent and satisfied the Gaussian probability function. The algorithm was very fast and required small storing space, but the result of the background image was not good. Later, Koller made improvement in background updating, which did litter work on the basic of the former algorithm and increased the calculation. To suit the complicated external environment, Stauffer and Grimson carried out the background subtraction method based on Gaussian mixture model [8]. The algorithm obtained good performance for target detection, but was restricted to the calculation. Though many researchers proposed modifications for the model [9], it was difficult to solve the problem. The algorithms above are assessed in terms of the computing speed, the storage volume and complexity under the premise of the favourable detection. Then the target detecting methods based on data compression was emerged. B.Ugur suggested the wavelet-domain target detection algorithm [10]. Considering that the vehicle target possesses a small part in the background image which agrees to the characteristic of compressive sense sparse, this article integrates compressive sensing [11-13] and background subtraction method. The algorithm operates compressive sample on background image and input image respectively, from which the compressive measurement will be received, then subtracts the measurements of background image and input image to get the measurement of the target vehicle, and precisely reconstructs the vehicle information by orthogonal matching pursuit algorithm at last. As the background update is just conducted on the measurements, the calculation is largely decreased.

2. The compressive sensing theory

Suppose that we have an image X of size $N_1 \times N_2$ and we vectorize it into a column vector **x** of size $N \times 1$ ($N = N_1 \times N_2$) by concatenating the individual columns of X in order. The *n*th element of the image vector **x** is referred to as *x*(n), where $n = 1, \cdots, N$. Let us assume that the basis $\Psi = [\psi_1, \cdots, \psi_N]$ provides a K-sparse representation of **x**:

$$x = \sum_{n=1}^{N} \theta(n)\psi_n = \sum_{l=1}^{K} \theta(n_l)\psi_{n_l}, \tag{1}$$

where $\theta(n)$ is the coefficient of the *n*th basis vector ψ_n ($\psi_n : N \times 1$) and the coefficients indexed by n_l are the K-nonzero entries of the basis decomposition. Equation (1) can be more compactly expressed as follows

$$x = \Psi\theta \tag{2}$$

where θ is an $N \times 1$ column vector with K-nonzero elements. Using $\|\bullet\|_p$ to denote the ℓ_p norm where the ℓ_0 norm simply counts the nonzero elements of θ, we call an image X as K-sparse if $\|\theta\|_0 = K$.

In the CS framework, it is assumed that the K-largest $\theta(n)$ are not measured directly. Rather, $M < N$ linear projections of the image vector **x** onto another set of vectors $\Phi = [\phi_1',....,\phi']'$ are measured:

$$y = \Phi x = \Phi \psi \theta, \tag{3}$$

where the vector y $(M \times 1)$ constitutes the compressive samples and the matrix Φ $(M \times N)$ is called the measurement matrix. Since $M < N$, recovery of the image X from the compressive samples y is underdetermined; however , as we discuss below, the additional sparsity assumption makes recovery possible.

There exists a computationally efficient recovery method based on the following ℓ_1-optimization problem [11-12]:

$$\min \|\theta\|_1 \quad s.t. \quad y = \Phi \Psi \theta. \tag{4}$$

This optimization problem, also known as Basis Pursuit [11], can be efficiently solved using polynomial time algorithms.

3. Vehicle detection algorithm based on CS

Applying the background subtraction method based on CS, in this paper, the measurements of the video is firstly obtained through the compressive sample operated on the input video images. And then, the measurements of the background image will be achieved from the estimation of the former measurements. Besides, the background image needs real-time update considered about the changes in external environment. When conducting the background subtraction, the differential threshold operation should be undertaken on the measurements of background model and measurements of the real-time video frame image to determine whether there existed moving vehicle in the frame image. If there is no existence, drop the image. Otherwise, reconstruct the target vehicle image through the OMP image reconstruction algorithm in Ref. [14].

3.1. Background modeling and updating

As background subtraction target detection algorithm has been widely applied to monitoring systems, the method of background subtraction is expanded to the image data compression domain [10]. In this paper, we use the data compression based on CS to realize background subtraction that estimating the measurement of the background image from the video-image measurement. Suppose that X_n , B_n represents the input image at present and the background image, respectively. And y_{bn} is the measurement of B_n , y_{tn} is what to X_n . Then, at the time of $n+1$, the measurement y_{bn+1} of background image B_{n+1} could be stated as expression (5).

$$y_{bn+1}(i) = \begin{cases} \alpha y_{bn}(i) + (1-\alpha)(y_{tn}(i) - y_{bn}(i)), & there\ is\ moving\ in\ i \\ y_{bn}(i), & there\ is\ non-moving\ in\ i \end{cases} \quad i = 1, 2, ..., M \tag{5}$$

where α is a constant satisfied $0 \le \alpha \le 1$, M is the number of measurements, i represents the corresponding position of the measurement, y_{b0} is the measurement of the first frame image X_0 .

At position *i*, if the condition satisfies expression (6), it means the existed moving target at the position.

$$| y_{tn}(i) - y_{tn-1}(i) | > T_n(i) \tag{6}$$

where $T_n(i)$ is a threshold of the real-time update. The update strategy is depicted as below.

$$T_{n+1}(i) = \begin{cases} aT_n(i) + (1-a)(b\,| y_{tn}(i) - y_{bn}(i) |), & there\ is\ moving\ in\ i \\ T_n(i), & there\ is\ non-moving\ in\ i \end{cases} \tag{7}$$
$$i = 1, 2, \ldots, M$$

where a is an integer close to 1, b is a number greater than 1. The threshold could be adjusted by changing the value of a and b.

3.2. Sparse representation for background subtraction image

In traditional background subtraction method, the first step is to build the background model, then to conduct the subtraction between the input image and background image, set the threshold for subtracted image, and finally get the target. Though a great many of researchers' works on the background modeling method, it is difficult to achieve the perfect result. What's more, the estimation conducted through background modeling and updating for every pixel will make the calculation very large. The compressive sensing method used in this text overcomes the problem in traditional method which does not need modeling and updating for each pixel and is of no necessity for background image reconstruction. Instead, the proposed method subtracts on the measurement of background image compression sensing and it of the input image, as shown in expression (8).

$$| y_{tn}(i) - y_{bn}(i) | > T_\delta(i) \tag{8}$$

where $T_\delta(i)$ is the subtracted threshold updated by expression (7).

The flow chart of the vehicle detecting algorithm is illustrated as following.

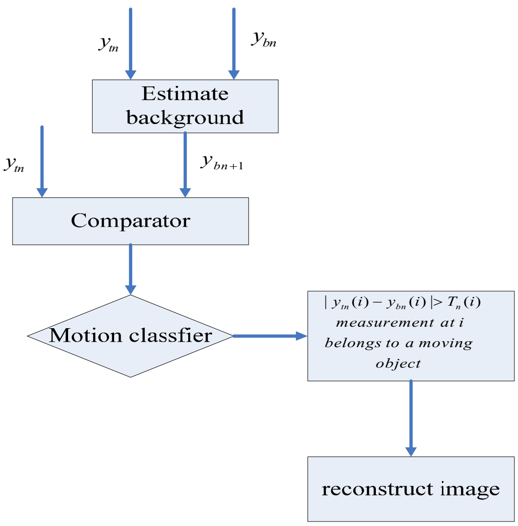

Fig.1 the flow chart

4. Experiment and analysis

The proposed algorithm was experimented under the environment of Matlab 2009. Fig.2 was the 50th frame of the traffic video self-recorded. Fig.3 was the result of the steps that compressively sampled from each frame of the image by random observation matrices, got the value of the 50th frame of the background image measured by background modeling and updating according to expression (5), and reconstructed the foreground image of vehicle for observation. The vehicle detecting result was shown in Fig.4, from which the complete and accurate vehicle contour was almost obtained.

Fig.2 the 50th frame of the self-recorded video

Fig.3 the background image of the 50th frame

Fig.4 the detecting result

5. Conclusions

As an important part of modern intelligent transportation system, the high-efficient vehicle detecting algorithm has great significance for improving the reliability of intelligent transportation. For the characteristics of small amount of data for compressive sample and high precision for construction, the compressive sensing theory is suitable to apply to the vehicle detecting algorithm. As the few amount of the measurements on each frame of image through background model calculation, it is greatly decreased on computing operation. Proved by the experimental result, the proposed vehicle detection algorithm could produce higher precision detection, smaller calculation and higher-quality reconstructed image compared to the traditional ones.

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