Optik 126 (2015) 386–390

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Smart road vehicle sensing system based on monocular vision

Hai Wang, Chaochun Yuan, Yingfeng Cai*

School of Automotive and Traffic Engineering, Jiangsu University, Zhenjiang 212013, China

ARTICLE INFO

Article history:
Received 30 December 2013
Accepted 15 September 2014

Keywords:
Vehicle sensing
Smart system
Monocular vision
Automatic sample labeling

ABSTRACT

In this paper, a smart monocular vision based system to sense vehicles with a camera mounted inside a moving car is developed. The "smartness" is that the sensing ability of our system can be self improved when used. This system maintains an online learning ability which consists of two main stages: an initialization stage by applying an offline trained classifier and a retraining stage with queried and labeled new samples. The unlabeled examples are queried base on "most uncertainty" criterion, and an automatic labeling mechanism is used to assign a class label to some of the queried examples. Finally, the newly labeled training examples are then used to retrain the classifier and improve its performance continuously. Experiments show that the developed system maintains smart learning ability and performs well on real road situation.

1. Introduction

Automotive accidents injure more than ten million people each year, including two or three million of them seriously. Vehicle accident statistics disclose that the main threats a driver is facing are from other vehicles, especially the vehicle in front. Based on this, with the aim to prevent those accidents or reduce accident severity, front vehicle sensing technology is becoming a hot area among automotive manufacturers, suppliers and universities. Besides, vehicle sensing systems also play important roles in many end use electrical applications, such as driver-assistance systems and automatic parking systems.

Although radar or laser based vehicle sensing maintain higher robustness and accuracy, vision is becoming more and more popular nowadays for its low cost and ability to get rich environment information such as vehicles, pedestrians, lane marks and traffic signs [1–5]. With the progress of hardware's computation ability, complicated sensing algorithm can be gradually implemented on these vision based vehicle sensing system and significantly improve the performance.

Traditional typical offline trained vision-based vehicle sensing algorithm is with two steps: (1) hypothesis generation (HG) and (2) hypothesis verification (HV) [6,7]. In the HG step, potential vehicles are identified in road images. In the HV step, the system verifies hypotheses generated in the HG step previously generated.

In this paper, a smart monocular vision based system to sense vehicles with a camera mounted inside a moving car is built. The "smartness" is that the sensing ability of our system can be self improved when used by customer. In another words, our system maintain an online learning ability. Our proposed smart vehicle sensing system consists of two main stages: an initialization stage by applying an offline trained classifier and a retraining stage with queried and labeled new samples. In the initialization stage, a set of training examples is collected and annotated to train an initial classifier. Once an initial classifier has been built, a query function is used to query unlabeled examples base on "most uncertainty" criterion, and an automatic labeling mechanism is used to assign a class label to some of the queried examples. The newly labeled training examples are then used to retrain the classifier

2. System architecture

In this paper, a real-time smart vehicle sensing system employing online trained classifiers is proposed, of which the sensing ability can be self improved when using. Specifically, the system performance, such as detection rate and false alarm rate, can be improved online by retraining classifier with online generated image samples.

Like many literature referred, firstly an offline trained initial classifier is built with labor selected initial training samples. Then, new image samples with most uncertainty are selected from real-time obtained image that needs to be classified. When the image samples are generated, a sample labeling system is employed to tag image samples as either positive or negative training samples. At last, the classifier is retrained and updated with those new labeled

* Corresponding author. Tel.: +86 18261977099.
E-mail address: wanghai1019@163.com (Y. Cai).

http://dx.doi.org/10.1016/j.ijleo.2014.09.010
0030-4026/

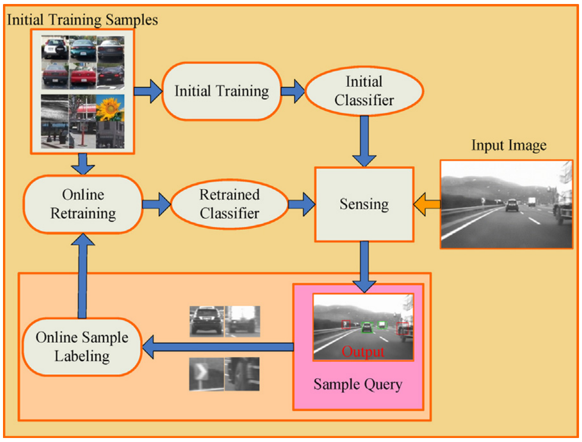

Fig. 1. Framework of the system architecture.

samples as well as initial training samples. The architecture of the proposed real-time vehicle sensing system is shown in Fig. 1.

3. Training with Haar-NMF feature and probabilistic neural network

3.1. Haar-NMF feature

Haar-like rectangular features was introduced by Viola and Jones [10] in the context of face detection. Various studies have incorporated this approach into on-road vehicle-detection systems such as [8,9,11]. The set of Haar-like rectangular features is well suited to the detection of the shape of vehicles. Rectangular features are sensitive to edges, bars, vertical and horizontal details, and symmetric structures. The algorithm also allows for rapid object detection that can be exploited in building a real-time system, partially due to fast and efficient feature extraction using the integral image.

However, there exists one big trouble to directly implement Haar-like feature to train the classifier, because the dimension of Haar-like feature vector generated from sample images are extremely high. For instance, the dimension of a Haar-like feature vector generated from a 24 by 24 image is more than 100,000. These will dramatically increase the computation time and require huge hardware storage which will be not suitable in our embedded system.

Here NMF (Non-negative Matrix Factorization) is utilized to reduce the dimension of Haar feature vectors and form Haar-NMF feature vectors. NMF is a matrix decomposition method under the constrain that all the elements of the matrix are non-negative [12]. This algorithm is also can be considered as an optimization process under the constraint of certain cost functions, whose approximate solution can be calculated by iteration.

The calculation process of Haar-NMF feature is as follows:

(1) Let $\boldsymbol{H}$ be the Haar feature vector and l be the vector dimension. Since not all elements of Haar feature vectors are non-negative, the absolute value of Haar feature is obtained. Then $\boldsymbol{H}$ is converted to a matrix $\boldsymbol{C}(m \times n)$, in which $l = m \times n$.
(2) Make NMF decomposition of rank r of matrix $\boldsymbol{C}$

$$\boldsymbol{C} = \boldsymbol{W}\boldsymbol{H}^T \quad (1)$$

In which, $\boldsymbol{W}$ is non-negative base matrix and $\boldsymbol{H}$ is non-negative coefficient matrix whose dimension are $m \times r$ and $n \times r$ respectively.

In the next part, Haar-NMF features will be loaded on a probabilistic neural network (PNN) to train the vehicle sensing classifier.

3.2. Probabilistic neural network

The probabilistic neural network (PNN) is developed by Donald Specht [13]. It is a model based on competitive learning with a 'winner takes all attitude' and the core concept is based on multivariate probability. The PNN provides a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian classifiers.

PNN is very suitable for our application because of two good features:

(1) Compared to other back feedback neural networks like BPNN, its training time is very small. This is very critical because our system need to retrain and update the classifier frequently.
(2) It can achieve any nonlinear transform and the decision surface is close to that of Bayes optimal rule. When training samples is big enough, the decision surface will be the most optimal. In our smart vehicle sensing system, new training samples will be continuously generated and its performance will be better and better theoretically.

4. Online sample query and multi-cue based sample labeling

In traditional offline learning based vehicle sensing system, all training samples are manually queried and labeled, which is not able to satisfy the requirement of online training. To solve this problem, an online sample query and multi-cue based automatic sample labeling strategy is proposed. Firstly, samples are queried with the principle of confidence which means selecting the "most uncertainty" samples. Because the uncertain samples are usually considered contain more rich information to the classifier than other samples. After that, the generated samples are judged and labeled to be "Positive", "Negative" or "Uncertain" by applying a proposed Multi-Cue based automatic sample labeling strategy.

When finally new generated samples are labeled as positive or negative, they will be grouped with existed samples and be retrained by the method proposed in Section 3. It should be noted that this labeling method is not able to be applied to sense vehicle directly due to the heavy computation requirement.

4.1. Confidence-based online sample query

Confidence-based query uses a confidence metric to query examples that lie near the classification boundary in the decision space [15].

Among many confidence-based query methods, the score-based query is the most simple and effective, which use a simple threshold on the value of a classifier's discriminate function evaluated on given samples. So that an implicit probability or confidence measure for binary classifiers can be obtained by just feeding the value of the discriminate function to the logistic function. Apply this method, in our case, each sample x with class conditional probabilities near 0.5 is queried. Indeed, in the real system the probabilities range P is chosen as 0.4–0.6.

4.2. Multi-cue based sample labeling

In order to automatically label the new generated samples, this paper proposes a Multi-Cue based sample labeling strategy. Three cue factors are utilized to make the judgments which are complexity, vertical plane and relative movement. Samples labeling realization diagram is shown in Fig. 2.

The three kinds of judgment factors are expressed as follows: