Real-time Automatic Traffic Accident Recognition Using HFG

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Abstract—Recently, the problem of automatic traffic accident recognition has appealed to the machine vision community due to its implications on the development of autonomous Intelligent Transportation Systems (ITS). In this paper, a new framework for real-time automated traffic accidents recognition using Histogram of Flow Gradient (HFG) is proposed. This framework performs two major steps. First, HFG-based features are extracted from video shots. Second, logistic regression is employed to develop a model for the probability of occurrence of an accident by fitting data to a logistic curve. In case of occurrence of an accident, the trajectory of vehicle by which the accident was occasioned is determined. Preliminary results on real video sequences confirm the effectiveness and the applicability of the proposed approach, and it can offer delay guarantees for real-time surveillance and monitoring scenarios.

Keywords—accident recognition; optical flow; logistic model.

I. INTRODUCTION

Road traffic plays an indispensable role in today’s life and many crucial services and human activities are becoming more dependent, either directly or indirectly, upon it. Therefore, efficient management of the road traffic is critical to efficient transportation and it has now become an imperative for those in charge of traffic surveillance. With current traffic management activities, traffic surveillance by means of monitoring cameras has already been put in place. However, the used methods predominantly rely on human observation of captured image shots. This requires a considerable effort and time supplied by human operator and does not support a real-time response to sudden events. In the other hand, intelligent traffic surveillance systems based on computer vision and image processing algorithms, are now tracking, localizing, and even recognizing vehicles in video sequences with little or no human intervention [1], [2], [3]. Furthermore these systems have the ability of analyzing vehicle behaviors and giving full and precise description based on the results of motion detection and tracking processes. This assists, in turn, in facilitating daily traffic management and allowing an instant response when sudden events take place.

This paper purposes to first investigate the problem of automatic traffic accident recognition and then tries to develop a real-time framework for traffic accident recognition. The proposed framework performs the following major functions. First, it detects the accident as it develops. Then, it traces the accident vehicle and records its trajectory during accident period. These information recorded by the system, are very important, which can provide guidance for investigators in determining accident causes and follow-up action. Furthermore, via the traffic behavior of vehicle, the system has the ability to predict beforehand the probability of accident occurrence and give a warning signal that may assist to avoid the accident.

The outline of the rest of the paper is as follows. Section 2 briefly reviews the relevant literature. In Section 3, the proposed framework is detailed. In Section 4, the experimental results are reported and compared with those of other similar studies. Finally, in Section 5, conclusions are drawn and suggestions for future work are provided.

II. RELATED LITERATURE

Over the course of the past two decades, researchers in computer vision and image processing fields have looked with more interest on automatic traffic accident detection. As a result, several approaches have been developed to solve this problem. In the literature, there are many methods based on decision trees, Kalman filters, or time series analysis, with varying degrees of success in their performance [4], [5], [6], [7], [8]. The work of Ohe et al. [9] is one of the closest works to ours. The authors use neural networks to detect traffic incidents immediately and automatically, which utilize one minute average traffic data as input, and decide whether an incident has occurred or not. In [10], the authors propose a system for automatic incident detection. The aim of this system is to distinguish between different types of incidents. While in [11], Merler presents a car detection system based on color segmentation and labeling, which performs color recognition. In [12], Kimachi et al. focus their attention on studying the abnormal behavior of vehicle causing an incident based on the concepts of fuzzy theory. The decision if an accident occurs or not relies on the behavioral abnormality of some continual image shots. Zeng et al. [13] develop a technique for automatic incident detection using D-S evidence theory data fusion based on the probabilistic output of multi-class SVMs. However, most of these methods mentioned above give unsatisfactory results.
What is more, such methods often employ sophisticated algorithms, creating a barrier to the real-time performance.

III. PROPOSED APPROACH

In this section, we present the outline of our framework to illustrate its essence and then we show how this framework is realized in order to be able to automatically recognize traffic accident. Our main goal is to develop a simple fast technique for solving the problem of automatic traffic accident recognition, which can efficiently operate under real-time constraints. We want the detection process to be relatively tolerant to changes in lighting conditions. Furthermore, the system is designed to be powerful and robust enough, and to yield the best accuracy-speed trade-off. The general outline of our framework is diagrammed in Figure 1. The suggested framework accomplishes its intended purpose by going through the following steps:

A. Optical Flow Computation

Optical flow is a very powerful and popular technique used in motion estimation. In this work, the optical flow is formulated as a global error functional that then needs to be minimized [14]. Thus the functional can be expressed as a solution of a second-order partial differential equation:

\[ \nabla E = \frac{\partial E}{\partial x} \frac{\partial x}{\partial t} + \frac{\partial E}{\partial y} \frac{\partial y}{\partial t} + \frac{\partial E}{\partial t} = 0 \]  

The function \( E \) can be rewritten in terms of spatio-temporal gradients of optical flow vector as follows

\[ E = \int \int (E_{\alpha}^2 + \lambda E_{\beta}^2) dx \, dy \]  

where \( E_{\alpha} = I_xu + I_yv + I_t \)  

\[ E_{\beta} = (\frac{\partial u}{\partial x})^2 + (\frac{\partial u}{\partial y})^2 + (\frac{\partial v}{\partial x})^2 + (\frac{\partial v}{\partial y})^2 \]  

\[ u = \frac{dx}{dt}, \quad v = \frac{dy}{dt} \]

where \( I_x, I_y, \) and \( I_t \) are the first derivatives of the image intensity along the \( x, y \) and time dimensions respectively, \((u, v)\) is the flow vector and the parameter \( \lambda \) is a regularization constant. To solve the above minimization problem, the variation calculus is used and ultimately we obtain

\[ u_{xx} - \frac{1}{\lambda} I_x(u_x I_y + I_y v + I_t) = 0 \]  

\[ u_{yy} - \frac{1}{\lambda} I_y(u_x I_y + I_y v + I_t) = 0 \]

These equations can be solved using an iterative method. After several iterations, the velocity field \((u, v)\) is determined. One of the most advantages of the above algorithm is that it yields a high density of flow vectors, but it is sensitive to noise.

B. Histogram of Flow Gradients (HFG)

HOG (Histogram of Oriented Gradient), first proposed by Dalal and Triggs in 2005 [15], is a feature descriptor originally used for the purpose of pedestrian detection in static imagery. This technique counts occurrences of gradient orientation in localized portions of an image. In this work, the original HOG algorithm is utilized, but with some adaption to be appropriate to deal with the flow field. Such a modified version of HOG is called HFG (Histogram of Flow Gradient). HFG algorithm is very similar to that of HOG, but differs in that HFG locally runs on optical flow field in motion scenes as shown in Figure 2(a). Furthermore, the implementation of HFG is computationally faster than that of HOG. The magnitude and the angle of the optical flow required to construct HFG are determined by

\[ \rho = \sqrt{u^2 + v^2}, \quad \theta = \tan^{-1}\left(\frac{v}{u}\right) \]

where \( \rho \) and \( \theta \) are the magnitude and the angle of the velocity of flow respectively. The orientation of flow is
C. Pattern Classification

In this section, the automatic classification stage of the proposed system is described, as well as some adaptations are made that allow the system to be robust against gradual and sudden changes in the scene. First, given the features extracted on the previous step, then the location of the center of gravity for each pattern \( \mathbf{v} \) is given as

\[
\mathbf{s}_i = \frac{1}{h_i} \sum_{\forall j} \mathbf{v}^{(i)}_j \quad \forall i \neq j
\]

where \( \mathbf{v}^{(i)}_j \in \mathbb{R}^2 \) and \( h_i \) are the flow vectors belonging to the pattern \( \mathbf{v} \) and the histogram of that pattern respectively. Then the Euclidean distance metrics (EDMs) between each two patterns are calculated as follows

\[
\lambda_{ij} = \| \mathbf{s}_i - \mathbf{s}_j \| \quad \forall i \neq j
\]

The distances are then normalized to get a quantitative parameter upon which classification is determined since the normalized distance is a characteristic quantity not easily influenced by sudden changes. Given normalized distances, \( \tilde{\lambda}_{ij} \) between each two patterns \( i \) and \( j \), then logistic regression (sometimes called the logistic model or logit model) can be used to predict the probability, \( p_{ij} \) of occurrence of an accident by fitting data to a logistic curve using a sigmoidal mapping defined by

\[
p_{ij} = p(\mathbf{s}_i \sim \mathbf{s}_j \mid \tilde{\lambda}_{ij} = \delta) = \frac{2}{1 + e^{-\alpha \delta}}
\]

where \( \delta \) is the observed distance value. The sigmoid parameter \( \alpha \) is determined using two-class logit regression technique. The orientation mean is considered and combined with the probabilities obtained from the above mapping. Note that some restrictions are enforced on the classification process by adjusting the pairwise probabilities. For example, the pattern pair probability is set to zero if the pattern density is too small (in the evaluations, ratio 0.2 was utilized as the limit). The pairwise probabilities obtained are finally compared with a threshold to determine the state of each vehicle and then decide whether the accident is likely to occur or not. Also, information as the trajectory of accident vehicle during the accident occurrence may be advantageous.

IV. Experimental Results

In this section, the experiments undertaken to evaluate the proposed framework are described and the results that confirm the feasibility of our proposed system are shown. Due to the difficulty (and danger) of capturing or simulating traffic accidents in real scenes, it was only possible to carry out the experiments in a relatively limited number of a real traffic accident scenes. The proposed framework has been tested on a set of 45 video streams depicting a total of over 250 real scenes of traffic accidents or abnormal vehicle events captured by traffic surveillance cameras. All these data were collected from Internet sites and supplied free of charge. Data comprise of a wide variety of different road types such as a straight roads, curves, ramps, crossings, and bridges, and also many vehicle events including turning left, turning right, entering, and leaving were involved in. In order to quantitatively evaluate the performance of the proposed framework in recognizing traffic accident, we have used a receiver operating characteristic (ROC) curve that defines the relationship between detection rate (DR) and false-alarm rate (FAR), which are given by

\[
DR = \frac{\# \text{ of correctly recognized accidents}}{\text{Total \# of accidents}} \times 100%\\
FAR = \frac{\# \text{ of falsely recognized accidents}}{\text{Total \# of non-accidents}} \times 100%
\]

Figure 3 shows the interpolated ROC curve of the proposed system. As can be seen in the Figure, the performance of the proposed system is very promising. The recognition rate of the system reaches up to 99.6% with false alarm rate at 5.2%. More importantly, these results are favorably competitive to the state-of-the-art techniques [13], [16], in terms of recognition rate and false alarm rate. The example shown in Figure 4 illustrates how the proposed system can successfully recognize the occurrence of a highway traffic accident and then track out and record the trajectory of the vehicle by which the accident was occasioned. All experiments were conducted on an Intel(R) Core(TM)2 Q9550 2.83GHz machine with 4GB of RAM running under Windows Vista platform, and the algorithms were implemented in Microsoft Visual Studio 2008 with OpenCV library. The low computational demand allows the method to be run at approximately 25fps. Such a high timing performance enables the accident recognizer to offer delay guarantees for real-time surveillance and traffic monitoring applications.
V. CONCLUSION AND FUTURE WORK

In this paper, a new real-time framework to automatically recognize traffic accident has been introduced. This framework is based on local features of flow gradient orientations and logistic regression modeling. All the above experiments conducted validate the effectiveness and the efficiency of the proposed approach, and demonstrate that it can offer timing guarantees for real-time traffic surveillance applications. Future work will be along two main axes. The first will be the further improvement of the classification stage by using advanced machine learning algorithms that help in improving the overall recognition accuracy. The second will look at the possibility of applying the approach to other video analysis applications that consider spatio-temporal features, such as human activity recognition, crowd behavior analysis, tracking of an individual in crowded scenes, etc.

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