A Traffic Accident Recording and Reporting Model at Intersections

Yong-Kul Ki, *Member, IEEE*, and Dong-Young Lee

***Abstract*—In this paper, we suggested a vision-based traffic accident detection algorithm and developed a system for automatically detecting, recording, and reporting traffic accidents at intersections. A system with these properties would be beneficial in determining the cause of accidents and the features of an intersection that impact safety. This model first extracts the vehicles from the video image of the charge-couple-device camera, tracks the moving vehicles (MVs), and extracts features such as the variation rate of the velocity, position, area, and direction of MVs. The model then makes decisions on the traffic accident based on the extracted features. In a field test, the suggested model achieved a correct detection rate (CDR) of 50% and a detection rate of 60%. Considering that a sound-based accident detection system showed a CDR of 1% and a DR of 66.1%, our result is a remarkable achievement.**

***Index Terms*—Accident detection at an intersection, accident recording and reporting system (ARRS), moving picture, traffic accident at an intersection, vehicle tracking.**

I. Introduction

EVERY year, vehicular accidents cause tragic loss of lives, cost many countries tremendous amount of money, and produce substantial congestion to a nation's transportation system. Approximately 50%–60% of the delays on urban freeways are associated with incidents, and on urban surface streets, a large percentage of traffic accidents and most delays occur at or near intersections [1]. Intersections are a common place for crashes, which may be due to the fact that there are several conflicting movements, as well as a myriad of different intersection design characteristics. Intersections also tend to experience severe crashes due to the fact that several types of injurious crashes, such as angle and left-turn collisions, commonly occur there. Therefore, accurate and prompt detection of accidents at intersections offers tremendous benefits of saving properties and lives and minimizing congestion and delay.

Traffic accident detection employing computer vision and image processing has attracted much attention recently [2]. Ikeda *et al.* [3] outline an image-processing-technology-based automatic abnormal incident detection system. This system is used to detect four types of incidents, namely 1) stopped vehicles, 2) slow vehicles, 3) fallen objects, or 4) vehicles that have attempted lane successive changes. Kimachi *et al.* [4] focus on abnormal vehicle behaviors causing incidents (e.g., a traffic accident), traffic jams, fallen-down obstacles, etc. They propose a method that employs image-processing techniques and fuzzy logic to predict an incident before it happens. The judgment of whether an incident has happened or not is made using the "behavioral abnormality" of some continuous images. Trivedi *et al.* [5] describe a novel architecture for developing distributed video networks for incident detection and management. The networks utilize both rectilinear and omnidirectional cameras. Blosseville *et al.* [6] successfully used video image processing to accurately detect shoulder incidents. Versavel and Boucke [7] presented a video incident detection method that uses many existing pan–tilt–zoom traffic monitoring cameras. Michalopoulos and Jacobson [8] carried out an autoscope video-detection system to detect incidents. This system is able to detect incidents almost 2 mi away.

Unfortunately, however, these methods have rather limited capability to detect accidents at an intersection because the intersection is a very complicated place. Hence, we suggested a new traffic accident detection algorithm using the features of moving vehicles (MVs) at intersections and developed a system for automatically detecting and recording the before/after accident moving picture (AMP) and reporting it to the traffic monitoring center (TMC). Such a device could be useful at high-traffic intersections where accidents are likely to occur. The AMP is a more reliable surrogate of crash data than the conflict data, and it provides a time-efficient method of analyzing intersection collisions compared to a conflict analysis or continuous videotaping. A system with these properties would assist in determining the cause of accidents. The information could also be useful in determining the features of the intersection that impact safety.

We begin with an overview of related works, then describe our approach, present our experimental results, and finally draw some conclusions.

II. Background

A. Related Work

A number of conventional expressway incident detection algorithms have been developed in the past several decades. Techniques based on decision trees for pattern recognition, time series analysis, Kalman filters, and neural networks have been attempted but met with varying degrees of success in their detection performance [9]–[17]. On the other hand, only a few researchers have investigated the detection of traffic crashes at intersections [18].

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In 2005, Green *et al.* [19] evaluated a sound-actuated video recording system used to analyze the reasons for traffic crashes at intersections. The system automatically records potential incidents when activated by sound (horns, clashing metal, squealing tires, etc.). It was deployed in 2001 at the intersection of Brook and Jefferson Streets in Louisville, KY. The transportation engineers used this information to make several enhancements to the intersection, which resulted in 14% reduction in accidents.

Another study described in a 2001 report considered the development of a system for automatically detecting and reporting traffic crashes at intersections [20]; the study would determine crashes directly from the acoustic signal of the crash. An acoustic database of normal traffic sounds, construction sounds, and crash sounds was developed using the sounds of crash tests, routine traffic sounds at intersections, and construction sounds from construction sites. Tests showed that the false alarm rate (FAR) (false positive) was 1%. The conclusion was that the system needed to be further evaluated in situations with routine traffic flow and accident occurrences.

To track MVs with video images, researchers generally use methods such as object segmentation and motion estimation. These methods are used to detect incidents that have caused the flow of traffic to stop. Recently, researchers have developed an algorithm that uses Gabor wavelet analysis and the Mallat wavelet transform for fast accurate vehicle tracking [21]. The image flow vectors can be quickly estimated using low-spatial-resolution data, and vehicles can be accurately detected, providing high-spatial-resolution results. Even in complex motion scenarios, the system could detect small disconnected objects of arbitrary numbers.

In 2000, Kamijo *et al.* [22] suggested a vision-based accident detection model. They applied a simple left-to-right hidden Markov model for accident detection at intersections. They considered three situations, namely 1) a bumping accident, 2) stop and start in tandem, and 3) passing, and conducted experimental tests. However, the conclusion was restrictive because there were not enough traffic accident data.

B. *Traffic Accident Recording and Reporting System (ARRS)*

The traffic ARRS is an image-actuated moving picture recording and reporting system used to analyze and evaluate the occurrence of traffic crashes at intersections. The system consists of a charge-coupled-device camera located on the corner of the intersection to obtain a view of incidents, an image processing unit that detects images that could be related to a traffic crash, a digital video recorder (DVR) that has recorded all the situations of the intersection for the previous two weeks, and a communication unit that send the AMPs to the TMC.

When the ARRS detects an event that could be a collision and captures the AMPs (which include 5 s before the event and 5 s after the event) from the DVR, the system sends the AMPs to the TMC by the virtual private network. This AMP consists of pictures taken 5 s before and after the event that activated the system. The signal phase is then encoded onto the recorded AMP (Fig. 1).

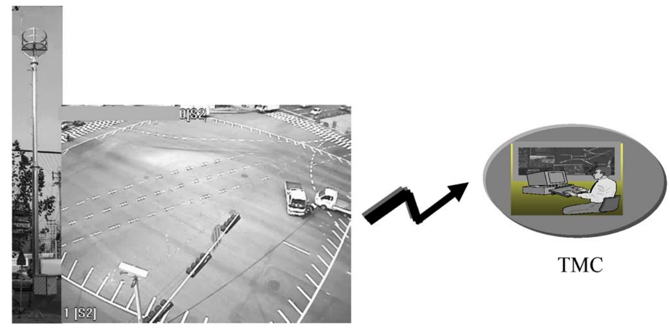

Fig. 1. Configuration of ARRS.

C. *Data Collection and Performance Measures*

DVRs were used to match each crash report to an AMP by the AARS. The performance of the accident detection model is mainly evaluated using three indexes, namely 1) detection rate (DR), 2) correct detection rate (CDR), and 3) FAR [16], [23], which are defined as

$$\mathrm{DR} = \frac{\text{no. of detected accident cases}}{\text{total no. of accident cases in the data set}} \times 100\% \tag{1}$$

$$\mathrm{CDR} = \frac{\text{no. of detected accident cases}}{\text{total no. of patterns detected by the model}} \times 100\% \tag{2}$$

$$\mathrm{FAR} = \frac{\text{no. of patterns in which a false alarm occurs}}{\text{total number of patterns}} \times 100\% \tag{3}$$

where a pattern is a 10-s moving picture for accident detection.

It is worth mentioning here that normally the FAR increases when one tries to boost the performance of the DR. Therefore, the challenge is to maintain a high DR and CDR while at the same time minimizing the FAR.

III. Algorithm Description

The accident detection algorithm generally includes three steps, namely 1) vehicle extraction, 2) feature extraction of an MV, and 3) accident detection. Based on the vehicle tracking results, we analyzed traffic images and detected the traffic accidents.

A. *Vehicle Extraction and Tracking*

Vehicles are extracted by detecting the moving parts in each frame based on a difference equation. This process consists of taking the difference of two continuous frames, binarization, and horizontal and vertical projection, and then extracting parts that exceed the threshold value. For the extraction of moving regions in a video sequence, an input image and a pair of gray-level images $I_{k-1}(x,y)$ and $I_k(x,y)$ acquired at successive time instants τ_{k-1} and τ_k, respectively, were used. The output is the moving regions in which significant changes have been

Fig. 2. Extraction of vehicles.

detected. For the extraction of moving regions, the difference image $D(x, y)$ is computed: $D(x, y) = I_k(x, y) - I_{k-1}(x, y)$. The equation for thresholding the difference image D is given as follows:

$$T(x, y) = \begin{cases} 1, & \text{if } |D(x, y)| > t \\ 0, & \text{otherwise} \end{cases}. \tag{4}$$

Tracking means the matching of individual vehicles from frame to frame by using the tracking data. In the second frame, from which a vehicle is recognized, we can estimate an area in which the same vehicle is expected to exist based on the direction of the motion. In this estimated area, a region of the vehicle with the same size as in the previous frame is extracted on the subtracted image. Based on the stored intensity of the vehicle, we search for a region of the same size within the estimated area so as to minimize the root-mean-square value of the subtracted intensity. Once the region is determined on the second frame, the velocity of the vehicle can be known by comparing its position with its position on the first frame, and the velocity is attached to the tracking data.

From the third frame, the estimated area can be reduced by utilizing both the direction of the vehicle motion and its velocity. It makes the processing speed fast. Repeating this procedure until the vehicle exits the study area, the trajectory of the vehicle motion is obtained (Fig. 2).

B. Feature Extraction

Depending on the tracking result, the ARRS extracts features for accident detection. Features such as the acceleration, position, area (size), and direction of the MV are used for accident detection.

1) Acceleration: Rapid velocity variation is a useful descriptor of a traffic accident. In general, a traffic accident causes rapid change to vehicle speeds. Hence, we used the variation rate of vehicle speed (acceleration) for accident detection. In the tracking process, we extracted the speeds of the MVs, calculated the positive or negative accelerations of the vehicles,

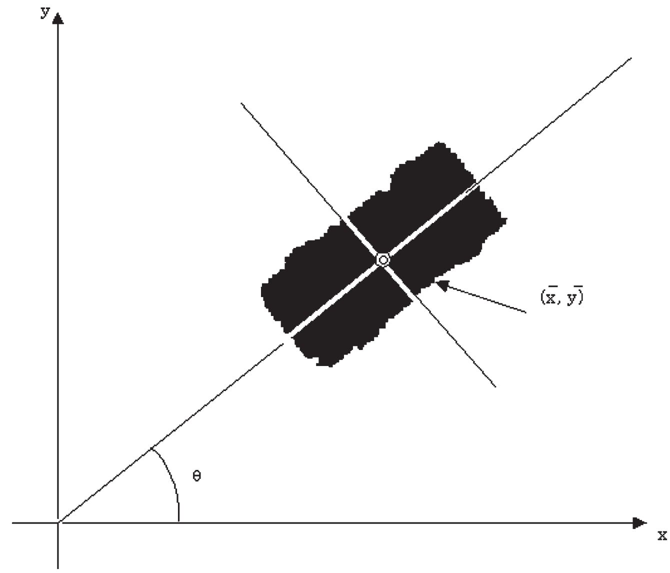

Fig. 3. Centroid of a vehicle.

and used them for accident detection. The following expression is used for the traffic accident detection algorithm:

$$VF = \begin{cases} 0 < VF \leq 1, & \text{if } b \leq a = \left|\frac{\Delta v}{\Delta t}\right| \leq c \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where VF is an accident index and b and c are the thresholds.

2) Variation Rate of the Position: Positions are useful descriptors of objects within images. An image that represents an object consists of positive-valued pixels that is set against a background of zero-valued pixels. Position refers to the location of the object in the plane. The objects' centroid is the point that is used to specify its position. The centroid is the point $(\overline{x}, \overline{y})$ that represents the center of an object. Fig. 3 shows the location of the centroid for a vehicle object. The suggested model uses the variance rate of the centroid position as a factor for traffic accident detection in

$$PF = \begin{cases} 0 < PF \leq 1, & \text{if } d \leq \left|\frac{\Delta \overline{x}}{\Delta t}\right| \leq e \text{ or } f \leq \left|\frac{\Delta \overline{y}}{\Delta t}\right| \leq g \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where PF is an accident index; $\overline{x}$ and $\overline{y}$ are the coordinates of the centroid; and d, e, f, and g are the thresholds.

3) Variation Rate of the Area: Area is a commonly used descriptor for regions in the plane. Let R denote the region whose points have a pixel value of 1. One way to calculate area S is simply to count the number of points in R. This can be accomplished with the image algebra statement $S = \Sigma$ s. When the vehicle moves away from the camera, the size of the MV decreases, and as it moves toward the camera, the size of the MV increases; however, its variation rate is small. On the other hand, the accidents can cause rapid change to the size of the MV. Therefore, we used the variation rate of area shown in the following expression as a factor for traffic accident detection:

$$SF = \begin{cases} 0 < SF \leq 1, & \text{if } h \leq \left|\frac{\Delta s}{\Delta t}\right| \leq i \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where SF is an accident index and h and i are the thresholds.

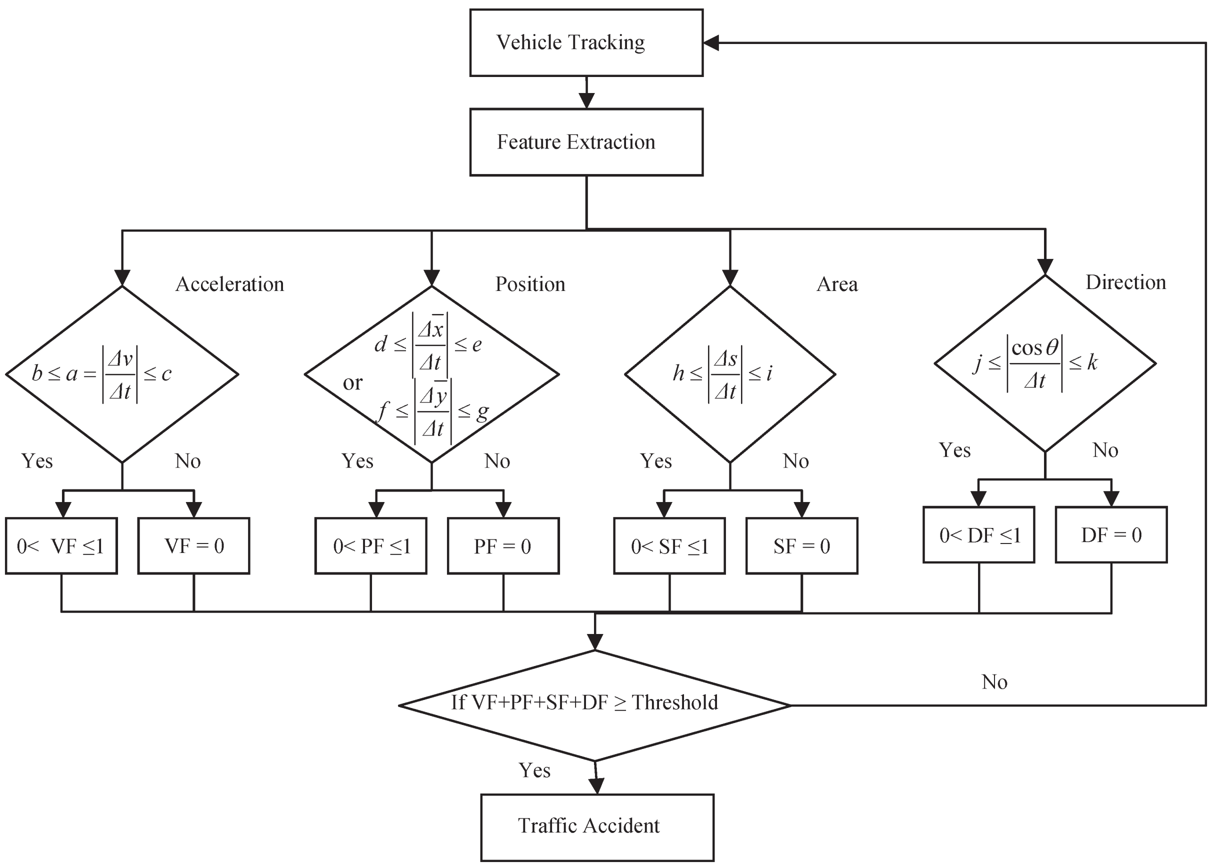

Fig. 4. Flowchart of the accident detection algorithm.

4) Variation Rate of the Direction: With reference to the extracted part in one frame, the corresponding part in the subsequent frame is searched by cross correlation. The motion vector spanning the two corresponding points in each image is defined as optical flow. The mean optical flow obtained by averaging the normal optical flow of each pixel in the extracted part is represented by V_n, and the motion vector obtained by cross correlation is represented by V_i. The angle θ formed between the two motion vectors can be expressed as follows:

$$\cos\,\theta = \frac{V_n \cdot V_i}{|V_n||V_i|} \tag{8}$$

$$DF = \begin{cases} 0 < DF \le 1, & \text{if } j \le \left|\frac{\cos\theta}{\Delta t}\right| \le k \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where DF is an accident index and j and k are the thresholds.

If $|\cos\theta/\Delta t|$ is large, it can be estimated that a vehicle is running abnormally, and the probability of an accident is high [4].

C. Accident Detection Algorithm

The traffic accident detection algorithm was established following a flowchart. The accident features in each image were calculated in the steps mentioned previously. Finally, considering the “feature indexes” in the sequence, it was determined whether or not the traffic accident had occurred. An outline of this process is shown in Fig. 4, and the accident detection algorithm is summarized as follows:

Step 1) Extract the vehicle objects from the video frame.
Step 2) Track the MVs by the tracking algorithm.
Step 3) Extract features such as variation rates of velocity, position, area, and direction of the MV as the accident index.
Step 4) Calculate VF, PF, SF, and DF as the accident indexes.
Step 5) Estimate the sum of the accident indexes $(VF + PF + SF + DF)$ and identify the accident.

IV. Test and Evaluation

A. Test Conditions

In this paper, we suggested a vision-activated accident detection algorithm at an intersection. To evaluate the performance of the proposed model in a real-world environment, we developed the ARRS and installed two of them at the Gwangjang and Jangpyung intersections in Seoul, South Korea. Crash reports from DVRs were obtained from August 13 to August 27, 2005 and compared to the available data from the ARRSs.

B. Test Result and Analysis

During the approximate two-week test period, a total of six traffic accidents and six moving pictures that were not

Fig. 5. Accident images detected by ARRS at an intersection. (a) Before an accident during the day. (b) Accident during the day. (c) Before an accident at night. (d) Accident at night.

related to traffic accidents were detected and recorded by the AARSs (Fig. 5). During the same period, ten crash reports from DVRs were identified to have occurred at the intersections. The comparisons of accidents and crashes resulted in the following summaries:

1) matches of AMPs and crash reports from DVRs: 6;
2) moving pictures not related to an accident: 6;
3) crash reports from DVR with no corresponding AMP: 4.

DVRs were used to match each crash report to an AMP of the ARRS. The results were evaluated by the three criteria: CDR, DR, and FAR. The CDR, DR, and FAR of the proposed model are 50%, 60%, and 0.00496%, respectively, as shown in the following:

1) CDR $= (6/12) \times 100\% = 50\%$;
2) DR $= (6/10) \times 100\% = 60\%$;
3) FAR $= (6/120960) \times 100\% = 0.00496\%$.

C. Evaluation

A good accident detection model should have a very high CDR and DR and a very low FAR. However, it is worth mentioning here that these objectives conflict with each other; normally, the FAR increases when one tries to boost the DR. Therefore, a challenge in this paper is to maintain a high DR and CDR and at the same time minimize the FAR.

In this paper, the performance of the proposed algorithm is compared to the auto incident recording system (AIRS) placed at an intersection in Louisville, KY, which is a sound-actuated video recording system used to analyze the reasons for traffic crashes at intersections. The study results compared with the police reports showed a CDR of 1% and a DR of 66.1% [19]. On the other hand, the ARRS showed a CDR of 50% and a DR of 60% for all crashes occurred at the intersections. At the level of CDR, the proposed algorithm showed its superiority to the AIRS (Table I).

Moreover, the ARRS excels in DR and FAR compared to existing freeway incident detection algorithms/systems. Most systems/algorithms with low FARs have DRs between 20% and 80% [1]. For example, the California #7a algorithm was reported to have DRs between 19.47% and 45.81%, and the Speed-Based Incident Detection Algorithm was reported to have DRs between 25.00% and 51.81% in [24]. Some systems did report a perfect DR of 100% but were accompanied with

TABLE I
COMPARISON OF THE INCIDENT DETECTION MODELS

Type		CDR(%)	DR(%)	FAR(%)
Accident detection algorithm at intersection	Vision-based Model (ARRS)	50	60	0.00496
	Sound-based Model (AIRS)	1	66.1	
Incident detection Algorithm in freeway	California #7a algorithm	-	19.47~45.81	0.08~0.34
	SBIDA	-	25.00~51.81	0.89~1.10
	Vision-based Model(AVDS)	-	80	3

a FAR in the range of 30%–40% [25]. However, the proposed system achieves an excellent DR of 60% with a low FAR of about 0.00496% at intersections.

Incident detection using video image processing on freeways has several distinct advantages over inductive loop-based technology [6]. Blosseville *et al.* [6] tested video image incident detection on a 1.7-km-long corridor in France. They tested several scenarios and compared them with the recorded video from each camera. The test result for the main traffic lanes showed a DR of 90% with only a FAR of 3%. In 1993, an autoscope video detection system is reported to have detected 80% of all incidents with only 3% FAR [8]. Through the use of incident detection algorithms, the system also detected incidents almost 2 mi away, which are well outside the range of the camera's vision. Unfortunately, however, these methods have rather limited capability to detect accidents at an intersection because an intersection is a very complicated place (Table I).

V. CONCLUSION

We have demonstrated a promising approach for an image processing system for automatically detecting, recording, and reporting traffic accidents at an intersection. An important objective in the current accident detection algorithm is a high accident DR and a low FAR; hence, a delicate balance has to be struck between these two conflicting requirements. Sound-based techniques have shown great promise in the development of such an automated accident detection algorithm at an intersection, the most promising of which is AIRS [19].

To evaluate the performance of the new model, we developed and placed the ARRS, which is a vision-based accident detection system, at two intersections in Seoul, Korea. A field test has been conducted for approximately two weeks, and the results were compared to the test results of AIRS [19]. The evaluation revealed that the proposed model can identify accidents more effectively than some other models. The CDR, DR, and FAR of the proposed model are 50%, 60%, and 0.00496% respectively, and at the level of CDR, the proposed algorithm is superior to the AIRS. In terms of the accident detection accuracy, the suggested method worked best.

We conclude, therefore, that the proposed model significantly improves accident detection efficiency at intersections. This accident detection and video-verification mechanism will be able to provide real-time crash warnings to the operators and drivers. The video clips are invaluable for intersection safety analysis.

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