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Pedestrian Collision Avoidance Systems: A Survey of Computer Vision Based Recent Studies

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Abstract— **This paper gives a survey of recent research on pedestrian collision avoidance systems. Collision avoidance not only requires detection of pedestrians, but also collision prediction using pedestrian dynamics and behavior analysis. The paper reviews various approaches based on cues such as shape, motion, and stereo used for detecting pedestrians from visible as well as non-visible light sensors. This is followed by the study of research dealing with probabilistic modeling of pedestrian behavior for predicting collisions between pedestrian and vehicle. The literature review is also condensed in tabular form for quick reference.**

I. INTRODUCTION

ACCORDING to the NHTSA report [1], there were 4641 pedestrian fatalities in United States during the year 2004, which accounted for 10.9% of the total 42636 traffic related fatalities. In countries of Asia and Europe, the percentage of pedestrian deaths is even higher. Intelligent vehicle systems have the capability to reduce the pedestrian deaths and injuries. However, in order to provide effective protection, such systems need to not only detect pedestrians in varying environmental conditions, but also predict the possibility of collision. They should relay the information to the driver in efficient and non-distracting manner or to the control system of the vehicle in order to take preventive actions.

Vehicle-mounted sensors are useful for detecting pedestrians and other objects on the road. However, the visibility from the vehicle is limited. It is often the case that it is difficult or impossible to observe the dangerous object from the vehicle itself. Hence, it is useful to complement the vehicle-based systems with sensors in the infrastructure. The latter would perform overall monitoring of traffic and send appropriate signals to the vehicle through wireless communication channels. Infrastructure-mounted cameras have been extensively studied for video surveillance. However, since mounting infrastructure is expensive, such systems would be useful for specific places such as busy and dangerous intersections, school areas, and blind curves. Their outputs when available could be combined with that of the vehicle based system.

There are a very few surveys in the Intelligent Transportation literature specifically for pedestrian analysis. Gavrila [2] has given a comprehensive survey of approaches used for pedestrian detection. Bertozzi et al. have surveyed pedestrian detection in their article on artificial vision in road vehicles [3]. We refer to these valuable surveys for earlier work in this topic. However, considerable research has been performed since then. A recent paper by Bu and Chan [4] discusses various sensors and approaches used for pedestrian detection for transit bus applications. In this

Table 1 Comparison between different sensor modalities for pedestrian detection.

Sensor type	Field of view	Angular resolution	Detection range	Range resolution	Illumination	Hardware cost	Algorithmic complexity
Conventional Camera	Med.	Med./High	Low/Med.	Med.	Passive reflective, needs ambient light	Low	High
Wide FOV Camera	Large	Low/Med.	Low	Low	Passive reflective, needs ambient light	Med.	High
Near IR	Med.	Med./High	Med.	Med.	Active illumination, works in dark	Low	High
Thermal IR	Med.	Low/Med.	Low/Med	Low	Emissive, works in dark	High	Med.
RADAR	Low	Low	High	High	Active, works in dark, rain, fog.	Med.	Low
LASER scanner	Large	Med.	Med.	High	Emissive, works in dark	High	Low

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Table 2 Pedestrian detection using visible light cameras

Paper	Approach	Description
Papageorgiou IJCV00[5]	Shape classification	Based on local multiscale oriented intensity differences using Haar wavelet transform. Uses SVM for classification. Pedestrian detection application is shown.
Abramson IV04 [6]	Shape, motion	Uses shape and motion based algorithms for detection. Algorithm fusion as well as impact prediction is performed in particle filtering framework.
Hashiyama C-SMC03 [7]	Motion, shape	Proposes a method for active background subtraction from moving camera. Motion estimation using gyrosensor. Also applies template matching for pedestrian detection.
Viola ICCV03 [8]	Motion, shape	Combines motion as well as appearance information in a single detector. Uses AdaBoost and cascading for classification, based on shape and motion features.
Havasi 04 [9]	Shape, motion	Feature extraction and tracking based on inherent structural changes of target shape, especially the legs. Proposes novel symmetry detection method using morphological operators. Performs temporal tracking of symmetries followed by classification of traces.
Shashua 04 [10]	Shape, motion	Performs classification on single frame using a novel scheme of breaking down class variability by repeated training of simple classifiers on training set clusters. Performs multi-frame approval process by using properties such as gait patterns, motion analysis, parallax, classifier consistency, tracking quality.
Zhao ITS00 [11]	Stereo, neural network	Segments into blobs using disparity discontinuity. Split-merge to form objects with size/shape constraint for pedestrians. Neural network with intensity gradient features used for recognition.
Gavrila IV04 [12]	Stereo, shape	Performs stereo-based depth segmentation, chamfer matching for shape, texture classification for verification using neural network, stereo-based verification, and tracking.
Hilario 05 [13]	Shape, stereo	Uses active contour model for pedestrian segmentation. Stereo is used to guide the active contour location since they are very sensitive to initial position.
Gandhi ICIP05 [14]	Stereo	Uses a pair of omni-directional cameras in binocular stereo configuration to detect pedestrians and other objects in front of the vehicle.
Lombardi IV04 [15]	Shape, motion, head detection	Models contextual evolution of scene parameters using HMM. Chooses appropriate algorithms to be used according to estimated context.

paper, we cover not only the recent research on pedestrian detection but also describe the research on collision prediction using pedestrian dynamics and behavior analysis.

II. Pedestrian Detection and Tracking

Commonly used sensors for detecting pedestrians are imaging sensors in various configurations using visible light and infrared radiation, as well as the 'time-of-flight' sensors such as RADARs and LASER scanners,. Imaging sensors capture detailed description of the scene but extracting information involves substantial amount of processing. On the other hand, time-of-flight scanners directly give accurate information about object distance, but resolution is often limited. In this sense, these two types of sensors are complementary and their fusion is expected to result in more robust detection. **Error! Reference source not found.** gives a comparison of various types of sensors used for pedestrian detection.

A. Visible Light Sensors

It is a marvel that the human visual system can process vast amount of data from the scene and extract information that enables driving. Video sensors would therefore be a natural choice for intelligent driver support systems. However, processing of video data to extract useful information is a complex task. In order to perform the specific task of pedestrian detection and tracking, various approaches are used as shown in Table 2

Shape-based approaches extract characteristic features from the images and use a trained classifier to separate pedestrian from background and other objects. Training is carried out using a large number of example images of positive and negative samples.

Papageorgiou and Poggio [5] have developed a general trainable object detection system. The feature set is based on overcomplete Haar wavelet transform that provides a rich description of the pattern. A Support Vector Machine (SVM) is trained and applied for detecting objects such as faces, people, and vehicles. A real-time application for on-vehicle detection of pedestrians is described. The paper also compares the use of other features such as raw pixels and principal components. Abramson and Steux [6] use four algorithms for initial detection: a 5x5 feature classifier, diagonal legs detector, pedestrian motion estimator, and vertical edge detector. Fusion is performed in particle filtering framework to detect and track the pedestrians.

Motion is an important cue in detecting pedestrians due to the characteristic rhythmic patterns of human movement [4]. An important problem in motion-based approaches is to separate the ego-motion of the background, which depends on camera motion as well as the scene structure. In the case of pedestrians moving laterally, it is usually feasible to separate the pedestrian motion from ego-motion. However, in the case of longitudinally moving pedestrians, the image motion is parallel to the ego-motion and therefore difficult to separate.

Hashiyama et al. [7] use gyrosensors to compensate the structure-independent rotational motion of the camera which leaves the structure-dependent translational motion. This is compensated using minimization over all feasible translational motions. Motion compensated images are used to perform active background subtraction. The difference image is combined with the edge image and searched for pedestrians using template matching.

Viola et al. [8] generalized their object detector by combining motion information along with appearance information in a single detector. They have developed an extremely efficient representation of image motion based on 5 types of shifted image differences. AdaBoost and cascading are used for classification based on these shape and motion features.

Havasi et al. [9] use symmetry characteristics of the legs of walking person in order to detect pedestrians. Feature extraction and tracking based are on inherent structural changes of target shape, especially the legs. Morphological operators are used to detect symmetries which are then temporally tracking followed by classification of traces.

Shashua et al. [10] generate candidate ROIs based on texture properties and compliance with perspective constraints. Single frame classification is performed on these ROIs. They have developed a novel scheme of breaking down class variability by repeated training of simple classifiers on training set clusters. Multi-frame approval process is performed by using properties such as gait patterns, motion analysis, parallax, classifier consistency, tracking quality. Distance to pedestrian is computed by aligning lower part of detected region with feet.

Binocular stereo can be used to obtain depths of scene points based on disparity analysis. These depths offer valuable cues for separating pedestrians from background. Zhao and Thorpe [11] use stereo cameras in order to segment the scene into blobs using disparity discontinuity. Split-and-merge procedure is applied to form objects with size/shape constraint for pedestrians. The objects are recognized using a neural network with intensity gradient features. Gavrila et al. [12] perform stereo-based depth segmentation, chamfer matching for shape, texture classification for verification using neural network, stereo-based verification, and tracking. Hilario et al. [13] use an active contour model for pedestrian segmentation. Stereo is used to guide the active contour location since they are very sensitive to initial position. Distance measures are applied on the disparity map to detect symmetries, initializing contours in regions with high vertical symmetry.

We have performed research on intelligent driver support systems using wide field-of-view cameras. In [14], we use a pair of wide field-of-view omni-directional cameras in binocular stereo configuration to detect pedestrians and other objects in front of the vehicle.

Most of the individual detection algorithms perform well in specific situations. Hence, contextual information can be very useful to select which algorithm to use in which situation in order to improve overall performance. Lombardi and Zavidovique [15] use Hidden Markov Models to represent contextual evolution of scene parameters over time. Three algorithms used for pedestrian detection are frame differencing, vertical symmetry detector, and color-based head detection. Each of these algorithms performs well under certain conditions. Hence, the situations are classified according to vehicle speed and scene clutter in order to obtain the context. This context would then decide what would be the best algorithm or combination.

B. Thermal Infrared Sensors

As described in the previous section, visible light sensors provide rich information for driving. However, separating objects from background clutter is a difficult problem for computer vision. Furthermore, vision becomes less effective during dark conditions. On the other hand, thermal Infra-red sensors are sensitive to the radiation emitted by the human body, and hence are very effective for detection of pedestrians especially in night time. Due to the decreasing cost of these sensors, they have been of considerable interest for night vision in vehicles. Luxury cars have already started offering systems that increase the range of sight in the car by displaying a thermal infrared image. A number of researchers have shown interest in these sensors for automatic detection and tracking of pedestrians as shown in Table 3.

For example, Broggi et al. [16] describe a pedestrian detection system based on detecting warm symmetric objects with appropriate size and aspect ratio using multiple resolutions. Fang et al. [17] applies a shape independent approach by finding horizontal and vertical projection profiles. Classification is based on multi-dimensional histogram, inertia, and contrast features. Meis et al. [18] propose a statistical approach for pixel classification for head detection. They also compare this with a classifier for body detection. Xu, Liu, and Fujimura [19] use SVM for detection, Kalman filter and mean shift for tracking pedestrians. Output of road-detection module is also used for validation. Liu and Fujimura [20] detect moving objects

Table 3 Pedestrian detection using non-visible light sensors

Paper	Objective	Sensors	Approach	Description
Broggi IV04 [16]	Detection	FIR	Shape	Detects warm symmetric objects with specific size and ratio at multiple resolutions.
Fang VT04 [17]	Detection	FIR		Shape independent approach using horizontal and vertical projection profiles. Classification based on multi-dimensional histogram, inertia, contrast features.
Meis IV04 [18]	Detection	FIR	Head detection	Statistical approach for pixel classification for head detection. Comparison with classifier for body detection.
Xu ITS05 [19]	Detection, tracking	FIR	Shape	Uses SVM for detection, Kalman filter and mean shift for tracking pedestrians. Output of road-detection module also used for validation.
Liu VT04 [20]	Detection	FIR	Stereo, motion	Detects objects with motion not consistent with background without explicit ego-motion computation. Works well with dominant translation but small rotation of camera.
Tsuji ITS02 [21]	Detection, collision prediction	FIR	Stereo, motion	Design of overall system. Discusses configuration, coordinate systems, simple IR based detection, tracking, computation of relative motion vectors, and conditions for collision judgment.
Fang 03 [22]	Detection comparison	Visible, FIR	Feature-based	Compares use of visible and IR sensors. Introduces multi-dimensional feature-based segmentation and classification. Proposes novel features for segmentation to take advantage of unique properties of IR.
Milch [23]	Detection	RADAR, monocular vision	Time-of-flight, shape	Target-list is generated using RADAR. These are verified by vision using flexible shape models trained from manually extracted pedestrians.
Scheunert IV04 [24]	Tracking	FIR, LASER scanner	Time-of-flight, hot object detection	LASER scanner detection using 1st and 2nd derivatives w.r.t. azimuth angles. IR detection using brightness and orientation. Uses Kalman filter for sensor fusion.

with motion not consistent with background. They have developed a two stage stereo correspondence and motion detection procedure that does not need explicit ego-motion computation. The approach is suited to the typical vehicular motion with dominant translation and small camera vibrations. Tsuji et al. [21] discusses the design of a complete pedestrian detection system. They discuss camera configuration, coordinate systems, simple IR based detection, tracking, computation of relative motion vectors, and conditions for collision judgment.

C. Sensor Comparison and Fusion

As described earlier, each sensor has its advantages and limitations which are often complementary to each other. Hence, fusion of multiple sensor modalities is likely to improve the reliability of pedestrian detection under all environmental conditions. Fang et al. [22] performs a comparison between the use of visible and IR sensors. They introduce a multi-dimensional feature-based segmentation and classification framework. To take advantage of unique properties of IR, they propose novel features for segmentation. Milch and Behrens [23] use a two-step fusion of RADAR and monocular vision sensors. The first step generates a list of potential targets using RADAR. The second step uses the images from vision sensor to verify the targets using flexible shape models trained from manually extracted pedestrians. Scheunert et al. [24] uses a combination of far infrared sensors and LASER scanner in order to obtain robust detection and accurate localization of pedestrians. The LASER scanner outputs the range and reflectivity data for every azimuth angle. Every object corresponds to a pair of steps in the plot of range against the azimuth angles. These are detected using the first and second derivatives. In far infrared images, pedestrians are characterized by high brightness and vertical orientation. Detection is performed using thresholding, grouping of valid pixels, and orientation checking. The outputs from LASER scanner and far IR sensors are integrated in the tracking module using Kalman filter.

III. Behavior Analysis and Collision Prediction

For effective collision prevention, the detection of pedestrians should be followed by the prediction of the possibility of collision between pedestrians and vehicles. Table 4 shows the current research on this topic. In the night vision system by Tsuji et al. [21], the relative motion vector between the vehicle and pedestrian is used to predict

Table 4 Research on collision prediction and pedestrian behavior analysis

Paper	Objective	Approach	Description
Tsuji ITS02 [21]	Collision prediction	Relative motion	Based on computation of relative motion vectors, and conditions for collision judgment.
Wakim C-SMC04 [25]	Behavior modeling for accident prediction	Probabilistic modeling	Models pedestrian dynamics using HMM with 4 states of static, walk, jog, run. Each state is modeled as truncated Gaussian. Monte-Carlo simulations are used to predict collision probabilities.
Abramson IV04 [6]	Detection and impact prediction	Probabilistic modeling with particle filter	Impact prediction is performed in the particle filtering framework by performing long term prediction of sample target paths.
Shimizu 03, IV04 [26]	Direction estimation	Pattern classification	Uses SVM on Haar wavelet coefficients to classify between different orientations.
Makris BMVC02 [27]	Pedestrian behavior model	Probabilistic clustering	Generates model of probabilistic distribution of trajectories in a scene using Bayesian HMM based approach.
Large 04 [28]	Long term motion estimation	Probabilistic clustering	Cluster-based technique to learn motion patterns using pair-wise clustering. Cluster mean value is used to predict motion of new partially observed trajectories.
Antonini 04 [29]	Detection and tracking	Pedestrian dynamics model	Bayesian framework for multi-object tracking. Uses discrete choice model for pedestrian dynamics for prior and correlation output for likelihood.
Antonini 05 [30]	Pedestrian behavior modeling	Pedestrian dynamics model	Expands the framework for modeling pedestrian walking behavior and interactions between pedestrians.

the possibility of collision. This assumes that the speed and direction of pedestrian as well as the vehicle do not change significantly during that time. Such a model is suitable when vehicle is traveling at high speed and the time to collision is too short for velocity changes to have a significant effect.

However, in situations where the speeds are small, such as at intersections and pedestrian crossings, effects of velocity changes become important. Also, unlike vehicles, pedestrians are capable of making sudden maneuvers in terms of the speed and direction of motion. Hence, a stochastic model of the pedestrian dynamics is most appropriate for predicting the collision probability. Monte-Carlo simulations can then be used to generate a number of possible trajectories based on the dynamic model. The collision probability is then predicted based on the fraction of trajectories that eventually collide with the vehicle.

Wakim et al. [25] propose a Markovian model for pedestrian behavior. The pedestrian dynamics is modeled using Hidden Markov Model with 4 states corresponding to standing still, walking, jogging, and running. A state transition diagram gives the probability of transition between states. For each state, the probability distributions of absolute speed as well as the change of direction modeled as truncated Gaussians. Monte-Carlo simulations are used to predict collision probabilities.

The Monte-Carlo approach can also be implemented in the particle filtering framework where probability density of the pedestrian location is modeled using a cloud of particles. Abramson and Steux [6] extends the particle filtering used for pedestrian tracking in order to perform impact prediction. Instead of predicting only one time step ahead as in case of tracking, a longer term prediction based on the model of evolution of pedestrian target is performed.

In addition, there is research on analyzing pedestrian behavior from stationary cameras. Some of this research could be useful for predicting the possibility of collision.

For example, the orientation of the pedestrian body often gives useful information about the future direction of motion. Hence, estimating the pedestrian orientation can potentially improve the motion prediction and give better estimates of collision probability. Shimizu and Poggio [26] estimate the pedestrian orientation using Support Vector Machines on Haar wavelet coefficients to classify between different orientations.

In the case of fixed cameras mounted in infrastructure, one can also use the property that pedestrians often follow particular paths. Tracking a large number of pedestrians in the scene can help to learn these paths. For example, Makris and Ellis [27] generate model of probabilistic distribution of trajectories in a scene using Bayesian HMM based approach. Large et al. [28] obtain long term estimate of object motion using cluster-based technique to learn motion patterns. Cluster mean value is used to predict motion of new partially observed trajectories. This research could be applied for predicting where a currently detected pedestrian is likely to go, and estimate the probability of collision with vehicles.

Other pedestrian behavior models could also be useful for predicting collisions. One such model is the "discrete choice model" for in which a pedestrian makes a choice at every step about the speed and direction of the next step. It is assumed that a pedestrian would normally move towards the destination direction, avoid frequent direction changes, and try to adjust speed to desired speed. Antonini et al. [29] have developed a Bayesian framework for multi-object tracking which uses this model to analyze pedestrian trajectory and give appropriate scores for following this behavior. In [30], Antonini and Bierlaire expand this framework to incorporate interaction between pedestrians.

IV. Conclusion and Future Directions

This paper discussed the recent research on pedestrian detection using various sensors, as well as that on collision prediction. For a pedestrian protection system to be deployable, the performance of the system needs to be characterized under various environmental conditions. Further improvement of performance would be possible by using proper combination of algorithms as well as sensor fusion in order to reduce the rate of false alarms while maintaining high detection rate.

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