Pedestrian Protection Systems: Issues, Survey, and Challenges

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Abstract—**This paper describes the recent research on the enhancement of pedestrian safety to help develop a better understanding of the nature, issues, approaches, and challenges surrounding the problem. It presents a comprehensive review of research efforts underway dealing with pedestrian safety and collision avoidance. The importance of pedestrian protection is emphasized in a global context, discussing the research programs and efforts in various countries. Pedestrian safety measures, including infrastructure enhancements and passive safety features in vehicles, are described, followed by a systematic description of active safety systems based on pedestrian detection using sensors in vehicle and infrastructure. The pedestrian detection approaches are classified according to various criteria such as the type and configuration of sensors, as well as the video cues and classifiers used in detection algorithms. It is noted that collision avoidance not only requires detection of pedestrians but also requires collision prediction using pedestrian dynamics and behavior analysis. Hence, this paper includes research dealing with probabilistic modeling of pedestrian behavior for predicting collisions between pedestrians and vehicles.**

Index Terms—**Active safety, computer vision, intelligent driver support, intelligent/safe vehicles, person detection and tracking.**

I. Pedestrian Safety: Significance and Problem Scope

PEDESTRIAN safety is an important problem of global dimensions. A World Health Organization report [101] describes traffic accidents as one of the major causes of death and injuries around the world, accounting for an estimated 1.2 million fatalities and 50 million injuries. In low-income countries, a large majority of deaths are not the vehicle occupants but the vulnerable road users (VRUs), consisting of pedestrians, bicyclists, two wheelers, and other small vehicles. In high-income countries, pedestrian fatalities are relatively lower but still represent large societal and economic costs to the nations. According to the World Bank website [47], pedestrians account for 65% of the fatalities out of the 1.17 million traffic-related deaths around the world, with 35% of these being children. In the United States, according to the National Highway Traffic Safety Administration report [93], there were 4641 pedestrian fatalities during 2004, which accounted for 10.9% of the total 42 636 traffic-related fatalities. In Britain, pedestrians are twice as likely to be killed in accidents as vehicle occupants [18].

In developing countries such as India and China, the problem is much worse. During 2001, there were 80 000 fatalities on Indian roads, which grew in last decade at 5% per year [82]. In fact, 60%–80% of the road fatalities are the VRUs [70], many of them from low-income groups. In China, pedestrians and bicyclists accounted for 27% and 23% of the fatalities, respectively, in 1994, compared to 13% and 2% in the United States [70]. With the rapid increase in the number of vehicles in these countries, the number of accidents and fatalities is likely to increase before they can be reduced. Furthermore, the problems faced by developing countries are often different from those faced by developed countries. In developing countries, there are a large number of two wheelers, three wheelers, bicyclists, and pedestrians sharing the same road space with cars, buses, and trucks [69], [71]. Hence, the solutions for developed countries may not all be directly applicable for developing countries. In fact, the first steps for these countries lie in improving infrastructure design and developing appropriate infrastructure-based solutions, as described in Sections II-A and C, particularly for new constructions.

Enhancing comfort and safety of the driver and the occupants of an automobile has been a major motivator in the innovations associated with Intelligent Vehicles (IVs) and Intelligent Transportation Systems (ITSs). In the United States, the Turner–Fairbank Highway Research Center, which is affiliated with the Federal Highway Administration (FHWA), conducts research on various topics related to transportation. In particular, the Pedestrian and Bicycle Safety Research Program [45] seeks to enhance the safety and mobility of pedestrians and bicyclists. The Pedsmart program [46] has the objective of applying the ITS technology to improve pedestrian safety. They have developed various devices that provide feedback to the waiting and crossing pedestrians as well as the motorists. They have also developed a software called the Pedestrian and Bicycle Crash Analysis Tool to analyze the interactions between pedestrians, bicyclists, and motor vehicles. This tool has an application for developing and testing countermeasures for enhancing pedestrian safety. The California Partners for Advanced Transit and Highways (PATH) [43] conducts research on transportation safety issues, including pedestrian protection, driver behavior modeling, and intersection collision prevention. In particular, they have

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performed research on analyzing the collision behavior at marked and unmarked crosswalks, automatic pedestrian detection systems at intersections, and LED signals to alert drivers to the presence of pedestrians.

The European Union (EU) has been conducting several projects in collaboration with industry and research institutes for IV systems in general and pedestrian safety in particular. The project PReVENT [44] deals with the development of safety technologies which help drivers prevent or mitigate the effects of an accident using sensor-based analysis of surroundings as well as the state of the driver. In particular, the subproject COMPOSE focuses on detection of pedestrians, cyclists, and other vehicles using data fusion from sensors and protection using autonomous or semiautonomous braking. The PROTECTOR project and its successor SAVE-U were particularly focused on reducing accidents involving VRUs [41]. The European project PUVAME proposes an infrastructure-based solution to prevent collisions between VRUs and transit buses. They use off-board cameras that observe intersections and bus stops to track the movement of buses as well as VRUs.

In Japan, the Ministry of Land, Infrastructure, and Transport has promoted the Advanced Safety Vehicle (ASV) project, which has spanned over three 5-year phases between 1991 and 2005 [2]. The final phase of ASV emphasized car-to-car communications in order to improve safety. Pedestrian detection was an important component of this research. Systems that warned the driver about the presence of pedestrians while making turns were demonstrated at the Tokyo Motor Show [108].

Recent conferences such as in [48] and [49] exhibit a state of the art in IV research. However, there are a very few surveys in the intelligent transportation literature specifically for pedestrian analysis. Gavrila [33] 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 [10]. We refer to these valuable surveys for earlier work on this topic. However, considerable research has been performed since then. The survey paper [32] covers not only the recent research on pedestrian detection but also describes the research on collision prediction using pedestrian dynamics and behavior analysis. Here, we expand on the survey to incorporate the most recent research in the field. We also discuss solutions for pedestrian protection, including the use of infrastructure and vehicle enhancements in addition to vehicle- and infrastructure-based sensor systems.

This paper attempts to organize ideas, issues, and approaches developed by the research community to allow better understanding of the problems and proposed solutions in the hope of providing some insights, as well as to promote accelerated growth of novel concepts to emerge out of the community. It presents important issues dealing with pedestrian safety and collision avoidance, including motivation for such research, what are the research challenges, what has been tried, a comparative discussion of different approaches, and finally, what remains to be done. This paper is organized as follows. Section II gives an overview of various ways in which pedestrian safety can be addressed, such as by improving infrastructure, passive safety systems involving vehicle design, and by active systems based on pedestrian detection and collision prediction. Section III specifically focuses on pedestrian detection approaches that are based on sensors in vehicles and infrastructure. It categorizes the methods by the types of sensors and computer-vision-based methods that are employed. Section IV describes the research on infrastructure-based traffic monitoring and surveillance, which is applicable to pedestrian detection. Detection of pedestrian is the first step in improving the pedestrian protection. For a complete system, it is necessary to predict the possibility of collision and to generate appropriate warnings for the driver or signals for the autonomous braking or maneuvering systems. Section V describes the research on predicting the possibility of collision. Section VI concludes this paper, showing directions for future work.

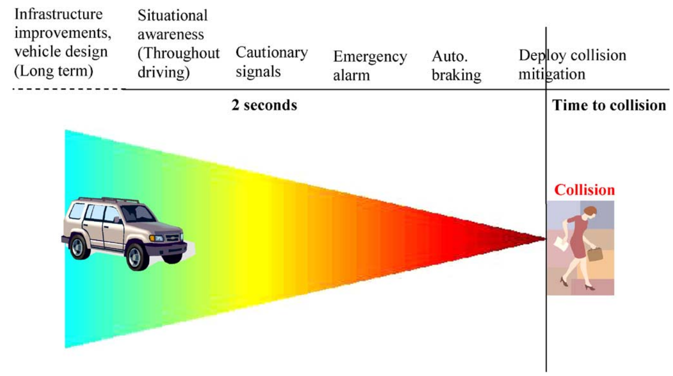

Fig. 1. Timeline of pedestrian protection measures (based on the study in [44]). The reaction time for a given distance decreases with vehicle speed.

II. Approaches for Improving Pedestrian Safety

Pedestrian safety can be improved at several stages, as shown in Fig. 1. Long-term measures include design enhancements in infrastructure as well as vehicles to reduce the fatalities. These enhancements can be complemented by systems that detect the pedestrians and prevent accidents by warning the driver or triggering autonomous braking. In the cases where an accident cannot be prevented, collision mitigation devices that are incorporated into vehicle design enhancement can be deployed to reduce the impact of the collision on the pedestrian. In this section, we briefly discuss the research conducted on these enhancements. The active safety systems involving pedestrian detection will be discussed in detail in the following sections.

A. *Infrastructure Design Enhancements*

Infrastructure enhancements to reduce pedestrian-related accidents can be divided into three categories of countermeasures: speed control, pedestrian–vehicle separation, and measures to increase visibility and conspicuity of pedestrians [77]. Reduction of speed results in fewer injuries due to the lowering of kinetic energy as well as greater reaction time (Fig. 1). The techniques for speed control include single-lane roundabouts, speed bumps, pedestrian refuge islands, and use of multiway stop signs [77]. Separation of pedestrians and vehicles can be performed by measures such as installing traffic signals, allocating exclusive time for pedestrian signals, in-pavement flashing lights to warn drivers, and automatic pedestrian detection at walking signals. Pedestrian visibility can be increased by improving roadway lighting, since a majority of pedestrian fatalities occur at night time. Since parked vehicles block the vision of drivers as well as pedestrians, removing on-street parking and implementing diagonal parking in residential streets would help in reducing accidents, especially those involving children. In [77], limited studies have been conducted on the effects of these measures, showing that more evaluations are required.

In [104], experiments comparing marked and unmarked intersections for pedestrian safety are described. For single-lane or low-density roads, there has been no significant difference between fatality rates on marked and unmarked intersections. However, multilane marked crosswalks with average daily traffic greater than around 10 000 have been observed to have greater rate of accidents than the unmarked ones, particularly for multilane crossings. A possible explanation given by them is that multilane roads with heavy traffic at high speeds are difficult to cross for many pedestrians. In such cases, the presence of marked crosswalks may be encouraging people to cross there instead of using a signal-controlled intersection, therefore increasing the number of at-risk pedestrians, particularly children and the elderly. They propose that marking intersections should be used in conjunction with other measures described above in order to increase safety. In [52], a similar conclusion is arrived at in experiments with older pedestrians. FHWA in [68] proposes flashing light warnings on pedestrian crosswalks in order to warn the drivers of the presence of pedestrians. These lights can be triggered by a button pressed by the pedestrian or an automatic detection system. Such systems are being tested on selected intersections in Virginia.

In [70], the seriousness of the accidents involving VRUs in India is discussed. The solutions proposed include putting regulators on buses, trucks, and other heavy vehicles to limit their speed, segregation of fast and slow traffic, providing safe walking and road crossing facilities, and traffic calming measures such as the use of roundabouts. Measures necessary in urban areas as well as those on highways and rural roads are specifically addressed.

B. *Passive Safety Systems Involving Vehicle Design*

The design of the vehicle has great impact on the extent of injury that a pedestrian sustains in case of a collision. In [18], the anatomy of a collision between a pedestrian and a vehicle is described in detail. In the case of small vehicles where the impact takes place below the pedestrian's center of gravity, the person falls and slides over the bumper, possibly with the head hitting the windshield or the windshield frame. Most of the injuries take place in lower limbs, whereas most of the fatal injuries are head injuries. In order to minimize the effect of these injuries, various collision-absorbing components such as compliant bumpers, pop-up bonnets, and windscreen airbags are suggested. Ford and Volvo research laboratories have developed the use a finite element model of a pedestrian to simulate accidents [51]. Such models help in predicting the effects of collision and in improving the vehicle design to minimize these effects. In [50], the concepts of structural hood design are described to make it compatible with pedestrian safety. It shows the effect of hood and hinge design parameters on head impact and acceleration in order to optimize the parameters. The EU has recently mandated the incorporation of pedestrian safety systems in cars in two phases (2005 and 2010).

In [40], an active hood has been designed, which automatically rises in case of collision with pedestrian, so that the surface that comes in contact with the head is deformable and flexible instead of hard and rigid. They have also developed a pair of airbags at the windshield pillar to prevent impact of windshield on the head. It is claimed that their pedestrian protection system can reduce risk of life-threatening injuries to 15% from nearly 100% for a collision at 40 km/h, which is enough to satisfy the EU requirement. According to the study in [20], pedestrian airbags can reduce head injuries by 90% and upper body injuries by 50%.

In India and other developing nations, collisions with heavy vehicles such as buses and trucks are the major cause of pedestrian fatalities. The differences between the kinematics of collision due to light and heavy vehicles are described in [70]. It is observed that collisions with heavy vehicles result in more serious chest, arm, and head injuries but less serious pelvic and leg injuries. In order to reduce these injuries, design changes for the fronts of bus and truck bodies are proposed. It is also proposed that truck bodies should be integrated with the chassis, and manufacturing should also be shifted from the local body builders to manufacturers where safety standards can be more effectively imposed.

C. *Active Safety Systems Based on Pedestrian Detection*

Considerable research is being conducted by various groups for designing pedestrian detection systems. Such systems can employ various types of sensors and computer vision algorithms in order to detect pedestrians and to predict the possibility of collisions. The output of the systems can be used to generate appropriate warnings for the driver or to perform autonomous braking or maneuvering in the case of an imminent collision.

Vehicle-mounted sensors are useful in detecting pedestrians and other objects on the road. However, 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 have systems with sensors in the infrastructure, which would perform monitoring of traffic and send appropriate signals to the vehicle through wireless communication channels. 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.

Infrastructure-based systems are particularly useful for transit buses that make frequent stops at designated bus stops with a large concentration of pedestrians. Such systems can monitor the pedestrians near bus stops and intersections along the bus routes and send warnings to the bus drivers in case of dangerous situations. Various sensors and approaches that are used for pedestrian detection for transit bus applications are discussed in [15]. An integrated vehicle–infrastructure system is proposed for pedestrian protection that uses wireless communications. The European project PUVAME proposes an infrastructure-based solution to prevent collisions between VRUs and transit buses. They use off-board cameras that observe intersections and bus stops to track the movement of buses as well as VRUs. Occupancy grids [19] over the ground plane are used to integrate several sensors in the same probabilistic framework. The risk of collision is computed based on the time to closest approach and the closest point of approach.

Pedestrian crossings at unprotected left turns are a serious cause of accidents. On such turns, the drivers turning left are supposed to yield to the vehicles approaching from opposite directions as well as the crossing pedestrians. In [8], the design of a system is proposed that detects these conflicts and warns the left-turning driver if there is insufficient time to make the turn. It is observed [16] that the presence of pedestrians produces significant increase on turning time as well as buffer with oncoming vehicles. Thus, it is helpful to complement the warning system with an infrastructure-based pedestrian detection system in order to adjust the warning thresholds when pedestrians are present.

In countries such as India and China, there has recently been a large amount of road construction and other transportation infrastructure. There is an urgent need to develop infrastructure-based solutions in these roads, since it would be easier and more efficient to build these systems along with the roads rather than to retrofit them at a later stage.

For effective enhancement of driver safety, vehicle as well as infrastructure-based system should have the perception of complete surroundings, including the events taking place in the front, back, and sides of the car. In [31], the importance of such a "Dynamic Panoramic Surround" (DPS) map is emphasized, and a novel approach for generating the DPS using a pair of omnidirectional cameras on the vehicle is proposed. The technical report [81] for California PATH program has defined a similar concept for infrastructure-based systems, which is called the Dynamic State Map, which plots the dynamic information at the intersection, including the traffic signal state, vehicles approaching the intersection, and local environmental conditions. They discuss the communications requirements in three scenarios: 1) rural intersection with low-density high-speed traffic; 2) suburban intersection at high-speed arterials; and 3) high-density low-speed gridlocked urban intersection.

Thus, it is seen that pedestrian safety can be improved using a variety of approaches. Infrastructure enhancements can be employed at selected places where there is high incidence of pedestrian accidents. Vehicle body modifications could be enforced by the government to improve pedestrian safety. The sensor-based vehicle systems may be initially introduced in luxury vehicles and, once the technology becomes affordable, could be mandated by the Government. Infrastructure-based sensors and detection systems can be deployed in dangerous zones. They could communicate with the vehicle-based systems so that the vehicles can obtain a complete picture of the scene and make proper judgments. In the following sections, we focus on the research conducted in vehicle and infrastructure-based systems for pedestrian detection.

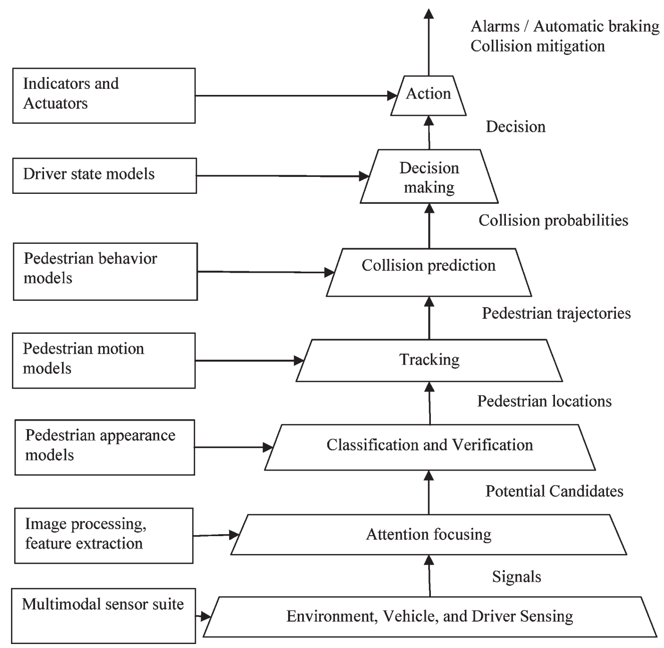

Fig. 2. Vehicle and infrastructure-based pedestrian detection. Data flow diagram showing distillation of information from raw signals up to appropriate action.

III. Pedestrian Detection for Active Safety Systems

Fig. 2 shows the information flow in a general pedestrian protection system that uses vehicle-based sensors. The processing is organized as a pyramid, with base having large quantity of raw signal data. As one climbs up the pyramid, the useful information is distilled in successive stages, until finally, one takes action based on a yes/no decision. The preprocessing or attention focusing stage processes raw data using simple cues and fast algorithms to identify potential pedestrian candidates. This stage needs to have high detection rate even at the expense of allowing false alarms. The classification and verification stage then applies more complex algorithms to the candidates from the attention focusing stage in order to separate genuine pedestrians from false alarms. However, the line between these stages is often blurred, and some approaches combine the detection and recognition stages into one. The detected pedestrians are tracked overtime to get trajectories. These trajectories can then be sent to collision prediction module that would predict the probability of collision between the host vehicle and pedestrians. In the case of high probability of collision, the driver is given an appropriate warning that enables corrective action. If the collision is imminent, the automatic safety systems could also be triggered to decelerate the vehicle and reduce the impact of the collision. A similar scheme can also be used for infrastructure-mounted sensors which can detect vehicles and pedestrians, compute the possibility of collisions between vehicles and pedestrians, and send warning signals to the vehicles using wireless communications. Pedestrian detection approaches can be grouped in various ways, as shown in Table I and described below.

TABLE I
TAXONOMY OF PEDESTRIAN PROTECTION APPROACHES

A. Infrastructure design enhancements
  a. Speed control [70][77]
  b. Pedestrian vehicle segregation [70][77]
  c. Improving visibility [68][77]
B. Passive safety systems involving vehicle design
  a. Vehicle front design [51][70]
  b. Collision absorbing components [18]
C. Active safety systems based on pedestrian detection
  a. Types of sensors
    i. Visible light imaging [1][11][17] [23][26][30][34][35][36][37][38][39] [61][67][72][74][79][84][85][88][89][91][99][103][105][106]
    ii. Infrared imaging [3][9][11][14][21][22][59][60][62][64][65][78][86][97][102]
    iii. Time of flight sensors [24][27][28][29][42][64][67][78][84][89][92]
    iv. Multiple types of sensors [11] [53][54][55][64] [67][78] [84] [89]
  b. Sensor placement and configurations
    i. Monocular [1][17][23][37][38][67][74][78][79][88][89][91][99][103][105]
    ii. Stereo [11][30][34][36][39][53][54][55][60] [61][83][85][97] [102] [106]
    iii. Infrastructure based [56][58][75] [98]
  c. Video cues for pedestrian extraction
    i. Shape/Appearance [1] [3][9] [14] [17] [21] [34] [36][37][38][39][61] [62][65][67][74][79][88][91][99][102][103]
    ii. Motion [1] [23] [37][38] [60][61] [79][84] [92] [97] [99] [102]
    iii. Depth (stereo, time-of-flight) [24] [27] [28][29] [30][34] [36][39] [42] [53][54][55][60] [61] [67][78][79] [83] [84][85] [89] [92][97] [102] [106]
  d. Classifiers for pedestrian discrimination
    i. Support Vector Machines (SVM) [3][9][17][36] [72][74][83][86][87][88] [91][103]
    ii. Neural Networks (NN) [1] [34] [72][89] [106]
    iii. AdaBoost [1][99]
    iv. Statistical Learning [103]
    v. Cascade of classifiers [1] [99] [103]
D. Collision prediction
  a. Simple collision geometry [7][25] [56] [97]
  b. Modeling pedestrian motion [1] [4][5][6] [100]
  c. Pedestrian orientation prediction [80]
  d. Learning of pedestrian paths [57] [63]
  e. Modeling crowd behavior [73]

TABLE II
COMPARISON BETWEEN DIFFERENT SENSOR MODALITIES FOR PEDESTRIAN DETECTION

Sensor type	Field of view	Angular resolution	Detection range	Range resolution	Illumination	Hardware cost	Algorithmic complexity
Rectilinear camera	Med.	Med./High	Low/Med.	Med.	Passive reflective, needs ambient light	Low	High
Omni camera	Large	Low/Med.	Low	Low	Passive reflective, needs ambient light	Med.	High
Near IR	Med.	Med./High	Med.	Med.	Active, works in dark	Low	High
Thermal IR	Med.	Low/Med.	Low/Med	Low	Emissive, works in dark	High	Med.
PMD sensor	Med.	Low	Med.	Low/Med.	Modulated light source	Med.	Med.
RADAR	Small	Low	High	High	Active, works in dark, rain, fog.	Med.	Low
LASER scanner	Large	Med.	Med.	High	Active, works in dark	High	Low

A. Sensor Modalities

Various types of sensors have been employed for vehicle as well as infrastructure-based pedestrian detection systems. Commonly used sensors for detecting pedestrians are imaging sensors in various configurations using visible light and infrared (IR) radiation, as well as the "time-of-flight" sensors such as RADARs and LASER scanners. Imaging sensors can capture a high-resolution perspective view 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,

TABLE III
PEDESTRIAN DETECTION USING VISIBLE LIGHT CAMERAS

Publication	Sensor(s), Configuration	Attention Focussing Stage	Classification/Verification Stage
Abramson IV04 [1]	Visible light, monocular	Detection of diagonal legs, motion, and vertical edges.	Cascaded AdaBoost on 5x5 subimages. Classifier selection using genetic algorithm.
Cheng IV05 [17]	Visible light, monocular		SVM on Sparse Gabor filters.
Gandhi ICIP05 [30]	Visible light, stereo omnicam	Stereo disparity clustering to detect nearby objects.	
Gavrila IV04 [34], IJCV07 [35]	Visible light, stereo	Stereo based depth segmentation, chamfer matching.	Texture classification with NN, stereo based verification.
Grubb IV04 [36]	Visible light, stereo	Stereo disparity based segmentation to obtain bounding boxes.	SVM, temporal integration.
Hashiyama C-SMC03 [37]	Visible light, monocular	Motion compensated background subtraction to detect independent motion.	Contour matching using distance transform.
Havasi ICIG04 [38]	Visible light, monocular	Symmetry of legs.	Temporal tracking and classification of traces.
Hilario 05 [39]	Visible light, trinocular stereo	Stereo disparity, high vertical symmetry.	Active contour model applied to output of previous stage. Stereo depth guides contour fitting.
Lombardi IV04 [61]	Visible light, stereo	Models contextual evolution of scene parameters using HMM. Chooses appropriate algorithms based on context.	
Papageorgiou IJCV00 [74]	Visible light, monocular	Can add motion/stereo modules for preprocessing	SVM classifier on Haar wavelet features
Shashua IV04 [79]	Visible light, monocular	Texture and perspective constraints to identify candidates.	Simple classifier on candidate subregions, Ada-Boost for combining, motion, gait, parallax, consistency.
Sotelo ITSC06 [83]	Visible light, stereo	Obtains sparse 3-D representation of interesting points, selects candidate bounding boxes based on subtractive clustering method.	Employs 2 stage SVM, with first stage recognizing body parts and second stage integrates the outputs to verify pedestrian.
Suard IV05 [85]	Visible light, stereo	Disparity analysis.	Normalized cuts on monocular as well as stereo disparity images to segment pedestrians from other features.
Szarvas IV05 [88]	Visible light, monocular		Convolutional Neural Network (CNN) on raw subimages.
Tian ICIG04 [91]	Visible light, monocular night time videos	Features of brightness, size, shape, position based detection.	SVM based classifier for shape analysis.
Viola ICCV03 [99]	Visible light, monocular		Adaboost on Haar-like motion and shape features.
Xu IV06 [103]	Visible light, monocular		Statistical learning on shape and motion features [99]. SVM on Haar-like feature subset from statistical learning step.
Zhang CVPR06 [105]	Visible light, monocular	Ego-motion estimation using sparse optical flow. Uses FOE to separate independently moving objects.	
Zhao ITS00 [106]	Visible light, stereo	Blob segmentation using disparity discontinuity. Filtering by size/shape constraints.	Neural network with intensity gradient features.

and their fusion is expected to result in more robust detection. Table II gives a comparison of various types of sensors that are used for pedestrian detection.

It is a marvel that the human visual system can process vast amount of data from the scene and extract information in real time that enables driving. Video sensors would therefore be a natural choice for intelligent driver support systems. Various approaches for detecting pedestrians in visible light images are shown in Table III. The video camera technology is mature and cost effective. However, processing of video data to extract useful information is a complex task. In particular, separating objects from background clutter is a difficult problem in computer vision. Furthermore, visible light becomes less effective during dark conditions. Thermal IR sensors are sensitive to the radiation emitted by the human body and, hence, are very effective for detection of pedestrians, particularly at night. Although these sensors are expensive at present, the costs have been decreasing, and 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 IR image. However, thermal imaging is less effective in hot daytime conditions where there is less temperature difference between the pedestrians and the background. Another type of sensor that can be useful for night

TABLE IV
PEDESTRIAN DETECTION USING NONVISIBLE LIGHT AND TIME-TO-FLIGHT SENSORS

Publication	Sensors	Attention focusing stage	Classification/Verification stage
Andreone ISPA05 [3], Bellotti IV04 [9]	NIR cameras, synchronized LASER illuminators	Pixel level correlation between image windows and pedestrian models to discard non-pedestrian areas.	Haar wavelets features and separate SVMs for frontal and lateral pedestrians.
Broggi IV04 [14]	FIR	Find warm symmetric objects with specific size and aspect ratio.	Match 3-D models based on shape and thermal characteristics.
Fang VT04 [22]	FIR	Shape independent detection using projection profiles.	Classification based on multi-D histogram, intertia, contrast features.
Fardi IV06 [23]	Infrared	Human motion features such as moments and power spectrum used to identify pedestrians.	
Fardi IV06 [24]	Photonic Mixer Device (PMD)	Image processing to detect objects.	
Fuerstenberg ITSC01 [27]	LASER scanner	Raw data is clustered into objects based on range discontinuities and tracked over time.	The objects are classified using models of the object outlines and dynamic behavior.
Fuerstenberg IV02 [28], ITSC05 [29]	Multi-layer LASER scanner	Detects objects by grouping the measurements that are near each other in 3D space, tracks them with Kalman filter.	Similar to [27]. The system also warns the driver or activates ABS in case of imminent collision.
Linzmeier IV05 [59]	FIR thermopile sensors	Hot-spot detection to identify candidates.	Dempster-Schafer based fusion for verification.
Liu VT04 [60]	FIR, stereo	Motion and stereo based detection of independently moving objects.	
Mählisch IV05 [62]	FIR		Uses chamfer based contour matching, cascade classification, and HPN network combined in particle filtering framework.
Meis IV04 [65]	FIR	Identify ROIs by simple pixel classification.	
Suard IV06 [86]	FIR		SVM classifier on histograms of oriented gradients.
Sun ICIG04 [87]	NIR	Shape representation based on polar coordinates to remove regularly shaped objects such as road signs.	SVM on reduced dimensional space to remove headlights, Probabilistic matching with 2D human model for final recognition.
Tsuji ITS02 [97]	FIR, stereo	Brightness thresholding, stereo correspondence, motion estimation, collision judgement.	
Xu ITS05 [102]	FIR , stereo	Detect hotspots as potential pedestrian candidates.	SVM based classifiers detect pedestrians. Kalman and mean shift filters used for tracking.

vision is a near-IR sensor accompanied by an illuminator. As of now, such systems are less expensive than thermal IR sensors, and they have been used for surveillance applications. In fact, an ordinary black-and-white charge-coupled device (CCD) camera is sensitive to the near-IR spectrum and can be used in these systems. Unlike thermal IR, these sensors produce images that resemble visible light images. Hence, image processing techniques that are developed for monochrome visible light images can be easily modified for analysis with these images. They also have higher resolution for comparable field of view (FOV) due to larger number of pixels in the CCD compared to thermal cameras. Table IV shows various systems that use thermal or near IR for performing pedestrian detection.

The imaging sensors give a 2-D perspective projection of the 3-D scene, losing the depth information in the process. Although binocular stereo can recover depth information, it needs the solution of the difficult and often ambiguous correspondence problem of matching significant features between the images. The time-of-flight sensors, such as RADARs and LASER scanners, directly give accurate depth information by measuring the time it takes for the emitted rays to return to the sensor. Pedestrian detection using time-of-flight sensors is shown in Table V. RADAR sensors use electromagnetic energy in the microwave region in order to measure the distance to the objects. In order to localize objects in azimuthal dimension, multibeam RADARs are often employed in vehicular applications. RADAR-based adaptive cruise control that maintains a distance to the lead vehicle has been introduced in luxury vehicles over the past few years. LASER scanners have recently invoked considerable interest in the IV community for detection, tracking, and classification of road users. A LASER scanner consists of a pulsed LASER transmitter, a receiver, and a mirror rotating around the vertical axis. The mirror reflects the LASER pulse in order to direct it at any azimuth angle in the horizontal plane. The scanner therefore generates a range map of a horizontal section of the scene called scanning plane,

TABLE V
PEDESTRIAN DETECTION USING MULTIPLE SENSORS

Publication	Sensors	Attention Focusing Stage	Classification/Verification Stage
Bertozzi IV06 [11]	Visible light and IR	Uses stereo pairs of visible light and IR. Performs separate disparity analysis for each modality.	Fuses the disparity results together to extract pedestrians.
Fang IV03 [21]	Visible, FIR comparison	ROI extraction based on depth, symmetry, background similarity, shape/size constraint, and temperature.	
Milch [67]	RADAR, mono vision	Target-list is generated using RADAR.	Candidates verified by vision using flexible shape models trained from manually extracted pedestrians.
Scheunert IV04 [78]	FIR, LASER scanner	LASER scanner detection using range discontinuities. IR detection of regions with high brightness and vertical orientation.	Uses Kalman filter for sensor fusion.
Steinfeld ITSC04 [84]	Cameras, LASER scanners, RADAR	Time-of-flight, video based detection, LASER based triangulation. Combines outputs from number of sensors to create a map.	Generates multiple levels of warnings from front and side components, such as for passing and cutting in. LASER line generator used for curb detector.
Szarvas IV06 [89]	LIDAR, visible light	LIDAR used to create range map that is used to identify image locations and scale to search pedestrians.	Convolutional neural network used for image-based feature extraction and classification.
Töns IV04 [92]	RADAR (5-beam), visible light, IR	Detects and fuses targets from RADAR beams with visible light and IR sensors.	The targets are classified in imaging sensors and tracked over time.

providing as outputs the range and reflectivity data at a number of azimuth angle samples. However, in the case of vehicles, pitching and road curvature would not always keep the scanning plane parallel to the road, therefore missing actual obstacles or detecting the road as an obstacle. Multilayer laser scanners have been designed to solve this problem. For example, the Automotive Multi-Layer LASER scanner ALASCA designed by IBEO uses four beams in order to cover the road scene. Currently, LASER scanner technology is very expensive, but mass production could make it economically viable for vehicles. According to IBEO, it may be possible to introduce initial application of LASER scanner as early as 2008 [12]. In [24], a novel 3-D sensor system using photonic mixer device is proposed. This system contains a 64×16 CCD camera with LED light sources emitting a modulated IR signal. The sensor calculates the object distance by measuring the phase difference between the transmitted and the reflected signals. Thus, a distance and amplitude images are created, which are used by the image processing step to identify the pedestrians.

Every sensor has its advantages and limitations. In order to enhance the advantages and overcome the limitations, one can use a combination of multiple sensors that give complementary information. For example, the day-time capabilities of visible light sensors could be combined with night-time capabilities of IR sensors. Higher resolution of imaging sensors could be combined with range information at low angular resolution from time-of-flight sensors to obtain 3-D information at higher resolution. Systems using multiple sensors are also shown in Table V.

B. Sensor Placement and Configurations

The number and configuration of sensors are important in ensuring successful detection of pedestrians. Monocular imaging systems are less expensive and simpler to set up. However, obtaining a 3-D information from monocular cameras is often

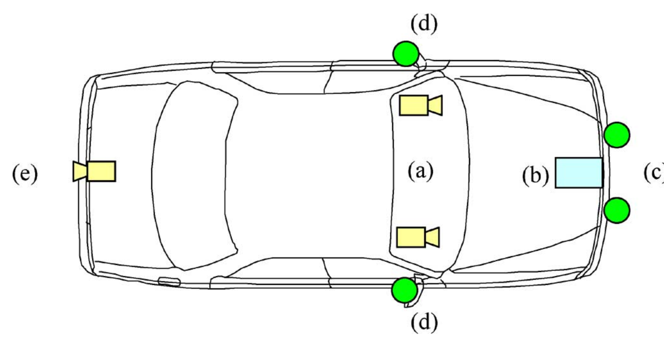

Fig. 3. Sensor configurations for detecting pedestrians and other objects. (a) Wide baseline stereo for distant objects. (b) RADAR for distance measurement in narrow FOV. (c) Narrow baseline wide FOV (omni) stereo pair for near objects. (d) Omnicameras to monitor blind spots. (e) Monocular reverse camera.

an ill-posed problem. Binocular stereo can be used to obtain depths of scene points that are based on disparity between images obtained from two cameras. The depth information offers valuable cues for separating pedestrians from background and for performing accurate 3-D localization of pedestrians in the scene. Narrow baseline stereo made from cameras that are mounted on a single rigid frame simplifies the problem of disparity computation, since the calibration between the cameras remains fixed. Hardware computation of disparity and 3-D structure is commercially available. However, narrow baseline systems are not effective in estimating distance to far objects. In such cases, wide baseline systems with cameras mounted independently are necessary. Due to relative vibrations between the cameras, dynamic calibration between the cameras is often required when the vehicle is moving. Stereo using more than two cameras can increase the robustness of range estimation at increased cost and hardware complexity.

Various configurations for mounting sensors are shown in Fig. 3. Sensors mounted in front are used for detecting pedestrians ahead of the vehicle. On the other hand, side-mounted

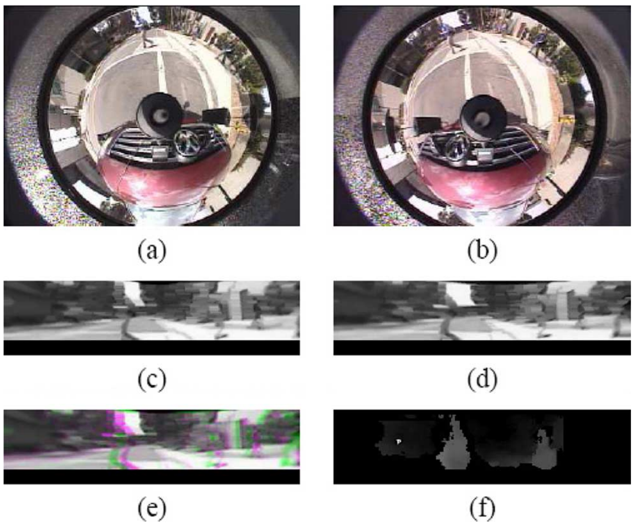

Fig. 4. (a) and (b) Images taken from stereo omnicameras in front of the vehicle. (c) and (d) Rectified perspective virtual views generated from the two omnicameras. The epipolar lines are along the rows of both the cameras. (e) Combined image. (f) Disparity map with pedestrians having large disparities [30].

sensors cover blind spots. Reverse cameras can be particularly useful for preventing accidents during backup. Omnidirectional cameras that get a panoramic view of the surroundings can be useful in continuously tracking the pedestrians moving from one side to the other. In [30], a pair of omnicameras is mounted in front of the vehicle, as shown in Fig. 4. The omni-images are rectified to get virtual front views. Disparity analysis is applied, and the blobs having large disparities are signaled as obstacles. Further analysis can be performed to distinguish between pedestrians, vehicles, and other obstacles. RADARs are often mounted in front of the vehicle to estimate the distance to the pedestrians. LASER scanners have a wide FOV and can be mounted in front or sides to observe ahead of the vehicle as well as in blind spots.

Sensors can be mounted on vehicles or embedded within the infrastructure. Vehicle-mounted sensors are very useful in detecting pedestrians and other vehicles around the host vehicle. However, they often cannot see dangerous objects that are occluded by other vehicles or stationary structures. Sensors mounted in infrastructure would be able to see many of these objects and help to get a much better view of the entire scene from top. Furthermore, detection of moving objects from stationary platform is much simpler than detection from vehicle since the background is not moving. In the case of infrastructure-based systems, a single camera has a limited FOV of the scene. Hence, systems with multiple nonoverlapping cameras have been used for tracking vehicles and pedestrians over large areas. On the other hand, multiple overlapping cameras form a wide baseline stereo that obtains views of the scene from different directions. This helps in resolving occlusions, particularly in crowded scenes and determining accurate location of people using triangulation.

If vehicles can communicate with each other and the infrastructure, they can exchange information about objects. Hence, infrastructure-based scene analysis as well as infrastructure–vehicle and vehicle–vehicle communications have the potential to contribute toward robust and effective working of ITSs.

C. Video Cues for Pedestrian Detection

In the case of imaging sensors, the shape and appearance of the pedestrians can be used to separate them from the background. For this purpose, characteristic features are extracted from images, and a trained classifier is used to separate pedestrian from the background and other objects. Some of the features used for appearance-based detection are raw subimages [88], size and aspect ratio of bounding boxes [14], Haar wavelets [74], Gabor filter outputs [17], symmetry [14], [38], intensity gradients [106] and their histograms [86], and active contours [39]. In [99], texture information is extracted using simple masks, and classification is performed based on integrating the weak classifiers obtained from these masks. In thermal IR images, pedestrians that are warmer than the background form hot spots, which are used for detection, as in [102]. In [22], features based on histogram, inertia, and contrast are used to distinguish pedestrians.

Motion is also an important cue in detecting pedestrians. In the case of stationary infrastructure-based cameras, background subtraction is used to separate moving objects from static background. However, in the case of moving platforms, the background undergoes ego-motion that depends on the camera motion as well as the scene structure. For laterally moving pedestrians, it is usually feasible to separate the pedestrian motion from ego-motion. However, for longitudinally moving pedestrians, the image motion is parallel to the ego-motion and, therefore, difficult to separate. The vehicle ego-motion can be split into rotation and translation. Rotational motion in video does not depend on the distance of the scene feature and is sometimes neglected [60], [105] or compensated for using gyrosensors [37]. The translational motion is inversely proportional to the distance to the scene and, hence, can be used in determining the scene structure. In the absence of rotational motion, the image motion vectors converge at a single point in the image called the focus of expansion (FOE). In [105], ego-motion estimation is performed using sparse optical flow at corner-like features. Motion of outliers corresponding to independently moving objects do not pass through FOE and are clustered using region-growing segmentation on the residual image. In [60], a two-stage stereo correspondence and motion-detection procedure is developed to distinguish an object motion that is inconsistent with the background. This procedure does not need explicit ego-motion computation. Motion information can also be combined with texture information, as in [99]. An extremely efficient representation of image motion is developed based on five types of shifted image differences.

Features characteristic to periodicity of human body motion which is within a frequency range are useful in detecting pedestrians and separating them from other moving and stationary objects. Spatial motion distribution represented by moment features [23], power spectral distribution of the motion time series [23], symmetry characteristics of the legs [38], and gait

TABLE VI
CLASSIFIERS USED FOR PEDESTRIAN DETECTION

Classifier	Mechanism	Examples
Support Vector Machine (SVM)	Finds a hyperplane decision boundary based on maximizing the minimum separation between classes. Can be generalized to find non-linear boundaries by the use of kernel functions.	Cheng IV05 [17], Munder PAMI06 [72], Papageorgiou IJCV00 [74], Sotelo ITSC06 [83], Suard IV06 [86], Xu ITS05 [102]
Artificial Neural Networks (NN)	Uses multiple layers of ëneuronsí to obtain highly non-linear decision boundaries between classes. Variations such as LRF, CNN reduce degrees of freedom in neural networks and enable training from fewer samples.	Gavrila IV04 [34], Munder PAMI06 [72], Szarvas IV05 [88], Zhao ITS00 [106]
Adaboost	Combines a number of weak classifiers into strong classifier using weighted averaging. Weights are iteratively learned based on mis-classified samples.	Viola ICCV03 [99]
Classifier cascade	Optimizes performance and speed by combining multiple classifiers by feeding output of fast but less discriminative classifier to the input of slow but more discriminative classifier.	Xu IV06 [103]

patterns [79] are some of the cues used to detect and verify pedestrian candidates.

Stereo cameras as well as time-of-flight sensors return information from which the distance of the object from the camera can be computed. This information is very useful for disambiguating pedestrians from background, handling occlusion between pedestrians, and eliminating extraneous features based on the image size. Disparity discontinuities can be used to aid segmentation, as in [34] and [106], to divide the image of the scene into layers. In [39], stereo is used to guide the active contour model for pedestrians.

LASER scanners output radial distance at discrete azimuth angles in the scanning plane. These data are clustered into objects based on range discontinuities [27] and grouping measurements near each other in the 3-D space [28], [29]. The objects are tracked and classified into number of classes using models of object outlines and their dynamic behavior. The system also warns the driver or activates automatic braking in case of imminent collision.

D. *Classifiers for Pedestrian Discrimination*

Various types of classifiers have been employed to distinguish pedestrians from nonpedestrian objects. The input to the classifier is a vector of raw pixel values or features extracted from them, and the output is the decision showing whether the object is detected or not. In many cases, the confidence values are also returned. The classifiers are usually trained using a number of positive and negative examples to determine the decision boundary between them. After training, the classifier processes unknown samples and decides the presence or absence of the object based on which side of the decision boundary the feature vector lies. Some of the classifiers that are used for pedestrian detection are the following: support vector machines (SVMs), various types of neural networks, and statistical learning classifiers such as AdaBoost, as shown in Table VI.

SVMs form a hyperplane decision boundary by maximizing the "margin," i.e., the separation between the nearest samples on two sides of the boundary. They are used for pedestrian detection in conjunction with features such as Haar wavelets [74], sparse Gabor filters [17], image regions corresponding to hot spots in thermal IR images [102], and histograms of oriented gradients [86].

A neural network can obtain highly nonlinear boundaries between classes based on the training samples given to it from each class and, therefore, can account for large-shape variations [106]. In [106], neural networks are used on intensity gradient-based features to recognize pedestrians. In [34], a neural network with local receptive fields (LRFs) and shared weights is used to perform texture-based verification of pedestrians. LRF and shared weights reduce the degrees of freedom of the neural network and therefore allow training to be carried out with fewer samples. In [88], a convolutional neural network (CNN) classifier, which is similar to the LRF [34], is used to automatically learn appropriate features and obtain improved detection performance. A fivefold improvement in false alarm rate is claimed over the SVM classifier which used Haar-wavelet features.

AdaBoost is a method to combine several weak classifiers into a strong classifier using a weighted sum whose weights are iteratively learned from the samples misclassified by the current classifier. This is often used in the form of a cascade of classifiers of increasing complexity. In [99], AdaBoost and cascading are used with appearance and motion features to identify pedestrians. Cascade classifiers are also used in [103], where a statistical learning classifier quickly identifies candidates and the more complex SVM-based classifier checks for genuine targets.

In [72], an elaborate experimental study of pedestrian detection is performed, comparing the use of various features (PCA coefficients, Haar wavelets, and LRFs) and classifiers (feed-forward neural network, SVM, and the baseline of k-nearest neighbor). It is observed that LRFs combined with SVM give best performance in terms of rates of detection and false alarms. The publication also establishes a public benchmark dataset for pedestrian classification, which is downloadable from the web. In [83], a two-stage classifier based on SVM is used to detect pedestrians. The first stage is trained to detect parts of the body such as head, torso, and legs. The second stage integrates the

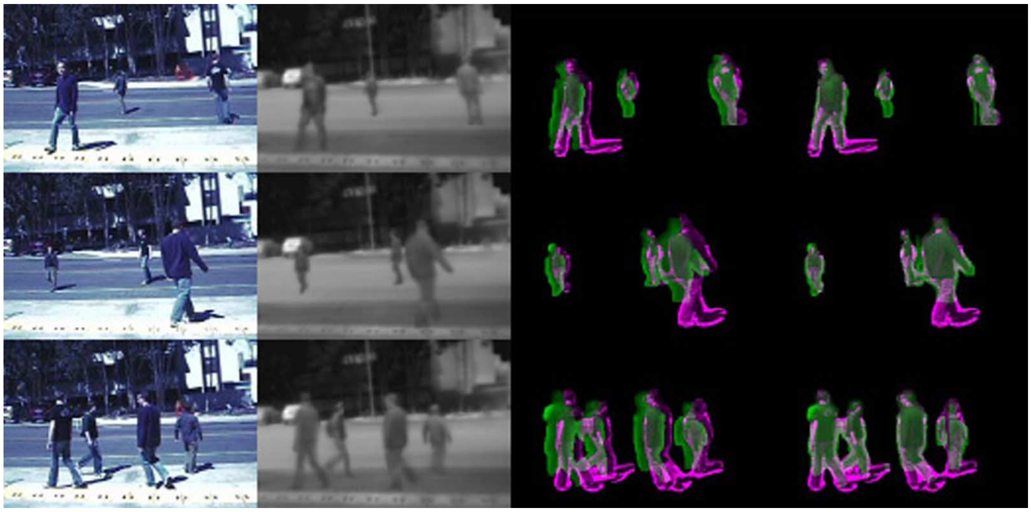

Fig. 5. Stereo registration between visible light and thermal images (a) input color image, (b) input thermal IR image, (c) unaligned overlay of color and IR foregrounds before registration, and (d) aligned overlay of color and IR foreground after registration [53].

outputs of the first stage to verify pedestrian presence. The two-stage classifier helps to handle occlusions as well as body pose variations.

E. Sensor Fusion

Fusion of multiple sensors is used in many systems to improve the performance of pedestrian detection (also see Table V). Sensor fusion can be performed using sequential or parallel configuration. In sequential configuration, one sensor such as RADAR or LASER scanner is used in the attention focusing stage to detect potential candidates. These candidates are projected onto the imaging sensor into areas of interest where the target presence is verified. On the other hand, in parallel configuration, inputs from multiple sensors are processed independently and then fused using a decision mechanism. The sequential and parallel approaches can also be combined in multisensor systems.

In [67], a sequential fusion of RADAR and monocular vision sensors is performed. The first step generates a list of potential targets using RADAR. The second step uses the images from the vision sensor to verify the targets using flexible shape models that are trained from manually extracted pedestrians. In [89], a sequential combination of LIDAR-based object detector and an image-based classifier using CNN is used. The former gives a coarse resolution range image over its FOV, which is used to create a 3-D map with candidate object positions. This map is projected into the image in order to identify the locations and scale to search for pedestrians in the image.

In [78], a combination of far IR sensors and LASER scanner is used in parallel in order to obtain robust detection and accurate localization of pedestrians. 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 IR 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. In [11], the "tetra-vision" system that combines stereo pairs of visible light and IR cameras is described. Disparity analysis is performed separately for each stereo pair, and the results are fused together. This processing removes the background and gives a list of candidates that are compatible with the size and shape of pedestrians.

In [84], a side collision warning system for transit buses is described, illustrating the use of multiple sensors in order to cover the surroundings of the vehicle. The sensors used include a pair of front-mounted cameras, RADAR, a LASER scanner, and a curb detector, as well as LASER scanners and blind spot cameras on sides. Multiple levels of warnings are generated for both front and side components. The system handles threats that span multiple views, such as passing and cutting in of a vehicle. The system architecture is designed to be flexible, which is composed of modules such as object tracker, warning generator, and data logger, which can be developed individually and plugged in to the overall system. Detection and tracking is performed from the LASER scanner. The curb detector consists of a LASER line generator and a camera separated by a known distance. The distance to the sidewalk edges can be computed by triangulation.

An important issue in multisensor fusion is the registration of images from each sensor. A survey of registration methods is presented in [107]. Recently, in [53], a novel approach is proposed for registration of thermal IR with visible light imagery for pedestrian detection using maximization of mutual entropy (Fig. 5). Unlike many other registration approaches that assume global model for alignment, this approach uses stereo disparities of individual persons, which are detected and tracked in both images in order to obtain the 3-D locations of the persons. In [54] and [55], a detailed comparative analysis of stereo approaches using color, IR, and their combination is described. A four-camera testbed consisting of two color and two IR cameras is used to analyze various configurations including as follows: 1) visible light binocular stereo; 2) thermal IR stereo;

3) multimodal trifocal stereo using two color cameras and one thermal camera, and 4) cross-spectral stereo with one color and one thermal camera. It is concluded that the multimodal trifocal stereo approach gives benefits of multimodality and robustness. On the other hand, the cross-spectral stereo is potentially the more cost-effective solution, but obtaining robust registration between two modalities is still a challenging problem.

F. Representative Systems for Pedestrian Protection

The European Commission funded projects PROTECTOR (preventive safety for unprotected road user) and its extension SAVE-U (sensors and system architecture for VRUs protection) were established for developing systems for enhancing pedestrian safety. Two car manufacturers Volkswagen and DaimlerChrysler had worked on this project to develop pedestrian protection systems.

The DaimlerChrysler's research system is described in [35], which builds on their earlier research in [34]. This system combines pedestrian detection, trajectory estimation, risk assessment, and driver warning. It uses a pair of visible light sensors in stereo configuration and combines multiple algorithmic stages to dramatically reduce the false alarm rate while keeping reasonably high detection rate. The system consists of the following modules.

1) Stereo Preprocessing: This is the attention focusing stage that is based on the study in [26], which computes the depth map and divides it into N discrete layers. These are scanned using windows of appropriate sizes to obtain regions of interest where pedestrians are likely.
2) Chamfer matching: The distance transform of original image is formed, and pedestrian templates are matched in a hierarchical coarse-to-fine manner to efficiently lock into desired objects.
3) Texture classification: This stage uses a neural network with LRFs on image patches as inputs to verify the Chamfer system detections. This particular approach was chosen based on evaluations in [72].
4) Stereo verification: This stage filters out false detections using dense cross correlation between left and right images in disparity search range.
5) Tracking: A simple α–β tracker is used on 2.5-D bounding boxes of the objects in order to improve reliability of the detection results.
6) Risk assessment and driver warning: Estimates the risk for each pedestrian based on the position and time to collision and gives a warning alarm when the risk exceeds a certain limit.

Special attention is paid to the integration of modules to incorporate as much information as possible from the previous module into the next module. Performance of individual modules is characterized using receiver operating curves (ROCs) that plot the detection rate against false alarm rate. A sequential optimization technique has been developed for combining the individual ROCs to optimize the performance of the complete system. This avoids *ad hoc* tuning of parameters. The system has been extensively tested in difficult urban traffic conditions. It achieves false alarm rate of 3.6 per minute while maintaining a detection rate of 62%–78% with a 162-ms average processing time. However, for pedestrians in "risky" positions, i.e., those within the lateral offset of 1.5 m (instead of 4 m), where detection is most important, the system gave much better performance of 90%–100% detection with one false alarm per 3 min. It was also observed that stereo gives an order of magnitude improvement in performance compared to monocular vision. However, they contend that more research is still needed to bring these rates to acceptable levels for real-world use.

The system described in [64] and [92] has been built by Volkswagen in the SAVE-U extension of the PROTECTOR project. It uses RADAR sensors, color cameras, and IR cameras to detect pedestrians in front of the car and to apply automatic braking to reduce the vehicle speed and, therefore, the severity of injury to the pedestrian. The RADAR network provides the range and the azimuth of the objects, enabling the generation of their trajectories. The cameras are used to identify the pedestrians. Sensor fusion is performed using a mix between RADAR-driven fusion (sequential) and cooperative fusion (parallel). Detection is performed separately in individual sensors. The fusion algorithm combines the detections of five RADAR beams. The visible light and IR detections are also fused together. The targets detected by the RADAR are then sent to the imaging sensors, which then try to check in the corresponding image areas if a target is present. The targets obtained are combined at pixel level to generate the regions of interest. Image-based classification is then used to distinguish between pedestrians and other objects.

IV. Infrastructure-Based Solutions for Pedestrian Detection

Infrastructure-mounted cameras have been extensively studied for video surveillance as well as traffic analysis [95]. Detection and tracking of objects from these cameras is easier and more reliable due to the absence of camera motion. Background subtraction, which is one of the standard methods to extract moving objects from stationary background, is often employed, followed by classification of objects and activities. Shadow removal is important in getting a robust performance of object detection in outdoor scenes. A detailed comparative evaluation of various shadow detection algorithms in the literature is performed in [76]. In [66], a shadow analysis algorithm, which is based on color and brightness changes due to cast shadows, is proposed.

Here, we briefly describe the research on detecting and analyzing people from stationary cameras. Ideas used in many of these systems would also be useful for pedestrian protection. In [98], vehicles and pedestrians are tracked by combining low-level blob analysis using a mixture of Gaussian background models with high-level Kalman filtering to determine position and shape. Occlusions between objects as well as between the object and the background are handled based on detecting the shape changes. In crowded scenes, there are severe occlusions between people due to which the silhouettes of the persons are not well separated. In such cases, it is useful to combine global

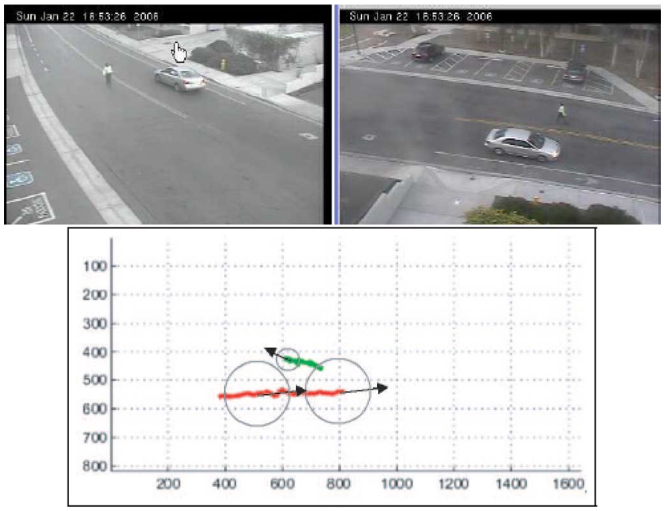

Fig. 6. Estimation of interaction patterns of moving objects with different velocities using the homography-mapped footage regions in the projection planes. Green track corresponds to the walking person, and red track corresponds to the car [75].

models with local models at body part level. An approach for detecting pedestrians in crowded scenes is proposed in [58]. The first stage uses local features to generate hypotheses about potential object locations using the scale invariant extension of implicit shape model. The hypotheses are verified using a probabilistic top–down segmentation that is based on minimum description length principle. A comprehensive video surveillance system for traffic-monitoring application is described in [56]. The system detects and tracks moving vehicles and pedestrians, classifies these objects, and analyzes their behaviors. A Bayesian network classifier is proposed, which uses the target attributes such as size, position, velocity, type, and track to deduce the target class in probabilistic terms.

Our laboratory has been actively involved in research based on multicamera systems for traffic analysis. The research project Autonomous Agents for On-Scene Networked Incident Management (ATON) aimed at making contributions to the realization of powerful and integrated traffic-incident detection, monitoring, and recovery system to reduce congestion on highways and to make travel safer, smoother, and economical, and to reduce pollution. In [13], hierarchical database architecture is proposed for detecting, storing, and querying of traffic incidents. The semantic abstractions are arranged hierarchically as events (atomic), activities (spatio-temporal composition of events), behaviors (set of related activities), and incidents (higher level abstraction from events, activities, and behaviors). A prototype of such a database was designed, developed, and used for detecting complex traffic activities such as exiting the freeway, tailgating, and simultaneous entering of a lane while turning. The details of sensor network using rectilinear and omnidirectional cameras, with algorithms for detecting vehicles and removing shadows, are described in [94]. Although this research was conducted for freeway traffic, many of the concepts developed in this research would also be useful for pedestrian incident detection.

Activities and interactions of people and vehicle are analyzed in [75], as shown in Fig. 6. For detection, wide baseline stereo cameras are used, with planar homography for robustly generating tracks on the ground plane. A semantic event grammar is designed for the representation of the spatio-temporal relationship between people and vehicle tracks to identify events. The future prediction of tracks is performed using piecewise velocity history. A quad-tree-based indexing scheme is used for efficient querying of events that are stored in the database.

The systems described above perform detection and analysis of humans and vehicles, including their motion and behavior from stationary cameras that are mounted on the infrastructure. Wireless communication would enable these systems to communicate with the vehicles, which can then generate appropriate warnings for the driver or activate the autonomous protection systems.

V. Approaches for Collision Prediction

For a complete safety system, detection should be followed by prediction of the possibility of collision. The system should relay the information to the driver in efficient and nondistracting manner or to the control system of the vehicle in order to take preventive actions. Table VII shows the current research on collision prediction and pedestrian behavior analysis.

Deterministic collision prediction approaches project the current trajectories of objects into future and determine the possibility of collision based on geometric computations. In [29], which uses LASER scanners for detecting pedestrians, the concept of the region of no escape (RONE) is introduced based on bounds on velocity and acceleration, where the pedestrian–vehicle collision is inevitable. The point of contact and time to collision are accurately determined within this RONE. A traffic-monitoring system proposed in [56] is designed to predict various behaviors, including collision between vehicles and pedestrians. The possibility of collision is determined using the zone of interaction, which is defined as an outer ellipse with the same orientation as the target but with larger size. Events where targets are close and have dangerously high relative velocities trigger a potential collision event.

Many of the deterministic approaches assume 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 a 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 the 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. Particle filtering is a natural framework for simultaneously tracking the object and predicting the collision probability [1].

TABLE VII
RESEARCH ON COLLISION PREDICTION AND PEDESTRIAN BEHAVIOR ANALYSIS

Publication	**Objective**	**Approach**	**Description**
Abramson IV04 [1]	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.
Antonini ACIVS04 [4]	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 TR06 [5]	Pedestrian behavior modeling	Pedestrian dynamics model	Expands the framework for modeling pedestrian walking behavior and interactions between pedestrians.
Antonini IJCV06 [6]	Behavior based tracking	Pedestrian dynamics model	Integrates the discrete choice behavioral model with image-based detection and tracking in order to improve performance.
Atev ICIRS05 [7]	Vehicle collision prediction	Trajectory intersection	Collision prediction is performed by "extruding" vehicle base along time axis and finding overlap between the extrusions.
Ferrara IV04 [25]	Collision avoidance	Collision cone geometry	Splits the velocity into radial and axial components. Derives the conditions for collision by assuming constant speed.
Fuerstenberg ITSC05 [29]	Collision prediction	Region of no escape	Defines a Region of no escape (RONE) where collision is unavoidable. Finds the time to collision and point of first contact in this zone.
Kumar ICIRS05 [56]	Collision prediction	Zone of interaction, relative motion	Events where targets are close and have dangerously high relative velocities trigger potential collision.
Large IV04 [57]	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.
Makris BMVC02 [63]	Pedestrian behavior model	Probabilistic clustering	Generates model of probabilistic distribution of trajectories in a scene using Bayesian HMM based approach.
Osaragi AAMS04 [73]	Behavior modeling for crowd	Stress-based model	Models the pedestrian behavior based on pedestrian-stress (P-stress) due to other pedestrians and destination-stress (D-stress) due to destination.
Shimizu 03, IV04 [80]	Direction estimation	Pattern classification	Uses SVM on Haar wavelet coefficients to classify between different orientations.
Szemes T-IM05 [90]	Controlling interactive mobile robots	Three-layer behavior model	Pedestrian behavior is modeled as three layers: strategic, tactical, and reactive. Each of the objectives creates forces that would guide pedestrian behavior. Similar layers used for robots.
Tsuji ITS02 [97]	Collision prediction	Relative motion	Based on computation of relative motion vectors, and conditions for collision judgment.
Wakim C-SMC04 [100]	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.

In [4], the "discrete choice model" is used 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 toward the destination direction, avoid frequent direction changes, and try to adjust speed to a desired speed. In [5], the model is expanded to incorporate the interaction between pedestrians. In [6], the discrete choice behavioral model is integrated with person detection and tracking from static cameras based on image processing in order to improve performance. This approach differs from the conventional tracking since it uses behavior rather than appearance for detection. Also, instead of making hard decisions about target presence on every frame, it integrates the evidence from a number of frames before making a decision. In [100], the pedestrian dynamics is modeled using a hidden Markov model (HMM) with four states corresponding to standing still, walking, jogging, and running. For each state, the probability distributions of absolute speed as well as the change of direction are modeled as truncated Gaussians. In [73], a model of pedestrian behavior in crowds is developed based on "stress" that the pedestrians experience while walking in crowd, including pedestrian stress (P-stress) from other pedestrians, which would push them away, and destination stress (D-stress), which pulls them toward their destination.

Other cues, such as orientation of the pedestrian body, can give 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. In [80], the pedestrian orientation is estimated using the SVM on Haar wavelet coefficients in order 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, in [63] a model of probabilistic distribution of trajectories in a scene is generated using a Bayesian HMM-based approach. In [57], a long-term estimate of object motion is obtained using a 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.

Thus, it is seen that there are various models that are developed for pedestrian behavior analysis. Some of these models have been applied for collision prediction. Monte Carlo simulations to predict future behavior based on pedestrian dynamic models seem to be the most promising approach in obtaining the probability of collision. This approach also fits the particle filtering framework that is widely used for tracking in computer vision systems. For developing a robust system for pedestrian protection, a thorough evaluation of these models, the conditions under which they work, and their performance in real world is required.

VI. Concluding Remarks

Pedestrians are the most vulnerable road users, and therefore, they require maximum protection on the road. The large number of fatalities and injuries show the importance of developing pedestrian protection systems. This paper discussed the global nature of the pedestrian safety problem and the initiatives taken by research groups to address it. It provided a comprehensive understanding of various issues, approaches, and challenges in improving pedestrian safety, including a comparative discussion of different approaches that have been developed recently.

Pedestrian protection systems offer many important research problems to work on, such as development of different types of sensors, processing of sensor information to extract relevant features, analysis and classification of these features to detect and track pedestrians, behavior and intent analysis of drivers and pedestrians, as well as human factors and interfaces. In the last five years, we have seen a considerable research activity throughout the world, particularly in Europe and Japan. This is a very positive development. Such research has already produced a lot of important results and also produced a clearer and better understanding of the remaining challenges to work on.

Much of the current research on pedestrian protection systems is toward improving and characterizing their performance. In order to ensure robust and reliable performance in all kinds of environmental conditions, it is necessary to carry out systematic experimental validation. In comparing the performance of different systems, it is also important to test the systems using standardized data sets and performance metrics. Availability of large standardized data sets capturing pedestrians in various environmental conditions is therefore important to accelerate the development of reliable pedestrian protection systems.

New types of nonvisible light sensors such as thermal IR and LASER scanners show promise of improving the detection in situations where visible light sensors would be less effective. Although these sensors are expensive at present, mass production is likely to reduce the costs of these devices. Research on sensor fusion and registration would also be very important to ensure performance enhancement using the combination of sensors. Infrastructure-mounted sensors are also likely to complement vehicle-mounted sensors in generating a complete picture of surroundings by filling blind spots of vehicles. Furthermore, detection from infrastructure-based sensors is less complex due to the static background. Research on detecting pedestrians and vehicles for surveillance as well as traffic analysis would therefore be very valuable in the development of infrastructure-based collision avoidance systems. For a complete system, effective communication between infrastructure and vehicles would be essential.

An effective pedestrian protection system needs to not only detect pedestrians but also predict the possibility of collision, which is based on modeling of pedestrian behaviors. Behavior modeling and prediction is an active area of research. In particular, Monte Carlo method in particle filtering framework is a promising approach for integrating pedestrian detection with collision prediction. One of the challenges in behavior modeling, specifically for collision predictions, is the scarcity of real-world data, since accidents are rare events, and performing the experiments to collect data would involve human subjects in potentially dangerous situations. Hence, a large number of experiments using trajectory simulation in addition to the available real-world accident data would be the only acceptable method in developing and characterizing such systems [100].

Finally, in addition to the extraction of information about surrounding objects, it is also important to ascertain the driver's state in order to generate appropriate warnings or actions so that the system would help the driver rather than cause distraction. For example, if a driver has already seen a pedestrian and is taking appropriate action, one may not want to alarm the driver unnecessarily. For this purpose, it is important to not only look outside the vehicle to detect dangerous situations but also look inside the vehicle in order to assess the state and intent of the driver [96].

It is seen that the research on pedestrian protection systems is in the process of reaching maturity. The success of this research should eventually find systems in future automobiles and help in saving lives and reducing injuries to pedestrians on the road.

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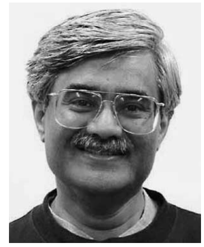

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