Pedestrian Safety Using the Internet of Things and Sensors: Issues, Challenges, and Open Problems

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Abstract

Pedestrian safety has emerged recently as a public health challenge worldwide. People are being physically harmed due to losing focus on their surroundings and putting safety at risk. Though pedestrian safety is a shared responsibility, researchers suggest that distractions by smart devices and reduced cognitive skills are major causes of accidents. There is a scope to assist pedestrians through amplifying cognitive skills using heterogeneous Internet of Things (IoT) and sensors. These technologies could discover and warn users about unanticipated events such as just-in-time warnings about the hazards, distractions, extreme weather calamities, and potential impending dangers. An automated personalized agent helps monitor, diagnose problems, and protect people in an urban environment. Researchers have proposed various systems and implemented them in multiple domains. In this survey, we assessed, analyzed, and compared the most recent research on pedestrian safety. We identified the challenges, research gaps, and future directions toward using technology to improve pedestrian safety.

Keywords: Pedestrian Safety, Smartphone Zombies, Internet of Things, Obstacle Detection, Bystanders Privacy

1. Introduction

In recent years, pedestrians engage in various risky activities due to the increasing popularity of mobile devices and easy accessibility to the internet. For example, people use their smartphones to text, talk, play games, watch videos, etc., while walking. People use smartphones at busy intersections and on crowded sidewalks [1, 2, 3]; as a result, they are unaware of their surroundings [4]. This is known as "*Distracted Walking*" [5, 6], while the people who engage in distracted walking are referred to as "*Smartphone Zombies*" or "*Smombies*" in short [7, 8]. Smartphone Zombies are not aware of situational changes and impending obstacles. One study found that pedestrians who text while walking are 50% less aware of environmental changes [9]. Another study found that 75% of participants distracted by a smartphone failed to notice a clown on a unicycle as they walked by it [10]. Such distractions can lead to fatal accidents [5, 11]. For example, Nasar et al. show that an estimated 69.5% of injuries accounted for pedestrians who talk on the phone in public places [12].

It is possible to provide timely interventions that increase situational awareness and reduce distraction by the Internet of Things (IoT), wearable devices, smart sensors, and smartphones [8, 13, 14]. These technologies allow people to efficiently conduct their daily activities, simplifying many tasks that once were difficult to perform. Currently, there are 23 billion IoT devices deployed worldwide [15]. These devices are heterogeneous and use different protocols, architecture, and standards. In addition, multiple cities implemented various infrastructure and proposed policies to mitigate the risk of pedestrian injuries. For example, a separate lane has been set up for smartphone users who use their devices while walking in Washington, D.C[1]. In Delaware, special signage has been installed on sidewalks and zebra crossings to warn the pedestrians at the busy intersections. In Xi'an, China, city authorities have designated a cellphone lane, which attempts to alert distracted pedestrians[2]. In addition, some states in the U.S. and multiple countries have imposed fines for distracted behaviors; law enforcement reminds drivers to look for pedestrians everywhere [16].

On the other hand, modern vehicles are getting intelligent with smart sensors and technologies. Vehicles can warn drivers and pedestrians by detecting a potential collision beforehand [17]. The automobile industry has adopted various collision detection techniques, including Pre-Collision Systems (PCS), Collision Prevention Systems (CPS), Collision Avoidance Systems (CAS), etc. [18]. However, these systems have limitations and are inefficient in giving timely alerts to distracted pedestrians and drivers. Before the concept of Vehicle to Pedestrian (V2P) communication, previous studies concentrated on driver-side warnings rather than warning the pedestrians. However, most accidents occur when pedestrians walk on the pavements and cross the intersections [19, 20]. The risk increases when pedestrians' cognitive skills are split into multiple tasks or distracted by anything. Researchers focused on localizing and tracking the

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[1]https://finance.yahoo.com/news/cellphone-talkers-get-their-own-sidewalk-lane-in-d-c-92080566744.html

[2]https://www.cnbc.com/2018/06/08/for-chinese-pedestrians-glued-to-their-phones-a-middle-path-emerges.html

pedestrians and potential obstacles, but the existing techniques of localization track on a coarse-grained level. Wearable device-based systems mostly rely on shoes, waist, and head-mounted sensors, which require additional hardware. In recent years, active research has been conducted using smartphones or dedicated sensors to warn pedestrians and sense the surrounding environment. Therefore, this research survey provides a comprehensive study of such safety systems in terms of effectiveness, accuracy, discuss challenges, and future research directions.

Contributions: The contributions of this survey are as follows:

1. This study identifies a wide range of safety systems offered for pedestrians and discusses their efficiency and usability.
2. The survey provides a competitive analysis of existing obstacle detection and collision alert systems, their advantages, and limitations.
3. Finally, we discuss the research challenges and future direction of pedestrian safety based on current systems and technology.

Organization: The rest of this survey is organized as follows: Section 2 explains the methodology of this survey. Section 3 provides the motivation. We explore various safety systems for pedestrians in Section 4. Section 5 and Section 6 present existing applications for obstacle detection, their advantages and limitations, respectively. We discuss privacy issues in Section 7. Section 8 presents research challenges and future directions. Finally, concluding remarks in Section 9.

2. Methodology

This study follows the systematic literature review guidelines for providing an overview of pedestrians' safety applications that include the following steps. (i) we highlight the problems of pedestrians' safety and highlight the motivations for using the Internet of Things and sensors, (ii) we search for relevant literature on pedestrian safety, (iii) we define the selection criteria to filter out high-quality and relevant articles, and (iv) we extract and synthesize the findings from the studies.

2.1. Search Strategy

To identify relevant articles for this survey, we performed a literature search on Google Scholar, IEEE Xplore, ACM Digital Library, SpringerLink, and ScienceDirect. The first literature search was conducted in March 2021 and found 724 articles. The studies retrieved articles that were published between 2015 and 2021. The following search strings have been used to find relevant articles and references.

(Pedestrian OR Distracted OR Smartphone Zombies OR Bystander OR V2 OR Inattentional) AND (safety OR collision* OR privacy OR vehicles* OR injuries OR alert* OR behavior OR *crossing* OR trust* OR traffic* OR smartphone* OR accident OR *obstacle* OR awareness* OR *sensors* OR *automated*)*

We manually deleted certain articles that appeared in search results but were unrelated to our survey. We have emphasized high-quality publications that were peer-reviewed in reputable venues. After applying the selection criteria, we retrieved 113 relevant articles. We analyzed each article's bibliography during the literature review. If an item in the bibliography referred to an article relevant but not yet been downloaded, we downloaded that article. We retrieved a total of 143 articles after the first cycle. In January 2022, we applied the same selection strategy and retrieved 18 more articles.

2.2. Selection Criteria

We have conducted a manual review after retrieving the articles from the sources. Therefore, inclusion criteria were adopted to identify and analyze relevant articles. The criteria for inclusion are as follows.

- Articles focus on technologies from the pedestrians' perspective.
- Articles demonstrate pedestrian safety prototypes include obstacles detection, collation avoidance, everything to pedestrian communication, etc.
- Articles present the evaluation of such systems or consequences, such as privacy, security, behavior analysis, etc.

3. Motivation

Walking is the most basic form of transportation. It is inexpensive, healthy, and environmentally friendly [21]. Though there are several preferences in vehicles, everyone is pedestrian, even for a moment in life. Unfortunately, pedestrian safety has come at risk in recent years whether people walk for work or exercise with dogs at the park. For example, In the United States, pedestrian fatalities have increased sharply [20]. According to the Governors Highway Safety Association (GHSA), the number of pedestrian fatalities increased by 53%; in contrast, the combined number of all other traffic deaths increased by 2% in the last ten years from 2009 to 2018 (Figure 1)[16]. In addition, pedestrian fatalities rates are more significant in third world and low-income countries [22].

Multiple factors are related to this alarming fatality rate. Research suggests distraction by smartphones is one of the major reasons for pedestrian injuries and deaths [5, 23]. Some recent accident studies support this claim too. For example, an estimated 150,000 traffic accidents and 256 deaths were caused by the Pokémon Go[3] mobile game in the first 148 days after introduce; the economic cost is between \$2 billion to \$7.3 billion in the United States [24]. People have also died by road crashes while using the Tiktok app[4] [25]. The increasing number of active smartphone users also supports the claim. For example, active smartphone users increased by 50 million in 2019 in the United States [16]). Recent data shows that 96% of

[3]Pokémon Go - https://www.pokemongo.com/en-us/
[4]Tiktok - https://www.tiktok.com/en/

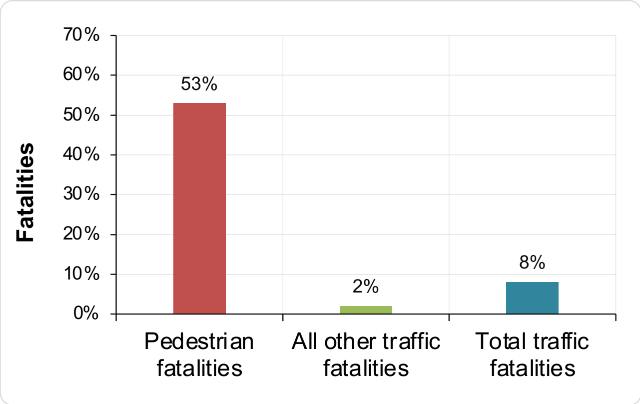


Figure 1: The percentage increase in pedestrian fatalities, all other traffic fatalities, and total traffic fatalities from 2009 to 2018 [16].

Americans now own cellphones and more than 81% of those are smartphones [26].

Distracted pedestrians face at least three types of attention impairment – visual, aural, and cognitive. If the pedestrians' vision is partially or fully directed to the smart devices while crossing the street, they could suffer impaired visual attention [27]. Imperfect visual attention limits the ability to detect and avoid obstacles while walking [28]. The pedestrian would suffer hearing or auditory impairment when talking on the phone or listening to music while walking on the street or crossing the intersection. There is initial evidence that auditory cues are used extensively by safe adult pedestrians [29, 30, 28]. Finally, a distracted pedestrian suffers from reduced cognitive attention. Smart devices can make our brain lazy and reduce cognitive skills [31]. Pedestrians require a substantial processing of stimuli and extremely rapid decision-making during a walk in the urban environment.

One effective strategy to improve pedestrian safety is to increase cognitive ability through assistive technologies and sensors [32, 33, 34]. Such systems identify potential dangers and improve cognitive ability by guiding pedestrians as *Guardian Angel*. These techniques help to protect from the collision between pedestrians and other potential obstacles. Another approach is integrating pedestrians into the smart vehicle communication loop [35, 36]. Modern connected vehicles interchange data to build fast and safe transportation. Such a system would protect pedestrians from collisions and avoid dangers based on data received by pedestrians' devices. Despite such progress in developing the technology to support intervention systems and vehicle-pedestrian communication, little progress has been achieved in reducing fatalities.

3.1. Scope of this survey

Several components are involved in pedestrian safety systems, including vehicles, pedestrians, road conditions, traffic rules, etc. These components have different perspectives and guidelines to reduce accidents and make roadways safe. However, pedestrians are the prime factor in all these safety components. This survey will focus on safety systems and technologies that pedestrians use.

4. Pedestrian Safety Systems

Multiple studies have been conducted to reduce pedestrian fatalities and some proposed systems have already been implemented in real life. We have divided the existing and proposed safety systems into three broad categories – (i) Active Intervention, (ii) Smart Vehicles, and (iii) Infrastructure and Traffic Signal.

4.1. Active Intervention

Warning pedestrians for potential threats is important for improving pedestrian safety. With technological advancements in smartphones and wearables, various systems have been proposed to alert the pedestrian based on the surrounding environment if the system identifies a situation as dangerous. These systems consist of multiple sensors and sense contextual data, including pedestrian location, surrounding objects, posture, motion, etc. These applications not only monitor potential collisions [37, 38, 34, 39] but also influence pedestrian behavior [40, 3]. Pedestrian safety systems emerge in both industries and academic sectors due to technological advancement. For example, Wang et al. [41] proposed *Walksafe*, a system for detecting incoming vehicles for pedestrians on an active call while crossing streets. The back camera of phones captures vehicles' front views and rear views then apply machine learning techniques to identify the approaching vehicles. Tung et al. [42] proposed *BumpAlert*, which identifies nearby obstacles by combining camera, speaker, and microphone inputs. In both cases, systems alert the pedestrian after detecting the potential accident. We discuss the obstacle detection and active alert systems in Section 5.

4.2. Smart Vehicles

Recent developments in the automobile industry are dramatically evolving through modern technologies that help to protect pedestrians on the road; one such example is autonomous cars, which are equipped with various sensors for pedestrian safety [43]. In 2005, Automated Advanced Driver Assist Systems (ADAS) started to be adopted by vehicle manufacturers. ADAS is the active protection system that offers pedestrian detection and crashes avoidance on roads. It took twenty years of research to make ADAS available for vehicles in the market [44]. After that, multiple approaches have been proposed to avoid collisions with pedestrians and bicyclists, such as Automated Driving Systems (ADS) [45]. ADS is still in the early testing phase and is limited in its capabilities [46, 47]. However, multiple manufacturers have adopted ADS for public road testing in recent years. In terms of pedestrian safety, we can divide automobile safety systems into two categories – (i) Built-in Sensor-based Systems and (ii) Vehicle-pedestrian Communication.

4.2.1. Built-in Sensor-based Systems

Modern vehicles are equipped with various exteroceptive sensors, which are related to information in the vehicle's surroundings [48, 49]. These sensors are not directly related to the vehicle state (e.g., speed, accelerations, component integrity, etc.). Exteroceptive sensors are part of passive safety systems because they detect pedestrians and warn drivers. Active safety features, such as Pedestrian Automatic Emergency Braking (PAEB), constitute lifesaving technology that is quickly becoming prevalent in passenger vehicles [50]. The system use cameras or a combination of cameras and radar. The PAEB system provides breaking while any pedestrian is in front of the vehicle, and drivers' actions are insufficient. Besides that, vehicle manufacturers are adopting various safety measures for pedestrians. For example, *Lexus RX 2017* warns drivers after detecting pedestrians by Pre-Collision warning systems [51]. If any potential collision is detected and the human driver has not performed any action, the automated system gets control of the vehicle (e.g., Ford Fusion 2017, BMW 3 Series, etc.). Usually, sensors collect data independently, and safety systems use those data from multiple sensors to get results. Here are some built-in sensor-based systems for pedestrians:

a) Camera-based Solutions: There are multiple configurations of camera-based systems available, including monocular, infrared, stereo, etc. Li et al. [52] and Wu et al.[53] propose a stereo camera-based pedestrian detection system. The stereo camera provides 3D information about the pedestrian and surroundings. Additionally, Far Infrared Ray (FIR) technology-based system uses infrared light waves to spot obstacles at night [54]. Usually, pedestrians are hot and are easy for FIR detection [55, 56]. Recently, convolutional neural network-based techniques have been used to detect pedestrians accurately [57, 58].

b) LiDAR-based Solutions: Light Detection and Ranging (LiDAR) based systems provides 3D positions and shapes of objects. LiDAR works at night because the performance is not affected by the scene's illumination and can detect the surrounding elements. Several approaches for LiDAR-based detection are shown in Liu et al. [59] and Navarro et al. [60]. In both cases, LiDAR is used to obtain the contour, position, and distance information of objects. Next, the safety systems apply either training-based algorithms or segmentation methods to detect pedestrians.

c) Radar-based Solutions: The Radar sensors guarantee system credibility regardless of environmental conditions (e.g., dust, light, weather, etc.) [61]. That is why the main uses of Radar are to trace and track other vehicles on the road. However, Severino et al. [62], and Hyun et al. [63] utilized Radar to detect pedestrians using the Doppler Effect.

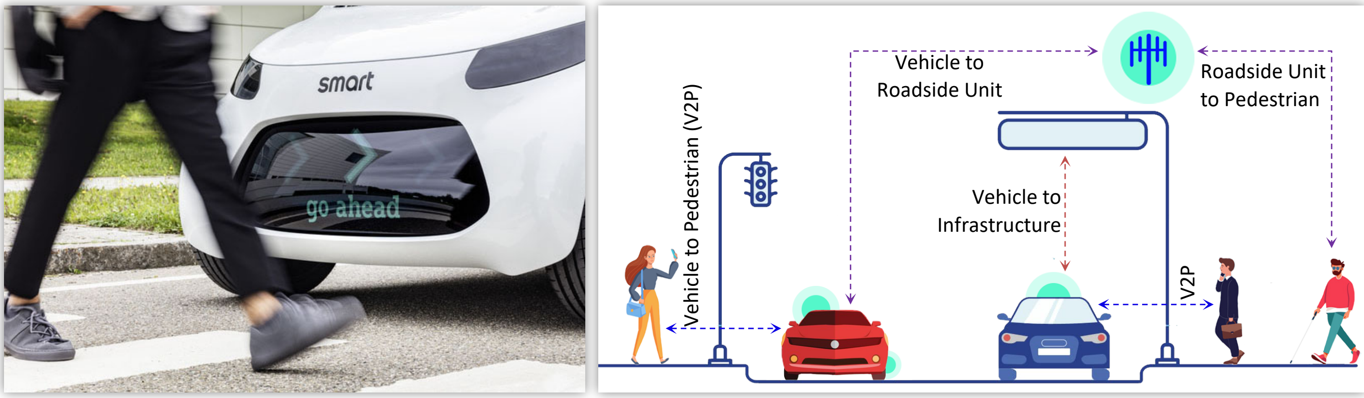
4.2.2. Vehicle-Pedestrian Communication

Recently, Vehicle-to-Pedestrian (V2P) has emerged in the autonomous vehicle industry [64]. It is the system of identifying and communicating with pedestrians known as Vulnerable Road Users (VRUs), and V2P is a subset of Vehicle-to-Everything(V2X) communication [65]. It facilitates warnings to the pedestrian about an approaching vehicle and provides information to the driver for the vulnerable road users. Figure 2(a) shows how an autonomous car communicates with pedestrians, and 2(b) illustrates the V2P communication systems architecture.

In the V2P, associated parties (e.g., vehicles, pedestrians, bicyclists, etc.) communicate by safety messages [67]. Usually, these messages exchange periodically and carry real-time status and position-related data. The communication channel could be through direct ad-hoc technologies, such as IEEE 802.11p [68], or infrastructure-based communication, such as cellular technology [69]. Ultimately, V2P communication makes pedestrians visible to the driver even when they are not in the line of sight, and pedestrians reacts appropriately to approaching cars. Hussein et al. developed a mobile application that exchanges information between nearby drivers and pedestrians and alerts them for potential collisions [36]. *V2ProVu*, is a V2P communication system proposed by Anaya et al. [35]. The Venerable Road Users (VRU), or pedestrians, use a smartphone as the communication device and receive safety messages from nearby vehicles [35]. Then, the smartphone predicts the collision probability based on the received WiFi data. *V2PSense*, developed by Li et al. [70], sends alerts to pedestrians by the cellular network. Previously, Liu et al. [71] developed *POFS*; the system uses IEEE 802.11p and WiFi to support V2P and Vehicle to Vehicle (V2V) communication.

The interaction between pedestrians and autonomous vehicles is essential because, in real life, pedestrians decide by exchanging some familiar gesture, sign, or sound with the drivers irrespective of language and their skills. However, autonomous technology limits the interaction with pedestrians and raises a safety issue regarding trust between VRUs and vehicles [72, 73]. For example, how vehicles would show messages for pedestrians or what would be an effective warning, etc. Researchers have proposed various communication mechanisms to support the interaction between humans and vehicles. One such way is vehicle-mounted interfaces. For example, Eyes on a car, developed by Chang et al. [74], proposes to use digital eyeballs mounted on the front lights to replace traditional eye contact between pedestrians and drivers. When the sensors on vehicles detect pedestrians intend to cross, the eyes start staring, which ensures to the pedestrian that the vehicle will stop to allow crossing. The LED stripe-based system called Smiling car is proposed by Löcken et al. [72]. In normal driving conditions, the interface shows a horizontal yellow line. The line change to a smile when vehicles detect a pedestrian. Table 1 shows the latest development of communication for V2P based on vehicle-mounted interfaces.

Another way to show messages to pedestrians is projection-based interfaces. The main limitation of vehicle-mounted interfaces is visual impairments. For instance, the mounted display could be poorly visible due to bad weather or the vehicle being too far from the pedestrians. Burns et al. proposed a system in which a stripe of parallel lines is projected directly in front of the vehicle [83]. This animated stripe comes up with arrows that indicate the vehicle's next move. Nguyen et al. proposed a more sophisticated pattern projection [84]. The vehicle project the



(a) (b)

Figure 2: (a) An autonomous car is communicating with the pedestrian indicating that safe to cross the intersection. Source [66]. (b) Vehicle-to-Pedestrian (V2P) communication architecture.

Table 1: Vehicle-to-Pedestrian communication Interface

Paper	**Technology Used**	**Content Type**	**Modality**
Mahadevan et al. [75]	WiFi, Bluetooth, Car External Display, Motion, Speaker, Actuator, Laser Projection, LED	Information	Visual, Auditory, Haptic
Li et al. [76]	Car External Display	Advice	Visual
Fridman et al. [77]	Car External Display, Projection, Vehicle Lights and Signals	Information, Advice	Visual
Ackermann et al. [78]	Light strip, Car External Display, Projection	Information, Advice	Visual
Böckle et al. [79]	Light strip, Speaker	Information	Visual, Auditory
De Clercq et al. [80]	Car External Display, Vehicle Lights and Signals	Information, Advice	Visual
Hudson et al. [81]	Car External Display, Speaker	Advice	Visual, Auditory
Stadler et al. [82]	Car External Display	Advice	Visual

wave-shaped red light when running; the light turns yellow when the vehicle slows down and projects the green light when the vehicle stops completely. In addition, the multi-modal interface, which is especially beneficial for visually impaired persons, and Augmented Reality Based systems have been proposed for V2P [85, 86].

4.3. *Smart Infrastructure and Traffic Signaling*

In urban areas, accidents between pedestrians and vehicles at traffic intersections are common issues. According to one study, 71% of all accidents in which one party was pedestrians and 58% of all accidents in which one party was bicycles occur inside the urban areas in Europe, especially at intersections and crosswalks [87]. Therefore, cities offer extensive facilities for pedestrian safety through a citywide network of infrastructure and adaptive traffic systems. Traffic lights have been used to regulate traffic and protect public safety for a long time. Recently, the smart traffic control system has been introduced to ensure safety and improve performance. Usually, traffic lights switch their states (i.e., walk, stop, etc.) periodically, and it is fixed. In contrast, the intelligent signaling system can extend or reduce the time based on road conditions and pedestrian status. This system is connected with sensors and can identify the pedestrian on the street while crossing [88]. If the system identifies pedestrians crossing the street but cannot reach the other side within time, it delays the switching. In contrast, it reduces the switching time if no pedestrians or vehicles wait. As the dynamic traffic intersection is complex, the computational complexity increases exponentially. Recent advancements in deep learning techniques are extensively used to solve this dimensionality issue [89, 90, 91]. One of the safety issues for pedestrians is crossing the road at undesignated places and right of way accidents. The traditional traffic system is incapable of mitigating the accident caused by undesignated crossings [92]. However, automated vehicles (AVs) and vehicle-to-pedestrian communication showing promising prospects [73, 93]. Hoggenmueller et al. suggested a prototype to improve pedestrian safety when crossing busy roadways without designated pedestrian crossings [94]. The proposed system would use 3D 360-degree video recordings of the street and render them in virtual reality.

Nowadays, people engage in their phone screens intensely, and they are unaware of the signal light and are not taking their eyes away from their screen while they cross the street. Some cities (e.g., Tel Aviv, Israel; Augsburg, Germany; Bodegraven, Netherland, etc.) installed pavement lights synced with the actual traffic signal. Therefore, pedestrians can see the green and red lights on the ground without looking at the light post [95].

5. Obstacle Detection and Alert

This section will discuss details of obstacles detection and collision detection systems. The technology used in the pedestrians' safety systems is directly related to the end-users. For instance, pedestrians have to adopt these technologies or need to carry gadgets. Therefore, we believe it is understandable to categorize them according to the technology. This study categorized the existing applications into ten groups based on the technology used. Table 2 shows ten groups and a list of existing applications.

5.1. Motion Sensor Based

Modern devices are equipped with inertial sensors, such as accelerometers, gyroscopes, magnetometers, etc. [122]. These sensors have the functionality to provide object states (i.e., orientation, acceleration, and angular velocity). Inertial sensors measure these quantities with three axes and are based on basic motion laws. For example, the typical coordinate system of the mobile phone is shown in Figure 3(a). The working procedure of inertial sensors in other devices (e.g., wearable devices, dedicated sensors, etc.) is similar to smartphones. Motion sensors measure how the device is oriented in space and how it accelerates when moving. The typical motion sensor found on devices triggers screen rotations and is used for various applications to detect shakes, fist bumps, hand gestures, bumpy roads, and other features. Figure 3(b) shows a generic pedestrian safety architecture based on motion sensors.

Zhou et al. [114] proposed *HeadsUp*, a walk pattern recognition system. *HeadsUp* locks the phone screen if pedestrian looks at their phone while walking. The system identifies the user states by measuring the phone's accelerometer and gyroscope reading. It defines three-stage mobile phones' position during a crossing – phone in the pocket, watching, and calling state. Vinayaga et al. [102] use activity recognition techniques to detect distraction and propose a new model called Concurrent Activity Recognition (CAR). This model identifies various pedestrian activities, including running, walking, climbing, etc., by frequency matching of sensors data. Jain et al. [96] proposed *LookUp*, a shoe-mounted sensors-based system that automatically detects pedestrians' transition from sidewalk to road. The target is to create ground profiling based on the roadside curb's slope rather than step counting. *LookUp* detects street entrance events whenever the sidewalk descends into the street either through a ramp or a curb and warns the pedestrian. However, it requires additional shoe-mounted sensors to detect a potential collision. *WatchOUT* is another pedestrian warning system developed by Ou et al. [120], that differentiates sidewalks and ramps. It segments the steps with smartphones' built-in sensors (accelerometer, gyroscope, and magnetometer) data by the magnitude and warns pedestrians on the ramp.

5.1.1. Potential Drawbacks

Implementing an effective safety system based on inertial sensors is challenging. Several issues are associated with signal processing and computation (i.e., noise filtering, calibration, etc.). In addition, motion sensor-based pedestrian safety systems are highly energy-consuming. For better detection accuracy, the system required continuous data. In contrast, the large volume of raw sensor data is challenging to process in lower-end wearable devices and smartphones. For instance, *LookUp* [96, 102] required an extra computation layer for high-frequency data. Besides, these proposed systems cannot give a pre-alert to warn pedestrians. For example, the user would not get a warning until they step down to the road from the sidewalk [96].

5.2. Camera Based

The mobile camera has developed over time, and it supports a multitude of techniques that were difficult less than a decade ago. Smartphone cameras are increasingly used to detect approaching vehicles towards pedestrians, discover the sidewalk accessibility, incoming hazard, etc. The camera-based applications work based on image recognition algorithms. There is a predefined model – the model is either uploaded to the server or in the users' device. Then the camera captures the real-time pictures and identifies the incoming obstacles or hazards using the existing model. Wang et al.[41] developed *WalkSafe*, which uses a smartphone camera to warn the user from incoming vehicles. The system detects vehicles that are in direct line of sight using the rear camera. It divides the process into *offline training* and *online detection*. In *offline training*, *Walksafe* used the MIT CBCL car dataset [5] and the Caltech Cars dataset [6]. *Walksafe* builds a model with positive and negative training images and uses it to recognize positive matches in *online detection* steps. However, this system can only detect vehicles when the camera is in a direct line of sight with vehicles, limiting its use. Jain et al. [105] proposed *TerraFirma*. It can characterize the material and texture of the ground surface by a smartphone camera. The system captures a large set of images in various lighting and weather conditions. To reduce battery consumption, it took multiple snaps instead of videos. *TerraFirma* detects pedestrians' transition from the sidewalk to the street based on the texture. It also determines users' actions based on images and sensor data, including in motion, whether actively using the smartphone, indoor/outdoor, etc. The *AutoADAS* [108] and *Inspector* [99] developed by Wei et al. and Tang et al. respectively warns the pedestrian while distracted. The *AutoADAS* detects the obstacle or hazardous object, while *Inspector* can identify the traffic hazard based on the distinctive surface pattern. *SpareEye* developed by Foerster et al.[113] proposed an idea to detect an object which significantly differs from the background. Then, if the object is continuously and quickly getting closer to the user, the user will get a warning. However, continuous image streaming is not energy efficient, and it will need much computation power. Yang et al. [111] used an omnidirectional camera attached to the front side of the

[5] CBCL car dataset - http://cbcl.mit.edu/software-datasets/CarData.html
[6] Caltech Cars dataset - http://www.vision.caltech.edu/archive.html

Table 2: Existing research categorized by technology

ID	Paper/Reference	Application	Accuracy	Technology Used									
				Inertial Sensors	Camera	Acoustic	GPS	Infrared	Wearable	Crowd Sensing	AR/VR	Wireless	Hybrid
A1	Wang et al. [37]	*ObstacleWatch*	92%			✓							
A2	Jain et al. [96]	*LookUp*	80 - 95%	✓									
A3	Liu et al. [97]	*InfraSee*	80%					✓					
A4	Wang et al. [41]	*WalkSafe*	77%		✓								
A5	Gruenefeld et al. [14]	*Guiding Smombies*	N/A								✓		
A6	Li et al. [98]	*Auto++*	91%			✓							
A7	Tang et al. [99]	*Inspector*	92-99%		✓								
A8	Riaz et al. [100]	*SightSafety*	N/A	▪			▪					▪	✓
A9	Hesenius et al. [101]	-	N/A								✓		
A10	Vinayaga et al. [102]	-	75 - 81%	✓									
A11	Kanamori et al. [103, 104]	-	N/A								✓		
A12	Jain et al. [105]	*TerraFirma*	90%		✓								
A13	Lin et al. [38]	*pSafety*	46-100%				✓						
A14	Ishikawa et al. [40]	-	87%	▪			▪						✓
A15	Kim et al. [106]	*TrailSense*	80%							✓			
A16	Wen et al. [107]	*UltraSee*	94%			✓							
A17	Wei et al. [108]	*AutoADAS*	N/A		✓								
A18	Patankar et al. [109]	-	97%						✓				
A19	Tung et al. [42]	*BumpAlert*	95%		▪	▪							✓
A20	Kayukawa et al. [110]	*BBeep*	N/A			✓							
A21	Tong et al. [33]	-	88%								✓		
A22	Li et al. [32]	*Safe Walking*	91%	▪	▪								✓
A23	Yang et al. [111]	*Surround-See*	N/A		✓								
A24	Wang et al. [112]	*CrowdWatch*	83.3%							✓			
A25	Foerster et al. [113]	*SpareEye*	N/A		✓								
A26	Kang et al. [13]	-	N/A								✓		
A27	Zhou et al. [114]	*HeadsUp*	N/A	✓									
A28	Uchida et al. [115]	-	N/A	▪								▪	✓
A29	Sobhani et al. [116]	*IHMVR*	83%								✓		
A30	Xia et al. [117]	*PAWS*	95-97%						✓				
A31	Wang et al. [118]	*CrackSense*	80%							✓			
A32	Kang et al. [119]	*SafeAR*	N/A								✓		
A33	Won et al. [39]	*SaferCross*	90%	▪			▪						✓
A34	Ou et al. [120]	*WatchOUT*	80%	✓									
A35	Müller et al. [34]	*Walk the line*	94%								✓		
A36	Hincapié et al. [121]	*CrashAlert*	N/A		✓								

"✓" represents the application group
"▪" represents the part of hybrid application

smartphone to sense the surroundings as the built-in smartphone camera can be busy or blocked during active use. They developed a system called *Surround-See* to sense the devices' external environment and detecting user activities.

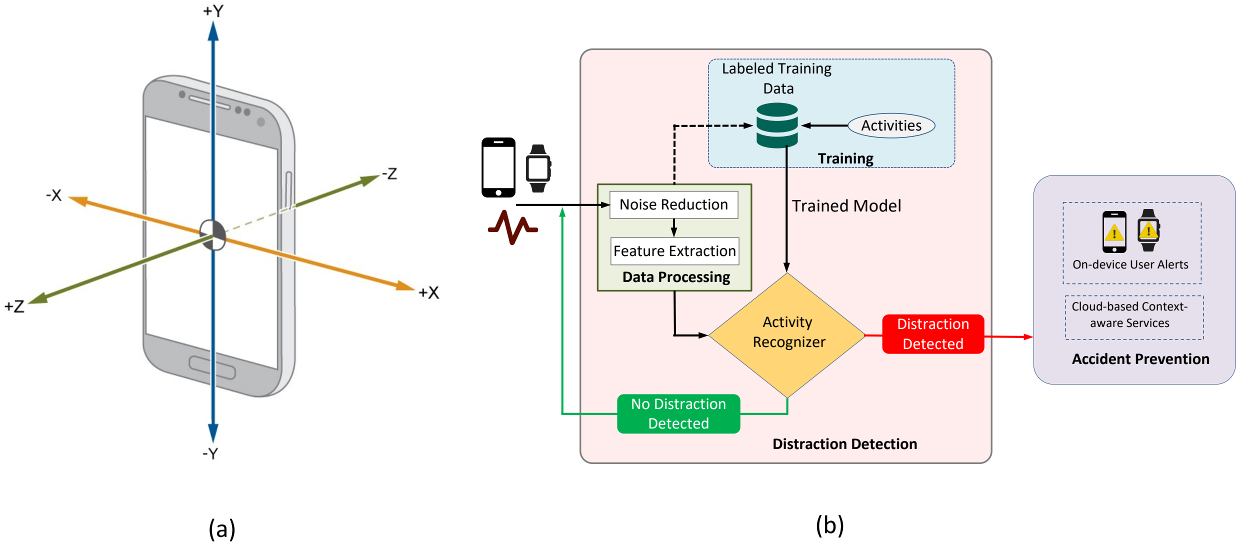


Figure 3: (a) Coordinate system of mobile phone. (b) A generic pedestrian safety system based on motion sensors. Source [102]

5.2.1. *Drawbacks of Camera*

The image or video-based warning systems highly depend on lighting conditions. For example, the detection efficiency would decrease at night or in crowded areas, and the noise pixels are created by ambient lighting. The phones' orientation with respect to objects and image quality due to mobility makes the camera system challenging. In addition, the processing of image-based systems is computationally expensive, if not carefully designed, can quickly drain the computational resources and batteries of smartphones. Besides, some researchers used extra equipment or hardware with the camera, which is not usable in real life. The direction and alignment of the camera are other drawbacks of detecting incoming objects. For example, in the *WalkSafe* [41] application, the back camera has to align with the car to avoid an accident.

5.3. *Acoustic Based*

Nowadays, the high-definition audio capabilities of smartphones are used to sense surroundings. For example, current smartphones have equipped with a dual-microphone, which can detect the relative position between users and potential obstacles. Besides, some modern smartphones (e.g., iPhone 7, 8, 10, 11, Samsung Galaxy S8+, etc.) have a frequency response of up to 23 kHz. This high-frequency response is inaudible to humans and distinguishable in normal environmental noises. All major operating systems of smartphones support playback and recording at 192 kHz sampling frequency. Researchers have able to detect the obstacle in sub-centimeter level accuracy in this frequency. The key idea of this technique is to create an acoustic sonar from the built-in smartphone speaker. The signal has an inaudible frequency and disseminates spherically in every direction. The top and bottom microphones record the reflected signal, and the system identifies the obstacle based on these captured signals. The system calculates the distance between pedestrians and obstacles by the Round Trip Time (RTT) of received signals. Figure 4 illustrates a simple acoustic-based system to detect obstacles.

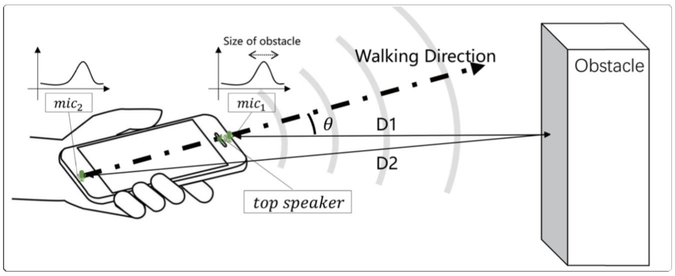


Figure 4: A generic obstacle detection systems using acoustic sensors. Source [37]

ObstacleWatch developed by Wang et al. [37], a collision detection system based on smartphone acoustic sensors. The smartphone generates beep sounds and receives them after reflection from the obstacles. *ObstacleWatch* first filters out the received signals, which are reflected from the user's body and ground. Then it locates the closest obstacle based on RTT of the corresponding reflected signals and estimates the collision based on the direction and angle. This system has multiple modules, including an obstacle detection module, size estimation module, etc. *UltraSee* [107] is an ultrasonic sensor-based system attached to the user's smartphone and can identify the difference of ground surfaces. *UltraSee* identifies changes when pedestrians step off the sidewalk. *Auto++* developed by Li et al. [98] is another acoustic-based system. It detects sounds of cars from different directions and warns pedestrians if any cars are approaching. The system uses machine learning techniques to extract features from environmental sounds and calculates the number of cars and their direction. However, this system only works for moving vehicles that actively emit acoustic noises.

BBeep [110] is another sonic collision avoidance system for the visually impaired and pedestrians. It is equipped with a suitcase that emits sounds. *BBeep* detects obstacles based on the captured signals in the crowded areas and warns pedestrians about the visually impaired.

5.3.1. Drawbacks of Acoustic

The holding behavior and orientation of receivers (i.e., smartphones, sensors) are important in acoustics-based systems. For example, users typically hold their phones vertically, but they may have their phones horizontally (i.e., during play games or watching full-screen videos). Therefore, detection angles would be different if the orientation and position changed. Multiple sources of acoustics reduce the detection accuracy. For example, if more than one device transmits the beep signal, the receiver would be confused about the origins. Assigning different frequencies of origin could mitigate this problem if the sample size is small (i.e., FDMA - Frequency Division Multiple Access), where sources would transmit signals in different frequency bands. However, this solution would not be feasible in urban and crowded areas where more than a hundred pedestrians cross an intersection at a time. Besides, acoustic-based systems cannot provide the types and nature of the obstacles.

5.4. AR/VR Based

Augmented Reality (AR) is a technology where digital information, sensory data, visual effect, sounds, etc., adds a layer to the real-world environment. For example, the mobile game app *Pokemon Go*[7], or the virtual furnishings app *IKEA Place*[8]. In contrast, Virtual Reality (VR) creates a computer-generated artificial environment by replacing the real world. Portable devices (e.g., smart glasses, smartphones, etc.) support the AR applications; only an extra headset is needed sometimes. The pedestrian can experience these applications while walking and running. VR allows us to display information about paths and traffic directly into the field of vision. Though the procedure and technology are different in the devices, AR uses computer vision, Simultaneous Localization and Mapping (SLAM), and depth tracking to show the relevant contents to users. AR applications render virtual images over real-world objects with various sensors (e.g., GPS, digital compass, velocity meter, accelerometer) and calculate the distance to the objects. It uses device cameras to collect, process, and show the pedestrian's potential obstacles in the direct sight of view. Kang et al. proposed *SafeAR* [119], an obstacle alert system for the pedestrians using AR applications while walking. The system extracts 3D feature points which are visually exclusive and the 6DOF (Six Degrees of Freedom or 6D position) camera pose from the input image. Then *SafeAR* calculates the distance between each feature point and the ground (reference plane). If the distance is greater than a certain value, the feature points (object) are identified as obstacles. Hesenius et al. [101] designed a navigation system with augmented reality to guide pedestrians in autonomous traffic. The applications provide multiple features to pedestrians, including the exact navigational path, safe zone to cross the street, and information of incoming vehicles. It augments the navigational direction over the natural world with the input imagery, traffic data, vehicle information, and pedestrian position. Tong et al. [33] proposed an effective warning interface prototype of AR applications for pedestrians. It discusses what information should be displayed in a warning system, how effectively presented to the user, and when it needs to warn the pedestrians. Sobhani et al. [116] use a head-mounted virtual reality device to evaluate distracted pedestrians. The system warns the pedestrian by flashing LED lights when they initiate crossing. The system used VR tools to simulate better traffic conditions closer to reality for participants. Gruenefeld et al. [14] developed a prototype of peripheral vision-based glasses to protect pedestrians in critical traffic encounters. The system protects pedestrians at the intersection, where a car is approaching from the pedestrian's left or right side.

5.4.1. Drawbacks of AR/VR

In AR/VR-based systems, efficiency mostly depends on feature extraction accuracy. Because it applies other components (e.g., safety tips, object information, advice, etc.) based on obstacle types after extraction. However, textureless objects cannot provide high accuracy during extraction from the inputs. Also, a sudden change of illumination, angle, and distance leads to an error to detect an obstacle and impedes the visual process. Besides, pedestrians need to wear AR-supported devices (e.g., AR glasses, headsets, etc.) while crossing the intersection and walking.

5.5. GPS Based

Most GPS-based collision detection systems are designed for the driver. However, with the improvement of GPS technology in wearable devices, researchers have developed safety systems for pedestrians. Generally, the pedestrians and objects (e.g., vehicles, obstacles, etc.) share their GPS positions. After that, the distance and relative velocity calculate, then identifies the collision possibility. There is an advantage of this technique; the detection could be a non-line-of-sight approach; the obstacle does not need to be within the eyesight of the pedestrian. Lin et al. [38] proposed *pSafety*, which adopts the intrinsic GPS receiver of smartphones and instantly alerts a pedestrian to potential collision events. To reduce the error positioning in smartphones, they designed the Sector Overlap Detection Algorithm (SODA). Each user's location should be a sector and be detected if they overlap at a specific time. There is a threat ranking method in *pSafety* to measure the degree of risk to reduce warning fatigue in each overlapping event.

5.5.1. Drawbacks of GPS Based Applications

The smartphones' GPS receiver is an intuitive solution, usually not sophisticated and with low computational power. The received signal is inaccurate and not updated in real-time in urban areas [123, 124]. The accuracy of GPS depends on sufficient signal quality received. In addition, GPS signal is affected by the atmosphere (i.e., multipath) electromagnetic interference, ionosphere, etc. The signal accuracy in the low-powered device is

[7] Pokemon Go - https://pokemongolive.com/en/
[8] IKEA Place - https://apps.apple.com/au/app/ikea-place/id1279244498

about 5 to 10 meters (e.g., in the iPhone 6, the position accuracy is 7-13 m [123]). However, different receivers have different levels of accuracy. In addition, the GPS denial environment and the crowded urban area do not provide the actual position. The GPS chip is hungry for power, which drains the smartphone battery. It requires replacement or recharge of the battery quite frequently.

5.6. *Infrared Based*

Infrared (IR) sensors are used to detect objects by *Infrared Radiation* or emitting heat. It is also used to detect an object's motions and surroundings. IR is invisible to humans as the wavelength is longer than the visible light. There are mainly two types of Infrared sensors: Active Infrared (AIR) - which can emit infrared radiation and later receive it by the receiver. In contrast, the Passive Infrared (PIR) can only detect infrared radiation and does not emit it. The AIR is commonly used for obstacle detection as proximity sensors. The IR sensor broadcast signals to determine the distance between pedestrians' device and the ground. If an obstacle reflects this signal, the system identifies it as a potential hazard on the pavement. Although it is a simple idea, the implementation and experiments in real-life raise challenges. Identifying any changes in the ground surface is not accessible due to surrounding noises, especially in the urban areas. *InfraSee* [97] developed by Liu et al. which detect a sudden change in the ground using an infrared sensor that is augmented with the smartphone. To remove the human walking-induced noise, *InfraSee* uses smartphone embedded sensors. After receiving the infrared sensor data, the system fixed the orientation using data calibration. It applies forward-backward zero-phase filtering to reduce the noise. Statistical analysis is applied to the filter data to identify the hazard with the pre-processed infrared data. Unlike the smartphone camera and positional sensors, the infrared signal and sensors consume less energy. However, a continuous stream of an infrared signal can drain the battery.

5.6.1. *Drawbacks of Infrared*

The IR signal frequencies are sensitive to environmental factors and can be affected by sunlight, smoke, dust, etc. Hence the detection accuracy would vary under different conditions. In addition, it requires the line of sight between the transmitter and receiver to detect any obstacle. As pedestrians have to use infrared sensors (augment an extra device) with their smartphones, the usability could reduce. In addition, the detection performance decrease on the urban roadside due to heavy infrastructure and induced noise.

5.7. *Wearable Based*

Nowadays, wearable devices are ubiquitous, which users wear or attach to body parts most of the time. Sensors in wearable devices can continuously receive various users related data in real-time. For example - Smart Watches (e.g., Apple Watch[9], Samsung Watch[10]), Fitness Tracker (e.g., Fitbit[11], Garmin[12]), Head Mounted Display (e.g., Oculus[13]), etc. Researchers have used several wearable sensors to detect obstacles for pedestrians such as ultrasonic sensors, smart clothing, smart shoes, etc. Collision detection depends on the sensor used in identifying obstacles and algorithms. PAWS developed by Xia et al., a pedestrian safety system that uses multichannel audio sensors and able to detect approaching vehicles [117]. PAWS can identify the collision to pedestrians from car's honks, engine, tire noises with the help of machine learning. The system combines five microphones, signal processing, and feature extraction electronics; the smartphone does the machine learning part. The four microphones are distributed over the user at the left-right ear, back of the head, and chest. They combinedly provide the sources of the incoming sounds. The signal processing hardware synchronously acquires analog signals from these microphones and locally extracts acoustic features used by a smartphone application. There are two-phase of development: PAWS - basic segmented architecture and PAWS low-energy - to reduce energy consumption through internal design. The system shows a promising result in three different real-world setups (e.g., residential neighborhood, side of a highway, and metropolitan area). However, there are some limitations to detect incoming cars with this technique. For example, the system would confuse about multiple approaching cars. Besides, the noisy urban roads would provide the same type of sounds in numerous directions, making the system ineffective. Patankar et al. [109] developed a human assistance system to detect obstacles using multiple wearable ultrasonic sensors. At first, they implemented a system with three sensors, but the system cannot detect obstacles from other directions. The array of nine sensors successfully detects obstacles from multiple sides of the pedestrian. The system is divided into three parts, signal generation-reception, processing, and output. In the output phase, the system generates a map of obstacle position and surroundings. Although the system can detect an object, it cannot provide any information of the object type. In addition, it cannot detect multiple objects at the same time.

5.7.1. *Drawbacks of Wearable based applications*

In obstacle detection, most of the wearable devices connected with other computation sources (i.e., smartphones, servers, etc.) cannot detect an obstacle individually. Unlike the smartphone, a wearable is not versatile. The pedestrian needs to wear different devices to collect diversified data (e.g., vision data, motion data, Bluetooth signals, etc.). Wearables collect the raw sensor data; it needs to be better calibrated to get high accuracy and flexibility. Sensors need to be correctly positioned, and data needs to be better analyzed. In addition, security and privacy are a concern for wearable-based applications due to data transfer and always-on features. We discuss details about privacy issues in Section 7.

[9] Apple Watch - https://www.apple.com/watch/

[10] Samsung Watch - https://www.samsung.com/us/mobile/wearables/all-wearables/

[11] Fitbit - https://www.fitbit.com/us/home

[12] Garmin - https://www.rei.com/s/garmin-fenix-5-watches

[13] Oculus - https://www.oculus.com/quest/

5.8. Crowdsensing Based

Mobile Crowd Sensing (MCS) or Wearable Crowd Sensing (WCS) or simply, Crowd Sensing is a technique to collectively gather, compute, and analyze data. Usually, a large group of individuals carry sensing devices that collect data and share it with others to achieve common interests. Single devices can gather information from one direction and within the scope in other obstacle detection systems. In contrast, with crowdsensing, the system can get data from multiple sources. Therefore, crowdsensing provides a more detailed description of the surrounding area of pedestrians than individual smartphone sensor data. *CrowdWatch* is a crowdsensing application developed by Wang et al. [112], which leverages mobile crowdsensing and crowd intelligence aggregation to detect temporary obstacles. If there is any obstacle on the pavement, the non-distracted pedestrian would detour to avoid them. The built-in sensors (e.g., accelerometer, orientation sensors, etc.) of this pedestrians' smartphone adopt this turn and record it. When multiple users take this turn, the system assumes there may be an obstacle on the sidewalk. Then the system reminds distracted walkers about the dangers in front of them. However, every time making turns does not mean an obstacle. To avoid this, *CrowdWatch* adopted the Dempster-Shafer evidence theory [125] to calculate the confidence of obstacle existence. Wang et al. [118] developed *CrackSense* to detect urban road cracks based on mobile crowdsourcing. After aggregating the multi-sourced data, it recognizes the crack type into the horizontal crack, vertical crack, and net crack by an algorithm named Road Crack Type Recognition (RCTR). *CrackSence* also estimates the crack damage degree.

5.8.1. Drawbacks of Crowd Sensing

In crowdsourcing, individual users collect surrounding data; the behavioral reaction to an obstacle is different from person to person. The users can react or sense data for many reasons other than obstacles. The data may not be credible, and the process of validation is laborious. To determine an obstacle from crowdsensing data is not trivial. As nature and characteristics are complicated on the sidewalk, it is difficult to identify an object as an obstacle. This technique would only provide an accurate warning for the static obstacle. In addition, distinguishing the individual obstacles and characterizing any dangerous area is challenging, especially in a rapidly changing environment. It is not sufficient to only localize or mark a place as dangerous. Characterizing an obstacle in a granular manner is needed to ensure pedestrian safety.

5.9. Hybrid Applications

A specific sensor is often insufficient to detect potential danger successfully. Significantly, in an urban area where the environment and surroundings are ever-changing. Therefore, several safety systems use a set of input sensors to achieve higher accuracy. For example, Tung et al. [42] developed *BumpAlert* using the acoustic sensor, inertial sensor, and phone camera. *BumpAlert* consists of four components, including distance estimation, which uses the acoustic detector; obstacle presence determination uses the visual sensor; pedestrian walking speed uses the motion estimator; generates alerts from all the above components using the fusion algorithm. The application provides more than 95% accuracy for the static objects in a controlled lab environment; however, the system cannot detect moving obstacles. *BumpAlert* provides the distance information of the obstacle, but only the distance is not enough to properly estimates a potential collision. In addition, the false alert annoys users and reduces usability. Li et al. [32] proposed *Safe Walking*, an Android-based safety system for pedestrians. *Safe Walking* uses the smartphone inertial sensor and smartphone built-in front camera to detect walking behavior. One interesting thing is that the system identified the distracted pedestrian behavior instead of detecting an obstacle. Specifically, *Safe Walking* detects the pedestrian speed using inertial sensors to identify if the user is walking or not. Then, it measures the face and eye movement by an image detection algorithm. Finally, the system identifies the distraction level and gives alerts to pay attention. *Safe Walking* introduced eye-movement tracking, a new layer to avoid the obstacle for a pedestrian when unattended on the street. However, the system would always warn the pedestrian even if there are no potential threats around them. Uchida et al. [115] proposed an accident prevention system using smartphones by the chronological changes of sensors and radio signals. The smartphone continuously monitors the user's (driver, bicycle, and pedestrian) motions by various sensors. If the system detects any abnormal behavior of the driver and bicycle, then the smartphone gives an alert to the pedestrian. However, all types of users (drivers, bicyclists, and pedestrians) must use smartphones in this proposed system. Ishikawa et al. [40] designed a road anomaly (e.g., cracks, pits, puddles, etc.) detection system based on pedestrian walking patterns and behaviors. The system uses inertial sensors, GPS, and Geographical Information System (GIS) to detect an anomaly. The GIS is used to eliminate the false classified event (e.g., a real curve on the road). The detection accuracy depends on the user's smartphone data. However, people carry their smartphones in various positions, such as trousers pocket, chest pocket, hand, etc. It creates noise and overhead, which negatively impact accuracy. *SightSafety* developed by Riaz et al. [100], a hybrid health management system to prevent collision between pedestrians and vehicles in the sites. *SightSafety* uses GPS, inertial sensor data, and wireless networks to track and notify the users. The system creates multiple zones (e.g., green zone, amber zone, and red zone) based on the positions and types of vehicles. Then *SightSafety* delivers alert signals depending on the context of the user (e.g., pedestrian, site worker, manager, etc.), and task (e.g., plant operator, ordinary worker, etc.). Won et al. [39] developed *SaferCross* using smartphone inertial sensors, GPS, and Direct WiFi. *SaferCross* is useful for localizing pedestrians in urban areas with skyscrapers where accurate positioning based on GPS is challenging.

5.9.1. Drawbacks of Hybrid

We found the hybrid system is most promising in terms of accuracy and usability. However, the unnecessary use of multiple services and sensors is expensive in terms of energy consumption. For example, in *BumpAlert* [42], the visual detection module causes twice the CPU usages than acoustic detection.

The computation resource is also affected if the resources are not correctly used.

6. Advantages and Limitations of Existing Systems

Every safety systems have some drawbacks and benefits. Some of the proposed techniques performed better in a controlled lab environment but are not usable in real life. For that, we have identified the advantages and limitations of current obstacle detection systems. It would help to identify the usability of these systems and potential research direction. Table 3 shows the advantages and limitations of the systems group-wise. Here, the *"ID"* column represents the individual paper reference listed in Table 2.

7. Privacy

Pedestrian safety systems adopted various holistic approaches and technologies. As a result, these technologies have raised unforeseen security and privacy concerns. Usually, previous research on pedestrian safety rarely considered user privacy and security risk. There was a tendency to overlook these issues of the proposed systems to make them fully mature and then retroactively try to develop safeguards. However, we argue that we should develop the security and privacy protocol from the sketch when the technologies are still young and malleable. This section discusses potential privacy issues and mitigation in pedestrian safety systems. Therefore, we divided the privacy issues of the pedestrian system into the following categories based on the nature of existing applications and systems.

7.1. Privacy of Sensor Data

Safety systems require access to various sensor data, including audio-video, motion, GPS, infrared data, etc., to provide intended accuracy to the pedestrians. Though the privacy of sensor data are well handled in some other area, it has become more sensitive for pedestrian safety as their nature of always-on, always-sensing (i.e., camera, GPS, microphone). Besides, some device needs to communicate with other devices by wireless technology. Thus, the device needs to provide some access to sensor data to others. However, maintaining a balance between personal data from stealing or misusing and giving access to functionality is challenging. For instance, a malicious safety system can steal or leak the pedestrian location data to third parties [126]. There should be a safeguard to limit access to these data. A system should not require sensor data all the time; perhaps it could access sensors for a specific period or at a particular location [127]. In addition, the system has to implement user-driven access control [128] and adopt a two-way user-centric approach – first, safety systems have to get permission from pedestrians before collecting any data. Second, only unidentifiable and consented data can be stored. The system has to take proper safety measures to protect these data, including obfuscation [129], strong encryption, anonymity method [130], etc.

7.2. Bystander Privacy

The always-on sensing of obstacles detection systems creates privacy concerns for bystanders [131]. Though the issue of bystander's privacy is not new, the overwhelming use of cameras, acoustics, GPS, and motion sensors has risen in importance. For example, one of the main reasons that failed Google Glass was it made bystanders uncomfortable about their privacy [14]. The questions arise when a pedestrian device collects data to identify the surrounding pedestrian when they have not given consent to be part of the collection. Bystanders usually respond when they are being recorded. For example, Hoyle et al. conducted a study on bystander's privacy with lifelogging cameras where people avoided interaction with those who wore a camera. In addition, people prefer to manage privacy during recording instead of reviewing after collection [132]. Denning et al. explored the bystander's reactions toward the augmented reality devices [133]. The camera, acoustics, and augmented reality-based obstacle detection systems should adopt the proper safety measures to protect the surrounding user's identity. For example, the device can alert bystanders when sensing or recording, user-centric sensor designs [134], synthesizing makeup to prevent identification, etc. [135, 136]. However, current technology has shown little success in protecting the bystanders' privacy [137, 138]. In addition, the advancement of deep learning and image processing can recreate the obfuscated and blurred image of pedestrians [131, 139].

7.3. Cross-app Privacy

The multiple pedestrians in the same obstacle detection system can exchange the data with each other. For example, in a crowd-sensing system or augmented reality-based system, or any system where the central predefined model helps to detect the obstacles. Recently, cross-app privacy has emerged when Apple Inc. gives users the option to control tracking settings[15]. Therefore, new approaches have to be adopted with the traditional access control. For example, in the AR systems, gesture-based drag and drop sharing has been introduced [140]. Sliwa proposed a data exchange framework where privacy is preserved and takes only required data which unaware of the semantics [141]. In addition, the wearable and AR-based applications would need to evolve new user gestures to indicate sharing intent.

7.4. Cross-system Privacy

The communication of the cross-system applications can lead the data leakage (i.e., communication between pedestrians and vehicles (V2P or P2V)). In these systems, both vehicles and pedestrians share their position, velocity, and intended destination with other systems (sometimes with different protocols) [142]. Malicious applications can steal users' locations, hot spots, and habits [143]. However, without sharing these data, safety would not be achieved. So there should be a trade-off between privacy and safety [144, 145]. All contemporary safety

[14]https://www.theguardian.com/commentisfree/2017/jul/23/the-return-of-google-glass-surprising-merit-in-failure-enterprise-edition

[15]https://support.apple.com/en-us/HT212025

Table 3: Advantages and limitations of the existing applications

Tech.	ID	Advantages	Limitations
Inertial Sensors	A2, A10, A27, A34	• Ubiquitous to all modern smartphones. • It can measure acceleration, tilt, shock, vibration, rotation, and multiple degrees-of-freedom (DoF) motion. • Proficient in detecting activity recognition, fall detection, speed calculation, sudden change of pedestrian state, etc.	• To process raw data, the system needs high computational power. • High frequency and continuous sensor data are needed for better accuracy. • Gives noisy data, needs a personalized model to detect. Insufficient for pedestrian safety in dense urban environments.
Camera	A4, A7, A12, A17, A23, A25, A36	• The camera-based system detects an obstacle ahead of time. • Camera can identify distracted pedestrians by eye-tracking. • It is possible to recognize the shape, size, texture, and materials of obstacles.	• Image recognition is a computationally-intensive process. • The obstacle must be in the direct line-of-sight to detect. • Detection accuracy depends on the environment, lighting conditions, and camera quality.
Acoustic	A1, A6, A16, A20	• Acoustic system provides unsupervised classification where no preliminary data are needed. • Inaudible to humans, it can continuously monitor users without annoying them. • Relatively low power consumption than other smartphones sensor (e.g., Camera, GPS, etc.)	• Difficult to identify from multiple sound sources, noisy environment, and sound absorber obstacles. • Get confused by the legit barriers, such as body reflection, crowded areas, etc. • The obstacle angle estimation depends on how the pedestrians hold their devices, which is different from person to person.
GPS	A13	• Able to detect obstacles from both line-of-sight and non-line-of-sight. • A pedestrian can share the position with others. • The GPS signal is available worldwide. Therefore the GPS-based system will work in most places.	• Larger distance error due to the GPS signal accuracy. • No other information about the obstacle but points. • Would not functional in GPS denied environment and crowded urban areas.
Infrared	A3	• Used to detect sudden changes of ground and object presence/motions. • Invisible, Infrared based system works at night as well. • Relatively low power consumption than smartphones GPS, Camera.	• It requires the obstacles within the line-of-sight of the pedestrian. • The receiver will be confused if it receives the same multiple signals from different sources. • The signal can be blocked by other pedestrians, walls, trees, and sunlight.
Wearable	A18, A30	• It is specially built for obstacle detection by multiple sensors and devices. • Wearable based systems can monitor the pedestrian continuously even if their phone is not in use. • Vision-based wearable give an extra insight into obstacles to the pedestrian.	• Low computational power, high latency in data communication. • The multipart system is ineffective if any part is not properly worn. • The sensors, camera, acoustics-based limitations also exist.
Crowd Sensing	A15, A24, A31	• It can provide a detailed description of the obstacles from different sources. • The obstacle does not need to be in the eyesight, even not within the sensor range. • Automatic obstacle detection with the manually labeled crowdsensing data gives better accuracy.	• Crowdsensing cannot work in real-time detection and is unsuitable for moving obstacle detection. • The pedestrian has to be non-distracted while sending data to others. • Personalized pedestrian data can be imperfect; validation is time-consuming and difficult.
AR/VR	A5, A9, A11, A21, A26, A29, A32, A35	• AR/VR-based system provides extensive information about the obstacle. • AR-based systems operate simultaneously with real-world occurrences; the obstacle can detect in real-time. • The application offers an arrow-pointed redirection path or a safe passing zone to avoid obstacles.	• Overlaying digital elements on the natural environment masks real-world danger and make pedestrian less cautious. • Full fledged AR application with details of the obstacle is costly and technologically taxing. • Sometimes, the application itself is a distraction as pedestrians fall in danger as their attention is focused on the contents.
Hybrid	A8, A14, A19, A22, A28, A33	• A combination of multiple approaches is necessary because it is challenging to detect obstacles by utilizing only the built-in sensors in commodity phones. • Possible to collect information about the surrounding environment/obstacles from multiple aspects.	• Multiple input source causes high energy consumption and computational resources. • Maintaining the correlation between resources and sensors is challenging.

measures must be adopted throughout the components and consistent to make a secure and safe system. On the user side, pedestrians must review uses logs to verify the access.

8. Challenges and Future Directions

8.1. Real Time Detection

The human visual system extracts information from moving objects in real-time. It can auto-focus on multiple things in its surroundings without any biological changes. However, detecting obstacles using the camera is considered challenging because of the absence of the optical flow or the motion parallax. It is vital to keep track of other objects (e.g., non-hazard obstacles, possible flying objects, etc.). Though the recent advancement in camera technology, it is still challenging to trace and track multiple objects simultaneously in low-level devices. Because tasks considered easy by humans are certainly tricky in computer vision, we humans can easily recognize a person regardless of the orientation or vehicles in various positions or multiple vehicles are together seen from any angle. However, object detection techniques face common challenges, including viewpoint variation, occlusion, illumination conditions, etc. For example, occlusion happens when two or more objects approach too close together and seem to mix or join, a common scenario at the street. The other important factor is speed, which means that object detection algorithms must accurately classify important objects and be incredibly fast during prediction to identify objects in motion. The computer vision and mapping technology, such as simultaneous detection and tracking [146], the deep learning [147] approaches could overcome this challenge.

8.2. Lack of Information

Detailed object information (e.g., size, position, materials, speed, etc.) is needed to detect the potential collision. Safety systems can detect the presence, characterize objects, and measure the distance of the obstacles from the pedestrian. The system gets this information by coarse-grained data without correlation of materials, nature, and the intention of the obstacles. Such data is insufficient to detect a potential collision accurately. For example, objects angle information, surrounding environments, obstacle types, etc. Safety systems can use Geographical Information Systems (GIS) to get surroundings data beforehand. For example, there is a possibility of the presence of VRU's in schools and recreation areas. If any safety system has those data, it can make the decision and warn the pedestrians/drivers beforehand.

8.3. Hardware Limitation

Smartphones and wearables have equipped with sensors for limited computation power and functionalities. However, these sensors are well enough for the users' daily activity but do not provide high accuracy to detect obstacles. For example, the commodity smartphone is primarily designed for everyday use and is not equipped with dedicated sensors. It has a limited number of microphones and speakers. In contrast, the radar and sonar systems are specifically designed and equipped with dedicated multiple transmitters and receivers. To ensure pedestrian safety in an urban area, sometimes it needs granular level accuracy in a matter of seconds [148]. Current smartphones and low-powered wearables are not capable of handling large data. Smartphone GPS is another example of hardware limitation. If we want high positional accuracy, the phone battery will drain significantly.

8.4. Human Factor

In collision detection systems, human factors are important due to inconsistency. Pedestrian body pose, inter-pedestrian/social-related behavior, and consciousness affect safety. These factors are different from human to human. Some studies explore the use of pedestrians' contour [149], posture, and body language [150]. However, estimating pedestrians' movement is even more challenging due to uncertainties regarding their impending motion. Researchers can adapt trajectory prediction [151] or activity recognition [152] in safety systems.

8.5. Dynamic Environment

The dynamic surrounding is challenging for pedestrian safety in the real world, especially in the urban area. The street in a city, the movement of vehicles, and the crowded pedestrian are different problems for the safety systems every time. Most research detects the static obstacle from this changing environment but not the moving one. However, recent development in SLAM (i.e., Dynamic SLAM) and Robotics technology shows success in overcoming this problem [153, 154].

8.6. Noisy Sensor Data

Noisy sensor data and environmental disturbance are important concerns in obstacle detection. Raw data contains noises caused by unpredictable hand or body jitters, affecting accuracy. For example, built-in smartphone sensors need calibration, filtering, and face difficulties in identifying different motions. Acoustics and inertial sensor-based solutions also get impacted severely by the noise. The presence of noise in data may increase the processing complexity and time, which affect performance. The detection system should differentiate the sounds from multiple sources. For example, environmental noises (e.g., walking induced noise, non-hazard sounds, human sound, etc.) and desired input signals need to classify correctly. Researchers proposed some filters and techniques to handle these noises [155, 156]. In the deep learning technique, noise can be in multiple levels, such as class level noise, feature level noise, etc. Previous research found that noise can easily overfit the model, which leads to poor generalization performance [157]. Some research suggests relabeling the noisy data; however, this technique only benefits the data for the static environment [158, 159]. Several studies have recently presented noise-resistant object detection [160]. However, accuracy is still low.

8.7. Sidewalk Data

Pedestrian safety and obstacle detection depend on sidewalk accessibility data. The quality of data helps to improve the accuracy. Usually, the presence and quality of the sidewalk in a city audits by the transportation department via in-person inspections. However, this process is laborious and expensive; most importantly, not frequent. Therefore, safety systems cannot use these data to identify potential dangers in real-time. For instance, while map service provider companies offer pedestrians-focused features, they do not provide sidewalk accessibility information [161]. Recent research has included a small set of sidewalks data to detect obstacles [162, 163].

8.8. Complete Ecosystem

All the existing applications contributed to certain aspects of pedestrian safety or obstacle detection. Such a system cannot protect the user from other potential dangers. For example, *Auto++* cannot detect static obstacles, *BumpAlert* cannot identify moving obstacles, etc. To this end, we need a complete ecosystem where all the elements can interact. Such a system can be built with multiple modules (e.g., an application for pedestrians and drivers, a communication module, an object tracker module, etc.).

9. Conclusion

Pedestrians are the most vulnerable road users, and therefore, they require maximum protection. Recently, numerous research has been conducted in the context of *Pedestrian Protection Systems*. For example, obstacle detection, collision prediction, alert systems, etc. The fusion of multiple sensors and augmented reality-based obstacle detection systems has shown promising results. However, most of the current research on pedestrian safety is coordinated toward a specific domain, and those systems are usually not competent for the real-world scenario. It is necessary to carry out systematic experimental validation to ensure robust and reliable performance in all kinds of environmental conditions. In addition, the privacy and security of this type of safety system should be guided from the early stage of development. A systematic performance matrix could be developed to compare the performance of multiple research and applications. Some standardized datasets will help achieve this goal. A personalized agent or *Guardian Angel* application could save lives from unsought accidents in the future. These systems would be able to predict the potential dangers and warn the pedestrians successfully.

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