# Micromobility sensing systems and safety services: a brief review

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# Micromobility Sensing Systems and Safety Services: A Brief Review

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***Abstract*—Micromobility refers to small, lightweight and low-speed personal devices including motorized (e-scooters) or non-motorized (bicycles) vehicles. However, the most vulnerable road users are riders of micromobility, including bicycles, e-bikes, e-scooters and motorcycles. Additionally, the safety of micromobility devices is considered the most significant factor that influence the adoption of this mode of transportation in urban environments. Therefore, different sensing systems have been used for collecting micromobility motion data and detecting various aspects of micromobility safety. This review summarises research on micromobility sensing systems and safety services. It is organised into four topics: micromobility and sensing approaches, micromobility safety challenges and potential solutions, micromobility sensors and data acquisition methods, and micromobility safety and hazard detection. Therefore, a brief account of micromobility sensing approaches and their roles in tackling micromobility safety challenges is given. Additionally, the applications of various types of micromobility data collection methods and sensos are described. Finally, a brief overview is given of possible applications micromobility sensing data in hazard detection techniques and therefore in shaping the micromobility safety schemes.**

***Keywords—micromobility, vulnerable road users (VRUs), sensor, transportation, safety, hazard detection.***

## I. Micromobility and Sensing Approaches

Micromobility refers to lightweight and personal vehicles which have a maximum weight of 350 kg and a maximum speed of 45 km/h. This may include both human- and electric-powered vehicles such as bicycles, scooters, e-bikes and e-scooters [1]. Effectively, all easy-to-push or easy-to-carry vehicles (motorized or non-motorized) that allow the increase of pedestrians are known as micromobility vehicles [2]. However, bicycles and e-scooters represent the most widespread modes of micromobility [2], [3]. Additionally, bicycles became more attractive mode of travel due to their great advantages that it offers in terms health and environmental sustainability [4], [5].

Micromobility concept of mobility is an important mode of urban transportation and modern life. This travel mode involves a wide range of vehicles and services and has become increasingly popular in modern cities during the last decade [1], [2], [3], [6]. Additionally, the widespread use of micromobility mode of transport to a large extent related to the decreased number of traffic accidents and collisions involving micromobility vehicles [7]. Therefore, micromobility can be promoted to tackle urban transportation challenges and this mode of transportation can be considered a safe, sustainable and feasible alternative [5].

Micromobility sensing systems can collect data for analysing safety metrics in terms of speed changes, experienced vibration events, and proximity to surrounding objects including vehicles [8]. Additionally, micromobility sensing systems can detect the safety conditions, riding styles and manoeuvre behaviours of riders and also can monitor the micromobility movement status [9]. Effectively, vehicle kinematics and controls data can be collected by different sensors and this data can be used for assessing multiple vehicle safety aspects such as steering and braking [10], [11]. Therefore, micromobility motion data can be collected and used to provide safety-related services [12].

Bicycles are usually equipped with video cameras, global positioning system (GPS) to collect speed and position data, and laser systems to collect speed and distance data [3]. Hence, a low-cost open-source sensor can be used for measuring lateral passing distance between motorized vehicles and bicycles and identifying dangerous overtaking [13]. Additionally, the dynamic of bicycles can be monitored and analysed to recognise hard braking and evaluate micromobility safety [3]. On the other hand, surface quality of road pavement can be assessed by monitoring several key variables related to micromobility (i.e. speed, steering and acceleration) [4]. To study parameters that affect the anxiety level of cyclists and their safety, Pejhan et al. [14] equipped a bike with inertial measurement unit (IMU), potentiometer, GPS, five ultrasound sensors and three GoPro cameras to monitor the bike balance, speed and its proximity to other vehicles. However, a heart rate sensor and a peripheral detection task were used to measure the stress and mental workload of micromobility rider.

Methods of using micromobility-related big data which has been passively generated are reviewed by Schumann et al. [1] and the reviewed studies have been categorised according to data type, research aims, methods, and results. Additionally, the challenges related to micromobility have been identified and categorised into four classes; society, safety, environment, and system design. In another study, Lee and Sener [15] reviewed non-motorized travel (i.e. walking and bicycling) monitoring including emerging data sources, applications and challenges.

## II. Micromobility Safety Challenges and Potential Solutions

The safety of micromobility devices, cyclists and e-scooters, in urban environments represents one of the main concerns which affects the adoption and sustainability of this travel mode [5], [16]. Poor infrastructure, road accidents and conflicts with other road users are some examples of risks which may be faced by micromobility users [5]. Therefore, such safety concerns need to be addressed to improve the acceptance of micromobility in urban areas. Zhang et al. [17] provided an international evidence review of literature and investigated what elements affect the safety of micromobility with a focus on e-scooters. It has been found that head injury represents one of the most commonly seen consequences of e-scooters-related collisions and helmets can provide significant head protection in such cases.

Micromobility vehicles often operate on roadways, bike paths or footpaths and this may lead to congestion and collisions between these micromobility vehicles and other road users such as pedestrians and car users. Additionally, the comfort of micromobility rider can be measured and improved by using information about the infrastructure (e.g. potholes), micromobility vehicle position and speed [18]. Therefore, the safety of micromobility is significantly affected by infrastructure and the design of micromobility paths can increase safety [17]. Moreover, poorly maintained infrastructure, including road potholes and pavement defects present potential safety hazards for micromobility users and implicitly means low perceived safety and riding comfort of cyclists [4], [5]. Thus, collision risk of vulnerable road users (e.g. e-scooter and bicycle riders) and the severity of experienced crashes will most probably be affected by the type and characteristics of the infrastructure (e.g. uneven pavement) [8]. Also, information about micromobility-car collisions and conflicts (i.e. near misses) and micromobility only crashes (i.e. because of curbs or uneven path) including their locations are very important for infrastructure redesign and for improving the safety of micromobility.

Data-driven services of micromobility safety requires accurate and real-time data collection (e.g. measuring the lateral passing distance of vehicles passing cyclists) in a dynamic, outdoor environment. However, this involves several technical challenges due to the effects of various factors (i.e. vibration of the moving bicycle and lighting conditions) on the quality of the measured data [16]. Various automatic techniques can be used for detecting road surface damage (i.e. analysing vehicle vibrations caused by direct contact with the roadway). However, such incidents can be detected only if they (e.g. potholes) were touched by the vehicle tires [19]. Additionally, distinguishing real hazards from road's anomalies represents a significant challenge and this could be tackled by setting absolute thresholds on the sensors (i.e. accelerometer) measurements [20]. Restricted riding environments, experienced vibrations and speed variations of micromobility vehicles (i.e. e-scooter) may increase the safety challenges. Therefore, potential micromobility collisions can be avoided by identifying dangerous riding facilities and analysing the effects of fixed obstacles (e.g. pedestrians and trees) and nearby moving vehicles (present in the riding environment) on the riding experience [8].

Micromobility safety can be increased by using intelligent lights that increase visibility at night or during bad weather conditions and this may reduce the chance of a collision or the impact of the collision [18]. In another study and with the aim to enhance micromobility rider safety, Ma et al. [8] used GPS and accelerometer data from micromobility devices to predict the riding habits of micromobility users and identify factors contributing to accidents. Effectively, anxiety levels of micromobility riders could influence their safety and therefor the parameters that increase rider's nervousness need to be investigated and identified [14]. Additionally, intersections with poor visibility and road with heavy traffic are examples of hazards that may be faced by micromobility users and represent micromobility safety challenges which need to be addressed [21]. However, fast rear approaching vehicles represent a major problem for a cyclist and may lead to fatal accidents. To overcome such hazardous situations and increase the safety of cyclists, a methodology is required to enable cyclists to perceive the rear approaching vehicles [22]. Therefore, a bicycle can be equipped with a system containing 1) audio and video sensing to monitor the environment behind a biker continuously, and 2) computational capabilities to processes the sensed data and automatically detects the rear-approaching vehicles and alerts the biker in real time [23].

To identify potential risk factors on cycling routes and enhance the safety of micromobility users, Tamagusko et al. [5] created a safety map and a smart route planner by utilising Google Street View images, advanced computer vision and deep learning techniques. Therefore, hazard map can support micromobility riders and provide them with information regarding potential risks and hazardous locations [21]. However, intersections with poor visibility and road with heavy traffic are examples of hazards that may be faced by micromobility users and represent micromobility safety challenges which need to be addressed [21].

## III. Micromobility Sensors and Data Acquisition Methods

There are different types of sensors that can be installed on micromobility vehicles as well as various acquisition methods that can be used to collect micromobility-related data. Mostly, a data logger device, such as Raspberry Pi which is a single-board computer, is used for logging the data coming from different sensors [24], [25]. Raspberry Pi platform can be used to integrate and connect many sensors including GPS, IMU, and light detection and ranging (LiDAR) for safety-related data collecting, processing and storing [8], [13]. Therefore, a low-cost data acquisition system based on Raspberry Pi can be mounted on an e-scooter to collect its acceleration, speed and position [3]. Effectively, Ambrož [26] conducted a study to test the performance of a Raspberry Pi as a riding dynamics data acquisition system for use on human powered vehicles and confirmed that the performance of this system is comparable to some higher-priced and less portable data acquisition systems. However, Duran Bernardes and Ozbay [6] presented a novel data acquisition system for collecting crucial data for bicycle safety, including cyclist behavior, bicycle trajectory and lateral passing distance. This system utilizes a Raspberry Pi microcomputer, an IMU, two ultrasonic sensors and GPS antenna and receiver.

### A. *Global positioning system (GPS)*

GPS is one of the global navigation satellite systems (GNSS) that provides geolocation and time information and plays a pivotal role in real time vehicle tracking. Additionally, GPS data may include the speed, direction and travel mode of an individual or vehicle. Effectively, GPS has been considered as a data collection technique for collecting micromobility vehicle position and speed [18]. Therefore, vehicles can be tracked via specific GPS sensors installed on micromobility vehicles or mobile phone apps. Also, GPS loggers can capture the non-motorized (i.e. walking and bicycling) activity [15]. Micromobility vehicles equipped with handlebar mountable GPS devices may record time-stamped x, y and z coordinates and determine the vehicles' speeds and accelerations at every point on their journey [27]. Therefore, GPS sensors can provide the speed and travel distance of micromobility vehicles at each sampling interval [4], [13]. Moreover, GPS can provide timestamp and coordination information (e.g. latitude and longitude) to determine the position of hazardous spots [6], [8], [28], [29].

### B. *Inertial Measurement Units (IMU)*

IMUs are made up of integrated sensors like magnetometers, gyroscopes, and accelerometers which can sense orientation, velocity, and gravitational forces. Therefore, IMU is used to measure acceleration, orientation or attitude angle (roll, pitch and yaw angles), magnetic field and angular velocity (roll, pitch, and yaw angular velocities) of micromobility vehicles [24]. A mobile sensing system has been developed by Ma et al. [8] and it includes an IMU motion sensor (combining an accelerometer and gyroscope) to track the motion status of micromobility. However, Han et al. [9] proposed a micromobility sensing system with two IMU sensors (each contains an accelerometer and gyroscope), the first one is fixed on the rider's helmet to monitor the rider's head movement while the second one is mounted on the bicycle's handlebar to analyse the rider's riding style. In another study and to build 3D environmental maps, Yoshida et al. [7] equipped a smart helmet with a LiDAR to detect surrounding objects and IMU which gets the attitude angle and angular velocity of the micromobility rider. Effectively, IMU may be used to collect micromobility-related data about vehicle kinematics, braking and steering performance [10]. So, acceleration data collected by the IMU can be used to calculate the speed and position of micromobility vehicle. Additionally, IMU incorporating an accelerometer, gyroscope, magnetometer, temperature and pressure sensors, light-emitting diode (LED) and a push button may be used to monitor the effects of cycling infrastructure on the riding comfort of cyclists [4].

Using accelerometer for transportation mode recognition represents one of the most important applications of this sensor. Therefore, accelerometers and GPS can be combined for distinguishing various transportation modes [30]. Additionally, vehicle's velocity values (from GPS sensor) and the data collected by accelerometer can be used to detect and classify critical road surface anomalies (i.e. pothole, speed bump) [31]. Therefore, a data collection system that utilizes 3 - axis acceleration sensors integrated into micromobility devices represents an effective system to collect real time motion data [12].

Micromobility sensing system may involve an accelerometer to measure gravitational acceleration or dynamic acceleration forces along 3 axes [6], [8]. Therefore, micromobility vibration information can be collected and quantified using motion detection sensor such as 3D accelerometer for evaluating vibrations encountered by riders. So, data collected by accelerometer can be used to identify and classify where the cyclist is performing the ride [19], [29], [32]. Additionally, acceleration waveform data has two main factors: the frequency and amplitude (the vibration strength) [8]. Thus, accelerometer sensor can be mounted on a bicycle to measure the roughness of road surface and bicycle lanes. Effectively, the roughness of the surface is measured using the vertical acceleration data (hit location) at each sampling interval and the signal (hit) magnitude value is used to categorize the severity of the road defect (i.e. low, moderate or high) [4]. So, accelerometer can be used for detecting the hazardous spots on the road, measuring the steps (or potholes) dimensions and emergency braking time [28].

Accelerometer data may be used to determine if an accident has occurred or if there is a fall during the riding [33]. Additionally, accelerometer can be implemented on the helmet for detecting abnormal magnitude peaks (i.e. fall) and determining the level of risk to cyclist's head [34]. Micromobility vehicles may be equipped with a sensor system containing a built-in accelerometer to detect micromobility accidents [25]. Therefore, three-axis accelerometer represents an excellent tool for recognising bicycle behaviours and predicting dangerous riding behavior [35].

Micromobility sensing system may involve a gyroscope to measure rate of change of the angular position over time or rotational velocity along 3 axes [6], [8], [32]. Additionally, three-axis gyroscope can be used for monitoring the angular velocity of micromobility vehicle, recognising the behavior of micromobility behavior and detecting fall incidents [34], [35], [36]. Therefore, a gyroscope sensor provides the direction and orientation information (yaw, pitch, and roll angles) which can be used to enhance the accuracy of a micromobility fall detection system [33].

Magnetometer is a device that measures magnetic field or magnetic dipole moment to sense the orientation in space. It always points in the direction of Earth's geometric north to determine orientation and direction. Effectively, magnetometers can be used to detect the presence and movement of vehicles, counting bicyclists and detecting fall incidents [33], [37].

### C. *Ultrasonic sensors*

The main goal of ultrasonic sensors is to accurately estimate the separation or distance between itself and any item within its detection range. Therefore, micromobility data collection system may include ultrasonic sensor to collect clearance distance data and measure the lateral distance between the instrumented vehicle and the edge of the opposite lane [2].

Therefore, ultrasonic distance sensors can be used to identify areas of risk based on the proximity of objects from bicycle [29]. Effectively, multiple low-cost ultrasonic sensors can be used to detect a wide range of possible obstacles in front of micromobility vehicle [6]. Therefore, these sensors have been may be incorporated in a collision avoidance safety system to enable safe operation of micromobility vehicles in pedestrian areas [38]. However, there are many types of distance measuring sensors such ass laser, LiDAR, and ultrasound sensors [16]. Additionally, these sensors have different reliability, accuracy and range which need to be analysed and assessed at diverse conditions.

### D. *Light Detection and Ranging (LiDAR)*

LiDAR is a ranging device, which measures the distance to a target by sending a short laser pulse and calculating the time lapse between outgoing and reflected light pulse [3]. Micromobility sensing system may involve a LiDAR scanner to measure the distance to surrounding objects (e.g. pedestrians and trees) [8]. Therefore, LiDAR can be used to track the planar motion of micromobility vehicles as well as to obtain measurements about distance, direction, and reflected light intensity [24], [39].

Micro LiDAR distance sensors may be used for measuring lateral passing distance between motorized vehicles and bicycles (i.e. overtaking distance) [13]. For example, an automated and robust framework has been provided by Yap et al. [16] to measure and analyze vehicle–cyclist passing distance and speed. This framework integrates a microcontroller (Raspberry Pi 4) with a LiDAR distance sensor and an AI camera. Additionally, a stationary LiDAR sensor may be used to collect vehicle kinematics (e.g. vehicle speed and position) and compute braking and steering performance of micromobility [10].

To enhance the active safety of micromobility, micromobility vehicles (i.e. two-wheeled vehicles) equipped with a LiDAR have been used to build environmental maps in narrow road environments [7]. 3D LiDAR technology represents one of the surrounding environmental sensing for micromobility, such as environmental map building and moving-object recognition (i.e. cars, two-wheelers, and pedestrian) for active safety in sidewalks and streets [39]. Therefore, building a 3D point-cloud map in sidewalk and roadway environments can be effectively achieved by using LiDAR attached to the rider's helmet of a micromobility [7], [40].

LiDAR technology has many applications in ITS fields and it can be used to detect alcohol in motorcycle riders, detect collision-accidents and to confirm rider safety after accidents [39]. Therefore, micromobility devices can be protected by fusing 2D LiDAR with other types of sensors (e.g. camera) to detect and track vehicles by predicting car-micromobility device collision [41]. The reliability, accuracy and range of three types of distance measuring sensors: laser, LiDAR, and ultrasound sensors have been tested and evaluated against a stationary wall at varying distances (both indoor and outdoor) [16]. As a result, LiDAR sensors outperformed other types of distance measuring sensors and considered the most suitable candidates for outdoor experiments.

### *E. Camera*

A single monocular camera can be fused with LiDAR sensor data to detect vehicles, find the corners of target vehicle and estimate the location, velocity, and orientation of the target vehicle [41]. Additionally, smart cameras can be combined with data processing algorithms to estimate micromobility vehicle speed, flow and queue length [18]. Therefore, cameras can be installed on micromobility vehicles and analysing the captured video recordings may support the visual validation of journeys and identify road topology, manoeuvre type, clearance distance and speed [2], [4].

Videos and images can be automatically obtained from a camera and then computer algorithms can be used to capture both screenline volumes and intersection turning movement volumes of pedestrians or bicyclists [37]. However, manual interpretation of the collected video data represents another method to count bicycles and pedestrians. Additionally, camera videos and images collected about road situations can be used to determine the hazardous locations through reviewing the video and discussing its content [21].

Computer vision model that uses a camera placed in front of the vehicle and analyses the captured video feed has been developed to increase the safety of the micromobility [25]. This model predicts in real-time the type of lane in which the user is riding and warn users when they are not complying with the regulations. In another study, more than 4000 camera images for roads and object detection algorithms have been employed to detect road hazards such as potholes and debris [42]. Additionally, camera images showing road surface anomalies have been utilised to calculate the level of road risk or road hazard index [19]. However, Han et al. [9] proposed a micromobility sensing system with two GoPro cameras to record the rider's head movements and rider's behaviour and manoeuvre. Effectively, two cameras (front and lateral) may be used to analyse overtaking distance, identify the types of vehicles involved in the overtaking and verify the presence of parked vehicles on the road [13]. Additional, divided framework image of captured video and a computer vision API can be used to recognise input image (i.e. human, bicycle or car) [28]. Therefore, recorded videos, Image segmentation techniques and object detection algorithms represent the most widely used methodology to identify potential hazards and risks on cycling routes [5], [23].

### *F. Survey and crowdsourcing*

Surveys and questionnaires represent one of the main sources of data used to analyse and study the riding behaviour of micromobility [8]. Therefore, traditional travel surveys can be used to collect data from micromobility users about their travel activities in detail. Effectively, a web-based questionnaire or interview may provide a good understanding of travel behaviour such as trip purpose, driving style and using mobile phone while driving [15]. Additionally, online questionnaire can be used to assess the perceived risk of micromobility users (e.g. lane edge conditions, infrastructure conditions, and comfort while driving) during the meeting and overtaking manoeuvres [2]. Therefore, voluntary participants may perform different tasks with different micromobility vehicles and fill in a questionnaire regarding the experienced safety and performance of the vehicles (i.e. comfort, manoeuvrability and stability) [24]. Additionally, a questionnaire can be filled in by riders after they conduct some experiments and then this can be used to investigate the perceptions of micromobility users about their braking, steering and other safety performances [10]. This questionnaire collects the ranking of riders regarding their comfort level during various scenario (e.g. braking at high speed and steering at low speed) and provides subjective data about the safety, manoeuvrability, and comfort of the vehicles [10].

Crowdsources Volunteered Geographic Information and open source application have been used to collect data about lane types, hazards perceptions and categories in cycling [43]. Therefore, a wide amount of data can be collected via crowdsourcing as there are various platforms (i.e. websites) to report micromobility-related collisions, near misses, obstacles, barriers and other perceived safety issues (i.e. dangerous places) [18]. Effectively, a web-based crowdsourcing platform may be developed to allow road users to report hazard spots and provide other road users with road safety information [44]. Therefore, Karakaya et al. [45] designed a smartphone-based crowdsourcing platform (SimRa) to identify accident and dangerous near miss hotspots. In another study, Nelson et al. [46] developed a website for crowdsource mapping of cycling collisions and near misses. This tool allows people to report incident locations and information such as crash time and injury severity which represent the base for building a bicycle incident map [15].

### *G. Other sensors*

Microphone can be used as an acoustic detection sensor to capture the data from the nearby surroundings (i.e. record the sound from the rear vehicles) and support real time generation of alarm signal [13], [22], [23], [47]. Therefore, when a micromobility use a vehicle tracking system and predict potential dangers or car-micromobility crashes, it can generate a loud audio alert (via a speaker) to warn the drivers of other vehicles about the presence of the micromobility vehicle [41].

Additionally, acoustic-based system for micromobility collision detection may use a speaker to emit high-frequency acoustic signals and then use a receiver to capture and analyse the reflected signal [47].

Hall effect sensor measures the revolutions of the rear wheel to monitor the effects of cycling infrastructure on the riding comfort of cyclists [4]. Additionally, potentiometer can measure the steering angle and steering rate of micromobility vehicle [14], [24], [26]. However, generated signals from potentiometer may be converted by means of analogue-to-digital converter (ADC) to collect vehicle kinematics data and compute braking and steering performance of micromobility [10].

Absolute encoder, which measures the steering angle, represents an effective tool for monitoring the effects of cycling infrastructure on the riding comfort of cyclists [4]. Therefore, micromobility steering angle can be directly observed by a rotary encoder and used to identify potentially hazardous locations such as intersections [21]. However, optical sensors (e.g. passive infrared, active infrared, and automated video) are sometimes used to measure the speed of micromobility vehicles as these sensors can detect speed variations during the roll of the vehicle's tires [21], [37]. Effectively, environmental sensors (e.g. air pressure, temperature, humidity, brightness and PMx sensors) are used to improve the monitoring density of natural ecosystems [48]. Therefore, micromobility vehicles can be equipped with such environmental sensors for city-scale environmental monitoring and to determine to what extent environmental factors influence riding behaviour.

The micromobility sensors and data acquisition methods identified in this section along with the references that consider and discuss each class are summarised in Table 1.

TABLE I. SUMMARY OF MICROMOBILITY SENSORS AND DATA ACQUISITION METHODS WITH THE RELEVANT REFERENCES

| Micromobility Sensor Data acquisition Method | References |
|---|---|
| Global Positioning System (GPS) | [1],[3],[4],[6],[8],[11],[13],[14],[15],[18],[27],[28],[29],[31],[36] |
| Inertial Measurement Units (IMU) | [1],[3],[4],[6],[7],[8],[9],[10],[11],[12],[14],[19],[20],[21],[24],[25],[28],[29],[30],[31],[32],[33],[34],[35],[36],[37],[45] |
| Ultrasonic sensors | [2],[6],[14],[16],[29],[38] |
| Light Detection and Ranging (LiDAR) | [3],[7],[8],[10],[13],[16],[24],[39],[40],[41] |
| Camera | [2],[4],[5],[9],[13],[14],[16],[18],[19],[21],[23],[25],[28],[37],[41],[42] |
| Survey and crowdsourcing | [2],[8],[10],[15],[18],[24],[43],[44],[45],[46] |
| Other sensors | [4],[10],[13],[14],[21],[22],[23],[24],[26],[37],[41],[47],[48] |

## IV. MICROMOBILITY SAFETY AND HAZARD DETECTION

Machine learning (ML) concepts can be used to analyse and classify micromobility sensor data [29], [36]. Additionally, it is quite important to develop artificial intelligence and machine learning services for micromobility riders safety and for learning from the collected sensor-data [12]. Therefore, Artificial Neural Network (ANN) model based on GPS, accelerometer and gyroscope time series data may be used to detect micromobility incidents and near misses automatically [36]. Additionally, smartphone sensor data (i.e. accelerometer, gyroscope and GPS) can be used for training transformer-based machine learning model and detecting hard-braking events [11]. On the other hand, heuristic represents another approach for detecting micromobility incidents and hazards automatically by relying on the data collected from sensors (i.e. accelerometer) [45]. Therefore, sudden acceleration spikes and size of these spikes determine if this data refer to incidents or poor road conditions (i.e. pothole). Effectively, recognising bicycle behaviours and predicting dangerous riding behavior (i.e. using ML) can be used for preventing accidents beforehand [35].

One of the main reasons for collecting pedestrians and bicycle counts is safety analysis. As an aspect of micromobility safety, accidents involving micromobility users need to be detected in real time and this detection (e.g. accident type and user's location) may alert relatives or emergency services promptly [34]. Therefore, micromobility accident detection system can use a sensor unit to monitor riding status and then use principal component analysis (PCA) and ML algorithms (i.e. SVM) to detect fall accidents [33].

To analyse cycling safety, deceleration rates at intersections can be extracted and used from GPS data [3]. Effectively, micromobility riders immediately decelerate before intersections and make a sharp turn (i.e. large angle). However, they slow down to avoid obstacles such as cars and then speed up after passing this obstacle [21]. To prevent right hook crashes, cyclists may be alerted in real time if such conflicts are detected [47]. Acoustic-based system may detect such collision and allow the micromobility rider to react (i.e. apply brakes) in a sufficient time and avoid the hazard.

The systematic usage of micromobility sensors and data could help to detect and eliminate infrastructure-related safety threats such as potholes and road faults [1]. Usually, cycling over defected roadway causes some vibrations and the quantity and magnitude of these occurred vibrations can be measured by an accelerometer to assess the riding safety and comfort of cyclists [4]. Additionally, when a cyclist attempt to avoid a road pothole or experience a road surface defect then these can be detected from the variations of bicycle, speed and steering angles. Therefore, the riding quality (i.e. comfort) of cycling and infrastructure quality (i.e. pavement conditions) can be assessed by measuring vibration using GPS and accelerometer [3].

There are various factors that may lead to discomfort of micromobility rides such as steps, obstacles and crowded sidewalks [28]. These hazardous spots can be detected by using data collected by an accelerometer and camera attached to a micromobility device (i.e. bicycle). Effectively, smart mobile applications can be used for detecting obstacles and defects on the road, such as potholes and speed bumps and informing nearby users about the hazard [31]. This application relies on analysing and processing the data collected from multimodal sensors (accelerometer and GPS) and camera videos and aims to automatically detect hazardous events on the road while driving. Therefore, Convolutional Neural Networks and object detection algorithms (e.g. YOLO detector) represent road hazard detectors which are able to spot potholes, debris and cracks. Consequently, estimating the level of risk due to road surface conditions allows drivers to adjust their driving speeds in advance to minimize the risk of accidents [19].

A probe bicycle and machine learning (i.e. decision-tree classifier) may be used to detect the road status (i.e. dangerous intersections and congested road conditions) and bicycle location [32]. Therefore, sensors in vehicles can help to detect abnormalities in rides, such as sudden stopping or changes in vehicle orientation [1]. For example, potentiometer provides handlebar angle and steering rate signals which can be used to measure micromobility manoeuvrability, balancing and control [10]. Effectively, accident detection system represents one of the micromobility safety services which uses the vehicle 3D accelerations to detect vehicle fall (i.e. the gravity vector is closely parallel to the vehicle platform plane) [25]. Therefore, micromobility sensors can potentially help detecting riders falling and accidents through GPS sensors or gyroscopes [1].

Motorists are required to maintain a minimum distance (i.e. 1.5m) when passing a cyclist [16]. Typically, LiDAR provides trajectory and distance signals which can be used to measure micromobility safety and manoeuvrability [10]. However, ultrasonic sensor data (clearance distance data) and video recording can be used to identify meeting and overtaking manoeuvres (i.e. sudden reductions of clearance distance) [2]. Effectively, the dynamic proximity of motor vehicles overtaking micromobility riders represents a primary factor affecting micromobility safety [16]. Therefore, the measuring framework of vehicle–cyclist passing distance provides a better understanding of interactions between motor vehicles and micromobility devices as well as data-driven urban safety interventions [16].

The IMU generates acceleration, deceleration and roll rate signals which can be used to measure micromobility comfort, stability and manoeuvrability [10]. However, micromobility vehicle kinematics can be linked to one or more safety dimensions by using performance indicators (PIs). Therefore, various performance indicators (PIs) can be measured and calculated in order to assess the safety of the e-vehicles in terms of stability, manoeuvrability and rider comfort [24]. For instance, if the standard deviation of the speed is low it indicates a high manoeuvrability and comfort. On the other hand, a high acceleration or deceleration indicates a high manoeuvrability and less comfort. However, a high steering (and roll) angle and rate indicates a low stability (the rider needs to do a lot of correction to manoeuvre the vehicle) while a low steering angle indicates high manoeuvrability.

Road lane recognition system represents one of the micromobility safety aspects which use the data collected from micromobility sensors. This system may use camera data, computer vision and an image classifier (i.e. convolutional neural network) to recognize different lane types (e.g. sidewalk and road) [25]. Additionally, traffic safety indicators (i.e. time to collision) can be calculated and analysed by using traffic simulation tools. Therefore, acceleration and deceleration models of bicyclists may be developed to simulate the speed profiles of bicyclists in microscopic traffic simulations [49]. Furthermore, simulation environments can be used to test methods developed to recognize dangerous micromobility conditions and based on sensors (i.e. accelerometer and gyroscope) data [20].

Effectively, analysing and understanding the riding style (e.g. manoeuvre) of micromobility vehicle riders may help the riders to change their behaviour (e.g. reckless riding) and riding style and therefore protect them from potential collisions [9]. Therefore, the safety, comfort and behaviour of micromobility users can be analysed and investigated by using the data collected about the vibrations experienced by the micromobility users as well as the distances to other vehicles during manoeuvres [3].

## V. Conclusion

Micromobility, including bicycles and scooters became the most important and attractive mode of transportation in urban areas. However, there are various danger factors, such as falls and collisions, that apply to micromobility because the micromobility vehicles share existing road infrastructure with other vehicles and road users. This paper provided a brief review for micromobility safety challenges, sensing systems and the applications of sensor data in detecting micromobility safety conditions. It provided a brief description of micromobility sensing systems, the type of data these systems can collect, and the safety aspects related to the data collected. Additionally, micromobility safety elements, the challenges and users concerns that affect the acceptance of micromobility in urban areas have been summarized. Furthermore, micromobility data acquisition methods (e.g. crowdsourcing and camera), the sensors that can be installed on micromobility vehicles (e.g. GPS, IMU and LiDAR ), and the type of data that can be collected (e.g. acceleration, speed and location) have been reviewed. Finally, analysis methods of micromobility sensor data (e.g. machine learning) and detection techniques of micromobility incidents (e.g. obstacle, near miss and accident) have been briefly described.

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