Laser-Based Algorithms Meeting Privacy in Surveillance: A Survey

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This work did not involve human subjects or animals in its research.

ABSTRACT Privacy of people is a key factor in surveillance systems. Video camera brings us well-off color information. How would the privacy be secured then? Besides, privacy protection should not create a hindrance for finding of objects or people under specific cases. Laser scanner takes way affluent color information. It functions with eye-safe and invisible laser beam. Yet, it provides us robust object recognition map. Images can be interpreted by humans, but laser-based systems need software applications to explain the data. Camera-based surveillance system does not focus on the problem of private life conservation. On the contrary, laser-based surveillance system ensures privacy of people inherently, as it does not record real world videos except laser scanned data points. In this paper, first, the privacy issues of people for both surveillance systems have been compared to realize their significance. Second, a qualitative performance comparison between laser-based and RGB camera-based systems has been made to hint that laser-based algorithms should be used instead of common RGB cameras. Third, a succinct survey of laser-based detection and tracking algorithms of movers has been conducted. Final, a superiority measure of the leading laser-based people-vehicles related algorithms has been performed on the basis of statistical test scores deeming the ineffectualness metrics (e.g., errors and failures) of each algorithm.

INDEX TERMS Kalman filter, particle filter, people, privacy, laser scanner, SVM, tracking, vehicle.

I. INTRODUCTION

Detection and tracking movers (e.g., pedestrians, vehicles, and etc.) should be an important issue for surveillance systems and traffic analysis in conurbations. Surveillance systems on both public and private spaces often expect to detect and track unusual activities [1] or behaviour of movers [2] to ensure high degree of security and safety. A nonautomated and human functioned surveillance system is very expensive and erroneous. But those existing problems can be reduced by an automated surveillance system. Any kind of automated surveillance system demands smart algorithms to process data obtained by sensors and to prepare informative information for making fruitful decisions. Due to algorithmic assumptions and large amount of data processing, an existing smart algorithm cannot attend to its all desire level of applicabilities. Thus, a smarter algorithm is developed. Henceforth, the series of developing smarter algorithms to handle high quality of surveillance keeps on continuing.

Nowadays, like home automation [3]–[5], traffic automation became one of the key factors for a smart city [6]. The sidewalk occupancy is a serious problem in the urban life [7], [8]. If sidewalk occupancy will occur, then pedestrians will tend to walk on the street which would lead many potential traffic hazards. A civil engineer would like to realize how the sidewalks along with streets can be built to give the maximum comfort and safety to the dwellers. A smart city planner would design roads for autonomous cars and fair traffic flows. In smart cities, connected cars can pair with automated traffic management systems to provide a flawless driving experience for the commuters. Getting precise trajectories of movers from the surveillance system is one of the key requirements for the accomplishment of such tasks smoothly. Indeed, it is a challenging effort to get the workable quality of trajectories for individual person and vehicle with a view to studying traffic and vision related activities from an automated surveillance system with sundry video cameras or laser (Light Amplification by Stimulated Emission of Radiation) scanners. Images from video camera-based surveillance system can be interpreted by any human. Nonetheless, this
option is missing in laser-based surveillance system, where software applications are needed to explain the associated data. Seemingly, a smart surveillance system with laser scanners would be more competent and commodious than that of video cameras.

In essence, surveillance requires proper identification and searching of objects by law and enforcement agencies. A crucial issue in a surveillance system is the privacy of people. In principle, a surveillance system should be smart as well as it should protect privacy of people. However, privacy protection should not create a hindrance for the identification of objects or people under specific conditions (e.g., crime scenes, searching a stolen vehicle, and a missing person) by the law and enforcement agencies. A camera is a popular image sensor for recording visual images. In surveillance many different kinds of cameras (e.g., action, infrared, and so on) can be used. The human eye is tactful to red, green, and blue (RGB) bands of light. Many surveillance cameras can capture the same RGB bands as what our eyes see for producing colorful images to be analyzed by human and/or software. An RGB camera uses a standard CMOS (Complementary Metal Oxide Semiconductor) sensor through which the colored images of persons and objects are obtained [9]. The majority of surveillance cameras today feature RGB and infrared (IR) sensors as standard [10]. Surveillance cameras mostly work on IP (Internet Protocol) networks, which can link the cameras from the remote area to the assigned security location. Beyond cameras and lasers, other sensors including RADAR (RAdio Detection And Ranging) [11]–[14], IMU (Inertial Measurement Unit) [15]–[17], GPS (Global Positioning System) [18]–[20], GNSS-R (Global Navigation Satellite System - Reflectometry) [21]–[23], SONAR (Sound Navigation And Ranging) [24]–[26], DMC (Digital Magnetic Compass) [27], fiber optic [12], [28], [29], and temperature measuring devices [30]–[32] are used in surveillance systems. Yet, based on the availability and adoption of movers monitoring algorithms, the surveillance of crowds and/or vehicles can be roughly divided into video camera-based and laser-based surveillance systems.

Almost all video camera-based surveillance systems grant us rich color information under a fixed condition of light illumination alternations. How would the privacy of people be secured from such systems? Intuitively speaking, such systems contribute a very limited privacy of people using so-called privacy masking. On the other hand, laser-based surveillance systems hand over the solution of these existing problems in good way. The trademark of common laser scanners includes SICK [33], Velodyne [34], IBEO [35], and Hokuyo [36]. For example, Fig. 1 (a) shows two devices of SICK namely LMS-511 and LD-MRS. The LD-MRS has 110° scanning range. It has 4 layers to scan with various heights. Its maximum recognition-distance is 250 meters. Its angular-resolution can be 0.125°, 0.25° or 0.5° [33].

Laser scanner functions with eye-safe laser beam. Human eyes are unable to see the laser beam. Fig. 1 (b) explains hypothetically the emission of laser beam from two LMS-511 devices and hits on human legs. Laser scanner does not give color information as a camera does. Still, it equips solely data points of objects from heads, chests, hands, legs, trees, walls, vehicles (e.g., Fig. 1 (c)), bicycles, or other region of interest (ROI). Hence, data processing becomes not only quicker and easier as compared to video cameras but also it shows special advantages in protecting privacy of people.

During the past two decades, an enormous amount of research has been dedicated to propose sundry laser-based algorithms for recognizing and/or tracking movers from laser scanned data points using various laser scanners. Accordingly, several short survey reports can be found in the literature. For examples, Zhao et al. [37] surveyed the suggested rules for designing secure communication systems using chaotic lasers; Bianchini et al. [38] compared between laser scanner surveys and low-cost surveys; Wan et al. [39] fascinated a survey adjustment method for laser tracker relocation; Zhong et al. [40] addressed a combination of stop-and-go and electro-tricycle laser scanning systems for rural cadastral surveys; Barbarella et al. [41] focused on uncertainty in terrestrial laser scanner surveys of landslides; Deng et al. [42] discussed a panorama image and three-dimensional (3D) laser point cloud fusing method for railway surveying; and Wang et al. [43] hinted a survey of mobile laser scanning applications and key techniques over urban areas. Nevertheless, due to the prompt progress of the field such surveys are
to a fixed extent outdated. Additionally, a developed algorithm may function well for a specific surveillance plan, but it might be dysfunctional for other applications. Henceforth, it is extremely difficult to find a generic algorithm for solving many problems in diverse applications. Still, a superiority measure based on statistical tests of existing state-of-the-art laser-based tracking algorithms can help to understand which algorithms would be fitting better in ascending or descending order of performance for solving certain kind of problems. Be that as it may, the existing surveys in the literature do not attract any attention to measure such superiority among the available laser-based algorithms.

The aim of this paper, first, is to focus on privacy issues of people for both video camera-based and laser-based surveillance systems. Its second aim is to make a qualitative performance comparison between laser-based and RGB camera-based systems. Such comparison helps to establish the fact that one system is conditionally superior to its alternative. Its third aim is to provide a thorough overview of the advances of algorithms concerning the laser-based system for detecting and tracking of movers. Its final aim is to work out a superiority measure of the dominant-alternative people-vehicles laser-based algorithms deeming statistical tests by employing unfulfillment metrics (e.g., see TABLE 7 and Fig. 11) of algorithms. Errors of each selected algorithm have been considered using identical dataset (explicitly Galip et al. [7]), whereas the failure metrics have been referenced from the data analysis and the manuscript of each selected algorithm. To conduct statistical tests, we have used available statistical-software applications from University of Granada [44].

The main scope of this paper is focused on applications that seek to smart cities [45], [46], urban environment monitoring [47], [48], autonomous vehicles [49], [50], advanced driver assistance systems (so-called ADAS) [51], [52], robotic vision systems [53], [54], visual sensor systems [55], risk analysis [56], [57], intelligent traffic flow and analysis [6], [58].

This paper is designed as follows. Section II focuses on significance of camera-based and laser-based surveillance with privacy; Section III qualitatively compares the performance of laser-based and RGB camera-based systems; Section IV surveys briefly the state-of-the-art algorithms; Section V qualitatively discusses selected people-vehicles related algorithms; Section VI estimates ineffectualness metrics of those algorithms; Section VII makes superiority measure using statistical tests; Section VIII hints some future works and challenges; and Section IX concludes the paper.

II. JUXTAPOSITION OF TWO SURVEILLANCE SYSTEMS

Surveillance, crowd control, and privacy are three key things for crowd analysis [59]–[66]. The surveillance system should be smart. It should protect privacy. Surveillance plays a huge part in today’s society with cameras all around us. Our regular lives are experiencing higher levels of security each day. Roughly, surveillance systems of crowds and/or vehicles can be classified into two elite groups: (i) Camera-based surveillance and related privacy of people, and (ii) Laser-based surveillance and associated privacy of people.

A. SIGNIFICANCE OF CAMERA-BASED SURVEILLANCE

An early-warning camera system could anticipate dangerous situations as they arise when large crowds gather. Surveillance cameras (e.g., CCTV, PTZ, etc.) have, and will prevent many crimes. Nowadays, CCTV (closed circuit television) is used as a generic term for a variety of video surveillance technologies. Surveillance cameras keep our personal property safe. CCTV system protects against property theft and vandalism. It is very difficult to get away with stealing something if there are cameras filming all times. So, the thief will often get caught. CCTV system will catch the thief before, or during the process of committing the crime. The police can identify criminals recorded with cameras. Through surveillance cameras, the police can both prevent crimes from happening and can quickly solve criminal cases with material evidence. CCTV system may reduce fear of crime and increase public participation in public space. Other benefits, beyond a reduction in crime, would be accrued from a CCTV system, including aid to police investigations, provision of medical assistance, place management, and information gathering. Gips [67] and Hess [68] stated a trend toward local jurisdictions legislating CCTV use. For example, in Chicago and Milwaukee, bars and nightclubs are required to post surveillance cameras on their premises. Baltimore County has required all shopping centers to install CCTV. In El Cer­rito, California, an ordinance has been proposed that would require 73 local businesses, including liquor stores, convenience stores, takeout restaurants, banks, shopping centers, check cashing establishments, pawnshops, and secondhand brokers and firearms dealers to install surveillance cameras at all structural entrances and exits to park areas, customer and employee parking areas, and entrances and exits to parking areas [67], [68]. Moreover, the National Violent Death Reporting System [69] shows that “in the United States more than seven people per hour die a violent death”. Usually, CCTV system helps to reduce violence notably.

However, some people say that we should not have surveillance cameras in public places because of the violation of privacy. We should consider the impact of a CCTV system from a societal point of view. It has been suggested that ever-increasing surveillance can make the local environment a less pleasant place to live [70]. Benjamin Franklin (17 January 1706 - 17 April 1790), one of the founding fathers of the United States, once said [71]: “Those who would give up Essential Liberty, to purchase a little temporary Safety, deserve neither Liberty nor Safety.” This quote frequently comes up in the context of new technology and concerns about government surveillance. In the United States, privacy issues related to the use of CCTV surveillance are first and foremost in regard to the Fourth Amendment of the United States.
This problem easily. Besides, a system with laser scanners is
they have trouble relaxing if CCTV camera is watching and
Patrons claim that they go out to have a drink and relax, and
feel that the entire bar or club should be deemed as private.
Businesses cannot install CCTV cameras
using laser scanners. The most general argument proposed
his/her bath room. But we can monitor such a patient by
ease affected person easily by putting a CCTV camera in
and objects. For instance, we cannot monitor a heart dis-
and henceforth, data processing becomes faster and easier.
do not record real world videos except scanned data points
localization projected into 3D space is poor as compared to
boxes and categorize objects) [76]. Even so, the resulting
localize objects in the image itself (e.g., find out bounding
surfaces are weak or scattered. This fact results in lost pixels
the RGB-D camera has awkwardness in getting depth data
problem for estimating depth if objects lack textural cues. The
stereo cameras need extensive processing and repeatedly have
on texture, shape, and color. RGB stereo cameras can be
detected and estimate 3D positions of objects. Still,
monochromatic and cannot differentiate objects based on
illumination. They can accurately localize objects via their
3D reflections. Routinely, they require vast data processing
in software to create images and identify objects. They are
BLINDNESS AND GHOST OBJECTS
A smart vision or surveillance system may consist of either
laser-based technology or RGB camera-based technology or
or a hybrid. Ideally, such system should detect and track all
occurring events within its range. Basically, in two key ways
such system can go wrong namely false negatives (so-called
blindness) and false positives (also called ghost objects).
In case of false negative, the system cannot detect an event
or an item, but in reality that must be detected to keep away
from any potential hazard. For example, with a false negative
a self-driving car would be unable to safely avoid hitting an
obstacle in its way. In case of false positive, the system sees
an event or an item, but in reality that is totally absent there.
For example, a false positive may cause a self-driving car
to jab on the brakes or swerve. This is very annoying to its
occupants. It may cause some possible injurious conditions
of its occupants if they do not use seat belts. It may also
cause accidents if the vehicle swerves dangerously or brakes
very hard. Generally, these kinds of potential problems end
up the safety and reliability of the system. If they occur very
frequently, then its users give up on the system. Normally,
good system should almost never get any false negative or
positive.
LOCALIZATION OF OBJECTS
The laser-based systems can work regardless of the natural
illumination. They can accurately localize objects via their
3D reflections. Routinely, they require vast data processing
in software to create images and identify objects. They are
monochromatic and cannot differentiate objects based on
color. Besides, for far-way objects the laser may have few
beams intersecting the object, thus creating reliable detec-
tion problematic. Unlike laser-based systems, standard RGB
camera-based systems can make detection decisions based
on texture, shape, and color. RGB stereo cameras can be
used to detect and estimate 3D positions of objects. Still,
stereo cameras need extensive processing and repeatedly have
problem for estimating depth if objects lack textural cues. The
most existing models to calibrate depth and the relative pose
between a depth camera and an RGB camera are not univer-
sally applicable for sundry RGB-D cameras [73]. Usually,
the RGB-D camera has awkwardness in getting depth data
of shiny and dark surfaces as IR rays reflected from these
surfaces are weak or scattered. This fact results in lost pixels
in a depth map [74]. In addition, RGB-IR cameras together
suffer from three common problems namely pixel multi-
plexing, channel crosstalk, and chromatic aberrations [75].
An RGB camera-based system can be used to accurately
localize objects in the image itself (e.g., find out bounding
boxes and categorize objects) [76]. Even so, the resulting
localization projected into 3D space is poor as compared to
the laser-based system [76].
C. RELIABLE DETECTION
Lasers are not fooled by shadows, bright sunlight, the oncoming lights of other sources, day, and night. The laser-based systems have been hailed for being able to see objects even in bad lighting conditions, but they may not always reliable.

As a laser scanner sees only parts of the object currently facing the scanner, when the object moves it is usual to get different moving point clouds from the same object for detecting and tracking. This issue may lead to a significant degradation of tracking performance. Besides, due to the laser absorption by glass like surfaces or any occlusion, an object can be divided into few segments. This matter makes object detection and tracking much harder, specially when dealing with objects merging and tracking groups [77]. A defined shape of an object can keep down this problem, but that can face limitations when applied on others [78], [79]. For example, a defined geometric shape of an object (e.g., two dots [78] as a pedestrian) may be detected correctly from a pool of its shape-like objects, but it cannot work well when the shape is changed (e.g., three dots [78] as a car). Analogously, if we employ the motion of laser point clouds (e.g., [80]) to segment and track vehicles of various types, it does not work well for pedestrians due to the slowly-moving pedestrians which do not bestow enough motion cues. Wang [81] discussed an example that in case of a 2D laser scanner mounted on a moving platform, occlusion and viewpoint alternations give the appearance of dynamic behaviours even in a purely static scene. This confusion creates the reliable detection of the true dynamic objects arduous without giving high false alarm rate [81], [82]. Mertz et al. [83] suggested that a good prediction algorithm (e.g., Kalman filter or particle filter) can solve any temporarily occlusion problem of an object. On the other hand, pedestrian detection at night using an RGB camera provides with insufficient information [84]. Numerous surveillance systems take in applications of autonomous vehicles, headcounters, search and rescue operations. Yet, these systems freeze themselves in night surveillance due to the use of RGB cameras [85].

D. COST AND PRIVACY CONCERNS
Interference and jamming are two potential problems with laser-based systems. For example, in a smart city application if a large number of autonomous vehicles would generate laser beams simultaneously, it could cause interference and potentially blind the vehicles. In consequence, manufacturers will need an extra effort to prevent this latent interference. In addition, RGB camera-based systems are far better suited for reading street signs and interpreting colors. The laser-based systems are already getting cheap. Yet and setting-aside, RGB cameras are much less expensive than laser scanners. The laser-based systems are currently very bulky as compared to the RGB camera-based systems. For instance, to capture and share images and video of a crash or other safety related incident with the automaker, the RGB camera-based systems as implemented on current Tesla vehicles are almost invisible. Nonetheless, Tesla’s in-car cameras have heightened privacy concerns [86].

E. TECHNOLOGY FUSION
One feasible solution to the debate for the employment of laser-based and RGB camera-based systems is to combine both technologies. Such hybrid systems would cut back on privacy concerns to some degree. To a certain extent, such hybrid systems would be helpful for specialized identification of things including birds, traffic lights, traffic cones, and road debris. For example, if a flock of birds will appear in the way of a self-driving car, the car will not be immediately slowed down. The laser will see the birds and the RGB camera will give extra information about what to do.

Recently, hybrid systems that cooperatively use tracking along with semantics and soft computing have been successfully proposed to support the data explanation and help object detection and event interpretation. For examples, Cavaliere et al. [87] built ontological knowledge on the tracking and environmental data to support the comprehension of the video scenes, and Gomez-Romero et al. [88] improved tracking results by exploiting ontology reasoning on contextual information. Bozorgi et al. [89] integrated data obtained from 2D laser and 3D camera for tracking human trajectory. Zhao et al. [78] integrated a video camera with their LMS291 laser scanner to evaluate their processing results for tracking and classifying moving objects. Azim et al. [90] performed detection and classification of moving objects from 3D laser data. They used images from their camera to manually label the data for training the classifiers. Mertz et al. [83] applied both laser scanners and video cameras for moving object detection. Their employed video cameras helped a lot to analyze collected data. Even so, those cameras were not involved in creating warnings (e.g., for the bus driver). Besides, sometimes a malfunction of their retraction mechanism misaligned the laser scanner and resulted in hundreds of false alarms. Kim et al. [91] installed an IBEO LUX2010 and a camera on a Kia K900 car for object segmentation. They aimed to compensate the drawbacks of the laser scanner and also improve the recognition accuracy. On the average, they confronted a failure rate of about 20%.

However, hybrid systems expect further efforts to reach their high level of applicabilities. This is widely due to their algorithmic assumptions, calculation of stable features, lofty computational cost, higher hardware requirements, reasoning about the geometry of occlusions, and fusing data from multiple sensors.

F. A DIFFICULT CHOICE BETWEEN TWO OPTIONS
It is interesting to note that the most used modalities, both laser scanners and RGB cameras, are two completely contrasting sensors with their own strengths and weaknesses. For example, laser-based cameras play an important role for obstacle detection and tracking, but they are very sensitive to heavy rain, snow, and fog; whereas RGB cameras are often used to get a semantic interpretation of the scene, but
Laser-based technology revolutionized the entire paradigm of their vehicles [93]. In the vein of defensive countermeasures, Uber, and Toyota) are implementing laser-based systems in days the leading automotive manufacturers (e.g., Waymo, mon video recording RGB cameras. In the same vein, nowa-

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see in any type of condition as a human does for avoiding

well enough to avoid hazard, mainly when weather condi-

they are immensely sensitive to ambient light, night, day,

clouds, shadows, sun, and sunlight. These issues can cause significantly large potential false positives and/or false neg-

atives in both laser-based and RGB camera-based systems with respect to their associated ground truths. Subsequently, the installed algorithmic performances (e.g., time efficiency, space efficiency, complexity theory, function dominance, and asymptotic dominance) of both systems become the common influential factors. Both systems can use artificial intelligence techniques to analyze data with a high level of accuracy. As the employed algorithms get better, the obtained results show high accuracy and precision in object detection and tracking. For example, with a smarter algorithm a self-driving car can make better decisions to spell the difference between an accident and safe driving. Based on the complexity of the employed algorithms, such decision may be made faster in the laser-based system as compared to the RGB camera-based system. The car with surrounding information every moment laser-based system requires huge data processing on-board software to create 3D maps and identify objects. This provides a 360 degree view that helps the car-drive in any type of condition. On the other hand, RGB camera-based systems are identical to how our brain processes the stereo vision from our eyes for calculating distance and location. Explicitly, RGB camera-based systems should first ingest the images and then analyze those images to calculate the distance and speed of objects, demanding far more computational power. Some smart surveillance systems are based on RGB cameras, which can only cover a small area; however, due to the occlu-

sion occurred by their fixed optical centers [72], it is very difficult for them to work robustly in real world exceptionally crowded scenarios including subway stations, public squares, and intersections [92]. Unlike a camera or a radar, a laser scanner can be used as the sole sensor for some systems (e.g., ADAS) without being combined with other sensors [91].

One of the key supremacies of laser is its accuracy and precision. Laser is extremely accurate as compared to RGB cameras. In fact, RGB cameras provide all visual images, and they do not rely on ranging and detection as the laser does. Anyhow, critics say that RGB cameras still cannot see well enough to avoid hazard, mainly when weather condi-

tions are demanded. RGB cameras should be able to exactly see in any type of condition as a human does for avoiding remarkably huge false positives and false negatives. In gen-

eral, laser-based algorithms have been proposed to avoid the limited range and field of view of video cameras. Besides, when the issue of privacy protection comes into the spot-

light, the laser-based algorithms gain an extra credit over their alternative RGB camera-based algorithms. Therefore, the laser-based algorithms should be used instead of the common video recording RGB cameras. In the same vein, nowa-
days the leading automotive manufacturers (e.g., Waymo, Uber, and Toyota) are implementing laser-based systems in their vehicles [93]. In the vein of defensive countermeasures, laser-based technology revolutionized the entire paradigm of destructive weapons by starting a wider range of airborne and ground-based weapons with skills to precisely carry large-scale destruction to electronic systems, combat troops, optical devices, high-speed approaching missiles, and even physical installations [94].

IV. REVIEW OF STATE-OF-THE-ART LASER-BASED ALGORITHMS

Laser scanners are mostly eye-safe, compact, light-weighted, and with full-circle fields of view. Mobile laser scanning (MLS) systems can be mounted on vehicles, trolleys, boats, robots, and backpacks [43], [95]. The main com-

ponents of such system include 3D laser scanners, global navigation satellite system, inertial measurement unit, and cameras. The SICK laser range measurement devices send a laser beam every 0.25° within their respective scanning planes, which yielded to 761 measurements in one time frame since they scan between −5° and +185° [33], [96]. The sensors of Velodyne have a range of up to 300 meters. They can be used for immediate object detection without additional sensor fusion [97]. The IBEO LUX laser scanner is a unique full-range sensor applied for object detection and classification to support ADAS applications [98]. Mostly, Hokuyo laser scanners are used in automated guided vehicle (AGV), unmanned aerial vehicle (UAV), and mobile robot applications [36].

However, the existing miscellaneous algorithms for detect-
ing and/or tracking objects from laser scanner data points can be roughly categorized into four groups as shown in Fig. 2. TABLEs 1, 2, 3, and 4 summarize them. The common abbreviation of N/A in those tables elaborates to either not-available or no-answer.

V. PROMINENT PEOPLE-Vehicles RELATED ALGORITHMS

A. SELECTED ALGORITHMS AND FLOW DIAGRAMS

Detection and tracking of moving vehicles with a laser scanner is interesting for autonomous driving applica-
tions. Yet, people-vehicles detecting and/or tracking algo-
rithms are more interesting in wide range of surveillance than solely either people or vehicles tracking algorithms. In this subsection, we have focused on people-vehicles related algorithms in TABLE 1 rather than TABLE 2 or TABLE 3, or TABLE 4. However, all algorithms in TABLE 1 have not taken into account due to mainly three problems: (i) Accuracy and precision [173] of algorithms are not explicitly provided by the authors of associated manuscripts (e.g., Wang et al. [100], Lindstrom et al. [103], Asvadi et al. [105], and Kanaki et al. [106]); (ii) Implement-

ation difficulties (e.g., Lehtomaki et al. [104]); and (iii) The computational complexity of $N \times N$ post-hoc nonparametric procedures to calculate $p$-values will go with a comparatively higher order polynomial for the augmentation of high num-

ber of algorithms and datasets. As a result, we have chosen key eight algorithms related to the people-vehicles from TABLE 1 for our results analysis and superiority measure. Fig. 3 compares their simplified flow diagrams. It is noted that
interesting readers would get the detailed of each algorithm in respective reference. As a sample, Fig. 4 views the graphical abstract of the algorithm of Sharif [8]; where (a) points to the laser scanner of LMS-511 and a real world video frame; (b) depicts the obtained blobs (as colored in blue) for all laser scanned data points per frame; (c) denotes the foreground data points as colored in red; (d) hints the extracted movers as marked by white points and the L-shaped structure belongs to a vehicle, while others are most likely pedestrians; (e) displays recognized record of SVM; and (f) shows trajectories of movers for several frames.

### B. QUALITATIVE DESCRIPTION OF ALGORITHMS

Galip et al. [7] used Hungarian method [2], [174]–[176] and Kalman filter [177] to get trajectories of movers from their own laser scanned dataset. But detection of movers was done based on various thresholds. Estimation of multiple thresholds is often a daunting task. Azim et al. [90] suggested an algorithm to detect moving objects (e.g., bus, car, bike, and pedestrian). In spite of this, their algorithm cannot separate individual pedestrians walking together in a group. Trees, light poles, and street signs were often wrongly detected as moving objects. To overcome the threshold estimation problem of Galip et al. [7], Sharif et al. [99] relied on supervised learning based methods (e.g., SVM) along with Hungarian method and Kalman filter to recognize and get better trajectories of movers from the dataset of Galip et al. [7].

Zhao et al. [78] tracked and classified moving objects at intersection using spatially and temporally processing on laser scanned data points. Moving objects are classified into 92400
### TABLE 2. People tracking algorithms.

| Reference | Techniques | Scanner | Scan | Camera | Filter | Occlusion | Setting | Dataset | Accuracy |
|-----------|------------|---------|------|--------|--------|-----------|---------|---------|----------|
| Zhao et al. [107] | Laser point integration, clustering | IBEO LD-A | Feet | Included | Kalman | Handled | Indoor | People | 85% |
| Spinello et al. [106] | Clustering, histograms of oriented gradients, SVM | IBEO ALASCA XT | ROI | Included | N/A | N/A | Outdoor | 750 positive and 5250 negative samples of people | 90% |
| Weinrich et al. [109] | Segmentation, classification of leg, crutch, and wheelchair | SICK S300 | ROI | Excluded | Own | N/A | Indoor | Spinello et al. [108] | 95% |
| Xavier et al. [110] | Segmentation and Clustering | SICK LMS | Legs | Excluded | N/A | N/A | Indoor | People | N/A |
| Schulz et al. [35] | Probabilistic data association | RFI Robot B2i | Legs | Included | Particle | Handled | Indoor | 6 persons and simulated data | 90% |
| Shao et al. [111] | Background subtraction, calibration, analysis | IBEO model HOKUYO UTM 30LX | RIO | Included | MeanShift | Handled | Indoor | A total of 36 persons | 92% |
| Shao et al. [112] | Background modelling, feet clustering | SICK 291 | LMS | Feet | Included | Particle | Excluded | Outdoor | 12000 frames | 68% |
| Song et al. [113] | Background modelling, human body recognition | SICK 291 | LMS | Body parts | Included | Particle | Handled | Outdoor | 200 frames | N/A |
| Song et al. [114] | Background modelling, feet clustering | SICK 291 | LMS | Feet | Included | Particle | Handled | Outdoor | 5000 frames | 89% |
| Topp et al. [116] | Laser data transformation | SICK 200 | LMS | Legs | Excluded | Particle | Handled | Indoor | Several persons | N/A |
| Lin et al. [117] | Background modelling, vision algorithms | UTM 30LX | Body parts | Included | Particle | Handled | Indoor | Kalman | 55 persons | 91% |
| Mendes et al. [118] | Segmentation, classification, tracking | SICK 200 | LMS | Legs | Excluded | Particle | Handled | Indoor | Freewalk | N/A |
| Mozos et al. [119] | Ada Boost, probabilistic voting | CRG 041X | Body parts | Included | N/A | N/A | Indoor | 17286 segments | 92% |
| Mutlu et al. [120] | Composite matching, classification | SICK 291S05 | LMS | Legs | Included | Motion | Handled | Outdoor | Few people | 86% |
| Nakamura et al. [121] | Background subtraction, people recognition | SICK 200 | LMS | Legs | Included | Particle | Handled | Indoor | Some people | 95% |
| Navarro et al. [122] | Points grouping, SVM | SICK model | Body parts | Excluded | Kalman | Handled | Outdoor | Real and simulated data | 75% |
| Puehrsenberg [123] | Leg motion analysis | IBEO ALASCA XT | Legs | Excluded | Own | N/A | Outdoor | N/A | N/A |
| Gade et al. [124] | Clustering, line fitting | IBEO model | RIO | Included | Particle | Handled | Outdoor | Not simulated data | 74% |
| Gidel et al. [125] | Segmentation, vision based algorithms | IBEO ALASCA XT | RIO | Included | Particle | Handled | Outdoor | 5 persons video frames | 94% |
| Gidel et al. [126] | Segmentation, vision based algorithms | IBEO ALASCA XT | RIO | Included | Particle | Handled | Outdoor | 5 persons video frames | 94% |
| Kaneko et al. [127] | Clustering of points, motion analysis | SICK 200 | LMS | Body parts | Included | Time series | N/A | Indoor | 1500 frames | 98% |
| Katahira et al. [128] | Background subtraction | SICK 200 | LMS | Legs | Excluded | Own | Handled | Indoor | 69 persons | 89% |
| Leigh et al. [129] | Clustering, detection | HOKUYO UCMG 06LX | Legs | Included | Particle | Handled | Indoor | 82 persons | N/A |
| Arras et al. [130] | Ada Boost, vision algorithm | SICK LMS | Legs | Excluded | N/A | N/A | N/A | 5734 segments | 90% |
| Arras et al. [131] | Adaptive probabilistic | SICK LMS | Legs | Excluded | Particle | Handled | Indoor | N/A | N/A |
| Cui et al. [132] | Color histogram matching | IBEO LD-A | Feet | Included | Mean shift | Handled | Outdoor | A group of 167 people | N/A |
| Cui et al. [133] | Background subtraction | SICK 200 | LMS | Feet | Included | Kalman | Handled | Outdoor | 1000 frames | 94% |
| Meissner et al. [134] | Gaussian mixture background segmentation | SICK LD-MRS | ROI | Excluded | Particle | Handled | Outdoor | Data obtained from a park | N/A |
| Song et al. [92] | Moving points detection, clustering, learning | SICK LMS291 | ROI | Excluded | Particle | Handled | Indoor | 3000 frames from JR subway station of Tokyo | N/A |
| Bozorgi et al. [89] | Data association, Euclidean distance | RPLIDAR-A3 | Legs | Included | Particle | Handled | Indoor | One and three persons walking scenarios | N/A |
| Fotiadis et al. [135] | Segmentation, SVM, Ada Boost | SICK 200 | LMS | Grid | Included | N/A | N/A | Outdoor | 6641 human segments | 95% |
| Adavakoy et al. [136] | Background subtraction, segmentation | SICK 200 | Legs | Included | Monte Carlo | Handled | Outdoor | 2960 frames having 20 people | 87% |
| Kato et al. [137] | Grouping and counting | HOKUYO model | Heads | Included | Particle | Handled | Indoor | 365 persons entry and 388 persons exit | 94% |
| Taftag et al. [138] | 3D shape recognition, tracking | HOKUYO UTM 30LX | Legs | Excluded | Own | Handled | Indoor | People | N/A |
| Zou et al. [139] | 3D mapping, motion estimation | N/A | ROI | Included | Bayesian | Handled | Outdoor | KT11 [140] | 83% |
| Liu et al. [141] | Background subtraction, segmentation, recognition | Velodyne HDL 32E | ROI | Excluded | N/A | N/A | Outdoor | 165 out of 2031 frames with pedestrians | 82% |
pedestrians (0-axis object), bicycles (1-axis object), vehicles (2-axis object). They claimed that the performance of their algorithm reached a successful ratio of above 95% for tracking and classification on a 10-minute laser data at an intersection. Through their experiment, it was reported that the classification results of 1-axis objects are rather sensitive to the definition of the likelihood measure. This problem should be solved through further study. There are some reported failure cases. For example, when heavy vehicles run across the intersection and pedestrians wait for signal blocked the measurement to another vehicle. Mertz et al. [83] detected and tracked successfully several movers from laser scanned data points. Notwithstanding, the main errors of their algorithm include over-segmentation and under-segmentation, association problems, false and missed detections. Their algorithm fails to detect a target if it is occluded, or if it has poor reflectivity, or if objects are very close to each other and it is not clear whether to segment the data as one or more objects. Both Galip et al. [7] and Sharif et al. [99] used Kalman filter and identical data set of Galip et al. [7]. Kalman filter is a linear quadratic estimator. It may be the best to estimate linear system having Gaussian noise. It has low computational requirements. But if the system does not suit nicely into a linear model or if the sensor uncertainty [4] does not fit with Gaussian model, then performance degradation occurs drastically. If the linearity or Gaussian conditions do not exist, its variants (e.g., Extended Kalman filter, Unscented Kalman filter) can be used. However, those variants cannot give a reasonable estimate for highly nonlinear and non-Gaussian problems. Besides, movers data points of laser scanners behave very differently in some regions than others. In such case, Kalman filter is not a good choice. The particle filter [178] is a better solution. Nonetheless, particle filter gets exponentially worse if a model has many state variables. Even so, a particle filter can handle almost any kind of model by digitizing the underlying problem into separate particles. Each particle is one possible state of the model. A sufficiently large number of particles can handle any kind of probability distribution. Inspired by these facts, Sharif [8] proposed SVM along with Hungarian method and particle filter to get trajectories of movers. On the same dataset (e.g., Galip et al. [7]), the algorithm of Sharif [8] reported the best minimization of error rates. Wang et al. [82] formulated a unified framework that jointly estimated the pose of the sensor with the focus on detection and tracking of moving objects. They applied EMST-EGBIS (Euclidean Minimum Spanning Tree - Efficient Graph Based Image Segmentation) clustering technique to produce perceptually coherent clusters. Only instantaneously moving objects (no parked or no instantaneously stationary vehicles) can be detected and tracked by their system. Two modes of failure can be reported in their algorithm. A recoverable case, where despite initial tracking failure, their system can recover from the incorrect states. An unrecoverable case, where an object is erroneously tracked or missed until it moves out of the field-of-view of the sensor. If an unexpected object is observed or if the object class would not be detected with confidence, then the system can
fall back to model-free tracking. Kim *et al.* [91] separated objects using techniques of segmentation and outlier elimination. Their algorithm worked somehow good under complex urban road conditions. Still, when outliers happen (e.g., during raining, car goes uphill, etc.) frequently, the algorithm can fail in eliminating them. The inlier survival ratio is a sensitive factor of their algorithm. Because if an inlier is accidently removed by the algorithm, then it will lead to a serious accident.

### VI. ESTIMATION OF INEFFECTUALNESS METRICS

#### A. LABELED DATASET

Galip *et al.* [7] used Ethernet cable for the connection between laser scanners (both LMS-511 and LD-MRS) and computer. Data were captured by SOPAS Engineering Tool, which is a program developed by SICK AG (Aktiengesellschaft). There were more than one laser scanners, thus those coordinates of points were changed by taking a laser scanner as reference. Afterwards, those distances were converted into X-Y coordinates [1] as well as their timestamps using MATLAB. At the end, Galip *et al.* [7] employed a total of 550 ground truth images to conduct their experiment. A total of 258 pedestrians and 292 vehicles were leveled properly.

#### B. CODING AND PARAMETERS

Algorithms were implemented by using MATLAB. An 8 GB RAM HP 64-bit workstation with an Intel Core i5-7200U CPU utilizing Windows 10 Pro was used throughout the experimentation to evaluate various algorithms. Standard parameters of each algorithms, if applicable, were employed. For example, in case of Sharif [8], randomly 25 pedestrians and 25 vehicles were selected for training and the rests for testing purposes. Polynomial kernel with order 3, Gaussian radial basis function kernel with a scaling factor of 1, and multilayer perceptron kernel with scale [1 1] were deemed.

#### C. GROUND TRUTHS AND ALGORITHMIC OUTPUTS

The Listing 1 demonstrates sample tracking output of each algorithm for pedestrians (Ped) and vehicles (Veh) with respect to ground truths (GrdTrh) of each frame from the first 500 frames of Galip *et al.* [7] dataset. It describes the ground
truths and the outputs of a frame for each algorithm starting from the line 3 to the line 102 by taking a multiple of 5 frames (i.e., frame 1 at line 3, frame 5 at line 4, frame 10 at line 5, frame 15 at line 6, etc.). Thus, we may analyze and reduce the result from 500 frames to (500/5 = ) 100 frames without losing significant performance. The data of the Listing 1 have been depicted in Fig. 5 for pedestrians and Fig. 6 for vehicles. Basically, Figs. 5 and 6 portray the outcomes of the mainstream laser-based people-vehicles algorithms on an identical ground. Seemingly, these algorithms failed to correctly identify a number of objects as compared to ground truth. The main reasons for this shortcoming include that the existing laser-based algorithms usually use segmentation of laser point clouds or use bounding-boxes of laser segments to represent objects. It is noticeable that average algorithmic performance of vehicles detection and/or tracking is better than that of pedestrians. This might be a reason that vehicles are rigid bodies and cannot be mixed up as human does.

**TABLE 5.** Qualitative and quantitative analysis of data in Listing 1.

| References | tp | fp | fn | tp/n | fp/n | fn/n | ACC | AUC |
|------------|----|----|----|------|------|------|-----|-----|
| Galip et al. [7] | 797 | 103 | 193 | 42 | 242 | 30 | 0.627 | 0.294 |
| Azim et al. [90] | 797 | 103 | 193 | 42 | 242 | 30 | 0.627 | 0.294 |
| Sharif et al. [99] | 797 | 103 | 193 | 42 | 242 | 30 | 0.627 | 0.294 |
| Zhao et al. [82] | 797 | 103 | 193 | 42 | 242 | 30 | 0.627 | 0.294 |
| Mertz et al. [83] | 797 | 103 | 193 | 42 | 242 | 30 | 0.627 | 0.294 |
| Shaf [8] | 797 | 103 | 193 | 42 | 242 | 30 | 0.627 | 0.294 |
| Wang et al. [82] | 797 | 103 | 193 | 42 | 242 | 30 | 0.627 | 0.294 |
| Kim et al. [81] | 797 | 103 | 193 | 42 | 242 | 30 | 0.627 | 0.294 |

TABLE 5 describes the qualitative and quantitative analysis of data in Listing 1, where number of true positive movers (tp), number of false positive movers (fp), number of false negative movers (fn), number of true negative movers (tn) with tn = 0, recall rate (R_r) with R_r = tp/(tp + fn), precision rate (P_r) with P_r = tp/(tp + fp), accuracy (ACC) with ACC = (tp + tn)/(tp + fp + fn + tn), and the area under the receiver operating characteristic curve (AUC) with trapezoidal numerical integration method [179]. The values of R_r, P_r, ACC, AUC for pedestrians and vehicles are
presented by pairs $p_{Rr}$, $v_{Rr}$, $p_{Pr}$, $v_{Pr}$, $p_{Ac}$, $v_{Ac}$, $p_{Au}$, and $v_{Au}$, respectively.

Figs. 7 and 8 plot the performance data from TABLE 5 for pedestrians and vehicles, respectively. The overall performance of pedestrians and vehicles tracking algorithms in Figs. 7 and 8 would be satisfactory and applicable for many laser-based applications including smart cities, ADAS, and intelligent traffic analysis. Nonetheless, future developments would take into account their existing algorithmic assumptions and other shortcomings to propose smarter algorithms.

### D. ESTIMATION OF ALGORITHMIC ERRORS AND FAILURES

To estimate conventional errors from Figs. 5 and 6, we have performed several statistical measures, e.g., RMSE ⇒ Root Mean Squared Error, $CV(RMSE)$ ⇒ Coefficient of variation of the root mean squared error, $MAE$ ⇒ Mean Absolute Error, and $MAPE$ ⇒ Mean Absolute Percentage Error. Their formulas are formulated in Eqs. 1 and 2:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{100} (G(i) - A(i))^2}{100}};
\]

\[
CV(RMSE) = \frac{RMSE}{\sqrt{\frac{\sum_{i=1}^{100} G(i)^2}{100}}};
\]

\[
MAE = \frac{1}{100} \sum_{i=1}^{100} |G(i) - A(i)|;
\]

\[
MAPE = \frac{1}{100} \sum_{i=1}^{100} \frac{|G(i) - A(i)|}{G(i)};
\]

where $G, A,$ and $i$ indicate ground truth, algorithmic detection, and number of frame, respectively. TABLE 6 demonstrates various errors estimated from data in Figs. 5 and 6 using Eqs. 1 and 2. The pairs $p_{RMSE}$, $v_{RMSE}$, $p_{MAE}$, $v_{MAE}$, $p_{MAPE}$, and $v_{MAPE}$ indicate $RMSE$, $CV(RMSE)$, $MAE$, $MAPE$ for pedestrians and vehicles, respectively. Figs. 9 and 10 represent the plotting of the error data from TABLE 6 for pedestrians and vehicles, respectively.

| References | $p_{RMSE}$ | $p_{CV}$ | $p_{MAE}$ | $p_{MAPE}$ | $v_{RMSE}$ | $v_{MAE}$ | $v_{MAPE}$ |
|------------|------------|----------|-----------|-----------|------------|-----------|-----------|
| Galip et al. [7] | 2.394 | 0.257 | 2.070 | 0.272 | 1.016 | 0.582 | 0.706 | 47.17% |
| Azim et al. [9] | 3.148 | 0.524 | 4.791 | 0.546 | 2.163 | 0.765 | 0.660 | 59.03% |
| Sharif et al. [99] | 2.393 | 0.257 | 2.070 | 0.272 | 0.757 | 0.392 | 0.530 | 97.19% |
| Zhao et al. [78] | 2.185 | 0.276 | 1.993 | 0.257 | 0.585 | 0.286 | 0.347 | 22.89% |
| Mertz et al. [83] | 2.049 | 0.379 | 1.022 | 12.88% | 0.901 | 0.598 | 0.580 | 31.55% |
| Sharif et al. [8] | 1.149 | 0.212 | 0.820 | 0.94% | 0.587 | 0.298 | 0.360 | 23.67% |
| Wang et al. [82] | 2.944 | 0.327 | 1.317 | 27.03% | 1.366 | 0.593 | 0.480 | 57.46% |
| Kim et al. [91] | 1.437 | 0.326 | 1.124 | 13.89% | 0.794 | 0.585 | 0.360 | 25.73% |

### TABLE 6. Estimation of errors from data in Figs. 5 and 6 with Eqs. 1 and 2.

### TABLE 7. Estimated ineffectualness metrics of various algorithms.

| References | $M_{RMSE}$ | $M_{MAE}$ | $M_{MAPE}$ | $F_{RMSE}$ | $F_{MAE}$ | $F_{MAPE}$ |
|------------|------------|-----------|-----------|-----------|-----------|-----------|
| Galip et al. [7] | 1.7020 | 0.374 | 1.3855 | 0.244 | 1.016 | 0.582 | 0.706 | 47.17% |
| Azim et al. [9] | 2.0555 | 0.500 | 2.7355 | 0.242 | 1.147 | 0.375 | 0.530 | 97.19% |
| Sharif et al. [99] | 3.148 | 0.524 | 4.791 | 0.546 | 2.163 | 0.765 | 0.660 | 59.03% |
| Zhao et al. [78] | 2.185 | 0.276 | 1.993 | 0.257 | 0.585 | 0.286 | 0.347 | 22.89% |
| Mertz et al. [83] | 2.049 | 0.379 | 1.022 | 12.88% | 0.901 | 0.598 | 0.580 | 31.55% |
| Wang et al. [82] | 1.149 | 0.212 | 0.820 | 0.94% | 0.587 | 0.298 | 0.360 | 23.67% |
| Kim et al. [91] | 1.437 | 0.326 | 1.124 | 13.89% | 0.794 | 0.585 | 0.360 | 25.73% |
TABLE 7 depicts the estimated ineffectualness metrics of miscellaneous algorithms. The mean values of \( \text{RMSE} \), \( \text{CV(RMSE)} \), \( \text{MAE} \), and \( \text{MAPE} \) are defined as:

\[
M_{\text{rmse}} = \frac{(p\text{RMSE} + v\text{RMSE})}{2},
\]

\[
M_{\text{cv}} = \frac{(p\text{CV} + v\text{CV})}{2},
\]

\[
M_{\text{mae}} = \frac{(p\text{MAE} + v\text{MAE})}{2},
\]

and

\[
M_{\text{mape}} = \frac{(p\text{MAPE} + v\text{MAPE})}{200},
\]

respectively using data in TABLE 6. The failures of \( R_r \), \( P_{rate} \), \( \text{ACC} \), and \( \text{AUC} \) achievements are defined as:

\[
F_{r} = 1 - \frac{(pR_r + vR_r)}{2},
\]

\[
F_{P} = 1 - \frac{(pP_r + vP_r)}{2},
\]

\[
F_{\text{acc}} = 1 - \frac{(p\text{ACC} + v\text{ACC})}{2},
\]

and

\[
F_{\text{auc}} = 1 - \frac{(p\text{AUC} + v\text{AUC})}{2},
\]

respectively using data in TABLE 5. The failure of an algorithm \( (F_{\text{fail}}) \) is defined by dint of (3), as shown at the bottom of the page 17.

For example, the accuracy of the algorithm of Azim et al. [90] is 86% (as the authors claimed), thus its \( F_{\text{fail}} \) will be \( (100\% - 86\%) / 100 = 0.14 \) and so on. From data in TABLE 7, it is extremely difficult to say accurately which algorithm outperforms its alternative.

VII. SUPERIORITY MEASURE USING STATISTICAL TESTS

A. MULTIPLE COMPARISON WITH STATISTICAL TESTS

Fig. 11 depicts performance evaluation of various algorithms deeming the numerical values of the ineffectualness metrics from TABLE 7. From this graph, it is extremely hard to rank each algorithm. How would it be possible to demonstrate that one algorithm is superior to its alternative algorithms?

Statistically, it is possible to show that one algorithm is better than its alternatives.

Usually, multiple comparisons with a control algorithm can be employed to statistically demonstrate that one algorithm is better than its alternatives in areas related to computer science and engineering [180]. The key concept of applying the non-parametric tests [181] includes that they can deal with probabilistic and non-probabilistic methods without imposing any circumscription. We have considered data from TABLE 7 to conduct statistical tests for multiple comparisons along with a set of post-hoc procedures to compare a control algorithm with others (i.e., \( 1 \times N \) comparisons) and to perform all possible pairwise comparisons (i.e., \( N \times N \) comparisons).

For these purposes, we have used the open source statistical software applications from University of Granada [44].

To conduct a statistical test of significance, the \( p \)-value of test statistic and the level of significance \( \alpha \) play an important role. Both \( p \)-value and \( \alpha \) might be misdirected. Because both of them are indeed probabilities, i.e., values between zero and one. The \( p \)-value states directly how extreme that statistic should be by using data from TABLE 7. The \( \alpha \) gives evidence of how extreme observed results should be to reject the null hypothesis of a significance test. A smaller \( p \)-value expresses briefly that the observed sample is more unlikely. In statistical significance testing, the \( p \)-value is the probability of obtaining
a test statistic result minimum as drastic as the one that was in effect observed by taking into account the null hypothesis is not false [182]. Flacks of _p_-values say that the circumstances employed to determine statistical significance is based on any option of level (e.g., _p_ = 0.05) [183]. If a significance testing is applied to hypotheses that are known to be not-true in advance, then a non-significant result will plainly cogitate a deficient sample size. Any _p_-value remains in a certain state exclusively on the information obtained from a fixed experiment.

Friedman test [184] and its derivatives (e.g., Iman-Davenport test [185]) are usually referred to as one of the most well-known nonparametric tests for multiple comparisons. Consequently, we have performed the Friedman test [184]. An available characteristics of the Friedman test [184] is that it takes measures in preparation for ranking of a set of algorithms with performance in descending order. Notwithstanding, it can solely inform us about the appearance of differences among all samples of results under comparison. As a result, its alternatives e.g., Friedman’s aligned rank test [186] and Quade test [187] can give us further information. Thus, we have performed both Friedman’s aligned rank test [186] and Quade test [187]. They express opposition through rankings. They would provide a better results based on the features of a given experimental study. After rejecting null-hypotheses, we have continued to post-hoc procedures to find the special pairs of algorithms which give idiosyncrasies.

In the case of _1 × N_ comparisons, the post-hoc procedures make up of Bonferroni-Dunn’s [188], Holm’s [189], Hochberg’s [190], Hommel’s [191], [192], Holland’s [193], Rom’s [194], Finner’s [195], and Li’s [196], procedures; whereas in the case of _N × N_ comparisons, they consist of Nemenyi’s [197], Shaffer’s [198], and Bergmann-Hommel’s [199] procedures. In the case of Bonferroni-Dunn’s procedure [188], the performance of two algorithms is substantially divergent if the corresponding mean of rankings is at least as large as its discriminating divergence. A better one is Holm’s procedure [189]. It examines in a sequential manner, where all hypotheses ordered based on their _p_-values from inferior to superior. All hypotheses for which _p_-value is less than _α_ divided by the number of algorithms minus the number of a successive step are rejected. All hypotheses having larger _p_-values are upheld. Holm’s procedure [189] adjusts _α_ in a step-down manner. Similarly, both Holland’s [193] and Finner’s [195] procedures adjust _α_ in a step-down method. But the Hochberg’s procedure [190] works in the opposite direction of Holland’s procedure [193]. It compares the largest _p_-value with _α_, the next largest with _α/_2, and so on, until it encounters a hypothesis that can be rejected. The Rom [194] suggested

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**FIGURE 5.** Comparative plot of ground truths and outputs of algorithms deeming pedestrians.
a modification to Hochberg’s step-up procedure [190] to intensify its power. In turn, Li [196] recommended a two-step rejection procedure.

The available statistical software applications [44] calculate multiple comparison procedures: Friedman [184], Iman et al. [185], Bonferroni et al. [188], Holm [189],
Hochberg [190], Holland [193], Rom [194], Finner [195], Li [196], Shaffer [198], and Bergamnn et al. [199] tests as well as adjusted $p$-values. The Nemenyi’s procedure [197] is the easiest one for all possible pairwise comparisons. It deliberates that the value of $\alpha$ is adjusted in a single step by dividing it only by the number of comparisons performed. It is easy but less practical. The Shaffer’s static routine [198] adopts the Holm’s step-down method [189]. At a given stage, it rejects a hypothesis if the $p$-value is less than $\alpha$ divided by the maximum number of hypotheses.
which can be true provided that all previous hypotheses are false. The Bergmann et al.’s [199] procedure provides the best performance, but it is very sophisticated and computationally expensive. It consists of finding all the possible exhaustive sets of hypotheses for a certain comparison and all elementary hypotheses which cannot be rejected. The details of the procedure are described in Bergmann et al. [199], Garcia et al. [200], and the rapid algorithm to conduct this test in demonstrated in Hommel et al. [192].

B. AVERAGE RANKING OF ALGORITHMS
To achieve the test results, Friedman [184], Friedman’s aligned rank test [186], and Quade [187] nonparametric statistical tests are applied to the obtained results of eight algorithms in TABLE 7. Explicitly, statistical tests are applied to a matrix of dimension 8 × 9, where 8 belongs to the number of algorithms and 9 corresponds to 9 parameters (as 9 datasets while applied to the statistical software environment [44]) of each algorithm. TABLE 8 shows the average ranking computed by using Friedman [184], Friedman’s aligned rank test [186], and Quade [187] nonparametric statistical tests. The aim to apply Friedman [184], Friedman’s aligned rank test [186], and Quade [187] nonparametric tests is to determine whether there are significant differences among various algorithms considering over the data in TABLE 7. These tests provide ranking of the algorithms for each individual dataset, i.e., the best performing algorithm receives the highest rank of 1, the second best algorithm gets the rank of 2, and so on. The mathematical equations and further explanation of the nonparametric procedures of Friedman [184], Friedman’s aligned rank test [186], and Quade [187] can be found in Quade [187] and Westfall et al. [201].

Fig. 12 makes a visualization of the average rankings using the data in TABLE 8. From Fig. 12, it is noticeable that the algorithm of Sharif [8] became the best performing one, with the longest bars of 0.6428, 0.0783, and 0.5844 for Friedman test [184], Friedman’s aligned rank test [186], and Quade test [187], respectively. This hints that algorithm of Sharif [8] gives great performance for the solution of underlaying problems of detecting and tracking both pedestrians and vehicles from laser scanned data points. Friedman [184] statistic considered reduction performance (distributed according to chi-square with 7 degrees of freedom) of 40.861111. Aligned Friedman [186] statistic considered reduction performance (distributed according to F-distribution with 7 and 56 degrees of freedom) of 34.336679. Iman-Davenport [185] statistic considered reduction performance (distributed according to F-distribution with 7 and 56 degrees of freedom) of 34.336679. Iman-Davenport [185] statistic considered reduction performance (distributed according to F-distribution with 7 and 56 degrees of freedom)
TABLE 8. Average ranking of each algorithm using nonparametric statistical tests. The best results are shown in bold.

| Algorithms      | Friedman Ranking | Multiple Comparison Tests | Quade Ranking |
|-----------------|------------------|---------------------------|---------------|
| Sharif [8]      | 1.5556           | 12.7778                   | 1.7111        |
| Zhao et al. [78]| 2.2222           | 17.2222                   | 2.5333        |
| Kim et al. [91] | 3.5030           | 26.5000                   | 3.2556        |
| Sharif et al.   | 4.4444           | 41.3333                   | 4.7333        |
| Mertz et al.    | 5.1667           | 36.6111                   | 4.6333        |
| Galip et al.    | 5.4444           | 50.3333                   | 5.8889        |
| Wang et al.     | 6.5556           | 50.6667                   | 6.3556        |
| Azim et al.     | 7.1111           | 56.5556                   | 6.8889        |
| Various Statistics | 40.861111      | 34.336679                 | 7.848328      |

### Performance Evaluation Deeming Errors and Failures

![Graph showing numerical values of errors and failures](image.png)

**FIGURE 11.** Plotting of the numerical values of errors and failures using data from Table 7.

of 14.76537. Quade [187] statistic considered reduction performance (distributed according to F-distribution with 7 and 56 degrees of freedom) of 7.848328. The p-values computed through Friedman statistic, aligned Friedman statistic, Iman-Daveport statistic, and Quade statistic are 0.000001, 0.00001489707, 0.000000000099, and 0.000001331163, respectively. TABLE 9 demonstrates the results obtained on post-hoc comparisons of adjusted p-values, $\alpha = 0.05$, as well as $\alpha = 0.10$.

### C. POST-HOC PROCEDURES FOR $1 \times N$ COMPARISONS

In the case of $1 \times N$ comparisons, the post-hoc procedures consist of Bonferroni-Dunn’s [188], Holm’s [189], Hochberg’s [190], Hommel’s [191, 192], Holland’s [193], Rom’s [194], Finner’s [195], and Li’s [196] procedures. In these statistical analysis tests, multiple comparison post-hoc procedures considered for comparing the control algorithm of Sharif [8] with the others. The results are shown by computing p-values for each comparison. TABLE 10 depicts obtained p-values using the ranks computed by the Friedman [184], Friedman’s aligned rank test [186], and Quade [187] non-parametric tests, respectively. Based on the computed results, all tests show significant improvements of Sharif [8] over Zhao et al. [78], Kim et al. [91], Kim et al. [91], Mertz et al. [83], Galip et al. [7], Wang et al. [82], and Azim et al. [90] for all the post-hoc procedures considered. Besides this, the Li’s [196] procedure does the greatest performance, reaching the lowest p-values in the comparisons.

### D. POST-HOC PROCEDURES FOR $N \times N$ COMPARISONS

In the case of $N \times N$ comparisons, the post-hoc procedures consist of Nemenyi’s [197], Shaffer’s [198], as well as Bergmann-Hommel’s [199] procedures. TABLE 11 presents 28 hypotheses of equality among 8 different algorithms and
p-values achieved. Using level of significance $\alpha = 0.05$: (i) Nemenyi’s [197] procedure rejects those hypotheses that have an unadjusted $p$-value $\leq 0.001786$, (ii) Holm’s [189] procedure rejects those hypotheses that have an unadjusted $p$-value $\leq 0.002273$, (iii) Shaffer’s [198] procedure rejects those hypotheses that have an unadjusted $p$-value $\leq 0.001786$, and (iv) Bergmann’s [199] procedure rejects following hypotheses: Galip et al. [7] vs Sharif [8], Galip et al. [7] vs Zhao et al. [78], Sharif [8] vs Azim et al. [90], Sharif [8] vs Wang et al. [82], Azim et al. [90] vs Zhao et al. [78], as well as Zhao et al. [78] vs Wang et al. [82]. Similarly, using level of significance $\alpha = 0.10$: (i) Nemenyi’s [197] procedure rejects those hypotheses that have an unadjusted $p$-value $\leq 0.003571$, (ii) Holm’s [189] procedure rejects those hypotheses that have an unadjusted $p$-value $\leq 0.004545$, (iii) Shaffer’s [198] procedure rejects those hypotheses that have an unadjusted $p$-value $\leq 0.003571$, and (iv) Bergmann’s [199] procedure rejects following hypotheses: Galip et al. [7] vs Sharif [8], Galip et al. [7] vs Zhao et al. [78], Sharif [8] vs Azim et al. [90], Sharif [8] vs Wang et al. [82], Azim et al. [90] vs Zhao et al. [78], as well as Zhao et al. [78] vs Wang et al. [82].
TABLE 10. Adjusted p-values for various tests considering Sharif [8] as control method.

| Tests | Algorithms | Not adjusted | 1-2 step-procedures | Step-down procedures | Step-up procedures |
|-------|------------|--------------|---------------------|---------------------|-------------------|
| Zhao et al. [78] | 0.727836 | 5.499010 | 0.723811 | 0.772380 | 0.772380 | 0.772380 | 0.772380 |
| Kim et al. [91] | 0.013899 | 0.624761 | 0.974391 | 0.624761 | 0.974391 | 0.624761 | 0.974391 |
| Sharif et al. [99] | 0.058140 | 0.035490 | 0.024241 | 0.024241 | 0.013787 | 0.024241 | 0.024241 |
| Mertz et al. [83] | 0.021146 | 0.007213 | 0.0072 | 0.007213 | 0.007213 | 0.007213 | 0.007213 |
| Galip et al. [7] | 0.000144 | 0.000144 | 0.000144 | 0.000144 | 0.000144 | 0.000144 | 0.000144 |
| Wang et al. [82] | 0.000355 | 0.000355 | 0.000355 | 0.000355 | 0.000355 | 0.000355 | 0.000355 |
| Zhao et al. [78] | 0.000240 | 0.000240 | 0.000240 | 0.000240 | 0.000240 | 0.000240 | 0.000240 |
| Wang et al. [82] | 0.007139 | 0.007139 | 0.007139 | 0.007139 | 0.007139 | 0.007139 | 0.007139 |
| Zhao et al. [78] | 0.007139 | 0.007139 | 0.007139 | 0.007139 | 0.007139 | 0.007139 | 0.007139 |
| Wang et al. [82] | 0.007139 | 0.007139 | 0.007139 | 0.007139 | 0.007139 | 0.007139 | 0.007139 |

TABLE 11. Adjusted p-values for tests for multiple comparisons among all methods.

| Index | Hypothesis | Not adjusted | 1 × N post-hoc procedures and p-values |
|-------|------------|--------------|---------------------------------------|
| 1     | Sharif [8] vs Zhao et al. [78] | 0.000010 | 0.000268 | 0.000268 | 0.000268 |
| 2     | Sharif [8] vs Wang et al. [82] | 0.000055 | 0.006902 | 0.006902 | 0.006902 |
| 3     | Sharif [8] vs Zhao et al. [78] | 0.000055 | 0.006902 | 0.006902 | 0.006902 |
| 4     | Zhao et al. [78] vs Wang et al. [82] | 0.000019 | 0.006902 | 0.006902 | 0.006902 |
| 5     | Galip et al. [7] vs Sharif [8] | 0.000013 | 0.000564 | 0.000564 | 0.000564 |
| 6     | Zhao et al. [78] vs Wang et al. [82] | 0.000013 | 0.000564 | 0.000564 | 0.000564 |
| 7     | Zhao et al. [78] vs Mertz et al. [83] | 0.000013 | 0.000564 | 0.000564 | 0.000564 |
| 8     | Zhao et al. [78] vs Wang et al. [82] | 0.000013 | 0.000564 | 0.000564 | 0.000564 |
| 9     | Zhao et al. [78] vs Mertz et al. [83] | 0.000013 | 0.000564 | 0.000564 | 0.000564 |
| 10    | Zhao et al. [78] vs Wang et al. [82] | 0.000013 | 0.000564 | 0.000564 | 0.000564 |

Wang et al. [82], Azim et al. [90], Zhao et al. [78], and Zhao et al. [78], Wang et al. [82].

E. WILCOXON SIGNED-RANK TEST

The Wilcoxon signed-rank test [202], named after Irish American statistician Frank Wilcoxon (2 September 1892 – 18 November 1965), is a nonparametric statistical test that compares two paired groups, and comes in two versions, the rank-sum test or the signed rank test. The goal of the test is to determine if two or more sets of pairs are different from one another in a statistically significant manner. In short, the Wilcoxon signed-rank test [202] determines whether two dependent samples are selected from populations having the same distribution. Considering Wilcoxon signed-rank test [202] and open source statistical software of [44], TABLE 12, TABLE 13, and TABLE 14 show ranking of 8 algorithms, results of Sharif [8], and summary of test, respectively. The symbol text-bullet • in TABLE 14 indicates the method in the row improves the method of the column, whereas the symbol text-open-bullet ◦ hints the method in the column improves the method of the row. Level significance for upper and lower diagonals are 0.9 and 0.95, respectively.

In sum and substance, based on the aforementioned experimental and statistical results, it would be easy to make an explicit conclusion that the algorithm of Sharif [8] outperforms over Zhao et al. [78], Kim et al. [91], Kim et al. [91], Sharif et al. [99], Mertz et al. [83], Galip et al. [7], Wang et al. [82], and Azim et al. [90]. The algorithm of Zhao et al. [78] owned the second best position with marginal...
TABLE 12. Ranks of various algorithms computed by Wilcoxon signed-rank test [202].

| Algorithms       | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Galip et al. [7] | 76  | 74  | 55  | 39  | 32  | 51  | 61  | 54  |
| Azim et al. [9]  | 81  | 83  | 69  | 44  | 36  | 67  | 76  | 74  |
| Sharif et al.    | 47  | 51  | 40  | 22  | 30  | 43  | 59  | 56  |
| Zhao et al. [8]  | 45  | 45  | 30  | 14  | 12  | 43  | 56  | 56  |
| Mertz et al. [7] | 30  | 30  | 20  | 10  | 8   | 26  | 37  | 37  |
| Sharif et al.    | 45  | 45  | 30  | 14  | 12  | 43  | 56  | 56  |
| Wang et al. [2]  | 22  | 22  | 30  | 10  | 10  | 26  | 37  | 37  |
| Kim et al. [1]   | 15  | 15  | 30  | 10  | 10  | 26  | 37  | 37  |

TABLE 13. Results obtained by Wilcoxon signed-rank test [202] for the algorithm of Sharif [8], where E. p-value ⇒ Exact p-value, A. p-value ⇒ Asymptotic p-value, Con. Int. ⇒ Confidence interval, E. Con. ⇒ Exact confidence.

| Algorithms       | Wilcoxon parameters | t | p-value | Confidence interval | E. Con. |
|------------------|---------------------|---|---------|---------------------|--------|
| Galip et al. [7] | 0.0005984 | 5.69448 | 56  | 19.832  | 56   | 45  | 45  | 30  | 8  | 12  | 9  | 15  | 15  |
| Zhao et al. [8]  | 0.0005984 | 5.69448 | 56  | 19.832  | 56   | 45  | 45  | 30  | 8  | 12  | 9  | 15  | 15  |
| Mertz et al. [7] | 0.0005984 | 5.69448 | 56  | 19.832  | 56   | 45  | 45  | 30  | 8  | 12  | 9  | 15  | 15  |
| Sharif et al.    | 0.0005984 | 5.69448 | 56  | 19.832  | 56   | 45  | 45  | 30  | 8  | 12  | 9  | 15  | 15  |
| Wang et al. [2]  | 0.0005984 | 5.69448 | 56  | 19.832  | 56   | 45  | 45  | 30  | 8  | 12  | 9  | 15  | 15  |
| Kim et al. [1]   | 0.0005984 | 5.69448 | 56  | 19.832  | 56   | 45  | 45  | 30  | 8  | 12  | 9  | 15  | 15  |

TABLE 14. Summary of the Wilcoxon test.

| Algorithms       | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Galip et al. [7] | -   | -   | -   | -   | -   | -   | -   | -   |
| Sharif et al.    | *   | -   | *   | -   | -   | -   | -   | -   |
| Zhao et al. [8]  | *   | *   | -   | *   | -   | -   | -   | -   |
| Mertz et al. [7] | *   | *   | -   | *   | -   | -   | -   | -   |
| Wang et al. [2]  | *   | *   | -   | *   | -   | -   | -   | -   |
| Kim et al. [1]   | *   | *   | -   | *   | -   | -   | -   | -   |

behavior by proposing new algorithms using other technique rather than clustering. To propose such algorithms is a real challenge for the laser-vision research community.

The existing lased-based tracking algorithms take the brimming benefits of Kalman filter along with its updated versions (e.g., extended and unscunted). Accordingly, tracking of movers using Kalman filter has been performed about five times more than that of particle filter in the literature. Particle filter has taken the second position among all filters applied in lased-based tracking algorithms. This is due to the fact that particle filter is generally more computationally expensive than Kalman filter. Even so, particle filter can be used to solve non-Gaussian related problems in a better way. Besides, the most common variants of Kalman filters cannot provide a level-headed estimation for highly nonlinear and non-Gaussian problems. In consequence, additional particle filter based algorithms would be proposed in the long run.

Hereetofore, we have performed various nonparametric statistical tests for eight key algorithms of detecting and/or tracking both people and vehicles from TABLE 1. But we have not performed any statistical tests for the only-people tracking algorithms in TABLE 2, the only-vehicle tracking algorithms in TABLE 3, and the diverse-object detection or tracking algorithms in TABLE 4. Therefore, a key question still remains for these tables. Which algorithm would be superior to its alternative algorithms? Our incapacities behind this unworked out problem include mainly the unavailability of common datasets and a lesser extent implementation difficulties of multitude algorithms. Besides, it is not possible to make statistical tests with a single parameter (e.g., accuracy). Different authors used their own defined and suitable datasets with diverse sizes and conditions. As a result, the obtained accuracy of their own algorithms would vary widely based on datasets. An available common data set can help to judge algorithms on a common ground to measure algorithmic performance. Unfortunately, there existed no such datasets up until now. In general, it is a challenging task to build common datasets for test many algorithms on the identical basis. Future work would predominantly highlight this issue. In addition, carefully optimized code can always give a better performance [203]. But the codes of implemented algorithms are not optimized. Consequently, code would be optimized by using manual and software optimization techniques [204] to obtain an optimal execution time of each algorithm.

**VIII. FUTURE WORKS AND CHALLENGES**

Laser-based algorithms have been emerged as the alternatives of camera-based algorithms. The solution of privacy problem of people has been embedded into the laser-based detection and tracking algorithms, whereas camera-based algorithms need special masking to maintain privacy. In spite of those facts, one of the major challenges working with laser scanners is the difficulty of recognizing any kind of objects using only the relatively low information that essentially the laser scanners provide. From TABLEs 1, 2, 3, and 4 as well as associated discussion, we can conclude that the detection of objects has been done by clustering laser scanned data points in depth images or 3D laser scans. Future work would go beyond this inferiority to Sharif et al. [99]. Intuitively speaking, algorithms of Zhao et al. [78] and Sharif [8] can be applied interchangeably with minor performance degradation. However, it is observed that the performance of the algorithm of Sharif [8] (i.e., SVM and Hungarian method with particle filter) surpassed those of its alternatives for detecting and tracking pedestrians and vehicles using laser scanned datasets (e.g., Galip et al. [7] and others). In other words, statistically any of other seven algorithms can be replaced with the algorithm of Sharif [8] for either a better performance improvement or without any performance degradation.

**IX. CONCLUSION**

We provided an overview of methods to classify objects using laser scanners instead of common video recording RGB cameras. We pointed up a special feature of laser scanners which cannot see or identify identifiable features of objects and humans. Therefore, laser-based algorithms inherently await privacy masking. Privacy protection should provide privacy protection, whereas RGB camera-based algorithms would be proposed in the long run.
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REFERENCES

[1] M. Haidar Sharif and C. Djeraba, “An entropy approach for abnormal activities detection in video streams,” Pattern Recognit., vol. 45, no. 7, pp. 2543–2561, Jul. 2012.

[2] M. H. Sharif, “A numerical approach for tracking unknown number of individual targets in videos,” Digit. Signal Process., vol. 57, pp. 106–127, Oct. 2016.

[3] S. M. M. Ali, J. C. Augusto, and D. Windridge, “A survey of user-centered approaches for smart home transfer learning and new user home automation adaptation,” Appl. Artif. Intell., vol. 33, no. 8, pp. 747–774, Jul. 2019.

[4] M. H. Sharif, I. Despot, and S. Uyaver, “A proof of concept for home automation system with implementation of the Internet of Things standards,” Periodicals Eng. Natural Sci., vol. 6, no. 1, pp. 95–106, 2018.

[5] G. M. Toschi, L. B. Campos, and C. E. Cugnasca, “Home automation networks: A survey,” Comput. Standards Interfaces, vol. 50, pp. 42–54, Feb. 2017.

[6] H. A. Shehu, M. H. Sharif, and R. A. Ramadan, “Distributed mutual exclusion algorithms for intersection traffic problems,” IEEE Access, vol. 8, pp. 138277–138296, 2020.

[7] F. Galip, M. Caputcu, R. H. Inan, M. H. Sharif, A. Karabayir, S. Kaplan, M. Oruysal, B. Sengoz, A. Guler, and S. Uyaver, “A novel approach to obtain trajectories of targets from laser scanned datasets,” in Proc. Int. Conf. Comput. Inf. Technol. (ICCIT), 2015, pp. 231–236.

[8] M. H. Sharif, “Particle filter for trajectories of movers from laser scanned dataset,” in Proc. 3rd Mediterranean Conf. Pattern Recognit. Artif. Intell. (MedPRAI), Istanbul, Turkey, Dec. 2019, pp. 133–148.

[9] D. Avola, G. Foresti, C. Picarielli, M. Vernier, and L. Cinque, “Mobile applications for automatic object recognition,” in Encyclopedia of Information Science and Technology, vol. 10, D. M. Khosrow-Pour, Ed. 4th ed. Hershey, PA, USA: IGI Global, 2018, ch. 538, pp. 6195–6206.

[10] S. Edge. (2019). RGB-IR Real Time Fusion for the Security and Surveillance Industry. [Online]. Available: https://agilitypr.co.uk/wp-content/uploads/2019/10/20190301-Spectral-Edge-RGBIR-Fusion-for-Surveillance-Market-White-Paper-Approved-002.pdf

[11] A. Jouade and A. Barka, “Massively parallel implementation of FETI-2LM methods for the simulation of the sparse receiving array evolution of the GRAVES radar system for space surveillance and tracking,” IEEE Access, vol. 7, pp. 128968–128979, 2019.

[12] M. Watanabe, J. Honda, and T. Otsuyama, “Moving target detection and two-receiver setup using optical-fiber-connected passive primary surveillance radar,” IEICE Trans. Commun., vol. 102-B, no. 2, pp. 241–246, 2019.

[13] R. Amiri and A. Shahzadi, “Micro-doppler based target classification in ground surveillance radar systems,” Digital Signal Process., vol. 101, Jun. 2020, Art. no. 102702.

[14] N. Fiscante, P. Addabbo, C. Clemente, F. Biondi, G. Giunta, and D. Orlando, “A track-before-detect strategy based on sparse data processing for air surveillance radar applications,” Remote Sens., vol. 13, no. 4, p. 662, 2021.

[15] W. Jiang and Z. Yin, “Combining passive visual cameras and active IMU sensors for persistent pedestrian tracking,” J. Vis. Commun. Image Represent., vol. 48, pp. 419–431, Oct. 2017.

[16] J. Zhang and P. Zhou, “Integrating low-resolution surveillance camera and smartphone inertial sensors for indoor positioning,” in Proc. IEEE/ION Position, Location Navigation Symp. (PLANS), Monterey, CA, USA, Apr. 2018, pp. 410–416.

[17] A. Baghdadi, “Application of inertial measurement units for advanced safety surveillance system using individualized sensor technology (ASSIST): A data fusion and machine learning approach,” in Proc. IEEE Int. Conf. Healthcare Inform. (ICHI), New York, NY, USA, Jun. 2018, pp. 450–451.

[18] R. Abbas, K. Michael, M. G. Michael, and A. Aloudat, “Emerging forms of covert surveillance using GPS-enabled devices,” J. Cases Inf. Technol., vol. 13, no. 2, pp. 19–33, 2011.

[19] J. Karp, “GPS in interstate trucking in Australia: Intelligence, surveillance?Or compliance tool?” IEEE Technol. Soc. Mag., vol. 33, no. 2, pp. 47–52, Summer 2014.

[20] S. S. Sen, M. Ciciglo, and A. Calhan, “Iot-based GPS assisted surveillance system with inter-WBAN geographic routing for pandemic situations,” J. Biomed. Informat., vol. 116, Apr. 2021, Art. no. 103731.

[21] A. D. Simone, H. Park, D. Riccio, and A. Camps, “Ocean target monitoring with improved revisit time using constellations of GNSS-R instruments,” in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), Jul. 2017, pp. 4102–4105.

[22] A. Di Simone, G. Di Martino, A. Iodice, D. Riccio, G. Ruello, L. M. Millefiori, P. Braca, and P. Willetl, “Maritime surveillance using spaceborne GNSS-reflectometry: The role of the scattering configuration and receiving polarization channel,” in Proc. IEEE 4th Int. Forum. Technol. Soc. Ind. (RTSI), Sep. 2018, pp. 1–5.

[23] A. Di Simone, P. Braca, L. M. Millefiori, and P. Willetl, “Ship detection using GNSS-reflectometry in backscattering configuration,” in Proc. IEEE Radar Conf. (RadarConf18), Apr. 2018, pp. 1589–1593.

[24] A. Saksena and I. J. Wang, “Dynamic ping optimization for surveillance in multistatic sonar buoy networks with energy constraints,” in Proc. Conf. Decis. Control (CDC), 2008, pp. 1109–1114.

[25] H. Johannsson, M. Kaess, B. Englot, F. Hover, and J. Leonard, “Imag- ing sonar-aided navigation for autonomous underwater harbor surveil- lance,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., Taipei, Taiwan, Oct. 2010, pp. 4396–4403.

[26] V. Maljy, “Modeling of surveillance zones for bi-static and multi- static active sonars with the use of geographic information systems,” in Information Fusion and Intelligent Geographic Information Systems (IFA&GIS) (Lecture Notes in Geoinformation and Cartography). Cham, Switzerland: Springer, 2017, pp. 139–152.

[27] B. Livada, S. Vujic, D. Radić, T. Unkalievı̈ž, and Z. Banjac, “Digital magnetic compass integration with stationary, land-based electro-optical multi-sensor surveillance system,” Sensors, vol. 19, no. 19, p. 4331, Oct. 2019.

[28] T. A. Kass-Hout, D. Buckeridge, J. Brownstein, Z. Xu, P. Mcmurray, C. T. Ishikawa, J. Gumm, and B. L. Massoudi, “Self-reported fever and measured temperature in emergency department records used for syndromic surveillance,” J. Am. Med. Inform. Assoc., vol. 17, no. 2, p. 355, Feb. 2010.

[29] M. M. Nahas, “Fiber-optic based solutions for long-tunnels radio coverage and surveillance,” Int. J. Interdiscipl. Telecommun. Netw., vol. 11, no. 4, pp. 32–47, Oct. 2019.

[30] T. A. Kass-Hout, D. Buckeridge, J. Brownstein, Z. Xu, P. Mcmurray, C. T. Ishikawa, J. Gumm, and B. L. Massoudi, “Self-reported fever and measured temperature in emergency department records used for syndromic surveillance,” J. Am. Med. Inform. Assoc., vol. 17, no. 2, p. 355, Feb. 2010.

[31] S. Kim and T. Kim, “Radiometric temperature-based pedestrian detection for 24 hour surveillance,” in Proc. IEEE Int. Conf. Multimedia Expo Workshops (ICMEW), San Diego, CA, USA, Jul. 2018, p. 1.

[32] M. Chen, L. Chen, and Y. Wang, “An intelligent wearable temperature monitoring system for epidemic surveillance,” in Proc. 5th Int. Conf. Universal Village (UV), Boston, MA, USA, Oct. 2020, pp. 1–5.
[81] D. Wang, “Laser-based detection and tracking of dynamic objects,” Ph.D. dissertation, Dept. Eng. Sci., Univ. Oxford, Oxford, U.K., 2014.

[82] D. Z. Wang, I. Posner, and P. Newman, “Model-free detection and tracking of dynamic objects with 2D lidar,” Int. J. Robot. Res., vol. 34, no. 7, pp. 1039–1063, Jun. 2015.

[83] C. Merz, L. E. Navarro-Serment, R. MacLachlan, P. Rybski, S. Steinfeld, A. Aaron, C. Urmon, N. Vandapel, M. Hebert, C. Thorpe, D. Duggins, and J. Gowdy, “Moving object detection with laser scanners,” J. Field Robot., vol. 30, no. 1, pp. 17–43, 2013.

[84] Nightowls Dataset. (2020). [Online]. Available: https://www.nightowls-dataset.org/nightowls-competition-2020.

[85] Y. Khandhediya, K. Sav, and V. Gajjar, “Human detection for night surveillance using adaptive background subtracted image,” CoRR, vol. abs/1709.09389, pp. 1–5, Sep. 2017. [Online]. Available: http://arxiv.org/abs/1709.09389

[86] Reuters. (2021). Tesla's In-Car Cameras Raise Privacy Concerns: Consumer Reports. [Online]. Available: https://www.reuters.com/article/us-tesla-privacy-idUSKBN2BF2MM

[87] D. Cavaliere, V. Loia, A. Saggese, S. Senateiro, and M. Vento, “Context-based reasoning using ontologies to adapt visual tracking in surveillance,” in Proc. Int. Conf. Adv. Video Signal Based Survell. (AVSS), Genova, Italy, Sep. 2011, pp. 231–236.

[88] H. Kozuma, K. Nakamura, H. Zhao, Y. Shi, and K. Sakamoto, “3D crowd surveillance and analysis using laser scanner range,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS), Oct. 2007, pp. 2174–2179.

[89] X. Song, J. Chai, H. Zhao, and H. Zha, “Tracking interacting targets based on online supervised learning,” Robot. Auton. Syst., vol. 50, no. 2500, 2000.

[90] X. Song, J. Cui, X. Wang, H. Zhao, and H. Zha, “Tracking interacting pedestrians via on-line learning,” Neurocomputing, vol. 115, pp. 92–105, Sep. 2013.

[91] X. Song, J. Cui, H. Zhao, and H. Zha, “Bayesian fusion of laser and vision for multiple people detection and tracking,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS), Oct. 2007, pp. 3014–3019.

[92] X. Song, J. Cui, H. Zhao, R. Shibasaki, and H. Zha, “Laser-based tracking of multiple interacting pedestrians via on-line learning,” Neurocomputing, vol. 114, pp. 92–105, Sep. 2013.

[93] E. A. Topp and H. L. Christensen, “Tracking for following and passing persons,” in Proc. Int. Conf. Intell. Robots Syst. (IROS), 2005, pp. 2321–2327.

[94] B. Ling, S. Tiwari, Z. Li, and D. R. Gibson, “A multi-pedestrian detection and counting system using fusion of stereo camera and laser scanner,” Int. J. Intell. Comput. Cybern., vol. 3, no. 3, pp. 799–810, Sep. 2010.

[95] A. Mendes and U. Nunes, “Situation-based multi-target detection and tracking with laser scanner in outdoor semi-structured environment,” in Proc. Int. Conf. Intell. Robots Syst. (IROS), vol. 1, 2004, pp. 88–93.

[96] O. M. Mozos, R. Kurazume, and T. Hasegawa, “Laser-based tracking and counting system using fusion of stereo camera and laser scanner,” in Proc. Int. Conf. Robot. Autom. (ICRA), 2001, pp. 1364–1369.
