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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.

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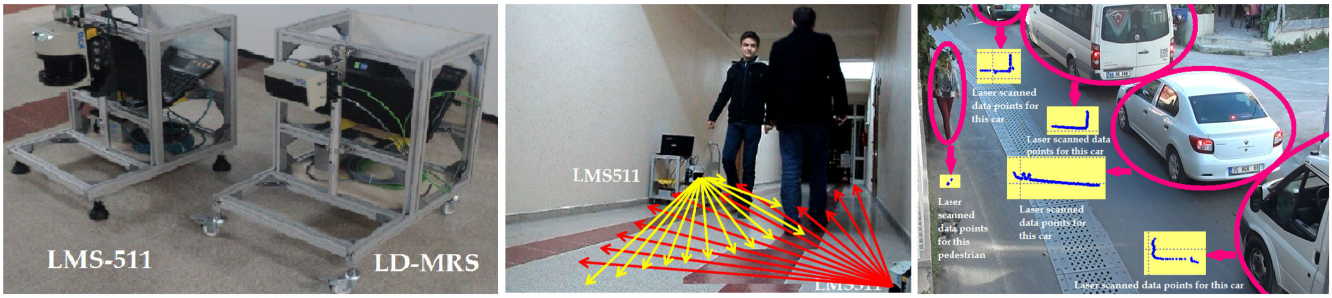
Nowadays, like home automation [3]–[5], traffic automation became one of the key factors for a smart city [6]. The sidewalk occupancy is a serious problem in the urban life [7], [8]. If sidewalk occupancy will occur, then pedestrians will tend to walk on the street which would lead many potential traffic 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



(a) (b) (c)

FIGURE 1. **(a) LMS-511 and LD-MRS are ready for usage, (b) Schematic emission of laser beam that hits legs, (c) Data points group from real world objects.**

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 focusses 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 Constitution, which protects a citizen from unreasonable searches and seizures by law enforcement and other government agencies. Some possible solutions of this debt include privacy masking and laser-based monitoring. The privacy masking method concerns each surveillance camera with privacy masking capability can selectively block portions of the video image for the purpose of protecting privacy. For example, PTZ (pan-tilt-zoom) cameras may be used to monitor a parking lot adjacent to an apartment building with the images of the windows in the building masked. This is a feature of the system configuration (software or hardware) and can be very complex and costly. Besides, in spite of the primacies of employing cameras with variable (PTZ) or large (omnidirectional) fields of view, cameras have still restricted applicability on large-area surveillance as well as they are still prone to the occlusion problem due to their fixed optical centers [72].

B. SIGNIFICANCE OF LASER-BASED SURVEILLANCE

Although some problems of private life safekeeping can be solved by CCTV systems after making appropriate masks, there are several major problems remain: (a) Normally they take photos of the whole objects (except masked regions if applicable) and hence they need high speed processor for data processing; (b) If light illumination changes, then the quality of videos change dramatically; (c) Sometimes masking is extremely difficult, and hence CCTV cannot be placed in general everywhere to monitor activities of people.

On the other hand, laser-based monitoring systems administer the solution of these existing problems in good way. Laser scanners hand over information of objects (e.g., heads, hands, legs, trees, walls, vehicles, and etc.) such as distance and angle between device and echo-pulse width. They scan two dimensional (2D) area by sending beams and then each beam hits objects. They return distances with angles that the laser beams hit. We cannot see any laser beam with human eyes. Laser beam is not harmful for our eyes. Laser scanners do not record real world videos except scanned data points and henceforth, data processing becomes faster and easier. They also solve the problem of private life conservation. They can be placed everywhere to monitor activities of people and objects. For instance, we cannot monitor a heart disease affected person easily by putting a CCTV camera in his/her bath room. But we can monitor such a patient by using laser scanners. The most general argument proposed against installing CCTV cameras in bars and clubs pertains to privacy issues. Businesses cannot install CCTV cameras in explicitly private areas (e.g., restrooms). Many people feel that the entire bar or club should be deemed as private. Patrons claim that they go out to have a drink and relax, and they have trouble relaxing if CCTV camera is watching and recording. Even so, a system with laser scanners can solve this problem easily. Besides, a system with laser scanners is more convenient and efficient than that of cameras.

III. QUALITATIVE PERFORMANCE OF LASER-BASED AND RGB CAMERA-BASED SYSTEMS

A. BLINDNESS AND GHOST OBJECTS

A smart vision or surveillance system may consist of either laser-based technology or RGB camera-based technology 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, a good system should almost never get any false negative or positive.

B. 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 detection 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 universally 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 multiplexing, 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 absorbtion 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 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 negatives 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 occlusion 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 conditions 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 general, 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 spotlight, 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, nowadays 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 components 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 detecting 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 applications. Yet, people-vehicles detecting and/or tracking algorithms 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) Implementation 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 number 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

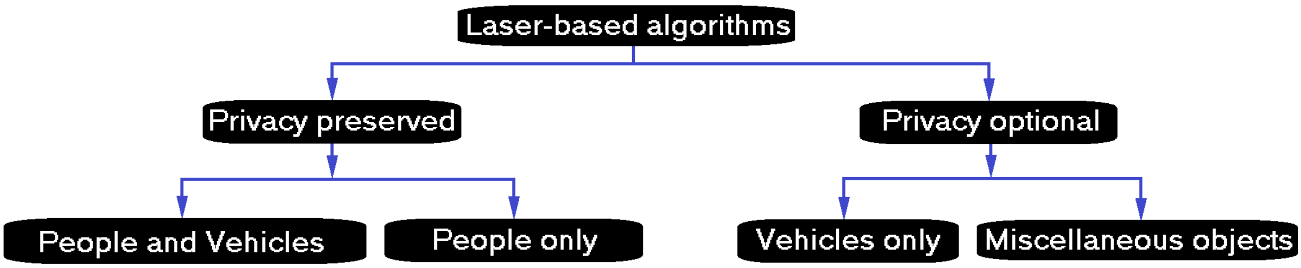


FIGURE 2. Classification of laser-based detection and tracking algorithms.

TABLE 1. People-vehicles related algorithms.

Reference	Technique	Scanner	Scan	Camera	Filter	Occlusion	Setting	Dataset	Accuracy
Galip et al. [7]	Image processing, background removing, threshold estimation, perception	SICK LMS 511	ROI	Excluded	Kalman	Handled	Outdoor	500 frames of vehicles and pedestrians with ground truth	61%
Azim et al. [90]	Octomap, odometry, scan matching	Velodyne HDL 64E	ROI	Included	N/A	Detection	Outdoor	Highway (195), urban (532), pedestrian zone (518)	86%
Sharif et al. [99]	Image processing, background subtraction, recognition	SICK LMS 511	ROI	Excluded	Kalman	Handled	Outdoor	500 frames of vehicles and pedestrians with ground truth	68%
Zhao et al. [78]	Background subtraction, clustering, classification	SICK LMS-291	ROI	Included	Beyesian	Handled	Outdoor	Intersection information	95%
Mertz et al. [83]	Segmentation, line fitting	SICK LMS	ROI	Included	Kalman	Handled	Outdoor	Gen III LADAR data	80%
Sharif [8]	Image processing, background subtraction, recognition	SICK LMS 511	ROI	Excluded	Particle	Handled	Outdoor	500 frames of vehicles and pedestrians with ground truth	79%
Wang et al. [100]	Background modelling, data association	SICK LDMRS	ROI	Excluded	Kalman	Handled	Outdoor	7500 labelled objects	N/A
Wang et al. [82]	Background modelling, data association	SICK LDMRS	ROI	Excluded	Kalman	Handled	Outdoor	7500 labelled objects	42%
Kim et al. [91]	Segmentation, outlier elimination	IBEO LUX 2010	ROI	Included	Own	Handled	Outdoor	Highway vehicles and pedestrians	80%
Fayad et al. [101]	Shape detection, clustering	SICK model	Shape	Included	Kalman	Handled	Outdoor	Highway vehicles and pedestrians	N/A
Galip et al. [102]	Image processing, setting removing, SVM (support vector machine)	SICK LMS 511	ROI	Excluded	N/A	N/A	Outdoor	500 frames of vehicles and pedestrians with ground truth	N/A
Lindstrom et al. [103]	Clustering, computer vision algorithms	SICK Proximity	ROI	Excluded	Beyesian	N/A	Intdoor	Moving person in a living room	N/A
Lehtomaki et al. [104]	Segmentation, classification	FARO Photon 80	ROI	Excluded	N/A	N/A	Outdoor	148 poles and 142 targets	81%
Asvadi et al. [105]	GPS/IMU localization, motion grid	Velodyne HDL 64E	ROI	Excluded	Kalman	Handled	Outdoor	Highway vehicles and pedestrians	N/A
Kanaki et al. [106]	Point clouds merging, estimation of poses and sizes	HDL-32E Velodyne	ROI	Excluded	Kalman	Handled	Outdoor	Video of moving cars, motorcycles, and pedestrians.	N/A

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

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. [108]	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. [53]	Probabilistic data association	RWI B21 Robot	Legs	Included	Particle	Handled	Indoor	6 persons and simulated data	90%
Shao et al. [111]	Modelling of walking pattern	IBEO model	Legs	Excluded	Particle	Handled	Indoor	300 persons	N/A
Shao et al. [112]	Background subtraction, calibration, analysis	Hokuyo UTM 30LX	RIO	Included	MeanShift	Handled	Indoor	A total of 36 persons	92%
Song et al. [113]	Background modelling, feet clustering	SICK LMS 291	Feet	Excluded	Particle	Handled	Outdoor	12000 frames	88%
Song et al. [114]	Background modelling, human body recognition	SICK LMS 291	Body parts	Included	Particle	Handled	Outdoor	200 frames	N/A
Song et al. [115]	Background modelling, feet clustering	SICK LMS 291	Feet	Included	Particle	Handled	Outdoor	5000 frames	89%
Topp et al. [116]	Laser data transformation	SICK LMS 200	Legs	Excluded	Particle	Handled	Indoor	Several persons	N/A
Ling et al. [117]	Background modelling, vision algorithms	UTM 30LX	Body parts	Included	Kalman	Handled	Outdoor	55 persons	91%
Mendes et al. [118]	Segmentation, classification, tracking	SICK LMS 200	Legs	Excluded	Kalman	Handled	Outdoor	Few people	N/A
Mozos et al. [119]	Ada Boost, probabilistic, voting	URG 04LX	Body parts	Excluded	N/A	N/A	Indoor	17286 segments	92%
Musleh et al. [120]	Composite matching, classification	SICK LMS 291S05	Legs	Included	Motion	Handled	Outdoor	Few people	86%
Nakamura et al. [121]	Background subtraction, people recognition	SICK LMS 200	Legs	Included	Kalman	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%
Fuerstenberg [123]	Leg motion analysis	IBEO ALASCA	Legs	Excluded	Own	N/A	Outdoor	N/A	N/A
Gate et al. [124]	Clustering, line fitting	IBEO model	ROI	Included	Kalman	Handled	Outdoor	Not simulated data	74%
Gidel et al. [125]	Segmentation, vision based algorithms	IBEO ALASCA-XT	ROI	Included	Particle	Handled	Outdoor	5 persons video frames	94%
Gidel et al. [126]	Segmentation, vision based algorithms	IBEO ALASCA-XT	ROI	Included	Particle	Handled	Outdoor	5 persons video frames	94%
Kaneko et al. [127]	Clustering of points, motion analysis	SICK LMS 200	Body parts	Included	Time series	N/A	Indoor	1500 frames	98%
Katabira et al. [128]	Background subtraction	SICK LMS 200	Legs	Excluded	Own	Handled	Indoor	69 persons	89%
Leigh et al. [129]	Clustering, detection	Hokoyu UHG 08LX	Legs	Included	Kalman	Handled	Outdoor	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	Kalman	Handled	N/A	5734 segments	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 LMS 200	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	Leg	Included	Kalman	Handled	N/A	One and three persons walking scenarios	N/A
Fotiadis et al. [135]	Segmentation, SVM, Ada Boost	SICK LMS 200	Grid	Included	N/A	N/A	Outdoor	6611 human segments	95%
Adiaviakoye et al. [136]	Background subtraction, segmentation	SICK LMS 111	Feet	Included	Monte Carlo	Handled	Outdoor	2960 frames having 20 people	87%
Akamatsu et al. [137]	Grouping and counting	Hokuyo model	Heads	Included	Kalman	Handled	Indoor	365 persons entry and 388 persons exit	94%
Tsugita 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	KITTI [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%

TABLE 3. Vehicles tracking algorithms.

Reference	Techniques	Scanner	Scan	Camera	Filter	Occlusion	Setting	Dataset	Accuracy
Vu et al. [77]	Segmentation, shape detection	SICK LMS 291	ROI	Excluded	Particle	Handled	Outdoor	Navlab, CMU [142]	N/A
Sanchez et al. [143]	Background modelling	SICK LMS 221	ROI	Included	Particle	Handled	Outdoor	Some highway video	N/A
Kim et al. [144]	Re-ordering, time synchronization, matching	IBEO LUX	ROI	Included	Kalman	Handled	Outdoor	Some highway	99%
Zhang et al. [145]	Clustering, shape detection	IBEO model	ROI	Included	N/A	N/A	Outdoor	On-road vehicles	N/A
Kim et al. [146]	Clustering, association and model switching	IBEO LUX	ROI	Excluded	Kalman	Handled	Outdoor	Some highway	70%
Goyat et al. [147]	Background extraction, shape map	1D laser scanner	ROI	Included	Particle	Handled	N/A	Telemetric data	N/A
Zhao et al. [148]	Data integration, clustering, labeling, mapping	Hokuyo UTM-30LX	ROI	Excluded	N/A	N/A	Outdoor	Data from some freeways	N/A
Scheel et al. [149]	Association of laser and radar data	Planar laser	ROI	Excluded	Bayes	Handled	Outdoor	Data from some urban scenarios	N/A
Vanpoperinghe et al. [150]	Segmentation, data association	Telemetric Lidar	Edges	Excluded	Particle	Handled	Outdoor	Data of ego-vehicle moving on three-lanes road	N/A
Fujita et al. [151]	Pairing, matching, integration	UTM-30LX Hokuyo	ROI	Excluded	N/A	N/A	Outdoor	Vehicles data from urban arterial road or highway	91.2%
Gruyer et al. [152]	Data association, clustering, temporal and spatial information	1-layer laser scanner	ROI	Included	Kalman	Handled	Outdoor	Data from ego-vehicle	N/A
Fortin et al. [153]	Clustering, shape estimation, merging	IBEO LD	ROI	Excluded	Particle	Handled	N/A	Synthetic and real data from a road scenario	N/A
Kumar et al. [154]	Clustering, distance, amplitude, acceleration	Leddar Vu8	ROI	Included	Kalman	Handled	Outdoor	Road objects	N/A
Dai et al. [155]	Clustering, nearest point search, Euclidean distance	SICK LMS 511	ROI	Excluded	Bernoulli	Handled	Outdoor	Data from traffic scenarios of a crossroad	88.43%

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 underlaying 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

TABLE 4. Algorithms for miscellaneous objects detection or tracking.

Reference	Techniques	Scanner	Scan	Camera	Filter	Occlusion	Setting	Dataset	Accuracy
Moon et al. [156]	Manipulation of cloud points, visualization	SICK LMS 511	Ship	Excluded	N/A	N/A	Outdoor	48598 points of cargo ship	N/A
Shalal et al. [157]	Tree trunk recognition	Hokuyo UTM 30LX/LN	Trunk	Included	Kalman	Handled	Outdoor	Orchard mapping with 96 tree trunks	92%
Halmheu et al. [158]	Detection and localization	R2000 UHD	ROI	Excluded	N/A	N/A	Outdoor	Robot	N/A
Balado et al. [159]	Acquisition, segmentation, classification	Mobile Laser Scanner	ROI	Excluded	N/A	N/A	Outdoor	Road, sidewalk, tread, riser, curb	97%
Barnea et al. [160]	Mean-shift segmentation, data fusion, classification	Terrestrial laser scanner	ROI	Included	N/A	N/A	Outdoor	Trees, shrubs, poles	N/A
Guan et al. [161]	Georeferencing, extraction algorithm	RIEGL VMX-450	ROI	Included	N/A	N/A	Outdoor	Road surfaces, road markings, and pavement cracks	93%
Han et al. [162]	Line segment extraction	SICK LMS291-S05	ROI	Excluded	Kalman	Handled	Outdoor	Road boundary	95%
Yang et al. [163]	Merging adjacent segments, classification, extraction	RIEGL VMX-450	ROI	Included	N/A	N/A	Outdoor	Ground, building, pole, traffic sign, tree, street lamp, car	92%
Zhan et al. [164]	Voting, classification	Vehicle-borne LS	ROI	Excluded	N/A	N/A	Outdoor	Roof, road, slope, tree	82%
Rabah et al. [165]	Median filter, background subtraction	Leica C10 TLS	ROI	Included	N/A	N/A	Indoor	Crack detection in Macca tunnels	N/A
Jung et al. [166]	Morphological segmentation	FARO Focus 3D	Room	Excluded	N/A	N/A	Indoor	Narrow passages/Vertical walls	89%
Ravaglia et al. [167]	Hough transform, reconstruction of tubular shapes	Terrestrial Laser Scanner	Shape	Included	N/A	N/A	Indoor	Pipes, poles, stems or monument pillars	75%
Huang et al. [168]	Background subtraction, multi-condition filtering	RIEGL VMX-450	ROI	Excluded	N/A	Handled	Outdoor	23.68 km long highway	85%
Prabhakar et al. [169]	Classification by SVM, last line check method, powered 2-wheeler	SICK LMS 111	ROIs	Included	N/A	N/A	Outdoor	Urban expressway	98.5%
Subirats et al. [170]	Background subtraction, width information	Single layer LIDAR	Motor cycle	Included	N/A	N/A	Outdoor	1295 light vehicles, 37 heavy vehicles, and 343 powered two wheelers	99.2%
Zhang et al. [171]	Density-based spatial clustering, SVM, decision tree	IBEO LUX 4L	Cyclist	Included	Kalman	Handled	Outdoor	1500 positive and 2000 negative samples	93%
Kuzelka et al. [172]	Point clouds processing, segmentation	RIEGL VUX-SYS	Tree	Included	N/A	N/A	Outdoor	Samples of spruce and pine trees	99%

fall back to model-free tracking. Kim *et al.* [91] separated objects using techniques of segmentation and outlier elimination. Their algorithm worked some how 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

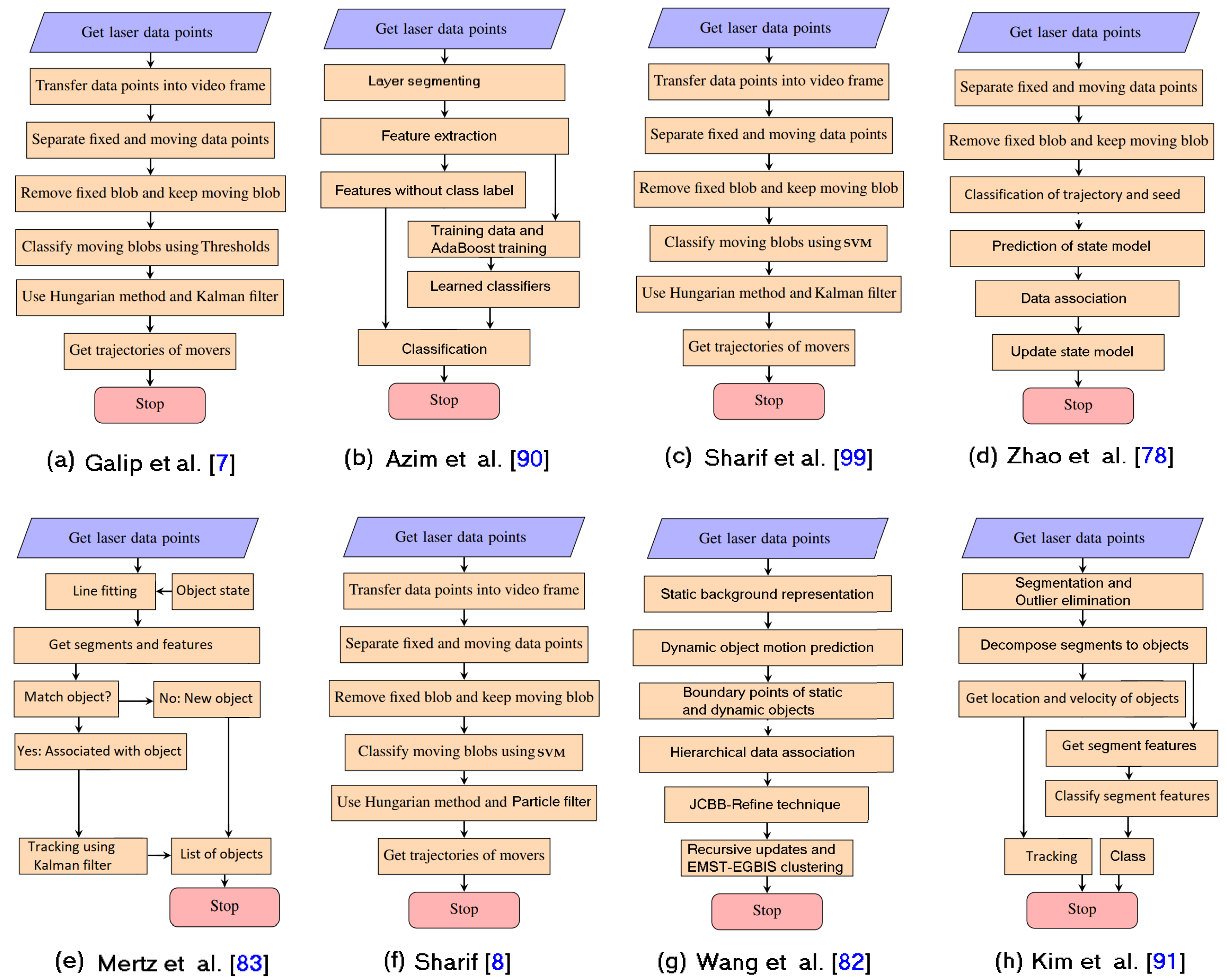


FIGURE 3. Comparison of simplified flow diagrams of eight people-vehicles related algorithms.

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 loosing 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 portrait 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	t_p		f_p		f_n		R_r		P_r		ACC		AUC	
	Ped	Veh	Ped	Veh	Ped	Veh	pR_r	vR_r	pP_r	vP_r	pA_c	vA_c	pA_u	vA_u
Galip et al. [7]	770	185	45	065	162	05	0.8262	0.9737	0.9448	0.7400	0.7881	0.7255	0.8630	0.8712
Azim et al. [90]	672	187	66	112	260	03	0.7210	0.9842	0.9106	0.6254	0.6733	0.6192	0.8132	0.7966
Sharif et al. [99]	765	184	37	058	167	06	0.8208	0.9684	0.9539	0.7603	0.7895	0.7419	0.8889	0.9063
Zhao et al. [78]	876	183	64	031	056	07	0.9399	0.9632	0.9319	0.8551	0.8795	0.8281	0.9279	0.9567
Mertz et al. [83]	708	185	51	073	224	05	0.7597	0.9737	0.9328	0.7171	0.7202	0.7034	0.8605	0.8461
Sharif [8]	888	185	38	023	044	05	0.9528	0.9737	0.9590	0.8894	0.9155	0.8685	0.9444	0.9589
Wang et al. [82]	703	187	42	096	229	03	0.7543	0.9842	0.9436	0.6608	0.7218	0.6538	0.8478	0.8555
Kim et al. [91]	752	184	34	057	180	06	0.8069	0.9684	0.9567	0.7635	0.7785	0.7449	0.9000	0.9104

TABLE 5 describes the qualitative and quantitative analysis of data in Listing 1, where number of true positive movers (t_p), number of false positive movers (f_p), number of false negative movers (f_n), number of true negative movers (t_n) with $t_n = 0$, recall rate (R_r) with $R_r = t_p/(t_p + f_n)$, precision rate (P_r) with $P_r = t_p/(t_p + f_p)$, accuracy (ACC) with $ACC = (t_p + t_n)/(t_p + f_p + f_n + t_n)$, 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

GrdTrh		G.al [7]		A.al [90]		Sh.al [99]		Z.al [78]		M.al [83]		Sh. [8]		W.al [82]		K.al [91]	
Ped	Veh	Ped	Veh	Ped	Veh	Ped	Veh	Ped	Veh	Ped	Veh	Ped	Veh	Ped	Veh	Ped	Veh
5	1	5	2	4	2	5	2	5	1	4	2	5	1	4	2	5	2
8	1	7	2	4	2	7	2	7	1	4	2	7	1	4	2	7	2
8	1	10	1	6	3	10	1	9	1	7	1	9	1	5	2	10	2
8	1	10	1	6	3	10	1	8	1	7	1	8	1	5	2	10	2
10	2	9	3	9	3	9	3	8	1	7	3	9	2	9	3	10	2
10	2	11	3	11	3	10	2	9	1	9	2	10	2	10	3	10	2
10	2	12	2	14	2	12	2	9	2	9	2	10	2	12	2	10	2
10	2	12	2	14	2	10	2	9	2	9	2	10	2	13	2	10	2
10	2	12	2	14	3	10	2	10	2	10	2	11	2	13	4	10	2
10	2	12	2	14	3	12	2	10	2	10	2	10	2	13	4	13	2
10	2	13	2	14	3	13	2	10	2	10	2	11	2	13	4	13	2
10	2	13	2	14	4	13	2	10	2	14	2	11	2	13	3	13	2
10	2	13	2	14	4	12	2	10	2	14	2	12	2	13	3	13	2
10	2	11	2	13	4	11	2	10	2	14	2	11	2	12	3	13	2
10	2	12	2	13	4	12	2	10	2	14	2	10	2	13	3	10	2
10	2	10	2	13	2	10	2	12	2	12	2	11	2	13	2	10	2
10	2	11	3	13	3	11	3	12	2	12	3	11	2	12	3	10	2
10	2	10	4	13	4	10	3	12	2	12	3	11	2	13	4	10	2
10	2	13	4	14	4	12	4	12	2	12	5	11	2	13	4	11	4
10	2	13	4	14	4	12	4	9	2	12	5	11	2	13	4	11	4
10	2	11	4	12	4	11	4	9	2	13	5	11	2	11	4	11	4
10	2	11	4	12	4	11	4	9	2	13	5	11	2	11	4	12	4
10	2	11	3	12	3	11	3	10	3	13	4	11	2	11	3	12	3
10	3	9	3	8	3	9	3	10	4	8	4	10	2	8	3	10	3
10	3	9	4	8	4	9	4	10	4	8	4	10	3	8	4	10	4
10	3	8	4	6	4	8	4	10	4	8	4	10	3	8	4	7	4
10	3	9	4	6	4	9	3	8	3	8	3	9	3	7	4	7	3
10	3	8	3	6	3	8	3	8	3	8	3	9	3	7	3	7	3
10	3	8	3	6	3	8	3	8	3	8	3	9	3	7	3	7	3
10	3	7	2	5	2	7	2	9	3	6	3	9	3	6	2	8	2
10	3	7	2	5	2	7	2	9	3	6	2	10	3	6	2	8	2
10	2	7	2	5	2	7	2	9	2	6	2	9	2	6	2	8	2
10	3	7	2	5	2	7	2	9	2	6	2	9	3	6	2	8	2
10	2	8	2	6	2	7	2	8	2	6	2	9	3	8	2	8	2
10	2	6	2	6	2	6	2	8	3	4	2	9	3	8	2	5	2
10	2	6	2	6	2	6	2	8	3	4	2	9	2	8	2	5	2
10	3	6	3	6	3	6	3	8	3	4	3	9	2	5	3	5	3
10	3	6	3	6	5	6	3	8	3	4	3	9	2	5	3	5	3
10	3	5	3	5	5	5	3	11	3	5	3	10	3	5	3	6	3
10	3	5	3	5	5	5	3	11	2	5	3	10	2	5	3	6	3
10	3	6	4	6	4	6	3	11	2	4	3	10	2	6	5	5	3
10	3	6	4	6	4	6	3	11	3	4	3	10	3	6	5	5	3
10	3	6	3	6	5	6	2	10	3	4	2	10	3	6	5	5	2
10	3	6	2	6	5	6	2	10	3	4	2	10	3	6	5	5	2
10	3	7	3	4	3	6	3	10	3	7	3	10	3	5	3	5	3
10	3	7	3	4	3	7	3	10	3	7	3	9	3	5	3	6	3
10	3	7	3	4	5	7	3	11	4	7	5	9	3	5	5	6	3
10	3	8	3	7	5	8	3	11	4	7	5	9	3	7	5	6	3
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10	1	8	3	6	3	8	3	12	3	8	3	11	3	5	3	7	3
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7	1	6	3	6	3	6	3	7	2	5	3	6	2	5	4	8	3
7	1	6	3	6	3	6	3	7	1	5	3	6	1	5	4	8	3
7	1	7	3	6	3	7	3	5	1	5	3	7	1	5	4	8	3
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7	2	6	1	4	2	6	1	8	2	9	1	6	2	5	2	4	1
7	1	6	2	4	2	5	2	8	2	9	2	6	2	5	2	4	2
7	1	6	1	4	1	5	1	8	1	9	1	6	1	5	1	4	1

Listing 1. Ground truths and algorithmic tracking results.

presented by pairs $pR_r, vR_r, pP_r, vP_r, pA_c, vA_c, pA_u$, and vA_u, 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

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

References	pRMSE	pCV	pMAE	pMAPE	vRMSE	vCV	vMAE	vMAPE
Galip et al. [7]	2.394	0.257	2.070	21.72%	1.010	0.532	0.700	47.17%
Azim et al. [90]	3.148	0.524	4.791	29.46%	1.063	0.476	0.680	39.03%
Sharif et al. [99]	2.393	0.257	2.070	21.72%	0.757	0.392	0.530	37.19%
Zhao et al. [78]	2.185	0.276	1.993	10.27%	0.588	0.286	0.270	22.89%
Mertz et al. [83]	2.049	0.379	1.022	12.88%	0.901	0.598	0.580	31.55%
Sharif [8]	1.149	0.121	0.820	09.54%	0.567	0.298	0.280	23.67%
Wang et al. [82]	2.944	0.327	1.317	27.03%	1.066	0.491	0.480	53.46%
Kim et al. [91]	1.437	0.326	1.124	13.89%	0.914	0.583	0.360	25.73%

TABLE 7. Estimated ineffectualness metrics of various algorithms.

References	Errors				Failures				
	M_{rmse}	M_{cv}	M_{mae}	M_{mape}	F_{r_r}	F_{p_r}	F_{acc}	F_{auc}	F_{aa}
Galip et al. [7]	1.7020	0.3945	1.3850	0.3444	0.1000	0.1576	0.2432	0.1329	0.39
Azim et al. [90]	2.1055	0.5000	2.7355	0.3425	0.1474	0.2320	0.3538	0.1951	0.14
Sharif et al. [99]	1.5750	0.3245	1.3000	0.2945	0.1054	0.1429	0.2343	0.1024	0.32
Zhao et al. [78]	1.3865	0.2810	1.1315	0.1658	0.0485	0.1065	0.1462	0.0577	0.05
Mertz et al. [83]	1.4750	0.4885	0.8010	0.2221	0.1333	0.1751	0.2882	0.1467	0.20
Sharif [8]	0.8580	0.2095	0.5500	0.1661	0.0368	0.0758	0.1080	0.0484	0.21
Wang et al. [82]	2.0050	0.4090	0.8985	0.4025	0.1308	0.1978	0.3122	0.1483	0.58
Kim et al. [91]	1.1755	0.4545	0.7420	0.1981	0.1123	0.1399	0.2383	0.0948	0.20

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 formulae are formulated in Eqs. 1 and 2 as:

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

$$CV(RMSE) = \frac{RMSE}{\frac{1}{100}\sum_{i=1}^{100} G(i)} \tag{1}$$

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

$$MAPE = \frac{1}{100}\sum_{i=1}^{100}\frac{|G(i) - A(i)|}{G(i)} \tag{2}$$

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 $pRMSE$, $vRMSE$, pCV, vCV, $pMAE$, $vMAE$, $pMAPE$, and $vMAPE$ 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.

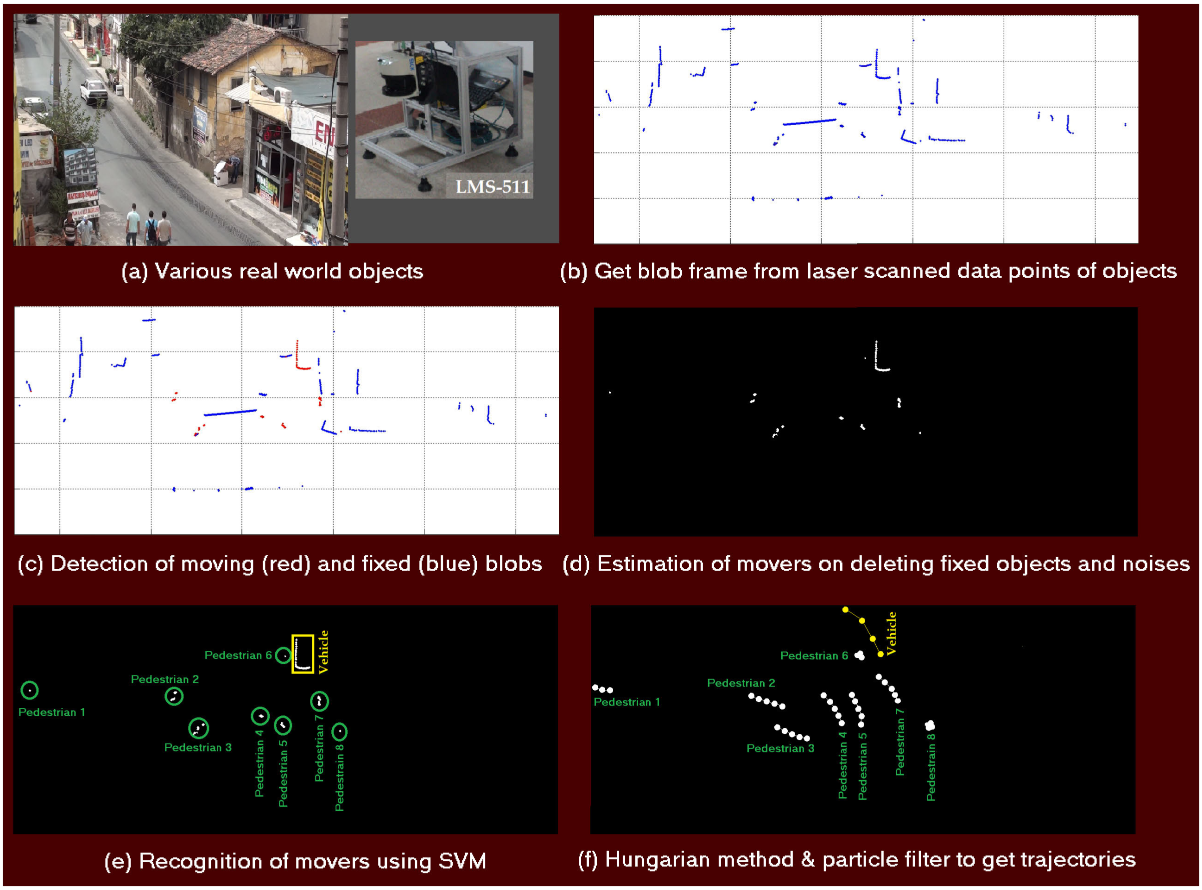

FIGURE 4. **Graphical abstract of the algorithm of Sharif [8].**

TABLE 7 depicts the estimated ineffectualness metrics of miscellaneous algorithms. The mean values of $RMSE$, $CV(RMSE)$, MAE, and $MAPE$ are defined as: $M_{rmse} = (pRMSE + vRMSE)/2$, $M_{cv} = (pCV + vCV)/2$, $M_{mae} = (pMAE + vMAE)/2$, and $M_{mape} = (pMAPE + vMAPE)/200$, respectively using data in TABLE 6. The failures of R_r, P_{rate}, ACC, and AUC achievements are defined as: $F_{r_r} = 1-(pR_r+vR_r)/2$, $F_{p_r} = 1-(pP_r+vP_r)/2$, $F_{acc} = 1-(pA_c+vA_c)/2$, and $F_{auc} = 1-(pA_u+vA_u)/2$, respectively using data in TABLE 5. The failure of achievement of an algorithm (F_{aa}) 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_{aa} 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 α play an important role. Both p-value and α 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 α 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

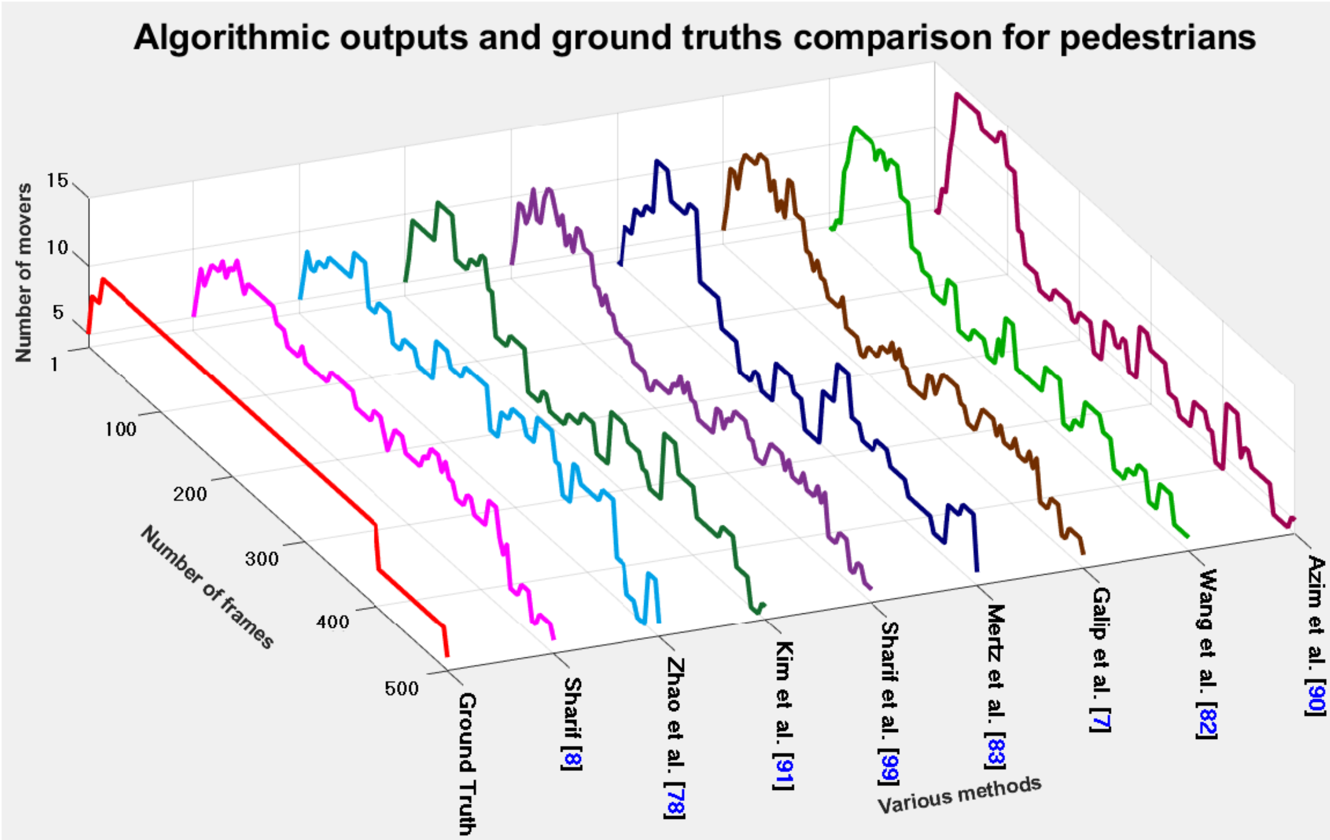

FIGURE 5. Comparative plot of ground truths and outputs of algorithms deeming pedestrians.

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 $1 \times N$ 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 $N \times N$ 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 $\alpha/2$, and so on, until it encounters a hypothesis that can be rejected. The Rom [194] suggested

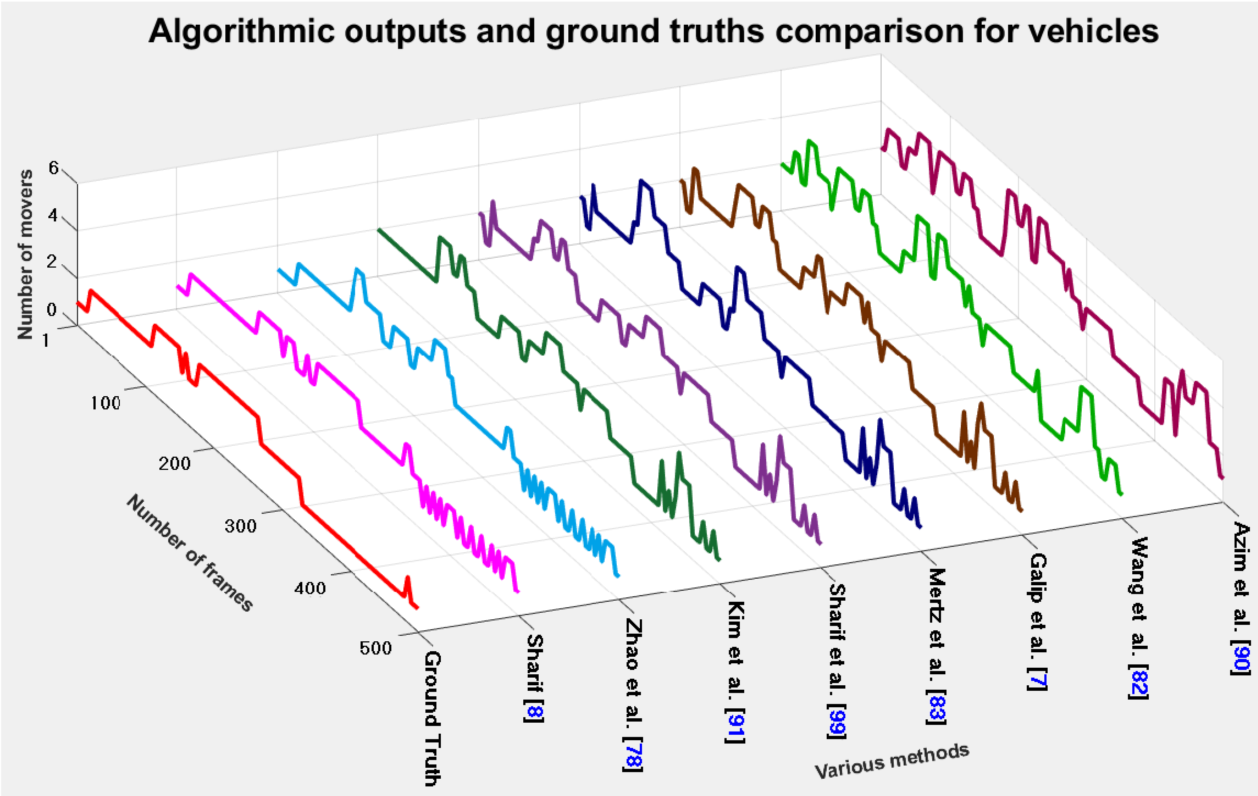

FIGURE 6. Comparative plot of ground truths and outputs of algorithms deeming vehicles.

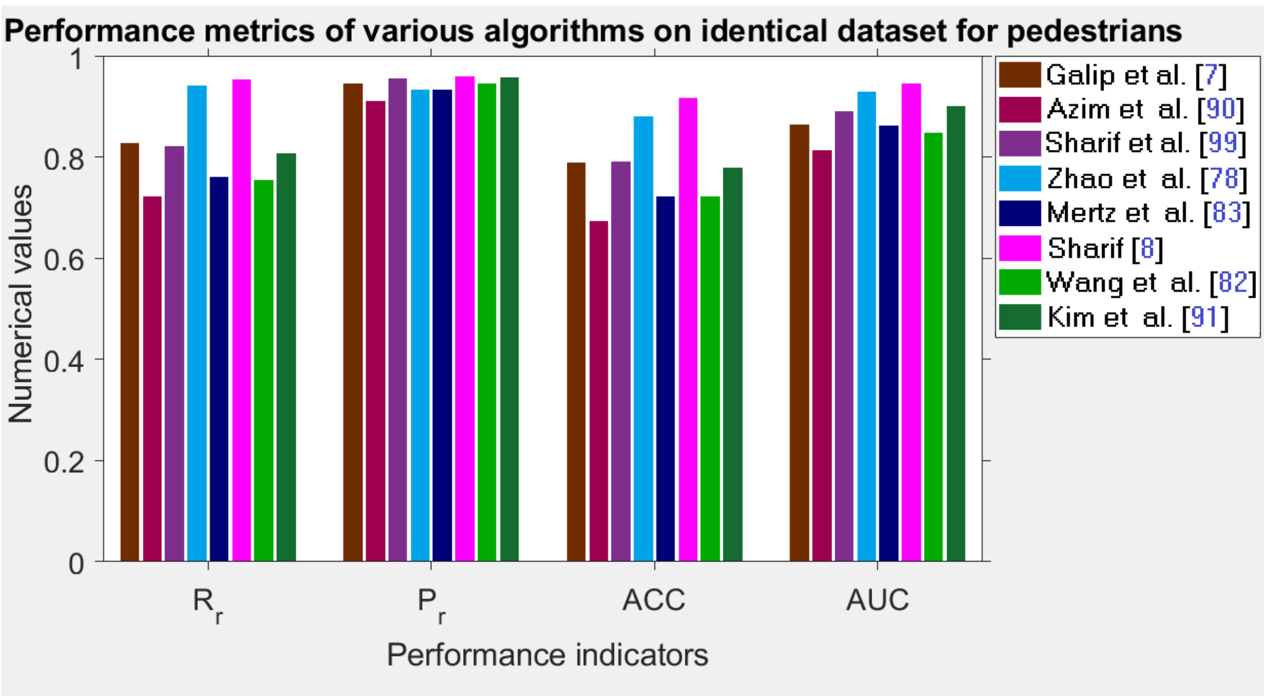

FIGURE 7. Plotting of performance data for pedestrians from Table 5.

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],

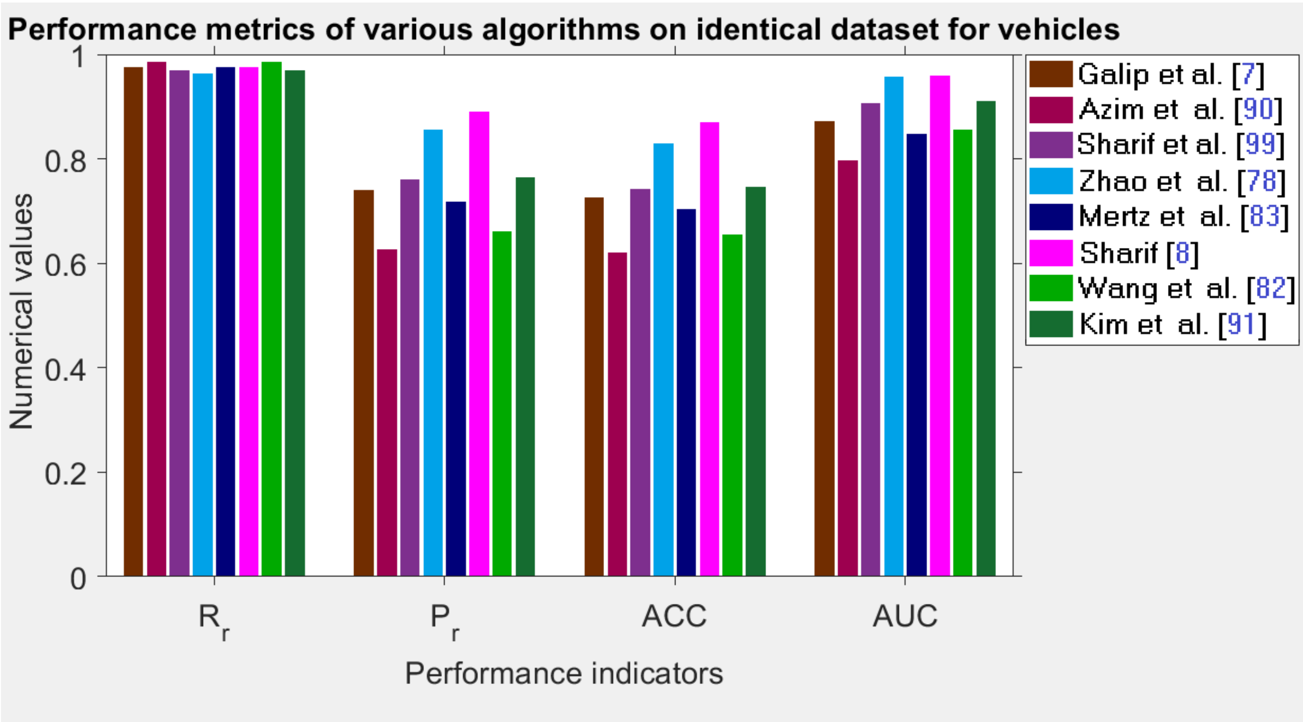

FIGURE 8. Plotting of performance data for vehicles from Table 5.

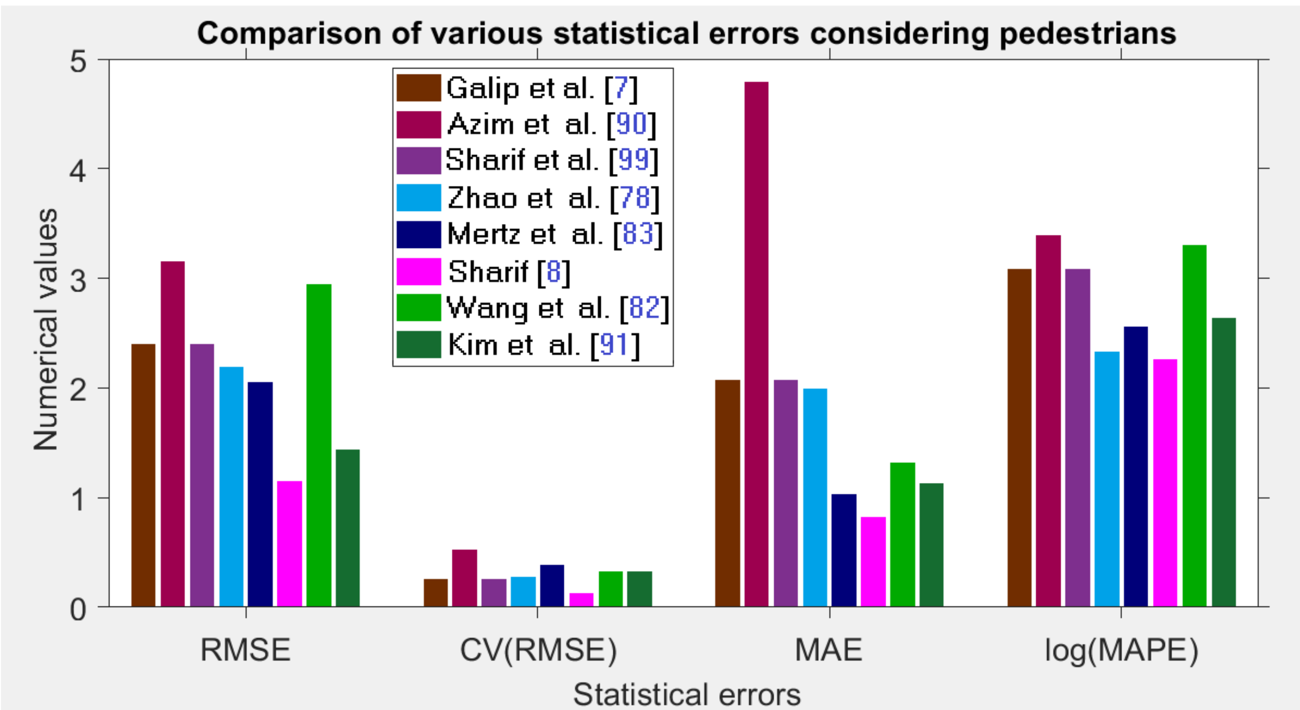

FIGURE 9. Plotting of errors occurred for pedestrians in Table 6.

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 α 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 α divided by the maximum number of hypotheses

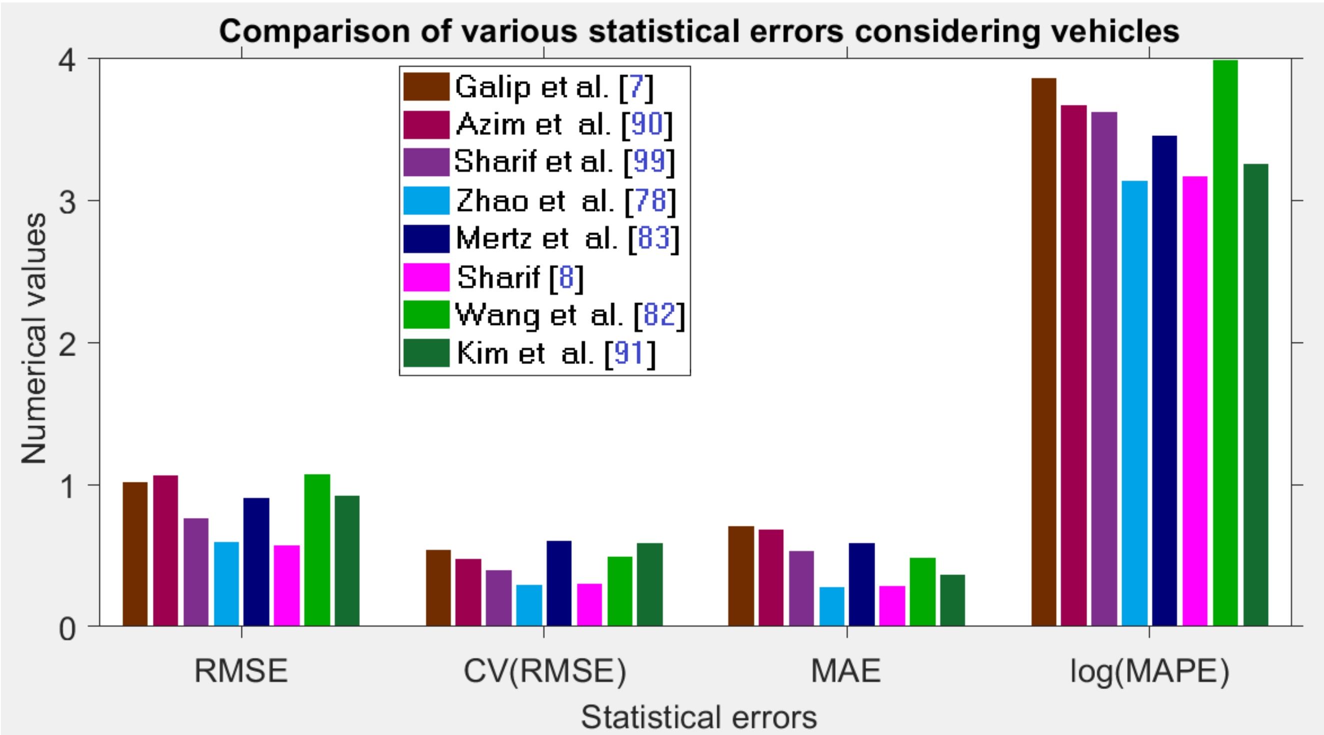

FIGURE 10. Plotting of errors occurred for vehicles in Table 6.

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)

$$F_{aa} = \frac{100\% - (\text{Accuracy of the corresponding algorithm in TABLE 1})}{100}. \tag{3}$$

TABLE 8. Average ranking of each algorithm using nonparametric statistical tests. The best results are shown in bold.

Algorithms	Multiple Comparison Tests		
	Friedman Ranking [184]	Aligned Friedman Ranking [186]	Quade Ranking [187]
Sharif [8]	**1.5556**	**12.7778**	**1.7111**
Zhao et al. [78]	2.2222	17.2222	2.5333
Kim et al. [91]	3.5000	26.5000	3.2556
Sharif et al. [99]	4.4444	41.3333	4.7333
Mertz et al. [83]	5.1667	36.6111	4.6333
Galip et al. [7]	5.4444	50.3333	5.8889
Wang et al. [82]	6.5556	50.6667	6.3556
Azim et al. [90]	7.1111	56.5556	6.8889
Various Statistics	40.861111	34.336679	7.848328
p-value	0.000001	0.00001489707	0.000001331163

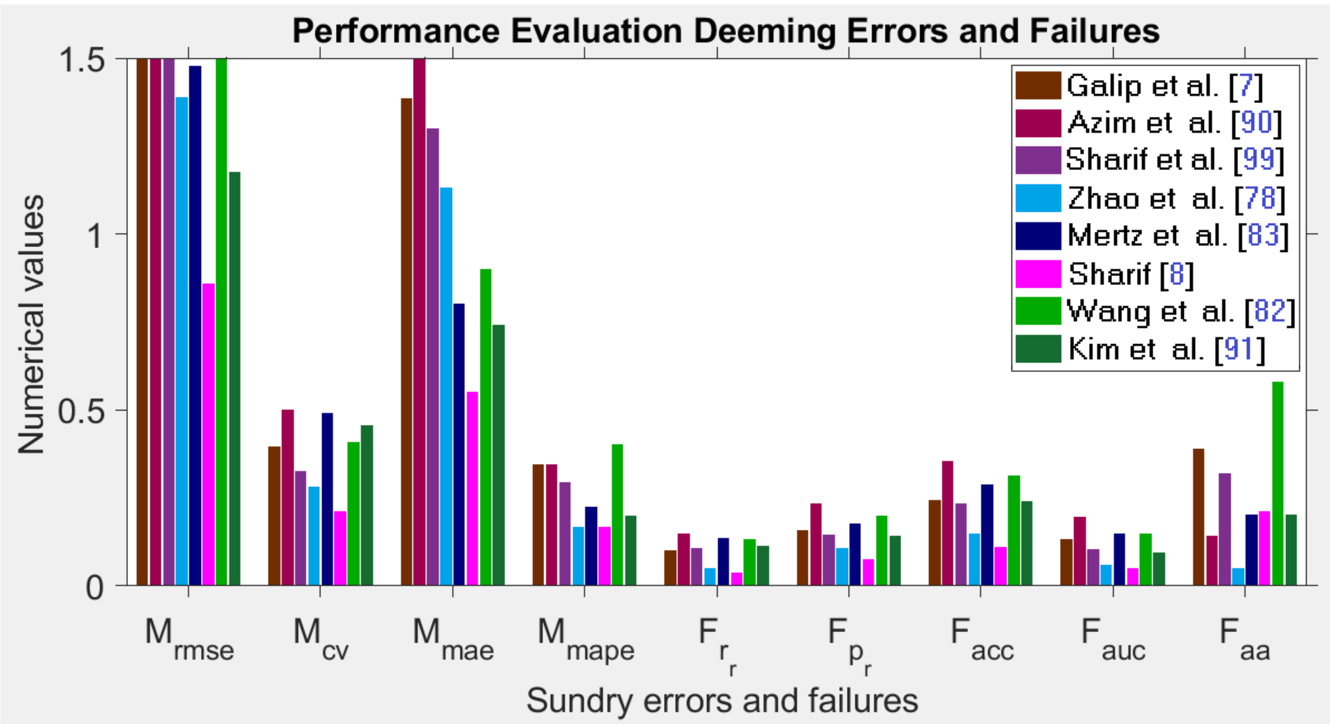

FIGURE 11. Plotting of the numerical values of errors and failures using data from Table 7.

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

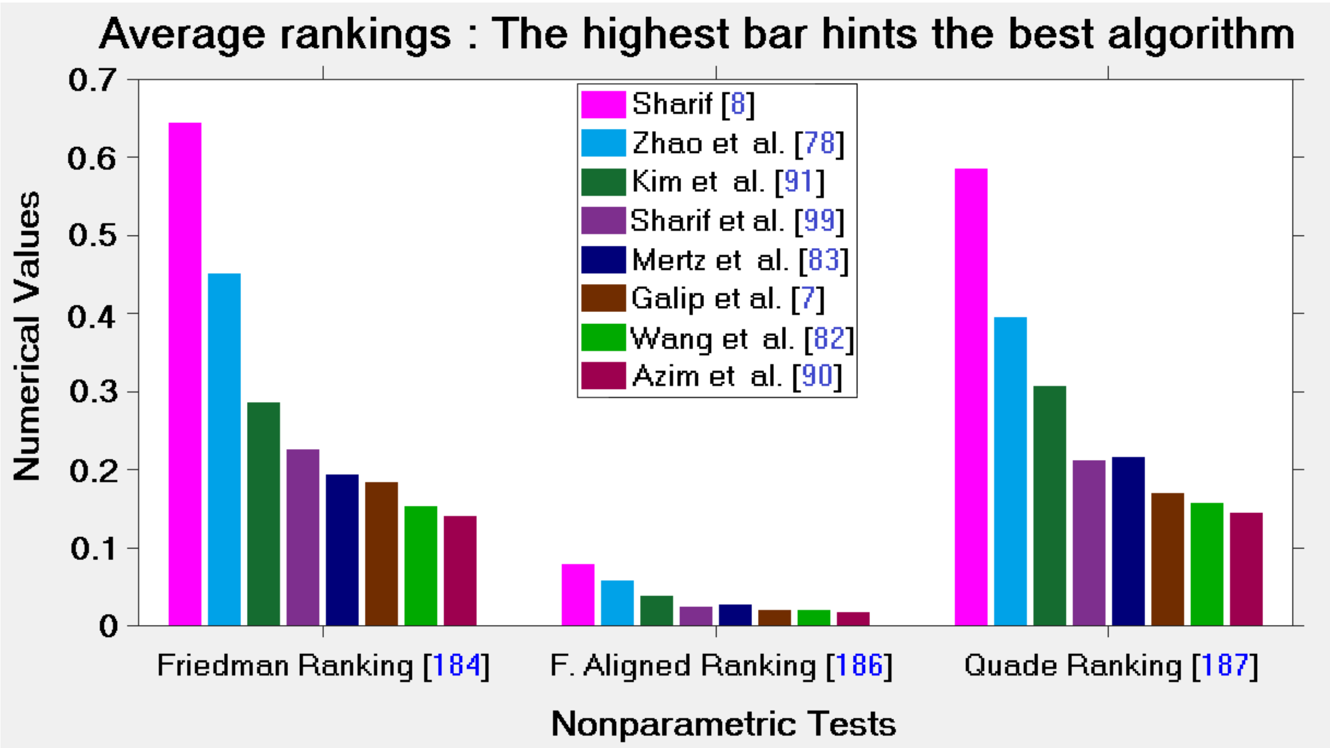

FIGURE 12. Plotting of average rankings data from Table 8; where each value x is plotted as $1/x$ to visualize the highest ranking with the tallest bar.

TABLE 9. Results achieved on post-hoc comparisons for adjusted p-values, $\alpha = 0.05$, and $\alpha = 0.10$.

Index	Algorithms	p-values	$\alpha = 0.05$		$\alpha = 0.10$	
			Holm [189]	Shaffer [198]	Holm [189]	Shaffer [198]
1	Sharif [8] vs Azim et al. [90]	0.053308	0.001786	0.001686	0.003771	0.003871
2	Sharif [8] vs Wang et al. [82]	0.053408	0.001752	0.001852	0.003604	0.003604
3	Azim et al. [90] vs Zhao et al. [78]	0.061602	0.001823	0.001923	0.003846	0.003846
4	Zhao et al. [78] vs Wang et al. [82]	0.061602	0.002000	0.002000	0.004000	0.004000
5	Galip et al. [7] vs Sharif [8]	0.193931	0.002083	0.002083	0.004167	0.004167
6	Galip et al. [7] vs .Zhao et al. [78]	0.193931	0.002174	0.002174	0.004348	0.004348
7	Sharif [8] vs Mertz et al. [83]	0.193931	0.002273	0.002273	0.004545	0.004545
8	Sharif et al. [99] vs Sharif [8]	0.248213	0.002381	0.002381	0.004762	0.004762
9	Zhao et al. [78] vs Mertz et al. [83]	0.248213	0.002500	0.002500	0.005000	0.005000
10	Sharif et al. [99] vs Zhao et al. [78]	0.248213	0.002632	0.002632	0.005263	0.005263
11	Sharif [8] vs Kim et al. [91]	0.312321	0.002778	0.002778	0.005556	0.005556
12	Azim et al. [90] vs Kim et al. [91]	0.302321	0.002741	0.002941	0.005882	0.005882
13	Zhao et al. [78] vs Kim et al. [91]	0.003125	0.003125	0.006250	0.006250	0.006182
14	Wang et al. [82] vs Kim et al. [91]	0.386476	0.003333	0.003333	0.006667	0.006667
15	Sharif et al. [99] vs Azim et al. [90]	0.386476	0.003571	0.003571	0.007143	0.007143
16	Azim et al. [90] vs Mertz et al. [83]	0.471386	0.003846	0.003846	0.007692	0.007692
17	Sharif et al. [99] vs Wang et al. [82]	0.472486	0.004167	0.004167	0.008333	0.008333
18	Galip et al. [7] vs Kim et al. [91]	0.471586	0.004545	0.004545	0.009091	0.009091
19	Mertz et al. [83] vs Wang et al. [82]	0.471486	0.005000	0.005000	0.010000	0.010000
20	Galip et al. [7] vs Sharif et al. [99]	0.583703	0.005556	0.005556	0.011111	0.011111
21	Galip et al. [7] vs Mertz et al. [83]	0.568703	0.006250	0.006250	0.012500	0.012500
22	Galip et al. [7] vs Azim et al. [90]	0.666006	0.007143	0.007143	0.014286	0.014286
23	Mertz et al. [83] vs Kim et al. [91]	0.770828	0.008333	0.008333	0.016667	0.016667
24	Galip et al. [7] vs Wang et al. [82]	0.774828	0.010000	0.010000	0.020000	0.020000
25	Sharif et al. [99] vs Kim et al. [91]	0.888234	0.012500	0.012500	0.025000	0.025000
26	Sharif [8] vs Zhao et al. [78]	0.886234	0.016667	0.016667	0.033333	0.033333
27	Azim et al. [90] vs Wang et al. [82]	0.895234	0.025000	0.025000	0.050000	0.050000
28	Sharif et al. [99] vs Mertz et al. [83]	1.000000	0.050000	0.050000	0.100000	0.100000

p-values achieved. Using level of significance $\alpha = 0.05$: (i) Nemenyi's [197] procedure rejects those hypotheses that have an unadjusted p-value ≤ 0.001786, (ii) Holm's [189] procedure rejects those hypotheses that have an unadjusted p-value ≤ 0.002273, (iii) Shaffer's [198] procedure rejects those hypotheses that have an unadjusted p-value ≤ 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 ≤ 0.003571, (ii) Holm's [189] procedure rejects those hypotheses that have an unadjusted p-value ≤ 0.004545, (iii) Shaffer's [198] procedure rejects those hypotheses that have an unadjusted p-value ≤ 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 Mertz *et al.* [83], Sharif [8]

TABLE 10. Adjusted *p*-values for various tests considering Sharif [8] as control method.

Tests	Algorithms	Not adjusted	$1 \times N$ post-hoc procedures and p-values							
			1-2 step-procedure		Step-down procedures			Step-up procedures		
		p-values	p_{Bonf} [188]	p_{Li} [196]	p_{Holm} [189]	p_{Hol} [193]	p_{Finn} [195]	p_{Hoch} [190]	p_{Hom} [191]	p_{Rom} [194]
Friedman [184]	Zhao et al. [78]	0.772830	5.409810	0.772830	0.772830	0.772830	0.772830	0.772830	0.772830	0.772830
	Kim et al. [91]	0.018398	0.128784	0.074919	0.036796	0.036457	0.021431	0.036796	0.036796	0.036796
	Sharif et al. [99]	0.008140	0.056983	0.034594	0.024421	0.024223	0.011378	0.024421	0.024421	0.024421
	Mertz et al. [83]	0.006099	0.042693	0.026146	0.024396	0.024174	0.010649	0.024396	0.018297	0.023262
	Galip et al. [7]	0.000144	0.001009	0.000634	0.000721	0.000721	0.000336	0.000721	0.000721	0.000686
	Wang et al. [82]	0.000035	0.000246	0.000154	0.000211	0.000210	0.000123	0.000211	0.000211	0.000200
	Azim et al. [90]	0.000010	0.000067	0.000042	0.000067	0.000067	0.000067	0.000067	0.000067	0.000064
Fri. A. R [186]	Zhao et al. [78]	0.973047	6.811330	0.973047	0.973047	0.973047	0.973047	0.973047	0.973047	0.973047
	Kim et al. [91]	0.395157	2.766097	0.936147	0.790313	0.634165	0.443776	0.790313	0.790313	0.790313
	Sharif et al. [99]	0.001465	0.010253	0.051541	0.005859	0.005846	0.002562	0.005859	0.005859	0.005586
	Mertz et al. [83]	0.234766	1.643361	0.897016	0.704297	.5518920	0.312438	0.704297	0.592735	0.704297
	Galip et al. [7]	0.000151	0.001056	0.005564	0.001056	0.001055	0.001055	0.001056	0.000905	0.001004
	Wang et al. [82]	0.000372	0.002607	0.013630	0.002141	0.002139	0.001248	0.001862	0.001862	0.001771
	Azim et al. [90]	0.000357	0.002497	0.013064	0.002141	0.002139	0.001248	0.001862	0.001784	0.001771
Quade [187]	Zhao et al. [78]	0.970835	6.795848	0.970835	0.991026	0.970835	0.970835	0.970835	0.970835	0.970835
	Kim et al. [91]	0.348828	2.441798	0.922843	0.991026	0.699697	0.429581	0.697657	0.697657	0.697657
	Sharif et al. [99]	0.152593	1.068151	0.839541	0.610372	0.484334	0.251553	0.610372	0.465104	0.582000
	Mertz et al. [83]	0.330342	2.312395	0.918876	0.991026	0.699697	0.429581	0.697657	0.660684	0.697657
	Galip et al. [7]	0.057883	0.405184	0.664960	0.343695	0.298077	0.201988	0.289417	0.289417	0.275233
	Wang et al. [82]	0.031719	0.222033	0.520978	0.222033	0.201988	0.201988	0.222033	0.173650	0.211099
	Azim et al. [90]	0.057282	0.400977	0.662630	0.343695	0.298077	0.201988	0.289417	0.286412	0.275233

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

Index	Hypothesis	$N \times N$ post-hoc procedures and p-values				
		Unadjusted	Nemenyi [197]	Holm [189]	Shaffer [198]	Bergmann [199]
1	Sharif [8] vs Azim et al. [90]	0.000010	0.000268	0.000268	0.000268	0.000268
2	Sharif [8] vs Wang et al. [82]	0.000035	0.000982	0.000947	0.000737	0.000737
3	Azim et al. [90] vs Zhao et al. [78]	0.000035	0.000982	0.000947	0.000737	0.000737
4	Zhao et al. [78] vs Wang et al. [82]	0.000119	0.003321	0.002965	0.002491	0.001779
5	Galip et al. [7] vs Sharif [8]	0.000144	0.004037	0.00346	0.003028	0.002307
6	Galip et al. [7] vs .Zhao et al. [78]	0.000444	0.012443	0.010221	0.009332	0.004888
7	Sharif [8] vs Mertz et al. [83]	0.006099	0.170770	0.134177	0.128078	0.079286
8	Sharif et al. [99] vs Sharif [8]	0.008140	0.227932	0.170949	0.170949	0.105826
9	Zhao et al. [78] vs Mertz et al. [83]	0.014138	0.395863	0.282759	0.226208	0.155518
10	Sharif et al. [99] vs Zhao et al. [78]	0.018398	0.515138	0.349558	0.294365	0.202376
11	Sharif [8] vs Kim et al. [91]	0.018398	0.515138	0.349558	0.294365	0.239171
12	Azim et al. [90] vs Kim et al. [91]	0.038561	1.079715	0.655541	0.61698	0.616980
13	Zhao et al. [78] vs Kim et al. [91]	0.038561	1.079715	0.655541	0.61698	0.616980
14	Wang et al. [82] vs Kim et al. [91]	0.075049	2.101379	1.125739	1.125739	0.825542
15	Sharif et al. [99] vs Azim et al. [90]	0.075049	2.101379	1.125739	1.125739	0.825542
16	Azim et al. [90] vs Mertz et al. [83]	0.092194	2.581421	1.198517	1.198517	0.825542
17	Sharif et al. [99] vs Wang et al. [82]	0.135833	3.803334	1.630000	1.630000	0.950834
18	Galip et al. [7] vs Kim et al. [91]	0.148915	4.169611	1.638061	1.638061	1.191317
19	Mertz et al. [83] vs Wang et al. [82]	0.162936	4.562222	1.638061	1.638061	1.191317
20	Galip et al. [7] vs Sharif et al. [99]	0.248213	6.949966	2.233918	2.233918	1.241065
21	Galip et al. [7] vs Mertz et al. [83]	0.289839	8.115484	2.318710	2.318710	1.241065
22	Galip et al. [7] vs Azim et al. [90]	0.531667	14.886686	3.721672	3.721672	3.721672
23	Mertz et al. [83] vs Kim et al. [91]	0.700311	19.608718	4.201868	4.201868	3.721672
24	Galip et al. [7] vs Wang et al. [82]	0.736277	20.615755	4.201868	4.201868	3.721672
25	Sharif et al. [99] vs Kim et al. [91]	0.772830	21.639240	4.201868	4.201868	3.721672
26	Sharif [8] vs Zhao et al. [78]	0.772830	21.639240	4.201868	4.201868	3.721672
27	Azim et al. [90] vs Wang et al. [82]	0.772830	21.639240	4.201868	4.201868	3.721672
28	Sharif et al. [99] vs Mertz et al. [83]	0.923342	25.853572	4.201868	4.201868	3.721672

vs Wang *et al.* [82], Azim *et al.* [90] vs Zhao *et al.* [78], and Zhao *et al.* [78] vs 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] (1)	-	37.0	1.0	0.0	15.0	0.0	36.0	7.0
Azim et al. [90] (2)	8.0	-	7.0	0.0	5.0	1.0	13.0	3.0
Sharif et al. [99] (3)	44.0	38.0	-	0.0	18.0	0.0	37.0	12.0
Zhao et al. [78] (4)	45.0	45.0	45.0	-	36.0	8.0	39.0	28.0
Mertz et al. [83] (5)	30.0	40.0	27.0	9.0	-	1.0	38.0	0.0
Sharif [8] (6)	45.0	44.0	45.0	37.0	44.0	-	45.0	44.0
Wang et al. [82] (7)	9.0	32.0	8.0	6.0	7.0	0.0	-	2.0
Kim et al. [91] (8)	38.0	42.0	33.0	17.0	36.0	1.0	43.0	-

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				α=0.90				α=0.95			
	R^+	R^-	E. p-value	A. p-value	Con. Int.	E. Con.	+	±	Con. Int.	E. Con.	+	±
Galip et al. [7]	45.0	0.0	0.003906	0.006434	[-11.96, -0.4315]	0.90234	0	2	[-12.3725, -0.327]	0.96094	0	2
Sharif et al. [99]	45.0	0.0	0.003906	0.006434	[-7.122, -0.22]	0.90234	2	4	[-7.385, -0.172]	0.96094	1	5
Azim et al. [90]	38.0	7.0	0.07422	0.058024	[-10.274, -0.364]	0.90234	0	3	[-10.508, 0.4645]	0.96094	0	6
Zhao et al. [78]	23.0	22.0	$\geq$0.2	0.905695	[-0.189, 0.81]	0.90234	6	7	[-0.3335, 6.9175]	0.96094	6	7
Mertz et al. [83]	45.0	0.0	0.003906	0.006434	[-4.041, -0.29]	0.90234	3	5	[-4.09, -0.268]	0.96094	1	5
Wang et al. [82]	45.0	0.0	0.003906	0.006434	[-19.605, -0.3815]	0.90234	0	2	[-19.8495, -0.216]	0.96094	0	4
Kim et al. [91]	45.0	0.0	0.003906	0.006434	[-2.3075, -0.2545]	0.90234	4	5	[-2.384, -0.219]	0.96094	2	5

TABLE 14. Summary of the Wilcoxon test.

Algorithms	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Galip et al. [7] (1)	-	○	○		○	○		○
Sharif et al. [99] (2)	●	-	○		○		●	○
Sharif [8] (3)	●	●	-	●		●	●	●
Azim et al. [90] (4)				-	○	○		○
Zhao et al. [78] (5)	●	●		●	-	●	●	●
Mertz et al. [83] (6)	●		○		○	-	●	
Wang et al. [82] (7)			○		○		-	○
Kim et al. [91] (8)	●		○		○		●	-

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.

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 behavior by proposing news 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 unscented). 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.

Heretofore, 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.

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 provide privacy protection, whereas RGB camera-based algorithms await privacy masking. Privacy protection should not make a hindrance for uncovering of objects or people under specific circumstances. It has been suggested that laser-based algorithms should be used instead of common

RGB cameras. Kalman filter has been applied widely in laser-based algorithms due to its lower computational cost. We noticed that a common characteristic of the existing laser-based algorithms is that the detection of objects has been performed by clustering laser scanned data clouds in depth images or 3D laser scans. We conducted a quite thorough and exhaustive review of the laser-based detection and tracking algorithms. Covering a variety of solution methods, we also highlighted the comparative strengths and weaknesses of existing approaches. Furthermore, the conducted rigorous statistical analysis helped boosting confidence in the practical results and confirmed their statistical significance. This analysis also helped interpreting the insights in a better way and shed some light on why certain algorithms performed better than others. Future work would widely include proposing new smarter algorithms for laser-based intelligent surveillance and datasets for statistical tests.

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