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Review

A Review of Wi-Fi-Based Traffic Detection Technology in the Field of Intelligent Transportation Systems

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Abstract: With the increasing innovation and development of Wi-Fi technology, its penetration in the various fields of industry and academia is becoming more and more profound. As the core infrastructure of traffic data collection in the field of Intelligent Transportation Systems (ITS), Wi-Fi-based traffic detectors have great potential for use in traffic target positioning, perception, and pattern recognition due to their low cost and extensive infrastructure deployment. This paper conducts a comprehensive review of three major Wi-Fi-based traffic detection applications in the field of ITS: target positioning, traffic parameter extraction, and travel mode identification. Among these, target positioning is one of the most widespread applications of Wi-Fi technology, which is also the basis for two other research aspects. Moreover, Wi-Fi-based positioning can be divided into two categories: ranging-based positioning and range-free one; in the field of transportation, it can also be categorized into pedestrian positioning and vehicle positioning based on travel mode. To further demonstrate the effectiveness of Wi-Fi-based ITS applications in practice, this study compares the various Wi-Fi-involved models and algorithms around the world, as well as provides some ideas and inspiration along with this direction.

Keywords: traffic detection; Wi-Fi technology; target positioning; traffic parameter extraction; travel mode identification

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Citation: Lin, Y.; Li, Q.; Lyu, D.; Wang, X. A Review of Wi-Fi-Based Traffic Detection Technology in the Field of Intelligent Transportation Systems. *Buildings* **2022**, *12*, 428. https://doi.org/10.3390/buildings12040428

Academic Editors: Xiaopei Cai, Huayang Yu and Tao Wang

Received: 7 February 2022
Accepted: 16 March 2022
Published: 1 April 2022

1. Introduction

In recent years, the continuous innovation and development of Micro-Electro-Mechanical System (MEMS) technologies has driven the rapid progress of Wireless Sensor Networks (WSNs). With the popular applications of mobile Internet technology, smart infrastructures and terminals equipped with wireless sensors can be found everywhere, such as in smartphones, smartwatches, tablet PCs, and connected vehicles. As the core infrastructure of traffic data collection in the field of Intelligent Transportation Systems (ITS), WSN is also widely used in vehicle tracking, personnel monitoring, environmental monitoring, security surveillance, intelligent buildings, healthcare, and other fields [1–3]. Typical wireless communication techniques include Bluetooth [4], Zigbee [5], UWB [6], and Wi-Fi [7]. Among these, Wi-Fi technology is often applied in localization and trajectory tracking for indoor and outdoor targets because of its advantages such as longer communication distance, lower cost, high penetration, less interference from the environment, low dependence on user cooperation, and no need to establish direct communication connections [8]. Meanwhile, the experiment in [9] revealed that the participants turned on Wi-Fi for 12.4 ± 5.9 h on average and the average access points (APs) connection time can be up to 8.5 ± 6.1 h in a day, which makes it reasonable to explore users' Spatio-temporal trajectory by utilizing Wi-Fi data. Nowadays, Wi-Fi technology has been widely deployed in several ITS fields such as individual traffic target localization and tracking [10], traffic parameter estimation and travel mode recognition [11,12], and traffic monitoring [13].

ITS refers to the deployment of modern technologies and applications to provide novel solutions to traffic congestion concerns [14]. Innovative applications of traditional or emerging technologies in the field of traffic engineering can bring positive and beneficial improvements to traffic problems, such as congestion, accidents, and environmental pollution. For example, heterogeneous data sources can be used to estimate the dynamical evolution of traffic flow and density in large urban traffic networks [14]; the origin-destination flows can be obtained through basic information extracted from automated vehicle monitoring (AVM)/floating car data (FCD) [15]; some researchers used FCD to infer travel behavior [16], and predict delivery patterns [17]. In these areas, Wi-Fi technology has the ability to accomplish similar or even identical tasks. Compared with traditional technology, Wi-Fi has a broader performance stage in traffic engineering due to its low cost and high penetration.

Early Wi-Fi positioning is mainly applied in Global Navigation Satellite System (GNSS) denied environments, such as indoor environments. It could be integrated with GNSS [18–20] in GNSS failure scenarios, such as satellite visibility degradation, multipath propagation, tree and building occlusion, malicious interference, etc. With the intensive and extensive deployment of wireless access points in cities, Wi-Fi technology will become both a feasible and economical method for target localization, vehicles classification [21], traffic parameter measurement, etc. Thus, this paper mainly reviews the application of Wi-Fi technology in three areas of ITS: target localization, traffic parameter estimation, and traffic pattern recognition, with a focus on Wi-Fi-based outdoor traffic target localization and tracking technology.

The remaining portion of this paper is organized as follows: Section 2 provides a specific introduction to Wi-Fi positioning techniques and focuses on Wi-Fi-based traffic target positioning. Section 3 introduces the applications of Wi-Fi-based traffic parameter extraction and travel mode identification. Section 4 presents and summarizes some future applications and research directions of Wi-Fi-involved technologies in transportation.

2. Wi-Fi-Based Positioning Technology

2.1. RSSI-Based Wi-Fi Positioning

As smart terminals (smartphones, wearable devices, connected vehicles, etc.) become more and more popular, they also integrate abundant sensing modules, such as Bluetooth, Wi-Fi, and other wireless communication units [22]. At the same time, the deployment of Wi-Fi networks is conducted worldwide in modern cities and on blooming smart roads. Compared with Global Positioning System (GPS) positioning, Wi-Fi positioning has lower power consumption [23], which is more friendly for mobile devices with low battery capacity. Based on the above, utilizing Wi-Fi signals and wireless mobile devices to locate pedestrians and vehicles in complex urban road environments has become a feasible and meaningful method in the field of ITS.

Nowadays, wireless localization techniques can generally be achieved based on Time of Arrival (TOA) [24], Time Difference of Arrival (TDOA) [25], Angle of Arrival (AOA) [26], Channel State Information (CSI) [27], and Received Signal Strength Indicator (RSSI). Among these, RSSI (which is often confused with RSS) is the RSS indicator, a relative measurement of the RSS that has arbitrary units and is mostly defined by each chip vendor [27]. CSI is not easily accessible with most commodity hardware [28]. Compared to other commonly used measurement methods (TOA, TDOA, and AOA), the RSSI measurement method does not require time synchronization or the employment of an antenna array, which makes it more effective and cost-efficient for mobile phone localization in the view of both software and hardware [29]. Therefore, this paper mainly reviews the RSSI-based Wi-Fi positioning method.

As a widely adopted technique, RSSI-based Wi-Fi positioning can be generally divided into two categories: ranging-based positioning and range-free positioning.

2.1.1. Ranging-Based RSSI Positioning

Ranging-based RSSI positioning refers to a two-stage method including the distance estimation and the positioning process. The first stage is to measure the physical distance between the unknown node (target location) and the anchor node (sensor location) in real-time, and the second refers to estimating the coordinate of the unknown node based on the measured distances and the known coordinates of the anchor nodes.

As usual, the wireless signal follows a certain propagation regulation in the air, and the relationship between the RSSI and propagation distance can be obtained by using propagation law. The common propagation model for describing the distance—RSSI relationship is the lognormal shadowing model expressed as follows [30,31]:

$$P(d) = P(d_0) - 10\eta \lg(d/d_0) + X_\sigma \tag{1}$$

where $P(d)$ denotes the detected RSSI corresponding to the transmission distance d; $P(d_0)$ is the RSSI at the reference distance d_0; η represents the path loss parameter, and X_σ represents a zero-mean Gaussian random variable with a standard deviation σ. Although the lognormal shadowing model is quite widely used, its performance is not guaranteed for accurate distance estimation in the complex urban road environment. Recently, researchers have proposed many effective methods for fitting the RSSI—distance relationship, such as polynomial fitting [32], piecewise fitting [33], piecewise polynomial fitting [10], segmentation heterogeneous fitting [34], and neural network fitting [35].

The key to ranging-based RSSI positioning is to measure the distance between the unknown node and each anchor node and then compute the specific coordinate of the unknown node according to the estimated distances and the coordinates of the anchor nodes. If the number of anchor nodes in the network is set to three, the common method is trilateral positioning. Moreover, for more anchor nodes, one can conduct multilateral positioning. Assuming that the number of anchor nodes is n in the multilateral positioning network, the coordinate of the ith anchor node is set to (x_i, y_i), the coordinate of the unknown node is (x, y), and the estimated distance between the ith anchor node and the unknown node is $d_i{}'$, the real physical distance between the ith anchor node and the unknown node is d_i. Multilateral positioning can be expressed in Figure 1.

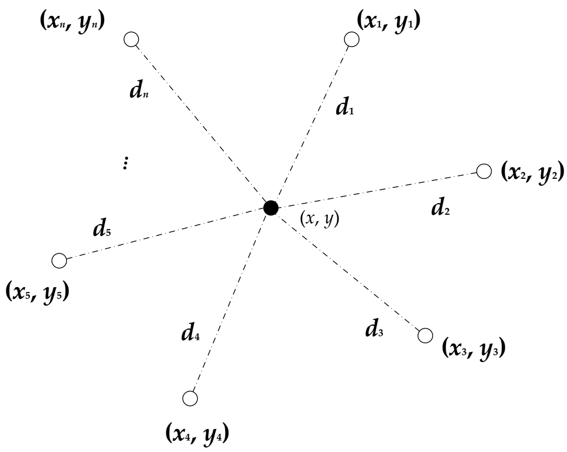

Figure 1. Schematic diagram of multilateral positioning.

After obtaining the estimate of d_i by measurement, $d_i{}'$, one can obtain the following relationship:

$$(x - x_i)^2 + (y - y_i)^2 = d_i'^2, i = 1, \cdots, n \tag{2}$$

The localization problem can be defined as estimating the position of the unknown node given the equation set (2) [36]. The Linear Least-Squares (LLS) technique [37] is an alternative solution for this problem. Assuming that the rth anchor node is chosen as the reference anchor one, and correspondently the rth term is subtracted from the ith term ($i \neq r$), then the least-squares solution can be obtained by:

$$X = \left(A^T A\right)^{-1} A^T B \tag{3}$$

with

$$A = \begin{bmatrix} 2(x_1 - x_r) & 2(y_1 - y_r) \\ \vdots & \vdots \\ 2(x_{r-1} - x_r) & 2(y_{r-1} - y_r) \\ 2(x_{r+1} - x_r) & 2(y_{r+1} - y_r) \\ \vdots & \vdots \\ 2(x_n - x_r) & 2(y_n - y_r) \end{bmatrix} \tag{4}$$

$$B = \begin{bmatrix} {d'_r}^2 - {d'_1}^2 + x_1^2 + y_1^2 - x_r^2 - y_r^2 \\ \vdots \\ {d'_r}^2 - {d'}^2_{r-1} + x_{r-1}^2 + y_{r-1}^2 - x_r^2 - y_r^2 \\ {d'_r}^2 - {d'}^2_{r+1} + x_{r+1}^2 + y_{r+1}^2 - x_r^2 - y_r^2 \\ \vdots \\ {d'_r}^2 - {d'_n}^2 + x_n^2 + y_n^2 - x_r^2 - y_r^2 \end{bmatrix} \tag{5}$$

Alternatively, the Taylor series expansion method [38] is also a classical algorithm to solve localization problems. Assuming that the actual coordinate of the unknown node is (x, y) and the initial value of the iteration is (x', y'), the actual coordinate can be expressed as the summation of the initial coordinate and the position offsets.

$$\begin{cases} x = x' + \delta_x \\ y = y' + \delta_y \end{cases} \tag{6}$$

The distances between the unknown node and each anchor node can be expressed as follows:

$$d_i = f_{(i)}(x, y) = \sqrt{(x - x_i)^2 + (y - y_i)^2}, i = 1, \cdots, n \tag{7}$$

Expanding the distance function $f_{(i)}(x, y)$ at (x', y') with a first-order Taylor series:

$$f_{(i)}(x, y) = f_{(i)}(x' + \delta_x, y' + \delta_y) = f_{(i)}(x', y') + \left.\frac{\partial f_{(i)}(x, y)}{\partial x}\right|_{(x', y')} \delta_x + \left.\frac{\partial f_{(i)}(x, y)}{\partial y}\right|_{(x', y')} \delta_y \tag{8}$$

Thus, the corresponding equations can be obtained, and the solution of the equations can be used to correct the initial coordinate. By setting the proper threshold of the error and iterating, it's possible to obtain an accurate estimation of the coordinate.

In addition to the least-squares techniques, the maximum likelihood algorithm (MLA) can also be used for solving the localization problem [39]. In the absence of non-line-of-sight (NLOS) bias, assuming that the measured distance d_i' ($d_i' \in \mathbf{d}'$) follows a Gaussian normal distribution $N(d_i, {\sigma_i}^2)$, the location of the unknown node is $\mathbf{x}$. The probability density function can be expressed as follows:

$$p(\mathbf{d}'|\mathbf{x}) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi}\sigma_i} e^{-(d_i' - d_i)^2 / 2\sigma_i^2} \tag{9}$$

The maximum likelihood solution can be obtained:

$$X = \underset{\mathbf{x}}{\operatorname{argmax}}\, p(\mathbf{d}'|\mathbf{x}) \tag{10}$$

In practical localization situations, RSSI is susceptible to the influence of the surrounding environments and includes noise with large fluctuations, which in turn leads to large localization errors [40]. Some researchers have proved that the filtering technique is an effective solution to suppress the negative effects of noise on positioning, such as the Gaussian filter [41,42], Kalman filter (KF) [43,44], and robust Kalman filter (RKF) [45].

2.1.2. Range-Free RSSI Positioning

As with the aforementioned localization methods, the ranging-based positioning cannot achieve a very high accuracy because the collected RSSI signals from user devices are unstable due to noise disturbance in the outdoor environment. By contrast, the range-free localization does not need to utilize the physical distance to determine terminal location. Fingerprinting positioning is one of the most widely used range-free methods. In practice, the fingerprint positioning procedure can be divided into two phases: the offline phase and the online phase [46]. In the offline phase, RSSI fingerprint vectors are constructed at reference points (RPs) through a site survey where Wi-Fi signals between known RPs and access points are collected, and then an RSSI fingerprint database is constructed. In the online phase, the user measures the RSSI vector at her/his position in real-time and records it. After receiving the measured RSSI vector, the server performs location matching based on matching algorithms and then deduces the real-time user's location. The basic procedure of RSSI-based fingerprint positioning is shown in Figure 2.

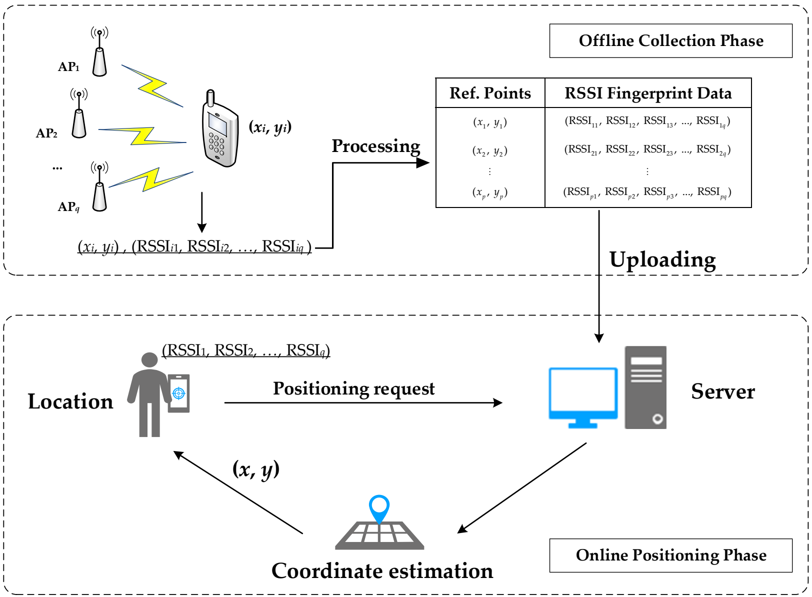

Figure 2. Schematic diagram of RSSI-based fingerprint positioning.

Suppose that there are q APs deployed in the network and the number of RPs is p. The set of RPs and APs can be expressed as W_{RP} and W_{AP}, $W_{\mathrm{RP}} = \{\mathrm{RP}_1, \ldots, \mathrm{RP}_i, \ldots, \mathrm{RP}_p\}$ and $W_{\mathrm{AP}} = \{\mathrm{AP}_1, \ldots, \mathrm{AP}_j, \ldots, \mathrm{AP}_q\}$. The RSSI vector collected at the ith RP is S_i, $S_i = \{\mathrm{RSSI}_{i1}, \ldots, \mathrm{RSSI}_{ij}, \ldots, \mathrm{RSSI}_{iq}\}$, and the coordinate of the ith RP is $l_i = (x_i, y_i)$. The RSSI data contained in the fingerprint database is $R = \{S_1, \ldots, S_i, \ldots, S_p\}$, and the coordinate set is $L = \{l_1, \ldots, l_i, \ldots, l_p\}$. The RSSI vector collected in real-time at the unknown node is $S = \{\mathrm{RSSI}_1, \ldots, \mathrm{RSSI}_j, \ldots, \mathrm{RSSI}_q\}$.

Location matching algorithms for fingerprint positioning can be generally classified into deterministic and probabilistic ones [47]. There are many typical deterministic algorithms, such as nearest neighbor (NN) algorithm, K-nearest neighbor (KNN) algorithm, and weighted K-nearest neighbor (WKNN) algorithm. Among these, NN is one of the most basic fingerprint positioning algorithms [48]. Firstly, the Euclidean distance between the RSSI vector S and the fingerprint S_i might be calculated according to the following equation:

$$E_i = \sqrt{\sum_{j=1}^{q} (\mathrm{RSSI}_j - \mathrm{RSSI}_{ij})^2} \quad (11)$$

Next, the coordinate of the RP with the smallest Euclidean distance is chosen as the estimation of the unknown node coordinate. As the typical deterministic algorithms, KNN [48] and WKNN [48] match the collected RSSI vector with the fingerprint dataset and use the average or weighted average of the top K RPs' coordinates with the shortest Euclidean distance as the coordinate estimation of the unknown node. These two algorithms are simple and easy to solve, but the choice of the K value directly affects the positioning accuracy.

By contrast, Maximum A Posteriori (MAP) estimation might calculate the location of the unknown node by maximizing the conditional probability of the location given the received online measurement [49]. The coordinate of the unknown node can be obtained as:

$$X = \underset{i=1,\cdots,p}{\mathrm{argmax}}[P(l_i|S)] \quad (12)$$

where $P(l_i \mid S)$ is the conditional probability that the unknown node is at the location of l_i by given a signal S.

Moreover, machine learning methods have been increasingly used in localization problems, such as support vector machines (SVM) [50,51], decision trees (DT) [52], and deep learning (DL) [53,54]. In [51], SVM was applied to obtain an initial estimated position of the target based on the RSSI, which was also modified by using an improved Kalman filter. The study in [52] compared two decision trees by considering two major factors: the amount of training data and the number of reference radio signals. The testing results showed that the decision tree based on the gradient boosted algorithm yielded much more accurate results than typical DT, and the best result could be achieved with 19 reference radio signals and 50 samples of training data. To enhance the ability of fingerprints to express the change characteristics of environments, the authors in [55] adopted the Hybrid Wireless fingerprint (HW-fingerprint) with the combination of Ratio fingerprint and RSSI fingerprint. In addition, a convolutional neural network (CNN) architecture was constructed to learn important features from the hybrid fingerprint. To deal with challenges (spatial ambiguity, RSSI instability, short RSSI collection time per location, etc.), the authors in [56] presented recurrent neural network (RNN) to determine the user's location by exploiting the sequential correlation of RSSI measurements.

To clearly and briefly compare the proposed methods presented in the literature, this study conducted a comprehensive review of the main methods for RSSI-based Wi-Fi positioning in detail in Table 1.

Table 1. Summary of RSSI-based Wi-Fi positioning methods.

Category	Technique	Method	Reference	Complexity	Performance
Ranging-based RSSI positioning	RSSI-Distance relationship fitting	Lognormal shadowing model	[30]	Simple	Fitting accuracy: smaller than the curve fitting one (fitting degree = 2)
		Polynomial fitting	[32]	Simple	The 90% error of distance estimation: • 2.6 m (polynomial degree = 2) • 5.5 m (lognormal shadowing model)
		Piecewise fitting	[33]	Simple	-
		Piecewise polynomial fitting	[10]	Moderate	Mean error (m): 1.58 (the first fitting), and 1.56 (the second fitting)
		Segmentation heterogeneous fitting	[34]	Moderate	Mean error (m): 1.57 (workstation environment), and 2.26 (indoor badminton court)
		Neural Networks	[35]	Complex	-

Table 1. *Cont.*

Category	Technique	Method	Reference	Complexity	Performance
Ranging-based RSSI positioning	Coordinate estimation	Linear least-squares	[57]	Simple	-
		Taylor series expansion	[33]	Moderate	The probability of large positioning errors can be effectively reduced.
		Maximum likelihood algorithm	[57]	Complex	-
	Filtering the noises	**RSSI filtering**	**References**	**Filtering effect**	**Performance**
		Gaussian filter	[41,42]	Static processing	-
		KF	[43]	Static processing	Error for calculated distance: 6% (1 m) and 9.5% (2 m)
			[44]	Dynamic RSSI smoothing	Minimize large fluctuations with a quick response time
		RKF	[45]	Static/Dynamic RSSI smoothing	A better signal smoothing effect due to adaption to changes in both static and dynamic environments
Range-free RSSI positioning	**Algorithm**	**References**	**Specific application**	**Complexity**	**Performance**
	NN/KNN/WKNN	[48]	-	Low	-
	Probabilistic algorithms	[49]	-	Complex	-
	Support vector machines	[50]	LS-SVM	Moderate	Median error: 0.6–1 m
		[51]	SVM + KF	Complex	RMSE (experimental results): • 0.87 m (entire trajectory) • 0.98 m (turning region)
	Decision Trees	[52]	Typical DT algorithm, Gradient boosted tree algorithms	Moderate	Accuracy: • 55.56% (Typical DT algorithm) • 73.33% (Decision tree model based on Gradient boosted algorithm) Error distance: • 2.408 m (Typical DT algorithm) • 0.754 m (Decision tree model based on Gradient boosted algorithm)
	Deep Learning	[55]	Hybrid Wireless fingerprint (HW-fingerprint), Convolutional neural network	Complex	Average daily location accuracy during 15 days: • 67.79% (KNN) • 79.97% (SVM) • 84.17% (CNN)
		[56]	Recurrent neural network, Long short-term memory (LSTM)	Complex	Average error: 0.75 ± 0.64 m

2.2. *Wi-Fi RSSI Signal-Based Traffic Target Positioning Technology*

Currently, most research on Wi-Fi positioning remains indoors [58–61], and quite a few industrial practices have started to provide outdoor positioning services based on Wi-Fi infrastructures [62]. From the perspective of data in the field of outdoor traffic target positioning, GPS and CSI data might also be integrated into RSSI-based positioning technique. Therefore, this paper categorizes Wi-Fi-based traffic target positioning methods into two groups: single RSSI-based and RSSI-based combination with other data.

2.2.1. Single RSSI-Based Positioning

Considering the effect of the mobile user's orientation on RSSI, the authors in [63] proposed a direction-based fingerprint positioning model, in which the RSSI values from four directions were collected at each RP. The test results indicated that this model can accurately calculate the user's position and identify the user's orientation. Although this method only uses RSSI values, it is still possible to improve the positioning accuracy by expanding the richness of the fingerprints. Experiments with high-dense AP deployment in the Sydney CBD area confirmed that the Wi-Fi positioning system based on fingerprinting works well for outdoor localization, especially when directional information is utilized [64].

In the offline phase, the construction of the fingerprint database was an important issue because its deployment and maintenance are costly, requiring large amounts of resources of humans, materials, and funding. These problems are even more prominent in outdoor positioning than indoors. Crowdsourcing is a very promising solution to tackle these issues [65]. For example, the researchers in [66] divided the geography target area into several fingerprint clusters identified by Position Feature Vectors (PFVs) via crowdsourcing data for building the offline Wi-Fi fingerprint database. In the online phase, the detected Wi-Fi signal vector is first compared with PFVs to find the most matching cluster, and then the KNN algorithm is employed to calculate the accurate position.

Depending on the focus, the authors in [67] investigated some critical parameters affecting outdoor positioning accuracy via extensive experiments, such as grid spacing and the number of APs. However, in reality, device diversity is also an unavoidable factor affecting accuracy. Notably, the deviation between the users' devices and the devices used to construct the RSSI fingerprints is likely to cause positioning deviation. A novel power-gap elimination algorithm was reported to address this issue in the outdoor environment. The results demonstrated that it is feasible to conduct vehicle positioning solely based on the Wi-Fi fingerprinting approach even in the presence of device diversity [68].

In fingerprint-based positioning, dense labeled data points (also known as reference points or labeled ones) need to be obtained through extensive field experiments. It is difficult and expensive to conduct this operation in a complex traffic environment. Therefore, it is a challenging and highly rewarding task to maintain a good balance between positioning accuracy and fingerprint database construction cost [69]. A semi-supervised extreme learning machine (SSELM) with a locally linear embedding (LLE) algorithm was proposed to achieve the RSSI fingerprint positioning with as few fingerprints as possible. Experimental results demonstrated that the proposed method could provide ideal positioning performance for vehicles with different driving speeds in sparse or dense sensor deployment environments at the cost of shorter training time consumption and lower dependence on sample size than traditional models [70].

Compared with fingerprint-based positioning, ranging-based positioning does not require the search and comparison process with the fingerprint database [71]. However, in realistic traffic environments, it is a challenge to accurately formulate the relationship between RSSI and physical distance, and to eliminate the perturbation of RSSI in the online positioning phase to guarantee accuracy in real-time. Some researchers designed a series of filtering algorithms for noise reduction, such as the constant velocity Kalman filter and the unscented Kalman filter (UKF). In [40], a constant velocity KF algorithm integrating constant velocity filter and KF was proposed to filter the collected RSSI values in real-time pedestrian positioning. Compared with [40], the researchers proposed a two-stage filter method [10]. In detail, the real-time RSSI was filtered by the constant velocity KF algorithm, and the estimated target trajectory was also smoothed by UKF.

2.2.2. Combination Positioning

GPS is an attractive option for outdoor environments but is not suitable for indoor applications because it needs a clear line-of-sight to orbital satellites for target tracking [72]. Therefore, GPS technology might be combined with Wi-Fi to connect indoor and outdoor positioning to improve user experience.

In [19], the authors proposed a seamless navigation system with Wi-Fi/GPS/Inertial Navigation System (INS) integration for both indoor and outdoor environments. By adding step detection and enhanced Wi-Fi positioning technologies to the standard GPS/INS integration system, the navigation performance for indoor environments has been improved.

The scene switching solution is a challenging task to achieve seamless indoor-outdoor positioning. In [73], the authors proposed the positioning algorithms switching strategy according to the number of connected GPS satellites, Wi-Fi signal number, and Geometric Dilution of Precision (GDOP). In [74], the authors presented a detailed positioning switch strategy combining GPS positioning, cellular positioning, and Wi-Fi positioning, which can be used for indoor and outdoor seamless positioning. Based on the AdaBoost algorithm, the researchers in [20] constructed a classifier using the RSSI values for the detection in indoor and outdoor environments to design a seamless indoor-outdoor navigation system using Wi-Fi, Pedestrian Dead Reckoning (PDR), and GNSS. Firstly, the indoor/outdoor environment was judged, and the indoor navigation algorithm combining Wi-Fi fingerprint positioning and PDR is used if it is indoors; otherwise, the outdoor navigation algorithm is developed by combining GNSS and PDR.

In [75], the authors used Wi-Fi localization to create a new type of Assisted-GPS. When the GPS receiver was activated, all received Wi-Fi signal strengths were sent to the server to make a preliminary estimation of the mobile terminal's location, and then the server sent useful ephemeris data to the terminal. This solution could avoid the GPS drawbacks, such as a long time to first fix (TTFF) and huge power consumption [76]. Otherwise, a selective weighting scheme with GPS and Wi-Fi was reported, and the location might be associated with the weighted summation of GPS location and Wi-Fi one according to the weather conditions [77]. Among, the algorithm requires the user to input the weather conditions to present an accurate estimator.

Depending on the input data, the researchers proposed a hybrid outdoor localization scheme by utilizing crowdsourced Wi-Fi signal data and the smartphone's built-in sensors [78]. This scheme could restrict the matching operation in a small space with the consideration of moving direction and travel distance. Finally, the WKNN was proposed to estimate the position in terms of the dissimilarity in RSSI and the GPS states (e.g., the number of satellites, signal noise ratio). Experimental results showed that the proposed localization scheme outperforms the GPS-based method in both positioning accuracy and power consumption.

CSI can also be used with RSSI for outdoor positioning. In [79], the authors proposed a CSI/RSSI-based positioning scheme with two stages. In the offline stage, the collected CSI/RSSI data was divided into several clusters by a clustering algorithm, and a deep learning-based classification model was constructed for each cluster. In the online stage, the clusters corresponding to the measurements are determined using KNN (K = 1), and each CSI/RSSI measurement can be mapped to a final location via the classification model.

Information from other communication networks can also be integrated with Wi-Fi for positioning. In [80], the authors proposed a mobile positioning method based on integrated heterogeneous networks (e.g., cellular networks and Wi-Fi networks) for urban areas with many shelters where GPS positioning may generate large errors. Results showed that the proposed method could be well adapted to commercial vehicle operation systems as well as outdoor positioning.

Based on the above, the RSSI-based applications in the field of traffic target positioning are summarized in Table 2.

Table 2. Summary of traffic target positioning technologies based on Wi-Fi and others.

Category	Technique	References	Key Method	Accuracy
Single RSSI-based positioning	Fingerprint	[64]	Use directional information in outdoor environment	Average error: • 35.8 m (traditional approach) • 23.5 m (direction-based approach)
		[66]	Construct an offline database using crowdsourced data and divide geography area into several fingerprint clusters based on clustering algorithms	Achieve higher positioning accuracy and low computation complexity
		[67]	KNN in outdoor environment	-
Single RSSI-based positioning	Fingerprint (vehicle)	[68]	Propose a power-gap elimination (PGE) algorithm to address the device diversity problem in Wi-Fi fingerprinting in the outdoor environment	Training device: Nexus5 • Nexus5 (testing device): 18.2 m (mean error), 13.6 m (50%), 35.2 m (90%) • Huawei (testing device): 16.2m (mean error), 12.7 m (50%), 32.5 m (90%) • Samsung (testing device): 17.8m (mean error), 12.5 m (50%), 38.6 m (90%)
		[70]	Propose a semi-supervised extreme learning machine (SSELM) with a locally linear embedding (LLE) algorithm to achieve the RSSI fingerprint positioning	• 3.09 m (minimum mean positioning error, simulation for different speed scenarios) • 8.04 m (mean positioning error, measurement)
	Ranging-based positioning	[40]	Propose a fused algorithm by integrating constant speed filter and KF	Average error: 0.16 m (X-axis), and 0.15 m (Y-axis)
		[10]	Develop the least-squares Taylor series expansion (LS-TSE) to calculate the coordinate instead of existing trilateral localization	Mean error of 1.67 m
Combination positioning based on Wi-Fi RSSI and other data	Wi-Fi + GPS + INS	[19]	Propose seamless navigation with a Wi-Fi/GPS/INS integrated system both in outdoor and indoor environments	The navigation accuracy is improved by more than 1.30 m by using enhanced Wi-Fi positioning.
	Wi-Fi + GNSS + PDR	[20]	Use RSSI to train weak classifiers and combine weak classifiers to get a strong classifier for indoor and outdoor detection based on the AdaBoost algorithm	The overall navigation accuracy based on Wi-Fi indoors and outdoors detection has increased by 71.5% compared to GNSS.
	GPS + Wi-Fi	[77]	Selective weighting scheme combined with GPS and Wi-Fi	Average error: • 11.09 m (selective weighting scheme) • 14.89 m (GPS) • 18.9 m (Wi-Fi)
	Wi-Fi + sensor information + GPS	[78]	Restrict the matching operation in a small space according to direction and travel distance, and determine the weighted factors of positioning algorithm in terms of the GPS signal state and dissimilarity in RSSI	Achieve high-positioning accuracy and low power consumption
	Wi-Fi (CSI + RSSI)	[79]	Propose a novel deep learning based positioning scheme that utilizes both CSI and RSSI	Mean error of 6.45 m
	Heterogeneous networks with cellular and Wi-Fi	[80]	Mainly use the collected RSSI, time series data, and transmission distance for mobile position	Mean error of 3.36 m

3. Other Applications of Wi-Fi Technology for ITS

In addition to outdoor traffic target positioning, Wi-Fi technology can also be an effective detection method in traffic flow parameter extraction, such as travel mode, traffic volume, travel time, and speed. These parameters are of great significance for traffic flow analysis, traffic condition recognition, traffic control and management optimization, traffic guidance, etc.

Traditional traffic detection techniques mainly include inductive loops [81,82], pneumatic road tubes [83], and video detection [84]. However, intrusive sensors like inductive loops and pneumatic road tubes have some drawbacks, such as causing traffic disruptions during installation or maintenance [85]; video cameras are easily affected by environmental factors (e.g., weather, sunlight) [86]. Unlike vehicle-oriented sensors, Wi-Fi devices, which are widely deployed in cities, also have the possibility and potential to detect all traffic targets and extract parameters for all non-motorized and motorized vehicles. Thus, this Section provides a preliminary introduction to Wi-Fi-based traffic parameter extraction and travel mode identification.

3.1. Wi-Fi-Based Traffic Parameter Extraction

Bus passenger volume is an important parameter in ITS, which supports public transportation planning, bus fleet size, and bus scheduling. It varies between routes and stations in a specific city or area. Existing bus passenger volume extraction methods include IC card counting, infrared detection, and video detection [87]. Apart from those, the mobile devices carried by passengers could also be used to extract passenger volumes. In [87], the authors developed a statistical model to predict the number of on-board passengers based on manual passenger counts and logging of wireless data frames detected using a computer with a Wi-Fi card in monitor mode. The results are promising, but the MAC randomization problem of mobile devices might need further attention. In [88], the authors proposed a MAC address cleaning and processing scheme that considers speed, bus stop zoning, and route circulation to obtain the Origin-destination (OD) matrix and passenger volumes for bus route sections. Although the results showed that the estimated passenger volume would usually be smaller than the actual value, the former follows the same trend as the latter.

Real-time pedestrian volume data is also an indispensable parameter. For example, it is important for business strategy adjustment and guidance in shopping malls and tourist attractions, and its extraction method is getting more and more attention from researchers. In [89], the authors focused on the optimal Wi-Fi probe layout and estimation model of real-time pedestrian volume. According to the RSSI value and time information of captured signals, the proposed optimal layout scheme is also capable of distinguishing the direction of the detected mobile devices. In [90], the researchers established the passive Wi-Fi sensing model by probabilistically analyzing the interactions between a moving pedestrian flow and Wi-Fi sniffers and developed a sequential filtering algorithm based on the Rao-Blackwellized particle filter (RBPF) to simultaneously estimate the pedestrian volume and the pedestrian flow speed via the real-time Wi-Fi sniffing data. In another study [91], the researchers empirically evaluated Bluetooth Media Access Control Scanner devices and Wi-Fi Media Access Control Scanners devices in terms of the availability of traffic data and the accuracy of travel time estimation. Depending on the focus, Abedi et al. [92] empirically assessed the impact of different antenna characteristics on tracking movements of pedestrians and cyclists based on MAC address datasets. They reported that the higher gain antenna could collect more unique samples from available Wi-Fi devices carried by runners and cyclists compared to the lower gain antenna. The lower gain antenna collected less efficient data from runners and cyclists due to covering smaller areas and less scanning time, but it provided a more accurate estimation of the walker's travel time for the larger distance between detection zones of each sensor at the entrance and the exit. Others have conducted performance tests on detection systems integrated with Wi-Fi and Bluetooth [12] to detect pedestrian-bicycle networks, including travel time/speed estimation, classification of pedestrians and cyclists, and passenger counting.

Unlike the above applications, Wi-Fi can also be used for vehicle monitoring. In [93], the authors presented a Wi-Fi-based traffic monitoring system, WiTraffic, which captured the unique Wi-Fi CSI patterns of passing vehicles to effectively perform vehicle classification, lane detection, and speed estimation. They presented the Butterworth low-pass filter and a simple threshold-based detection method to remove the noise of collected raw CSI data and detect passing vehicles. A C-Support Vector Machine (C-SVM) was also employed to train the vehicle classification models. The results showed that more accurate vehicle speed estimation could be obtained with the more sophisticated vehicle classification models defined for various kinds of vehicle types.

Depending on the collected data input, other researchers also reported the traffic parameter extraction methods based on RSSI. For example, Kassem et al. [94] investigated RSSI data for vehicle detection and speed estimation and developed a multi-class SVM classifier to distinguish three states: an empty street, a stationary car, and a moving car. Both the statistical and curve fitting methods were proposed for speed estimation, respectively. The former method estimated the vehicle speed by the time taken by a vehicle to pass the area of interest, which was measured by observing the change in variance of border streams that bound the area. The latter method calculated the vehicle speed by capturing the relationship between the signal strength variance and vehicle speed.

Nowadays, Wi-Fi technology has been widely used in traffic parameter extraction. However, there are still many interference factors under different traffic scenarios which will influence the usage of Wi-Fi data for large-scale, high-precision traffic data mining. Therefore, future work along this research line should focus on reducing the interference of environmental factors at a lower cost.

3.2. Wi-Fi-Based Travel Mode Identification

For the planning, design, and operation of ITS, it is crucial to infer travel modes in the network [95]. The travel mode choice information provides decision support for urban transportation planning, public facilities layout design, and travel route recommendation. It is feasible to use smartphones and widely deployed Wi-Fi infrastructure to recognize travel mode. This section will systematically introduce the blooming Wi-Fi-based travel mode identification technology.

Prentow et al. [96] compared the challenges for outdoor and indoor travel mode detection and conducted field experiments based on Wi-Fi and accelerometer data in a large hospital complex. Mun et al. [97] proposed a method to discriminate between the three human activity states (dwelling, walking, or driving) using Global System for Mobile Communications (GSM) and Wi-Fi. This study used four features to classify states: the number of unique cell IDs, residence time in a cell footprint, the variance of Wi-Fi signal strength, and the duration of dominant Wi-Fi access point in view. Considering movement during dwelling states often causes incorrect classification, the indoor dwelling mobility states were removed from the dataset, and the authors built a classifier to infer either pedestrian or vehicle movement. Lesani and Miranda-Moreno [12] developed four kinds of classifiers to recognize pedestrians or cyclists for each detected MAC address: the classifier with threshold, logit model with speed, logit model with time-seen, and the combined model with speed and time-seen duration. Among these, the last one has the highest accuracy with an average classification error percentage of 3.7%.

Later, Montoya et al. [98] designed a new system to infer multi-modal itineraries traveled by a traveler based on a combination of smartphone sensor data (e.g., GPS, Wi-Fi, accelerometer) and the transport network infrastructure data (e.g., road and rail maps and public transportation timetables). In the first phase, they distinguished some modes (walking, cycling, road vehicle, and rail) using a developed dynamic Bayesian network that modeled the probabilistic relationship between paths in the Transportation network and sensor data, and in the second phase they attempted to match the recognized road vehicle or rail in the first stage with several possible transportation types: bus, train, metro, or tram. Coroamă et al. [99] presented a travel mode recognition method by considering GPS and accelerometers and the proximity patterns of Wi-Fi and Bluetooth devices in the surrounding environment because they assumed these data depended on different travel modes. The results showed that for trains with a relatively stable collection of Bluetooth devices in proximity and not-so-stable GPS signal, the precision of classification based on Bluetooth and Wi-Fi proximity is higher than the one based on GPS and accelerometer.

Recently, deep learning has been applied to travel mode identification. For example, Wang et al. [100] reported a framework for real-time identification of personal travel mode, i.e., DeepTravel, which used deep neural networks to realize high-precision travel mode (walking, bus, car, and metro) identification with the usage of Inertial Measurement Unit (IMU) and Wi-Fi sensors. Compared to preceding work with an identical experimental setup, they performed similar classification performance at the cost of fewer features and easier models. Subsequently, Kalatian and Farooq [101] developed a deep neural network along with three decision tree-based classifiers (decision tree, bagged decision tree, and random forest) to detect three human mobility modes (walking, biking, and driving) by utilizing Wi-Fi data. Based on [101], a semi-supervised deep residual network (ResNet) framework was developed in [95] to utilize Wi-Fi communications obtained from smartphones. The semi-supervised framework allowed the use of large amounts of low-cost unlabeled data that can be easily collected, as well as relatively small amounts of labeled data.

Notably, many researchers have reported that Wi-Fi technology is a promising methodology in the field of traffic parameter extraction and travel mode identification in Table 3. It can provide more information for motorized and non-motorized vehicles than traditional sensors.

Table 3. Summary of Wi-Fi-involved technologies in traffic parameter extraction and travel mode recognition.

Application	Parameter Estimation	References	Collected Data	Method	Comments
Traffic parameter extraction	Bus passenger volume	[87]	MAC address, time information, signal strength	Expectation-maximization algorithm and Gibbs sampling	-
		[88]	Wi-Fi log (time and MAC address data), GPS log (time and coordinate data)	MAC cleaning and processing based on speed/bus stop zoning/route circulation	Estimated volume is less than ground truth data but follows the same trend.
	Pedestrian volume and moving direction	[89]	MAC address, RSSI, timestamp	Cubic spline interpolation	Root Mean Square Error of 15.32 persons
	Pedestrian flow speed and pedestrian volume	[90]		Rao-Blackwellized particle filter	The experiments at a metro station verified the feasibility of monitoring pedestrian flows.
	Travel time	[91]	MAC address, timestamp from Wi-Fi and Bluetooth	Only the last occurring instance of the MAC address was used in the analysis.	-
	Travel time	[92]		Time gap between the last observation of the MAC address at the upstream scanner to the first observation of the same MAC one at the downstream scanner	Although the lower gain antenna collected less efficient data from runners and cyclists, it provided a more accurate estimation from the walker's travel time.
	Travel time/speed, and pedestrian/bicycle volume	[12]		Compute travel time/speed for each MAC address based on the difference between the first time and the last time by a pair of sensors, propose a simple flow extrapolation methodology to estimate pedestrian/bicycle flow	• 11.5% (average error of speed estimation) • 17.1% (average error of pedestrian flows estimation)
	Vehicle classification, lane detection and speed estimation	[93]	CSI from Wi-Fi	A machine learning technique is adopted to train vehicle classification models and efficiently categorize vehicles. An Earth Mover's Distance (EMD)-based vehicle lane detection algorithm and vehicle speed estimation mechanism are proposed to further use CSI to identify the lane in which a vehicle is located and to estimate the vehicle speed.	• Vehicle classification accuracy: 92% (local road), 96% (highway) (peak classification accuracy) • Vehicle lane detection accuracy: about 90% (in both the local road and the highway: the average lane detection accuracy) • Speed estimation accuracy: 5mph (highway: RMSE)

Table 3. *Cont.*

Application	Parameter Estimation	References	Collected Data	Method	Comments
Traffic parameter extraction	Vehicle detection, and speed estimation	[94]	RSSI	Multi-class SVM classifier, and speed estimation based on statistical technique and curve fitting	• The accuracy of vehicle detection is 100%. • The quadratic curve fitting has the best accuracy compared to other degrees of fitting with an accuracy of 90% (curve fitting technique for speed estimation).
Travel mode recognition	Travel mode classification of stationary, walking, scooter, biking, e-bedpusher, and e-bus	[96]	Wi-Fi data, accelerometer data	KNN C4.5 Decision Tree SVM Random Forest (RF)	F-scores of time-folded cross-validation for each of the classifiers: • C4.5 Decision Tree: 78.6% • KNN: 81.2% • SVM: 81.6% • Random Forest: 84.1%
	Movement state classification: dwelling, walking, or driving	[97]	GSM data, Wi-Fi data	Decision Tree	Precision: • 90.26% (dwelling) • 65.45% (walking) • 75.73% (driving)
	Classification of pedestrian and cyclist	[12]	MAC, timestamp from Wi-Fi and Bluetooth	Compare four kinds of classifiers including threshold-based classifier, statistical speed approach, statistical time-seen approach, and combined logit model	Average error (%): • 15% (threshold-based classifier) • 13.7% (statistical speed approach) • 16.2% (statistical time-seen approach) • 3.7% (combined logit model)
	Travel mode classification and travel route recognition for a journey	[98]	GPS data, Wi-Fi data, cellular data, accelerometer data, Bluetooth data, transport network infrastructure data	Dynamic Bayesian network	Precision: • Walking: 91% • Biking: 36% • Car: 96% • Bus: 80% • Train and metro: 81% • Tram: 92%
	Travel mode classification: tram, bus, walking, train, car, and biking	[99]	GPS data, accelerometer data, Bluetooth data, Wi-Fi data	Random Forest	Precision: • Tram: 88.1% • Bus: 64.9% • Walking: 83.1% • Train: 95.8% • Car: 98.1% • Biking: 96.6%
	Travel mode classification: walking, bus, car, and metro	[100]	IMU sensors data, Wi-Fi data	Deep Neural Network	Overall accuracy: • 87.4% • 89.4% (exclude windows with mixed labels when the mode changes)
	Movement state classification: walking, biking, and driving	[101]	Wi-Fi data (MAC address, signal strength, timestamp)	Multilayer Perceptron	Precision: • Walking: 92.86% • Biking: 86.96% • Car: 81.03%
		[95]		• Semi-supervised learning • ResNet	Precision: • Walking: 83.3% • Biking: 75.0% • Car: 86.9%

4. Summary

The accurate and appropriate traffic-related data can help guide passengers to choose the best travel mode, route, and journey time, as well as create a foundation for traffic planners in designing and improving transportation systems. Due to its efficiency and dependability, Wi-Fi technology has been widely employed in traffic target positioning, traffic data collection, traffic status perception, and travel assistance in recent years.

4.1. Future Application Directions of Wi-Fi Sensing

Wi-Fi technology might be further applied in three fields of the transportation system in the future. First, the Wi-Fi-based positioning could be used in autonomous positioning or provide users with high-precision positioning services as the main supplement to GNSS or in collaboration with GNSS when the dominant technology is unreliable. It could also be used when GNSS is unavailable in dense urban environments owing to the signal attenuation or blocking caused by skyscrapers, tunnels, underground space, and other construction materials.

Secondly, based on the relationship between Wi-Fi signal and traffic flow parameters, the varying individual data for all travel modes can be estimated and recognized with high accuracy and reliability, so as to support advanced traffic operation, control, guidance, etc. Wi-Fi-based detection can provide the time-varying individual travel trajectory in the road network to develop the path-level large-scale network optimization methodologies and technologies of ITS.

Finally, with the increasing penetration of Wi-Fi-enabled personal devices and other traffic infrastructures, it is cost-effective to recognize individual travel modes and realize real-time traffic monitoring based on Wi-Fi sensor data by avoiding costly component deployment and investment. These kinds of recognized traffic information could be easily transferred into Origin-transfer-destination (OTD) travel demand to conduct top-level city planning and specific transportation planning in the inner-city or metropolitan area.

4.2. Challenges and Future Research

As reviewed in Sections 2 and 3, Wi-Fi technology has great potential for traffic target positioning, traffic parameter extraction, and travel mode recognition. However, the effectiveness and reliability of Wi-Fi-based applications in transport and transportation vary greatly due to their research scopes, methods, factors, and scenarios. Therefore, the following challenges should be continuously investigated as future perspectives:

1. MAC address randomization

Mobile devices publicly sending a unique MAC address may help track users during the movement. Thus, major mobile phone manufacturers such as Apple and Huawei have used the MAC address randomization technology to solve these privacy issues [87]. MAC address randomization refers to the rotation of mobile devices through random hardware addresses to prevent observers from picking out their traffic or physical location from other nearby devices [102]. The experimental results in [87] show that most Android phones did not use randomization when the experiments were conducted, while Apple devices running on iOS 9 seemed to change MAC addresses only when the user turned the screen on and off. It is inevitable for the randomization of the MAC address to cause a great interference to the application of Wi-Fi technology in the fields of positioning and traffic parameter extraction. Therefore, it is extremely necessary to solve the MAC address randomization while considering user privacy issues.

2. Uncertain broadcasting interval of probe requests

In addition, the broadcasting interval of probe requests is worthy of attention. The low-frequency broadcasting of probe requests may cause an inability to obtain useful information (e.g., MAC address and RSSI) in time during positioning operations, which may result in the loss of positioning trajectory. The data processing results in [103] show that most probe requests are sent with an interval of more than 5 s. Although this can meet the needs of passenger behavior analysis, it is far from meeting the needs of high-precision positioning using Wi-Fi.

3. Unpredictable fluctuation of Wi-Fi signals

The fluctuation of Wi-Fi signals is difficult to avoid and capture. Even in the fixed location for standstill, the RSSI will beat violently [104]. In practice, RSSI is easily affected by the surrounding environments and is doped with the large fluctuation noise leading to unpredictable error [40]. Therefore, it is important to develop an in-depth signal processing method balancing both cost and accuracy.

4. Parallel detection of mass of traffic targets

Transportation systems have high requirements for the multi-target detection capability of Wi-Fi technology, especially where many people gather at transit stations, congested intersections or links, freeways, and stadiums. In each scanning cycle, the Wi-Fi detector should be extended to scan many terminals simultaneously. However, the Wi-Fi Media Access Control Scanner used in [91] can only capture 5 Wi-Fi devices in each scanning cycle. Too low detection capacity is bound to affect the performance of traffic target monitoring.

4.3. Conclusions

Compared to traditional technologies, Wi-Fi-involved sensors are not the most widely used in ITS, but the reported existing research showed that this technology has great promise in traffic target positioning, traffic parameter extraction, and traffic mode recognition with the increase of Wi-Fi-enabled devices. With the development of ITS demands for higher data integrity and accuracy, traffic detection technologies may be more dependent on the Wi-Fi sensors with the private label data because it has much more advantages in terms of lower cost, better performance, and more extensive deployment than the existing. More importantly, those kinds of data from Wi-Fi can be used not only to support traffic control and surveillance optimization, but also to help transportation planning and traffic improvement design for controlling traffic congestion, reducing energy consumption and air pollution, and increasing traffic safety.

Author Contributions: Conceptualization, Y.L. and X.W.; investigation, Y.L. and Q.L.; writing and preparation of original draft, Q.L. and D.L.; writing—review and editing, Y.L. and Q.L.; supervision, Y.L. and X.W.; funding acquisition, Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China, grant number 61903145.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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