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Mobility Prediction: A Survey on State-of-the-Art Schemes and Future Applications

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ABSTRACT Recently, mobility has gathered tremendous interest as the users' desire for consecutive connections and better quality of service has increased. An accurate prediction of user mobility in mobile networks provides efficient resource and handover management, which can avoid unacceptable degradation of the perceived quality. Therefore, mobility prediction in wireless networks is of great importance and many works have been dedicated to this issue. In this paper, the necessity of mobility prediction, together with its intrinsic characteristics in terms of movement predictability, prediction outputs, and performance metrics is discussed. Moreover, the learning perspective of solutions to mobility prediction has been studied. Specifically, an overview of the state-of-the-art approaches is provided, including Markov chain, hidden Markov model, artificial neural network, Bayesian network, and data mining based on different kinds of knowledge. At last, this paper also explores the open research challenges due to the advent of the fifth-generation mobile system and puts forward some potential trends in the near future.

INDEX TERMS Mobility prediction, quality of service (QoS), resource reservation, handover management, the fifth-generation mobile system (5G).

I. INTRODUCTION

Mobility is an inherent characteristic of user in mobile networks and involves many important issues in mobile communication systems, such as handover, offered traffic, dimensioning of signaling network, user location updating, registration, paging and multilayer network management [1]. Mobility represents a great advantage for user comfort while on the other hand it could cause great degradations if not managed properly. Moreover, with small cell networks becoming a clear trend of the fifth-generation mobile system (5G), the impact of user mobility is enlarged with the decrease of the cell coverage radius [2]. Therefore, mobility has attracted increasing attention in academia and industry, where many critical issues remained to be solved.

To the best of our knowledge, an efficient way to manage mobility and maintain user's continuous connections is the implementation of mobility prediction [3]. The ability to predict a user's next cell or even the path it will traverse is an important aspect of future mobile network system [4]. Generally, the applications of mobility prediction in mobile network can be categorized as handover management, resource management and location-based applications. The typical challenges for mobile networks is represented by the consequence of handover. Unacceptable delay or even call dropping events may happen when a user left a coverage area but could not connect to new cell smoothly, which needs proper handover management [5]. Besides, the only way to guarantee continuous services, without any need to reserve the huge amount of resources across the whole network, is the implementation of passive resource reservation policy [6]. This kind of approach can pre-reserve a certain amount of bandwidth in the coverage areas that will probably be visited by users, which avoids reserving bandwidth over the whole system and therefore a lot of unnecessary resources can be saved. Moreover, if network could evaluate users' future movements accurately, some location-based contents which are highly correlated to users can be distributed and network will have the ability to predict the traffic condition as well as to design more efficient plans. Therefore, mobility prediction is a promising candidate in future networks and its categorization of applications is described in detail as follow.

- *Handover management.* During the handover process in mobile networks, users detach from the current transmission points (TPs) and attach to other TPs so as to get better service. Generally, handover is executed based on the reference signal received power (RSRP). However, handover may happen frequently due to the fluctuation of RSRP, which results to the fluctuation of services.

Mobility prediction can provide user's long-term movements (e.g., subsequent transitions of TPs, next segment of user trajectory and user's future locations), then many key performance indicators (KPIs) of handover such as the number of handover, handover failure rate and handover latency can be improved significantly. Khan and Sha [7] presented a scheme for handover ordering and reduction and predicted user's movement by accurate positioning and advanced data processing capacities embedded in user equipments, showing effective reduction in the amount of handovers and new call blocking. Besides, Mohamed *et al.* [8] considered mobility prediction for predictive handover management under control/data plane separation architecture, and results showed that this scheme can provide significant savings in signal overhead and reduce a large amount of handover failures.

- *Resource management.* In mobile network, quality of service (QoS) degradation or even call termination may happen frequently when there are insufficient resources to support new call request. Bandwidth is an extremely valuable resource which drives us to design efficient resource reservation scheme for increasing resource utilization [9]. Armed with the prediction information of user mobility, TPs are able to reserve resource for users who are going to attach in advance, which can reduce the resource collision and coordinate the interference between different users. For example, Soh and Kim [10], [11] proposed a dynamic resource reservation scheme relying on accurate positioning to achieve efficient call admission control and significant resource efficiency. Furthermore, mobility prediction is helpful to estimate the sojourn time of users in specific TPs. If the duration of users staying in specific TPs is known in advance, the energy efficiency in the systems can be improved by managing the available resources more intelligently.
- *Location based service pre-configuration and network planning.* Location based service (LBS) aims to provide users with enhanced wireless services and some information related to the specific location based on their geographical locations [12], such as sending target advertisements, local traffic information, instant communication with people nearby and merchant recommendation. Despite those benefits, services based on real time geographical location may be out-of-time which steer us towards foreknowing where the users will be in the future. Mobility prediction is able to provide future destinations of user, which is helpful in service pre-configuration [13]. Moreover, mobility prediction provides the network with more intelligent and efficient way to manage travelers by traffic forecasting.

However, all the applications mentioned above are based on the knowledge of user mobility, which appears random and unpredictable. So here comes a question: can we predict the user's behavioral characteristics through a large amount of observations? Fortunately, by measuring the entropy of each individual's trajectory, up to 93% potential predictability in user mobility across the whole user base was found in [14], which indicates that there is a potential 93% average predictability in user mobility. There have been many researches on user mobility modeling and pattern analysis. From the existing works, we have found that for a majority of users, especially those frequent users, the mobility of them are not purely random but rather direction or destination oriented [15]. Since the mobility behavior of users can be learned after monitoring user movement for a couple of days, by exploiting users' movement history and context information, user mobility is predictable in most cases [16].

Mobility prediction can be defined as a tool to estimate the future locations of users. However, predicting user's future locations is difficult especially from the perspective of network. In this survey, a general architecture during the implementation of mobility prediction is presented and can be divided into six components, as is shown in Fig. 1. These components are: data source, required information, prediction algorithms, prediction outputs, performance metrics and categories of applications.

Data plays a crucial and irreplaceable role in 21st Century like ''Oil in the 18th Century'' [17]. Due to the rapid advance of data acquisition and storage technologies, many relevant information can be collected largely for tracking the traces of moving objects. For example, location information can be provided by localization systems, such as global positioning system (GPS), radio frequency identification (RFID), smart phone sensors and so on; besides, a large amount of user records are stored in the base station (BS) and server. Different scenarios have different data requirements for mobility prediction. In some scenarios like shopping mall, crowd movement characteristics is dominant while in desolate areas, cell transition histories is more worthy of our attention. Most of the existing algorithms and schemes predict user mobility based on the movement history data and context information. These researches can be grouped into two major types according to the types of movement history data [18].

The first type is based on individual movement histories [19], [20]. In this class, predictions are performed on individual users rather than the entire users. The advantage of this class is that useful knowledge hidden under mobility history of a user would be fully discovered to predict his future movement. However, it performs poorly in predicting a new user or with movements on novel paths due to the lack of information on personal movement profile.

The other category is based on popular movement histories [21], [22]. In this situation, mobility prediction focuses on group of similar mobility behavior instead of eliminating random movements from the entire body of mobile users' profiles. However, by doing so, the quality of clustering process would degrade due to the noise of random movements. Interestingly, some works address the deficiencies

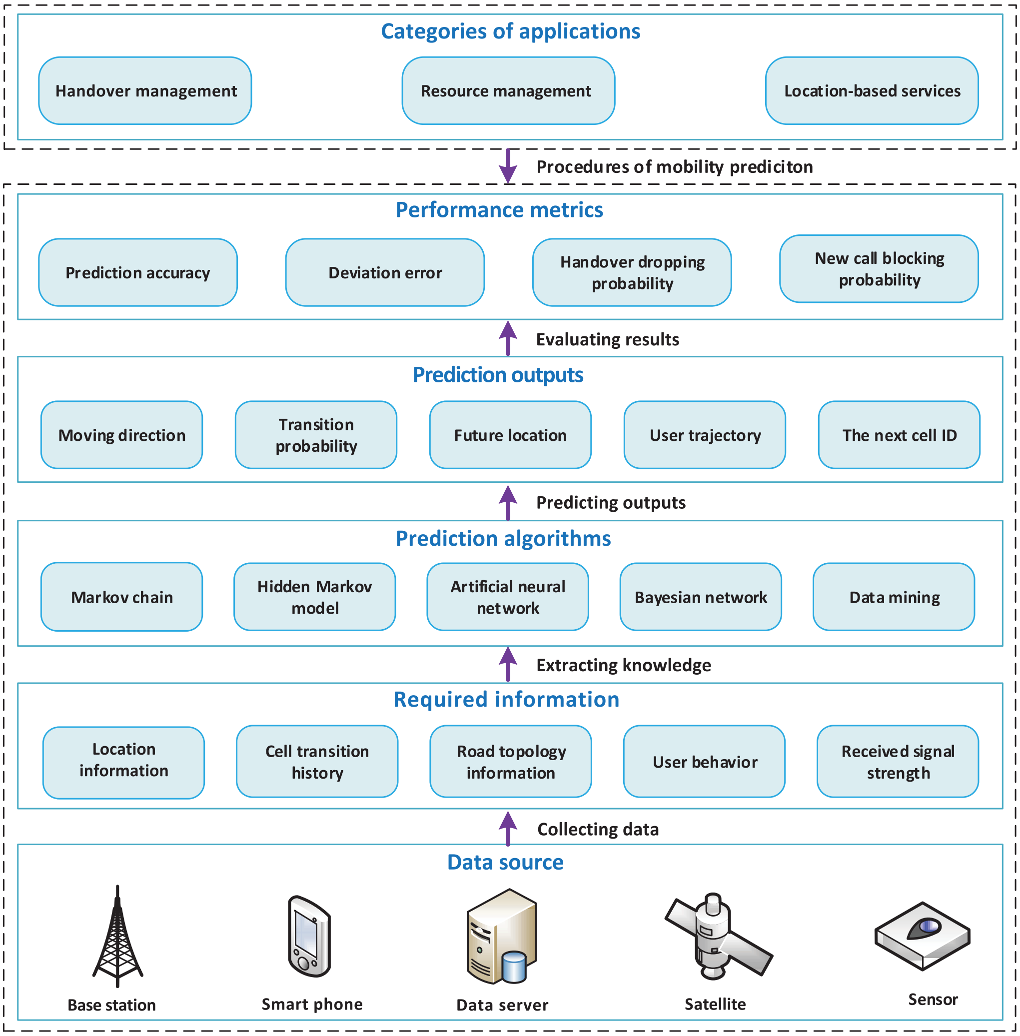

FIGURE 1. An overall structure of mobility prediction. It includes six parts. The first part in the bottom explains the source of the required information; then the second part interprets what information is needed to predict user's movement; algorithms denote comprehensive prediction tools in the literature; outputs represent what we desire to acquire through prediction; prediction metrics give criterion on how to evaluate the prediction results. At the top, the categories of applications on how mobility prediction acts for the improvement of user's QoS are presented.

of two classes and attempt to solve these problem. Duong and Tran [23] combined the mobility rules derived from multiple similar users with clustering and sequential pattern mining, which is said to handle the lack of individual information and avoid some noise due to random movements by some users.

Once information of user mobility (e.g., user movement, cell transition history, users' behavior pattern as well as environment information listed in Fig. 1) is available in the control center of mobile communication systems, appropriate steps (for example, resource reserved in advanced) could be taken to guarantee QoS during the connection lifetime of users [24]. Proper approaches need to be chosen carefully based on the data type, the condition of environment and outputs that we desired. Mobility prediction have been widely exploited in existing works, where different approaches and scenarios are considered. These methods have their own applicable domains and can not be extended directly to other scenarios and environments. Therefore, in Section IV of this survey, we make a detailed comparison of existing works about mobility prediction based on their proposed models and algorithms, such as Markov chain (MC), hidden Markov model (HMM), artificial neural network (ANN), Bayesian network, data mining based on different knowledge and other conventional or novel approaches. Besides, many works have verified the accuracy and effectiveness of their proposed schemes in real world scenarios or simulations. Generally, prediction outputs can be classified into future location of users, subsequent transition probability to neighboring TP, the prediction of TP that user will attach to and users' moving trajectory. Moreover, criteria of evaluating prediction outputs is introduced here because we have to estimate which scheme is better, and the metrics listed in Fig. 1 are directly related to the QoS of users.

II. OVERVIEW OF SURVEY PAPERS AND MAIN CONTRIBUTIONS

Over the last two decades, mobility prediction have been widely researched with the aim to forecast user's future location and improve their QoS. These researches exploit various approaches for different goals, i.e., handover management, resource management and LBSs. Such diversity on this field, led to the generation of several surveys that focus on different topics. In this section, the existing surveys on the mobility prediction field is compared to distinguish our work.

In contrast to [18], which focused on surveying existing solutions for geolocation prediction from the angle of mobility big data. Similarly, Feng and Zhu [25] and Zheng [26] also surveyed various applications of large-scale data mining but focused on providing a quick understanding of the field of trajectory data mining. Balico *et al.* [27] have studied and analyzed proposed approaches for localization, target tracking and time-series prediction techniques that can be leveraged to estimate the future location of a vehicle in vehicular ad hoc networks (VANETs) rather than common mobile networks. And in [4], which compared the most commonly found machine learning (ML) algorithms in terms of certain self organizing networks (SON) and provided a guideline of applying ML techniques to SON, only part of self-optimization (mobility management, resource optimization) has mentioned the aspect of mobility prediction. Or even [28], a comprehensive overview of location prediction including definitions, concepts, algorithms and applications, is provided but it only focused on mining trajectory data.

Much like [5], this paper considers the concept of cell-mobility prediction and discusses different conventional or unconventional approaches that consider in-advance resource reservations to achieve service continuity and improve user's QoS. However, Fazio *et al.* [5] also considered existing protocols for passive reservation requests and failed to provide the panorama of mobility prediction, for example, which output is useful during prediction and what is its performance criteria.

In addition, with the advent of new technologies, for example, the ultra dense deployment of low-power and small-coverage TPs, user-centric networks (UCN), heterogeneous networks (HetNets), massive multiple inputs multiple outputs (MIMO), mmWave communication and so on, the dominant pattern of traditional cellular networks is broken and there will be more new research spots springing up in the near future. In this work, we mainly exploit the promising scenario and clear trend in future 5G network which is dense deployment of small cells, i.e., ultra-dense network (UDN) [29]. However, the impact of mobility on UDN is enlarged as handover will happen more frequently and severe interference is caused especially for cell edge users. As for the latter, UCN comes out as a great solution by forming virtual cell (VC) dynamically, which is a promising technology to manage interference and provide better QoS for users [30]. And in terms of the former issue, mobility prediction can avoid unnecessary handover and reduce handover failures. Besides, mobility prediction can lay the foundation for the forming and reforming of the UCN, which can improve the QoS significantly. Therefore, mobility prediction is a promising candidate in 5G UDN and UCN but many issues remained to be solved are discussed in Section V.

Regardless of many issues in UDN and UCN, there exists many challenges and opportunities in future applications of mobility prediction. With the rapid development of artificial intelligence and processing power of computers nowadays, many complicated techniques become available. A lot of applications of mobility prediction in the future scenes (e.g., vehicular network, smart city, Internet of things (IoT) and so on) have benefited from it and users will experience a huge leap in the communication comfort, which directly or indirectly demonstrates the necessity in implementing mobility prediction.

The main contributions of this paper are listed as follows:

- The paper is focusing on the learning perspective of state-of-the-art algorithms applied to mobility prediction and providing the readers with a comprehensive understanding and classification of not only the conventional but also the most popular ML approaches to achieve those applications in mobility prediction;
- Different with other surveys in the field of mobility prediction, this paper also explains the predictability of user mobility and gives a brief summary of localization methods. Besides, various prediction outputs as well as its performance metrics are presented to provide a guideline of predicting user's future movement for readers;
- The paper also discusses the trends of 5G mobile networks and the resulting crucial issues in mobility prediction. Moreover, an extensive and heuristic overview of the challenges that will be encountered in the process of applying mobility prediction to future networks, is proposed elaborately.

The remainder of this survey is structured as follows. In Section III, we mainly explain mobility prediction related issues including mobility predictability, positioning methods, prediction outputs and performance metrics. In Section IV, the state of the art in user mobility prediction is provided and we also analyze the challenges of mobility prediction. In Section V, the concept of 5G is introduced and we discuss the related mobility prediction issues in future 5G networks. Section VI discusses future applications and challenges of mobility prediction and Section VII concludes this survey.

III. CHARACTERISTICS OF MOBILITY PREDICTION

In this section, we mainly discuss the characteristics of mobility prediction. Firstly, we explain why user mobility is predictable by utilizing the methodology of entropy theory in existing studies. After that, frequently-used prediction targets are introduced. Finally, metrics that are used to evaluate the prediction performance are defined.

A. USER MOBILITY PREDICTABILITY

Mobility is an inherent characteristic of users in mobile networks. A better understanding of user's mobility behavior is crucial for all investigations in which the relative locations of mobility users are important. Key challenges in communication systems are understanding user mobility and utilizing mobility prediction which are vital for helping to build efficient communication networking. Before analyzing existing works which mainly focus on designing algorithms for mobility prediction and exploring utilization of these algorithms, we first discuss the crucial questions: To what degree is user mobility predictable?

Entropy is probably the most fundamental quantity to capture the degree of predictability characterizing a time series. Three entropy measures were assigned to each individual's mobility pattern in [31], including the random entropy, the temporal-uncorrelated entropy and the actual entropy. Besides, an important measure of predictability π is defined as the probability that an appropriate predictive algorithm can predict correctly the user's future whereabouts.

By analyzing the distributions of entropy measures, maximum of π is determined for each user. It is narrowly peaked near 0.93 which indicates that despite the apparent randomness of the individual's trajectory, a historical record of the daily mobility pattern of the users hides an unexpected high degree of potential predictability [31]. For people who travel less frequently, it should be easier to foresee their location (small entropy), whereas those who regularly cover hundreds of kilometers should have a low predictability (high entropy). Despite this inherent population heterogeneity, the maximal predictability varies very little and there is no user whose predictability would be under 80% through observation.

Additionally, the predictability of vehicular mobility has been investigated extensively in [32] based on the same methodology of entropy theory. The main results obtained show that there exists some stronger regularity in the daily vehicular mobility in both the temporal and spatial dimensions, which can be exploited to predict the vehicular mobility with a high degree of prediction accuracy. Specifically, for both Shanghai and Beijing traces, the location predictability limit of 80%-99% can be achieved, where above 70% of the staying-time predictability limit can be reached with appropriate quantization precision by exploiting the temporal regularity.

Therefore, there exists widely strong regularity in the mobility of human and vehicles in both temporal and spatial dimensions, which can be exploited to predict the user mobility with a high degree of prediction accuracy.

B. HOW TO OBTAIN USER'S POSITION INFORMATION

In mobile communication systems, a user would move from one position to another due to user mobility. Finding the position of mobile users is the most critical issue in mobility prediction although many related researches are built on the assumption that users' coordinates are perfectly known. There are two main approaches to design a wireless positioning system: the first primarily focuses on location application by developing a signaling system and a network infrastructure of location measuring units; the other is to locate a target by leveraging an existing wireless network infrastructure [33].

Typically, positioning system can be categorized into indoor positioning system (IPS) and outdoor positioning system (OPS) according to their application environments [34]. There are many OPSs (e.g., GPS-based [35], cell identification (CID)-based [36]) having been deployed in people's daily life, where GPS is one of the most successful positioning systems mainly applied in outdoor environments. However, as for indoor environments, its accuracy decreases due to the severe attenuation for satellite signals, which makes GPS unsuitable for indoor location estimation. Therefore, IPSs are proposed to fill the gap of GPS signals to improve the performance of indoor positioning by using indoor wireless signals [37], such as wireless local area network (WLAN) [38], Bluetooth [39], radio frequency identification (RFID) [40], ZigBee [41] or even visible light communication [42], [43]. Note that with the evolution of positioning systems and the growth of user's requirements, the boundary between IPS and OPS is no longer that clear and many methods can apply to both indoor and outdoor environments.

From the perspective of positioning principles, the fundamental positioning techniques can be classified as four types: trilateration, scene analysis, proximity and hybrid [33], [34]. Trilateration is most widely applied positioning technique which uses the geometric properties of triangles to estimate the target location, including time of arrival (ToA) [44], time difference of arrival (TDoA) [45], angle of arrival (AoA)-based [46], etc. RF-based scene analysis first collects features (i.e., fingerprints) of a scene and then estimate the location by matching measurements with the closest a priori location fingerprints [47]; proximity algorithms provide symbolic relative location information, where assigns the position of the terminal to the known transmitter position and an example is the CID method; moreover, a combination of the previous positioning methods can be implemented to improve the precision. The brief summary of some positioning solutions are listed in Table 1, as is shown in the top of next page.

C. PREDICTION OUTPUTS

1) MOVING DIRECTION

Direction would first come out in our mind when it comes to users' mobility prediction as it is the most important attribute of mobility. Mobility of commuters is not random purely but rather direction-oriented [48] and it will be easier to know where the user is heading if the direction is known in advanced. For example, Kuruvatti *et al.* [49] made a prediction of user cell transitions based on estimation of user group; besides, moving direction was predicted in [50] in order to find which region the user is most likely to go.

TABLE 1. The summary of existing works on most utilized localization methods.

Positioning solutions	Environment	Measuring principles	Precision [33] [34]	Brief description	Ref.
GPS	Outdoor	Trilateration	$\sim$ 10m	Can not be applied indoors due to the severe attenuation of satellite signals	[35]
CID	Outdoor	Proximity	$>$ 50m	Additional information are required to improve precision, such as the cell sector, ranging measurements, etc.	[36]
E-CID	Outdoor	Proximity	$10-50$m	Accuracy is low and this method need to combine the cell coverage with additional measurements, such as AoA, round trip time (RTT), etc.	[36]
WLAN	Indoor	Trilateration& Scene analysis	$3-30$m	The possible signal fluctuations that may occur can increase errors and inaccuracies in the path of the user	[38]
Bluetooth	Indoor	Proximity & Scene analysis	$3-30$m	Lack of synchronization of indoor small cells and the rich multipath environment.	[39]

2) TRANSITION PROBABILITY

Transition probability refers to the probability of transition from current state to another. These states can be cells, locations or other parameters which can describe user's position information. In general, the prediction results consist of more than one state and each state has its own transition probability in a particular situation [51]. Therefore, we can select one or several states with the highest transition probability as the prediction output.

3) FUTURE LOCATIONS

An interesting problem to be solved nowadays is how to provide highly accurate and reliable localization information anywhere and anytime [52], which directly determines whether the resource management is effective. Therefore, location information is the most important output in mobility prediction. Generally, location is represented by the longitude and the latitude of current position or Cartesian coordinates. The prediction results can be a coordinate pair of the next location or a location sequence, which depends on the algorithms used. Ariffin *et al.* [53] perform resource reservation prior to the actual handover in a Long Term Evolution (LTE) femtocell network by predicting the places where the users are going, which can reduce the scanning time and the handover latency.

4) USER TRAJECTORY

A trajectory is the path that a moving object follows through space as a function of time. It can be described mathematically either by the geometry of the path or as the position of the object over time. The latter is the most frequently-used one. Besides, if the trajectory is in a two-dimensional plane and can be described by a polynomial, user's moving direction can be determined by the one ordered derivative of the trajectory polynomial. If the network anticipates the need of users on the move and reserves radio resource at cells along the path to the destination, the communication efficiency can be improved largely [54].

5) THE NEXT CELL ID

The next cell ID means the identity of the cell that a specific user may visit in the near future. In general, users may access to different cells when they are on the move, which causes the process of handover. If we can foreknow the next one or even more cells, radio resource such as bandwidth can be preconfigured in the cell(s) before the user visits. In [55], the trajectory characteristics of eNodeB and a sequence of historical service eNodeBs are leveraged to predict the next service eNodeB, which will exhibit more merit for network planning and resource preservation.

D. PERFORMANCE METRICS

Different techniques and performance metrics are used in predicting user's mobility among the existing literature. In this section, we focus on the definition of the KPIs that are used to quantify the performance of the proposed techniques and schemes. There are two kinds of metrics including observable metrics and application metrics. Observable metrics can be obtained from prediction result directly such as prediction accuracy and deviation error while application metrics are used to describe the performance of the application of prediction result, for example, handover dropping probability and new call blocking probability.

1) PREDICTION ACCURACY

The prediction accuracy is the most commonly used performance metric to evaluate whether the forecast is accurate and determine whether the method used is valid or not. Prediction accuracy is generally defined as the ratio between the numbers of correct predictions over the total number of predictions, as is shown below.

$$\text{prediciton accuracy} = \frac{\text{number of correct prediction}}{\text{total number of prediction}} \quad (1)$$

Note that the criterion of correct predictions varies among different literature because authors may have different definitions of prediction accuracy. For example, different from most utilized definition–if the predicted state (cell, position and so on) is identified with user's actual state, then it is called a successful prediction. However, Qioa *et al.* [56] defined prediction accuracy as the ratio between the hit rate (the value is set to 1 if the Euclidean distance between a predicted point and corresponding practical point is less than a threshold) of a trajectory sequence and the length of points in predicted sequence.

2) DEVIATION ERROR

Sometimes, it is not so easy to determine whether a prediction is accurate or not. Therefore, deviation error is introduced to measure the average magnitude of the errors in a set of predictions without considering their direction. For instance, Qiao *et al.* [57] gave a definition of deviation as follows.

$$Deviation = \frac{1}{N}\sum\nolimits_{i=1}^{N} d_i \tag{2}$$

where $d_i = \sqrt{(x_{i,\text{pre}} - x_{i,\text{pra}})^2 - (y_{i,\text{pre}} - y_{i,\text{pra}})^2}$ is the Euclidean distance d between the predicted location $(x_{i,\text{pre}}, y_{i,\text{pre}})$ and the practical location $(x_{i,\text{pre}}, y_{i,\text{pre}})$. And N is the total number of predictions. Similarly, root mean square error (RMSE) of position and speed was introduced in [58] to assess the closeness of the estimated trajectory $(\hat{x}_k, \hat{y}_k)$ to a given trajectory (x_k, y_k), with k being the discrete time in the problem of mobility tracking, which was defined as (in m):

$$RMSE = \sqrt{\frac{1}{N_{mc}}\sum\nolimits_{m=1}^{N_{mc}} (\hat{x}_k - x_k)^2 - (\hat{y}_k - y_k)^2} \tag{3}$$

where N_{mc} denotes the number of Monte Carlo runs. The speed RMSE (in m/s) can be formulated by substituting the estimated speed $(\dot{x}_k, \dot{y}_k)$ into (3).

3) HANDOVER DROPPING PROBABILITY

The handover dropping probability (HDP) is defined as the ratio between the number of handover drops over the number of total handover. As the prediction result is used for handover management, it is an indirect evaluation of the prediction schemes. In the current LTE communication system, if the signal-to-interference-plus-noise-ratio (SINR) of the target cell is lower than a threshold, handover dropping would happen, which will bring great degradation to user comfort. That's why, Soh and Kim [11] proposed a predictive bandwidth reservation scheme aiming to reduce the handover dropping probability efficiently. Most commonly, the HDP is defined as below.

$$\text{HDP} = \frac{\text{number of dropping handover}}{\text{total number of handover}} \tag{4}$$

4) NEW CALL BLOCKING PROBABILITY

New call blocking probability is defined in user mobility prediction-based resource reservation scheme. In user's perspective, the dropping of an on-going call is obviously more frustrating than the blocking of a new call [59]. In resource reservation schemes, the call blocking probability would be inevitably increased so as to meet the target of HDP. With the help of mobility prediction, on the premise of the same HDP, a lower new call blocking probability means better performance of mobility prediction. Resource reservation scheme in [11] that only utilized forthcoming handover predictions can reduce unnecessary blocking of new calls, which would benefit those users who attempt to access to this cell.

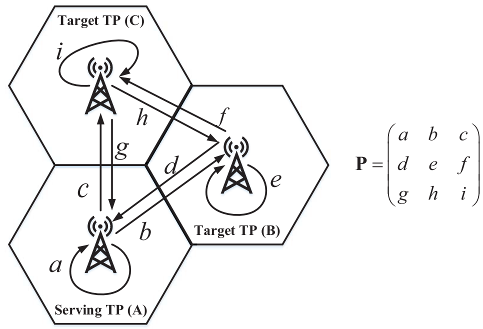

FIGURE 2. The transition probability of three cells scenario.

IV. MOBILITY PREDICTION SCHEMES

In this section, an in-dept overview on the state-of-the-art algorithms that exploit and analyze past mobile users movements for mobility prediction is given. As prediction techniques, we have surveyed Markov chain, HMM, ANN, data mining and other approaches, since they are presented in literature used to make mobility predictions. These approaches aim to improve the prediction accuracy and further enhance network performance, in terms on user latency, blocking and dropping probabilities. Therefore in the following, a comprehensive description and comparison of different schemes is provided to give a guideline for the readers.

A. MARKOV CHAIN

A Markov chain is a stochastic process with the Markov property "memoryless". The term "Markov chain" refers to the sequence of random variables such a process moves through. The Markov property defines serial states only on the dependence of adjacent periods (as in a "chain"). It can thus be used for describing systems that follow a chain of linked events, where what happens next depends on the current state or last several states of the system. Due to the Markov property, Markov chain has been applied to user mobility prediction in wireless networks for a long time.

Ulvan *et al.* [51] and Ariffin *et al.* [53] both predicted user's movement using the original Markov chain technique and the former explored various forms of user's movement, including linear, reside, random and patterned. Based on the Markovian characteristic, user's movement would be start at a particular position and user may stay at the current position or move to any other cells or positions. The transition probability from one state to another is based on current state rather than the previous states. An example of three-cell scenario in cellular network is shown in Fig. 2. There are three cells (A, B, and C) in this scenario corresponding to three states in a Markov chain, and note that the state is not restricted to cells, but can be locations or movements. The value of the transition probability matrix used here is predefined. For example, supposing a user is attached to cell A; at the next time slot, it may stay at the current position, move to cell B or cell C with probabilities of a, b and c, respectively. Also, the transition probabilities of cell B and cell C is d, e, f and g, h, i, respectively. And the total probability of a, b and c must be equal to 1.

$\mathbf{P}$ is the transition probability matrix. The next transition probability ($\mathbf{P}_n$) from the serving cell to the target cell is calculated as:

$$\mathbf{P}_n = [\mathbf{P}_{n-1}] * [\mathbf{P}]$$

where $\mathbf{P}_{n-1}$ is denoted as current transition probability matrix and n is the number of transition state.

Similarly, a mobility prediction scheme via Markov chain was proposed in [60] to predict user's movement in femtocells deployment to reach the goal of seamless and fast handover. A log file consists of user ID, time and location is created to store the history of user's movement. Time represents the date and time at which the user is connected to the particular BS, while location represents the base station ID at which the user is connected at a particular time. From the log file, a transactional database is created to identify a relationship between source and destination base station. From the database, most frequently visited base station can be identified and we can obtain the transition matrix from this database.

Hadachi *et al.* [61] proposed an enhanced Markov chain algorithms by applying embedded association rules including the universal behavior rule and the temporal rule. Users' trajectories are first extracted from the historical database. During the training phase, the transition information used in the online mode is exploited to predict the next movement of users. The performance of the proposed enhanced Markov chain is unsatisfied when it comes to unknown users during the training phase but other predicting algorithms such as particle filter or Kalman filter can be added to improve the performance of the system.

However, Gambs *et al.* [19] highlighted that the standard Markov chains have ignored previous visited locations and it would cause a negative impact on the prediction performance. In order to solve this limitation, a novel Markov chain named n-MMC which incorporates the n previous visited locations was proposed. Nevertheless, since the extended version of standard Markov chains considered the n-previous locations, transition probability matrix would become more complex. Consequently, this technique is not appropriate for the network that consists of a large number of BSs like femtocells network.

From analysis above, we can realize that the advantage of the Markov chain based schemes is due to its simplicity, which is easy to understand and implement. However, the performance of these schemes is mainly influenced by the transition probability matrix, and the most important part in the Markov chain based scheme is how to acquire the transition probability matrix. Analysis found that the length of time to collect the data has strong correlation with the performance of Markov chain based scheme. Moreover, the Markov chain based schemes have poor extensibility, which makes it very difficult to obtain the transition matrix when the state space is large.

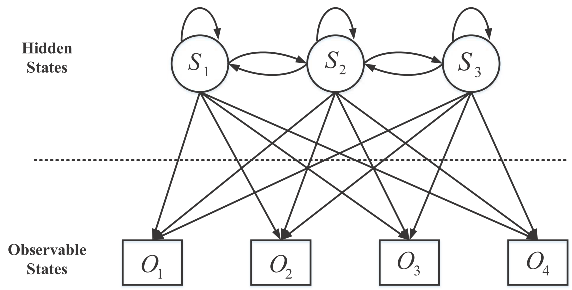

FIGURE 3. An example of HMM.

B. HIDDEN MARKOV MODEL

In simpler Markov models (like a Markov chain), the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. Hidden Markov model is a doubly stochastic process with an underlying stochastic process that is not observable (which is hidden), but can only be observed through another set of stochastic processes that produce the sequence of observed symbols [62]. In HMM, there are two kinds of states named hidden states and observable states. As additional information about hidden states can be obtained from observable states, HMM outperforms the Markov chain in predicting user mobility in most cases.

An illustration of HMM is provided in Fig. 3. Each node in Fig. 3 represents a state and $\{S_1, S_2, S_3\}$ contains 3 hidden states while $\{O_1, O_2, O_3, O_4\}$ contains 4 observable states. $\lambda = \{A, B, \pi\}$ is introduced for the description of HMM in which π is the initial state distribution, A is the state transition probability distribution and B is the observable symbol probability distribution.

Given the form of HMM, there are three key problems of interest that must be solved for the model, which are listed and answered as follows [62]:

- *Problem 1:* Given the observed sequence $\{O_1, \ldots, O_T\}$ and the model $\lambda = \{A, B, \pi\}$, how to compute the probability of the observed sequence $\Pr(O|\lambda)$? Using Forward-backward algorithm [62], the HMM described by $\lambda = \{A, B, \pi\}$ can give the probability that a given observed sequence $\{O_1, \ldots, O_T\}$ can be generated by this model.
- *Problem 2:* How to adjust the model parameters $\lambda = \{A, B, \pi\}$ to maximize $\Pr(O|\lambda)$? Using Baum-Welch algorithm [62], a learning solution can be used to adjust the above parameters.
- *Problem 3:* Given the observed sequence $\{O_1, \ldots, O_T\}$, how do we choose a state sequence which is optimal in some meaningful sense? Using the Viterbi algorithm [62], the optimal state sequence S that defines the most likely positions or cells would be visited by the user can be solved.

For instance, a serving eNodeB prediction in LTE cellular network leveraging HMM was proposed in [55]. The trajectories characteristics of eNodeBs and sequences of historical eNodeBs are defined as hidden states and observable states respectively. Specially, the eNodeB topology is considered. The first part of mobility prediction in [55] was parameter learning. In these process, optimal parameters $\lambda = \{A, B, \pi\}$ was determined by fitting history data and Baum-Welch approach was widely used to estimate the parameters of HMM. In the prediction part, the most probable next eNodeB is calculated by three steps: a) acquire eNodeB sequences corresponding to possible next eNodeB according to the eNodeB topology; b) compute the probability of all such sequences using the forward algorithms; c) choose the most probable eNodeB which maximizes the probability of eNodeB sequences.

Trajectory prediction in transportation networks is a very challenging and critical problem. To solve this problem, Qiao *et al.* [57] proposed a HMM-based trajectory prediction algorithm in. The observable states and hidden states are cells and trajectory segments respectively. Unlike most of existing works which focus on predicting slices of trajectory, the main contribution of Qiao *et al.* [57] is a proposal of predicting continuous paths of moving objects. Forward algorithm is used to solve the trajectory evaluation problem and Viterbi algorithm is used to discover trajectory hidden state sequence. Moreover, a trajectory partition algorithm which traverses trajectory points in a breadth-first fashion was proposed. It did not need to visit each point in the clusters iteratively and could improve the efficiency in processing trajectory data. Besides, one important characteristic of the algorithm proposed by Qiao *et al.* [57] was the ability to capture the parameters necessary for real-world scenarios in terms of objects with dynamically changing speed.

The works in [63]–[65] were mainly about HMM-based mobility prediction in cellular networks but they focused on the application of prediction results. The performance of resource allocation was enhanced in these works by solving Problem 2 in HMM-based mobility prediction. The prediction results were combined with a control theoretic feedback model for resource utilization in [63] while the mobile reservation protocol was adopted in [64] and [65] to manage handover events in an adequate manner. Yap and Chong [66] proposed an intelligent location-awareness access point selection algorithm based on HMM to enjoy the advantages of power consumption reduction while sustaining good communication quality and improve the number of connection to AP with a better signal quality. Result showed that the number of connection to high signal level AP increased and number of connection to low signal level AP decreased in comparison with conventional approach.

From the analysis of these literature above, it's obvious that unlike the Markov chain, HMM can improve the performance of mobility prediction as it reduces the lost information. Besides, HMM is able to enable the mobile node to learn the environment and update the information itself and as a result, the performance is improved. However, HMM has to consider hidden states which results in the higher computation complexity. As for future application of HMM, the computation complexity would increase dramatically due to the clear trend of ultra-dense deployment of BSs.

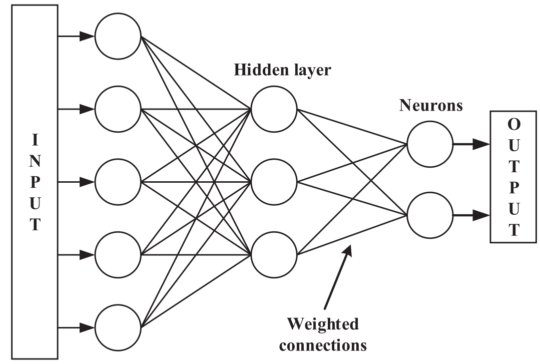

FIGURE 4. General structure of ANN with a hidden layer.

C. ARTIFICIAL NEURAL NETWORKS

In machine learning and cognitive science, ANNs are a family of models inspired by biological neural networks (the central nervous systems of animals, in particular the brain) and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown [67].

As shown in Fig. 4, ANNs are generally presented as systems of interconnected neurons which exchange messages with others. The connections have numeric weights that can be tuned based on experience, which makes the neural nets adaptive to inputs and capable of learning.

Parija *et al.* [68] proposed a multilayer neural network model to predict the future location of subscriber based on the past predicted information. The movement patterns were given in terms of a distance and direction pair (ds_j, dr_j), in which ds_j (in meter) is the distance traveled by user at j-th time interval and dr_j is the possible direction a user move at j-th time interval. Due to the limitation of the definition of movement patterns, this work could only predict those users with uniform and regular movement patterns.

The seemingly random movement is actually a logical function of the user's position, speed, acceleration and direction. As speed, acceleration and direction can be obtained from continuous user positions, a neural location predictor was proposed by Liou and Huang [69] to predict a future location based on three location updates of the nearest past. User positions in [69] were described by Cartesian coordinates. Unlike most of existing works, (x, y) of a coordinate were treated independently, which resulted in higher computing efficiency. Besides, a two-tier cell structure was introduced and only when users moved into the cell edge did the procedures of mobility prediction begin, which could improve the performance of bandwidth reservation.

In order to solve the critical issue of mobility management in mobile networks, Parija *et al.* [70] provided us with two neural network models by analyzing the main differences between them, including multilayer perceptron back propagation neural network (MLP-BP) and functional link neural network (FLNN). These two models were trained with respect to the data obtained from the movement pattern to predict the location of mobile host. MLP-BP is feed-forward with back propagation which requires a large amount of computation time for learning the network while FLNN is a single layer structure in which the input pattern is enhanced with nonlinear functional expansion. Moreover, the simpler FLNN was proved to outperform MLP-BP in terms of performance error and classification accuracy.

Similarly, comparisons between polynomial perceptron network (PPN) and MLP-BP were provided in [71]. PNN was built based on Weierstrass approximation theorem. It stated that any function that is continuous in a closed interval can be uniformly approximated within any prescribed tolerance over that interval by some polynomial. MLP-BP was proved to outperform PNN while the computational cost of PNN was better than MLP-BP as the computational complexity was reduced with less number of biases and weights.

Besides, there are many other factors considered in a ANN model. Wickramasuriya *et al.* [72] built a simple road model with the predetermined probability of users moving model. They presented a method based on recurrent neural network (RNN) to predict effectively the next BS that a user will probably connect to. Its training process did not use users' positions but took RSS distribution into consideration and achieved an accuracy of over 98%.

Artificial neural network is a well investigated algorithm and is famous for its adaptive and self-organization characteristics, where back propagation is the most widely used algorithm in ANNs. From [68]–[72], we can find that as the inputs and outputs of ANN, user position is the most important parameter in the ANN-based mobility prediction schemes. With the development of mobile communication system, ultra-dense deployment of small cell becomes a clear trend in the future. Although this trend would not impact directly the ANN-based schemes, it is related to the procedures of acquiring user positions, for example the fingerprint scheme. Moreover, ANN is also famous for its stunning computational complexity especially when there are many hidden layers, which can be called a deep neural network and requires lots of training time in the tuning of neuron weights.

D. BAYESIAN NETWORK

Bayesian network is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph [73]. It has great advantages in solving the uncertainty and finding the relationship between different variables in a complicated environment. As a result, Bayesian network has been widely applied to many fields. For example, given user movement historical data, the Bayesian network can be used to compute the probabilities of the presence of user at a specific place.

FIGURE 5. **Construction of Bayesian network.**

Zhang *et al.* [74] proposed a location prediction model based on Bayesian network. Most of known prediction model only take parts of predictive factors into account, however, multiple restricting factors are considered, including cell topology information, road typology information and user movement information. As is shown in Fig. 5, the Bayesian network structure is constructed by the following process: 1) construction of cell and road topology (CRT) based on cell environment, 2) construction on road state transition (RST) based on CRT, 3) construction of probability distribution network (PDN) based on RST and 4) construction on Bayesian network based on PDN. The distribution of predictive factors is also analyzed. The state transition chain of mobile user is assumed to be conditionally independent with each state. Based on the Bayesian network theory, the probability of state transition chain can be calculated according to the predictive factors vector of each node in the transition route. Moreover, the residence time in the target cell is predicted according to the current position, predicted position and the current velocity.

Liu *et al.* [75] proposed a novel approach based on Bayesian network to predict a moving object's future location under uncertainty. Similar to [74], the approach includes space-partitioning schemes, popular region extraction, transformation of trajectory sequence and region sequence, frequent sequential pattern mining and the Bayesian network construction. Popular regions were used to approximate a moving object's trajectory sequences and were regarded as random variables. The frequent region patterns were used to construct the Bayesian network and the traversal paths of regions were used to construct the arcs between nodes of the Bayesian network. Moreover, several algorithms were proposed to transform the trajectory information into the Bayesian network structure.

Bayesian network that models the sequence of variables is called dynamic Bayesian networks (DBN). DBN models that considered locations, day of the week, time of the day and their combinations, were proposed to predict the next place in [76]. Three combined models using least entropy, highest probability and ensemble were developed to adapt to different situations. Finally, these three models were compared over two different mobility data sets including call detail records data and Nokia mobile data.

Bayesian network can be combined with other models such as neural networks to enhance its performance. For example, a novel hybrid Bayesian neural network model for predicting locations on cellular networks was suggested in [77]. Different parallel implementation techniques on mobile devices were investigated and the authors also compared the performance of the proposed model to many standard neural network techniques such as back-propagation, Elman, resilient, Levenberg-Marqudat, and one-step secant models. The proposed hybrid model was proved to outperform other tested standard models.

Therefore, we can learn that Bayesian networks are a type of probabilistic graphical model that uses Bayesian inference for probability computations. Bayesian networks aim to model conditional dependence, and therefore causation, by representing conditional dependence by edges in a directed graph. Through these relationships, one can efficiently conduct inference on the random variables in the graph through the use of factors. However, in large networks, exact inference is very computationally intensive, so methods must be used to reduce the amount of computation. Moreover, the cell environment is important to the construction of Bayesian network. As a result, with the dense deployment of small cells, the cell environment would be more complicated which results in a higher difficulty of constructing Bayesian network.

Limited by the article length, detailed description of other approaches, such as Kalman filter (KF) [58], [78], [79], support vector machine (SVM) [80], time series model [81], biomedical algorithms [82]–[84] and so on, will not be expanded. The brief comparison of main approaches in mobility prediction is listed in Table 2.

E. DATA MINING

Data mining is the computing process of discovering patterns from knowledge in large data sets involving approaches at the intersection of machine learning, statistics, and database systems [88]. And it's one of the analysis steps of the "knowledge discovery in databases (KDD)" process. In order to forecast the moving trend of the observed user, a large data set, including not only trajectory information but also other knowledge from the user or network aspect, is used to improve greatly the accuracy of prediction. More detailed description can be seen in Table 3.

1) ROAD TOPOLOGY INFORMATION

Many existing works have ignored the fact that the cell boundary is normally fuzzy and irregularly shaped due to terrain characteristics and the existence of obstacles that interfere with radio wave propagation. For some mobility prediction schemes analyzed above, the cell geometry is ignored, which may result in incorrect result. As mobile terminals (MTs) travel on roads, the incorporation of road topology information into the prediction algorithm could potentially yield better accuracy. In this section, we are going to introduce several road topology based prediction schemes.

Soh and Kim [10] proposed a road topology based mobility prediction scheme which requires the serving BS to receive updated information about user's position at regular time intervals. Besides, each BS needed to maintain a database of the roads within its coverage area. Using the road topology shown in Fig. 6 as an illustration, consider two MTs (MT1 and MT2) that were currently traveling from junction

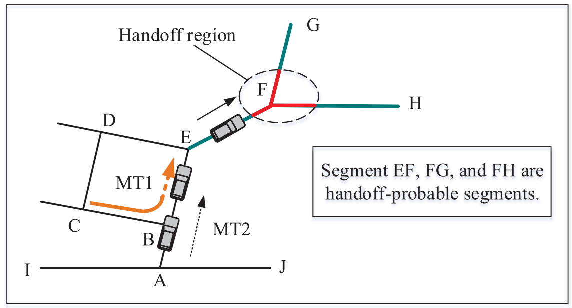

FIGURE 6. Utilizing road topology information for mobility prediction [10].

B toward junction E. MT1 came from segment CB, while MT2 came from segment AB. Based on the proposed model, the conditional probability of MT1 going to segment EF was computed differently from that of MT2. With the help of mobility prediction, the handover efficiency can be improved.

Inspired by the widespread availability of digital road maps, which were previously designed for navigational devices, dynamic bandwidth reservation scheme using similar road topology based prediction scheme was proposed in [11] and [59]. However, those works were built upon the assumption that users were equipped with reasonably accurate positioning capability, which may not correspond to reality. Besides, the effects of positioning errors would result in an incorrect result.

Li and Ascheid [89] introduced a learning-based graphical model which allows a fine-level prediction of the movements and velocities of mobile users inside a cell. They first divided mobile users into different user groups by velocities and then learned the path patterns and user type transitional probability. The transitional probability of future path and user type at the node were predicted by two steps including the expectation step and maximization step.

A novel framework for mobility prediction that can accurately predict the traveling trajectory and destination using spatial conceptual maps was proposed in [54]. Besides, knowledge of user's preferences, goals, and analyzed spatial information without imposing any assumptions about the availability of users' movement history were also employed. The innovation of this scheme is incorporating the notion of combining user context and spatial conceptual maps in the prediction process. The proposed scheme does not require a warm-up period to collect history of previously visited locations. Therefore, the scheme maintains the same degree of accuracy in predicting users' movements independently of the time span. Another two examples of handover management using road topology-based mobility prediction were illustrated in [7] and [90].

From the analysis above, we can learn that one of the critical premises in mobility prediction schemes is the actual road topology. Fortunately, the road topology map can be obtained by GPS or SINR map. After the acquisition of road topology map, some models can be trained based on this map. Due to this requirement of acquiring road topology map first,

TABLE 2. A comparative description of different algorithms in mobility prediction.

Prediction algorithms	Main feature and accuracy range (%)	Distinctions	Required information	Prediction outputs	Prediction metrics	Ref.
MC (see IV.A)	Stochastic process with simple structure, and easy to implement especially for discrete sequence modeling; predictions are based on the short memory principle (last n symbols), if n is low, the relationships between symbols could not be captured and if n is high, the model could "overfit" the training sequence. Low performance in "complicated" environment. **[25-72]**	Predicting individual movement in an extended model called n-MMC	User behavior and location information	Future location	Prediction accuracy	[19]
		Proactive and reactive schemes to enhance to handover strategy were compared for broadband wireless access based on the IEEE802.16m	RSS and location information	User trajectory and transition probability	Prediction accuracy	[51]
		Predicting user's moving direction to obtain the transition probability matrix in LTE femtocell network	Location information and cell transition history	Future location	Moving direction and the next cell ID	[53]
		Mobility prediction with an input of user's mobility history in LTE femtocell network	Location information and user behavior	Future location and the next cell ID	Prediction accuracy	[60]
		An embedded association of rules related to the behavior patterns and the temporal aspects of the mobile phone users' movements were based on real dataset	Location information, cell transition history and user behavior	Future location	Prediction accuracy	[61]
		Predicting human mobility using sina weibo check-in data	Check-in data	Future location	Prediction accuracy	[85]
HMM (see IV.B)	Based on Markovian approaches, HMM is able to find the relationships among different user behaviors and achieve better accuracy than Markov chain, at the cost of much more dedicated training. **[68-82]**	Human mobility based eNodeB prediction in LTE cellular network information	Cell transition history and eNodeB topology	The next cell ID	Prediction accuracy and invalidity	[55]
		HMTP* could predict continuous paths, automatically adjust parameters in the sizes of cells, clusters and trajectory segments, and process large-scale data	User trajectory	User trajectory	Deviation and prediction accuracy	[57]
		Model the process of mobility prediction in a wireless network in conjunction with a closed loop feedback control system	Cell transition history and location information	User movement and the next cell ID	Prediction accuracy, resource utilization	[63]
		Distributed mobility prediction was performed for bandwidth reservation regardless of wireless systems	Location information and cell transition history	The next cell ID	Prediction accuracy, dropping and blocking probability	[64] [65]
		Location-awareness AP selection algorithm in WLAN	Location information	The next cell ID	Number of handovers and signal quality	[66]
		Investigate the effect of living habits on the individuals and groups based on large-scale factual mobile data to predict users' points of interest	Location information and user behavior	Future location	Prediction accuracy	[86]
ANN (see IV.C)	Extensively investigated and applied approach that could "learn" the inherent characteristics of training sample and have pretty good performance. However, it has huge training complexity, which is hard to interpret and sensible to over-fitting problems. **[74-92]**	Multi-target location prediction based on individual past movements	Location information	Future location and moving direction	Prediction accuracy	[68]
		Two-tier cell structure and logical function of the user's position, speed, acceleration and direction were used to maintain seamless handoff	Location information	Future location and the next cell ID	Prediction accuracy and deviation	[69]
		Single-layer functional link neural network (FLNN) was proposed for location management in cellular network	Location information and user behavior	User trajectory	Deviation error	[70]
		Soft-computing approach, PPN, was applied for intelligent location management system and is compared with MLP	Location information	Future location	Deviation error and CPU time	[71]
		RNN was used to predict the optimal set of BSs (virtual cells) via LSTM based on sequences of RSS values	RSS, cell transition history	Optimal virtual cell topology	Prediction accuracy	[72]
Bayesian netowrk (see IV.D)	Bayesian network can efficiently conduct inference on the random variables in the graph through the use of factors, and can be integrated with other approaches like ANN to improve the prediction performance; However, it requires huge complexity in developing a tractable approximation to probabilistic inference and becomes more difficult when the cell environment is complicated. **[35-70]**	An influential friend selection strategy was proposed based on temporal-spatial Bayesian model	Location information	Future location	Prediction accuracy	[21]
		Multiple predictive factors were coded in Bayesian network node for improve teh efficiency of the model in LTE cellular network	User behavior, cell and road topology information	Future location	Prediction accuracy	[74]
		Space-partitioning and hot-spots extraction were considered in the Bayesian network construction	Location information	Future location	Transition probability	[75]
		Spatial-temporal parameters and entropy, highest probability and ensemble were considered	User behavior and location information	Future location	Prediction accuracy	[76]
		A hybrid model making use of Bayesian inference in artificial neural networks	Cell transition history, user behavior and location information	The next cell ID	Prediction accuracy	[77]
KF	The accuracy of the model is highly related to the corrections frequency and it can be used to predict only one possible next cell. **[60-70]**	A Rao-Blackwellised particle filter was proposed and compared with an EKF	RSSI and location information	Future location and speed	Deviation	[58]
		REKF was proposed to predict user's next mobile BS from the user's location, heading, and altitude	Location information and RSSI	The next cell ID, moving direction and velocity	Deviation	[78]
		Location prediction of vehicles in VANETs using a KF compared with NN	Location information	Future location and user trajectory	Deviation	[79]
		Predicted position based routing protocol (PPRP) for VANET using KF to minimize the effect of position error	Location information	Future location	Packet delivery ratio, delay and throughput	[87]

TABLE 3. Data mining based on different knowledge.

Knowledge	Main feature and accuracy range (%)	Distinctions	Required information	Prediction outputs	Prediction metrics	Ref.
Road topology information (see IV.E.1)	Prediction performance could be enhanced greatly with the knowledge of road topology information but the acquisition of road topology map could be difficult and the road topology based model could not be directly applied to other regions. **[50-90]**	Road topology information and changes in RSS were used to calculate HO probability and target BS at the user side	RSS, location information and road topology information	The next cell ID	Calls accepted rate and number of handovers	[7]
		Each BS maintained a database of road information, using prediction for handoff privatization and resource reservation	Road topology information and location information	User trajectory	New call blocking probability and handoff dropping probability	[10] [11] [59]
		Probability, second-order Markov chain and Dempster-Shafer processes were applied to predict the likelihood of the next destination in cellular network	User behavior, location information and road topology information	The next cell ID and transition probability	Prediction accuracy and energy consumption	[54]
		A learning-based graphical model was proposed to learn the path patterns and user type transitional probabilities	Location information, road topology and user velocity	Future location and user trajectory	Prediction accuracy	[89]
		Vertical handoff decision-making in HetNets based on the exploitation of road topology map of the destination hot-spot	Mobile terminal speed, WLAN dynamic traffic and topology information	Amount of data obtained by users	Average amount of received data	[90]
User behavior (see IV.E.2)	User behavior is crucial for analyzing how a user behaves in the future, which requires reasonable training time and is easy to implement but its accuracy depends on the size of data and complexity of the scene. **[20-87]**	The association rules between cells	Cell transition history	The next cell ID	Prediction accuracy	[22]
		Group, time-of-day, and duration characteristics of mobile users were considered in IEEE 802.11 networks	Location information and user behavior	The next cell ID	Prediction accuracy, average delay	[91]
		Combining sequential pattern mining and clustering techniques in WLAN	Location information and user behavior	Future location	Prediction accuracy	[92]
		Intra cell movement prediction was performed based on the network database and positioning techniques	Network information, location information and user behavior	Future location	Prediction accuracy	[93]
		Population modelling shared temporal parameters between people and kept the spatial parameters of individuals over Nokia dataset	User behavior	Future location	Average conditional log likelihood and confidence	[94]
		The use of filtered historical movement pattern and contextual knowledge, both approaches use spatial conceptual maps	Location information, user behavior and contextual knowledge	Future location	Prediction accuracy	[95]
		The length of time user would stay in the current place is predicted	Contextual information and location information	Stay duration and future location	Prediction accuracy and deviation error	[96]
Movement parameters (see IV.E.3)	It represents a typical mathematical/systems approach which is easy to implement but requires accurate moving parameters and cannot guarantee the performance of prediction.**[0-98]**	Trajectory learning and destination prediction based on Markovian model and context-aware tensor decomposition	Location information and road topology information	Future location	Deviation error and prediction accuracy	[13]
		Predict cell transition probability based on angular deviation and distance	Location information and contextual information	Cell transition probability and congestion	Prediction accuracy, dropping and blocking probability	[49]
		Lagrange's interpolation formula was used to fit user's moving path in UDN	Location information	The next cell ID	Handover latency	[50]
		Spatiotemporal context prediction is regarded as context classification based on supervised learning	Location information and contextual information	Future location	Prediction accuracy	[97]

the applicability of the road topology is limited, especially when it comes to a new environment or the map is difficult to obtain.

2) USER BEHAVIORAL INFORMATION

As is discussed in Section I, user behavioral information is the most important data in predicting user's future movements, which can be achieved by analyzing users' historical activities and subdividing the time into different segments [5]. In general, almost all the works in literature characterize user's behaviors with the same criteria, such as location, group pattern, time of day, sojourn time in a cell and so on.

Wanalertlak *et al.* [91] presented a behavior-based mobility prediction scheme to capture short-term and periodic behaviors of mobile user in order to provide accurate next-cell prediction in which location, group, time-of-day and duration were considered. The next point-of-attachments were predicted by maintaining the handoff history of all the users in the network and monitoring direction of movements of users relative to the topological placement of cells. Specially, the next cell predictions were based on the frequencies of occurrences rather than signal strength, and users that have similar mobility patterns are divided in the same group.

Duong and Tran [92] analyzed several mobility prediction schemes so as to find out their deficiencies. And inspired by it, a mobility scheme with the combination of clustering and sequential pattern mining was proposed. Sequential pattern mining techniques were utilized to discover frequent mobility pattern from the movement histories of all mobile users in the coverage region. In addition, since global scale mobile users behaved as groups due to geographic, social and friendship constraints, clustering techniques were applied to extract similar mobility behaviors of multiple users to deal with the lack of mobility behavior of individuals.

Abo-Zahhad *et al.* [93] proposed a future location prediction scheme based on three levels of location detection, including intra-sector prediction, sector to sector prediction and cell to cell prediction. All of these three levels of predictions consisted of four main processes. They were moving sequences' creation process, extraction of frequent movement patterns, finding movement rules and prediction of user's next movement. In the second process, frequent-1 pattern and frequent-k patterns were found. Based on the known frequent patterns, movement rules and movement prediction were then investigated.

Mcinerney *et al.* [94] predicted the future location of users by modeling the habitual location behavior of users based on the hierarchical Dirichlet process. One of the key contributions was that the proposed model could overcome the problem of cold starts and this ability was proved by using the Nokia Lausanne dataset containing detailed mobility observations of 38 people for a year.

From these works above, we can find that in the user behavior-based mobility prediction schemes, clustering and pattern mining are the most frequent used algorithms. Due to the group effect, users with similar behavior can be divided into the same groups based on clustering algorithm, which can reduce the algorithmic complexity. Besides, pattern mining techniques are applied to discover frequent mobility pattern efficiently.

3) MOVEMENT PARAMETERS

In this kind of approaches, the main concept is to predict user's movement based on historical moving parameters such as moving direction, past movement and distance. These information has low dimension, which can be exploited by mathematical formula and simple algorithms like Markov chain. Therefore, these schemes are easy to implement while cannot guarantee high performance.

Kuruvatti *et al.* [49] exploited movement data and context information of diurnal user movements to predict cell transitions in mobile networks. Diurnal mobility model was adopted in which user group direction was probable in only two directions and zero in other directions. Hence, a user group can transit into one of the two adjacent cells from its present cell with respect to user's moving direction. Distance between user and adjacent cells, user's moving direction and their combination were considered. This scheme is easy to implement but depends on the precondition of the known direction. Besides, it requires a uniform distribution of cells as it would be difficult for us to obtain the cell transition when cells are distributed randomly.

Inspired by [49], Li *et al.* [50] extended the scheme proposed in [1] to UDN in which small cells were deployed according to Poisson point process. But unlike [49], user's moving trajectory was fitted according to Lagrange's interpolation and user's moving direction can be obtained by analyzing the slope of the trajectory at a specific position. Li *et al.* [50] expanded the range of interested region and more small cell around a user are considered. Moreover, the impact of small cell density, the radius of interested region and user speed on the performance of the proposed schemes were analyzed.

V. 5G AND MOBILITY PREDICTION RELATED ISSUES

A. THE CURRENT STATUS OF 5G

With the popularization of high-traffic demand applications and the advent of diverse QoS requirements, the next generation of mobile communication system has taken on the challenge of cost-effectively supporting a 1000-fold increase in traffic demand [98] and providing better QoS, which requires a paradigm shift in all aspects of the current mobile networks. 5G, a new generation mobile communication technology in order to ensure data-rate, latency, reliability, and energy efficiency, targets three main usage scenarios with specific capabilities and requirements [99], [100]:

- *Enhanced mobile broadband (eMBB):* wide-area coverage and hotspots for seamless user experience and high throughput.
- *Ultra-reliable and low latency communications (URLLC):* high throughput, low latency and high availability.
- M*assive machine type communications (mMTC):* very large coverage and number of connected low-cost devices with a very long battery life.

To improve the communication performance, 5G needs to apply various technologies, such as UDN, HetNets, massive MIMO, mmWave communication, coordinated multipoint (CoMP) and so on. Among those techniques, CoMP, MIMO and some enhanced coding techniques can increase spectral efficiency [101] while wireless system capacity can be mainly attributed to increase in the number of wireless access points [102]. UDN is considered as one of the most important topics toward the mobile system for 2020 and beyond by METIS [103], where lots of cells are deployed by the customers in their premises, or by the operators in the streets (e.g., on lampposts, trees, and walls) and hotspots (e.g., airports, metro/train stations, and markets) [104].

However, the capacity of system is not necessarily proportional to cell density as densification also brings many challenges, including interference, mobility and energy consumption [105]. Due to the number of cells is comparable to the number of users in UDN, there exists significant gain through advanced interference mitigation techniques like CoMP, which many cells jointly serve users to improve spectral efficiency and enhance capacity. But cell edge users still suffer severe inter-cluster interference in traditional CoMP, which drives the development of UCN. Users are supposed to discover neighboring APs and organize dynamic AP groups (APGs) to serve every user in the network seamlessly without the user's involvement, through which users could enjoy satisfactory and secure service following their movement [30], [106], [107]. Therefore, as the increase of users' diverse QoS requirements, many technologies are proposed to address the tremendous pressure, which brings many issues in applying mobility prediction to 5G networks.

B. MOBILITY PREDICTION ISSUES IN 5G

Mobility prediction is a critical issue across the decades up to the present. In Section IV, we have discussed many state-of-the-art approaches from the perspective of improving the accuracy in mobility prediction. However, with the advent of many new technologies, there will be unprecedented challenges in the applications of mobility prediction.

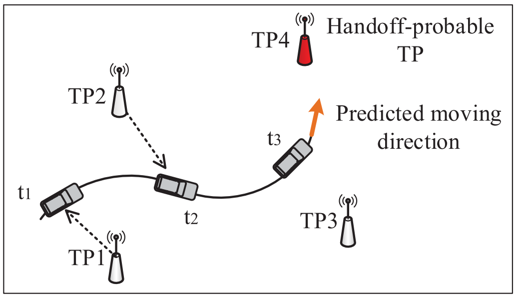

FIGURE 7. An example of handoff management via direction prediction based on trajectory history in UDN.

Therefore, here comes the question, what is the challenge of applying mobility prediction in future 5G networks? In this section, we are going to explain why mobility prediction is desirable in future 5G and discuss the main issues in four aspects, including direction prediction, access points grouping, resource reservation and interference coordination.

1) HANDOVER MANAGEMENT

Handover plays an irreplaceable role in maintaining user's continuous services, which could faces many challenges in 5G. For example, in small and densified mmWave cellular networks, frequent handover and the resultant high switching latency will degrade the performance greatly, which is further exacerbated by the fact that a mmWave channel is vulnerable to the line-of-sight (LOS) blockage and leads to a sudden drop or outage of the signal [108]. Besides, in the architecture of dual-connectivity [109] or multi-connectivity [110], connection setup and switching would happen more frequently, which requires a more effective and predictive handover management strategy. Mobility prediction can alleviate this problem with the prior knowledge of user's speed, direction and handover history, which can narrow down the potential range of TPs and start the handover process ahead of time [111]. Fig. 7 gives an example of handover prediction by predicting moving direction of user in UDN, where historical position coordinates were used for fitting user's trajectory and further predicting its moving direction as well as the handoff-probable TP.

2) ACCESS POINTS GROUPING

UDN provides opportunities to cooperate among several APs for serving a given user, which is well-known as CoMP. Under this framework, investigating the access scheme that organizes multiple APs into respective APG jointly to provide access service for each user, contributing to maximizing the system energy efficiency [112]. Similarly, having the priori information of where a user is going and how long he will stay at a specific place help a lot in virtual cell member updating. In traditional LTE communication systems, users select the next accessing cell depends on RSRP and cell load. However, in 5G UCN, if we update VC members according to RSRP and cell road, it would happen more frequently due to the dense deployment of TP and updating procedures will be executed many times. As a result, with the help of mobility prediction, unnecessary VC update process can be reduced effectively.

3) RESOURCE RESERVATION

With the explosive growth of user equipment, radio bandwidth resource shortage will become more serious in future 5G networks. Besides, due to users' mobility, optimal allocation of the computational resources at the BSs will change inevitably over time. As mentioned before, mobility prediction works well in assisting resource reservation. Plachy *et al.* [113] made use of prediction for dynamic virtual machines placement and tried to find out the most suitable communication path based on expected users' movement. As users are moving and VCs are updated according to users' movement, predicting users' movement is able to reserve bandwidth for the coming users, which can reduce the resource collision. How to assign the resources and balance the load among APs are important issues to satisfy users, especially in high speed movement. As a result, in order to allocate resource properly and improve the energy efficiency, the importance of mobility prediction should be highlighted.

4) INTERFERENCE COORDINATION

Interference is usually caused by APs that use the same resource blocks and it is the main factor affecting the lifting of capacity, especially obstructing the implement of massive MIMO and some wide beam scenarios. Though there are many techniques can handle interference effectively by signal processing, (e.g., [114], [115]), proper resource management is more efficient and energy-saving. In 5G UCN, the relationship between APs in a VC is more complicated, how to manage the limited resource between members of VC is critical. Therefore, designing mobility prediction based resource management scheme to coordinate the interference between different users also makes sense.

5) LOAD BALANCING

To meet the drastic growth of the mobile traffic, 5G network is envisioned to optimize the transmission efficiency and provide higher QoS. Small cell is considered as a promising approach to meet the demand, which results in 5G HetNets. Typically, when the traffic load of the macrocell is dramatically increasing, HetNets could offload parts of the traffic load to small cells for preventing network from congesting and collapsing [116]. Therefore, with the knowledge of user mobility, we are able to predict time-varying traffic load and adopt some strategies like BS on/off to guarantee the load balancing.

VI. CHALLENGES AND FUTURE

With the progress of computer processing capacities and the rapid development of artificial intelligence, mobility prediction gradually becomes a reality and there will be a huge potential for development in this field. However, there still exists many challenges with the advent of new technologies and more needs, which we will discuss as follows.

A. APPLICATIONS IN VEHICULAR NETWORKS

Vehicular network, which related to vehicles, vehicle traffic, drivers, passengers and pedestrians, is a promising addition to our future intelligent transportation systems (ITS). And it is vital to provide safety, assistance to drivers, traffic control, guaranteed QoS and various infotainment applications [117]. Vehicular networking applications can be classified as follows [118]:

- **Active road safety applications:** Active road safety applications are those that are mainly implemented to decrease the probability of traffic accidents and the loss of life, which can be achieved by provide information and assistance to drivers such as intersection collision warning, lane change assistance, traffic condition warning and so on.
- **Traffic efficiency and management applications:** Traffic efficiency and management applications focus on improving the vehicle traffic flow, traffic coordination and traffic assistance and provide updated local information, maps and in general, messages of relevance bounded in space and/or time, concluding *Speed management* and *Cooperative navigation*.
- **Infotainment applications:** This type of application focus on infotainment that can be obtained from locally based services and global Internet services.

These applications, in other words, requirements, push the vehicular network in future to find solutions to meet user's increasing QoS, where mobility prediction plays an important role in handling these issues.

1) MOTION PLANNING

Motion planning is just like route planning, which is responsible for selecting a safe, comfortable, and dynamically feasible trajectory from the vehicle's current configuration to the goal provided by the behavioral decision making hierarchy [119]. With the predicted knowledge of all vehicles on-the-way, it's convenient for traffic management center to predict the traffic condition and dynamically schedule vehicles' route and planning [120]. Based on the advantages of mobility prediction in vehicular networks, the probability of traffic accidents can be reduced largely and traffic management can be performed more efficiently. People or robots (like autonomous driving [121], [122]) can drive to their destination through the journal safely and unimpededly, which is a great envy for those people stuck in traffic nowadays.

2) CONTINUOUS SERVICES

The high node mobility in vehicular networks imposes new challenges on maintaining a long-lasting and low-delay connection between vehicular nodes, and adding IP services to vehicular networks remains an issue due to the frequent handover causing overhead and latencies unsuitable for the faster movement of vehicles [123]. Mobility prediction can provide next positions of vehicle, and reserve sufficient resource for them, which will keep the seamless handover and therefore guarantee the data delivery performance with near-zero delay. For example, Zhao *et al.* [124] proposed a vehicle mobility prediction module to estimate the future connected roadside units (RSUs) by using data traces from a real-world VANET testbed, and then implemented a learning-based method to proactively prefetch the user content to edge caching at RSUs. Imagine how comfort it is for you when travel on the high-speed train at 300 km/h and watch online video without any lag.

B. MOBILITY OPTIMIZATION

As we discussed in Section V, the ultra dense deployment of small-coverage and low-power BSs has become a clear trend in the future and there will be several access points associated with users for higher data rate and more reliable services. However, the network environment is dynamic and changeable according to traffic variations, network failure or users mobility, which results in services interruption. Moreover, frequent handovers and waste of resource boost the researchers to design intelligent and efficient enablers that can manage the future networks such as SON [125], [126]. Mobility prediction can help users switch to the most appropriate cell(s) to avoid collision of cluster-round users according to the estimated location and sojourn time, which is convenient for resource pre-provisioning and handover optimization.

1) HANDOVER OPTIMIZATION

Generally, there are three main phases of any type of described handovers above, including handover measurement and initiation, handover decision and handover execution. In most of existing works, handover decision schemes can be classified into five types: RSS-based schemes, QoS-based schemes, Decision Function-based schemes, Network Intelligence-based schemes and Context-based schemes [127]–[129]. For now, RSS-based handover scheme is applied widely around the world because of its convenient and scalability. However, these traditional criteria are passive due to the lack of knowledge of users mobility, leading to extra signal overhead in the procedures of handover and discontinuous connection; besides, user is "selfish" cause it selects the "best" BS according to its RSS without regard to other users, which degrades the overall performance of the network.

With context information provided by mobility prediction, a target TP is selected not only based on the signal quality but also the knowledge of context information from users and the networks, which can make the handover decisions more intelligent and more "selfless". Therefore, users can get more comfort in this way compared to traditional RSS based handover scheme and the performance of network is ensured to be near optimum. Moreover, the tradeoffs between traditional handover scheme and mobility-prediction-based handover scheme have been studied before implementing in the future. For example, Huang *et al.* [130] have evaluated the impact of mobility prediction accuracy on the performance improvement in handoff calls to make sure whether it is worthwhile to deploy such computationally intensive mobility prediction techniques.

2) RESOURCE OPTIMIZATION

Another crucial aspect of future networks is the optimization and provisioning of radio resources. Existing passive resource allocation scheme cannot adapt to the dynamically changing environment caused by user mobility and congestion of the serving cell, which degrades user experience; while reserving resources over all the cells is impractical and is a great waste of resources. Mobility-prediction-based resource reservation policy can per-reserve a certain amount of resource in the cells that users will probably visit with the help of two following mechanisms:

Traffic prediction: Traffic prediction in future networks is becoming extremely important due to the explosively growing demand for radio access, which drives a traffic-aware energy-saving network architecture. Traffic entropy becomes incredibly small with 10 hours or more information as a prior which means that the predictability of traffic in the future is completely possible [131]. With the prediction of traffic, users can selectively access some cells rather than the nearest one to circumvent "crowded" cell for sufficient resource or to adopt on-off policy from the perspective of energy efficiency. Li *et al.* [132] have given an use case: AI center learns the traffic variations and adjusts BS switching policy by forecast the traffic loads, and build a green cellular network.

Sojourn time estimation: Most of the literature mentioned above focus on giving users' next location or the next cell, which to some extent contributes to select the best cell(s). However, user's dwell time in different cells is not uniform distribution, which means that, in other words, people may stay a very short time in predicted cell because of limited coverage or their behaviors. Obviously, handover procedure performed here as usual is not what we want because they cost lots of resource and generate large overhead but get few service, especially in UDN scenario. Therefore, sojourn time estimation becomes increasingly important in cell selection and get a lot of attention. Aiming at the frequent handovers and handoff failures caused by that result from the increase in BS density, Tiwari and Deshmukh [133] and Merwaday *et al.* [134] both proposed a sojourn time based estimation method, accurately estimating the velocity of mobile users in HetNets. Results showed that proposed ML estimator based on sojourn time outperforms the Cramer-Rao lower bound (CRLB) based on handover count. Besides, many random walk mobility models including random waypoint, Brownian motion, tailored Brownian motion, and truncated Levy walk were tested in [135] to o derive the analytical mean sojourn time in the macro-cell-only area. However, the works ab

C. ASSIST POSITIONING

With the rapid development of technologies and increase of people's demand, LBSs has become extremely important and extensively applied in many domains (e.g., IoT [136], VANET [87] and vehicular network [117]). However, various applications impose great challenge on positioning accurately. Accurate location information helps suspect tracking, medical aid, missile precision hit and other LBSs under the premise of not infringing on privacy.

Though there are many localization approaches (as can be seen in Section III-B) that achieve high positioning accuracy, they can not be applied in some special scenarios, for example, in a smart building of IoT, the widely used GPS can not transmitted through obstacles; besides, a lot of electronic equipments deployed across the whole building unavoidably produce large amounts of signal interference, increasing greatly the difficulty for precise localization [136].

Mobility prediction comes out as a favorable supplement for accurate positioning. And many mobility prediction schemes have been applied to assist positioning more precisely. Lin *et al.* [136] proposed a localization method that takes advantage of the neighbor relative RSS to build the fingerprint database and adopted a prediction model based on MC to assist positioning. Simulation conducted in realistic environment showed that superior performance compared with other well-known schemes. Jaiswal and Jaidhar [87] proposed a predicted position based routing protocol (PPRP) for VANET to minimize the effect of prediction error. The vehicle location was predicted based on history location using Kalman filter to improve the packet delivery ratio, average delay and throughput. Besides, an enhanced localization prediction method on the data fusion localization system was reckoned as natural way to improve applications for VANETs due to VANETs' critical domains that are relying on high accurate and available localization systems, GPS has some unsatisfactory problems such as being unavailable or not so accurate.

D. BOOSTED BY DEEP LEARNING

For the past few years, the vast amount of mobile data has been created by the rapid spread of mobile devices and users. However, in the field of data mining, some shallow-structure algorithms such as SVM have difficulty in handling high dimensional data with the rapid development of mobile network due to the requirement of large amount priori knowledge to manually extract feature [137]. For high-dimension data, deep learning has been validated to outperform shallow-structure machine learning algorithm. Deep learning has recently attracted great interests and achieved significant results in many fields, such as computer vision, natural language processing, speech recognition, etc.

In order to have a better understanding of human mobility, mobile data need to be collected in higher dimensions and analyzed deeply, which makes deep learning a promising booster in mobility prediction. Actually, there are many works focusing on the prediction of human trajectories and mobility patterns but few of them involves applications in wireless networks [138]–[140]. For example, Do *et al.* [139] proposed a multi-entry neural network architecture named MENET combining the strength of deep learning and multiview learning to infer users' location with words, paragraph semantics, network topology, and timestamp information. However, prediction accuracy was focused in this paper and cellular applications or other LBSs were not exploited. More like [140], optimal handover controllers in wireless systems were learned by a deep neural network and reinforcement learning, and controlled the handover process via predicting user's pattern that partitioned in advance, which has improved the handover rates in contrast to traditional online schemes.

However, there are still many hard-to-tackle problems when applying deep learning to mobility prediction. Single model like convolutional neural network (CNN) may be difficult to deal with the long time series data while combination of CNN and other neural networks like recurrent neural network may lead to a more complex structure and make it hard to train; Besides, short-term forecasting is satisfactory while long-term prediction and a better understanding of the relationship of both the endogenous and exogenous variables in mobility prediction, are expected to be researched in the future [141].

VII. CONCLUSION

Due to the increasing popularity in the aspect of mobility prediction, we have carried out an overview on the items related to mobility prediction in this survey. Firstly, the necessity and predictability of performing this not-trivial technique are discussed in detail. Mobility prediction can provide satisfactory QoS for subscribers; besides, OPEX and CAPEX can be reduced largely with the prior knowledge of subscribers' mobility. Moreover, a wide range of traditional and unconventional approaches are classified and illustrated for the convenience of readers. Differences and similarities between these methods are listed in tables for fast query. Later, we discuss the trends of 5G network development and issues related to mobility prediction on account of it's key application in the future networks. Finally, many applications and accompanying challenges have been explored and categorized, which we expect to apply and handle in the future for the most important goal–improvement of user experience.

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