1-1-2019

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Recommended Citation

H. Zhou et al. (2019) "Exploiting Mobile Social Networks From Temporal Perspective: A Survey," in IEEE Access, vol. 7, pp. 180818-180834, 2019, doi: 10.1109/ACCESS.2019.2958951.

IEEE Access
SPECIAL SECTION ON INTELLIGENT DATA SENSING, COLLECTION AND DISSEMINATION IN MOBILE COMPUTING

Received November 14, 2019, accepted December 3, 2019, date of publication December 13, 2019, date of current version December 23, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2958951

Exploiting Mobile Social Networks From Temporal Perspective: A Survey

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This work was supported in part by the National Natural Science Foundation of China under Grant 61872221, Grant 61602272, Grant 61672117, and Grant 61902044, in part by the National Key Research and Development Program of China under Grant 2018YFF0214700, and in part by the Chongqing Research Program of Basic Research and Frontier Technology under Grant cstc2019jcyj-msxmX0589.

ABSTRACT With the popularity of smart mobile devices, information exchange between users has become more and more frequent, and Mobile Social Networks (MSNs) have attracted significant attention in many research areas. Nowadays, discovering social relationships among people, as well as detecting the evolution of community have become hotly discussed topics in MSNs. One of the major features of MSNs is that the network topology changes over time. Therefore, it is not accurate to depict the social relationships of people based on a static network. In this paper, we present a survey of this emerging field from a temporal perspective. The state-of-the-art research of MSNs is reviewed with focus on four aspects: social property, time-varying graph, temporal social property, and temporal social properties-based applications. Some important open issues with respect to MSNs are discussed.

INDEX TERMS Mobile social network, temporal perspective, temporal social properties, time-varying graph, temporal social properties-based applications.

I. INTRODUCTION

MSNs are a network of mobile devices (typically smart phones, ipads, PDAs, etc.) that communicate opportunistically and that are carried by human users [1]–[3]. Due to the sparse and dynamic nature of MSNs, nodes in the network may be disconnected at an indeterminate time, which makes it difficult to spread data in MSNs [4], [5]. Similar to Opportunistic Mobile Networks, MSNs do not need infrastructure and are highly dependent on human social behaviors. Therefore, mobility or, more generally, temporal nature has become a major factor affecting user service quality [6], [7].

Recently, social network analysis technology has provided a new perspective for the study of MSNs, e. g., community, centrality, similarity, social ties, and so on; community is an important metric for mobile social network analysis [8]–[10]. With the rapid development of MSNs, community detecting has attracted more and more researchers' interest, and its purpose is to explore a series of discrete relationships between individuals. In particular, detecting temporal communities from complex user networks has become extremely important, with the goal of discovering hidden community structures in time-varying networks. The current research work is not limited to discovering hidden community structures in time-based networks, but rather investing a lot of work to study the evolution of temporal communities over time. Conti et al. in [11] show that the behavior of dynamic networks can be more accurately captured by time-centrality indicators. Based on the similarity analysis, authors in [12] show that they can effectively detect the spatio-temporal clustering of MSNs and divide the community structure. Furthermore, some studies show that the knowledge of community structures can help improve data forwarding performances in MSNs. Authors in [13] studied the role of temporal communities in data dissemination in MSNs. The research of temporal community detection and its application in MSNs

The associate editor coordinating the review of this manuscript and approving it for publication was Xuxun Liu.

has been a hot topic. There are also many studies on link pattern prediction in MSNs. Through detecting reliable and effective links, the reliability of data forwarding can be improved and the forwarding cost can be reduced [14]. At the same time, the topology design problem in time evolution is also an important aspect, which also can help improve data forwarding efficiency and reduce data forwarding cost [15].

In the literature, there are several surveys addressing different aspects of MSNs. In [16], Huang et al. presented different research challenges on different layers of a protocol stack in MSNs. In [17], Kayastha et al. presented a comprehensive survey on the MSN specifically from the perspectives of applications, network architectures, and protocol design issues. In [18], Conti et al. analyzed four successful networking paradigms, i.e., mesh, sensor, opportunistic, and vehicular networks. They also pointed out that computing and communication solutions are tightly coupled with people in MSNs. In [19], Mota et al. discussed the commonly used tools, simulators, contact traces, mobility models and applications available. In [20], Cao et al. summarized the routing protocols into three categories, i.e., native replication based approaches, utility based approaches and hybrid approaches. They also discussed different applications, i.e., unicasting, multicasting and anycasting. However, none of them have exploited MSNs from the temporal perspective.

MSNs rely on a wide range of short-range wireless technologies to form temporal ad hoc networks for opportunistic communications [21], [22]. Therefore, the mobility of mobile devices will directly affect the topology of the network and the quality of the communication. MSNs have high mobile characteristics, and the network structure changes with the trajectory of human movement. Temporal characteristics cannot be ignored in MSNs analysis. Some studies have tried to study time-varying networks based on time-varying graphs, and focus on quantifying the impact of temporal properties on time-varying networks. Time-varying graphs are a natural model, which can effectively reflect the social relationship between nodes, and extend the concept of connectivity and the definition of graphical components to the time dimension. Therefore, in the following parts, we will first explore time-varying graphs and their applications, and then we will give a detailed survey about exploiting MSNs from the temporal perspective, i.e., temporal social property and temporal social properties-based applications.

The rest of the paper is organized as follows. In section II, we briefly introduce some essential issues of MSNs. Then, we introduce several important social properties used in MSNs. Section III introduces some recent studies about the time-varying graph. In Section IV, we introduce some recent studies about temporal social properties used in MSNs. In Section V, we introduce some recent studies about temporal social properties-based applications, i.e., data forwarding and data dissemination algorithms. Section VII gives a conclusion of this paper, and some future research directions are introduced in Section VI.

II. ESSENTIALS OF MSNs

In this section, we first introduce the architecture of MSNs, and then some social properties related to MSNs.

A. ARCHITECTURE OF MSNs

Based on the way in which nodes inject and access information, the architecture of MSNs can be divided into three categories: centralized, distributed, and hybrid. Centralized architecture is the most common mobile social network deployment architecture. The remote server stores all the information of the members of the social network, and the terminal nodes access the server through the wireless infrastructure to complete communication and other operations. The key feature of the distributed architecture is that there is no centralized server. Thus, mobile users can only communicate and access social information by connecting to other users. Hybrid is an combination of centralized and distributed architecture, which is created on the basis of these two architectures. Nodes can access centralized servers or exchange data directly with other nodes. Fig. 1 shows an example of the three system architectures for mobile social networking services. In this paper, we focus on investigating the distributed architecture of MSNs.

B. COMPONENTS OF MSNs

In this part, we introduce the components of MSNs. As shown in Fig. 1, a MSN is divided into three components: (1) Network infrastructures; (2) Mobile users; and (3) Content providers.

1) **Network infrastructures:** To deliver a data from the source node (content provider) to the destination node as a mobile user, network infrastructure plays an important role in the centralized architecture of MSNs. For example, network infrastructure, like Wi-Fi AP, Cellular basestation, provide Internet access point for mobile users in MSNs.
2) **Mobile users:** Mobile users in MSNs can be considered as mobile devices (typically smart phones, ipads, PDAs, etc.) carried by humans that communicate opportunistically. Mobile users must have network interfaces that can be used as a medium such as Wi-Fi, Bluetooth, and cellular network depending upon the suitability.
3) **Content providers:** Content providers in MSNs work as a fixed, and centralized dedicated server, for instance, a web-based news server that is interlinked via the Internet. Using network infrastructure, they can disseminate contents into a bunch of groups of mobile users.

C. SOCIAL PROPERTIES OF MSNs

The social and personal properties of MSNs are important basis for designing efficient data forwarding and dissemination protocols. By learning and analyzing user behavior, we can obtain social and personal properties. Common social properties include community, centrality, friendship, similarity and so on. These properties are closely related to the social relationship of human. Personal properties

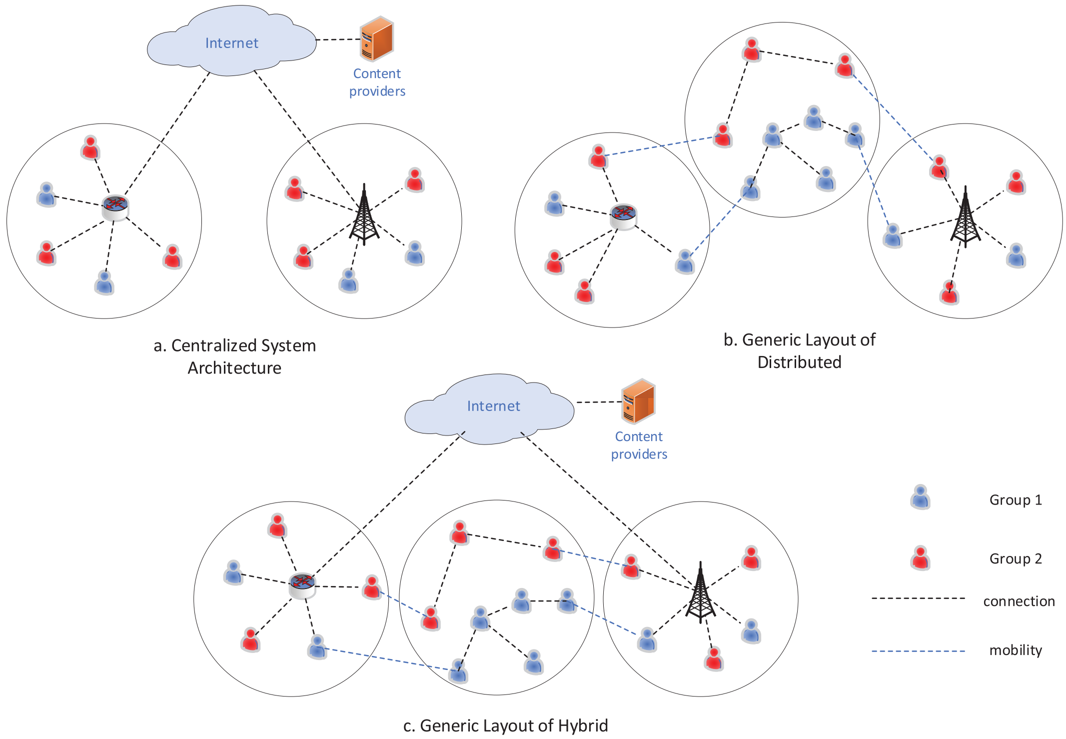


FIGURE 1. An example of three system architectures for mobile social networking services.

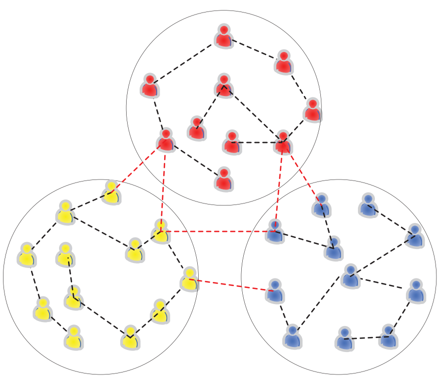


FIGURE 2. Community structure chart in Mobile Social Networks.

include preferences, willingness and selfishness. Authors in [23] designed a community-based data forwarding protocol for MSNs. Mobile nodes are grouped into communities through some community detection algorithms, and data is forwarded between nodes based on community. Authors in [12] used node similarity, centrality and other social attributes, to design a community-independent data forwarding protocol for MSNs, which focused on the context information of the node and the historical contact frequency between the users. Fig. 2 shows an example of the community structure chart in MSNs. Therefore, investigating the behavior of individuals and groups in MSNs is very important for designing efficient data forwarding and data dissemination algorithms.

In addition to the analysis of off-line MSNs, mobile software analysis based on social software is also a research hot-spot. Some research consider mining useful information from a person's social files and classifying them according to the type of social network. Through the analyst's interest preferences and historical browsing records, people with specific common interests are brought together and form a virtual social community. Based on this, researchers proposed a community-based malware time opportunity patch [24].

Social network analysis technology has caused widespread concerns in many areas, which can guide topology design in time-evolved MSNs and provide new ideas for application design and malware inclusion. Table 1 shows some social properties and conceptual metrics. Social relationships emphasize the interaction between two people. For example, people usually build closer relationships with familiar people rather than strangers. Friendship is a common indicator used to describe social relationships, indicating the degree of common interest between two nodes. In the next part, we will give a brief introduction about these social properties related to MSNs.

1) SIMILARITY

Similarity is another important concept in sociology. Similarity depends on the common connections or common interests of the nodes. Generally, the more the number of common neighbors in a mobile social network, the higher the similarity between nodes. Recently, several methods for discovering and detecting distributed spatio-temporal clustering in MSNs based on similarity have been proposed. Research based on

TABLE 1. Social Properties of MSNs.

Social Metrics	Description
Similarity	The common connections or common interests of individuals.
Social Tie Strength	The strength of the social interactions between individuals.
Social Graph	Vertices (nodes) indicate human individuals, and edges (links) indicate social relationships between individuals.
Community	A clustering of individuals that are closely connected to each other. Members in the same community are more likely to interact with each other.
Degree Centrality	The number of direct ties involving a given node.
Closeness Centrality	The reciprocal of the mean geodesic distance, which is the shortest path between a node and all other reachable nodes.
Betweenness Centrality	The extend to which a node lies on the geodesic paths linking other nodes.

community similarity can help improve data transmission efficiency of mobile opportunity networks [14].

2) TIE STRENGTH

Tie strength is a quantifiable attribute in MSNs. It is used to indicate the strength of the connection between two nodes. The characteristics of tie strength can be described by the following aspects: time quantity, emotional intensity and intimacy. The most commonly used indicators for describing tie strength are as follows: intimacy, recency, frequency, reciprocity, longevity and mutual trust. The strength of tie in MSNs directly affects the quality of data dissemination.

3) SOCIAL GRAPH

An important challenge in MSNs is to accurately represent the relationship between two nodes. Nodes in a social network are connected to a map based on the small world behavior, called a social graph. In a social graph, nodes represent human individuals, and edges represent social relationships between individuals. It can reflect node relationships in social networks in an intuitive way. To a certain extent, social graphs are equal to social networks. Based on the different connections between nodes, social graphs, interest graphs, neighbor graphs and regular graphs are proposed accordingly.

4) COMMUNITY

Community is an important sociological concept that reflects the social relationships between people. Since mobile devices are usually carried by people, information interaction has a significant correlation with human activities. It has been shown that members of the same community are more likely to interact with each other than to interact with members of another community [13]. Community detection is an interesting research area, and many studies have made some contributions to transient community detection. Past studies focused on detecting communities based on static networks, which emphasized the fixed links between community members.

5) CENTRALITY

Centrality is used to describe the importance of nodes in MSNs, mainly used for network topology analysis. Among them, degree centrality is one of the simplest centrality measures, and the closeness centrality is also a commonly used measure.

(1) **Degree centrality:** Degree centrality is measured by the number of links that may be touched with other nodes.
(2) **Closeness centrality:** Closeness centrality is equal to the reciprocal of the average shortest distance to other nodes.
(3) **Between-ness centrality:** Betweenness centrality is another centrality metric, which is equal to the number of shortest paths passing through a given node.

III. TIME-VARYING GRAPH AND ITS APPLICATIONS

In this section, we first introduce the difference between the static graph and the time-varying graph, and then introduce some recent studies based on the time-varying graph.

A. STATIC GRAPH AND TIME-VARYING GRAPH

Static graphs can be used to analyze the network structure, which represents the network topology as a snapshot. In earlier studies, static graphs were widely used to analyze stable networks because it can visually reflect the advantages of network topology. As mobile smart devices join the network at an unprecedented rate, network topologies are characterized by evolution over time. Static graphs ignore the time varying of network topology, and the time ordering of contacts. Therefore, it is not suitable to analyze the topology of MSNs by using static graph.

Time-varying graphs can be considered as an ordered sequence of graphs, which calculates the state of the network topology by setting a time window. Time-varying graphs can effectively capture the dynamic characteristics of time-varying networks. Therefore, many researchers have tried to use time-varying graphs to analyze the topology of MSNs rather than using static graphs. Time-varying graph represents the network topology as a series of snapshots by setting a time window. By studying the aggregation state of a specific time window, the state of the network topology can be calculated more accurately. Fig. 3 shows an example about the difference between the static graph and the time-varying graph. Fig. 3(b) shows a time-varying graph in a period of t1 to t5, and Fig. 3(a) shows the corresponding aggregated static graph. It can be found that the network topology of the time-varying graph is obviously different from that of the aggregated static graph. For example, as shown in Fig. 3(b), if we look at the time-varying graph in t2, node 10 does not

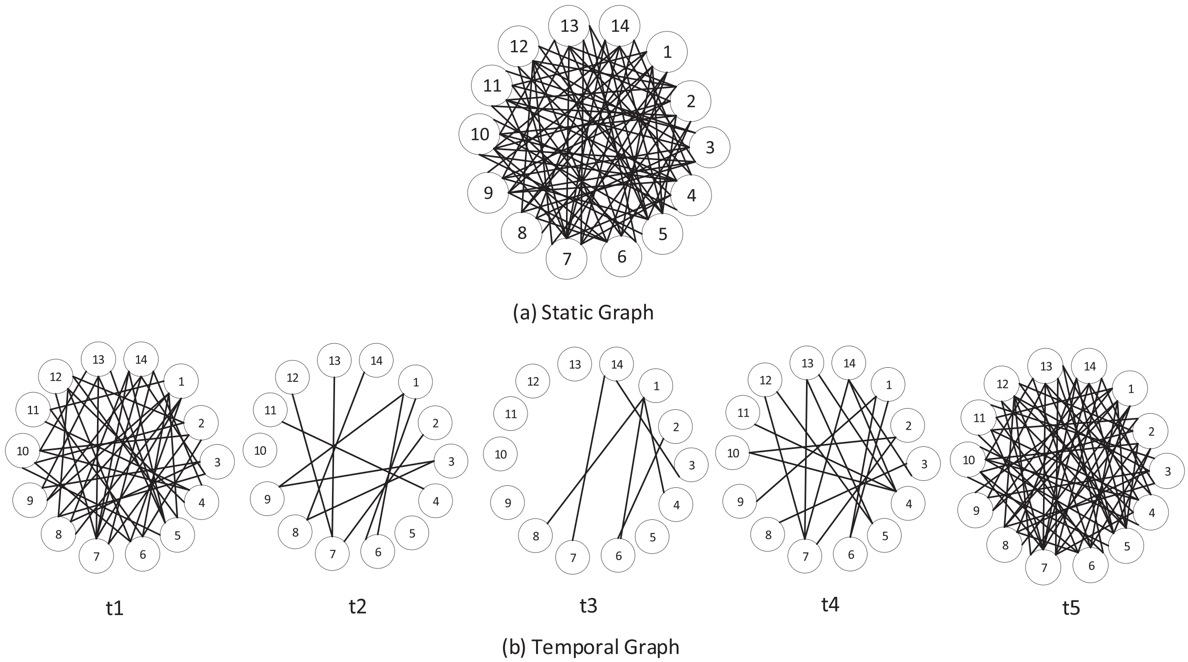


FIGURE 3. **(a) shows the corresponding aggregated static graph, and (b) shows the temporal graph in a period of t1 to t5.**

have contact with node 2; but if we take a look at the aggregated static graph in Fig. 3(a), node 10 has several contacts with node 2. Many researchers have tried to use time-varying graphs to analyze the network topology of MSNs, so as to design efficient routing and data dissemination protocols for MSNs. In the following, we give a brief overview about these studies.

B. TIME-VARYING GRAPH-BASED APPLICATIONS

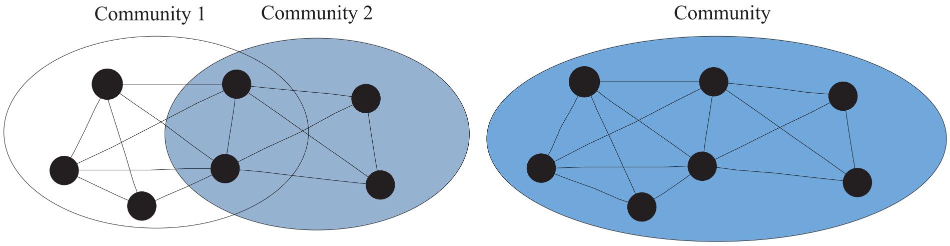
Time-varying is a very important concept in MSNs. In this part, we briefly review some recent studies based on time-varying graphs in MSNs.

The work in [25], studied the small-world behavior using time-varying graphs in MSNs, and gave the concept of standard static graphs and time-varying graphs. The authors defined a small world in time as a time-varying graph, in which the links were highly concentrated. The proposed system is essentially dynamic over time and the links are also fluctuating. At present, the phenomenon of small worlds in static graphs has been extensively studied. The high-cluster real network ignores the time dimension, and this study makes up for the shortcomings of previous research. The method proposed by the author introduces a measure of the temporal distance based on time-varying graph, considering the actual time sequence, duration and correlation between different links. Although the proposed method cannot fully capture the dynamic correlation of time-varying networks, it avoids the shortcomings of neglecting the time dimension in the study of time-varying small worlds.

In [26], Tang et al. discussed the potential of time-varying graph metrics in real-world networks from the field of popular communication. In particular, time-centricity was actively considered in order to capture the basic characteristics of time-varying graphs. First, based on the robustness of the intelligent attacks, the authors proposed a scheme to curb the spread of mobile malware based on the short-range radio transmission strategy. Second, the authors proposed how time-varying graph metrics can be used to study random errors. Finally, the authors provided an overview of the existing and potential applications of human epidemiology, summarized some of the research contributions in these areas, and presented some research directions for future work.

In [27], Ribeiro et al. proposed a mathematical framework to analyze the effect of time resolution on time-varying networks. The proposed mathematical model focuses on the basic random walk process, analyzes how the behavior of the dynamic process depends on the time aggregation window of the underlying time-varying graph in any Δt time, and gives a clear explanation of the role of Δt in the walker behavior. They provided an analytical representation of the asymptotic occupancy probability of RW as a Δt function, which can accurately describe the behavior observed on a real data-set and provide accurate results in a network environment driven by synthetic activity. The results showed that the proposed mathematical model can well describe the observed effects introduced by time aggregation, which indicated the effectiveness in a large class of time-varying networks.

In [13], Nicosia et al. extend the concept of connectivity and the definition of nodes and graphical components to the case of time-varying graphs, with particular attention to two important concepts in graph theory, namely graph connectivity and components. Based on the mapping relationship, the authors map the time-varying graph to a



(a) Temporal Community (4:00-8:00) (b) Aggregated Community (0:00-24:00)

FIGURE 4. **Comparison of temporal community and aggregated community.**

Time Interval	Temporal Centrality Value	Aggregated Centrality Value
0:00-6:00	0.83	0.345
6:00-12:00	0.25	
12:00-18:00	0.1	
18:00-24:00	0.2	

FIGURE 5. **Comparison of temporal centrality and aggregated centrality.**

static graph containing all the information about the time reachability of the pair of nodes, and prove that finding the strongly connected component in the time-varying graph is an NP-complete problem. Finally, the authors propose the results of time component analysis on three real-time changing systems based on time-varying graphs constructed from three different data sets of humans. This analysis verifies that the classical aggregation representation of networks that evolve over time eliminates most of the richness of the original system.

IV. TEMPORAL SOCIAL PROPERTIES

As introduced above, traditional network analysis uses static network, or models that aggregate node contact information during a period to analyze social properties in MSNs. Such methods may break down when the network topology changes very fast, especially MSNs. For example, as shown in Fig. 4, there exists two communities in the network if we only take 4:00-8:00 into consideration, but there exists only one community in the network if we take the whole day (0:00-24:00) into consideration. Similarly, Fig. 5 shows a comparison of the temporal centrality values and aggregated centrality values of a certain node. It can be found that temporal centrality values at different time intervals are obviously different, and the temporal centrality value at time interval 0:00-6:00 is the largest. However, if we take the whole day into consideration, the aggregated centrality value is 0.345. To overcome such limitations, some studies have tried to analyze social properties in MSNs from the temporal perspective. In this section, we will introduce some latest studies about temporal social properties.

A. TEMPORAL COMMUNITY

In this part, we give a brief overview about the temporal community detection and analysis in MSNs.

Authors in [28] proposed a contact-burst-based clustering method to detect temporal communities by exploiting the pairwise contact processes. In this method, they formulate each pairwise contact process as regular appearance of contact bursts, during which most contacts between the pair of nodes happen. Based on such formulation, they use the hierarchical clustering algorithm to detect temporal communities by clustering the pairs of nodes with similar contact bursts. Similarly, authors in [29] also proposed a methodology to break the temporal contact graph into clusters of nodes that contact more frequently and for longer periods of time. The proposed temporal community detection method consists of two steps. First, each snapshot graph is partitioned into smaller and denser clusters of nodes. Second, a hierarchical clustering algorithm is applied to aggregate the snapshot clusters into relevant communities.

In [30], Yusuf et al. proposed the concept of temporal social network, with emphasis on the management of community members in temporal social network. It was discussed that many major challenges need to be solved to create and maintain viable transient social communities, including managing dynamically created social graphs, maintaining connections across heterogeneous nodes and interfaces, and effective messaging between nodes in the community. The authors had innovatively used micro-graphs to provide qualitative and quantitative advantages for the realization of transient social networks, which enabled social network activities to take place in an environment where infrastructure support is inadequate. It helps nodes discover and participate in other nodes based on device-level or application-level properties. The work of this project was to implement micro-scale technology on the smart-phone running Android operating system, which laid a foundation for future research.

In [31], Du et al. proposed the concept of progression analysis of community strengths (PACS). In order to effectively track the time community strength in dynamic networks, they proposed a new method, which was coherent during the observation period. They expressed the tracking of the progress of community power as an optimization problem and established a framework. The proposed optimization framework can reduce the short-term noise impact of the network and calculate a reliable community strength score, which is highly adaptable to long-term network evolution. In order to validate this algorithm, they conducted extensive experimental research using a synthetic data set and five real data sets, demonstrating the effectiveness and robustness of the method in discovering community advantages.

In [32], Tang et al. proposed a new time distance measurement method for temporal communities in mobile and online social networks. Considering the evolution of the network from the global view and the delay in the information diffusion process, the time-varying time characteristic charts are captured using the proposed metrics. The metrics captured by this method are compared with those used in the static diagram, including duration, delay of contact interaction, and chronological order. The concept of internal component and external component is proposed to represent the reachability of the network. These technologies are applied to mobile time-varying networks and interactive online social networks. The authors introduced the concept of network accessibility, and provided the quantitative results of comparing the three social network data sets, which provides a reference for future research work.

In [23], Huang et al. studied the community-based topology design problem in predictable delay tolerant networks (DTN) and proposed five heuristic algorithms to ensure that any pair of devices in the tolerant delay network are guaranteed to ensure the total cost of the network topology is minimized. There is a spatiotemporal path connecting them and the reliability of the link is greater than the required threshold. The five heuristic algorithms proposed are listed below: a heuristic algorithm based on the least cost reliable path, a heuristic algorithm based on the greedy algorithm to find the least cost reliable path, a heuristic algorithm with the lowest cost path or the lowest cost reliable path, a link deletion algorithm based on the greedy algorithm, and a link addition algorithm for greedy algorithm. A large number of simulation results confirm that the proposed topology design method ensures the connectivity and reliability of the path between any pair of devices under the premise of significantly reducing the cost of the topology.

In [33], Tang et al. proposed a dynamic community detection method for identifying temporal communities with high time-varying characteristics. In order to improve the flexibility of the dynamic community detection method and realize the function of automatically estimating the number of communities in the dynamic social network without human intervention, they studied the random block model and the Dirichlet process hybrid model in detail, and proposed a new dynamic community detection method. The experimental results of a large number of simulation datasets show that the proposed method can naturally deal with node addition and node loss, and the dynamic community detection effect is better than the general method.

In [34], Orlinski et al. made a survey on the rise and fall of spatiotemporal clustering in MSNs. The prosperity of spatiotemporal clustering in MSNs is as follows: since the 1960s, distributed cluster detection technology has been developed, which is widely used in high-efficiency data transfer problems in high dynamic mobile ad hoc networks, and achieves effective data transfer performance. Later, researchers did a lot of work, using a larger data set to optimize spatiotemporal clustering. However, cluster-dependent data transfer algorithms may be inefficient in some cases, i.e., data transfer methods may suffer from efficiency loss due to the difficulty in inferring time information from the resulting cluster data.

In [35], Li et al. proposed a novel method to study dynamic and incomplete spatiotemporal data mining periodicity, which overcame the shortcomings of traditional periodic detection methods and does not need to be directly applied to motion data. Then they proposed a new generic framework, called Periodica, to detect the periodicity of time events and to process observed sparse and incomplete motion data. This periodic pattern mining technique in spatiotemporal data used a density-based approach to find reference points and used reference points to detect a large number of interleaved periodic behaviors. A large number of actual motion trajectory data experiments prove the feasibility and effectiveness of their method. However, the proposed method of inferring periodic behavior from motion data is not applicable to non-dense areas on the map.

In [36], Zhou et al. focused on the evolution of the community over time, proposed to discover transient communities (TC) from communication documents, and described the problem as a tripartite graph partition problem. The core idea was that the social network is a network of authors, text, and publishing sites, as a tripartite graph. The two main challenges in addressing this new problem were to incorporate the temporal aspects of data and to deal with heterogeneous networks. A new constrained partitioning algorithm was proposed to discover temporal communities by dividing threads into graphs of different time periods. The clustering accuracy of the proposed method was greatly improved in the synthesis of data sets.

In [29], Anna et al. focused on the information propagation in social networks. They combined the community detection techniques in the dynamic graph to identify clusters that are clustered more frequently and longer, and were named transient communities. Starting from the contact analysis, the authors analyzed four kinds of mobile user contact methods, and analyze the structure and evolution of the contact diagram with time graph model. This work defined the time contact diagram as a series of snapshots of the contact trajectory, each of which is a static diagram, $G_t(V, E_t)$, which used Jaccard Index to draw the similarity map between nodes. Data sets used hierarchical clustering to aggregate similar clusters, which work in the following three steps: Initialization, Distance Calculation, and Community Merge. It is an innovative finding that nodes that spend more time in transient communities have less impact on content propagation than nodes outside of temporal communities.

In [37], Hu et al. investigated the key role of communities with anomalous evolutionary behaviors, which can determine the mainstream of community evolution. They proposed an algorithm for mining outliers in the evolution of temporal communities to detect community evolutionary outliers that are significantly different from community actors and have dramatic changes in member roles in the community. They proposed the algorithm based on the transition matrix of community evolution, and the M-estimation regression of the robust transfer matrix optimizes the method. The algorithm can effectively detect community outliers and distinguish them from nomadic data. The experimental results showed that the proposed method is very effective in mining outliers that have an important impact on community evolution.

In [38], Chen et al. proposed a framework of principles that transcends regular time communities and presents the concept of overlapping communities with the aim of studying the potential stability of complex networks and enhancing the understanding of complex networks in the real world. In particular, the study presented a principled representation of the problem of detecting overlapping time communities by quantifying the quality function of the community structure in any snapshot. On the basis of two assumptions, nodes can belong to multiple communities at any given time, and these communities can persist over time, and the authors gave test formulas for overlapping community. Compared with the greedy heuristic algorithm, the real network dataset evaluates the superiority of the method and illustrates its efficacy.

In [39], Dabideen et al. investigated the temporal community detection in Mobile Ad-hoc networks (MANETs) and proposed a distributed real-time protocol, called CLAN, to detect efficient distribution temporal communities in MANET without global topology information. The essence of the protocol was based on the label adaptation algorithm to re-allocate the time-varying graph in MANET. The authors defined the concept of social entropy to achieve network topology weighting and designed a layered routing protocol. In CLAN, the local rules of the community are rediscovered as the network evolves, community information does not need to be discretized for a series of snapshots. Extensive simulation results show that CLAN is effective in time community detection and generates significantly less overhead than currently proposed methods.

B. TEMPORAL CENTRALITY

In this part, we give a brief overview about the temporal centrality definition and analysis in MSNs.

Authors in [40] proposed three temporal centrality metrics (Temporal degree, Temporal closeness, Temporal betweenness) based on the time-ordered graph in MSNs, which extends the existing static centrality metrics to the dynamic case. They applied the proposed temporal centrality metrics to real data sets from two real-world interpersonal contact networks and the simulation results demonstrated the validity and feasibility of the proposed metrics. The proposed three temporal centrality metrics are listed as follows:

(1) **Temporal Degree Centrality:** Different from the Degree Centrality, the Temporal Degree Centrality $TD_{t_1,t_2}(v)$ for a node $v \in \mathbf{V}$ on a time interval $[t_1, t_2]$ where $0 \le t_1 < t_2 \le T$ is constructed as the normalized total number of inbound edges to and outbound edges from v on the time interval $[t_1, t_2]$, disregarding the "self-edges" from v_{t-1} to v_t from all $t \in \{t_1 + 1, \cdots, t_2\}$.

(2) **Temporal Closeness Centrality:** The Temporal Closeness Centrality $TC_{t_1,t_2}(v)$ for a node $v \in \mathbf{V}$ on a time interval $[t_1, t_2]$ where $0 \le t_1 < t_2 \le T$ is the sum of inverse temporal shortest path distances to all other nodes in $V\backslash v$ for each time interval in $\{ [t, t_2] : t_1 \le t < t_2\}$. Formally, the Temporal Closeness Centrality for a node v is expressed as:

$$TC_{t_1,t_2}(v) = \sum_{t_1 \leqslant t < t_2} \sum_{u \in V\backslash v} \frac{1}{\Delta_{t,t_2}(v, u)} \tag{1}$$

where $\Delta_{t,t_2}(v, u)$ is the temporal shortest path distance from v to u on a time interval $[t, t_2]$. If there is no temporal path from v to u on a time interval $[t, t_2]$, $\Delta_{t,t_2}(v, u)$ is defined as ∞.

(3) **Temporal Betweenness centrality:** The Betweenness Centrality of a node is defined as the proportion of shortest paths passing through it, so the Temporal Betweenness $TB_{t_1,t_2}(v)$ for a node $v \in V$ on a time interval $[t_1, t_2]$, $0 \le t_1 < t_2 \le T$, should be the sum of the proportion of all the temporal shortest paths through the vertex v to the total number of temporal shortest paths over all pairs of nodes for each time interval in $\{[t, t_2] : t_1 \le t < t_2\}$. Let $S_{x,y}(u, v)$ denote the set of temporal shortest paths from source s to destination d on the time interval $[x, y]$ and $S_{x,y}(s, d, v)$ the subset of $S_{x,y}(s, d)$ consisting of paths that have v in their interior. Then, the temporal betweenness centrality for a node v is expressed as:

$$TB_{t_1,t_2}(v) = \sum_{t_1 \leqslant t < t_2} \sum_{\substack{s \ne v \ne d \in V \\ \sigma_{t_1,t_2} > 0}} \frac{\sigma_{t_1,t_2}(s, d, v)}{\sigma_{t_1,t_2}(s, d)} \tag{2}$$

where $\sigma_{t,t_2}(s, d) \equiv |S_{t,t_2}(s, d)|$ and $\sigma_{t,t_2}(s, d, v) \equiv |S_{t,t_2}(s, d, v)|$.

Similarly, in [41], Zhou et al. also tried to model temporal centrality of nodes based on the time-ordered graph in MSNs. However, to calculate the importance of nodes in MSNs more accurately, they defined a new centrality metric named Cumulative Neighboring Relationship (CNR). Then, they proposed three particular time-ordered aggregation methods, i.e., the Average Time-ordered Aggregation Method, the Linear Time-ordered Aggregation Method, the Exponential Time-ordered Aggregation Method, and combined with CNR to measure the temporal importance of nodes in MSNs.

In [42], Zhou et al. tried to predict three important centrality metrics, namely betweenness, closeness, and degree centrality from the temporal perspective by analyzing the extensive simulation results in different real mobility traces. Utilizing the observations from extensive real trace-driven simulations, several intuitive reasonable prediction methods were proposed to predict the future centrality of nodes in MSNs from the temporal perspective. To further improve the prediction performance, they proposed a K-order Markov chain model to predict the future temporal centrality for MSNs in [43].

In [44], Kim et al. first studied predicting the future topology of the network by not using ad-hoc prediction functions. Particularly, they evaluated the node importance by using empirical data collected by mobile devices, which focused on three important metrics: between-ness centrality, closeness, and degree centrality. The authors showed that natural human legacy effects and human periods correspond to node centrality. The calculation of such central metrics was based on two hypotheses. First, the study assumed that the relationships between nodes are known. Second, the authors assumed that the delay-tolerant opportunistic communication protocol is under the assumption of a fixed nature of human contact. Compared to predicting the centrality value using the ad-hoc prediction function, the study can be used to process real-time dynamic networks, and the average accuracy of the best performing prediction function was improved by 25%.

In [45], Tang et al. focused on dynamic interaction over time and proposed new time-centric metrics. The location of nodes relative to other nodes can be classified and utilized, and identifying key nodes is an important part of analyzing and understanding network systems. The authors pointed out that over time, a series of snapshots of the network topology can more accurately capture the behavior of dynamic networks. Based on the real enterprise email dataset, the authors used static and time analysis methods to measure the role of information dissemination and information mediators from both semantic and dynamic perspectives. Important node is chosen by static and time-critical centrality. The authors used a separate dynamic process to evaluate the proposed time-centered metrics. Compared with existing static analysis, time metrics can not only find important nodes that are more conducive to information dissemination, but also discover individuals who play an important role in most communication channels.

C. OTHER TEMPORAL SOCIAL PROPERTIES

In this part, we give a brief overview about other temporal social properties, except temporal community and centrality.

In [14], Huang et al. proposed a link pattern prediction model with kernel regression to predict future link patterns in opportunistic networks, called PreKR. Since the kernel-based link estimation algorithm selects the link probability prediction that can represent the baseline index of the local network structure, the time complexity is large. The authors used the k-means algorithm to optimize the complexity of kernel regression, which can be applied to mitigate heterogeneous network problems in two different scenarios. They proposed a three-layer heterogeneous architecture to realize PreKR and complete sending a response to the content applicant. The accuracy of this prediction method in the rough estimation of future link modes is over 90%. Experimental results showed that the kernel regression method is superior to the most advanced method in the current research.

In [46], Pham et al. analyzed social relationships by analyzing people's location information, and proposed an entropy-based model to infer social strength, which constitutes a community. In particular, the study focused on two separate approaches: diversity and weighted frequency, and also considered the characteristics of each location to compensate for only limited location information. This model can be used to process large data sets and can estimate the strength of social relationships by analyzing people's co-occurrence in space and time. A large number of real-world dataset experiments proved the superiority of the results. The model correctly predicts 88% of social advantages, and infers that the accuracy of friendship reaches 96.5%.

In [47], Wei et al. proposed that network activities in dynamic social networks can be measured by limiting the number of metrics. Then, they gave two dynamic metrics: Recency and Primacy, which were used to predict future network activities. In order to evaluate the performance of these two indicators, they used these two types of dynamic metrics to predict future network activity for three different temporal aggregation models: Aggregation Functions, Average Aggregation Model, and Linear Aggregation Model. They also proved the intrinsic characteristics of dynamic social networks: the activity patterns are highly dependent on historical activity information in dynamic social networks. Simulation experiments show that the proposed two indicators can be used to predict activity metrics based on human behavior-based network link changes, helping to study cyclical changes in the network.

In [12], Li et al. proposed a reliable topology design in a predictable MSN to establish a reliable link connection for any pair of devices with minimal cost. They formulated the topology design problem as a community-based probabilistic space-time graph, and proved it to be NP-hard. The core issue of the new reliable topology design is to find a subgraph in a given weighted space-time map. To solve this problem, they proposed five heuristics, which can significantly reduce the total cost of the network topology while ensuring the reliability link of the MSN. They have removed strong assumptions about perfect predictions and reliable links compared to current research. Numerical results showed that the proposed algorithm can greatly improve the efficiency of the data.

In [48], Zheng et al. proposed a new concept called supermodular degree for influence maximization in social network. In the literature, the influence propagation model is generally submodular. Therefore, a simple greedy algorithm can obtain an approximation ratio of $1 - \frac{1}{e}$ to the optimal algorithm. However, many real applications are not modeled as submodular and monotone functions. However, since connections in social networks are not random, approximations could be obtained by leveraging the structural properties. The supermodularity can measure to what degree our problem violates the submodularity. They proved that the supmodular degree, denoted as Δ, of most online social networks has the following property $\lim_{|V|\to\infty} \frac{\Delta}{O(|V|)} = 0$, i.e., $\Delta \in o(|V|)$ for most OSNs. Based on the property of online social networks, two

TABLE 2. A Summary of Existing Data Forwarding Algorithms based on Social Properties (Method, Performance Comparison and Social Properties).

Method	Methods for Comparison	Social Properties
UMCRP, GMCRP, LCP/MCRP, GDL, GAL [12]	GrdLCP, GrdLDB, ULCP	Community
MV [15]	Unlimited, Fifo queuing, No Buffer	Community
PACS [31]	PACSwithout, CID, KNN	Community, Tie strength
MaxProp [54]	Dijkstra, ME/DLE, Random	Community
PER1, PER2, PER3 [55]	Random, Utility, Direct, Epidemic Routing	Community
DR [57]	SimBet	Social relationship, Similarity
PeopleRank [58]	SimBet	Friendship, Similarity
LABEL [60]	WAIT, MCP, Control	Community
Zero-knowledge multi-copy routing [61]	Epidemic Routing, Spray and Wait	Community, Centrality
Homing Spread [62]	Epidemic Routing, Spray and Wait	Community, Centrality
SimBetTS [63]	Epidemic Routing, PRoPHET	Betweenness centrality, Similarity, Tie strength
BUBBLE RAP [103]	MCP, LABEL, Epidemic Routing, WAIT	Community, Degree centrality
LocalCom [104]	Prophet, Bubble Rap	Community, Tie strength, Betweenness centrality
CAR [105]	Epidemic Routing	Community, Friendship, Similarity, Tie strength
CAOR [106]	Bubble Rap, SimBet	Community, Similarity

approximation algorithms are applied with ratios of $\frac{1}{\Delta+2}$ and $1 - e^{-1/(\Delta+1)}$, respectively.

In [49], Shah et al. emphasized the important role of abstract node motion in spreading messages in sparse mobile data networks. The moving node is regarded as the vertex, and the contact opportunity between the mobile node and other nodes is taken as the edge, which is modeled as time-varying graph, and time measurement is defined: time distance, intermediation, centrality, diameter. On this basis, the author discusses the representation and design of the time algorithm. This strategy is based on sufficient network connection, and the message passing strategy should take advantage of the mobility of nodes to improve the rate of message passing and reduce the network overhead. Based on the property of development time mobility, the performance of message passing is further improved. A wide range of simulation experiments have been conducted to assess the temporary and central nature of real and synthetic mobile data sets.

V. TEMPORAL SOCIAL PROPERTIES-BASED APPLICATIONS

A lot of applications in MSNs have been proposed by using temporal social properties, especially data forwarding and data dissemination. In this part, we will give a brief summary of the lasted studies about temporal social properties-based applications in data forwarding and data dissemination.

A. DATA FORWARDING

A key part of the data forwarding algorithm design is to select the node with the highest relay or dissemination capability to meet the data transmission requirements while minimizing the data transmission latency and overhead [50]–[53]. Current studies have demonstrated that nodes are more likely to exchange information with nodes in the same community than nodes in different communities, and nodes with higher centrality values can disseminate data to the whole network more quickly. Therefore, many researchers use nodes' social properties to design efficient data forwarding algorithm for MSNs.

Table 2 shows a summary of the existing data forwarding algorithms based on social properties of nodes. Researchers tried various metrics to select the proper relay node.

In [15], Burns et al. proposed the MV protocol, which determined the relay node by using nodes' historical movement pattern. They also considered the limited buffer and data transmission bandwidth. In [54], Burgess et al. proposed to use the estimated path likelihoods to destination as a metric to select relay node. In addition, they also proposed a head-start for new packets to increase their chance of reaching the destination. In [55], Yuan et al. claimed that node's mobility pattern satisfies a time-homogeneous semi-markov process. Therefore, they could predict the future contacts of two specified nodes at a specified time and thus the node with higher probability is selected. In [12], [23], the authors constructed a weighted directed space-time graph to model spacial and temporal information in a predictable delay tolerant network and proposed a set of heuristics to find a reliable path to destination. In [56], Yang et al. further proposed a novel human mobility model based on heterogeneous centrality and overlapping community structure in social networks to help routing. In [57], Zhou et al. proposed the DR algorithm, whose idea is to statistically cluster the network into proximity-based social cluster and copies of a packet can be disseminated to at least a member of each cluster so that it has better performance in the worst scenario. In [58], Mtiba et al. proposed the PeopleRank algorithm, which is inspired by the PageRank [59] algorithm employed by Google to rank web pages. By crawling the entire web, this algorithm measures the relative importance of a page within a graph (web). Similarly, in a mobile social network, the node is like a web page.

The key idea of social community-based data forwarding is that the node with the same community should be able to meet each other frequently. In [60], Hui et al. conducted extensive real trace-driven simulations and proved that using node affiliation information can bring a large improvement in data forwarding performance, in terms of both data delivery ratio and cost. In [46], Pham et al. proposed an Entropy-Based Model (EBM), which successfully infers social strengths through co-occurrences of two people in the history. In [61], [62], Xiao et al. proposed the idea of home, which is the frequently visited locations of nodes. The nodes that frequently visit the same location will form a community with a common interest. In [63], Daly et al. presented several social network analysis metrics that may be used to support a novel and practical forwarding, such as betweenness centrality, similarity, tie strength. In [31], Du et al. tracked the progression of the community strength throughout the entire observation period.

However, the above mentioned studies design data forwarding algorithm for MSNs on the basis that the network is static, but they do not consider the highly dynamic change of network topology in MSNs. Therefore, in this part, we will examine data forwarding algorithm in MSNs from the temporal perspective.

In [64], Gao et al. proposed a new data forwarding algorithm to improve the performance of data forwarding for MSNs by exploiting the temporal social contact patterns, e.g., temporal contact distribution, temporal connectivity, and temporal community structure. They formulate these temporal social contact patterns based on real trace-driven simulations. Extensive real trace-driven simulations show that the proposed approach can significantly improve the performance of data forwarding in MSNs.

In [28], Zhang et al. proposed a clustering method based on contact bursts to detect temporal communities by modeling the pair-wise contact processes in MSNs, and then they proposed a new data forwarding strategy for MSNs using the proposed temporal community. Extensive real trace-driven results showed that the proposed strategy can effectively improve the data transmission rate and reduce network overhead.

In [65], Yuan et al. used the social attributes in the opportunity social network to complete the aggregation. In order to improve the data forwarding performance in MSNs, they comprehensively used two social indicators of similarity and centrality in MSNs. First, they calculated the social hotspot entropy between two nodes based on the study of node entropy to assess the similarity of social networks. Then, they used public hotspot entropy and personal hotspot entropy to calculate social network centrality. Finally, they integrated these two social indicators for data forwarding in MSNs, and proposed a data forwarding algorithm based on hotspot entropy in MSNs, called HOTENT (HOTspot-ENTropy). Extensive simulation experiments showed that the proposed approach can effectively improve the performance of opportunistic data forwarding.

In [66], Orlinski et al. investigated two important areas of MSNs, including autonomous neighbor discovery and distributed spatiotemporal clustering detection. They proposed a new autonomous neighbor discovery algorithm in MSNs and proved that the method is related to the burst mode associated with human encounters. Then, they proposed a novel detection algorithm to detect distributed spatiotemporal clustering in MSNs, which was used to analyze temporal social groups that form upon human interactions. On this basis, an opportunistic data forwarding algorithm that can be used to transfer data on multiple hops was proposed. In the tested autonomous neighbor discovery protocol, the proposed method is reliable for new neighbor detection. The simulation results showed that the performance of the proposed approach is better than other related approaches.

In [67], Zhu et al. aimed to improve the data delivery ratio in urban vehicular networks by exploiting the temporal dependency of Inter-Contact Times (ICTs). Through extensive real trace-driven simulations, they found that ICTs show strong temporal correlations. Therefore, they used the higher Morkov Chains to model vehicular mobility patters, and proposed a new data forwarding algorithm by using the predicted ICTs. Extensive simulation results show that the proposed approach can dramatically reduce 50% end-to-end delay and increase 80% delivery ratio in urban vehicular networks.

Furthermore, in [68], Zhu et al. proposed an opportunistic data forwarding algorithm called ZOOM by utilizing two level mobility, i.e., contact-level mobility and social-level mobility. To capture the contact-level mobility, they used k-order Markov Chain model to predict future temporal inter-contact times (ICTs). To capture the social-level mobility, they used the Louvain algorithm to detect communities, and Between-ness centrality to evaluate the importance of vehicles. Extensive simulation results show that the proposed approach ZOOM can achieve 30% performance gain compared to the state-of-the-art approaches.

In [69], Zhou et al. exploited the social contact patterns of nodes in MSNs from the temporal perspective. Through real trace-driven simulation and analysis, they find that temporal social contact patterns of nodes in MSNs show strong temporal correlations. With this knowledge, they design several intuitive methods, i.e., Last Method, Recent Average Method, Recent Weighted Method, and Periodical Average Method to predict nodes' future temporal social contact patterns, and propose a novel approach to improve the performance of data forwarding in MSNs by utilizing the predicted temporal social contact patterns.

B. DATA DISSEMINATION

MSNs generate large amounts of data every day. Content-based services want to push data to their descriptors, while intimacy-based services want to share content with their friends [70]–[72]. Data dissemination throughout MSNs is the core issue because of sparse connectivity consisting of limited node resources on the mobility. To ensure efficient data dissemination in MSNs, several underlying methods are used to address the most suitable forwarding nodes or groups to increase data delivery ratio and network efficiency. Table 3 shows a summary of the existing data dissemination algorithms based on social properties of nodes.

In [73], Lenders et al. considered the limited contact opportunity during a meeting and thus it is not sufficient to exchange all carried data. Therefore, it is very important to optimize the data exchange order. They proposed an evaluation of solicitation and caching strategies. In [74]–[76],

TABLE 3. A Summary of Data Dissemination Algorithms based on Social Properties (Method, Performance Comparison and Social Properties).

Method	Methods for Comparison	Social Properties
PodNet [73]	No caching, Most solicited, Least solicited, Uniform, Inverse proportional	Community
Cooperative [77]	Selfish	Community, Friendship
ContentPlace [74] [75] [76]	MFV, MLN, F, P, US	Community, Friendship
Mixcommunity [78]	Withincommunity	Community, Similarity
SocialCast [79]	No Prediction	Community, Friendship
MOPS [80]	Push, Pull, Neighbors	Community, Closeness centrality
Habit [81]	Epidemic, Wait-For-Destination, Oracle	Community, Friendship
MF-RRWP [82]	MF-ORWP, SODA, GADA	Community
Passive Refreshing [83]	Active Refreshing, Publish/Subscribe, Hierarchical Rereshing	Community

TABLE 4. A Summary of Temporal Social Properties-based Applications (Method, Performance Comparison, Temporal Social Properties and Application).

Method	Methods for Comparison	Social Properties	Application
Transient [64]	Epidemic, Spray-and-wait, Compare-and-Forwarded	Temporal Centrality	Data Forwarding
TC [28]	Epidemic, Label, Bubble Rap, AFOCS	Temporal Community	Data Forwarding
HOTENT [65]	SimBet, PeopleRank,	Temporal Centrality	Data Forwarding
ICT [67]	Epidemic, MED, MDP	Other: Temporal Dependency	Data Forwarding
DEBTT [66]	Bubble rap, PRoPHETv2, Nomads	Temporal Community	Data Forwarding
Dynamic Community Mining [85]	different detection threshold	Temporal Community	Data Dissemination
Temporal Community Detection [84]	no comparison algorithm	Temporal Community	Data Dissemination
POST [86]	Random and Static	Temporal Community	Data Dissemination

Boldrini et al. also addressed the data exchange optimization. However, they assumed that each node's buffer is limited. They proposed the ContendPlace algorithm, which exploited social information. In [77], Jaho et al. explored the locality-induced social group during data dissemination. Especially, they proposed a framework for modelling the nodes' dynamic association to social groups and the measurement of how useful a certain content is to the node. In [78], Yoneki et al. proposed to limit the number of relay nodes. They proposed to use the publish-subscribe paradigm and built an overlay for MSN and only selected relay nodes, i.e., the brokers, with the best visibility compared to the other nodes in MSN. They also proposed a distributed community detection scheme to find the proper brokers. In [79], Costa et al. proposed SocialCast framework, which exploited contacts of nodes and made prediction based on the Kalman filter technique. In [80] Li et al. further discussed how to guide brokers, e.g., what data they should collect, store, and propagate. In addition, different tradeoffs for content-based service can be achieved by adjusting the broker-to-broker communication scheme. In [81], Mashhadi et al. proposed to leverage information about nodes' movement events and their social interests to compute optimal data dissemination paths. In [82], Fan et al. studied the active data dissemination, where there is a superuser, whose route can be controlled. They proposed a flexible approach to design the superuser routes, considering the realistic user movements and a semi-Markov analytical model was used to model geographic regularity of human mobility. In [83], Gao et al. addressed data cache maintenance in MSN. To address the intermittent network connectivity, they proposed to organize the caching nodes as a tree structure during data access, and let each caching node be responsible for refreshing the data cached at its children in a distributed and hierarchical manner.

Similarly, the above mentioned studies design data dissemination algorithms for MSNs on the basis that the network is static, but they do not consider the highly dynamic change of network topology in MSNs. Therefore, in this part, we will introduce some data dissemination algorithms in MSNs from the temporal perspective.

In [84], Pietilainen et al. validated the existence of temporal community in various environments by using data from four real-life human mobility experiments. Since social information was collected, they also observed that temporal community exhibits a high level of correlation with participants' social characteristics. Furthermore, they first explored the role of temporal community in epidemic content dissemination. Specifically, they categorized nodes into four types based on its overall contact rate and contact rate within the temporal community and evaluated the performance degradation by not using a type of node. They found that high contact rate nodes that are more frequently involved in temporal communities contribute less to the dissemination process. In their experiments, removing high contact rate node with few contacts within temporal communities decreases the efficiency of the network by 50% to 80%.

In [85], Zhou et al. proposed an optimal method in user networking model based on social analysis to improve information sharing in social computing environments. The proposed dynamic community detection framework includes a series of functional modules that can simultaneously extract the user's static and dynamic features and detect dynamic communities based on time trends. Finally, they also built a user network model with dynamic tracking and transient community detection. A large number of data analysis experiments show that the proposed method can effectively identify the changing network environment and has a good performance in mining dynamic communities.

In [86], Qin et al. proposed to maximize the data delivery rate timely in the vehicular environment by hiring certain seed vehicles. They first proved that the proposed problem is NP-hard by reducing it to max k-cover problem.

Through empirical methodology, they explored the vehicle mobility by using three vehicular data traces and observed that vehicles demonstrate dynamic sociality and such vehicular sociality has strong temporal correlations. Therefore, they proposed the POST algorithm whose key idea is to adopt Markov chains of k^{th} order for capturing the temporal correlations and infer future network behavior. In terms of seed vehicle selection, the POST algorithm greedily selects the vehicle which has the highest estimated centrality information.

Based on the above introduction and analysis, it can be found that approaches which consider temporal social properties of MSNs perform much better. The key insight behind is that temporal social properties provide fine-grained level models, compared with models without temporal social information, and thus they reflect more features of MSNs and achieve better performances.

VI. FUTURE RESEARCH AREAS

We summarize the challenges of future research in mobile social networks into the following three points. First, algorithms that use only time or space metrics ignore the weak correlation between people, which may be the key to community connections. Second, it is difficult to predict the mobility of people based on past contact with others to improve the accuracy of information dissemination. Third, people may not agree to reveal their personal interests, which makes it difficult for the community to detect and discover common interests.

For future research, mobile social network analysis is still a very popular new research area. Although we have already introduced the existing research on mobile social network analysis, there are still many challenges in the current research. We emphasize the following two issues: social properties and temporal dependency, focusing on detecting the rise and fall of spatiotemporal clustering from mobile social networks. Our research provides new ideas for link mode prediction and reliable topology design in opportunistic networks. The ubiquity of mobile devices has brought new horizons to network development. The main advantage is that members of the mobile social network can take advantage of limited services as much as possible. The development of mobile social networks poses new challenges for future research.

1) *Hybrid networks:* A major challenge of mobile social networks is that it is hard to provide guaranteed delivery due to its opportunistic characteristics. On the other hand, the existing infrastructure-based networks, e.g., cellular networks, cannot utilize plenty of short-range communication opportunity especially in data dissemination. A hybrid network which leverages the massive free contact opportunities of MSNs and the wide coverage of cellular networks will significantly improve the data throughput and reduce the communication cost at the same time [87]–[89].
2) *Emerging Internet-of-Things applications:* Mobile devices' computation power and sensing capability have increased tremendously. As a result, the typical data in the MSNs has a much larger size compared with data in previous years. For instance, the majority of the traffic was short messages ten years ago but that has changed to video clips nowadays. Many of existing researches might not fit into the emerging Internet-of-Things (IoT) applications since they assumed that data size might not be a big issue [90], [91]. Another challenge is that the existing routing approach is designed for one-to-one or one-to-many applications. However, in the future, we might want to smartly sense our surrounding area by collecting data from multiple IoT devices. The routing adapts to many-to-one paradigm and new approaches should be developed to address the emerging IoT applications [92]–[95].
3) *Emerging data analytics tools:* Currently, the work of mobile social networks mainly focuses on how to effectively use limited data resources. Existing works have proposed various metrics to evaluate a node's importance during the routing and dissemination, e.g., degree, centrality, closeness, etc. However, different MSNs might have different movement pattern or social property. Therefore, proposed metrics might only fit to certain scenarios and thus it is not a general solution. The recent data analytics tools such as data/machine mining can be used in MSNs and help users to get a better understanding of the MSNs and select the proper metric [96].
4) *Cross-layer design:* In future research, considering mobile social networks as a combination of traditional wired social networks and mobile wireless networks is crucial. This requires cross-layer information exchange at the bottom of the network, and future research should focus more on the underlying architecture of mobile social networks. It is still a key challenge to coordinate routing design by jointly considering the social layer and physical layer [97]–[99].
5) *Datasets:* To further push forward the research in MSNs, a fundamental requirement is that people can validate their ideas through large-scale high-quality datasets. Also, many existing datasets are most related to movement during conferences or campuses and they cannot cover mobility pattern in other scenarios, such as people walking in the center city. It is true that we can simulate mobility pattern in these scenarios, but it will degrade the practicality to a certain degree [100].
6) *Standards:* To implement research ideas into commercial systems and applications, engineers and researchers first need to develop public standard protocols and interfaces for network information collection and data exchange. The current TCP/IP suite does not fit the data communication in MSNs. Otherwise, it will be very hard, if not impossible, for different devices to collaborate and communicate with [101], [102].

VII. CONCLUSION

MSNs have become a hot spot in network science research. Researchers introduce social properties into network design with the goal of using social relationships to improve the quality of network services. As dynamic communities evolve over time, there is an urgent need to infer social properties from time and spatial data. In this paper, we first briefly introduce the relevant content of MSNs analysis, with an emphasis on architecture, components and social properties of MSNs. Then, we try to exploit MSNs from a temporal perspective and analyze the temporal social properties of MSNs. Furthermore, some applications using temporal social properties in MSNs are also introduced and analyzed, especially in data forwarding and data dissemination. Finally, some important open issues with respect to MSNs are discussed.

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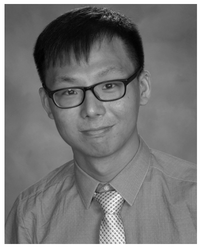

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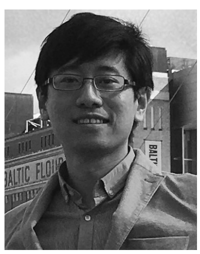

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