A Survey on Routing and Data Dissemination in Opportunistic Mobile Social Networks

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Abstract— Opportunistic mobile social networks (MSNs) are modern paradigms of delay tolerant networks that consist of mobile users with social characteristics. The users in MSNs communicate with each other to share data objects. In this setting, humans are the carriers of mobile devices, so their social features such as movement patterns, similarities, and interests can be exploited to design efficient data forwarding algorithms. In this paper, an overview of routing and data dissemination issues in the context of opportunistic MSNs is presented, with focus on (1) MSN characteristics, (2) human mobility models, (3) dynamic community detection methods, and (4) routing and data dissemination protocols. Firstly, characteristics of MSNs which lead to the exposure of patterns of interaction among mobile users are examined. Secondly, properties of human mobility models are discussed and recently proposed mobility models are surveyed. Thirdly, community detection and evolution analysis algorithms are investigated. Then, a comparative review of state-of-the-art routing and data dissemination algorithms for MSNs is presented, with special attention paid to critical issues like context-awareness and user selfishness. Based on the literature review, some important open issues are finally discussed.

***Index Terms*—Mobile social networks; opportunistic communications; human mobility; community detection; routing and data dissemination.**

I. Introduction

Today, a rapid growth of portable devices has enabled mobile users to be ubiquitously connected through wireless communications and networking technologies. However, unlike conventional mobile networks such as mobile ad hoc networks, intermittent and uncertain connectivity makes data forwarding a challenging issue in disruptive scenarios. Thus, new routing and data dissemination solutions based on opportunistic contacts between mobile users have been proposed in order to overcome the lack of connectivity. Mobile social networks (MSNs) are modern paradigms of delay tolerant networks (DTNs) [1],[2] in which mobile carriers (i.e., human beings) communicate with each other via their short-distance and low-cost devices to share data objects (e.g., pictures, MP3 files, advertisements, software updates) among interested mobile users.

In MSNs, portable devices are in the majority carried or controlled by humans. Therefore, their long-term behavioral characteristics and mobility patterns as well as their contextual and spatio-temporal information can be exploited to design social-aware protocols in MSNs. For example, people with the same interests form a community (i.e. a social group) and share their data through the community via mobile phones. Moreover, if they are attracted to some places like metro stations or some individuals like a tour guide, their movement patterns will be linked significantly. Therefore, today's mobile networks increasingly become human-centric and social features of mobile users are now exploited for designing efficient networking solutions.

MSNs have been introduced by combining concepts from two disciplines, i.e., social network and mobile communications networks. The social network defines the structures and ties among users, in which users and the system can use these properties to improve the performance of network services. In such a network, mobile users can access, share, and distribute data by exploiting their social relations [3]. Due to the proliferation and ubiquitous availability of mobile devices (such as smart phones), MSNs provide a more accurate mirror of social life in comparison to online social networks.

Typical MSNs have various applications in many areas such as pocket switched networks (PSNs) [4], vehicular ad hoc networks [5], and wireless sensor networks [6], etc. In addition, several other technologies such as mobile phone sensing [7], opportunistic computing [8] and social network analysis (SNA) [9] supports MSN applications to facilitate the convergence of human society and cyber physical systems. Generally, the main objective of MSN applications is to take advantage of users' social characteristics as well as wireless and mobile communications technologies to provide close relationships between mobile users in pervasive environments. PatientsLikeMe [1] and CaringBridge [2] are examples of MSN web-based healthcare services that connect its members to share treatment and symptom information. Location-based social networks such as Foursquare [3] and Gowalla [4] and wearable services such as Patches [11] are other prominent fields of applications in MSNs.

Broadly, MSNs can be categorized into two types: infrastructure-based MSNs and infrastructure-less (or opportunistic) MSNs [12]. Infrastructure-based MSNs (such as iPhone Facebook App) use social network services (e.g., Facebook) to acquire information through mobile devices. In this setting, the mobile users communicate with each other using web-based applications through the Internet given the availability of wireless connectivity. In opportunistic MSNs, mobile devices communicate with each other without connecting to a centralized server.

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[1] www.patientslikeme.com
[2] www.caringbridge.org
[3] www.foursquare.com
[4] blog.gowalla.com/

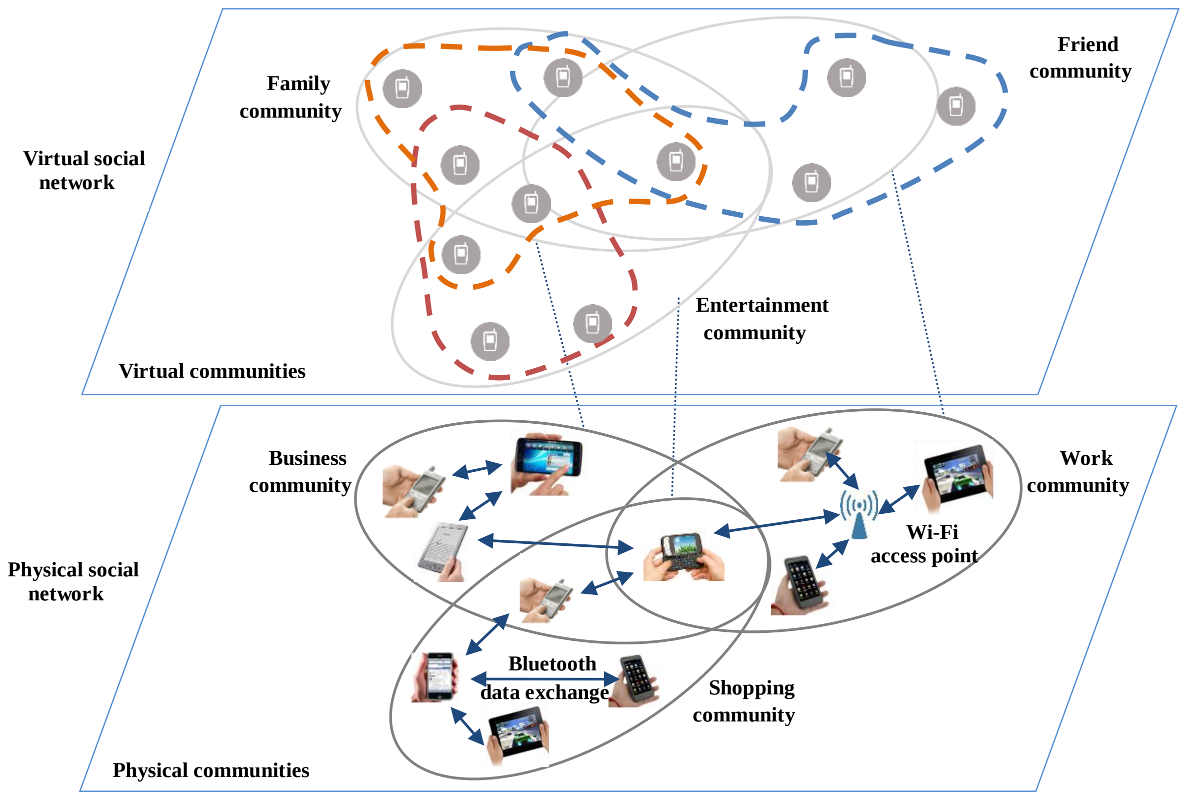

Fig. 1. Overall structure of opportunistic mobile social networks portraying two views: a physical social network and a virtual social network.

The overall structure of opportunistic MSNs can be depicted as Fig. 1. In this figure, it can be seen that by integrating the social relationships in the electronic world, two network levels can be defined: a physical social network which includes physical communities and a virtual social network over the physical social network that can be divided into several social communities. The physical communities such as work or business groups are created based on wireless contacts between mobile devices whereas social communities such as family or friend groups are formed based on social relationships between mobile carries. Communication in this decentralized setting is achieved by exploiting pair-wise contacts between users using wireless technologies such as Wi-Fi or Bluetooth. The short-distance mobile devices communicate with each other to exchange data objects, and bring them towards eventual destinations. Sporadic contacts of users with points of access to the Internet (e.g., Wi-Fi hotspots) are possible although not necessary. Data objects might be generated from within the Internet or be generated dynamically by the users of the opportunistic network according to the Web 2.0 model. In the rest of this paper, two terms, MSNs and opportunistic MSNs, will be used interchangeably.

SOCIALNETS [13] and Haggle [14] are two well-known social-based data forwarding and dissemination projects which attempt to exploit the underlying social network structure to develop effective protocols. SOCIALNETS exploits social interactions and user habits to drive the design of protocols for both online social networks and MSNs. Haggle identifies social communities and allows mobile devices to exchange data when they are in close communication range of each other. In this project, a publish/subscribe scheme is utilized for data exchange, where users express their interests using keywords and then receive data objects from others.

There are some major differences between conventional ad hoc networks and MSNs. An end-to-end path is expected to exist in traditional networks, while MSNs allow looser connections between source and destination nodes. Furthermore, network storage in MSNs allow mobile nodes to buffer data for a longer time until connections are available. Additionally, nodes in conventional ad hoc networks often move in a random manner whereas the movements of devices in MSNs mirror those of their owners which can be somewhat predicted. Successfully predicting the next venue a mobile user or a population will visit can streamline routing decisions and increase message delivery ratio which results in efficient forwarding and sharing algorithms.

MSNs share several ideas with opportunistic networks (OppNets) [15]. Initially, the network topologies in MSNs and OppNets are unstable and users appear in and disappear from the network dynamically. Secondly, data source and destination users might be completely unaware of each other, and may never be connected to each other at the same time and the same place. Thirdly, the involved protocols heavily rely on human mobility and contact opportunity, and hence, the prediction of future contact becomes a critical issue in both MSNs and OppNets.

Most of the current routing and data dissemination protocols in DTNs [16] are controlled flooding-based or based on contact frequency utility. However, these methods mainly consider contact frequency in calculating the utility while neglecting contact duration and influence of social characteristics on the throughput. Recently, a new trend has emerged which further considers SNA techniques and make routing decisions based on social similarity between mobile users to improve data forwarding. The motivation is that social characteristics of mobile users are less volatile than human mobility, providing more robust and reliable connectivity graphs. Essentially, these methods attempt to group nodes into communities and/or choose a node with high centrality (i.e., more contacts) or similarity (interest/context/common friends) with the destination node as the packet forwarder.

In this paper, we present a comparative survey of the routing and data dissemination issues in MSNs. Specifically, we study four important aspects of MSNs namely: (1) MSN characteristics and analysis metrics, (2) human mobility models, (3) dynamic community detection methods, and (4) routing and data dissemination protocols. Challenges and solutions around the topics are discussed and the most important characteristics of the algorithms are featured. Finally, we conclude the paper with a discussion of some open issues currently far from being fully recognized.

The four topics we study in this work are closely related to each other. Firstly, analyzing and quantifying social characteristics of mobile users lead to useful criteria and metrics. The properties such as centrality, similarity, and tie strength are of great value to formulate MSN forwarding protocols efficiently. Secondly, performance evaluation of the existing forwarding protocols in MSNs relies heavily on the human mobility models. In other words, various routing and dissemination scenarios could exploit such existing state of the art human mobility models to their advantage. This implies researchers should possess a deep knowledge of these foundation models. Thirdly, social relations and similarities between users are long-term in nature. This idea has brought the concept of a community into current MSN routing issues and several community-based forwarding algorithms have been proposed. However, in highly dynamic networks, community detection and information exchange between the communities is difficult as routing protocols have been presented without community support.

The remainder of this paper is organized as follows. Characteristics of MSNs are presented in Section II. In Section III, properties of human movements are discussed and an overview of human mobility models is provided. Recent community detection and evolution analysis algorithms for MSNs are outlined in Section IV. In Section V, routing and data dissemination algorithms in MSNs are reviewed. Some major open issues are discussed in Section VI. Section VII concludes the paper.

II. Mobile Social Network Characteristics

Introducing social network concepts and techniques into mobile and opportunistic communication systems has attracted a lot of attentions by the research community. In this section, the most important characteristics of social network theory and its applications in MSNs which are the most popular in the design of routing and data dissemination protocols will be examined.

A. Social Network Analysis

Social network analysis (SNA) techniques have recently gained much attention in many fields such as anthropology, communication studies, economics, information science, computer science and engineering. Contemporary researches in this area mainly focus on studying dynamics of relationships and ties among social actors and implications of these relationships. With the increasing popularity of new information technologies such as smart sensing, mobile networking, and e-commerce, SNA plays an important role in analyzing and designing of new policies, protocols, or applications for ubiquitous mobile environments. Using SNA techniques, important social properties including social graph, centrality, similarity, tie strength, human mobility, social community, etc., can be extracted. The available properties are of great value to design efficient routing solutions over MSNs.

B. Social Graph

A social graph is an intuitive source to extract and calculate various social metrics and structures such as communities and friendship relations in MSNs. In the social graph, nodes correspond to social entities (e.g. individuals), and edges represent social relationships (or social ties) between the entities. Depending on the kind of social network, the links between the nodes could be directed or undirected. Furthermore, the links may be known a priori or inferred from contact frequencies, user interests, or geographic preferences. Alternatively, a weighted edge can be inserted, with a weight representing the number (or duration) of contact opportunities between the two nodes. As an example, a social graph relevant to context of this paper is one in which nodes are the mobile carriers forming a MSN, and there exists a weighted edge between two nodes which is calculated based on their contact histories..

The formation of a social graph which contains some social communities is depicted in Fig. 2. In this figure, three kinds of network graphs: a wireless graph composed of available physical links between mobile devices; a contact graph, calculated from the aggregation of the wireless graph; and finally, a social graph with social ties formed by using SNA techniques are defined. After a social graph has been constructed, the concepts of social communities can be introduced.

C. Social Network Analysis Metrics

SNA techniques quantify spatial-temporal and connectivity properties of individuals and groups to deduce new analysis and evaluation metrics. These metrics can be utilized to improve the performance of various functions during the operations of routing and data forwarding processes in MSNs. Furthermore, the previously applied metrics such as centrality metrics have been changed by researchers to maximize the efficiency of their algorithms.

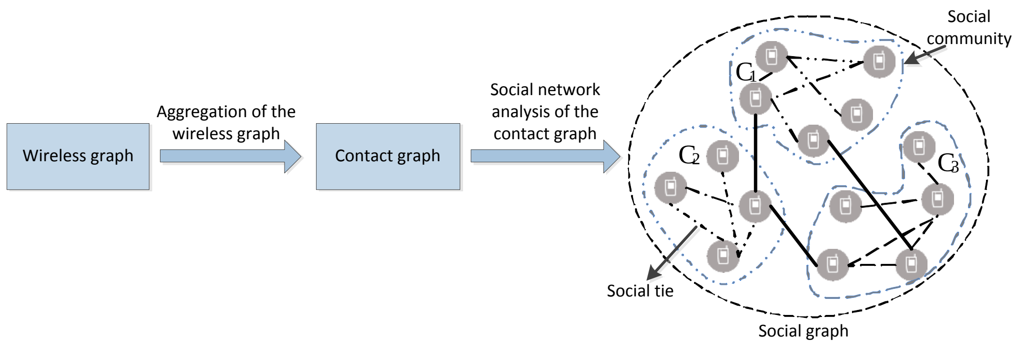

Fig. 2. Process of generating a social graph from wireless and contact graphs.

According to Daly and Haahr [17], centrality in network analysis is a quantification of the relative importance of a vertex within a graph. Three widely used centrality measures are *degree centrality*, *closeness centrality*, and *betweenness centrality*. Degree centrality is measured as the number of direct ties that involve a given node [18]. Nodes with high degree centrality can be seen as popular nodes with large numbers of links to others. For example, Bubble Rap [19] uses degree centrality as its centrality index. Closeness centrality measures the reciprocal of the mean geodesic distance, which is the shortest path between a node and all other reachable nodes. The closeness centrality can be regarded as a measure of how long it will take information to spread from a given node to other nodes in the network [20]. Betweenness centrality measures the extent to which a node lies on the geodesic paths linking other nodes. Betweenness centrality can be regarded as a measure of the extent to which a node has control over information flowing between others. A node with a high betweenness centrality has a capacity to facilitate interactions between nodes it links. Fig. 3 shows examples of three kinds of centrality metrics.

However, the centrality measures do not take into account the social interactions and strength of the links between nodes. Ties represent the existence of a meaningful social relationship between two individuals, e.g. friendship. *Tie strength* is a quantifiable property that characterizes the link between two nodes. This property was initially introduced by Granovetter [21] which is defined as "a combination of the amount of time, the emotional intensity, the intimacy, and the reciprocal services, which characterize a tie". In most cases, ties are represented by edges connecting two nodes of a graph, with a specific weight characterizing its strength. In [17], tie strength indicators are presented, including frequency, intimacy, longevity, reciprocity, recency, multiple social context and trust. A combination of the tie strength indicators can be used for information flow to determine which contact has the strongest social relationship to the destination. Meanwhile, the effects of weak ties in social networks are also crucial to data dissemination.

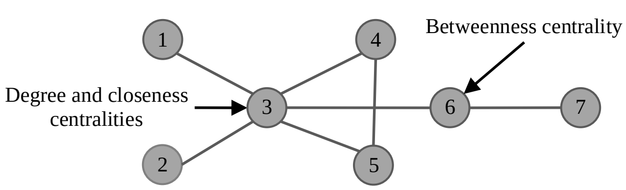

Fig. 3. Examples of degree, closeness and betweenness centrality metrics. Node 3 has the most direct connections. In the meantime, it has the shortest path to all the nodes, i.e., it is degree centrality as well as closeness centrality node. Node 6 connects all other nodes to node 7, i.e., it is betweenness centrality node.

In real life, everybody likes to make friends with others of the same hobby, profession, geographic location etc. This is a general expression of *social similarity*. The social similarity indicates the grouping of nodes depending upon common interests or contacts which can be calculated according to the number of common neighbors two nodes have.

By employing users' mobility patterns for a community detection problem, the following two broker selection metrics are adopted: *user popularity* and *inter-user closeness* [22]. The first metric is employed to describe a user's capability of meeting other people. The second metric describes the relationship strength between two users which is based on the assumption that users who are socially close to each other are also likely to encounter each other more frequently. *Cumulative contact probability* [23] is another similar metric that evaluates the probability of a node contacting others based on its cumulative contact rates.

The authors in [24] introduce a new metric called *social pressure metric* (SPM) that can be interpreted as a measure of a social pressure that motivates friends to share their experiences. Based on this metric, Friendship-based routing algorithm offers users the ability to exchange messages with the other members, by tracking their past contacts and defining the social pressure metric for every social relationship. This metric takes into account three behavioral features of close friendship: high frequency, longevity, and regularity.

Performance and *availability* are proposed in [25] which allow data to be forwarded fairly and efficiently to a next hop, without causing congestion. The performance attribute of a given next hop allows nodes to find out which of its next hop contacts have managed to forward packets for them, and more importantly, have successfully arrived at the destination. Moreover, they identified and proposed two locally disseminated availability parameters, *receptiveness* and *retentiveness*, aim to promote the use of routes that have lower levels of load by propagating usage parameters.

TABLE 1
CHARACTERISTICS OF COMMON ANALYSIS METRICS FOR MSNs

Social Metric	Characteristic
Degree centrality [18]	Determines popular nodes with large numbers of links to others. (e.g. node 1 in Fig. 5)
Closeness centrality [18]	Determines shortest path between a node and all other reachable nodes. (e.g. nodes 4 and 5 in Fig. 5)
Betweenness centrality [18]	Determines the links between communities. (e.g. node 8 in Fig. 5)
Tie strength [21]	Determines the strength between two nodes.
Social similarity [17]	Indicates the grouping of nodes depending upon common interests or contacts.
User popularity [22]	Indicates how many users a node is likely to meet within a time period.
Inter-user closeness [22]	Describes the relationship between two users which is based on historical encounter records.
Cumulative contact probability [23]	Indicates the average probability that a randomly chosen node is contacted by other nodes within a time period.
Social pressure metric [24]	Interpreted as a measure of a social pressure that motivates friends to meet to share their experiences.
Performance [25]	Determine which of a node's next hop contacts have managed to forward packets for them, and have successfully arrived at the destination.
Availability [25]	With this metric, even if a node has high centrality and similarity values, because it is busy, thus has limited bandwidth, or has limited storage, it lack the Availability to accept the traffic.
Node stability [26]	Calculates the tendency of an individual to interact with the same nodes over a time period.
Node influence [26]	If one node influences others to join (or leave) a community, it is an influential node.

Node stability and *node influence* [26] are two useful metrics to quantify active behavior of a node in a community-based dynamic network. The stability calculates the tendency of an individual to interact with the same nodes over the observation time. Thus, a high stability score is indicative of a stable individual who mainly interacts with the same people over time. If a node influences others to join a community then it may be a very influential node in the network. A high influence score indicates that when the node joins a community, a large number of follower nodes will also join that community.

Table 1 summarizes the basic metrics and characteristics which are utilized in the recent routing protocols in MSNs.

D. Human Mobility

Introducing SNA techniques into existing mobility models so as to understand regular movement patterns of mobile carriers has attracted a lot of attentions recently. Several human mobility models have been proposed to fill the gap between the real scenarios in our daily life and available human movement models [27]. In order to model such realistic patterns, dynamic characteristics and behaviors of individuals and groups in a large scale should be adopted. Furthermore, their interests and similarities as well as interrelationship between contact parameters and time-spatial properties should be considered. As a result, it is of paramount importance to consider the influence of social behaviors in mobility models to get more realistic models.

Several social-aware routing and data dissemination protocols in OppNets and DTNs have been proposed which take advantage of human mobility information to forecast future movement of mobile users and improve the performance of data delivery. In majority of these protocols, the movement and contact patterns of mobile carriers have been used to assist a mobile user in finding a message relay with a high probability of successfully sending data to the destination. Predicting the next venue a mobile user will visit, based on past interactions, can also be estimated to improve the performance of MSN routing protocols.

E. Community

A community is often defined as a group of individuals in a social network with stronger ties to members within the group than to members outside the group. Individuals belonging to the same community meet each other with high probability and regularly. On the contrary, individuals from different communities meet less frequently. Understanding the human structure and the rules which regulate social interactions and aggregations can be a great advantage. Knowledge of network community structure promises a wide range of applications enabled by mobile networking. However, understanding this structure to tackle with routing and data dissemination protocols is very challenging; especially in MSNs where social activities and interactions tend to come and go rapidly.

III. HUMAN MOBILITY MODELS

The primary routing and data forwarding protocols in traditional mobile networks was evaluated by means of simulation, using synthetic random movement traces that mostly followed random waypoint (RWP) model [28]. However, several research studies like [29] have shown that user movements are barely random, because they cannot reproduce the same registration patterns observed in the real scenarios. In addition, random models often fail to evaluate the protocols in human-associated networks accurately. Instead, human movements are heavily relying on human social characteristics and they can be predicted to a greater extent. In other words, the social and predictable features of human mobility can be leveraged to assist a node in finding a relay node with a high probability of successfully sending data to the destination.

The social aspects of human movements are usually interrelated to each other. For example, if a mobile carrier is attracted by some places like metro stations or some individuals like a tour guide, his or her location information and contact patterns will be linked significantly. In order to model realistic mobility models, dynamic characteristics of individuals and groups in a large scale should be also adopted. Moreover, their movement habits and similarities as well as interrelationship between contact parameters and time-spatial properties should be considered. As a result, it is important to study properties of social-based human mobility models to get more realistic models.

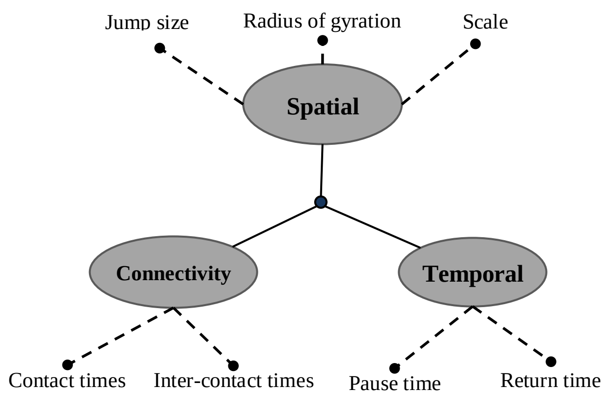

Fig. 4. The most important characteristics of human mobility [27].

To offer a comprehensive study on mobility models in MSNs, we first study statistical properties of human mobility and put them in three groups; trace-based human mobility models, agenda-driven and simulation-based human mobility models.

A. *Human Mobility Characteristics*

Statistical properties of human mobility traces have been analyzed in the recent literature in order to discover movement and communication patterns of mobile users. According to [27], the most important features of human mobility can be explored in three main categories, named spatial, temporal and connectivity properties (see Fig. 4). The spatial features refer to location information of users' trajectories in physical space. Temporal aspect of human motion is related to the time-varying features of users' mobility such as their travel or pause times, whereas connectivity properties are related to contact properties of users when their mobile devices are within transmission range of each other.

Spatial properties of human mobility indicate features which are extracted from physical trajectories of mobile carriers. These features mainly include *jump size* and *radius of gyration* (or gyradius). The jump size refers to the geographical displacements a human travels between two successive locations during a time period (*e.g.*, one hour). This feature ranges from a few to thousands of kilometers over short periods of time. This parameter is important in an opportunistic routing protocol since users that travel longer distances can be chosen as a message relays to bridge disconnected parts of MSNs. The radius of gyration is a scalar value which well indicates the spatial extent of a user's total mobility pattern during a time period.

Several features have been identified to analyze temporal properties of human mobility. *Pause time* (or waiting time) and *return time* are the most important temporal metrics of human walks. The pause time indicates the time period that a user stays in a specific position, i.e., the interval of time when the user's speed is zero or close to zero. The return time is the time period a user returns to the location they visited before regularly.

Some movement features have also been proposed in order to study connectivity (or contact) properties of human mobility. Since every contact between mobile users could result in data transmission, analyzing its characteristics is of paramount importance. Depending on the scenario considered, it can be the duration either of a Bluetooth association or of the staying under the coverage of the same access point. *Inter-contact time* is another important feature in this category which is the result of sociability of mobile users. It is defined as the time elapsed between two successive contact periods for a given pair of devices. Inter-contact time characterizes the frequency with which data can be transferred between networked devices. The work to identify the power-law distribution of inter-contact time has been performed by Chaintreau *et al.* [30] which is based on analysis of real-world traces.

As proposed by Karamshuk *et al.* [27], the human mobility models can be studied in three categories: real trace-based models, agenda-driven models and simulation-based models. In the rest of this subsection, some well-known proposals in each category are presented.

B. *Real Traces*

Study of non-random user movements in MSNs became possible with the generation of real life mobility traces collected from wireless LAN, Bluetooth, and GPS-based traces in campuses, conferences, and entertainment environments. These distinct traces demonstrate surprising common and realistic characteristics of human movements. Many human mobility models use these properties as their design foundations or the evidences to evaluate their reality.

Generally, different methods and tools such as a global positioning system (GPS), a global system for mobile (GSM) and WLAN access point associations can be used to collect real traces of human movements. Another approach to acquire traces is to use mobile devices that sniff for other mobile devices around them. Contacts may be traced by using Bluetooth or Wi-Fi in an infrastructure-less mode. For some kinds of networks, such as OppNets, contacts between the mobile nodes may be more interesting than the actual position of the nodes, hence contact traces can be used to examine movement and social characteristics of the users. In this paper, we specially focus on the traces which are collected by Bluetooth or Wi-Fi technologies.

Table 2 summarizes the most important characteristics of common real traces utilized in the recent proposals. An anonymous version of most of these data is available on CRAWDAD [5] archive. For a survey about the trace-based mobility models, readers can be referred to [31].

C. *Agenda-driven Human Mobility Models*

Almost all of real traces are environment specific (i.e., in colleges or conferences) and they are not yet collected on wide. In other words, most of the available real traces are not scalable. Furthermore, on contrary to network simulations, they are not robust and flexible for configuring network and node parameters. Furthermore, as the traces are collected for a specific situation, they may fail to present an unbiased and standardized comparison between protocols. These problems forced researchers to use simulations, where the parameters of the mobility models can be modified according to problem specifications.

[5] crawdad.cs.dartmouth.edu

TABLE 2
CHARACTERISTICS OF COMMON REAL BLUETOOTH/WI-FI TRACES

Trace	Device	Network type	No. of devices	Duration (day)
Cambridge 05 [32]	iMote	Bluetooth	223	5
Cambridge 06 [33]	iMote	Bluetooth	54	11
Dartmouth [34]	PDA	Wi-Fi	4248	60
ETH Campus [35]	Cell phone	Bluetooth	285	105
Mobile Data Challenge (MDC) [36]	Cell phone	Bluetooth	38	365
INFOCOM 2005 [37]	iMote	Bluetooth	264	3
INFOCOM 2006 [38]	iMote	Bluetooth	78	4
Europe [39]	Cell phone	Bluetooth	100000	180
MIT Reality [40]	Cell phone	Bluetooth	100	246
San Francisco [41]	Cab	Wi-Fi	483	24
Second Life [42]	Avatar	Bluetooth	2713	10
Proximity [43]	Motes	Bluetooth	27	~
UCSD [44]	PDA	Wi-Fi	275	77

The agenda-driven mobility models capture movement features of real world traces to create synthetic mobility models. The models in this category aim to deduce users' movement patterns and regularities, based on the real traces, and reproduce scalable mobility traces. Agenda driven mobility model (ADMM) [45] is the most pioneering model in this class. ADMM utilizes national household travel survey (NHTS) information from the U.S. Department of Transportation to obtain activity and dwell time distributions. In this work, a mobile ad hoc network in an urban scenario is simulated in order to analyze the geographic features of the network topology. The impact of the model on routing performance is also investigated in this work. Working day movement (WDM) [46] is another well-known method for DTN simulations that is able to produce contact time and inter-contact time distributions that follow closely the ones found in the traces from the real-world measurement experiments. This model incorporates some sense of hierarchy and distinguishes between inter-building and intra-building movements.

D. *Simulation-based Human Mobility Models*

The simulation-based models are the most widely used models which attempt to mimic the mobility behavior of nodes without the support of an existing real trace dataset. In other words, simulation-based models give the opportunity to evaluate networking protocols in different scenarios, and test their robustness to different mobility behaviors.

Broadly, the simulation-based models can be grouped into two main types: location-based and social-based models. The location-based methods use physical location information of mobile users to model movement trajectories of the users. These information can be monitored by particular tools such as a global positioning system (GPS) or captured by an access point. On the other hand, in the social-based models, social characteristics of mobile users are exploited to setup a mobility model. However, preferred location information of mobile users might not be considered in social-based models, since socially similar users tend to stay in the same area.

In the rest of this subsection, each category of simulation-based mobility models is explored comparatively.

1) *Location-based Models:* In this class of mobility models, a set of preferred locations for each user is defined and the algorithm is designed according to which users move across these locations. Sociological orbit aware location approximation and routing (SOLAR) [47] is a mobility framework in this category which takes advantage of the "macro-mobility" information obtained from the sociological movement pattern of mobile DTN users. This model is motivated by the observation that the mobility of a mobile user exhibits a partially repetitive orbital pattern. Although the SOLAR is not general enough to be realistic in conventional ad hoc networks, it can be specifically used without a need for constant location updates and flooding that makes it suitable to DTN settings.

Time-variant community model (TVCM) [48] is a prominent movement model in this class to capture the important mobility properties observed from daily lives. In this method, some locations called communities are defined to be visited by each node in order to capture skewed location visiting preferences. In addition, time periods with different mobility parameters are used to create periodical re-appearance of nodes at the same location. This approach is extended in [49] by proposing the self-similar least action walk (SLAW) which is one of the first mobility models to reproduce the preferences for shorter trips. The model is also able to model the pause time. The performance evaluation analysis using SLAW generated traces shows that this method demonstrates social contexts present among people sharing common interests or those in a single community such as university campus, companies and theme parks.

Small world in motion (SWIM) [50] is another prominent mobility model for ad-hoc networking approach based on location preference. SWIM is relatively simple which is easily tuned by setting a few parameters. In this model, a randomly and uniformly chosen point over the network area is assigned to each node. The node then selects the destination points of their movement based on their popularity among all nodes and their distance from the home point. In more recent work, Nguyen *et al*. [51] proposed spatio-temporal parametric stepping (STEPS) - a simple parametric mobility model which can cover a large spectrum of human mobility patterns. STEPS makes abstraction of spatio-temporal preferences in human mobility by using a power law to rule the nodes movement.

2) *Social-based Models:* Social characteristics of mobile users can be exploited to identify realistic mobility patterns and movement regularities of mobile carriers. The social based mobility modeling can be considered as the application of social network theory on the field of mobility modeling. Community-based mobility model (CMM) [52] is one of the first social-based mobility models. In this method, social relationships between the nodes using a weighted social graph are identified. Connected nodes in this graph are called friend nodes. Based on the friendship information, the friend nodes are grouped into the same communities. Then, the communities are mapped into different cells of a spatial grid. When a node decides to travel to another community, all nodes belong to the

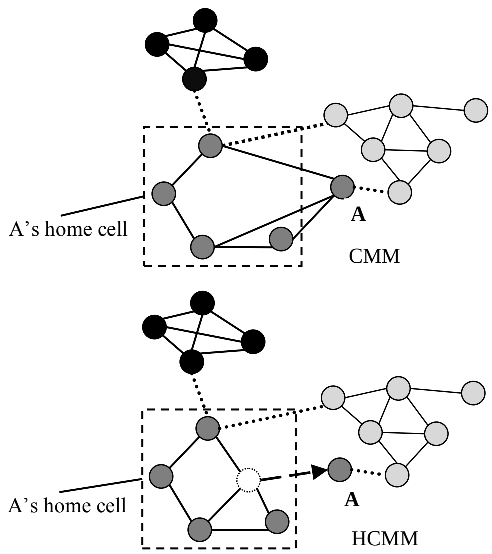

Fig. 5. Difference between cell community based mobility model (CMM) and home-cell community based mobility model (HCMM) with nodes that are outside their starting cell [54].

same community follow the movements of the node. This problem is called *gregarious behavior* of nodes. To tackle this problem, home-cell community-based mobility model (HCMM) [53] is proposed which integrates the concepts of CMM with the concept of preferential locations. HCMM maintains the social model of CMM, but some nodes have also social links with communities other than the home which is called foreign community.

Comparatively, CMM takes social relationships between the nodes into account when a node moves outside its home cell. In contrast, both social relationships between the nodes and attraction of home cells are considered in HCMM. In order to demonstrate this deference, a sample scenario is shown in Fig. 5. According to the figure, when node *A* moves outside its home cell in CMM model, the other nodes with social relationships in the same community follow the node *A*. This behavior does not allow CMM to model relevant mobility patterns, because nodes are only attracted by social relationships between each other. The authors of [54] have shown that this phenomenon has a destructive effect on mobility of the other nodes inside A's home. To tackle this issue, in HCMM, when *A* moves outside its home cell, it does not carry over its social links. Nodes having social relationships with *A* are still attracted towards *A*'s home cell.

It has been known that social relations do not only aggregate nodes but also separate them. The sociological interaction mobility for population simulation (SIMPS) [55] and general social mobility (GeSoMo) [56] are motivated by this idea. In SIMPS, nodes move according to two behavioral rules: the social interaction level, e.g. the personal status; and the social interaction needs, i.e. the social needs for individuals to make acquaintances. The nodes' movement occurs based on these two definitions, where a node is attracted by acquaintances, in order to socialize; or a node is repulsed by strangers, in order to isolate. These two behaviors alternate according to a feedback decision-making process which balance the volume of current social interactions against the volume of interactions needed by the node. In GeSoMo, the attraction between nodes is defined based on conformance requirement. The probability that a node chooses a certain physical location as its next destination is proportional to its anchor attraction, which is defined based on periodic anchor function. However, pauses are still not being considered in both SIMPs and GeSoMo models.

Geo-CoMM [57] is able to properly reproduce the spatial, temporal and social features. In this model, people move within a set of geo-communities, i.e., locations loosely shared among people, following speed, pause time and choice rules whose distribution is obtained by the statistical analysis. Arrival-based framework [58] takes the social graph representing the social relationships between the users as an input. Based on the input social graph, communities are identified and assigned to different locations. Thus people belonging to the same community share a common location where the members of the community meet. Then, users visit these locations over time based on a configurable stochastic process.

The important characteristics of the presented human mobility models are summarized in Table 3.

IV. Community Detection in MSNs

A community is often defined as a group of network members with stronger ties to members within the group than to members outside the group. The members in each community have stronger social ties or similarities and usually share different items such as pictures, movies, music or discussion topics. Hence, they tend to interact more frequently with each other than with members outside their community. Therefore, community detection is beneficial to forward data for other members within a community.

There has been a considerable amount of work done to detect communities based on heuristic measures, such as modularity methods [59]. Moreover, there are other proposals based on label propagation algorithm to identify communities [60]. Most of these methods aim at detecting communities in which each node is assigned to a single community statistically. However, in realistic social networks, users can be linked to many other nodes in another community. A complete review of the different community detection algorithms in static networks can be found in [61].

In MSN context, the community detection refers to the process of discovering evolving groups of mobile users sharing the same social similarities or interests. An evolving network is often defined as a sequence of static networks, each of them representing the state of the network at different timestamps as shown in Fig. 6. Through the time, characteristics of mobile nodes such as their locations, social relationship, interests and movement patterns can be changed dynamically which make community discovery a challenging issue in MSNs. In this section, state of the art of the community detection and evolution analysis algorithms are presented. We categorize community detection algorithms in MSNs according to their mechanisms to temporally-independent and temporal community tracking and evolution analysis algorithms.

A. *Temporally-independent Community Detection*

TABLE 3
COMPARISON OF AGENDA-DRIVEN AND SIMULATION-BASED HUMAN MOBILITY MODELS

Model			Characteristic	Properties								
				Spatial					Temporal		Connectivity	
				Scale								
				global view	city view	building view	radius of gyration	travel distance	pause time	return time	contact time	inter-contact time
Agenda-driven models		ADMM [45]	Contains personal agenda, geographic map, and motion generator components that model social activities, geographic locations, and movements of mobile users.	×	√	×	-	√	√	-	-	-
Agenda-driven models		WDM [46]	A combination of different movement models that is able to produce inter-contact time and contact time distributions.	×	√	√	-	-	-	-	√	√
Simulation-based human mobility models	Location-based models	SOLAR [47]	Each node selects a subset of predefined sets of locations and moves between them based on a customizable behavior.	√	√	√	√	-	√	-	-	-
Simulation-based human mobility models	Location-based models	TVCM [48]	Model the spatio-temporal preferences of human mobility by creating community zones.	×	√	√	-	-	×	√	-	-
Simulation-based human mobility models	Location-based models	SLAW [49]	One of the first mobility models to model pause time. Based on a global pause time perception, pause time is then randomly defined for each individual node.	×	√	×	√	√	√	-	√	√
Simulation-based human mobility models	Location-based models	SWIM [50]	Relies on the concept of home location: nodes select the destination points of their movement based on their popularity among all nodes and their distance from the home point.	×	√	×	-	√	√	×	√	√
Simulation-based human mobility models	Location-based models	STEPS [51]	Makes abstraction of spatio-temporal preferences in human mobility by using a power law to rule the nodes movement.	×	√	×	-	-	√	-	√	√
Simulation-based human mobility models	Social-based models	CMM [52]	Nodes are assigned to a number of subareas using preferential attachment. The attractiveness of one area is determined by the current number of nodes assigned to that area.	×	√	×	-	×	-	-	√	√
Simulation-based human mobility models	Social-based models	HCMM [53]	Combines notions about the sociality of users with spatial properties observed in real users movement patterns.	×	√	√	-	√	√	×	√	√
Simulation-based human mobility models	Social-based models	SIMPS [55]	Derives the motion of users in a way that individuals' movements are governed by both their social relationships and geographically surrounding individuals.	×	√	×	-	√	-	×	√	×
Simulation-based human mobility models	Social-based models	GeSoMo [56]	Separates the core mobility model from the structural description of the social network underlying the simulation.	×	√	×	-	√	-	√	√	√
Simulation-based human mobility models	Social-based models	Geo-CoMM [57]	In this model, people move within a set of geo-communities, following speed, pause time and choice rules whose distribution is obtained by the statistical analysis.	×	√	√	-	√	√	×	√	√
Simulation-based human mobility models	Social-based models	Arrival-based framework [58]	A mobility framework that takes a social graph as input. Then, The spatial and temporal dimensions of mobility are added.	×	√	×	-	-	-	√	√	√

("√" if the model satisfies the property, "×" if not, and "–" for ambiguous cases)

There are two steps to model the structural changes in an evolving network. At first step, an evolving network is converted into static graphs at different snapshots. Then, a classical algorithm is used to infer relationships between partitions at different periods more or less independently. Several attempts have been made to use static in order to characterize the evolution of the communities between two time steps. For example, a community may merge with another one, split or disappear. When we try to identity some common parts between two partitions, we are trying to solve a matching problem. There has been a considerable amount of work done to solve a matching problem in static graphs, such as stochastic methods [62].

Taking advantage of set theory and rules is other intuitive methods to perform the matching between partitions to decide whether sets of different partitions are similar or not. For instance, if two communities of successive snapshots share many nodes, they are related. The main problem is that given two partitions, one can find many different valid matching solutions between these partitions. Three valid matching solutions are illustrated in Fig. 7. First attempt to solve the matching problem in the context of evolving communities is proposed in [63]. The authors study a co-authoring network using the size of the intersection of communities: two communities at successive time steps are matched if they share enough nodes. This matching methodology has been

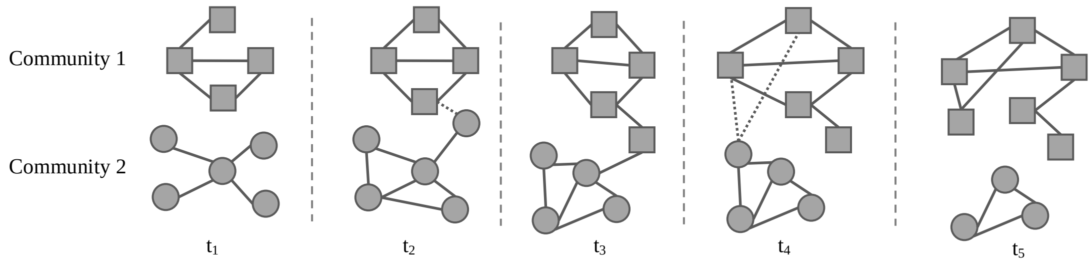

Fig. 6. An example of an evolving network containing two communities with dynamic relations between the nodes at different time steps.

generalized in [64] where the authors defined many similar rules to deal with other cases of communities' evolution: merge, split, appearance and disappearance.

Instead of computing the matching after having computed the communities, it is possible to perform the matching during the community detection. Solutions in this context have been studied from different aspects based on physical location and social relationship. Flocks [65] supports dynamic user group creation based on user profiles and physical proximity. Flocks has been prototyped as the basis of a new distributed object-oriented framework sculpted for the development of such applications called Urbiflock. MobilisGroups [66] is another location-based group creation service in which each created group is tied to a specific location.

Cluestr [67] leverages contacts from personal social networks to form groups. It aims to facilitate efficient initiation of group interaction from mobile terminals. Based on the fact that each user belongs to several social communities, Cluestr employs existing social networks to recommend contacts. ADESSO [68] supports opportunistic social networking based on a set of self-organizing brokers. A user who wants to participate in social activities specifies her or his preferences in a user task and publishes it to elected brokers. The brokers collect user tasks and perform task matching once they encounter each other. SOCKER [22] is based on social-aware broker selection strategies to cope with the size-fixed community creation problem. SOCKER gradually forms a mobile social community by dynamically selecting a broker during each opportunistic encounter, and the selected broker disseminates community creation requests to the encountered users for match-making.

Comparatively, it can be seen that while Flocks and MobilisGroups strived to cluster users that are physically close to a specific location or a specific person (community initiator), Cluestr can only recommend candidate members that are already in the initiator's personal contact list. SOCKER aimed to leverage the opportunistic encounter characteristics of OSNs to create communities. Secondly, when initiating a community creation process, different expectations can be considered by the initiator about the candidate members, whereas ADESSO doesn't support this issue. In addition, while ADESSO is merely proposed to facilitate social activities among users who actively specify and publish community creation requests, in SOCKER, inactive users are motivated to participate in more social activities.

B. Temporal Community Tracking and Evolution Analysis

Temporally-independent community detection algorithms model the dynamic network as a static graph by removing information about the time of the interactions. The natural extension of the community detection to dynamic networks is community tracking, which makes it possible to observe how communities grow, shrink, merge, or split with time. This new approach is based on building a temporal network representing the relations between communities at each time step. In this method, significant variations even between partitions close in time may appear, which results in artifactual community structure evolution [69].

The idea of ordering several snapshots side by side in one temporal graph is proposed in [70]. However, one major drawback to study dynamic communities using snapshots or more complicated ideas is validation tools. Additionally, incremental or online algorithms aim to process data stream instead of a full snapshot. As an example, the authors in [71] propose an incremental graph mining algorithm that discovers and adapts clusters over a network of interacting nodes. They consider only the nodes whose neighborhood size is bigger than a given threshold which are considered as a core vertex. Nodes that belong to the neighborhood of core vertex are border vertex, and others are noise vertex. The communities are then the transitive union of neighborhoods that share nodes.

Mining emerging communities in dynamic networks has raised new issues related to emerge, evolve, mutate or decline of the communities as time passes. A number of researchers work on identifying critical events that characterize the evolution of the communities in MSNs. Palla *et al.* [72] identified events by applying clique percolation method (CPM) [73] on a graph formed by the communities discovered at two consecutive snapshots. A similar algorithm for detecting a time-varying MSN based on CPM is proposed in [74]. The k-cliques community is redefined on the basis of contact duration by extracting the nodes which have heavy interaction within the community. Another recent work [75] proposed an innovative method for detecting overlapping communities; however, it is time consuming, especially on large scale networks. Similarly, Bubble Rap uses weighted network analysis and k-clique algorithms for community detection, and the contact threshold for extracting the k-clique community.

Discovering dynamic communities of people in an opportunistic scenario are explored in [76]. The proposed methods in this work are based on three distributed algorithms named SIMPLE, k-CLIQUE and MODULARITY, which are introduced in [77]. According to the descriptions, the three community detection algorithms have different memory and computational requirements. After discussing trade-offs between these algorithms, they finally proposed a new community detection algorithm, namely adaptive detection

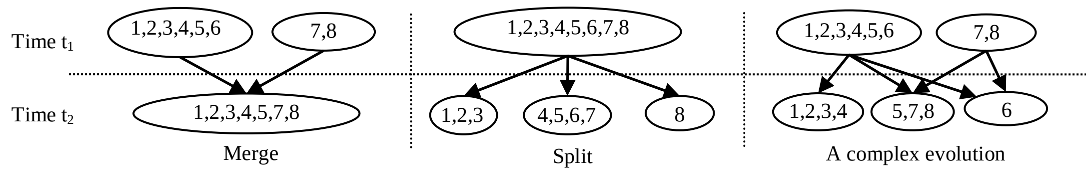

Fig. 7. Three valid matching solutions between two time steps.

SIMPLE (AD-SIMPLE), which is able to capture the evolution of social communities in dynamic scenarios, while keeping computation and storage requirements low.

Detecting critical events between detected communities at two consecutive snapshots were addressed in [78]. Then, a series of significant events and transitions are defined to characterize the evolution of networks in terms of its communities and individuals. In addition, to capture the changes that are likely to occur for a community, five events (form, dissolve, survive, split, and merge) and four transitions (size transition, compactness transition, leader transition, and persistence transition) are defined. In order to analyze dynamic social networks and study the evolution of its communities and individuals, in more recent work [79], they consider four stages for community modeling and evolution analysis: modeling, community mining, evolution analysis and future prediction as it is depicted in Fig. 8.

V. Routing and Data Dissemination in MSNs

There are generally no stable end-to-end delivery paths in a MSN. Therefore, delivering messages becomes a challenging issue in this paradigm. Most of the existing routing and dissemination protocols employ *store-carry-and-forward* fashion to carry messages between the network nodes. If there is no connection available at a particular time, a mobile node can store and carry the data until it encounters other nodes. When the node has such a forwarding opportunity, all encountered nodes could be the candidates to relay the data. Thus, relaying selection and forwarding decision need to be made by the current node based on certain routing strategies.

Based on a chosen strategy, forwarding policy varies from epidemic replication of all the messages to every node like Epidemic routing [80], through to multi-copy and single-copy forwarding. Flooding-based protocols with unlimited replicas of messages cause high demand on network resources, such as storage and bandwidth and cause congestion. However, multi-copy protocols typically aim to limit the number of replicas of the message in order to leverage a tradeoff between resource usage and probability of message delivery. On the other hand, single-copy strategies require routing algorithms to implement a next-best-hop heuristic that forwards the messages to those nodes with a highest probability to deliver the message to its destination.

Recently, the consideration of social characteristics has opened new horizons in design of data distribution and sharing protocols. The main reason is that social relations of mobile nodes have generally long-term characteristics and they are more stable than node mobility and/or the contact history. However, most state information is dynamic and hard to obtain without a global or long-term collection process. The knowledge of social properties between mobile nodes such as common habits and friends, social similarities and interests can be exploited to make better forwarding decisions. Using social features of mobile users, the main objective is to select the most optimal relay nodes with the highest probability to meet the destination(s) (e.g., socially similar destination nodes).

In this section, we present a comprehensive review on routing proposals in MSNs with respect to community structure, context-awareness, node selfishness and incentive schemes. Then, we categorize and give an overview of data dissemination algorithms in MSNs.

A. *Routing Protocols*

Almost all state of the art routing algorithms in MSNs make use of the community structure features and/or other social characteristics such as node centrality, tie strength or social similarity to bring messages close to a destination. Based on whether community is supported or other social characteristics are considered, we classify the current strategies as community-based routing and community-independent routing.

1) Community-based Routing: A group of users with social links, common interests, and similarities tend to interact with each other more frequently than those in other groups. These groups are called communities. The identification of social communities in MSNs can be used to improve the delivery of information by selecting appropriate forwarders instead of performing naive oblivious flooding. Firstly, mobile nodes are grouped into the communities by the certain community detection algorithm. The phase following the detection of existing communities is the design of a community structure. To forward data between the communities (inter-community forwarding), network overlays constructed using hubs or brokers can be used. In this phase, if the relay nodes are out of destination community, the inter-community forwarding strategy relays data to the destination community. Otherwise, the intra-community forwarding strategy is used to pass data to the centrality node until the data reaches the destination. However, these approaches suffer with the overhead of community formation.

LABEL [81] approach is one of the first community-based routing protocols to employ social characteristics into opportunistic routing. In this method, it is assumed that every node includes a label in order to inform others about its affiliation. With this, it compares the label of the potential relay nodes and the label of the destination node, and forwards the data objects to nodes that belong to the same community as the destinations. The problem for LABEL is that delivery ratio is very low in the case of messages with short time-to-live (TTL), and the routing performance is significantly degraded if nodes do not mix well. The reason is that LABEL performs only one-hop delivery and just to nodes belonging to the same community as the destination.

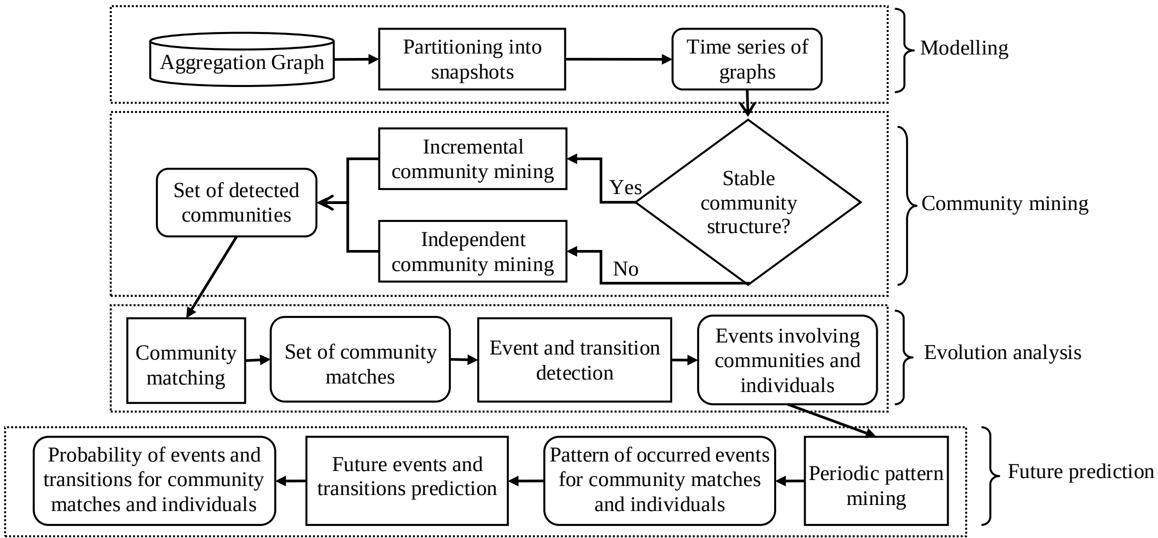

Fig. 8. Different stages of dynamic social network analysis [79].

Bubble Rap [19] focuses on social centrality, and nodes are structured into communities. This algorithm considers that nodes belong to different sized communities and that such nodes have different levels of popularity (i.e., rank). Nodes are grouped based on social parameters and have a local/global popularity index and each node is assumed to have two rankings: global and local. While the former denotes the popularity (i.e., connectivity) of the node in the entire society, the latter denotes its popularity within its own community. Messages are forwarded to nodes having higher global ranking until a node in the destination's community is found. Then, the messages are forwarded to nodes having higher local ranking within the destination's community.

Both phases of the Bubble Rap procedure are demonstrated in Fig. 9. When a node s has a message with destination of d, it first bubbles the message up based on the global centrality, until the message reaches a node which is in the same local community C_d as the destination d. This procedure is shown as blue arrows in the figure. After the message reaches d's community at node u, Bubble Rap switches to the second phase which uses members of C_d as relays. This later procedure is shown as dashed arrows in the figure.

More recently, a mathematical model of single-copy optimal routing, assuming the presence of a global observer, is formulated in [83] that can collect information about all the nodes in the network. Furthermore, social groups based routing (SGBR) is proposed which utilizes the social relations between nodes to reduce redundant copying of packets. Two nodes belong to the same social group if they contact with each other frequently. They are also expected to have around the same social relation with other nodes. Some routing algorithms such as Bubble Rap predict the path from source to destination by including nodes with strong social connections. In contrast, SGBR uses an exclusive social metric which sprays messages by excluding nodes that are not expected to add a significant value to the node carrying the message. Using exclusive metrics reduces the need to collect network-wide information, while improving the performance metrics.

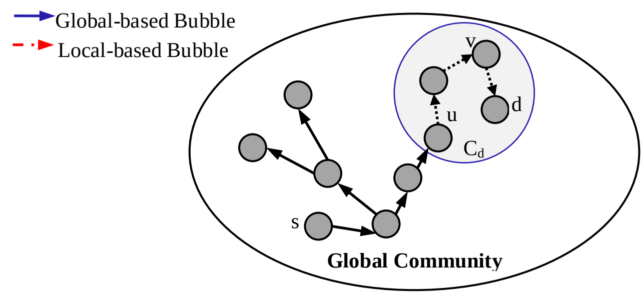

Fig. 9. An illustration of a data forwarding process in the Bubble Rap from source s to destination d [82].

Homing spread (HS) [84] is a zero-knowledge multi-copy routing algorithm like the Epidemic routing based on the flooding strategy, which incurs a significant number of message copies. Specifically, HS considers an MSN with nodes that have a common interest and visit some locations, called community homes, frequently, while the other locations are visited less frequently. It is assumed that each home supports a virtual throwbox [85], a mechanism that can store a message at a local storage device, or at another node currently at the same home. A message holder is either a mobile node or a home that has message copies. HS consists of three phases: homing, spreading, and fetching. In the first phase, the source spreads copies quickly to homes. In the second phase, the homes with multiple copies spread them to other homes and mobile nodes. Then, in the third phase, the destination fetches the message when it meets any message holder for the first time, which can be either a home or a mobile node.

Community-aware opportunistic routing (CAOR) [86] is a single-copy routing algorithm based on community homes which turn the routing in mobile nodes into a routing in community homes. This method is then extended to the case of the virtual throwbox by letting the members of a community with high centralities act as the home of this community. In this method, mobile users with a common interest autonomously form a community, in which the frequently visited location is

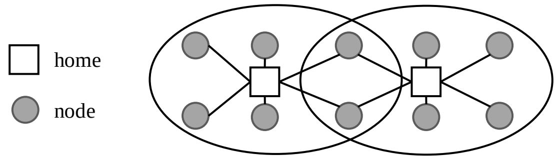

Fig. 10. An example of home-aware communities [86].

their common home. Each community has a star topology where its home is the center. The whole network is composed of some overlapped star-topology communities, as shown in Fig. 10. CAOR first turns the routing between lots of nodes to the routing between a few community homes. Then, a reverse Dijkstra algorithm by maintaining an optimal relay set for each home is adopted to determine the optimal relays and compute the minimum expected delivery delay. Each home only forwards its message to the node in its optimal relay set, and ignores other relays.

Some work consider the relationship between the communities and formulate inter-community forwarding decision. LocalCom [87], for example, is an epidemic forwarding scheme which forms the community structure and considers the forwarding between different communities. Firstly, similarity metrics according to nodes' encounter history are presented to construct the neighboring graph. Then, a distributed algorithm for the community detection is proposed which uses an *extended clique* to represent the underlying community structure. Finally, two schemes are presented to first select and then prune gateways that connect communities to control redundancy and facilitate efficient inter-community forwarding. LocalCom adapts single hop source routing for the intra-community communication and controlled flooding routing for the inter-community packet forwarding. Similarly, Gently [88] is based on context-aware adaptive routing (CAR) [89] and LABEL. It defines labels to identify communities of hosts. A recipient of message can be a single host or a group (community) of hosts. Gently uses CAR-like routing when no node of the destination community is in reach. When the message carrier meets a node of the destination community, Gently adopts a LABEL based strategy. Then, in the destination community, CAR-like routing is used to deliver the message to the destination.

dLifeComm [90] is a community-based routing which uses time-evolving social structures to model the dynamism of users' behavior found in their daily life routines. The assumption here is that the time nodes spend together can be used as a measure of the strength of the social ties among them. To achieve that, dlife defines two complementary utility functions: time-evolving contact duration (TECD) that captures the evolution of social interaction among pairs of users; and TECD importance (TECDi) that captures the evolution of user's importance, based on its node degree and the social strength towards its neighbors. dLifeComm combines the notion of community, as Bubble Rap, and the social strength for forwarding: when a user has a message to another user in a different community, it forwards the message towards the destination's community using TECDi. The assumption is that users with higher importance have higher probability to reach the destination's community faster. When the destination's community is reached, forwarding is done towards the destination by replicating the message to users with higher social strength (TECD) towards the destination, and not higher centrality, as in Bubble Rap.

Friendship community is another concept in sociology which describes close personal relationships. In MSNs, the friendship can be defined between a pair of nodes. On the one hand, to be considered as friends of each other, two nodes need to have long-lasting and regular contacts. Friendship based routing [24] is based on contact history between two nodes to indicate the tie strength of virtual link and to form friendship community. In this method, three behavior features of close friendship: high frequency, longevity and regularity are considered, and also two metrics SPM and conditional SPM are defined for direct and indirect friendship. The friendship community is a set of nodes having a link quality larger than a threshold. To reflect temporal differentiate, different friendship communities in different periods of the day are established for each node. When forwarding, current node with the message will choose the node that belongs to the same community with the destination and with a stronger friendship of destination than current node.

2) Community-Independent Routing: Dynamic nature of the network topology with no obvious social communities and changeable social relationship between mobile carriers make the community detection a challenging issue in MSNs. Therefore, some routing protocols have been presented without community support.

SimBet [17] is a prominent algorithm in this category based on the identification of the betweenness centrality and social similarity metrics. In this algorithm, ego network analysis technique is used to estimate the values of the betweenness centrality and the similarity for each node. The concept of ego network is exploited where only locally available information is considered. Messages are forwarded towards the node with higher centrality to increase the possibility of finding the potential carrier to the final destination.

SimBet has good overall performance regarding message delivery, which is close to the Epidemic routing. However, this proposal may suffer with high delay as well as congested traffic around central nodes. For instance, in the SimBet algorithm, the top 10% of nodes carry out 54% of all the forwards and 85% of all the handover. To tackle with this problem, some strategies are proposed to improve delivery ratio and reduce delivery delay and overhead. For instance, congestion-aware forwarding [91] supports optimization of high volume multipoint data flows transfer while maintaining high buffer availability. To fair the load distribution, FairRoute [92] exploits the social process of perceived interaction strength based on the interaction strength between nodes in a short term and long time scale. It forwards the message by the stronger social relation and uses assortative-based queue control to limit the exchange of messages to those users with similar social status. Contrary to the congestion-aware forwarding, FairRoute defines a large queue size as a high social status and therefore a more desirable next hop.

In social-greedy [93], a forwarding decision is made by the closeness and social distance. The closeness is calculated by the common attributes (address, affiliation, school, major, city, country, etc.) of the two nodes. The more common attributes, the closer the two nodes. Social-greedy forwards a message to the next node if it is socially closer to the destination. The social-greedy outperforms the LABEL protocol. However, the delivery ratio of the Epidemic routing and Bubble Rap is better than the social-greedy.

The above-mentioned approaches heavily build upon the ability of storing a large amount of information at the nodes. To tackle this problem, social aware networking (SANE) [94] is proposed which is a stateless forwarding protocol like the Epidemic routing. SANE is based on the observation that individuals with similar interests tend to meet each other more often. In the SANE, nodes exchange their interest profile. Then, each node starts scanning its buffer for messages to relay. In addition, data dissemination paradigms are required, in which individual nodes contribute a fraction of their resources to circulate data, selecting those data items to store based on their utility for the overall dissemination process.

Taking node mobility and social interaction into account, PeopleRank [95] is a fully distributed algorithm that ranks nodes in a social graph, i.e., it measures the relative "importance" of a node in a social graph. The message forwarding decisions can then follow a non-decreasing rank rule. PeopleRank makes use of stable social information between nodes to decide on forwarding. As its own name suggests, PeopleRank sets ranks to nodes according to their social interaction, and use this ranking to decide on the next hop for data exchange as it is known that socially well-connected nodes become the best forwarders for message delivery.

In SMART [96], each node builds its own social map consisting of nodes it has met and their frequently encountered nodes to record its surrounding social. The social map is not limited to one or two hops and reflects possible long relay paths to provide better forwarder selection. Based on both encountering frequency and social closeness of the two linked nodes in the social map, weight of each link is calculated to reflect the packet delivery probability between the two nodes. Packets are forwarded to nodes with higher delivery probability to their destinations. When two nodes meet, they only need to exchange the information of the top L most frequently encountered nodes for social map construction or update. Trace-driven experiments show that SMART is more efficient than previous routing algorithms such as SimBet because the social map offers a broader view for forwarder selection.

Hypercube-based social feature routing (HSFR) [97] uses internal social features of each node including affiliation, country, language, and so on, to perform the routing process. This approach is motivated from several real traces, such as the INFOCOM 2006 trace, where people contact each other more frequently if they have more social features in common. Based on this assumption, HSFR converts a routing problem in a highly mobile and unstructured contact space (M-space) to a static and structured feature space (F-space), as shown in Fig. 11. In Fig. 11(b), nodes with the same feature are grouped together. The groups in the static feature space can be mapped into an m-dimensional hypercube, in which two groups are connected if and only if they differ in only one feature. HSFR includes two unique processes: social feature extraction and multi-path routing. In the social feature extraction, entropy is used to extract the m most informative social. The routing method then becomes a hypercube-based feature matching process, where the routing process is a step-by-step feature difference resolving process. Feature differences are resolved

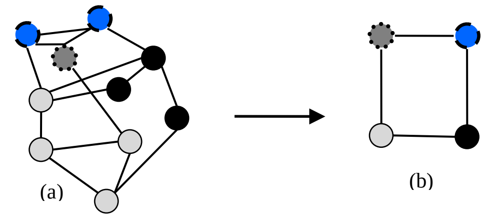

Fig. 11. Converting from a highly mobile contact space to a static and structured feature space in hypercube-based social feature routing [97].

step-by-step until the destination is reached. The performance of the HSFR by looking at the delivery rate and latency are analyzed extensively in [98].

SEDUM [99] is a social network oriented and duration utility-based routing protocol that fully exploits node movement patterns to increase routing throughput and decrease routing delay. The duration utility in this method is the ratio of total contact duration between two nodes over a time period T. SEDUM is distinguished by three features. First, it considers both contact frequency and duration in node movement patterns of social networks. Second, it uses multi-copy routing and can discover the minimum number of copies of a message using an optimal tree replication algorithm to achieve a desired routing delay. Third, it has an effective buffer management mechanism to increase throughput and decrease routing delay. The buffer management mechanism gives longer-lifetime messages a higher priority to be sent out from buffers, thus reducing the system's total transmission latency.

Wang *et al*. [100] explored how the social structure affects the forwarding algorithm in various configurations. They studied a collection of social-based forwarding algorithms, such as LABEL, PeopleRank, and Bubble Rap over Haggle testbed. In this work, it is concluded that the social structures influence the performance of the social-based forwarding significantly. Similarly, Zyba *et al*. [101] extends previous efforts in [17],[19],[95] by exploring the role and potential of non-social, vagabond devices for communication and data dissemination. In this work, the user populations in each trace are divided into two distinct groups: *socials* and *vagabonds*. The main idea is that the socials have significantly higher contact rates than the vagabonds, indicating that they have more opportunities for data dissemination, while inter-contact times are heavier tailed for the vagabonds.

B. *Context-aware Routing*

In addition to contact history, context of mobile users is of paramount importance for the routing algorithms. The definition of context mainly deals with the interaction between the user and the applications, and context awareness refers to having the knowledge of the situation in which a device is being used. In particular, a definition of context might be composed of e.g. user context, service context, device context, etc [102].

Based on the amount of knowledge about the context of users they exploit, different categorizations for the routing approaches in opportunistic environments can be identified. As stated in [103], the routing algorithms can be classified in three main types: context-oblivious, partially context-aware and fully context-aware algorithms. The context-oblivious protocols such as LABEL do not exploit any contextual information about the behavior of users. The partially context-aware protocols exploit context information, but assume a specific model for this context. When the environment matches the assumed context, they perform very well, but their operation may not be correct if the environment is different from the assumption. Fully context-aware protocols learn and exploit the context around them and, while they may not be as efficient as partially context-aware protocols, they are much more adaptive. In this subsection, some sample well-known partially context-aware and fully context-aware routing algorithms are introduced.

1) Partially Context-aware Routing Algorithms: social relation-aware routing protocol (SRRP) [104] is a partially context-aware algorithm for choosing the best forwarders in MSNs. This protocol exploits the social context between users to calculate forwarding nodes. The users' context interest is added to the routing table which can be used to estimate the likelihood of accessing the content by other users. Similarly, PROPHET [105] is an extended version of the Epidemic routing that makes use of delivery predictability metric to calculate how likely a node will be able to deliver a message to the destination. In this method, contact frequency between nodes is used as context information.

Context information prediction for routing in OppNets (CiPRO) [106] uses the temporal and spatial aspects of context information and back propagation neural network model to predict the encounter probability between the sender and the destination. Thus, CiPRO provides the sender with knowledge of when and where it can have a high probability to successfully deliver the message to the destination.

2) Fully Context-aware Routing Algorithms: CAR and history base opportunistic routing (HiBOp) [107] are examples of fully context-aware data forwarding protocols. CAR makes use of Kalman filter-based prediction techniques [108] and utility theory to combine and evaluate the multiple dimensions of the context in order to take routing decisions. These techniques do not require the storage of the entire past history of the system, making them suitable for a resource-scarce mobile setting. CAR is able to deliver messages synchronously and asynchronously. Each host maintains a routing and context information table used for asynchronous and synchronous routing. In HiBOp, each node exchanges context information only with other members of the node's community, and thus stores context information related to the node's community only. In the forwarding phase, just nodes of the destination community are selected as candidate forwarders. It selects packet forwarder according to nodes' historical encounter records with the context of the packet destinations. The main idea of HiBOp is looking for nodes that show an increasing match with the known context attributes of the destination. One of the main drawbacks of HiBOp is its high overhead.

The impact of context awareness in delay and overhead of opportunistic forwarding algorithms is shown in Fig. 12. It can be seen that fully context-aware routing protocols have minimum network overhead whereas the context-oblivious methods have minimum delay in message delivery. Table 4 summarizes representative data routing protocols in MSNs.

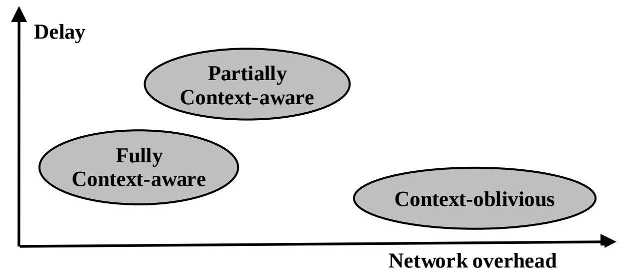

Fig. 12. Delay and network overhead of context-oblivious, partially and fully context-aware routing algorithms [103].

C. Data Dissemination Protocols

Today, a large volume of data are generated by mobile users, and they like to share them with people they have social relationships or similar interests with. In this setting, mobile users are completely decoupled from each other, hence data producers and consumers might never contact with each other in the network. Therefore, mobility feature of users should be assisted in order to deliver data items to interested users. In addition, resource constrains in mobile devices should be considered by the users when they want to store and carry data for other users [109].

A potential solution for data dissemination would be to flood the whole generated data object like the Epidemic routing. Clearly, this method would saturate both network and device resources. More realistic and applicable approaches for controlled data dissemination in MSNs can be fallen into two groups: publish-subscribe schemes and social-aware schemes. In this subsection, we analyze state of the art of data dissemination techniques in both the categories.

1) Publish-subscribe schemes: Publish/subscribe (Pub/Sub) paradigm recently emerges as a promising solution to data dissemination in interest-based scenarios. In such a paradigm, the network delivers a published message only to the nodes whose subscribed interests match it. Furthermore, the message producers and consumers are sharply decoupled, which is inherently suited to dynamic environments. The message producer or publisher simply injects a message in the network. Routing protocols no longer revolve around node identifiers, since these are not specified in the message. Instead, the network delivers the message to the interested subscribers based on some characteristic of the message, such as its topic or even its very content.

A prominent dissemination scheme in this category includes those defined in the PodNet project [110]. Assuming a network without infrastructure, the wireless podcasting service enables the distribution of content using opportunistic contacts whenever podcasting devices are in wireless communication range. The ad hoc podcasting service employs a Pub/Sub approach. Thus, it organizes content in channels, which allows the users to subscribe and automatically receive updates for the content they are interested in. However, this method does not exploit social information, but incorporate well-known caching policies such as uniform and greedy selection.

TABLE 4
COMPARISON OF DATA ROUTING PROTOCOLS IN MOBILE SOCIAL NETWORKS

	Protocol	Characteristic	Properties						Context		
			single-copy	multi-copy	centrality	similarity	tie strength	interest	oblivious	partially	fully
Community-based routing	LABEL [81]	A forwarding scheme in which every node compares label of potential relay and destination node, and forwards the data to nodes that belong to the same community as the destinations.	×	√	×	×	×	×	√	×	×
	Bubble Rap [19]	A community-based algorithm that messages are forwarded to nodes having higher global ranking until a node in the destination's community is found.	×	√	√	×	×	×	×	√	×
	SGBR [83]	A routing protocol based on social grouping among the nodes to maximize data delivery while minimizing network overhead by efficiently spreading the packet copies in the network.	√	√	×	×	×	×	√	×	×
	Homing Spread [84]	A zero-knowledge routing algorithm which utilizes the home feature and sets a higher priority for homes to spread messages quickly.	×	√	×	×	×	×	√	×	×
	CAOR [86]	A distributed algorithm that turn the routing between lots of nodes to the routing between a few community homes.	√	×	√	×	×	√	√	×	×
	LocalCom [87]	A scheme which defines similarity metrics to depict the neighboring relationship and uses limited local information to detect communities. Then, two schemes to select and prune gateways are proposed that connect communities and facilitate inter-community forwarding.	×	√	√	√	√	×	√	×	×
	Gently [88]	A protocol based on the combination of a social-tag based method like [81] and a predictive protocol like [89], implemented on top of the Haggle framework.	×	√	×	×	×	×	×	√	×
	dLifeComm [90]	A variation of dLife, which utilizes utility functions to exploit communities and capture the dynamics of the network represented by time-evolving social ties between pair of nodes.	×	√	√	×	×	×	√	×	×
	Friendship based routing [24]	First, SPM metric is used to define nodes' friendship community as the set of nodes having close friendship with itself. Then, the algorithm is used to make the forwarding decisions of messages.	×	√	×	√	×	×	√	×	×
	HiBOp [107]	HiBOp learns through context information, the users' behavior and their social relations, and uses this knowledge to drive the forwarding process.	×	√	×	√	×	×	×	×	√
Community-independent routing	SimBet [17]	A centrality-based forwarding algorithm which uses potential nodes to forward messages to destination based on SimBet utility function	√	×	√	√	√	×	×	√	×
	Congestion-aware routing [91]	A forwarding algorithm which uses a number of social, buffer and delay utility metrics to offload the traffic from congested parts of the network and spread it over less congested parts.	√	√	√	√	√	√	√	×	×
	FairRoute [92]	FairRoute exploits the social process of perceived interaction strength based on the interaction strength between nodes in a short term and long time scale to fair the load distribution,	×	√	×	×	×	×	√	×	×
	Social-greedy [93]	A routing algorithm for bootstrapping wireless devices, which uses a social distance derived from people's social profiles to route messages.	×	√	×	√	√	×	√	×	×
	SANE [94]	One of the first forwarding mechanisms that combines the advantages of both social-aware and stateless approaches in the routing.	×	√	×	√	×	√	√	×	×
	PeopleRank [95]	A fully distributed algorithm that ranks nodes in a social graph and makes use of stable social information between nodes to decide on forwarding.	×	√	×	×	√	√	×	√	×
	SMART [96]	A lightweight distributed algorithm that each node builds a weighted social map to reflect the packet delivery probability between the two nodes.	√	×	×	×	×	×	√	×	×
	HSFR [97]	A social feature-based scheme that consists of two parts: social feature extraction using entropy to extract the most informative social features and multi-path routing. The feature difference between the source and the destination is resolved during the routing process.	√	√	√	√	×	×	√	×	×
	SEDUM [99]	A multi-copy routing based on both contact frequency and contact duration which uses a buffer management mechanism to discover the minimum number of copies of a message.	×	√	×	×	×	√	√	×	×
	SRRP[[104]	SRRP chooses among alternatives a route based on similarity of interest to increase the utilization of contents replication in intermediate nodes.	×	√	×	√	×	√	×	√	×
	PROPHET [105]	A probabilistic protocol based on the observation that if a node has visited a location several times before, it is likely that it will visit that location again.	√	×	×	×	×	×	×	√	×
	CiPRO [106]	A social context-based routing scheme that considers both the spatial and the temporal dimensions of the activity of mobile nodes to predict the mobility patterns of nodes.	×	√	×	×	×	×	×	√	×
	CAR [89]	The solution is based on the application of Kalman filter based forecasting techniques and utility theory for taking routing decisions.	√	×	×	×	×	×	×	×	√

("√" if the protocol satisfies the property, "×" if not)

Socio-aware overlay [111] uses a Pub/Sub mechanism to create an overlay over detected communities. Community detection in this method is implemented using gossiping when nodes contact each other. The overlay is composed of certain nodes called brokers that have high centrality values in the community. At the data exchange phase, subscription and unsubscription information as well as a list of centrality values with a time stamp are exchanged. When closeness centrality of a broker node changes, the subscription list is transferred from the old one to the new one and an update is sent to all the brokers. During the gossiping stage, subscriptions are propagated towards the community's broker. When a publication reaches the broker, it is propagated to all other brokers, and then the broker checks its own subscription list. In the case there are members in its community that must receive the publication, the broker floods the community with the information.

SocialCast [112] presents a first attempt to exploit social information in a Pub/Sub system. In this method, there is an assumption that users with common interests tend to meet with each other more often than with other users. Taking shared interests of users into account, data forwarding in the SocialCast can be achieved not only based on social ties and mobility patterns, but also by the interest of destination nodes. Like CAR algorithm, SocialCast uses the Kalman filter to predict the future evolution of the movement based on previous observations. Routing in the SocialCast consists of three phases: interest dissemination, carrier selection, and message dissemination. During interest dissemination, each node broadcasts the list of its interests to its 1-hop neighbors. In the second step, the utility of the local node is recomputed for all interests. During message dissemination, the content of the buffer is reevaluated against the new subscriptions and utilities, and messages are forwarded to the interested nodes. A fallback of this method is that it works well when all members of each community are interested in the same type of content, but it is not clear how it works in the more general settings.

2) Social-aware schemes: The most advanced approaches for data dissemination in MSNs exploit information about users' social relationships to drive the dissemination process.

ContentPlace [109] is a social-aware dissemination system which forwards data by defining community-based relay selection policies. It assumes the same community detection mechanisms which is used in the socio-aware overlay. In this method, social behaviors of the users are exploited to select data object encounter users exchange. To do so, a utility function for each data object is provided. To exchange data, the encounter nodes calculate the utility value of all the data objects in their local buffer. Then, it selects the set of data objects that maximizes the local utility of its cache are selected considering the resource constraints.

Efficiency of data dissemination systems relies heavily on the swift and optimal selection of data objects. In other words, an efficient content forwarding should schedule when to forward which data objects to improve the total utility. Furthermore, it must be very lightweight and able to perform a sharp distinction between data items, since only a very limited part of them could be forwarded during a very short contact period. In order to retrieve the most useful data items by users simply, a fast cognitive heuristic called recognition heuristic is proposed in [113]. The recognition heuristic uses models of how the human brain assesses the relevance of information under partial knowledge. Similarly, PrefCast [114] targets on maximally satisfying user preference for content objects. To disseminate a suitable set of objects that can bring possible future contacts a high utility, a maximum-utility forwarding model is formulated in the protocol. Then, a dissemination algorithm is proposed that enables each user to predict how much utility it can contribute to future contacts and solve its optimal forwarding schedule in a distributed manner.

Fan *et al.* [115] address data dissemination from a single super user to other users among several communities and proposed an efficient super user route to broadcast data actively. To do so, the concepts of *geocommunity* and *geocentrality* into MSN analysis are introduced. Then, a semi-Markov process is proposed to model user mobility based on the geographic regularity of human mobility and geocentrality as the super user among communities. They formulate the super user route design as a combinational optimization problem of a convex optimization problem and traveling salesman problem to achieve the goal of minimizing the total duration and guaranteeing the required data dissemination probability.

Table 5 summarizes representative data dissemination protocols in MSNs.

D. Dealing with User Selfishness

In most of the routing and data dissemination protocols in MSNs, there exists a potential assumption that users are willing to cooperate with each other for packet forwarding. However, in real scenarios, energy, cache and bandwidth resources are limited, and a mobile carrier may not be perfectly willing to store or relay messages on behalf of the others. Furthermore, users may download messages from other users that they may be interested in, but they deny distributing messages for the benefit of other users. In other words, nodes might be selfish in message forwarding.

Two kinds of user selfishness can be observed from the social perspective. First, a selfish user is usually willing to help others with whom he has social ties (e.g., friends, coworkers, roommates), because he received help from them in the past or will probably receive help in the future. Second, for those with social ties, a selfish user may give different preferences. That is, he is willing to provide better service to those with stronger ties than those with weaker ties. For easier presentation and comparison, such refined selfishness model will be referred to as *social selfishness* and the previously well studied simple model is called *individual selfishness* [116].

In the rest of this subsection, the impact of node selfishness on the performance of MSN routing and data dissemination protocols are discussed. Then, some representative incentive strategies that stimulate selfish nodes to participate in message delivery are explored.

1) The Impact of User Selfishness on the Performance of Forwarding Algorithms: A problem in MSNs is that the quality of the delivery service provided by the system heavily depends on the users' willingness to co-operate. To study this phenomenon, some methods have studied the impact of node selfishness on the performance of routing algorithms in MSNs.

Theoretically, the impact of social selfishness on the Epidemic routing as two dimensional continuous time Markov chains is

TABLE 5
COMPARISON OF DATA DISSEMINATION PROTOCOLS IN MOBILE SOCIAL NETWORKS

Protocol		Characteristic	Properties				
			movement pattern	centrality	similarity	tie strength	community
Publish-subscribe	PodNet [110]	In this scheme, contents are organized into feed channels. Users subscribe to channels they are interested in and they are associated in pair-wise way when they come into the transmission range of each other.	×	×	×	×	×
	Socio-aware overlay [111]	A socio-aware overlay is built for Pub/Sub communications by using the community and centrality concepts.	×	√	×	×	√
	SocialCast [112]	A routing framework for publish-subscribe that exploits predictions based on metrics of social interaction to identify the best information carriers.	√	×	×	√	√
Social-aware	ContentPlace [109]	A social-oriented routing scheme for optimizing content delivery that disseminates data by defining community-based relay selection policies.	√	×	×	×	√
	Recognition heuristic [113]	A solution based on rapid, low-resource demanding, yet very effective scheme to let each node rapidly decide which is the utility of taking one data item instead of another upon making direct contact with other nodes.	×	×	×	×	√
	PrefCast [114]	A solution which takes heterogeneous user preference into account, and enables each forwarder to determine its optimal object forwarding schedule that can produce the maximal total utility for all users in an MSN.	√	×	×	×	×
	Geocommunity-based [115]	A one-hop protocol to facilitate data dissemination from a single super user to other users by exploring both geographic and social properties of users' mobility.	√	√	√	×	√

("√" if the protocol satisfies the property, "×" if not)

evaluated in [117]. Considering the case that nodes form two communities, the results show that social selfishness increases the message delivery delay, and at the same time decreases the delivery cost. Similarly, the authors of [118] investigated how the selfish behavior of nodes affects the performance of DTN multicast by a three dimensional continuous time Markov chain. The study shows that different selfish behaviors may have various impacts on performance metrics. In terms of different selfish behaviors, it is demonstrated that the individual selfishness of not forwarding messages increases the message transmission delay and cost, which is detrimental to the DTN multicast. On the other hand, the individual selfishness of not relaying messages increase the message transmission delay but reduce the transmission cost. Another interesting result is that without strict requirement of delivery delay, the social selfishness decreases the delivery cost.

2) Incentive-driven Data Forwarding: Most of the routing and data dissemination protocols in MSNs assume that the mobile users are cooperative and never decline service to the other users. Since nodes in MSNs are controlled by humans, they often behave selfishly with an aim to maximize their own revenues without considering the performance of others, unless cooperation is somehow incentivized. In such scenarios, stimulating nodes to collect, store, and share content is one of the key challenges. In the recent years, several incentive-based schemes have been proposed to stimulate selfish nodes for more cooperation. The existing incentive-aware strategies can be classified into four categories: *tit-for-tat (TFT)*, *game-theoretic*, *credit-based*, and *reputation-based schemes*.

In TFT mechanisms, every node forwards as much traffic for a neighbor as the neighbor forwards for it. The authors of [119] proposed a TFT mechanism that incorporates generosity to let nodes reward or punish their neighbors based on the history they have observed in the routing process. That is, rather than attempting to detect misbehavior, this method focuses on detecting good behavior. However, in case of DTNs, there are no reliable ways to detect misbehavior. The existing mechanisms designed for traditional ad hoc networks cannot work in DTNs since they assume that the sender can listen for the next hop's transmissions to detect if the next hop properly forwards the traffic. This assumption fails to hold in DTNs since these two nodes are often disconnected. In addition, due to large variability in mobility patterns and network condition, a node may not be able to deliver a packet within its target deadline in spite of its best intentions.

MobiTrade [120] is another well-known TFT incentive scheme which proposes a utility driven trading system to optimize content sharing and derives an optimal policy to split the buffer of a node in zones allocated to each channel. Simple TFT mechanisms can force nodes to "give one to get one". However, the inherent tendency of peers to take much but give back little in TFT based strategies can quickly lead to deadlocks when some interesting content must be somehow fetched across the network. To resolve this, MobiTrade uses a trading mechanism that allows a node to buy, store, and carry content for other nodes so that it can later trade it for content it is personally interested in.

Similar to MobiTrade, content subscribing (ConSub) [121] is a TFT mechanism for a Pub/Sub system to deal with the question: how should nodes act towards maximizing their own revenues when the storage space is limited? The proposed scheme, answers this question by introducing a novel content exchange protocol when two nodes contact each other. Specifically, during each contact, the exchange order is decided by a content utility function, and the objective of nodes is to maximize the future trading value of the content inventory

TABLE 6
COMPARISON OF INCENTIVE-BASED DATA FORWARDING STRATEGIES FOR MOBILE SOCIAL NETWORKS

Algorithm		Characteristic	Properties		
			single-copy	multi-copy	fairness
Tit-For-Tat based	TFT mechanism [119]	A mechanism that incorporates generosity to address bootstrapping and exploitation issues. The scheme helps selfish users to optimize their own performance without significant degradation of system-wide performance.	×	√	-
	MobiTrade [120]	A trading mechanism that allows a node to buy, store, and carry content for other nodes so that it can later trade it for content it is personally interested in.	×	√	√
	ConSub [121]	A pub/sub scheme which proposes a content exchange protocol to encourage nodes in the network to play as businessmen and carry contents to satisfy each other's interest.	×	√	-
Game-theoretic based	Barter trade [123]	A mechanism to discourage selfish behaviors based on the principle of barter. The users trade in messages, meaning that they can download a message from another user if they also provide a message in return.	√	√	√
	Game-theoretic approach [124]	An approach for probabilistic routing based on bargaining by the observation that message exchange in probabilistic routing is analogous to commodity exchange in markets.	√	×	-
	Coalitional game approach [125]	A bargaining game to find the optimal helping probabilities for all the mobile nodes. The method utilizes a coalitional game to model the decision making process of mobile nodes, that is, whether they will cooperatively deliver packets to other mobile nodes or not.	×	√	-
Credit based	Pi [127]	A protocol, such that when a source node sends a bundle message, it also attaches some incentive on the bundle, which is not only attractive but also fair to all participating nodes.	√	×	√
	SMART [128]	An incentive scheme which stimulate bundle forwarding cooperation with thwarting various attacks.	√	√	√
	MobiCent [129]	A system which makes use of a trusted third party to calculate payment and supports two types of client, namely clients that want to minimize cost or minimize delay.	×	√	-
	Incentive-aware [130]	The method presents effective schemes to effectively track the value of a message and estimate the expected credit reward, and formulated nodal communication as a two-person cooperative game.	×	√	-
	SID [131]	A self-interest-driven incentive scheme for ad dissemination which utilizes virtual checks to eliminate the needs of accurate knowledge about whom and how many credits ad provider should pay.	×	√	√
Reputation based	MobiID [132]	A user-centric incentive scheme which allows a node to manage its reputation evidence.	×	√	-
	IRONMAN [133]	An incentive mechanism that uses pre-existing social-network information to bootstrap the detection and discouragement of selfish nodes.	×	√	-

("√" if the model satisfies the property, "×" if not, and "–" for ambiguous cases)

stored in their buffer. The content utility is determined by the contact probability and cooperation level between the current node and its one-hop neighbours subscribing to the associated channel. This method is enhanced in [122] with the aim of guaranteeing the freshness of the contents.

Some works have laid the game-theoretic techniques to stimulate selfish nodes for message relaying. Barter trade [123] is based on the principles of barter: messages are trade between the users and a user can download a message from another user if he/she can give a message in return. First, encounter nodes send the description of the messages that they want to exchange. Then, a message selection process is applied in a way that the nodes agree to download from each other one by one. The authors in this method considered the message selection process as a two-person game to increase the message delivery ratio. However, the requirement of exchanging the same amount of messages is a crucial problem in barter-based methods which affect fairness considerably.

Similar to the barter trade, Wu *et al*. [124] propose a game-theoretic approach based on bargaining. This approach is motivated by the observation that message exchange in probabilistic routing is analogous to commodity exchange in markets. In this method, a message is transferred from a node with a lower delivery probability to a node with a higher delivery probability, just as in a market, a good is traded from a person with a lower valuation of the good to a person with a higher valuation.

The authors of [125] address the problem of cooperative packet delivery to mobile nodes in a hybrid wireless mobile network (both infrastructure-based and infrastructure-less communications). It is assumed that mobile nodes can be either well behaved or misbehaving (i.e., act selfishly). For such a network, the theory of coalitional games [126] is considered to send packets from the base station to the destinations which are out of the transmission range of the base station. After the coalitions of mobile nodes are formed, the well-behaved mobile nodes will agree to always help each other for packet delivery.

In this model, the mobile nodes' observations are used to update their beliefs (i.e., probabilities) about other mobile nodes' types and used when the next coalition formation game is played.

The credit-based approaches strive to avoid unfairness problem of TFT strategies. These kinds of strategies stimulate nodes to be cooperative by utilizing the concept of virtual credit. Practical incentive (Pi) [127] is a single-copy protocol which stimulates selfish nodes in order to cooperate in forwarding bundle packets in DTNs. In Pi, when a source node sends a bundle message, it also attaches some incentive on the bundle, which is not only attractive but also fair to all participating DTN nodes. In SMART [128], the concept of layered coins are used to provide incentives for bundle forwarding. One of its distinguishing features is to allow credits to be distributed by a current intermediate node without the involvement of any sender.

MobiCent [129] also makes use of a trusted third party to store key information for nodes and provides verification and payment services. It uses incentive-compatible payment mechanisms to cater to clients that want to minimize either payment or data delivery delay and handle the edge insertion and edge deletion attacks. In this scheme, nodes are paid for forwarding packets and the destination makes the payment decision. No node will be encouraged to tamper with the path that it reports to the destination.

Ning *et al.* [130] propose a credit-based incentive scheme based on the assumptions that data fall into a range of interest types and each node may have multiple interests. Content exchange between two nodes is formulated as a two-person cooperative game and a utility function is created for every node to maximize its expected credit reward. In this scheme, every node maintains an effective interest contact probability (ECIP) for each data category. Upon encountering each other, two nodes would exchange data messages based on the ECIP to maximize their own expected credit rewards. Given poor end-to-end connections, credits are rewarded to the final deliverer only. However, the incentive mechanism rewarding the last-hop relay node is not fair for all other relay nodes. Moreover, the performance of the incentive mechanism degrades when data items are sparsely distributed among nodes due to its overly restrictive replication mechanism.

Following the above work, the same research group proposes Self-Interest-Driven (SID) [131] scheme by introducing *virtual checks*. A virtual check is included in each ad packet and aims to eliminate the needs of accurate knowledge about whom and how many credits ad provider should pay. When an intended receiver receives the packet for the first time from an intermediate node, the former authorizes the latter a digitally signed check, which serves as a proof of successful ad delivery. When a node that owns a signed check meets the ad provider, it requests the provider to cash the check. Both ad packets and signed checks can be traded among mobile nodes. Interaction between two nodes is based on the Nash Bargaining solution. Through analysis, it is shown that the proposed scheme can achieve Pareto optimality.

Some recent work utilize the reputation-based methods to detect the selfish behavior in social-based DTNs. In MobiID [132], each intermediate node receives a receipt after forwarding a message to another node. The receipt is a proof about the cooperation of the intermediate node. IRONMAN [133] utilizes social network information to bootstrap the detection and discouragement of selfishness. In IRONMAN, the sender of a message keeps the records of the encountered nodes and the forwarding records which contain the identifier of the message, the destination of the message and the forwarding time.

Considering advantages and disadvantages of the incentive methods we discussed in this paper, the following features can be concluded. Firstly, making TFT practical for intermittently connected networks like MSNs is challenging due to the lack of contemporaneous end-to-end paths and high variation in network conditions. Secondly, the credit-based strategies require a centralized third party to manage the payment service. Thirdly, the performance of the reputation-based strategies is seriously impaired when the message loses. Finally, all the incentive strategies cannot deal with the selfish behavior if majority of the nodes have a high probability of selfishness.

Short description and important characteristics of discussed incentive schemes are featured in Table 6.

VI. Discussion and Open Issues

The performance of the routing and data dissemination algorithms in MSNs depends on the efficiency of various challenges from several dimensions such as human mobility, community structure, user selfishness, context information, etc. In light of the work on MSNs focusing on its various aspects, there are still several questions and problems left without any proper answer. In this section, we go one step forward by presenting some future research directions, which brings new visions into the horizon of MSN research.

A. Data Forwarding based on Human Mobility Prediction

Human mobility prediction is a crucial problem since human movement is relatively unscheduled and difficult to predict. Nevertheless, the prediction of a user's future steps can streamline data forwarding decisions and improve the performance of the routing algorithms significantly.

Some of the existing routing protocols such as PROPHET focus on the prediction of whether two nodes would have contact, without considering the spatial and temporal properties of the contact. Exploiting temporal and spatial information of human mobility, in addition to contact prediction, allow both a better resource usage and a higher delivery ratio, as well as avoiding useless transmission when the probability of reaching the destination is very low. As an example, CiPRO considers both spatial and temporal dimensions of the activities of mobile nodes to predict the context of nodes, so that the source device knows when and where to start the routing process to minimize transmission delay and network overhead. Similarly, predict and relay (PER) [134] considers the time of the contact and determines the probability distribution of future contact times and choose a proper next-hop in order to improve the end-to-end delivery probability.

Despite the above-mentioned solutions, further investigations in this area could be carried out in order to improve the efficiency and effectiveness of the data replication protocols, based on predicting the further walks of mobile users. For example, data forwarding based on prediction models which take into account human rhythms on a weekly basis could provide challenges for researchers.

B. Temporal Tracking of Dynamic Communities

Most of the temporally-independent community detection approaches in this paper are suitable for highly dynamic MSNs. However, incremental community detection techniques could find a sequence of communities with temporal similarity and hence, is suitable for MSNs with the community structures that are more stable over time. As such, an incremental community mining approach which considers both current and historic information into the objective of mining processes, is proposed in [135]. Nevertheless, new algorithms should be developed to detect the evolution of communities in highly dynamic MSNs. One potential solution is the identification of critical events and transitions for the evolving social communities.

Several other challenges related to the temporal tracking of communities are highlighted in the literature. One major challenge is in the validation of communities, both with and without ground truth information. Another major challenge is the selection of the number of communities at each time step. A poor choice for the number of the communities may create the appearance of communities merging or splitting when there is no actual change occurring.

C. Balance between Routing Trade-offs

There are several routing trade-offs that should be considered in a protocol design. For example, packet delivery vs. delivery cost, node cooperation vs. resource limitation, and information quality vs. delay, have conflicting requirements and goals. It is critical to determine the balance to satisfy both points of view. For example, maximizing delivery ratio requires increasing the number of packet copies spread throughout the network.

Another tradeoff is the compromise regarding the amount of information collected to guide the packets to their destinations. Collecting information from the network helps in selecting the relaying nodes to the destination, but requires time to collect the information which increases the packet delays. On the other hand, collecting little or no information form the nodes decreases the probability of reaching the destination unless a large number of copies were spread. Consequently, new metrics and measures should be introduced for studying the relationships between the routing conflicting trades-offs and establishing the balance between them.

D. Social Context

Context information of mobile users have been widely utilized to improve the performance of data sharing protocols in pervasive environments. There is no doubt that context information could be useful for many protocols and applications in MSNs. For instance, the socially-aware networking paradigm [136] basically takes advantage of social context. But collecting social context is considerably difficult. The main reason is that social context is dependent on group membership and activities, friendship information, etc. Additionally, environmental parameters change dynamically which result in large volumes of data. Hence, there is no applicable mechanism to collect large-scale social context information in the recent literature. This problem is further complicated by safety and privacy issues, e.g. when an outsider as a new member joins a community or a social group and needs to have access to context information of other members.

E. Social Selfishness

User selfishness is a very challenging and important issue in MSNs. To tackle with this problem, several techniques have been used to detect selfish nodes or study the impact of selfishness in MSNs. Furthermore, new incentive schemes have been proposed to encourage selfish nodes to cooperate in data delivery. However, majority of the studied methods assume that mobile carriers are individually selfish and they have the same degree of selfishness toward the other users.

Social selfishness, on the other hand, is a young and exciting research field. Socially selfish nodes want to maximize their social profits beside their individual benefits. For example, they willingly relay messages for their friends or the nodes inside their communities but not for strangers. In [137] social selfishness was introduced under the philosophy that social selfishness is a kind of user demand that should be satisfied. Then, social selfishness aware routing (SSAR) is proposed to cope with user selfishness and provide good routing performance. Nonetheless, there is not sufficient attempt to study the impact of social selfishness on the performance of the routing and data dissemination protocols. Additionally, there is a lack of incentive scheme to encourage socially selfish nodes to cooperate in data forwarding.

VII. Conclusion

MSNs are modern types of social media, which consolidate the ability of an omnipresent connection for mobile devices to share user-centric data objects among interested users. The close connection between ubiquitous mobile devices and the users' social relationships attracted researchers to explore the potential of introducing social properties into network design. In the light of recent investigations on MSNs, in this paper, the major social properties of MSNs were examined and an overall view of human mobility models and community detection algorithms was presented. Routing and data dissemination protocols in MSNs with respect to critical issues like context-awareness and user selfishness were reviewed. Some open research issues were explored and future research directions were discussed. We hope that this effort will instigate future research on this topic encouraging application and system designers to develop appealing routing and data dissemination solutions.

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