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Fuzzy Closeness-based Delegation Forwarding in Delay Tolerant Networks

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***Abstract*—Delay tolerant networks (DTNs) are envisioned to provide promising applications and services. One critical issue in DTNs is efficiently forwarding the messages within the delay requirements while avoiding the cost associated with blind flooding. To guide the forwarding process, nodes can evaluate their relationships with each other, in terms of "closeness", which summarizes both temporal and spacial information, based on contact history. However, due to the uncertainty in nodal mobility, the contact history usually contains fuzziness and incomplete information. In this paper, we first define and utilize a fuzzy trust evaluation system for nodes to summarize their relationships to other nodes, in terms of closeness. We then propose the fuzzy clusters to organize nodes into overlapped fuzzy communities based on nodes' evaluations of closeness. On top of the fuzzy communities, a novel fuzzy-weight-based delegation forwarding scheme is proposed to propagate the messages into all communities while avoiding repeated forwarding in the same community. Extensive simulation results based on real traces are presented to support the effectiveness of our scheme.**

***Index Terms*—Delay tolerant networks (DTNs), delegation forwarding, fuzzy logic, fuzzy clustering, relationship trust.**

I. Introduction

In highly mobile and wireless network environments, such as delay tolerant networks (DTNs) [1], the network topology constantly changes and end-to-end paths can hardly be sustained. The DTN is considered to be an important branch for the next generation of networks and many promising DTN applications have been proposed. Such networks have been deployed in the context of human-carried devices (such as pocket switched networking [2] and opportunistic podcasting [3]), buses [4], animal tracking [5], and underwater sensor networks [6].

Nodes' movements in DTNs are usually repetitive to a certain extent. Therefore, metrics based on contact history are usually good hints for predicting future forwarding opportunities. Based on multiple sets of real DTN traces, such as Haggle [7] and Reality Mining [8], we observe that a long-term *closeness* metric can be abstracted to depict the neighboring relationship between nodes. Based on this inherent property of the DTN, we propose a FuzzyCom, a packet forwarding scheme based on the fuzzy closeness metric. The proposed scheme contains three major components: 1) a fuzzy trust evaluation component, 2) a distributed fuzzy clustering component, and 3) a fuzzy delegation forwarding component.

Although the node mobility in DTNs is usually repetitive to a certain degree, the uncertainty, fuzziness, and incomplete information issues are unavoidable during the prediction based on the contact history. To provide a scheme that can serves in practical DTNs, we first develop a fuzzy evaluation component which can better handle the uncertainty, fuzziness, and incomplete information in the prediction. We utilize this component to form *relationship trust* opinions. The trust evaluation allows each node to forms its own prediction of others, based on collected history information. To guide the forwarding process, each node forms its own trust opinions towards the relationship to other nodes. A set of rules together with an inference process based on fuzzy logic [9], which can comprehensively measure the long-term relationship, are presented in this component.

A long-term stable neighbor relationship graph can be constructed based on the fuzzy trust values associated with the link between each pair of nodes. We build a heuristic scheme which can identify grouping structures, denoted as communities, from the fuzzy neighbor relationship graph. Nodes in the same community have strong connections between each other, and the communities may overlap. A node may be a member of multiple communities at the same time.

We then propose a fuzzy-membership-based delegation forwarding scheme to actually forward the packet. Since the inherent group structure of the DTN is available and nodes in the same community have a high chance of meeting each other because of the high closeness among these nodes, we aim to utilize the structural advantage and propagate each new message to all the communities while reducing redundant propagation to the same community. Therefore, each copy of the message maintains a set of thresholds for communities. The thresholds, representing the previous delegates' memberships to these communities, provide needed hints for forwarding decisions.

The contributions of this paper are three-fold. First, we exploit the fuzzy trust evaluation system to link the contact history in the DTNs with the prediction of future forwarding opportunities. Second, instead of the traditional hard clustering mechanism, we develop the concept of fuzzy communities in which nodes in the DTNs can belong to more than one community, and associate each node with a set of fuzzy membership weights. Third, we propose the delegation forwarding

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Table I List of notations

i, j, u, v, l	Nodes i, j, u, v, l
$\mathcal{D}$	Average inter-meeting time
$\mathcal{F}$	Contact frequency
$\mathcal{L}$	Longest inter-meeting time
$\mu(x)$ / x	Fuzzy membership function / variable
δ	Fuzzy trust level / closeness metric
d_i	Node i's fuzzy degree
$N(i)$	Node i's local neighborhood
T	Threshold for filtering / delegation forwarding
G_l	Community l
H / M / L	High / Medium / Low

mechanism based on the stable community structure and the fuzzy membership weights.

II. Related Work

The existing works that are closely related to FuzzyCom mainly belongs to the following three categories.

A. Characteristics of DTNs

DTNs attempt to route packets via intermittently connected nodes. Vahdat *et al.* proposed epidemic routing [10], which is a oblivious flooding scheme. Spray and wait [11] is another oblivious flooding scheme, but with a self-limited number of copies. MaxProp [12] and PRoPHET [13] both select forwarding nodes based on the nodes' encounter history, and both are examples of how to use system and mobility information to improve the efficiency of forwarding from oblivious flooding.

While early work in DTNs used a variety of simplistic random *i.i.d.* models, such as random waypoint, recent findings [14], [15] show that these models may not be realistic. Moreover, many recent studies [15], [16], [17] based on real mobile traces reveal that DTNs process certain social network properties. Therefore, the social network analysis mechanism is a good tool for determining the properties involving in improving the forwarding efficiency. Several social network metrics, which are measured based on nodes' direct or indirect observed encounters, are used to guide the packet forwarding in [16]. In [18], we also propose to facilitate the content-based service in DTNs using the social relationships among nodes. In this paper, the FuzzyCom scheme utilizes fuzzy trust evaluation to summarize the social relationships among nodes, and achieves comparable forwarding efficiency by utilizing local social relationship information.

B. Fuzzy trust evaluation

Fuzzy logic [19] is a form of multi-valued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than precise. Fuzzy trust evaluation systems aim to develop effective and efficient trust management schemes based on a fuzzy-logic approach, leveraging fuzzy-logic's ability to handle uncertainty, fuzziness, and incomplete information adaptively. Several Fuzzy trust evaluation systems have been proposed, such as a prototype P2P reputation system [20] that helps establish mutual trust among strangers in P2P transaction applications, and multi-agent systems [21] designed for business-interaction review and credibility adjustment. In this paper, we propose a unique application of fuzzy trust to comprehensively evaluate the time-space closeness between nodes in mobile networks.

More recent contributions to the evaluation of trust and reputation use fuzzy logic concepts [9], [20], [22] and provide a starting point to improve the modeling capabilities of social networks. However, these models lack individual trustworthiness and credibility computation. They also do not sufficiently recognize further applications of fuzzy trust values besides straightforward security goals.

Fuzzy logic is also widely used in many routing scenarios. For example, Aboelela *et al.* [23] propose to use fuzzy logic to assign different traffic flows to links, based on bandwidth requirements and pricing. In [24], fuzzy logic is used to determine the quality of links with regard to the present congestion situation in the network for shortest path routing. It combines the network delay with the current outward queue level at a node as the input of the fuzzy system. Although we also focus on forwarding efficiency in this paper, we utilize fuzzy logic to model the links between nodes in quite a different way. We try to model the long-term social relationships among nodes instead of combining link quality metrics as in the previous research results.

C. Relationship-based clustering mechanisms

In traditional social network analyses, one important step is to identify clusters. *Spectral clustering* [25] is a well studied and widely used centralized clustering mechanism. It usually involves taking the top eigen vectors of some matrix based on the distance between vertices (or other properties) and then using them to cluster the vertexes.

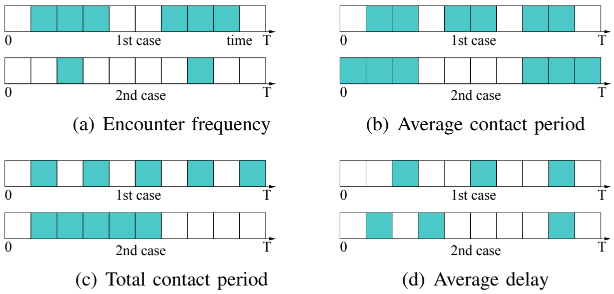
In [26], [27], Hui *et al.* analyze the community structure from mobility traces and use them for forwarding algorithms, showing a significant improvement in forwarding efficiency. However, with a limited number of hops of local information, neither the community detection nor the weighted network analysis presented in [26], [27] can be used, which restricts the practicality of these methods. Our previous work [28] also utilizes the community structure to guide the forwarding. However, the community is identified based on single time-space metric. The communities are also independent of each other. We provide simulation results by comparing FuzzyCom with our previous work to examine the advantages of the three components.

III. FuzzyCom scheme

In this section, we explain in details the three major components of the FuzzyCom scheme: the fuzzy trust evaluation component, the fuzzy clustering component, and the fuzzy delegation forwarding component.

A. The fuzzy trust evaluation component

The goal of a trust evaluation system is prediction of reliance on an action (future behavior) based on what a party knows about the other party (past experience). Since the DTNs



(a) Encounter frequency (b) Average contact period (c) Total contact period (d) Average delay

Fig. 1. Metrics comparison. A colored box represents the period that two nodes i, j are within each others' communication range in time interval $[0, T]$.

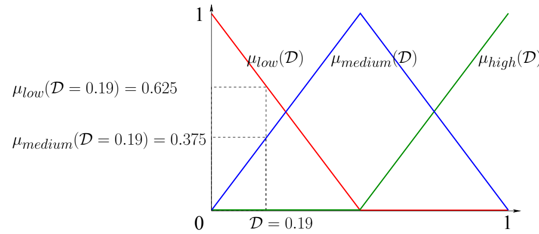


Fig. 2. The sample membership function of $\mathcal{D}$.

usually show a repetitive nature to a certain degree, it is reasonable to predict future encounters based on the contact history. Many existing forwarding mechanisms in the DTNs, such as the Maxprop [12] and Prophet [13], utilize metrics extracted from the contact history (e.g. encounter probability) to guide the packet forwarding process. Since the goal of the trust evaluation system is highly compatible with the application in the DTNs, we equip each node with a trust evaluation component. This component allows the node to form opinions on its relationships with other nodes in the network based on its collected history information, and use the trust value to guide the packet forwarding process.

Note that simple metrics, such as the encounter frequency shown in Fig. 1(a), can be extracted from the contact history. The calculations of these metrics are easier than forming relationship trust. However, these simple metrics may not condense the temporal and spacial previous contact information in a comprehensive way. Take Fig. 1(a) as an example; although the encounter frequencies in both cases are the same, the nodes in the first case clearly have a closer relationship than the nodes in the second case if the contact pattern repeats. Moreover, there is uncertainty in the nodes' future movements, and each node's collected information maybe incomplete and inaccurate. A fuzzy logic based trust evaluation system can handle these challenges in the DTNs gracefully. Therefore, the first step of our scheme is to introduce a fuzzy trust system to evaluate the relationship between each pair of nodes.

In this fuzzy trust evaluation system, each node collects the contact information with other nodes over time and abstracts basic temporal and spacial metrics. Several rules are summarized to link the relationship between each pair of nodes with these basic metrics. Fuzzy logic is then introduced to combine the reasoning results based on different simple metrics. Each node will form its own fuzzy trust towards its relationships with other nodes. Since a pair of nodes will record the same contact history between them, the formed fuzzy trust will be the same on both nodes in terms of the closeness between them.

Basic Metrics. Nodes' original knowledge, which includes both temporal and spacial information, is too complex to be directly used in community detection. Therefore, we should condense the encounter history associated with each edge between two nodes i and j in the DTNs with a numerical metric, which should comprehensively summarize the characteristics of the encounter history. There are straightforward candidate metrics, including encounter frequency, total contact period, average contact period, longest inter-contact period, and average inter-contact period.

Fig. 1 illustrates the encounter history of two nodes i and j. In both cases in Fig. 1(a), i and j encounter twice in time interval T. Although the encounter frequency is the same, nodes i and j in the first case are closer than in the second case. Using encounter frequency alone to depict closeness is not enough. Fig. 1(b) and (c) illustrate similar examples which indicate that average and total contact periods also have limits in describing the closeness. In Fig. 1(d), although the average inter-contact periods are the same, the second case is less preferable because the longest inter-connect period is larger. These four examples clearly show that a single simple metric cannot comprehensively describe the relationship of two nodes, since each of them only reflect one aspect of the time-space information.

Therefore, we adopt the fuzzy trust evaluation and form a trust opinion towards the future contact opportunity. This trust opinion should comprehensively aggregate a set of basic metrics, each of which reflecting one aspect of the temporal and spacial information in the encounter history, to predict the characteristics of the future encounters. The final trust value depicts the neighboring relationship.

Fuzzy Reasoning. In fuzzy theory, the membership function $\mu(x)$ for a fuzzy variable x specifies the degree of an element belonging to a fuzzy set. It maps x into closeness metric δ in the range $[0, 1]$, where 1 is full membership and 0 is no membership. δ represents the fuzzy trust level. Fig. 2 shows the membership functions for modeling the fuzzy trust based on the average delay $\mathcal{D}$. As one example in Fig. 2, when the normalized average delay between two nodes is 0.19, we will believe that the closeness between i and j is low with trust value 0.625, and believe the closeness is medium with trust value 0.375. Fig. 3 illustrates the complete fuzzy inference process. We consider the following three fuzzy variables: the average delay ($\mathcal{D}$), the contact frequency ($\mathcal{F}$), and the longest delay ($\mathcal{L}$).

To get comprehensive evaluations on the closeness between two nodes, we apply the fuzzy inference rules such as follows:

Table II Fuzzy inference rules

Rules	$\mathcal{D}$	$\mathcal{F}$	$\mathcal{L}$	$\rightarrow$	δ
1	H	H	H	$\rightarrow$	L
2	H	H	M	$\rightarrow$	M
$3 \sim 5$	$*$	H	L	$\rightarrow$	H
$6 \sim 8$	H	M	$*$	$\rightarrow$	L
$9 \sim 11$	H	L	$*$	$\rightarrow$	L
$12 \sim 14$	M	$*$	H	$\rightarrow$	L

Rules	$\mathcal{D}$	$\mathcal{F}$	$\mathcal{L}$	$\rightarrow$	δ
15	M	H	M	$\rightarrow$	M
16	M	M	M	$\rightarrow$	M
17	M	M	L	$\rightarrow$	M
18	M	L	M	$\rightarrow$	L
19	M	L	L	$\rightarrow$	M
$20 \sim 22$	L	$*$	H	$\rightarrow$	M

Rules	$\mathcal{D}$	$\mathcal{F}$	$\mathcal{L}$	$\rightarrow$	δ
23	L	H	M	$\rightarrow$	H
24	L	M	M	$\rightarrow$	H
25	L	M	L	$\rightarrow$	H
26	L	L	M	$\rightarrow$	M
27	L	L	L	$\rightarrow$	H

Basic metrics are the average delay ($\mathcal{D}$), the contact frequency ($\mathcal{F}$), and the longest delay ($\mathcal{L}$). H stands for high, M stands for medium and L stands for low. $*$ is the wildcard for H, M, and L.

- IF average delay $\mathcal{D}$ is low AND contact frequency $\mathcal{F}$ is high AND longest delay $\mathcal{L}$ is low, THEN δ is high.
- IF average delay $\mathcal{D}$ is medium AND contact frequency $\mathcal{F}$ is medium AND longest delay $\mathcal{L}$ is medium, THEN δ is medium.
- IF average delay $\mathcal{D}$ is high AND contact frequency $\mathcal{F}$ is low AND longest delay $\mathcal{L}$ is high, THEN δ is low.

Based on the differences of the basic fuzzy variables, we should develop 27 rules to enumerate all the possible situations. The detailed rules are listed in Table II. Here, the rule set is just one example that complies with our intuition towards the closeness concept in the DTNs. Other rule sets can be determined similarly, and can reflect different focuses of the designed system. For example, a rule set that focuses more on the longest delay $\mathcal{L}$ will make the worst case performance of the proposed scheme better.

One important step in fuzzy reasoning is to determine the membership function. Since the most typical fuzzy set membership function has the graph of a triangle, we also adapt such membership functions in the fuzzy trust system. As shown in Fig. 3 step 1, we interpret the input of all 27 rules using the corresponding membership functions. The inputs are the normalized $\mathcal{D}$, $\mathcal{F}$, and $\mathcal{L}$ (current value divided by the estimated bound).

We infer all rules in parallel and determine the resulting membership by assessing all terms in the premise. We apply the fuzzy operator AND to determine the support degree of the rules, as shown in Fig. 3 step 2, and the $AGGREGATE$ operator to superimpose the membership curves, as illustrated in Fig. 3 step 4.

The example in Fig. 3 shows the reasoning process. Assume that node i is evaluating its relationship with node j. We have $\mathcal{D} = 0.3$, $\mathcal{F} = 0.8$, and $\mathcal{L} = 0.4$. When we apply rule 5, which is $(L, H, L) \Rightarrow H$, the member function of $\mu_{low}(\mathcal{D})$ will be used to map $\mathcal{D}$ to a internal fuzzy weight. Similarly, we can get the weights of $\mathcal{F}$ and $\mathcal{L}$ in step 1. In step 2, the AND operator is applied, and the minimum of the three internal fuzzy weights implicates the weight that the corresponding rule can be applied to the current case, in step 3. The results of rules will aggregate in step 4 to prepare for defuzzifacation.

Defuzzification. Defuzzification is the process of producing a quantifiable result in fuzzy logic. A useful defuzzification technique must first add the results of the rules together in some way. Now, if this triangle was to be cut in a straight horizontal line somewhere between the top and the bottom, and the top portion was to be removed, the remaining portion forms a trapezoid. The first step of defuzzification typically chops off parts of the graphs to form trapezoids (or other shapes if the initial shapes were not triangles). In the most common technique, all of these trapezoids are then superimposed upon one another, forming a single geometric shape, as illustrated in Fig. 3 step 4. Then, the centroid of this shape, called the fuzzy centroid, is calculated. The x coordinate of the centroid is the defuzzified value. Therefore, we generate the final fuzzy trust on the closeness δ by defuzzifying from the aggregation result, taking the centroid of the superimposed membership curve. The final closeness value δ^* is calculated as follows:

$$\delta^* = \frac{\int \mu_{output}(\delta) \cdot \delta \cdot d\delta}{\int \mu_{output}(\delta) \cdot d\delta}, \tag{1}$$

where $\mu_{output}(\delta)$ denotes a membership function aggregated from the output of the proposed rules. An example defuzzification process is shown in Fig. 3 step 5.

B. The fuzzy clustering component

Based on each node's formed fuzzy trust, we propose a distributed scheme to identify the underlying communities. In general, the local community is a reflection of locality. A community can be defined based on the notion of clique in graph theory [29]. A clique is a subgraph in which every vertex is connected to every other vertex in the graph. If a reasonable threshold T is used to filter the fuzzy trust towards the closeness and identify cliques on the filtered graph, each pair of nodes in the clique will have a strong direct neighboring relationship (larger future encounter probability).

In this paper, we propose the *fuzzy clustering*. Nodes can belong to more than one community. Each node will be associated with a set of fuzzy membership levels. These membership levels indicate the strength of the association between that node and a particular community. In Fig. 4, the example shows the difference between hard and fuzzy community.

Fuzzy Community Definition. The community is a reflection of locality. As a criterion to determine whether the relationship between two nodes is strong enough to claim they are local neighbors, we adopt a threshold T on the fuzzy closeness value δ associated with each link in the neighboring graph. For two nodes u and v in the DTN, if there is a relationship between u and v, and $\delta_{uv} > T$, we consider u and v to be *local*

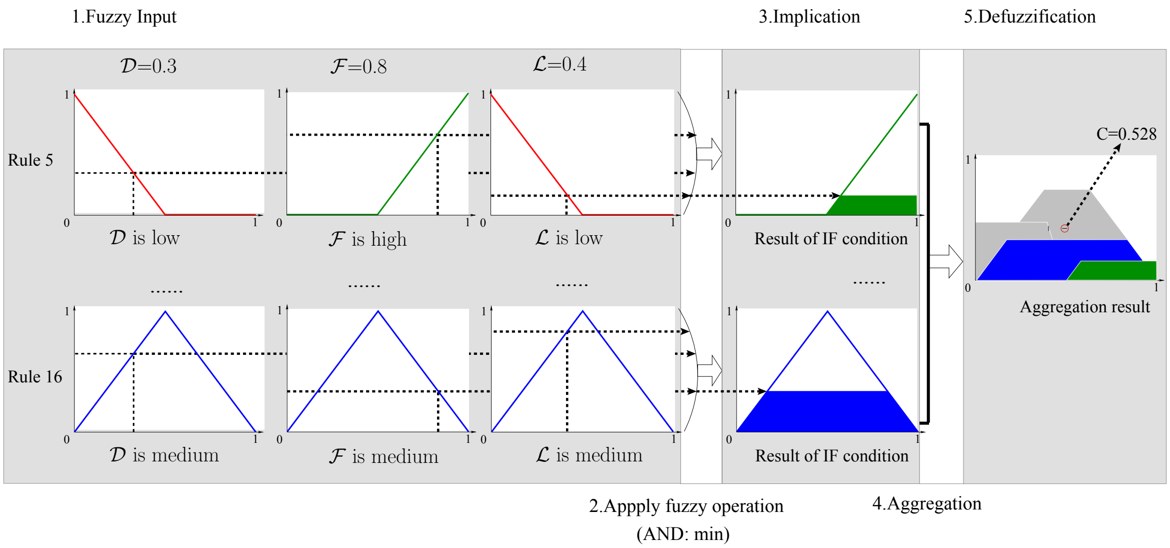


Fig. 3. The five steps of fuzzy reasoning.

neighbors. It indicates that u and v are close enough that they can be categorized in the same community.

Since the closeness metric reflects the fuzzy trust evaluation result based on the time-space metrics abstracted from the contact history, the expected delay between local neighbors u and v will follow certain constraints with this threshold-based filtering and the previous fuzzy reasoning rules.

In graph theory [29], a *clique* is a subgraph in which every vertex is connected to every other vertex in the graph. We extend this idea and define the *closeness-based fuzzy community* in the DTN as follows: For any pair of nodes in the community, they are local neighbors to each other, i.e. the fuzzy trust, representing the closeness of their relationship, is larger than the threshold value T. Due to the strong connections among nodes in the same community, if one of the nodes in a local community receives a packet, all the other nodes reside in this community will get the packet with short delay.

C. The fuzzy delegation forwarding component

In delegation forwarding [30], each message copy maintains a forwarding threshold T which is initialized as the quality of its source node, based on some simple metric such as the average inter-meeting time between the source and the destination. Whenever node i meets node j, node i forwards a message to node j if the forwarding quality of node j exceeds the message's threshold T, and then the thresholds of both copies in i and j are set to j's forwarding quality. In the case that j's quality is better than i's T but j already has the message copy, the copy is not forwarded, but the T of the copy in i will still be set to j's quality.

Instead of using the simple metric as in the original delegation forwarding [30], we develop a delegation forwarding component that utilizes the set of fuzzy membership levels associated with each node. The goal of our method is to propagate each message to cover all of the communities, and therefore to cover the intended destination, while reducing the unnecessary multiple propagations to the same community. After the previous two steps, fuzzy trust evaluation and clustering, for each node i, we will know the communities it belongs to G_l, and for each community that node i belongs to, i should calculate its membership factor M_i towards each community it belongs to. For example:

$$M(i, G_l) = \frac{\sum_{u \in G_l} \delta_{iu}}{|G_l - 1|} \tag{2}$$

which is the average fuzzy closeness value between node i and each node in G_l. For those communities that i is not a member of, the membership value will be 0.

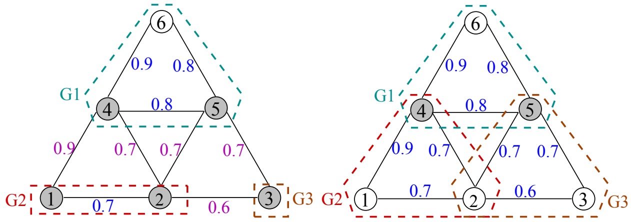
Algorithm 1 Fuzzy delegation forwarding

Update thresholds in m

for each community G_l **do**
  if $M(i, G_l) > t_{G_l}$ **then**
    Set $t_{G_l} = M(i, G_l)$;
  end if
end for

Decision process of node i

for each message m in i's buffer **do**
  Examine the thresholds of m;
  if $\exists\ l$ that satisfies $M(j, G_l) > t_{G_l}$ **then**
    if node j never receives message m before **then**
      Node i duplicate m and forward to j;
    end if
    for each l that satisfies $M(j, G_l) > t_{G_l}$ **do**
      Set $t_{G_l} = M(j, G_l)$ on m in node i;
    end for
  end if
end for



(a) Hard clustering (b) Fuzzy clustering

Fig. 4. Fuzzy community formation. Shadowed nodes will potentially propagate message among communities.

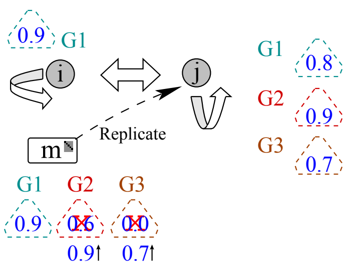
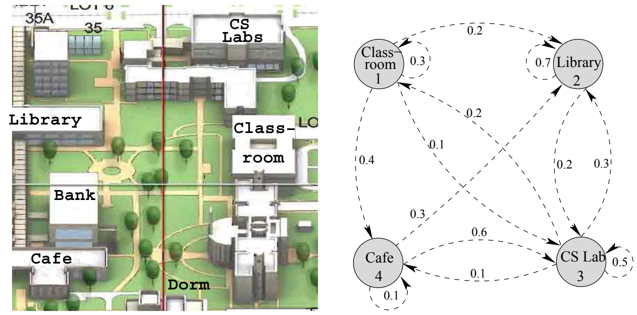


Fig. 5. The fuzzy delegation process. Each message m is associated with a set of thresholds represent the qualities of its previous delegates. When a node j that is closer to more than one communities than m's previous delegates encounters host i, m's thresholds will be updated and j will be assigned the duty of delegate.

The core of this process is that when a node i with a copy of a message m meets another node j which has never received m, i needs to decide whether it should propagate the message to j and ask j to act as one delegate of the message.

The basic idea of this decision is that node i needs to answer the question of whether node j has better forwarding quality than node i. Here, better forwarding quality means j can forward message m to more communities than i does, or j has closer relationships with the current communities that i can cover. If the answer is yes, node i should replicate and forward m to j.

To further reduce the unnecessary forwarding, we propose the following two rules. First, node i should only forward m to node j if j has better forwarding quality than all the nodes that i has met. We can examine one example. We assume u has better forwarding quality than j, and j has better forwarding quality than i. If i meets u first, i will forward the packet to u. Node i then meets node j. i should not forward to j because u already has the packet and u has better forwarding quality than j. Second, we should also piggy back information about the communities that the packet has traversed and prevent repeated replication back to these communities. These two rules can be guaranteed by Algorithm 1. In this algorithm, each message will be associated with a set of thresholds, $\{t_{G_1}, t_{G_2}, ...\}$, which are initialized to zeros.



(a) FAU map (b) Sample Markov chain

Fig. 6. The synthetic mobility traces are generated from map of FAU.

IV. Simulation

We conduct simulation studies to evaluate the effectiveness of the proposed scheme. Here we compare the effectiveness of the FuzzyCom scheme with three other methods: Epidemic [10], Delegation [30], and LocalCom [28].

A. Simulation setup

We ran trace-driven simulations in a customized simulator with two different datasets: Haggle project [7] and MIT Reality Mining [8]. In Haggle, 41 iMotes were distributed to students attending Infocom 2005. In Reality, 97 smart phones were deployed to students and staff at MIT. In both datasets, bluetooth contacts were logged and provided. Each contact record includes the start time, end time, and ID of the nodes in contact. For each round of simulation, a portion (default 30%) of the dataset is used as the contact history. The remaining portion is used to evaluate the performances of the forwarding schemes after the community detection.

We generated synthetic traces according to a community mobility model proposed in [15], which is considered to be more realistic than *i.i.d.* models. The traces were generated using maps of the Florida Atlantic University (FAU) buildings, as shown in Fig. 6(a). The class schedules and enrollment information of a certain number (default 200) of graduate and undergraduate students from four departments were collected. The trace of a node, which represents a network device carried by a student, was generated according to a Markov chain, as illustrated in Fig. 6(b). The states and probabilities in the Markov chain were determined by the students' class schedules and enrollment information.

All packets had an expiration TTL, which represented the delay requirement. Each node knew only its own contact history before the fuzzy clustering. Each simulation was repeated 30 times with different random seeds for statistical confidence.

We primarily focused on the delivery rates of different scenarios. We also investigated the *delay* and the cost in terms of the *total number of forwards*. We compare the effectiveness of our scheme with three other techniques: Epidemic [10], Delegation [30], and LocalCom [28]. In Epidemic forwarding, a node copies a packet to every new node it encounters that has not received a copy. The original Delegation scheme is a

TABLE I
Characteristics of three datasets

Dataset	$Haggle$	$Reality$	$Synthetic$
Device	iMotes	Phone	N/A
Network type	Bluetooth	Bluetooth	N/A
Duration (days)	3	246	10
Number of nodes	41	97	200
Number of contacts	$22,459$	$54,667$	Vary

non-oblivious forwarding scheme for DTNs. A node forwards a packet to a potential forwarder encountered if that forwarder has a higher quality (in terms of mean inter-meeting time between the potential forwarder and the destination) than other potential forwarders that the node met before. Our previous work LocalCom [28] also utilizes the community structure. However, the communities are constructed based on a single simple metric which is average delay. LocalCom also uses non-overlapped community definition and broker pruning to reduce redundant forwarding, which lead to a different performance compared with FuzzyCom.

To illustrate the effectiveness of our scheme uniformly, we set $T = 0.7$ and the rules are set the same as in Table II in all simulations. These two parameters are actually adjustable and a better result can be achieved if these parameters are tuned according to scenarios in the specific application. The maximum $\mathcal{D}$, $\mathcal{F}$, and $\mathcal{L}$ recorded in each dataset were used as the bound to normalize the input.

B. Simulation results

We examine the effectiveness (i.e. delivery rate) and the cost (i.e. number of forwards) of the four schemes in three very different scenarios in Figs. 7 and 8. The delivery rate and the total number of forwards both increase as the delay requirement on the packet lessens, as shown in Figs. 7 and 8. Since the Epidemic forwarding scheme includes all the paths that can satisfy the corresponding TTL requirement, the resulting delivery rate and total number of forwards represent the upper bound in each scenario and reflect the underlying characteristics of the contact distribution in the scenario.

The delivery rates of the forwarding algorithms are compared in Figs. 7 with different message TTL. The results show that our FuzzyCom delivers only about 5% fewer messages than Epidemic. The FuzzyCom scheme also shows a steady improvement in terms of delivery rate over the original delegation scheme, since it combines the underlying community structure with a deliberated forwarding plan. FuzzyCom also outperforms LocalCom (about 5% more), since it takes more information into considerations (e.g. longest delay) and uses the overlapped fuzzy communities.

Figs. 8 further illustrates the advantage of the FuzzyCom scheme. Since FuzzyCom utilizes a novel fuzzy weight based delegation forwarding scheme to propagate the messages into all communities while avoiding repeated forwarding in the same community, the cost is significantly lower than that of the Epidemic scheme. When counting the total number of forwards, we also included the messages used in collecting and evaluating the 'quality' of the neighboring relationships among nodes. The FuzzyCom scheme also shows a cost close to delegation forwarding in all three cases which represent a deliberated scheme that was mainly designed to significantly reduce the total number of forwards. The costs of FuzzyCom and LocalCom are close to each other. These two methods use quite different forwarding control schemes, but both achieve a satisfactory reduction of cost compared to other schemes. Combining the results in Figs. 8 with the improvements in Figs. 7, FuzzyCom shows steady performance in terms of forwarding efficiency in all three different DTN environments.

Simulation results confirmed that, compared with other algorithms, including the current community-based scheme and the original Delegation scheme, FuzzyCom has a high delivery rate and a low cost.

V. Conclusion

In this paper, we propose a delegation forwarding scheme based on the long-term neighboring relationship structure of the DTNs. We first exploit fuzzy trust to construct the weighted graph abstraction of the DTN to better support the packet forwarding. The fuzzy reasoning rules provide a comprehensive way to combine the time-space statistics from the contact history into a single closeness metric. We then propose the fuzzy clustering mechanism to organize nodes into overlapped fuzzy communities based on the closeness. A fuzzy weight based delegation forwarding scheme is proposed to propagate the messages into all communities while avoiding repeated forwarding in the same community. Extensive results of simulations based on real and synthetic traces are provided to further illustrate the efficiency of the proposed scheme. In the future, we plan to enhance the community formation scheme to incorporate the dynamically changing closeness metric in the distributed scheme.

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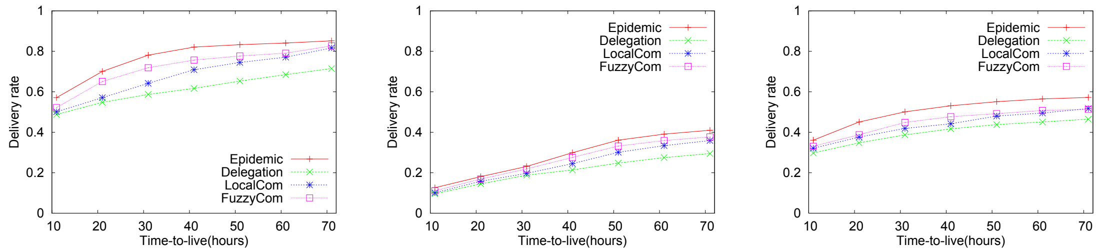
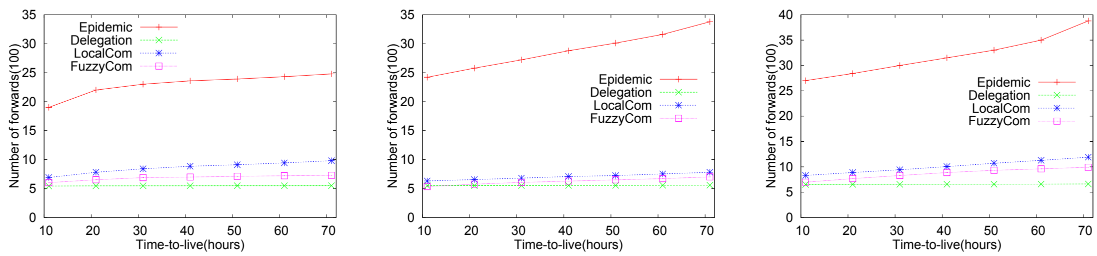


(a) Haggle (b) Reality (c) Synthetic

Fig. 7. Performance comparison on successfully delivery rate.



(a) Haggle (b) Reality (c) Synthetic

Fig. 8. Performance comparison on total number of forwards.

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