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ORIGINAL ARTICLE

New measures for characterizing the significance of nodes in wireless ad hoc networks via localized path-based neighborhood analysis

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Abstract The synergy between social network analysis and wireless ad hoc network protocol design has recently created increased interest for developing methods and measures that capture the topological characteristics of a wireless network. Such techniques are used for the design of routing and multicasting protocols, for cooperative caching purposes and so on. These techniques are mandatory to characterize the network topology using only limited, local connectivity information—one or two hop information. Even though it seems that such techniques can straightforwardly be derived from the respective network-wide techniques, their design presents significant challenges since they must capture rich information using limited knowledge. This article examines the issue of finding the most central nodes in neighborhoods of a given network with directed or undirected links taking into account only localized connectivity information. An algorithm that calculates the ranking, taking into account the *N*-hop neighborhood of each node is proposed. The method is compared to popular existing schemes for ranking, using Spearman's rank correlation coefficient. An extended, faster algorithm which reduces the size of the examined network is also described.

Keywords Centrality · Localized algorithms · Social networks · Ad hoc networks

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1 Introduction

During the last decade, the advances in device miniaturization and in the respective system/application software, along with the tremendous growth of wireless networks, have made the presence of ad hoc networks ubiquitous. A wealth of ad hoc networks is encountered today, such as mobile ad hoc networks (MANETs), wireless sensor networks (WSNs), wireless mesh networks (WMNs) and so on. They have potential applications in disaster relief, battlefield environments, wireless Internet connectivity and intelligent vehicles. An ad hoc network consists of wireless hosts (nodes) that communicate with each other in the absence of a fixed infrastructure; each host acts as a relay that forwards messages toward their destination.

The lack of fixed infrastructure makes the nodes of an ad hoc network to be strongly interdependent on each other. This fact helped realize the significance of borrowing concepts from the field of social network analysis (SNA) (Wasserman and Faust 1994) to the design of more efficient information transfer protocols. This borrowing was further enforced by the fact that many of the ad hoc networks were basically human centered and they follow the way humans come into contact. Moreover, because of lack of infrastructure, it is rather challenging to develop more systematic design optimization approaches, as for instance in cellular networks. Greedy, best-effort techniques are used primarily for opportunistic ad hoc networks and they may benefit significantly from the social networking perspective.

Informally, a *social network* is a collection of 'actors', a set of relational information on pairs of actors and possible attributes of the actors and/or of the links. In our context, the actors are the ad hoc network nodes and the relationship among pairs of actors is the existence (or not) of a wireless link among them. The attributes on the actors and links that can model node energy and link quality measures, respectively, are not investigated in the methods described in this article.

The notion of a social network and the methods of SNA is a quite old discipline and they have attracted significant interest initially from the social and behavioral communities, later from the data mining (Abdallah 2011; Hwang et al. 2008) and only recently from the networking community (Katsaros et al. 2010). This interest stems from the focus of SNA to relationships among entities and on the patterns and implications of these relationships. In the networking community, SNA is viewed as another network measurement task, while the traditional tasks of network measurement deal with issues such as traffic monitoring, latency, bandwidth and congestion. The analysis of the 'social' aspects of a network is the study and exploitation of the structural information present in the network, such as existence and strength of communities (Saravanan et al. 2011), node centralities, network robustness to node removal, topology evolution over time (Gilbert et al. 2011) and so on.

Among the most significant tasks involved in SNA is the calculation of centrality measures (Bonacich 1987). Point centrality in communication is based on the concept of betweenness, first introduced in Bavelas (1948). According to betweenness centrality, a node is central to the degree that it stands between others. PageRank (Brin et al. 1999) is another very popular method for measuring centricities in social networks, a spectral centrality measure; the basic idea behind PageRank is that a node is significant if it is connected to other significant nodes. Various other measures of centrality and ranking have been proposed to determine the importance of a node within a graph (Freeman 1979) (cf. Sect. 2).

These centrality indices are of great value in the understanding of the roles played by actors in social networks, and by the nodes in various webs (Web, Internet, Food/Sex web), but they are not appropriate for use in protocol design in ad hoc networks. Network protocols for these types of wireless networks are based on localized algorithms, which means that they are allowed—for performance and scalability purposes—to use only local information, e.g., two or three hop connectivity information. Such 'localized' centrality measure presents a potential for control of communication, safety issues (Leskovec et al. 2007), routing protocols (Hui et al. 2007; Maglaras and Katsaros 2011), information dissemination (Dimokas et al. 2008, 2011) and so on.

This article studies the problem of identifying the most central nodes in networks (graphs) by using only localized information, i.e., of a few hops. It is motivated by the design of protocols in wireless networks that seek for nodes "central" in the network to assign to them special roles, e.g., *mediator* nodes in cooperative caching for sensor networks (Dimokas et al. 2008, 2011), *message ferrying* nodes in Delay Tolerant Networks (Hui et al. 2007), *rebroadcasting* nodes in vehicular networks (Zhang and Wolff 2008) and so on. The relation of social networks and ad hoc networks is a well-established relation in many works, e.g., Sastry and Pan Hui 2011 and the references therein. In this context, the article makes the following contributions:

- argues for the inadequacy of network-wide centrality measures for use in ad hoc network protocol design and explains the importance and challenges of designing *localized* centrality measures, initiating the relevant research;
- proposes two measures, namely *AWeNoR* and *AWeNoR–Reduced* that can be used for ad hoc network protocol design;
- evaluates the qualitative characteristics of these two measures comparing them with two popular network-wide centrality measures, namely shortest-path betweenness centrality and PageRank centrality, using three real networks.

The remainder of this paper is structured as follows: Section 2 briefly describes the related work on centrality measures. In Sect. 3, the network model, the assumptions and the *AWeNoR* ranking technique are described. Section 4 shows the results of the comparison of *AWeNoR* to other centrality measures. Section 5 introduces another faster technique for computing final rankings through local weight, and the article concludes with Sect. 6.

2 Relevant work

There are really no true 'localized' centrality measures, except from the degree centrality (Wasserman and Faust 1994), which is loosely defined as the number of 1-hop neighbors of a node, and its variations, the lobby index (Korn et al. 2008) and the power community index (Dimokas et al. 2011). However, these indices are poor indicators of the local connectivity. The rest of the centrality measures are computed using knowledge of the complete (network-wide) connectivity information. Closeness centrality (Wasserman and Faust 1994) is defined as the inverse of the sum of the distances between a given node and all other nodes in the network. We easily realize that this index is practically meaningless in a narrow, e.g., a two-hop neighborhood.

Shortest-path betweenness centrality (Wasserman and Faust 1994) is defined as the fraction of the shortest paths between any pair of nodes that pass through a node. A similar technique that measures the extent of bridging capability of all nodes or links in the network is the bridging centrality (Hwang et al. 2008; Nanda and Kotz 2008) .

These centrality measures are relatively rich indicators of node 'positioning', but when these measures are to be used in ad hoc wireless networks, they suffer from several shortcomings. Betweenness centrality suffers from the fact that it leaves many nodes unranked, when these nodes do not participate in any shortest paths computed. Moreover, the existence of bridge links in the network graph results in increasing at an excessive amount the centrality value of the *articulation* node without this node being really "central".

Other similar centrality measures are flow-betweenness (Freeman et al. 1991) and betweenness centrality based on random walks (Newman 2005). Flow betweenness of a node i is defined as the amount of flow through the node i when the maximum flow is transmitted from node s to node t, averaged over all s and t. The method requires the computation of all the maximum flows in the network and suffers from some of the same drawbacks as shortest-path betweenness. The random walk betweenness centrality on the other hand for a node i is the number of times a message passes through i on its journey, averaged over a large number of trials of the random walk and all pairs s, t. This measure is not localized and demands $O((L + V)V^2)$ in computational time.

Apart from the aforemetioned graph-theoretic measures, a very popular family of centralities are the spectral centralities (Perra and Fortunato 2008). There are various definitions of such measures, which are referred to as 'spectral' because they are based on the spectral properties of the matrix, representing the relationships among the nodes. These measures define the prominence of a node recursively, i.e., a node is prominent if it is pointed to by other prominent nodes. The most popular of the spectral centrality measures is the PageRank metric (Brin et al. 1999), which is one of the methods used by Google to rank Web pages. PageRank suffers from the fact that nodes may be ranked very high due to the fact that they are adjacent to significant nodes even though they play no specific role in packet forwarding (e.g., the *sink* nodes). Additionally, the PageRank produces meaningfull rankings when applied only to relatively large graphs and not in narrow, e.g., two-hop neighborhoods. Moreover, the computation of PageRank requires cumbersome calculations and knowledge of the whole network topology, which is not possible in ad hoc wireless networks that require *localized* algorithms.

In this paper, a novel measure for calculating the centrality of nodes in networks (static or semistatic) is proposed. The basic idea is that the centrality of a node is to be calculated over its neighborhood. In this subgraph, all the paths connecting the considered node with all the nodes of the neighborhood are found and a local weight is computed. Local weights are accumulated to give an aggregated measure of centrality and subsequently a node ranking. The new measure called *"Aggregated Weight N-hop Ranking"* (*AWeNoR*) not only rewards nodes that belong to many neighborhoods, but also rewards those ranked high in the neighborhoods they belong to. Due to this attribute, no nodes (except from the isolated ones) remain unranked. To remedy the computational complexity of this measure, the article also describes a second measure, namely *AWeNoR–Reduced*.

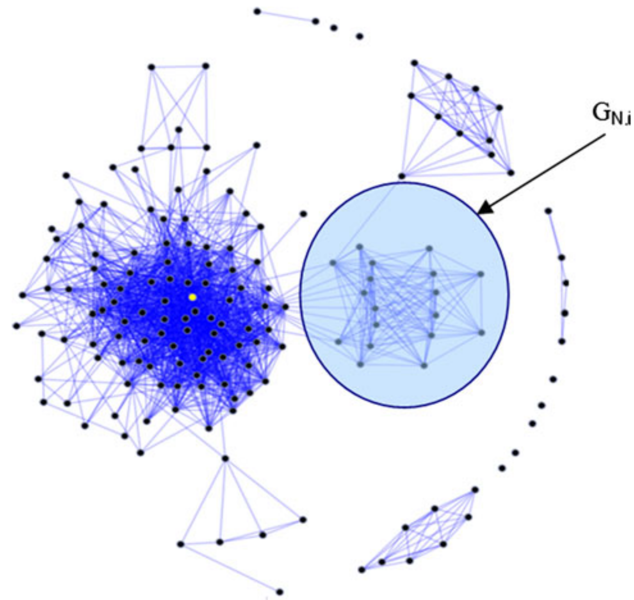

Fig. 1 Graph G and a neighborhood $G_{N,i}$

3 The *AWeNoR* node ranking method

As described earlier, the basic idea behind the proposed method is to create each node's neighborhood and compute the local weights in this subgraph. All these weights are then accumulated to give the final rank of each node. In Sect. 3.1 ,we describe the algorithm for this method, Sect. 3.2 shows how local weights are calculated and Sect. 3.3 demonstrates how the final rankings are computed by aggregating the local weights.

3.1 The *N*-hop neighborhood

We consider a network $G = (V, L)$, where V is the set of nodes and L is the set of links. Each link can be undirected or directed having weight equal to 1.[1] Each node is given a distinct ID; IDs start from the value one.

Definition 1 A node j belongs to neighborhood $G_{N,i}$ of the node i, if there exists at least one path from the starting node i to the end node j, in at most N-hops away (Fig. 1).

[1] Other weights can be assigned as well, when we want to model energy, latency issues, but these issues are not examined here.

To compute the ranking of each node, the proposed method operates as follows:

1. Find all the paths from node i to every other node j which is at most N hops away, thus creating the neighborhood $G_{N,i}$.
2. Calculate the local weight of all the nodes in $G_{N,i}$ (except from i) according to the *AWeNoR* method [explained later].
3. Accumulate local weights to obtain the final ranking of all the nodes.

Since ad hoc networks are relatively sparse, the space requirements are not really large; with an average node degree equal to d, each node i needs to construct a $d^N \times d^N$ table (both d and N are not expected to be larger than 10).

3.2 Local weight

The *AWeNoR* algorithm aims at computing the local weights of nodes which belong to $G_{N,i}$ neighborhoods. There are two intuitions behind this algorithm. Firstly, the nodes closer to the starting node of a path are more crucial than the more distant ones, with respect to disseminating information to the rest of the network. Secondly, all paths can be used to pass data in a neighborhood and not only the shortest path, as used by the betweenness centrality when it calculates node rankings. The algorithm for computing local weight proceeds by deriving all paths with starting node i. The paths are specified as $P_k^i = \left(u_i^0, u_i^1, \ldots, u_i^N\right)$, where P_k^i is the k^{th} path from start node i, and u_i^j is a node at a j-hop distance from the start node i. For each hop j, a weight is computed for each node l using Eq. 1.

$$W_l^j = \frac{a_l^j}{K_l}, \quad K_l > 0 \tag{1}$$

where K_l is the total number of nodes that appear at the j-th hop and $a_l^j s$ shows the number of times that node l appears in hop j through all the paths of the neighborhood $G_{N,i}$. The local weight for any node in neighborhood $G_{N,i}$ is computed using Eq. 2.

$$b_l^i = \sum_{\forall j} \frac{W_l^j}{j}, \quad \forall l \in G_{N,i} \tag{2}$$

The size of the neighborhood is a parameter that plays a significant role. Taking N equal to the network diameter, the neighborhoods coincide with the network graph G. In that case, to compute the ranking of a node, all paths between nodes have to be found, thus making the algorithm inappropriate even for medium-sized networks. On the other hand, giving to N a very small value, the obtained rankings may not be very representative at all.

As an example, consider the directed network shown in Fig. 2 where a neighborhood $G_{N,i}$ of a directed graph is shown. A directed graph is used to make it more clear for the reader to understand the steps of the method. Parameter N, which is the size of the neighborhood, has value 4, while the the initial node is a node with id 1. Thus, the neighborhood is $G_{4,1}$. The paths that exist in this neighborhood are shown in Table 1.

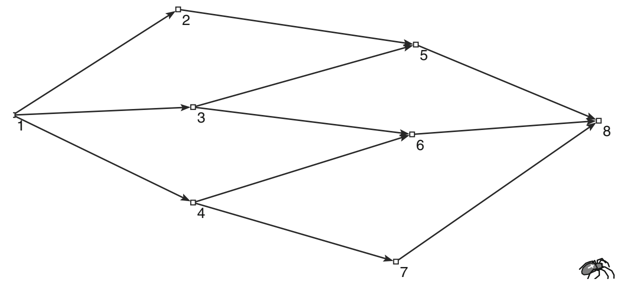

Fig. 2 Example neighborhood $G_{N,i}$

Values of parameter a_l^j are shown at Table 2 for every node except node 1, since it is the starting node of all paths and the value a_l^j for that node would be equal to one.

After computing parameter a_l^j for all nodes of the neighborhood, Eq. 1 is used. Parameter's K_j value for every hop is 5, 5, 5, 1, respectively. In the fourth hop, only one path has a node and thus K_4 equals one. It can be verified that $W_2^1 = 1/5$, $W_3^1 = 2/5$, $W_4^1 = 2/5$, $W_5^2 = 2/5$, $W_6^1 = 2/5$, $W_7^2 = 1/5$, $W_6^3 = 1/5$, $W_8^3 = 4/5$, $W_8^4 = 1$.

Final local weights of all nodes of $G_{4,1}$ according to Eq. 2 are $b_2^1 = \frac{1}{5}$, $b_3^1 = \frac{2}{5}$, $b_4^1 = \frac{2}{5}$, $b_5^1 = \frac{2}{5} * \frac{1}{2}$, $b_6^1 = \frac{2}{5} * \frac{1}{2} + \frac{1}{5} * \frac{1}{3}$, $b_7^1 = \frac{1}{5} * \frac{1}{2}$, $b_8^1 = \frac{4}{5} * \frac{1}{3} + \frac{1}{1} * \frac{1}{4}$.

3.3 Final rankings

The algorithm *AWeNoR* computes local weights for all nodes that belong to a neighborhood $G_{N,i}$. Since nodes may

Table 1 Neighborhood's paths

Initial node	1st hop	2nd hop	3rd hop	4th hop
1	2	5	8	–
1	3	6	8	–
1	3	6	8	–
1	4	6	8	–
1	4	7	6	8

Table 2 Parameter a_l^j

1st hop $j \mid a_l^j$	2nd hop $j \mid a_l^j$	3rd hop $j \mid a_l^j$	4th hop $j \mid a_l^j$
2 | 1	5 | 2	6 | 1	8 | 1
3 | 2	6 | 2	8 | 4	
4 | 2	7 | 1		

belong to multiple neighborhoods, the local weights have to be accumulated to obtain the final ranking of the node using Eq. 3.

$$b_l = \sum_{\forall G_{N,i}} b_l^i, \quad \forall l \in G \tag{3}$$

It must be stated that only acyclic paths are used from *AWeNoR* to compute local weights. Also, in every neighborhood $G_{N,i}$, the local weights are calculated for every node that belongs to $G_{N,i}$, except from i itself, since its weight, using Eq. 1, would be equal to one.

The time complexity of the method is $O((|L| + |V|)|V|)$, since every node and every link will be explored in the worst case for each neighborhood created. Parameter $|L|$ is the cardinality of the set of links (the number of links), and $|V|$ is the cardinality of the set of nodes. This is the total time consumed if the computation of local weights is performed in a sequential manner in all nodes. *AWeNoR* can be conducted either centrally or independently at every node. In the latter case, time complexity of the method is $O((|L| + |V|))$.

4 Evaluation of the proposed method

To evaluate the proposed ranking technique, since there is no "ground truth", we used two real networks. These graphs represent real social networks, with large connectivity among nodes. We used networks with both undirected and directed links. The visualization of the networks was performed with Pajek (http://vlado.fmf.unilj.si/pub/networks/pajek/) and the calculation of the shortest-path betweenness and PageRank centrality values of the network nodes was done with the aid of CentiBiN (http://centibin.ipk-gatersleben.de/) package.

The real graphs are the following:

– Zachary's karate club: a network of friendship between 34 members of a karate club at a US university in the 1970 (Zachary 1977).
– Dolphin network: an undirected network of frequent associations between 62 dolphins in a community living off Doubtful Sound, New Zealand (Lusseau et al. 2003).

We also examined the performance of the method in a medium-sized network of routers of the Internet called Autonomous Systems (AS). The network we used consists of 103 nodes. (http://snap.stanford.edu/data/as.html).

Except from the *AWeNoR* centrality measure, the betweenness and the PageRank centrality values were also computed for every graph to compare them. For every graph ranking, we measure the number of ties that each ranking algorithm produces and also compute the Spearman's rank correlation coefficient (Eq. 4) between pairs of ranking algorithms. The more ties an algorithm produces, the less useful the ranking is for use in wireless networks, because it does not discriminate among network nodes. This is also a crucial requirement for Web rankings when they are to be used in search engines. Spearman's is a non-parametric measure of correlation widely used to describe the relationship between two variables that is used to report the difference in ranking produced by two methods. Differences $d_i = | x_i - y_i |$ between the ranks of each observation on the two variables are calculated. In our case, this measure is used to evaluate the proposed measure in relation to PageRank and shortest-path betweenness centrality values.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}, \quad \forall i \in G. \tag{4}$$

For all the networks used to evaluate our method, the average distance D is computed and this parameter is used to create neighborhoods (Eq. 5).

$$N = \lceil D \rceil. \tag{5}$$

4.1 Undirected experimental graphs

The first real graph, the Zachary's karate club, is shown in Fig. 3 and the dolphins graph is depicted in Fig. 4. The visualization is used here as a means to confirm the obtained results via human intuition.

Table 3 shows the total number of ties that each of the three methods produces for the two networks. The numbers in parentheses represent the number of nodes with zero centrality value (non-ranked). It can be seen that the

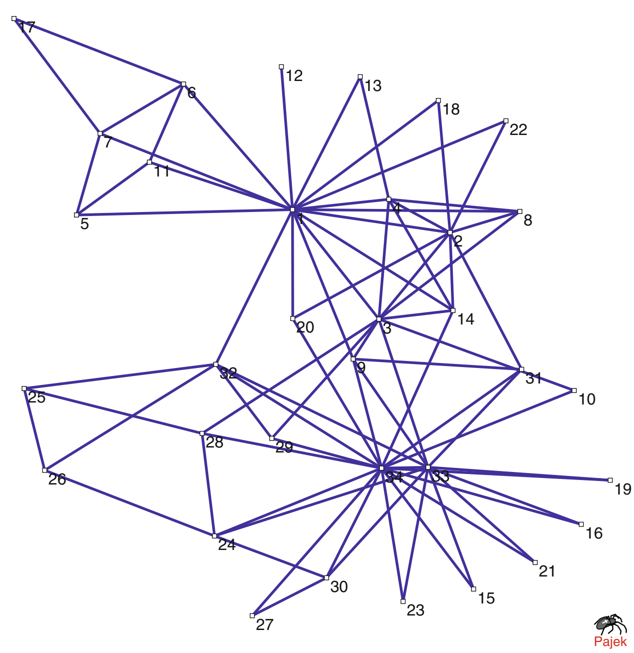

Fig. 3 Zachary's karate club undirected graph

betweenness centrality measure produces a significant amount of non-ranked nodes, which is a non-desirable effect when the centrality measures is used in wireless networks for characterizing the significance of nodes in the network topology.

Table 4 shows the Spearman's rank correlation coefficient computed for every pair of rankings. In the dolphins dataset, we can observe significant discrepancy in the rankings produced by *AWeNoR* with those produced by PageRank.

Table 5 shows the biggest rank difference observed between the three methods. For the dolphin and the autonomous networks, where the number of nodes is relatively large, it is observed that the *AWeNoR* gives results close to PageRank. The numbers in parentheses represent the node where the biggest difference is observed. Table 6 depicts the highest ranked nodes for each graph. We observe that *AWeNoR* makes similar to PageRank rankings for the top-ranked nodes, even though it is a localized measure, whereas PageRank requires cumbersome computations and knowledge of the whole network's topology.

To evaluate the proposed method against the competing ones for the autonomous network, we focus on the biggest differences observed since the graph is too large to be displayed in the paper. In the comparison of *AWeNoR* and PageRank, we see that node with ID 19 is ranked in position 95 by our method while PageRank puts it in place 33. On observing Fig. 5, we see that node 19 is rather isolated in the graph, but is two hops away from node 3 which is ranked high in both methods (PageRank: 16th, *AWeNoR* 17th). PageRank tends to reward such nodes with high score even though their significance in data dissemination is rather contradictory. Betweeness centrality on the other hand leaves too many nodes unranked (in the autonomous network 43 out of 103 nodes are unranked) making it rather impractical.

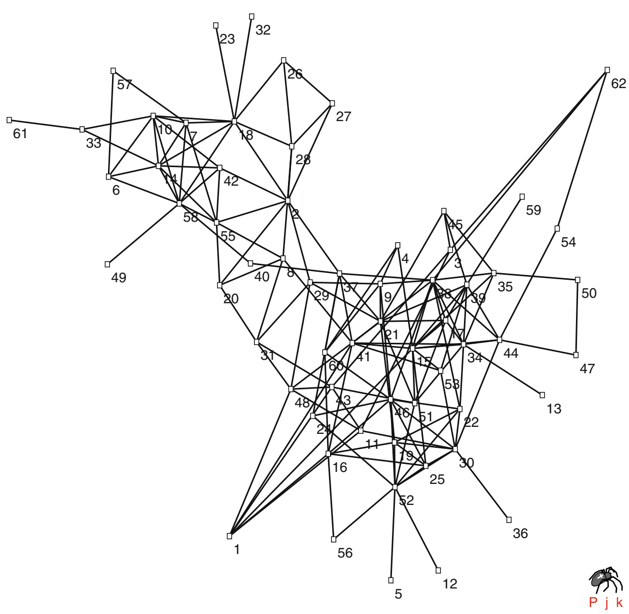

Fig. 4 The dolphins network

Table 3 The number of ties produced by each competitor

Graphs	Betweenness	PageRank	AWeNoR
Zachary's karate club	16 (12)	11 (0)	11 (0)
Dolphin social network	9 (9)	4 (0)	4 (0)
Autonomous system	45 (43)	31 (0)	30 (0)

Table 4 Spearman's rank correlation coefficient

Graphs	Betweenness-AWeNoR	PageRank-AWeNoR	Betweenness-PageRank
Zachary's karate club	0.8442	0.8512	0.8747
Dolphin social network	0.7712	0.9457	0.8171
Autonomous system	0.7196	0.8712	0.8566

Table 5 Biggest difference observed

Graphs	Betweenness-AWeNoR	PageRank-AWeNoR	Betweenness-PageRank
Zachary's karate club	14 (26)	12 (10)	13 (10)
Dolphin social network	38 (40)	13 (17)	41 (40)
Autonomous system	56 (67)	62 (19)	50 (67)

Table 6 Highest ranked nodes for karate (top), dolphins (middle) and autonomous (bottom)

Rank position	PageRank	AWeNoR	AWeNoR Reduced	Betweenness
1st	34	34	34	1
2nd	1	1	3	34
3rd	33	33	33	33
4th	3	3	2	2
5th	2	2	1	32
1st	15	15	5	37
2nd	18	38	58	2
3rd	52	46	18	41
4th	58	34	34	38
5th	38	52	44	8
1st	60	60	60	60
2nd	11	11	11	11
3rd	40	40	40	40
4th	16	16	31	16
5th	1	1	16	31

4.2 Directed experimental graphs

The new ranking technique was also tested in directed graphs. Taking the karate club real graph and converting each link to a directed arc, the network of Fig. 6 is created. The direction of each arc is selected randomly.

Table 7 shows that *AWeNoR* incurs significantly fewer ties than PageRank does. (Betweenness centrality is not possible to be computed for this network due to the lack of strong connectivity.)

Table 8 depicts the ids of the five highest ranked (top-5) nodes for this directed network. The numbers in parentheses represent the position of the node in the ranking produced by the competitor method, in the cases where this node does not appear in the top-5 list of the competitor. From Fig. 6 and Table 8, we gain an insight into why the *AWeNoR* algorithm is more accurate in determining the most significant nodes compared to PageRank in terms of data dissemination: for instance, node 33 (ranked 4th) is more crucial in terms of routing than node 19, which is a sink node. The three highest ranked nodes are the same for both methods in the karate club graph. Of course, such an observation is not a proof of the superiority of the algorithms, but it is a strong evidence that produces more meaningful rankings for the considered application scenaria.

In the dolphins network (Fig. 4), the nodes with id 38 and 46, which are among the highest ranked by *AWeNoR*, have very low ranking position in the PageRank measure. This is due to the fact that *AWeNoR* ranking rewards nodes that belong to many neighborhoods, though PageRank rewards only those connected to significant nodes. PageRank may rank in high position those nodes that have few (even just one) neighbors that are significant to the network, without examining if they play any role in larger neighborhoods, which is desirable by policies applied to ad hoc wireless networks. In the autonomous network due to the connectivity of the graph, the two methods give similar results. The network could not be displayed in the paper due to space limitations (the graph is too large to be able to distinguish the node's ids), but the reader can download the connectivity matrix from (http://snap.stanford.edu/data/as.html) and use pajek or any similar program to obtain a visual representation.

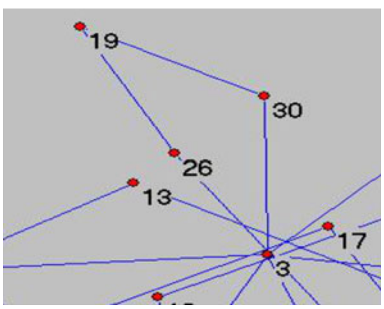

Fig. 5 A portion of the autonomous network

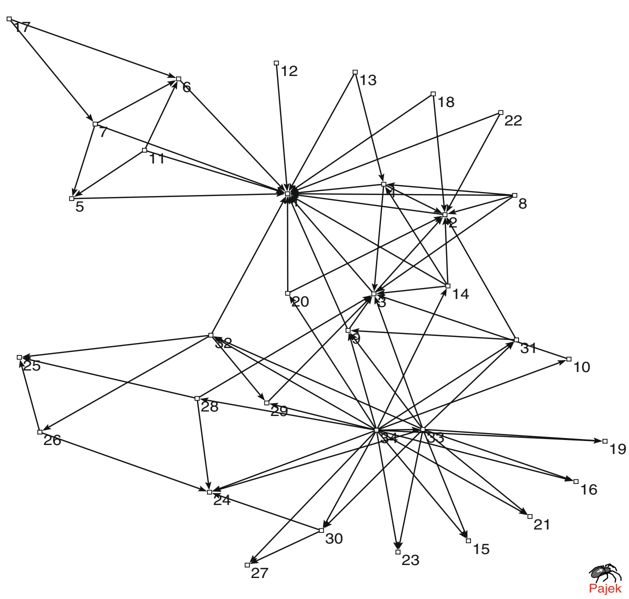

Fig. 6 Zachary's karate club directed graph

Table 7 Number of ties incurred by each algorithm

Graphs	PageRank	AWeNoR
Zachary's karate club	21	15
Dolphin social network	23	22
Autonomous system	70	56

Table 8 Highest ranked nodes for karate (top), dolphins (middle) and autonomous (bottom)

Rank position	PageRank	AWeNoR
1st	1	1
2nd	3	3
3rd	2	2
4th	19 (24th)	33 (7th)
5th	4 (6th)	9 (8th)
1st	1	1
2nd	15	15
3rd	16 (4th)	38 (23th)
4th	4 (6th)	16 (3rd)
5th	19 (8th)	46 (33th)
1st	1	60
2nd	11	11
3rd	60	9
4th	9	1
5th	5 (8th)	16 (6th)

5 The *AWeNoR–Reduced* centrality measure

As described in Section 4, to compute the aggregated weights, the *AWeNoR* algorithm has to add local weights of all neighborhoods in the network. So, for a K-hop 'long' network, the *AWeNoR* algorithm has to run K times, one for each node. Computing local weights for every neighborhood can be a very time-consuming task even for medium-sized networks. To improve the total running time of the proposed *AWeNoR* algorithm, we further describe here the *AWeNoR–Reduced* ranking method. The *AWeNoR–Reduced* algorithm creates neighborhoods only for some nodes, according to a parameter q_i and a threshold A. Parameter q_i is used to count the times that node i participates in paths of all the neighborhoods created by the algorithm in every step. The *AWeNoR–Reduced* runs only cenrtally or with an excessive change of information between nodes, in contrast to *AWeNoR* that can be executed independently at every node. At the first iteration of the algorithm, a node i (node with $id = 1$ is chosen) creates its neighborhood $G_{N,i}$ by detecting all paths of length N. Every node j that participates in any path of the node updates the parameter q_j (q_j++) for every instance. At every next iteration of the algorithm, another node is selected randomly and if its parameter q_i is below threshold A, the procedure follows the same steps. If q_i is over A, which means that node i has already participated in many other neighborhoods, the node i is discarded and the algorithm moves to next selected node.

The *AWeNoR–Reduced* ranking algorithm is described below in pseudocode:

1. Initiate algorithm. Set $i = 1$.
2. If $q_i < A$ then find all the paths from node i to every node j which are at most N hops away, thus creating the neighborhood $G_{N,i}$.
3. For every path $P_k^i = \left(u_i^0, u_i^1, \ldots, u_i^N\right)$ update parameter $q_{ui} \forall u \in P_i^K$ except u_i^N and u_i^0.
4. Calculate the local weight of all the nodes in $G_{N,i}$ (except from node i) according to the *AWeNoR* algorithm.
5. Set $i = i + 1$. If the last node of the graph is reached, then go to step 6 or else go to step 2 (Dimokas et al. 2011).
6. Accumulate local weights to obtain the final ranking of all the nodes.

The *AWeNoR–Reduced* algorithm, according to Tables 6 and 9, achieves the same performance in terms of finding the most important nodes in a graph, while requiring fewer neighborhoods to be created (Table 10).

The parameter A is used as a threshold to choose whether a node's neighborhood is created or not. Choosing the value of parameter A is an important issue. Giving A a rather big value, the *AWeNoR–Reduced* algorithm degenerates to *AWeNoR*, since all neighborhoods are created. Setting A equal to zero, a risk of creating disjoint neighborhoods arises, letting some nodes unranked. In the experiments conducted, a value close to zero was used to avoid these situations.

Figure 7 shows the effect of parameter A to the method's results compared to *AWeNoR*, along with the number of neighborhoods created for every such choice. A strict relation between the method's accuracy and cost, in terms of time consumption, is observed. The preferred policy is to have a value that changes according to the size or connectivity of the network, but its development is a subject of future work.

6 Conclusions

The issue of discovering which nodes in a wireless ad hoc network are central to the topology is of fundamental importance, since it can be used as a primitive method to perform routing (Hui et al. 2007; Zhang and Wolff 2008), cooperative caching (Dimokas et al. 2008) and contamination detection.

There exist several centrality measures in the literature, like shortest-path betweenness centrality, PageRank and closeness centrality. Betweenness is based on the shortest paths between nodes. Nodes that lie on many shortest paths between other nodes are given a high centrality value. In many cases though, this measure is not useful because it counts only a small subset of all the paths. Moreover, it creates hotspots in the communications because it consistently uses very few nodes (Pathak and Dutta 2010). When

Table 9 Spearman's rank correlation coefficient

Undirected graphs	Betweenness-AWeNoR reduced	PageRank-AWeNoR reduced	AWeNoR-AWeNoR reduced
Zachary's karate club	0.8105	0.8438	0.9175
Dolphin social network	0.7925	0.9207	0.8782
Autonomous system	0.7296	0.8517	0.9728

Table 10 Neighborhoods created

Undirected graphs	AWeNoR reduced ($A = 1$)	AWeNoR reduced ($A = 3$)	AWeNoR
Zachary's karate club	3	7	34
Dolphin social network	14	17	62
Autonomous system	31	38	103

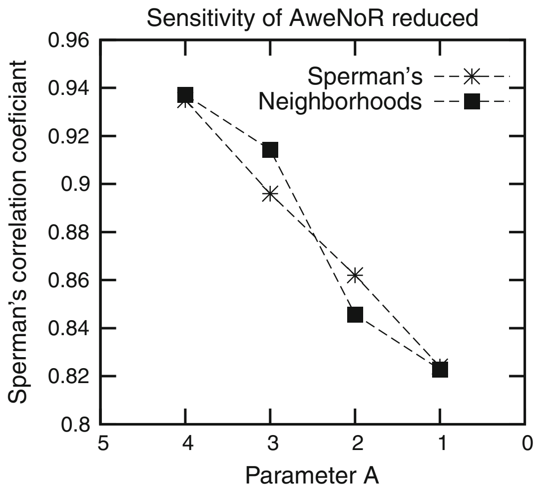

Fig. 7 Sensitivity of *AWeNoR–Reduced* ranking to parameter *A* (Zachary's karate club undirected graph)

PageRank is used, the significance of a node comes from the significance of its 1-hop neighborhoods, leading many times to misleading results. A sink node may be ranked very high just because it is adjacent to a very significant node, even though its contribution to communication is of no importance. Additionally, these measures need to take into consideration the whole network topology—they are "centralized", which is not acceptable when these centrality measures are to be used for ad hoc network protocol design.

This article proposes a new measure, namely *AWeNoR*, for determining significant nodes. For each node *i* a neighborhood is created and all paths with starting node *i* are created. For every "cluster" created, a local weight is computed and a final ranking measure is created by adding these local weights. The new *localized* centrality measure rewards nodes that belong to many neighborhoods and lie in many paths between nodes of the neighborhood. This measure was compared to the shortest-path betweenness and PageRank centrality, and achieved to provide meaningfull rankings with few ties and leave no nodes unranked for both directed and undirected networks. The *AWeNoR-Reduced*, a faster algorithm for finding localized centrality values, was also presented.

As future work, the proposed measures will be compared to other centrality measures as in Freeman et al. 1991 or Newman 2005. The main goal though of our future work is to use this centrality measure as a primitive method in the design of networking protocols, such as cooperative caching for ad hoc wireless networks (Dimokas et al. 2011), and routing in DTN networks where other attributes like energy of nodes or link quality could be incorporated in the centrality measure to better represent significance of actors in real time.

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