Social-based Forwarding of Messages in Sensor Networks

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Abstract: As we adopt the Internet of Things (IoT), the boundaries between sensor and social networks are likely to disappear. However, to this date, the use of social networks in the design of wireless sensor network protocols has not received much attention. In this paper, we focus on the concept of information dissemination in a framework where sensors are carried by people who are part of a social network. We propose two social-based forwarding approaches for what has been called Social Network of Sensors (SNoS). To this end, we exploit two important characteristics of ties in social networks, namely *strong ties* and *weak ties*. The former is used to achieve rapid dissemination to nearby sensors while the latter aims at dissemination to faraway sensors.

1 INTRODUCTION

Wireless Sensor Networks (WSNs) are an important area of research because they relate to many applications in the areas of transportation, military and agriculture. A typical WSN consists of many small devices deployed over a geographical area, where each device is called a *Sensor* and can measure environmental or physical conditions (e.g., temperature) in a particular area of interest. The structure of WSNs can be static or dynamic. In a static WSN, sensors are stationary while in a dynamic WSN, a sensor's position is subject to change. In this work, we design social-based approaches for message forwarding in SNoS (Tomasini et al., 2013) inspired by the concept of strong ties and weak ties. Following the definition and the hypothesis of Granovetter (Granovetter, 1973), we proposed information forwarding approaches to achieve nearby spreading of information, called Strong-Ties-Based Forwarding (STBF), and to achieve faraway spreading of information, called Weak-Ties-Based Forwarding (WTBF).

2 RELATED WORKS

The idea behind data forwarding in WSNs is to minimize the consumption of network resources by choosing appropriate receivers (relays) in the forwarding process (Lambrou and Panayiotou, 2009). In the network literature, several forwarding approaches have been described implementing different strategies.

Epidemic forwarding was proposed by Vahdat and Becker (Vahdat et al., 2000). Data messages are sent to all network nodes in the communication range of a particular node, all nodes are guaranteed to receive all data messages in the network. This approach has a high level of flooding due to the number of messages exchanged which leads to waste network resources. Yet, the Epidemic approach is widely used to benchmark other protocols.

PRoPHET was proposed by Lindgren et al. (Lindgren et al., 2003) and is based on a node's history of encounters, which means that if a node i encounters another node j frequently, node i is more likely to encounter node j again in the future. With the encounter ratios, a *delivery predictability* is calculated for each node destination, the value of the delivery predictability represents the chance to deliver a message to a particular destination.

Social ties in social networks have been studied by Granovetter (Granovetter, 1973) who argued that social relations come in two kinds: strong and weak ties. In social networks, these ties are used for different purposes but weak ties are mostly important for individuals to receive information from faraway locations in their network. These types can also be defined in the context of SNoS based on the sensor's encounter frequencies. That is, the strong ties of sensor i are the other sensors whose encounter frequency to i is high. By contrast, the weak ties are formed to those sensors that have low encounter frequencies with sensor i.

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3 THE MODEL

We initially start with an environment that represents a squared city of (6.2×6.2) sq. miles divided in to squared blocks (100×100 blocks). We deployed 2,040 mobile sensors in the environment, exponentially distributed from the center of the city (environment) since most metropolises follow this population distribution (Grossman-Clarke et al., 2005). The event that is used in the measuring of the information dissemination is generated in a random location which is then considered the center of the dissemination (for the purposes of measuring distances). The communication between sensors is peer-to-peer. The communication range of sensors (sensors' radius) is 55 yards (50 meters) in line Wi-Fi communication range. In the simulation environment, each sensor moves at a fixed speed of 1 block per tick (a *tick* is equal to 1.2 minute in real time considering the normal human walking speed is ≈ 3.1 miles/h (≈ 5 km/h) (Fitzpatrick et al., 2006). Sensors move according to the Individual Mobility model proposed by Song et al. (Song et al., 2010) because this model has the ability to accurately describe the characteristics of human mobility. We provide the average of 100 runs for each approach. The simulations stop when 90% of the network knows about the event.

We proposed two novel forwarding approaches, namely *Strong-Ties-Based Forwarding (STBF)* and *Weak-Ties-Based Forwarding (WTBF)*. These approaches are used for information dissemination, where the spreading process is based on relation type between sender and receiver (strong or weak relation). Our proposal is that sensors can maintain the strength of ties to use the strength to achieve different dissemination patterns.

Each sensor in the simulation has to be able to keep track of encounters with other sensors. For each sensor, all encounters are memorized in a dynamic list T_i, where i represents a particular sensor in the environment. The items in this list represent the IDs (e.g. MAC addresses) of the encountered sensors. Each sensor has another dynamic list which is derived from the T_i list: the CST_i list (the list of cumulative strong ties) contains the sensors (candidates sensors) that have strong ties with sensor i while the CWT_i list (the list of cumulative weak ties) contains this list contains the sensors (candidates sensors) that have weak ties with sensor i. These derived lists are used respectively by the STBF and WTBF approaches.

In STBF, we extract the strong ties for each sensor from the T_i list. As mentioned, the strong ties emerge with people we associate with frequently and frequency does not correlate with friendship. This means, the strength of a tie represents frequency and not affinity between two individuals. The friendship relation between two individuals may be derived from the strength of the relation, but the distribution of these encounters and their regularity also play a role (Bulut and Szymanski, 2010; Vaz de Melo et al., 2013; Bai and Helmy, 2004). For the purposes of this work, friendship definition is not important, but rather frequency; most of us meet many people frequently without considering them as friends (e.g., at work). The strong ties of a sensor can be extracted by taking the higher frequency sensors in its history of encounters (T_i list). This process can be performed based on the so-called "80/20" rule (Newman, 2005). This rule states that for many observations, approximately 80% of the effects caused by the other 20%. This rule is common in economical and natural processes, for example, 80% of a company's sales come from 20% of its clients. Statistically, this rule is applicable to the applications that follow a power law distribution (Newman, 2005). Based on this statistical phenomenon (since the degree distribution of nodes in our model follows a power law distribution), for each sensor i we take the higher 20% frequencies items of the T_i list at time t, and inserting the corresponding sensor ID into the CST_i in which contains the ID's of the sensors that have the higher frequencies (strong ties) of the T_i list.

In WTBF, we insert the sensor ID of the lower 80% frequencies items of the T_i list into the CWT_i list (weak ties). This process is performed by each sensor at every time step of the simulation. In order to have values that are statistically significant, we employ *(i)* a*training procedure* where we let all sensors freely move in the environment in the absence of any event for 100 time steps—this procedure represents a proactive step before executing any of the approaches we used in this work aiming to create a history of encounters and initiating the T_i list for each sensor; then we execute a *(ii) checking procedure*, at every time step t and for each sensor i, the decision of inserting an items into the CST_i and CWT_i lists is based on Algorithm 1 which describes whether an element is included in the CST_i or in the CWT_i of a particular sensor. In our algorithm, we take into considerations that a weak tie may, in the future, become a strong tie. In this case, we remove this item from CWT_i and insert it into the CST_i.

Once sensors have their CST_i and CWT_i lists (candidates lists), they can be used in the forwarding process of STBF and WTBF respectively. This means a sensor forwards data only to other sensors that are in their candidates list. Furthermore, to carry out the forwarding process, three conditions must be validated:

Algorithm 1: Algorithm for inserting a sensor ID into the CST_i and CWT_i. Note that t represents time.

for all ID $\in$ higher 20% frequencies in $T_i(t)$ **do**
  if ID $\notin CST_i$ **then**
    add ID to CST_i
  end if
  if ID $\in CWT_i$ **then**
    remove ID from CWT_i
  end if
end for
for all ID $\in$ lower 80% frequencies in the $T_i(t)$ **do**
  if ID $\notin CWT_i$ **then**
    add ID to CWT_i
  end if
end for

- The receiver must not have the event.
- The forwarder and the receiver must be in the communication range of each other.
- The receiver must be in the candidates list of the forwarder.

The two approaches described (STBF and WTBF) are designed to work in two modes:

Full Mode. In this mode, a sensor, i, forwards data to all sensors in its candidates list (CST_i and CWT_i lists in STBF and WTBF respectively).

Partial Mode. A sensor has a predefined number of sensor(s) to forward data to (we used 1 to 5 receivers). These receivers must be selected from sensor's candidates list (CST_i and CWT_i).

4 EXPERIMENTAL RESULTS

We benchmark the proposed approaches by highlighting their behavior according to two criteria: data-spreading distance and data-spreading coverage area. Moreover, for a deeper evaluation, we considered different scenarios for the Epidemic and PRoPHET approaches. In Epidemic forwarding, we forced it to work in *multiple mode* in addition to its default working mode (all). In the default mode a sensor spreads data randomly to all other sensors in its communication range, while in the multiple mode, we involve 1 to 5 receivers instead of considering all sensors as receivers. In PRoPHET, we involved 2 to 5 receivers rather than 1 (the default working mode).

4.1 Spreading Distance

The control of the spread distance is the main contribution of our approaches. We have proposed the two approaches aiming at having some control of the distance the event generated in a sensor will travel. The hypothesis that we adapted from social networks is that strong ties will restrict the forwarding to nearby sensors while the use of weak ties will spread the information to the farthest distances; spread to far distances may be useful to certain applications (e.g., emergency warnings).

The findings show that the farthest possible distance from the center of the simulation environment can be obtained using the default mode of Epidemic (up to 2.85 miles), followed by the full mode of WTBF (up to 2.67 miles), and then by the full mode of STBF (up to 2.26 miles), and finally, the default mode of PRoPHET (up to 2.05 miles). This means that WTBF can disseminate information to locations as far as the ones done by a full Epidemic model.

For a detailed view to their behavior, we tested the partial mode of STBF and WTBF, and the multiple-message mode of the benchmarking approaches under different number of receivers. It should be clarified that in Epidemic, when spreading to 1 sensor, this sensor may have a strong tie to the forwarder because Epidemic discards the type of ties during the spreading process. Therefore, this case may limit the forwarding process to include only the surrounded area (e.g., same group or community). Whereas in WTBF, when spreading to 1 receiver, the receiver will definitely have a weak tie to the forwarder. For this reason, the partial mode version of WTBF with 1 receiver outperforms Epidemic and the other approaches as shown in Figure 1; this is a very interesting result because it demonstrates that if we want to maintain a low message overhead, WTBF can be a better alternative for message dissemination to far locations than even Epidemic. Moreover, being able to replicate such behavior in the context of mobile sensor networks (or SNoS) confirms the idea that a weak tie plays a significant role in data flowing to different social communities by acting as a bridge or a broker (Granovetter, 1973).

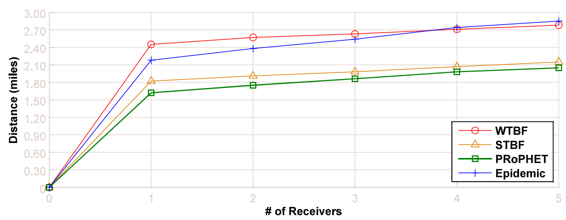

Figure 1: Overall behavior in terms of spreading distance when varying the number of receivers in each approach.

Furthermore, the results also show that the partial mode of STBF underperforms the multiple mode of Epidemic, and outperforms PRoPHET. Yet, the goal of STBF is to restrict the dissemination to nearby locations so the "underperforming" is actually the desired outcome for STBF. In more details, Figure 1 exhibits the average spreading distance that can be obtained for each approach using different number of receivers. We noticed that each approach reaches the equilibrium when the number of receivers approximates 4 sensors, this can be interpreted as an indicator of the convergence between both modes of the proposed approaches at this level of receivers. However, this exact level may vary depending on sensor density within the simulation environment. In Figure 2 we show the range of the distances that can be reached for each approach. This figure also shows the lowest and highest distances, the lower and upper quartiles, and the median for each approach.

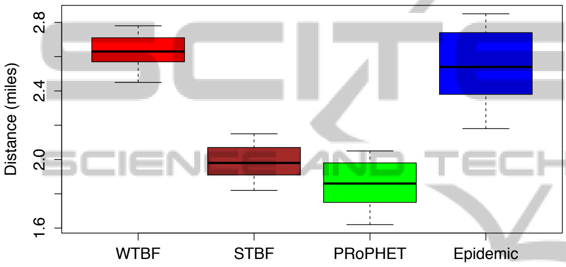

Figure 2: The average distances for the full modes and partial modes (using 1, 2, 3, 4, and 5 receivers) of the proposed approaches and the single and multiple message modes of the benchmarking approaches (using 1 to 5 receivers).

Figure 2 also allows us to observe that the variations achieved in WTBF and STBF are smaller than the competition. WTBF can be said to be more reliable with the range of distance the event will reach than Epidemic because the variance is smaller. Conversely, although PRoPHET can limit the spread to very short distances, the variance is quite high when compared to STBF.

4.2 Coverage Area

Data forwarding approaches try to cover as much area as possible in the network environment. The efficiency of these approaches in terms of *coverage area* depends on the size of the area they cover which in general should be maximized, and the consumption of network resources which should be minimized (Gaudette et al., 2014). Recall that our simulation environment is 38.61 sq. miles (or a square of 6.2×6.2 miles). In this evaluation, we calculate the minimum and the maximum areas that can be covered by the event during the spreading process, these areas can be defined as follows:

Minimum Coverage Area: part of the area that is always under the coverage of data spreading.

Maximum Coverage Area: part of the area which is not always under the coverage of data spreading but has been reached at least once.

As mentioned, we have 100 runs for each approach in our experiments, each run gives a particular coverage area. The intersection region of these areas represents the minimum coverage area, while the union of all the runs represents the maximum coverage area. We can clearly see that the disparity in the areas between the minimum and the maximum is very small (Figure 3). Table 1, illustrates the obtained results and their proportion to the environment area for each approach. We observe the following points:

- Minimum and maximum areas that can be covered using WTBF and Epidemic are very close.
- WTBF outperforms PRoPHET and STBF. This is expected since we want STBF to dissimulate the event around the location where it appeared.
- The intensity of data spreading is very high in Epidemic and very low in WTBF.
- STBF covers more area than PRoPHET in both the maximum and the minimum coverage area. However, STBF has higher intensity in data spreading than PRoPHET.

Given that STBF is proposed to avoid the spreading of information to faraway places, we had to investigate a little more what was taking place as the result above seems to negate our hypothesis of strong ties being useful for information dissemination to nearby locations. However, results in Figure 3 can be a side-effect of the settings of our model which stops when 90% of the network knows about the event.

Hence, we changed the stop condition to be independent of the number of sensors knowing about the event. We provide two other tests (each of 100 runs) with different stop conditions. First, running the simulator for 100 time ticks (Test 2) and then for 50 time ticks (Test 3). Figures 4 and 5 show minimum and maximum coverage area for each approach. We can observe that the disparity between the minimum and the maximum areas is more prominent than what we see in Figure 3. These new results reflect better the behavior of both WTBF and STBF confirming the hypothesis that weak ties spread events farther than strong ties. Tables 2 and 3 show the results of 100 ticks and 50 ticks respectively, and their proportion to the environment area. Lastly, we measured the proportion of the minimum to the maximum coverage area of each approach for every test. Clearly, the proportions for 100 ticks and 50 ticks resemble Granovetter's work better than the experiment using 90% of the sensors as shown in Table 4.

Table 1: Minimum and maximum coverage areas with the experiment runs until 90% of the sensors know about the event.

		Epidemic	PRoPHET	STBF	WTBF
Maximum Coverage Area	Area (sq. mile)	6.87	5.09	5.62	6.80
	the proportion to the total area	17.80%	13.20%	14.55%	17.60%
Minimum Coverage Area	Area (sq. mile)	6.62	4.49	4.82	6.43
	the proportion to the total area	17.15%	11.64%	12.50%	16.65%

Table 2: Minimum and maximum coverage area when the simulation runs for 100 ticks.

		Epidemic	PRoPHET	STBF	WTBF
Maximum Coverage Area	Area (sq. mile)	3.36	2.01	2.13	3.27
	the proportion to the total area	8.72%	5.20%	5.51%	8.47%
Minimum Coverage Area	Area (sq. mile)	2.55	1.04	1.21	2.48
	the proportion to the total area	6.60%	2.70%	3.13%	6.42%

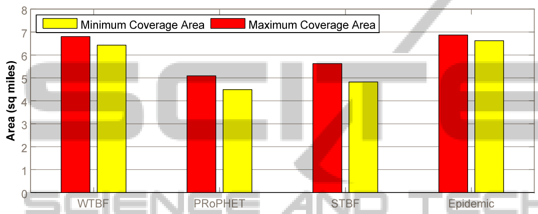

Figure 3: Minimum and the maximum coverage area when using the simulator with a condition to stop based on 90% of the sensors knowing about the event.

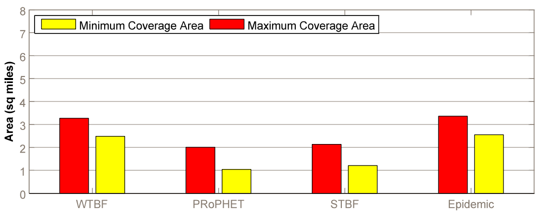

Figure 4: minimum and maximum coverage area when using the settings of the experiment in which the sensors are allowed to work for 100 ticks of the simulation.

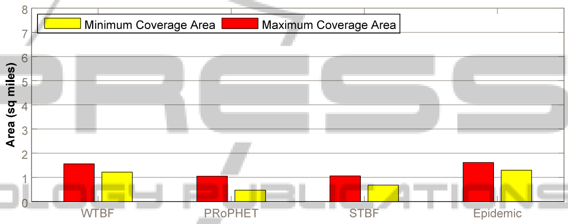

Figure 5: minimum and maximum coverage area when using the settings of the experiment in which the sensors are allowed to work for 50 ticks of the simulation.

5 CONCLUSIONS AND FUTURE WORKS

We analyzed the proposed protocols based on two criteria: data-spreading distance and data-spreading coverage area. Furthermore, we measured the intensity of message-spreading in the environment and delivery time for all the approaches in this work. We can summarize STBF and WTBF approaches by giving some recommendations when designing a SNoS:

- If the goal is to forward data to the farthest distance, the best option is to use the partial mode of WTBF, because its results reflect a good performance in terms of distance and the number of messages exchanged. However, we should not ignore the fact that WTBF approach spends more time than the other approaches.
- If we are looking to forward data to a wider coverage area with low data spreading intensity we can choose WTBF.
- If the goal is reducing the number of messages exchanged within the network, we recommend WTBF approach.

In this work, we did not investigate the issue spreading direction. However, as the future work, we are planning to investigate this issue using our proposed approaches. It is important to find whether the social network reconstructed from IM models lead to a bias towards certain directions in the environment.

Finally, the environment we currently use does not assume the existence of barriers or obstacles which may be common in urban environments. It may be interesting to investigate how the proposed forwarding mechanisms perform under configurations with obstacles (representing, for instance, buildings in a city). We believe the results will not change because the mobility model used has been shown to approximate human mobility in urban areas. In fact, the data used to evaluate the IM model comes from real cellular data in large cities.

Table 3: Minimum and maximum coverage area when the simulation runs for only 50 ticks.

		Epidemic	PRoPHET	STBF	WTBF
Maximum Coverage Area	Area (sq. mile)	1.62	1.05	1.06	1.56
	the proportion to the total area	4.21%	2.73%	2.74%	4.04%
Minimum Coverage Area	Area (sq. mile)	1.30	0.47	0.68	1.22
	the proportion to the total area	3.37%	1.22%	1.76%	3.15%

Table 4: proportion of the minimum to the maximum coverage area for all the approaches using all three experiments.

	Epidemic	PRoPHET	STBF	WTBF
90% of the sensors reached	96.3%	88.2%	85.7%	94.5%
Simulation runs for 100 ticks	75.8%	51.7%	56.8%	75.8%
Simulation runs for 50 ticks	80.2%	44.7%	64.1%	78.2%

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