Decongesting Opportunistic Social-based Forwarding

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***Abstract*—Social network based forwarding algorithms for opportunistic networks, such as Pocket Switched Networks, are primarily concerned with throughput and efficiency. In this paper we seek to improve our understanding of how forwarding based on a heuristic that favours connectivity causes unfair load distribution, which in turn leads to congestion. We propose a number of metrics, that help balance the load distribution and actively prevent congestion. We optimise and filter existing metrics such as Centrality and Similarity, and introduce Availability and Performance feedback mechanisms. We state a preliminary Utility formula that combines our observations allowing us to select a suitable next hop. We present initial modelling results showing that our refinement techniques improve the balance of load distribution, reducing the stress on individual nodes.**

***Index Terms*—Opportunistic Forwarding, Congestion**

I. Introduction

Over recent years research has shown that aspects of social network theory, applied to opportunistic packet forwarding in mobile disconnected environments provides efficient packet delivery. The desired outcome of the work by Hui et al [1], and Daly and Haahr [2] is to restrict the quantity of replicated packets by only forwarding packets to nodes that have a greater importance in the network, increasing the throughput and reducing the number of forwards required.

In Figure 1 our analysis of the Infocom 2005 dataset shows that forwarding based on next hop connectivity exhibits a unfair stress distribution, since the higher the centrality of the node, the higher the proportion of stress.

The work in [3] argues that in a simplified scenario where nodes forward randomly, better connected nodes have a higher probability of receiving a packet and thus the load distribution is naturally skewed towards the most connected nodes. Additionally to this they argue that by making informed forwarding decisions based on a heuristic that favours connectivity, load distribution becomes even more unbalanced.

This paper argues that it is important to consider a number of additional parameters in order to have a more robust solution in terms of congestion control / avoidance. We propose a combination of feedback and sending rate control mechanisms, along with introducing metrics to the forwarding heuristic that will make it less probable for a node to be selected for forwarding when it has little availability. Our target is to manage a trade-off between the most direct route, while preventing congestion and distributing load fairly.

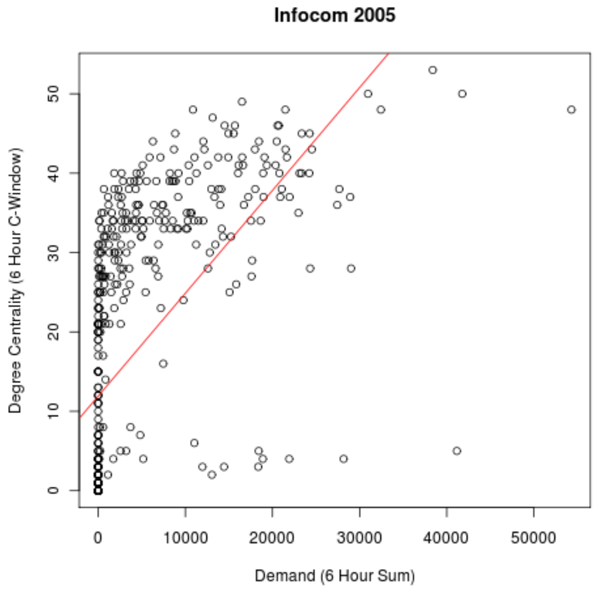

Fig. 1. Correlation between Centrality and Demand

The remainder of this paper is organised as follows: Section III reviews related work in this area. Section II identifies the relationship between congestion and centrality and introduces our framework. Section IV concludes the work and details future work.

II. Our Framework

Our work is motivated by the observation that if all data is traveling towards an ever decreasing subset of nodes, the nodes in the final subset will be in the greatest demand. We analysed the Infocom 2005 dataset [4], as we feel it is a reasonable size for our initial trials. Our analysis shows (in Figure 1) our motives for developing this framework are justified.

Our framework is split into two components 1) A Forwarding Heuristic: In the design of the forwarding heuristic we have incorporated a smoothed locally calculated centrality, a filtered neighbour similarity and a performance ratio. In order to forward efficiently in terms of high throughput, low delay and with a balanced load distribution. 2) A Congestion Control System: Our congestion control system identifies and proposes two locally disseminated Availability parameters, Receptiveness and Retentiveness that aim to promote the use of routes that have lower levels of load by propagating usage parameters. The remainder of this section is concerned with the individual components of our framework. Centrality with fairer load distribution is detailed in Section II-A, Filtered next hop similarity is specified in Section II-B - these metrics allow a node to send its packets to a node with a higher probability of reaching the destination. Performance based selection is presented in Section II-C, this value contributes to route optimisation. Congestion control through availability feedback is described in Section II-D, we measuring how congested a node is and scale it suitability according to its availability. Section II-E we give a preliminary Utility function that allows us to combine all our metrics into one value, that can be used to select a next hop.

A. Centrality

Many different metrics have been identified and used in graph theory to index vertices with a centrality value. This value represents a degree of importance in the network, what attribute is chosen depends on what is actually important. BubbleRap [1] uses degree as its centrality index, as this shows how well connected the node is in the network, while SimBetTS [2] integrates a locally calculated betweenness value as a centrality index, as betweenness shows that two neighbouring nodes require this node in order to communicate.

In this paper we analyse the use degree centrality to achieve high throughput. We agree with FairRoute that load distribution is unfairly weighted towards a minority of better connected nodes. In addition to the FairRoute observations we believe this unbalanced distribution will be a contributing factor towards network congestion.

When making informed forwarding decisions based on a heuristic that favours connectivity, the cardinality of the subset of nodes with a higher centrality than the current forwarding node becomes smaller at each hop, resulting in the smallest set of nodes having to cope with the highest level of demand. Our improvement aims to reduce the range of centrality values, this results in centrality based subsets with larger cardinality. Figure 2 shows that nodes with high unsmoothed centrality have a high connectivity variance, which identifies that a node with high centrality generally has a large amount of short period contacts. Short period contacts are not generally valuable when forwarding, rather than penalising a node for experiencing short periods of high popularity, as in FairRoute, we propose that this value is smoothed. By reducing the impact these short period contacts have on the nodes degree centrality we ensure that a nodes centrality accurately identifies the nodes importance, but also achieves our desire to reduce the range of centrality values.

$$Sd_t^+(v) = \alpha * d_t^+(v) + (1-\alpha) * Sd_{t-1}^+(v) \qquad (1)$$

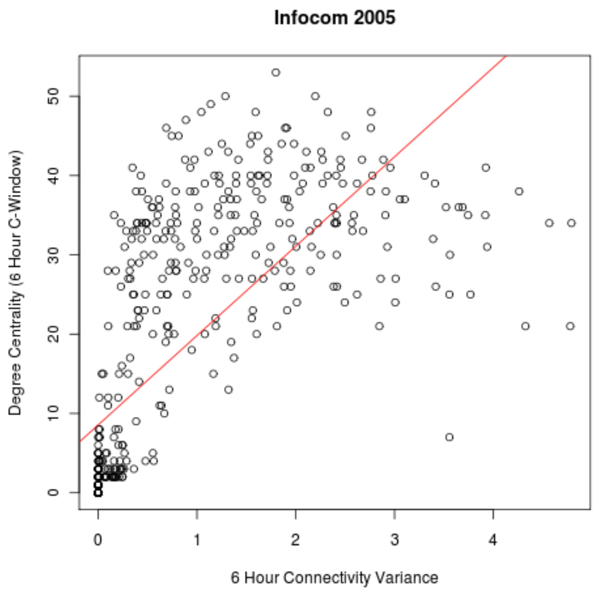

Fig. 2. Correlation between Centrality and Variance

Formula 1 shows how we calculate the EWMA smoothed out-degree (Sd^+) of node v at a given time t based on the current out-degree observation $d_t^+(v)$ and the previous smoothed out-degree value $Sd_{t-1}^+(v)$, given an influence value α between 0 and 1 which controls the extent of the smoothing. We apply Formula 1 to reduce the range of centrality, in order to increase the size of centrality subsets, resulting in a more even spread of load, as illustrated in Figure 3.

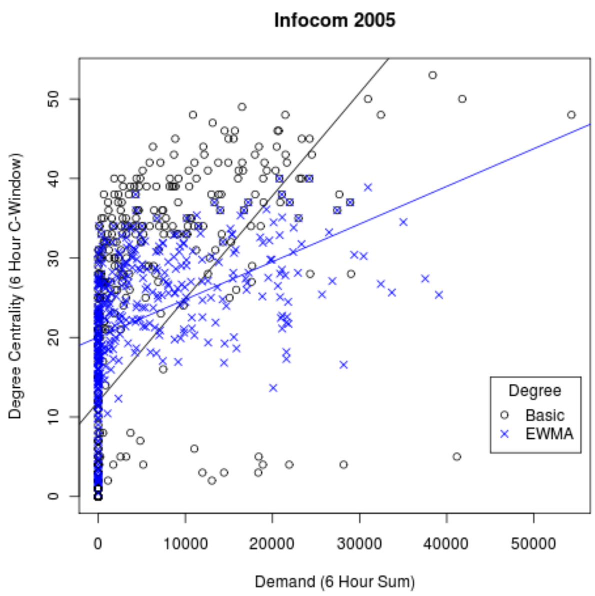

Fig. 3. Correlation between Centrality / EWMA Centrality and Demand

In addition to the use and smoothing of a centrality value, we also incorporate the C-Window technique described in

BubbleRap, as we believe this method is intuitive, grouping contact sightings into Morning, Afternoon, Evening and Night. Figure 4 shows four time-based groupings of day one from the Infocom 2005 dataset. It is easy to see that group 2 has much lower centrality values than any other grouping. The levels of connectivity are similar for each period, on each day of the trial.

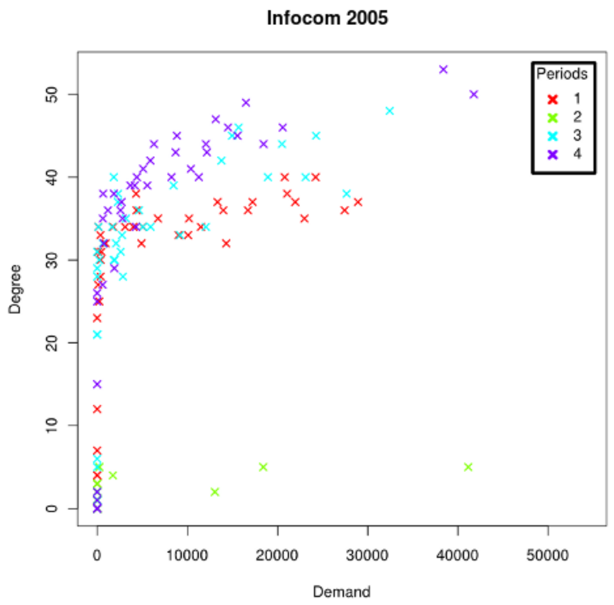

Fig. 4. Correlation between Centrality and Demand, per six hour period during the first 24 hours

B. Similarity

The common neighbour metric identified by Newman [5] and integrated in SimBetTS is a function $P(x, y)$ given in Formula 2.

$$P(x, y) = |N(x) \cap N(y)| \tag{2}$$

The resulting value of $P(x, y)$ in Formula 2 is the cardinality of the intersect of the neighbour sets of nodes x and y, identified as $N(x)$ and $N(y)$ respectively.

We improve the application of this formula on our data by filtering nodes neighbour sets $N(x)$ and $N(y)$, as the neighbour sets contain contact that vary in frequency and duration. By only including nodes that have strong values of connectivity frequency and duration, we will reduce the quantity of data exchanged between nodes x and y and optimise the application of $P(x, y)$.

In Figure 5 we show continues Bluetooth connectivity logs from two of many of the participants taking part in our project PARTICIPATE [6] that aimed to support mass scale environmental monitoring. It is easy to see that nodes friend, acquaintance and stranger distributions differ significantly. We aim to explore the effects of comparing contact cluster groups, for example, we may find it beneficial to forward to nodes that have a different set of friends but similar acquaintance group if we know that a node is not in this friendship group.

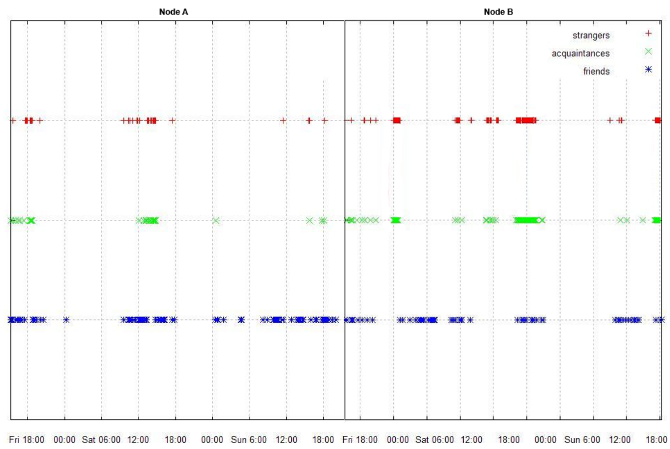

Fig. 5. Frequency of Friend, Acquaintance and Stranger contacts

C. Performance

The performance attribute of a given next hop will be based on a acknowledgement system, allowing nodes to find out which of its next hop contacts have managed to forward packets for them, and more importantly, have successfully arrived at the destination. This system allows nodes to re-transmit packets after a reasonable time has passed without acknowledgement, where a reasonable amount of time is judged by the time it takes from sending the first packet, to receiving the first acknowledgement and then adjusted based on later acknowledgements.

D. Availability

We identify and propose the addition of two node availability attributes, intended to favour nodes that are able to both receive and retain the packets sent to them.

We need both Receptiveness and Retentiveness, even if a neighbouring node has high centrality and similarity values, because if the neighbouring node is busy serving others, either currently, thus having limited bandwidth (not receptive), or previously, therefore having limited storage (not retentive) they lack the Availability to accept our traffic.

The availability information will need to be continually, locally, disseminated, in order for surrounding nodes to make informed forwarding decisions based on the current state of network resources, reducing or increasing the sending rate appropriately. This local Availability information decimation will naturally propagate, where appropriate, back along network paths allowing bottlenecks to be avoided.

1) Receptiveness: We define receptiveness as the nodes ability to receive packets and forward them on. This is calculated as the average delay between packets being received and being forwarded.

2) Retentiveness: We define retention as the nodes ability to retain the packets we send to them. Retentiveness is an important attribute to consider because of the store and forward nature of opportunistic networks. We see Retentiveness as the percentage of remaining storage.

E. Utility

In order for the our framework to be complete we need to combine our observations forming a Utility value that allows us to select a next hop. We view Centrality, Similarity and Performance as attributes that define nodes' suitability for being the next hop. We see availability as a limiting factor and therefore we scale the suitability values according to the proportion of availability.

$$Util(x, y, z) = (Sd_t^+(y) + P(x, y) + H(x, y, z)) * A_t(y) \quad (3)$$

Formula 3 shows a preliminary utility calculation. Our framework calculates a utility value for each neighbour in order to select the best available next hop. In this formula the forwarding node is x, the intermediary node is y and the destination node is z, $Sd_t^+(y)$ is the smoothed out-degree of y, $P(x, y)$ is the similarity function comparing x with y, $H(x, y, z)$ is the delivery history from x to z via y, and $A_t(y)$ is the current availability of y.

III. Related Work

The link between social network theory and mobile network connectivity has been evaluated in the Reality mining work by Eagle and Pentland [7]. Reality identified that by analysing mobile network connectivity you are able to extract social interactions - identifying friends as people who are long duration contacts; acquaintances as people who are contacts more frequently, but for shorter periods of time; and strangers as very loosely associated contacts.

Recently BubbleRap [1] and SimBetTS [2] have explored the use of Centrality as a forwarding heuristic.

BubbleRap counts the unique contacts discovered over a six hour period in order to assign a degree centrality value to the node; giving a morning, afternoon, evening and night centrality value to the node. These values are used the next day as the forwarding heuristic for the corresponding time period. BubbleRap has produced almost equal delivery success rate as 4-copy-4-hop replication, with only 45% of its cost.

SimBetTS calculates a localised (ego network) betweenness centrality value that represents the number of times a node is on the shortest path between two of its neighbouring nodes. In addition to betweenness centrality SimBetTS calculates a similarity value, based on the number of common neighbours and a Tie Strength value the represents the frequency, duration and recency of the contact.

FairRoute [3] calculates friend and acquaintance contact duration, subtracting the total acquaintance contact time from the total friend contact time to gather an aggregated interaction strength, they detail that this heuristic does not achieve a balanced traffic distribution. In order to produce a fair distribution of load the nodes queue length is evaluated, allowing nodes to only forward to nodes with a bigger queue size.

An alternate approach to opportunistic social-based forwarding is to utilise a probability based heuristic. PROPHET [8] is a common benchmark algorithm when comparing performance of probability based opportunistic forwarding.

Gentley [9] applies control theory prediction techniques to their probability based heuristic, a Social network LABEL [10] is added to nodes ensuring that messages are forwarded in similar social groups, and proactive MANET routing [11] is used for routing within islands.

IV. Conclusion and Future Work

We identify multiple metrics, Centrality, Similarity, Performance and Availability, that combined allow data to be forwarded fairly and efficiently in opportunistic networks, without causing congestion. Section II-C describes the benefits of transferring performance history knowledge and its application to improve forwarding decisions, Section II-D details how availability broadcasts can be used to propagate flow information. Section II-B suggests that by filtering out neighbours that are loosely associated to us when comparing similarity, we will improve the heuristic and reduce the amount of control data required. Section II-A and Figure 3 show that by smoothing centrality values we can distribute the load more evenly throughout the network.

Our future work will comprise of further development and evaluation of the parameters presented in this work, over additional datasets, in comparison with other state-of-the-art techniques in opportunistic data forwarding. We would also like to incorporate prediction techniques, such as Kalman Filters and Markov Chains, and compare the various localised centrality indices, such as Degree Centrality and Ego-Betweeness Centrality.

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