Poster: Social Mobility based Routing in Crowdsourced Systems

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ABSTRACT
In this paper, we formulate a generalized optimization problem to meet the profit problem for crowdsourced systems with considering three aspects of connectivity, profit and risk. We also propose a routing algorithm for this special scenario, featured by dynamic mobility and social graph. This algorithm has two parts: social graph extraction and social mobility based routing. The first part extracts each patrician's social graph to get the social knowledge. The second part gives a policy for the decider to assign the passages to the leaving nodes according to their social graph. We applied our algorithm into the realistic traces, and compare it with several existing methods. The result shows the competitive performance of this routing algorithm, both in connectivity, profit and risk.

Categories and Subject Descriptors
C.2.2 [**COMPUTER-COMMUNICATION NETWORKS**]: Network Protocols – *Routing protocols*

General Terms
Algorithms, Performance, Design.

Keywords
Crowdsourced Systems, Pocket Switched Network, Dynamic Mobility, Social Graph.

1. INTRODUCTION
"A new delivery concept uses the location of random strangers to TwedEx parcels directly to you – wherever you are", New Scientist News[2]. You can find some interesting apps in YouTube, featured by this delivery concept, which are good examples for the ultimate aim of a crowd-powered delivery system dreamed up by a group of Microsoft researchers [6]. It is possible to deliver purchases to customers on the move, as well as making it cheaper to send them with this idea [2].

Basic crowdsourced systems already exist, which hire strangers from the internet to deliver packages [4-5]. The relative research is just beginning. However, the existing research [4-6] mainly focuses the delivery and time, but neglects the profit and risk in practice. This paper tries to consider these three aspects (connectivity, profit and risk) in the crowdsourcing systems and formulate them as the profit problem. Due to the nodes in the crowdsourced systems are characterized by human, we can take the crowdsourced systems as a special case of Pocket Switched Network (PSN) and formulate the above scenario as the problem of optimizing the communication cost in PSN, a kind of delay tolerant network (DTN). However, there are still some differences comparing with the traditional PSNs. First, the package is just one. Second, there can be safety box stations in the crowd systems. Third, the profit and risk should be taken as important factors. Human mobility in PSN has appeared for several years. However, there is little works, which apply dynamic mobility features into the routing design. In [3], social communities are connected with some geographical locations. Inspired by that, our routing has two main parts. The first part is to extract the social graph from people's daily routing. The second part to decide which nodes should be carried with the packages when they leave.

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Problem Description. (The Profit Problem) Given a set of n nodes that go around their daily trajectories. Every trajectory associates a node with a location in space at each time instant. Each location is equipped with enough safety boxes. Besides, there is a set of m packages needed to deliver. The server connected with these safety boxes can send out messages to people along the possible route. A responder will be activated once a package has not arrived in its destination place before it expires. The demand cover problem can be formulated in the following ILP (Integer Linear Programming). The aim is to have the higher profit with lower cost and higher quality of service (Qos).

$$\max \quad \alpha\sum_{i=1}^{m} I_i - \beta\sum_{i=1}^{m} C_i + \gamma\sum_{i=1}^{m} Q_i$$

$$\text{s. t. } I_i = f_1(N_i^s, N_i^d; t_i^c, t_i^e) \quad (1)$$

$$C_i = hop_i * CPH_i + p_i * CPR_i \quad (2)$$

$$Q_i = -(t_i^e - t_i^c) \quad (3)$$

$$CPH_i = f_2(N_i^s, N_i^d; t_i^c, t_i^e) \quad (4)$$

$$CPR_i = f_3(N_i^s, N_i^d; t_i^c, t_i^e) \quad (5)$$

$$p_i = f_4(N_i^s, N_i^d; t_i^c, t_i^e) \quad (6)$$

$$I_i - C_i \geq \delta_{company},\ CRH_i \geq CPH_i,\ Q_i \leq \delta_Q \quad (7)$$

While α, β, γ are the importance of profit (I), cost(C) and the Qos(Q). The profit I_i for each delivery service, which should be a function of the starting node N_i^s, the destination node N_i^d, the creating time of the delivery service t_i^c and the deadline of the delivery service t_i^e. Constraint 2 models the cost for each delivery service. Each hop needs a fixed cost of human resources. Besides, to guarantee the delivery success, a responder may be activated by the probability p_i. The cost has two parts. One is the product of CPH_i (cost per hop) and the number of hops (hop_i) for the i-th delivery service. Another is the product of CPR_i (cost per responder) and the activation probability p_i. Constraint 3 models the Qos for each delivery service. Constraint 7 models the bound limit. However, in the reality, the variables of I_i, CPH_i and CRH_i are related to economics, and could be fixed after a period with statistic methods. But the other variables of hop_i and p_i are dynamic and related to the delivering strategy. The above problem can be modeled to minimize the sum of C_i. Here, the hop_i can be seen as analogous to the delivery cost and the p_i is analogous to the delivery ratio. Besides, the Qos can be taken as the delivery delay, if Qos is considered. In the following section, the routing algorithm in uncertain is discussed.

2. SOCIAL MOBILITY BASED ROUTING

In MIT Reality[1], it is almost impossible to know people's exact trajectories. Here we focus on the predicted environment. Through analyzing the history of people's trajectories, we try to establish a time-related society community model, connected with Geo-information, in order to predict people's trajectories in the next period. To decide whether to send a message when a person is near to the safety boxes, we give a relative routing algorithm. Once we have got everyone's daily mobility featured by locations, it needs to connect each location with a social network. For a specific person i, we statistic the contact number for the other j in each location. Once its percentages exceed a threshold, the j-th person is considered to be in i-th social network. Social Mobility based routing (SMBR) forwards the packet only to the passby individual whose social group contains the messages' destination. In details, every place has a basestation. When any node leaves this area, it should notify the basestation. Then the basestation decides whether let it take some messages according to its own predicted behaviors.

3. SIMULATION

We compare the performance of SMBR with several existing schemes with MIT Reality Dataset[1]. Our simulation concludes that although BSBR increases the delivery average cost compared with WAIT and so on, it has a significantly higher delivery ratio and lower latency and the social graph extracting method has a important impact in the performance of SMBR.

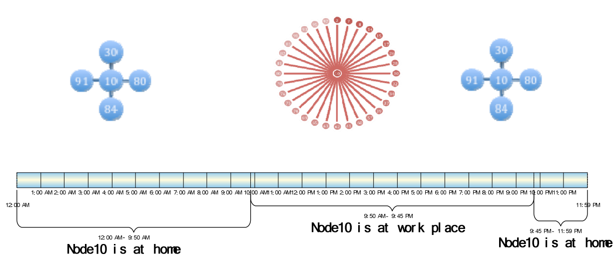

Figure 1. An example for a person's social group

Take Figure 1 as an example, the 10-th person is usually staying in two places in his daily life. The first place is his home place. And the other place is his workplace. In his home, he usually meet 4 people, shown in in social graph above the relative time axis. And in his work place, he usually sees 32 people. We could find person30 and person80 are in both the two graphs.

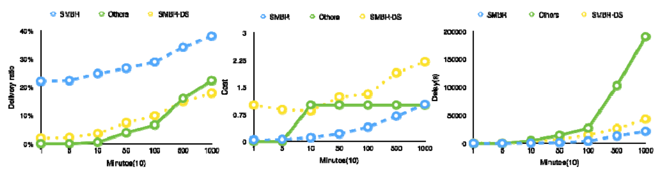

Figure 2. Comparing with Constraint Messages in MIT Reality: delivery ratio, cost and delay.

From Figure 2, the Time to Live (TTL) varies from 10 to 10,000 minutes. We can see that SMBR has the highest delivery ratio and the lowest hops and latency per message among all the schemes. SMBR-DS also has the higher delivery ratio and lower cost comparing with others. BTW, it has the lowest cost in the three types. From the view of our profit problem, SMBR has the highest profit, with lowest cost and risk. And SMBR-DS is also acceptable, comparing with others.

4. CONCLUTIONS

In this paper, we define the profit problem and proposed a social mobility based routing in PSN. Our scheme has two parts: social graph extraction and social mobility based routing. It extracts each patrician's social graph to get the social knowledge. In social mobility based routing, the sink node is the decider to assign the passages to the leaving nodes according to their social graph. Trace-driven simulation results showed that our proposed social mobility based routing performs better than the other five existing routing in some way. We believe that social graph will play an important role in routing in crowdsourced systems. Our future work will focus on different real traces to validate our observations.

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6. REFERENCES

[1] EAGLE, N. and PENTLAND, A., 2006. Reality mining: sensing complex social systems. Personal and ubiquitous computing 10, 4, 255-268.

[2] HODSON, H., 2013. Hand-delivered parcels find their way to you via the crowd. New Scientist 218, 2917, 17-18. DOI= http://dx.doi.org/10.1016/s0262-4079(13)61234-8.

[3] KARAMSHUK, D., BOLDRINI, C., CONTI, M., and PASSARELLA, A., 2011. Human Mobility Models for Opportunistic Networks. Ieee Communications Magazine 49, 12 (Dec), 157-165.

[4] MCINERNEY, J., ROGERS, A., and JENNINGS, N.R., 2013. Bus, bike and random journeys: Crowdsourcing aid distribution in Ivory Coast. Significance 10, 4, 4-9.

[5] MCINERNEY, J., ROGERS, A., and JENNINGS, N.R., 2013. Learning periodic human behaviour models from sparse data for crowdsourcing aid delivery in developing countries.

[6] SADILEK, A., KRUMM, J., and HORVITZ, E., 2013. Crowdphysics: Planned and Opportunistic Crowdsourcing for Physical Tasks. SEA 21, 10,424, 125-620.