A Study on Social Graph Analysis Using Beacon Bluetooth Radio Transmitter

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***Abstract*—Social graph analysis using Bluetooth radio transmitters called "Beacon" is discussed in this paper. Each person carries the beacon and a smart phone; the smart phone is performed for a receiver. Someone's smart phone can recognize another person's beacon and the distance between the two persons. As the result, our social graph can be generated using those data. Graph pruning is necessary, and we discuss how to determine the two threshold parameters for the distance between two persons and the received signal reception frequency. We show one guideline to determine the two threshold. A system simulation is shown in our experiments.**

***Index Terms*—Social graph; Bluetooth radio transmitter; beacon; graph centrality; pruning**

I. Introduction

Human relation is the greatest concern for our life. Human relation creates happiness, and sometimes it is the cause of serious troubles. It is always not obvious and often has complexities. It is wonderful if we can clearly show the relationship with a computer. Here, we try to visualize our relationship using scientific methods.

In our previous methods, we discuss social graph analysis using face recognition and authentication systems for preschool education [1], [2]. Our methods make a social graph which describes relations between children, moreover the children and teachers in the preschool. Preschool teachers wear eyeglasses equipped with a video camera to take video of the children, and our system performs personal identification from the video data using a face recognition and authentication engine. When some children appear in the same scene, we draw edges between each child node in the social graph, and we draw edges between the teacher node and the children nodes. In our previous method, the graph is generated from a teacher's point of view; however it is not a physical social graph; sometimes teacher's oversight occurs.

In this paper, we use Bluetooth radio transmitters called "Beacon," and our physical social graph is generated. The beacon is a small device and always broadcasts radio signals with "Beacon ID". Each person carries the beacon and a smart phone; the smart phone is performed for a receiver. Someone's smart phone can recognize another person's beacon ID and the distance between the two persons. As the result, our physical social graph can be generated using those data.

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We discuss graph pruning to generate a useful social graph for our analysis. Graph pruning is a common technique for any graph systems; we also discuss about it in our previous paper [1]. Our novelties in this paper are (1) the beacon system for our graph generation and (2) discussion how to achieve graph pruning based on our beacon system. We focus on the distance between two persons and the received beacon signal frequency; we define two thresholds on them for our pruning and show one guideline for the threshold decision. Furthermore, (3) a system simulation is shown in our experiments; it is also our original discussion.

In the next section, we explain "Beacon" and how to create our social graph. In Sec. III, we introduce to four kinds of graph centralities; these centralities are well known and common technique; we have also discussed in the previous paper. Graph pruning is necessary, and in Sec. IV we discuss how to determine the two threshold parameters for our pruning. Experiments with our laboratory members are performed, and our results are shown in Sec. V.

II. Beacon and Social Graph Generation

For our physical graph generation, each person always carries a beacon and a smart phone; the smart phone is performed for a receiver in our system; in Fig. 1, each person has a beacon in his left hand and a smart phone in his right hand. The beacon is a portable electric device for near field communication; it is coin size and sends its beacon ID. Fig. 2 shows the beacon ID described in the minor number. The figure is a captured image of application system on the smart phone for our receiver. The application system is always activated, and catch beacon signals and record them. The application can detect the received beacon power, and it compute the distance between each beacon and the smart phone.

We create a social graph using the recorded beacon ID. Picking up a beacon ID and if the distance between the two

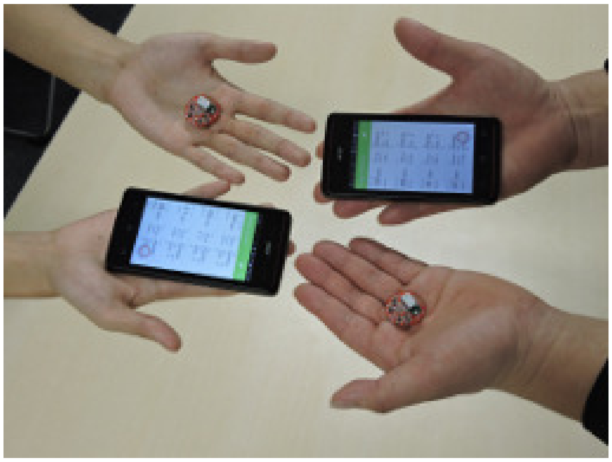

Fig. 1. Communicating using beacons and smart phone.

persons is less than the predefined threshold (the two persons are near), the node of smart phone owner and the node for a person of the beacon ID are generated, and the nodes are connected with an edge with an edge weight "1" called the received signal frequency. If the nodes and the edge have been already generated, the edge weight is only incremental. As the result, our social graph is generated as Fig. 3. After graph generation, graph pruning is performed if the edge weight which is received signal frequency is less than the predefined threshold. Our graph pruning is discussed in Sec. IV and Sec. V.

III. Graph Centrality [1]

Centralities are useful features on our graph analysis. Many kinds of centralities have been proposed [3]–[5]; we focus on the four graph centralities — degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality; we try to discuss the meaning of each graph centralities in our human relation. We can find leaders and some isolated person in our groups. The centralities are computed as follows.

Degree centrality: the number of edges on a focused node [6], [7]. For our application, the degree centrality means the number of friends whom a focused subject have. When the degree centrality is high, the focused subjects have many friends, and we can estimate that the focused the subject is an important leader in the group.

Closeness centrality: we compute the distance between each node and a focused node in the graph. The distance of two nodes is defined by the number of edge on the shortest path between the two nodes. The average of distance is the closeness centrality of the focused node [8], [9]. For our application, subjects with a high closeness centrality are the most familiar person for all members.

Betweenness centrality: when we pick up two nodes except for a focused node, we compute the shortest path between two nodes. We count the case that the shortest path passes through the focused node, and the ratio of the case is the betweenness centrality of the focused node [10], [11]. For our application,

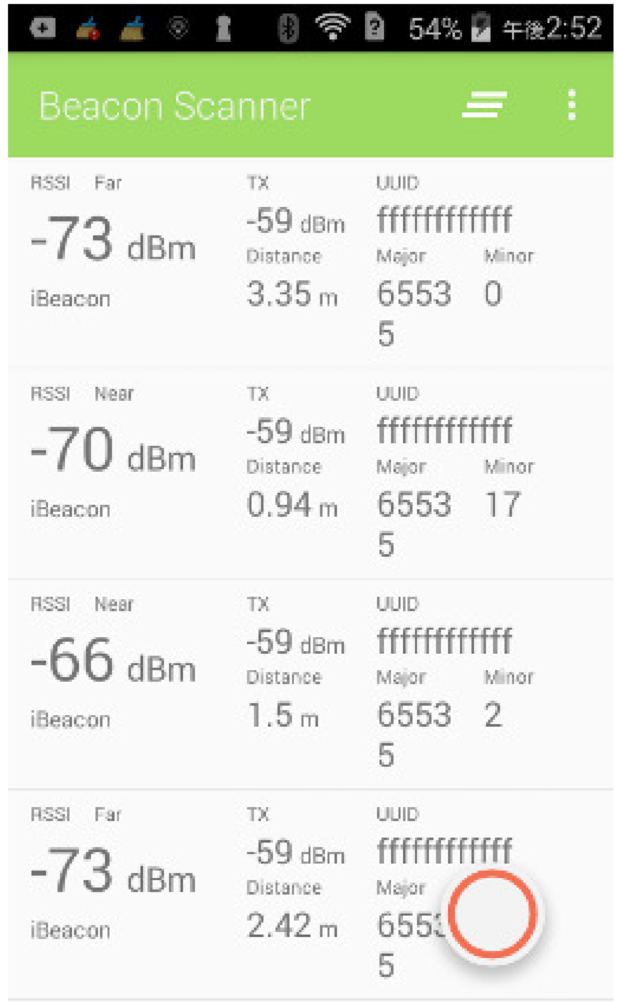

Fig. 2. The beacon reciever in our system.

subjects with high betweenness centrality is required in the members, and he or she is the foundation stone of human resource that connects the members.

Eigenvector centrality: In the case of a focused node connected to another high degree centrality node, the focused node's eigenvector centrality is high [12]–[14]. For our application, a person with high eigenvector centrality is connected to the person who has many friends.

IV. Graph Pruning

Each beacon sends a beacon ID signal for once every few seconds. Many persons take each person's beacon signals for a long time, then our social graph becomes a "complete graph," so that it becomes impossible to analyze the human relation. In Fig. 4, it is not a complete graph; however it is too complicated to analyze. Then, we have to perform graph pruning for our analysis.

In our system, the beacon receiver detects the distance between the two persons. The distance is larger than the predefined threshold called "the threshold of distance" (two persons are far). The edge weight increment is ignored. Since

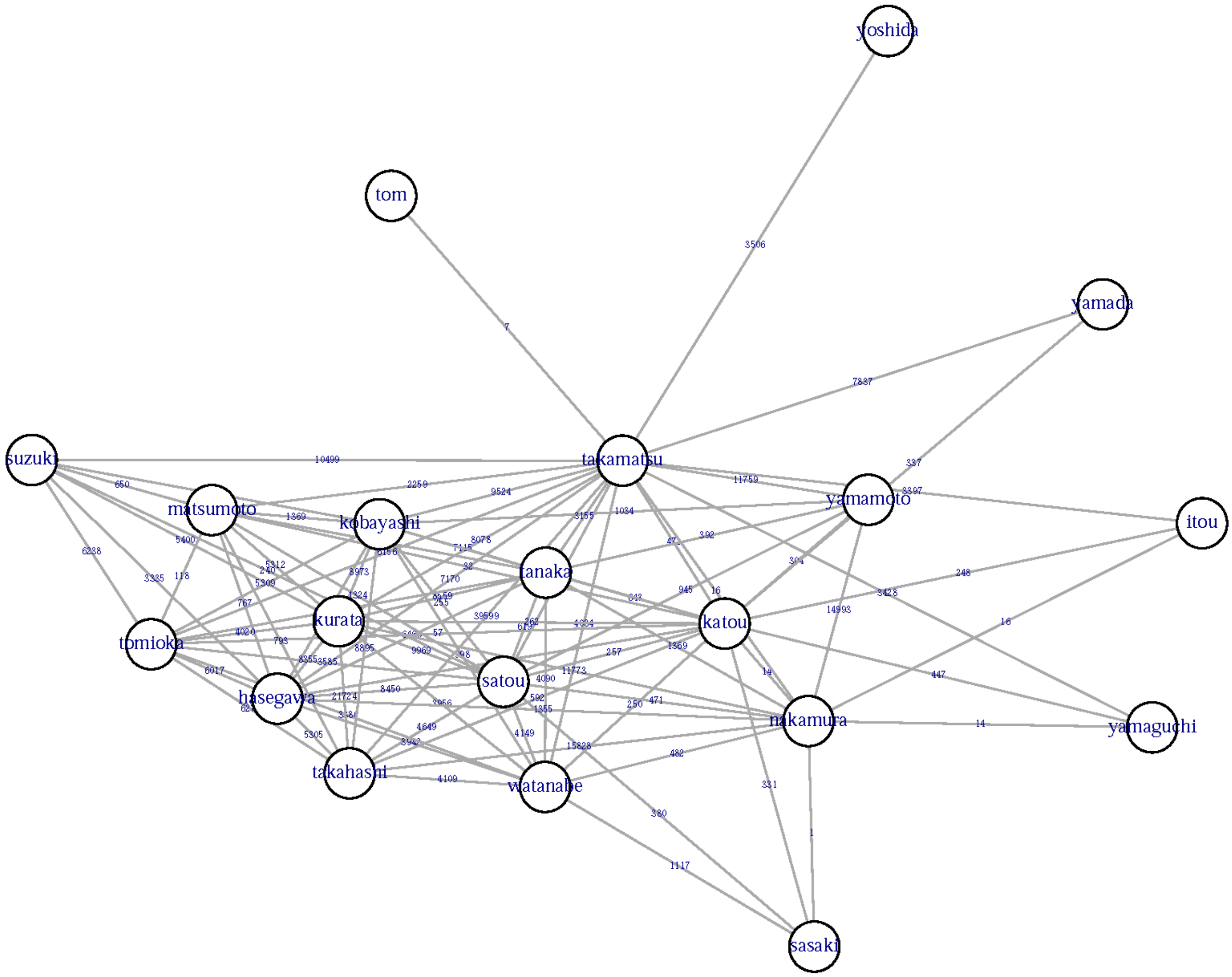

Fig. 3. A social graph with no pruning.

the threshold becomes small, our consideration is restricted on only the near relation.

Moreover, the graph pruning is achieved using the predefined threshold on the edge weight called "the threshold of signal frequency" While an edge weight is less than the threshold of signal frequency, its edge is removed from the social graph.

Focusing on the two thresholds, the graph pruning is achieved based on our beacon system. After determining the number of edges on a suitable graph for our analysis, we adjust the two thresholds and perform our pruning. Therefore, we have a technical issue how to determine the two thresholds. We will discuss in the next section.

V. Experimental results

Experiments with our laboratory members (20 persons) are performed in this paper. They always have beacons and Android smart phones for 7 days and record their log data. We use an iBeacon product "BVMCN1001CRH" provided by "Braveridge Co., Ltd.;" it is based on Bluetooth low energy protocol; its frequency range: 2402 MHz to 2480 MHz; transmit power (terminal output): -20 dBm to 4 dBm; its advertising interval is 100mS. We use an Android application called "iBeacon & Eddystone Scanner" provided by "Flurp laboratories" it detects beacon ID; the log data are recorded to csv files. Our social graph generation engine is developed using the programming language "R" and a graphic tool called "igraph."

A result of our social graph is shown in Fig. 3. Each name on the nodes is a pseudonym, and the received signal frequency is described on each edge. This social graph is too complicated to analyze using this figure.

Our graph pruning is performed; we adjust the two thresholds and create many social graph. The results are shown in Table I. Decreasing the threshold of distance decreases the number of edges. In the case that the threshold of signal frequency increases, the number of edges decreases. The two

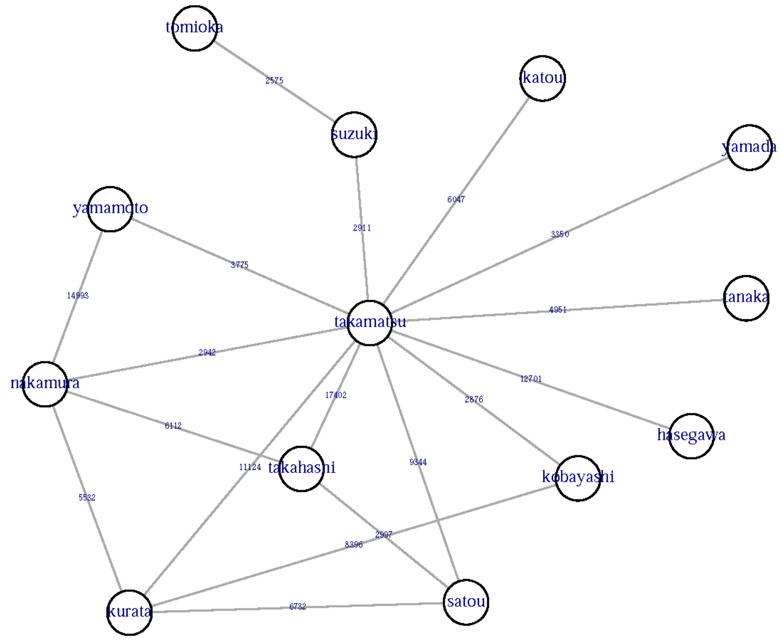

Fig. 4. A social graph with our pruning; the threshold of distance is 2 [m] and the threshold of signal frequency is 2,500.

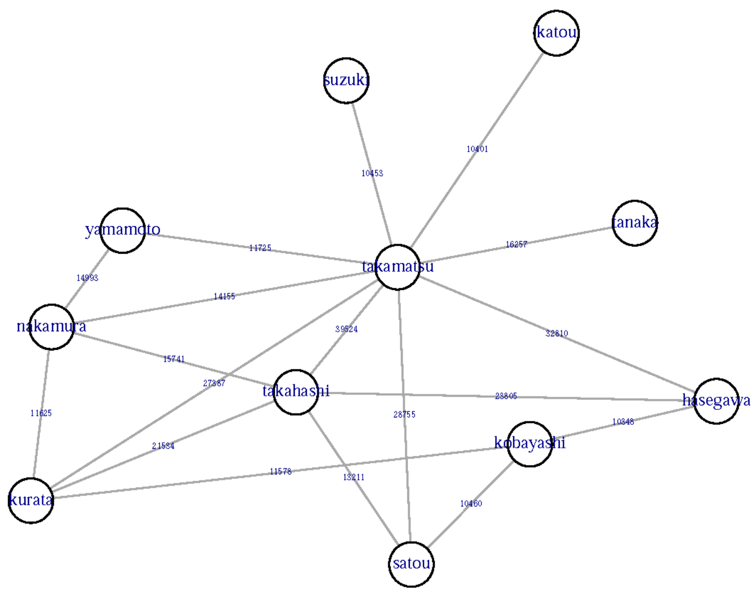

Fig. 5. A social graph with our pruning; the threshold of distance is 7 [m] and the threshold of signal frequency is 10,000.

cases with 18 edges are compared and shown in Fig. 4 and 5. Fig. 4 is a case with the threshold of distance is 2[m], the threshold of signal frequency is 2,500; Fig. 5 is a case with the threshold of distance is 7[m], the threshold of signal frequency is 10,000.

Furthermore, we compute network density on the two graphs and these are shown in Table II. The network density is defined as:

$$D = \frac{2|E|}{|V|((|V-1|)^2} \tag{1}$$

where $|E|$ is the number of edges and$|V|$is the number of nodes in the graph. As the network density is higher, the social graph is close to a complete graph, and it has not been a characteristic structure. As the results, Fig. 4 with a relatively lower network density has more characteristic structure, and it is better than Fig. 5. Even if we observe them visually, Fig. 4 is more structural.

Here, we can show one guideline for our graph pruning. After determining the number of edges in the graph (it is suitable for our analysis), we adjust the two thresholds and perform our pruning. As shown in Table I, we may find the determined number on the upper left or lower right, so that

TABLE I
NUMBER OF EDGES FOR VARIOS RESTRICTION ON OUR PRUNING

The threshold of distance [m]/ The threshold of signal frequency	2	3	4	5	6	7	8	9	10
500	45	53	59	61	63	63	64	64	65
1,000	39	48	51	54	56	57	58	58	58
1,500	33	46	50	50	51	51	51	51	51
2,000	23	42	49	49	49	51	51	51	51
2,500	18	36	43	47	49	50	50	50	50
3,000	13	30	39	45	47	49	50	50	50
3,500	12	25	36	41	44	45	45	46	46
4,000	11	20	30	34	40	41	42	42	42
4,500	11	20	27	31	34	36	37	37	37
5,000	10	19	26	30	31	34	36	36	37
10,000	4	7	11	13	16	18	19	19	19

TABLE II
NETWORK DENSITY OF SOCIAL GRAPH

Social graph	Network density
The threshold of distance 2[m] and the threshold of signal frequency 2,500 (Fig. 4)	0.198
The threshold of distance 7[m] and the threshold of signal frequency 10,000 (Fig. 5)	0.273

we have two choices for our tuning. However, we should take the upper left one (taking lower threshold of distance and the threshold of signal frequency should be less value), since the graph becomes structurally and suitable for our analysis.

The network centralities — degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality — of Fig. 4 are computed as Table III, and top three persons are described in Table IV. Persons with high degree centrality show that they have close relations with many persons on the social graph. “Takamatsu” is the highest person of all and the next top two and three are the same rate “Kurata and Nakamura.” They are presumed to be leaders of the group. Persons with the high closeness centralities mean that they have many friends and are familiar with all members. “Takamatsu” is also the highest person of all and the the subsequent top two and three are also the same rate “Kurata and Nakamura.” They are presumed to be another kind of leaders of the group. Persons with the high betweenness centrality connect each person of the group. “Takamatsu” is the top person, and “Suzuki” is the second one, and the resulting “Kurata and Nakamura” are the same rate. Especially, we want to pay attention to that “Suzuki” is an important entity that keeps the group together. Persons with the high eigenvector centrality connect to the person who has many friends. “Takamatsu” is the highest person of all and the next top two and three are the same rate “Kurata and Nakamura.” They are presumed to be leaders of the group.

Taken together all the results, “Takamatsu” has all kinds of high centrality, and it indicates that ”Takamatsu” is the central person of this subject group; and we can say he is a leader in the group.

VI. Conclusion

We have discussed social graph analysis using Bluetooth radio transmitters beacon. Each person carries the beacon and a smart phone for a receiver. An application system in the smart phone can recognize each person’s beacon and compute the distance between the two persons. We can create practical social graph using our beacon system.

To generate a useful social graph for our analysis, graph pruning is necessary for our system. We have shown a guideline for our graph pruning.

In this paper, we focus on the four centralities — degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality in the social graph. In our experiments, we show how to find the leader of the group.

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TABLE III
GRAPH CENTRALITY. FOR THE PROTECTION OF PERSONAL INFORMATION, THESE NAME IS PSEUDONYM.

Name	Degree centrality	Closeness centrality	Betweenness centrality	Eigenvector centrality
Tomioka	1	0.030	0.000	0.061
Suzuki	2	0.045	11.000	0.254
Yamada	1	0.042	0.000	0.239
Katou	1	0.042	0.000	0.239
Tanaka	1	0.042	0.000	0.239
Hasegawa	1	0.042	0.000	0.239
Satou	3	0.045	0.333	0.502
Kobayashi	2	0.043	0.000	0.382
Takahashi	3	0.045	0.333	0.502
Kurata	4	0.048	1.333	0.594
Nakamura	4	0.048	1.333	0.594
Watanabe	2	0.043	0.000	0.382
Takamatsu	11	0.076	55.666	1.000

TABLE IV
GRAPH CENTRALITY. FOR THE PROTECTION OF PERSONAL INFORMATION, THESE NAME IS PSEUDONYM.

Rank	Degree centrality	Closeness centrality	Betweenness centrality	Eigenvector centrality
1	Takamatsu	Takamatsu	Takamatsu	Takamatsu
2	Kurata/Nakamura	Kurata/Nakamura	Suzuki	Kurata/Nakamura
3			Kurata/Nakamura	

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