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SELECTION OF FRIENDS IN SOCIAL INTERNET OF THINGS BASED ON HEURISTICS

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ABSTRACT

Internet of Things (IoT) has objects that can automatically communicate with each other to achieve a common goal. Different types of sensors and actuators can be embedded within existing objects to make it smart. When social networking concepts are integrated into Internet of Things, then it is called social internet of things. The structure of Social Internet of Things can be shaped as required to guarantee network navigability. A set of objects which directly communicate with a device are called its friends. Service selection is a search which is carried out in Internet of Things using only the local information. Thus the search is carried out in a distributed manner. As the number of devices increases in Internet, the number of friendships a device can have is also increases. This leads to requirements for high computation and more memory for storing the information about friends which is needed for link selection during searching for a service. The proposed work aims at limiting the number of friendship a device can have without compromising the network navigability so that all devices can directly or indirectly communicate with all other devices in the network. This makes the service search more efficient. Memory needed is also limited to cope up with small devices having low configuration.

Key words: clustering coefficient, average degree, average path length, giant component

I. INTRODUCTION

Internet of Things represents a general concept for the ability of network devices to sense and collect data from the world around us, and then share that data across the Internet where it can be processed and utilized for various interesting purposes.

Some also use the term industrial Internet interchangeably with IoT. This refers primarily to commercial applications of IoT technology in the world of manufacturing. The Internet of Things is not limited to industrial applications, however.

II.RELATED WORK

IoT is the emerging technology with many research challenges in terms of link selection, security, searching, identification etc. Many people addressed different research challenges and proposed appropriate techniques for the research problems. Some of the notable works on service selection are as follows

Simon Mayer (2012) stated a web based searching to facilitate the integration, look up and interaction with smart devices for human users and machines. As the work focuses on location of the smart object as its main property, it is structured hierarchically according to logical place identifiers.

It also features some advanced caching mechanism that plays a vital role in decreasing the response time and the number of exchanged messages. These properties are demonstrated and evaluated in a simulated environment where web objects connected with the internet are visualized.

CharithPerera (2013) has addressed the issue of context aware sensor search. This work addressed a context-aware sensor search, selection, and ranking model (CASSARAM) for IoT. The research challenges of selecting sensors among large numbers of sensors with overlapping and sometimes redundant functionality are available. CASSARAM proposes the search and selection of sensors based on user priorities. CASSARAM considers a broad range of characteristics of sensors for search such as reliability, accuracy, battery life just to name a few. This approach utilizes both semantic querying and quantitative reasoning techniques. User priority based weighted Euclidean distance comparison in multidimensional space technique is used to index and rank sensors. The objectives are to highlight the importance of sensor search in IoT paradigm, identify important characteristics of both sensors and data acquisition processes which help to select sensors, understand how semantic and statistical reasoning can be combined together to address this problem in an efficient and effective manner. The performance enhancement is also discussed.

Atzori (2014) proposed techniques in IoT using social networking concepts. The techniques enhance the level of trust between objects that are friends with each other. This paper also analyze the major opportunities arising from the interaction of social networking concepts with the IoT, present the major ongoing research activities and point out the most critical technical challenges in the existing IoT environments. The objects are enhanced with social networking concepts thus making the smart objects in the IoT into social objects.

Michele Nitti (2014) proposed the complete technical concept of SIoT wherein the social networking concepts are integrated into IoT. The basic idea is to search for service in a distributed manner through its friends on considering only the local network properties. As the scalability of the devices increase, there arises an issue of managing large number of friends, this ultimately slows down the searching process. This paper intends to increase the overall network navigability by adopting various strategies to select efficient neighbors.

Michele Nitti (2015) takes the same problem of overpopulation of smart objects and analyzed the strategies which he had already proposed to effectively amplify the overall network navigability in the social IoT. This paper analyzed the strategies based on four parameters namely giant component, average degree, local clustering co-efficient and average path length. Various performance outcomes are analyzed and it is discovered that on decreasing the local clustering co-efficient, the average path length is decreased. When the average path length decreases the reachability of a node in the network with other nodes is obviously increased proportionally. The reason for the achievement of result is found to be based on the number of hubs that exist in the network.

From the literature, the main disadvantages observed are scalability and difficulty in searching for services. More efficient link selection protocols are to be incorporated for increasing efficiency in searching.

III.PROPOSED WORK

PROBLEM STATEMENT

IoT is the network of smart objects that automatically sense the environment and are connected through various communication protocols. In brief, things that talks with each other and exchange services to achieve a common goal. As every device becomes smart, it communicates automatically with other devices hence the number of devices connected with each other increases. This makes scalability as an issue in IoT.

In searching of devices for services, the IoT follows a distributed search technique. Due to scalability, the smart objects connected with a device increases exponentially and hence the storing of neighbor information also becomes a big issue. The device could be anything ranging from a single small sensor to a high end server system. This makes an environment heterogeneous not only in terms of communication protocols and device type but also in terms of memory and computing power.

This work addresses the problem of scalability and service search by restricting the number of friends as well as increasing the network navigability by adopting various techniques for selection of neighbors. The new techniques can be formulated using social networking concepts such as friendship suggestions

SYSTEM ELUCIDATION

In the recent past years, the problem of network navigability has been widely studied (Atzori Luigi, et. al,2015) had proposed this system to improve network navigability. A network is navigable if it "contains short paths among all pairs of nodes". Several independent works formally describe the condition for navigability: all, or the most of, the nodes must be connected, i.e. a giant component must exist in the network, and the effective diameter must be low. In other words, the greatest distance between any pairs of nodes should not exceed log2 (N), where N is the number of nodes in the network. When each node has full knowledge of the global network connectivity, finding short communication paths is merely a matter of distributed computation. However, this solution is not practical since there should be a centralized entity, which would have to handle the requests from all the objects, or the nodes they have to communicate and exchange information among each other; either way a huge amount of traffic would be generated.

There are structural clues that can help people to find a short path efficiently even without a global knowledge of a network. This means that there are properties in social networks that make decentralized search possible. Let us supposed to have a network as represented in Figure 3.1, where node 1 wants to get access to the information owned by node 10 (node ssss1 doesn't know where the information is located); obviously the optimum path leads through nodes 5 and 7. However, node 1

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has three possible paths to choose from and only knows little information about its neighbors: the property that will guide node 1 to select node 5 as a next hop is that node 5 has a high degree of centrality, i.e. it has many connections. As such, node 5 represents then a network hub, i.e. a node that is connected to many other nodes.

The ability for a node to quickly reach a network hub is assured by the existence of network clusters where nodes are highly interlinked: this characteristic is assured with high value of the local clustering coefficient (Watts and strogatz, 1998), and is calculated for each node in a network. It measures how close the neighbors of a node are to being a clique, i.e. a complete graph, and it is calculated using the Equation 3.1 and Equation 3.2. For undirected network,

$$C_n = 2e_n/(k_n(k_n-1)) \qquad (3.1)$$

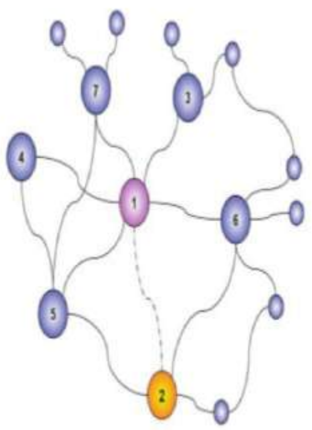

Figure 3.1 Decentralized Search

For directed network,

$$C_n = e_n/(k_n(k_n-1)) \qquad (3.2)$$

where k_n is the number of neighbors of n and e_n is the number of connected pairs between all neighbors of n. Still, node 5 needs some additional hints in order to choose node 7 over node 6, since both of them have the same degree. This characteristic is the node similarity, an external property to the network, derived from some additional information about the nodes.

In the SIoT, node similarity will depend on the particular service requested and on the types of relationships involved. The problem of global network navigability is then shifted to the problem of local network navigability, where neighboring nodes engage in negotiation to create, keep or discard their relations in order to create network hubs and clusters.

Heuristics:

IoT consists of objects that can create several types of relationships through the mimic of their owner's behavior. Other types of friendships could be added in the future, leaving to the node the hard work to cope with a huge number of connections. To make the service search process more efficient and scalable, nine heuristics are proposed to help the nodes in the process of selection of the best set of friends.

At first, a node accepts all the friendship requests until it reaches the maximum number of connections allowed is N_{Max}. This parameter is intended to limit the computational capabilities a node needs to resolve a service search request. Then, a node applies one of the following strategies, to manage any further request:

I. A node refuses any new request of friendships so that the connections are static.

II. A node accepts new friendships and discards the old ones in order to maximize the number of nodes it can reach through its friends, i.e. to maximize the average degree of its friends; the node sorts its friends by their degree and the node with the lowest value is discarded.

III. A node accepts new friendships and discards the old ones in order to minimize the number of nodes it can reach through its friends, i.e. to minimize the average degree of its friends; the node sorts its friends by their degree and the node with the highest value is discarded

IV. A node accepts new friendships and discards the old ones in order to maximize its own local cluster coefficient; the node sorts its friends by the number of their common friends and the node with the lowest value is discarded.

V. A node accepts new friendships and discards the old ones in order to minimize its own local cluster coefficient; the node sorts its friends by the number of their common friends and the node with the highest value is discarded

VI. A node removes node with minimum mutual friend and if the removed friend becomes lone, then it suggests one of its friends or friends of friends. This strategy reduces number of unreachable nodes in the network.

VII. A node removes the oldest friend in the list on receiving a new request after N_{Max} number of connections.

VIII. A node removes the oldest friend in the list on receiving a new request after N_{Max} number of connections and suggests friends or friends of friends, if the removed node is detached from the network

IX. Priority is generated for all nodes in the friend list and the node with least priority is removed on new request after N_{Max} connections

IV RESULTS AND DISCUSSION

All the nine strategies are applied to the network shown in Fig 3.1 and the statistics are taken after implementing each strategy with established network structure. The final results are analyzed in terms of average degree, average clustering coefficient, giant component and average path length.

AVERAGE DEGREE

The number of friends of a node is denoted as its degree. The average degree is computed to find the relationships since the average degree and the numbers of relationship are directly proportional. The average Degree for the example graph is 2.571. After implementing strategies average degree for all the strategies shown in the below table.

The average degree for all the strategies is analyzed and found that strategies 1, 2 and 9 have high average degree thus having many links. Other strategies have comparatively low average degrees

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and hence will have less number of connections. The strategies with high average degree are desirable as they have ability to communicate with many devices

Average degree

STRATEGIES	AVERAGE DEGREE
Strategy-1	2.57
Strategy-2	2.33
Strategy-3	1.33
Strategy-4	1.97
Strategy-5	1.33
Strategy-6	1.33
Strategy-7	1.97
Strategy-8	1.97
Strategy-9	2.33

AVERAGE CLUSTERING COEFFICIENT

It refers to the closeness of the nodes to form a complete graph. Clustering coefficient is calculated for each node and it ranges from 0 to 1. Average local clustering is the mean value of individual coefficients and is calculated based on main-memory triangle computations for very large graphs.

- Average Clustering Coefficient for example graph: 0.422
- The Average Clustering Coefficient is the mean value of individual coefficients.

After implementing strategies Average Clustering Coefficient for all the strategies shown in the below table

Average Clustering Coefficient

STRATEGIES	AVERAGE LOCAL CLUSTERING
Strategy-1	0.422
Strategy-2	0.21
Strategy-3	0.21
Strategy-4	0.44
Strategy-5	0.1
Strategy-6	0.1
Strategy-7	0.44
Strategy-8	0.44
Strategy-9	0.21

The average local clustering is larger for strategies 4, 7 and 8 as they are designed to achieve high average local clustering and it reduces for strategies 2, 3, 1, 6 and 5. By selecting the strategies 4,7 and 8, there is an increase in the reachability of nodes.

GIANT COMPONENT

The giant component is the node which is connected to most other nodes in the network. They act as the hub which connects the sub networks. The larger the giant component is the higher is the network navigability.

AVERAGE PATH LENGTH

The shortest distance between any two nodes in the network is averaged as average path length. It should be kept as low as possible so that the fast reachability of a node from another node increases. The analysis shows that all the strategies achieve almost same average path length. Average Path length for example graph is 1.61. After implementing strategies Average Path length for all the strategies shown in the below table

Average path length

STRATEGIES	AVERAGE PATH LENGTH
Strategy-1	1.61
Strategy-2	1.63
Strategy-3	1.63
Strategy-4	1.46
Strategy-5	1.81
Strategy-6	1.81
Strategy-7	1.46
Strategy-8	1.46
Strategy-9	1.41

The average path length should be kept as low as possible so that the fast reachability of a node from another node increases. The analysis shows that all the strategies achieve almost nearest average path length.

V CONCLUSION AND FUTURE WORK

CONCLUSION

This work has addressed the challenges imposed on service selection in the IoT network. It has extended the methodologies of incorporating the social networking concepts in IoT by introducing more heuristics to select efficient friends that makes the total network more navigable which in turn makes the service discovery more efficient. Heuristics or strategies are proposed for friendship selection which impacts the overall network parameters such as average degree, giant component, average local clustering coefficient and average path length. The proposed strategies are found to have a better network navigability. Heuristics are also proposed to meet the real world IoT.

FUTURE WORK

Enhancements of this work can be carried out by suggesting a strategy which is efficient to make the network more navigable. In past strategies, the external properties such as profile of the friends involved, its trustworthiness and the type of relationship that link to its requester node are not considered. Hence the future work will consider these aspects to propose more effective strategies.

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