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Article

Automated Service Search Model for the Social Internet of Things

Farhan Amin and Seong Oun Hwang*

Department of Computer Engineering, Gachon University, Seongnam, 13120, Korea
*Corresponding Author: Seong Oun Hwang. Email: sohwang@gachon.ac.kr
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Abstract: The social internet of things (SIoT) is one of the emerging paradigms that was proposed to solve the problems of network service discovery, navigability, and service composition. The SIoT aims to socialize the IoT devices and shape the interconnection between them into social interaction just like human beings. In IoT, an object can offer multiple services and different objects can offer the same services with different parameters and interest factors. The proliferation of offered services led to difficulties during service customization and service filtering. This problem is known as service explosion. The selection of suitable service that fits the requirements of applications and objects is a challenging task. To address these issues, we propose an efficient automated query-based service search model based on the local network navigability concept for the SIoT. In the proposed model, objects can use information from their friends or friends of their friends while searching for the desired services, rather than exploring a global network. We employ a centrality metric that computes the degree of importance for each object in the social IoT that helps in selecting neighboring objects with high centrality scores. The distributed nature of our navigation model results in high scalability and short navigation times. We verified the efficacy of our model on a real-world SIoT-related dataset. The experimental results confirm the validity of our model in terms of scalability, navigability, and the desired objects that provide services are determined quickly via the shortest path, which in return improves the service search process in the SIoT.

Keywords: Social internet of things; service discovery; local navigability; object discovery; query generation model

1 Introduction

The internet of things or IoT is a network of disparate objects that provide data transferability without human-to-human interaction or human-to-computer interaction [1]. The IoT has become a reality, with the exponential growth of connected devices. According to one survey, the number of objects in IoT networks by 2025, is expected to increase to 25 billion (Devices connected to the internet) [2]. This increases data sizes because a massive amount of data flows through IoT. IoT poses a new challenge for data management. Besides that, objects that provide the services, size of the search space are crucial challenges. Network traffic became heavy due to the number of access devices and the number of queries received by search engines [3]. Currently, the human–object interaction model is based primarily on users. The information is provided to people by objects, but in the future, this will shift to the object-object interaction model. One object asks the neighbors to provide the requested services. The scalability issue arises from the search for the right object with the right service, or for the best path to the right objects in the network. In this scenario, several service search methods have been proposed [4,5]. The common property between these two studies is that the search engines are mainly based on centralized systems or global network navigability. Therefore, they are not scalable in terms of processing multiple queries, especially when a large number of devices are connected in the network [6]. Generally, IoT devices will consume more energy from sensing data, for communications, in making computations, and when providing the required services.

Searching for objects, data, and services in the IoT is a crucial challenge, especially in real-time environments [7]. Several approaches for real-time search have been proposed in the literature, but none of them is offering a complete and satisfactory solution yet. The existing systems are inefficient because they are based on global network navigability [8]. Thus, the limited network navigability, and the selection and searching of suitable services will be a major challenge [8]. In general, service search and service composition both depend on network navigability, which is considered a major issue especially when the network is very large and has billions of connected devices [9]. The social relationships among devices will efficiently enhance the services and resource discovery. A recent development is the introduction of the social internet of things (SIoT) [7]. It refers to the convergence of IoT and social networking paradigms to create a network in which objects can establish social links, and can perform desired actions [10–12]. In SIoT, the objects can interact with each other and behave socially. They can request and provide the services in the network [13,14]. The induction of a social structure in the SIoT was inspired by Fisk's theory, which presented the social relationships among humans [15,16]. This model is very flexible, and therefore, it can be mapped to the object relationships for sharing resources and communications between objects. In addition, This model could help obtain highly mutual benefits from collaboration among devices [17]. As proven in [18,19], some properties of the SIoT ensure it is possible to find the short paths without global information of a network.

The primary motivation of this study is to build a new service search model to overcome the service search and discovery issue in the IoT. To the best of our knowledge, the literature still lacks research on service discovery and query processing. This social-oriented approach is expected to boost the discovery, selection, and composition of services and information provided by distributed objects and networks that have access to the physical world. The novelty of this algorithm is that the next hop to query is chosen based on property, i.e. object friendships and centrality metric.

1.1 Research Contribution

The main contributions of this study are as follows: The current state-of-the-art models [20–22] are based on global network navigability and lack the existence of short paths in the network and therefore, require large time for the service search. To address this issue, we propose an efficient service discovery model, since the proposed model is solely based on local network navigability, such as degree centrality and the neighborhood of objects that facilitate next-hop object discovery. Therefore, the object assists in determining short paths in the network for the requested object, and thereby, the required services can be accessed quickly. The distributed nature of our navigation model can discover the desired services in a fast and scalable manner. Therefore, our proposed model is highly navigable and requires less service execution time. This study is helpful for researchers who want to understand interactions among devices in a distributed manner, as well as neighborhood/hop discovery, low-cost routing, the design of search engines, and service search mechanisms.

The rest of the paper is organized as follows. In Section 2, we describe the background and previous work related to this study. In Section 3, we discuss the proposed query-based service search model. In Section 4, we discuss the experimentation results. Finally, Section 5 concludes the paper with suggestions for future work.

2 Background

The service search is the key challenge for the growth of IoT networks [23]. The objective of the SIoT paradigm is to mingle IoT devices and break the burden of network navigability. However, the number of connected devices and the exchange of services between these devices becomes a major challenge in heterogeneous environments for both users and devices. Generally, in a social network, an object that helps the requested services the user to find the required services quickly. However, we figured out that limited work has been reported in this direction, such as Nitti et al. in [7], which discussed the object discovery model in an IoT environment. Each object can autonomously establish social relationships with other objects according to rules set by the owner [7]. The authors proposed a decentralized algorithm for the discovery of objects that can provide specific application services for the social IoT. In particular, the choice of the next-hop object is determined based on two basic properties. The first is degree centrality, and the second is object similarity. Degree centrality is defined as; the number of links incident upon a node (i.e. the number of ties a node has). On the other hand, object similarity is an external property to the SIoT and it is expressed as how much the object is similar to the query requirements [7,24]. Similarly, Rehman et al. [25] addressed the problem of object service or the best path to the nodes in a network. To solve this problem, the authors discussed a query-based search mechanism for the SIoT—the concept of smart social agents (SSAs). The SSA is used to minimize human intervention in the network. Moreover, they used the concept of a small-word network in their proposed model. It is a two-step query-based search mechanism. First, the service request is initiated by using a service requester to the neighbors. In the second step, the search is performed by looking at services within the first hop neighbors. If the desired service is not available, the search operation is repeated in the next hop, and so on. When the required service is discovered, a link is established between those objects. The performance of the proposed algorithm was measured in terms of average degree, clustering coefficient, and average path length. The drawback of the study is that they did not consider the time and space aspects for the processing of a query. Mei et al. [26] utilized the features of a query-generation model based on a Poisson distribution. Their model can calculate the frequency of each independent term via the Poisson distribution. To rate a complete document, the authors first evaluate it using a multivariate Poisson model based on the document. Later, they assign a score based on the probability of the query being answered, as given by the estimated Poisson model. Ramachandran et al. [27] presented a problem-search sensor that uses a clustering technique because the human queries cannot be processed by a sensor. To overcome this issue, sensor devices are grouped into clusters, which reduces the search space. According to this model, the user first enters the query using complex and abstract natural English. These words are stored in a table, and a priority is assigned. The specific sensor search is performed by comparing the bits in the transformed query with the device that identifies it, which is assigned later. The formation of clusters helps reduce the search space. To improve search efficiency, Xia et al. [28] discussed a decentralized semantic-aware social service discovery mechanism for the social IoT. They have used fuzzy logic to calculate the correlation degree for device ranking. This is a straightforward strategy used to select a subset of neighboring devices in a preferred order. Service discovery is performed in a fast and scalable manner. The limitation of this study is it did not focus on privacy and security issues. Fu et al. [29] proposed the concept of a search engine for the IoT, the emphasis being on the idea that a search engine works as a medium between the IoT and the social network. The importance of search engines is that people can easily find smart devices in the SIoT. The proposed model consists of three entities: the search engine, the user, and objects. The efficiency of the proposed model was measured by using performance metrics including degree distribution and network density. Khanfor et al. [30]designed a concept for automated service discovery in social IoT systems. The objective of the model is to allow mobile crowdsourcing task requests for the IoT, to select a small set of devices from a large-scale IoT network, and to execute their tasks. To achieve this, they first apply two community detection algorithms [31] and it returns results in formations of different communities. Later, a natural language processing (NLP) approach is executed to handle the crowdsourcing textual request. A list of IoT devices has been effectively accomplishing the tasks. The proposed model extracts valuable information from the textual requests, such as the type of service information and its location. This approach is helpful in automation and also in reducing the time, it takes for service discovery [32,33].

3 Proposed Model

Herein, we present the problem definition and the reference scenario along with its explanation.

3.1 Problem Definition

Searching for the objects that provide services in a social network is like searching for a specific person who has a specific service [28]. For example, in normal life, one person recalls from memory a time when he was looking for a specific service. To do that, he looked to his circle of friends to find the right person who provides that service [28]. Then he contacted that person. But in many situations, friends cannot provide a recommendation for that service, but they may share valuable information about who potentially provides the service the initiator is seeking [34]. Finding short paths between pairs of nodes is accomplished if each object has complete knowledge of the network topology. This solution is possible and feasible when the network operates in a centralized manner. But it is not possible when there is a large number of devices in the IoT, as we know from the earlier discussion [28]. As specified by Kleinberg, a network is navigable if it "contains short paths among all (or most) node pairs." In other words, $\log^2$ does not exceed the maximum distance between any pair of objects (N) [35], where 'N' denotes the number of objects. The artifacts typically inherit certain capabilities of humans in social IoT networks, and they imitate that behavior when looking for new objects. That is, the objects become friends with each other based on their relationships. The lesson from Kleinberg's study is that people can find short paths efficiently without having global knowledge. The decentralized search algorithm is a good solution for finding short paths in a large social network [36]. A successful distributed search [37] can be done by using short paths or routes. The search operation prompts a node to quickly reach a network hub that has a high degree of centrality. This feature is assured by the existence of network clusters where objects are highly interlinked because they have a high clustering coefficient. Nevertheless, Kleinberg concluded, starting with the Milgram experiment [20], that there are systemic hints that can help people to find a short path effectively, even without having global knowledge of the network [18,38]. In social networks, this phenomenon suggests that certain properties make a decentralized search possible. Based on this discussion, the global network navigability problem turns into a local network navigability problem, thanks to the SIoT network, because efficient service discovery is possible due to its highly navigable structure. Marche et al. [20] worked on the query generation and the availability of IoT datasets for the researcher community. The challenging task is the modeling of queries that are generated by the objects when fulfilling the application request. Each application running in devices will be looking for the information and services by requesting an object towards the potential service provider. For efficient information or object discovery, two essential elements are necessary. First is the structure of a social network. The second is the type of information/service request that will mostly categorize the interaction in IoT. Based on these aspects, the authors proposed this query generation model. They analyzed the behavior of objects that generate queries of information and services when interacting with the peers in the SIoT. To define this model they had generated a dataset, which is mainly based on the real IoT objects, available in the city of Santander. The devices used in this dataset can be static or mobile and are mostly public. The query generation model can generate the application request from any given object in the network. They performed network analysis by using network navigability, comparing the degree distribution using different versions of relationships, such as the object–object relationship (OOR), the colocation–object relationship (C-LOR), and the parental object relationship (POR). The problem with this model is that the authors have used the global network navigability. In addition, they did not propose any service search mechanism. Therefore, to tackle this issue, we propose an efficient service search model. The proposed query-processing service search model is shown in Fig. 1. The first layer in this model is query processing, composed of type, location, and time. For example, the current temperature in New York is 32 degrees centigrade. The location is used to access the location of the data. It is used to find the source of a particular type (temperature) that needs to be handled by using a query search mechanism. The second layer is the service discovery layer. It allows the search and access to the requested services. Efficient and effective communication between the upper and lower layers has been performed. The social IoT network data is stored in repositories; i.e. “Historical Data storage”.

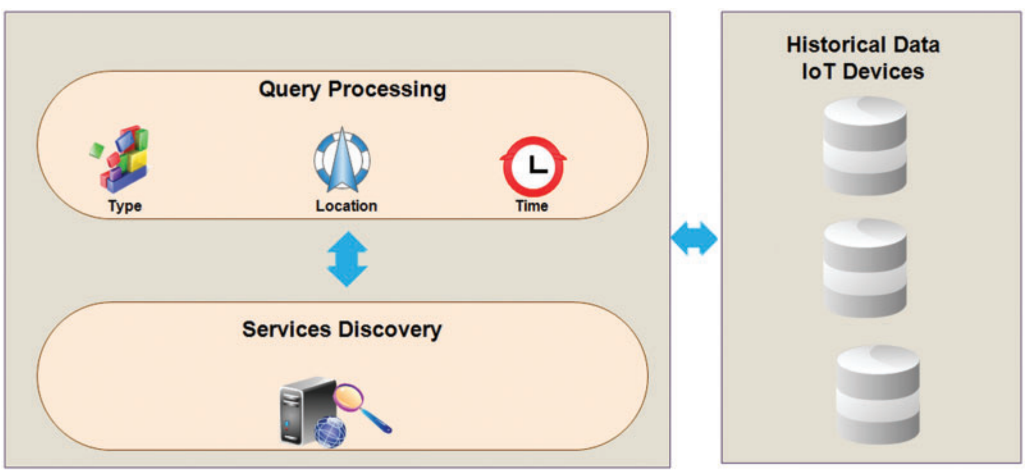

Figure 1: The proposed query processing model

3.2 Reference Scenario

Fig. 2 depicts the possible scenarios where a user may interact with IoT applications using our proposed model. To discover the requested service, two things are necessary; one is the application, and the second is the requested service. When a user applies a query (i.e. get the temperature of sensor data in a specific location). In response to the query, the specific device (resource) is accessed along with the device’s unique ID. A high-level observation is used to answer complex queries that require collaborative analysis from different sources for advanced applications, such as car speeds and acceleration, etc., but we did not consider that in this study. The first function is about the selection of an application when the user applies a query. This scenario is illustrated in Fig. 3. When a user is interested to get the temperature of a room. The corresponding object creates a query with the list of services needed to execute the temperature application and the related requirements. In this case, we assume that the reference is location and time. The search query for getting the temperature service is initiated, as shown in Fig. 3. The application that needs temperature requirements as input could be requested from different areas, such as a room, park, etc. It is accessed for different time intervals, such as historical data or real-time data.

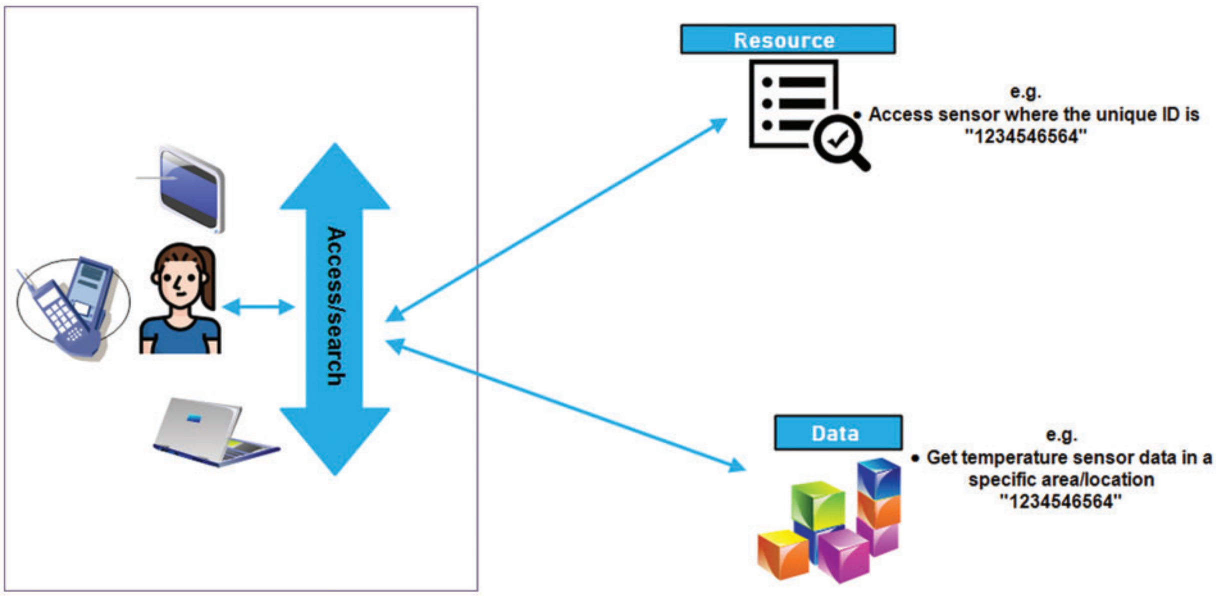

Figure 2: User interaction using the proposed model

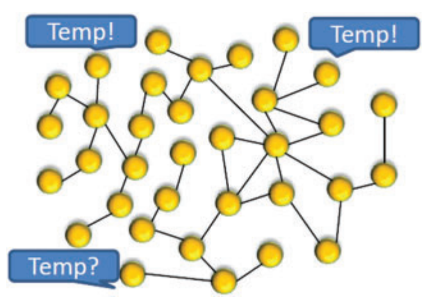

Figure 3: The temperature application and its network representation

3.3 Automated Service Search Model

The social network can be considered as undirected graph $\boldsymbol{G}$, where $\boldsymbol{G} = \{\boldsymbol{N}, \boldsymbol{\epsilon}\}$ in which $\boldsymbol{\epsilon} \cup \{\boldsymbol{N} * \boldsymbol{N}\}$ is the set of links, and each edge represents the relation between a set of nodes. $\boldsymbol{N}$ is the nodes, and the entire set is represented by $\boldsymbol{N} = \{\boldsymbol{n}_1, \ldots, \boldsymbol{n}_i, \ldots \boldsymbol{n}_I\}$ with cardinality $\boldsymbol{I}$. The node position is $\boldsymbol{L}_i = [\boldsymbol{l}_i^a, \boldsymbol{l}_i^b]$ and can be fixed or varying over time. We define the network topology for objects providing different services in different applications, i.e. temperature [20,39]. We define set $\boldsymbol{A} = \{\boldsymbol{t}_1, \boldsymbol{t}_x, \boldsymbol{t}_x\}$ as possible topologies of objects, such as cars, smartphones, lights, and temperature, etc. We define possible brands for every topology, $\boldsymbol{t}_{\mathrm{x}}$, and the set of possible brands is $\boldsymbol{B}_{\mathrm{x}} = (\boldsymbol{Bt}_{\mathrm{x}}) = \{\boldsymbol{B}_{\mathrm{x1}}, \ldots \boldsymbol{B}_{\mathrm{xy}}, \ldots \boldsymbol{B}_{\mathrm{xy}}\}$. On the other hand, the set of possible models for topology $\boldsymbol{t}_{\mathrm{x}}$ and brand $\boldsymbol{b}_{\mathrm{xy}}$ is $\boldsymbol{M}_{\mathrm{xy}} = \boldsymbol{Mb}_{\mathrm{xy}} = \{\boldsymbol{M}_{\mathrm{xy}}, \ldots \boldsymbol{M}_{\mathrm{xy}}, \ldots \boldsymbol{M}_{\mathrm{xyz}}\}$. In addition, the possible models can be described as $\boldsymbol{M} = \{\boldsymbol{UM}_{\mathrm{xy}}\}$. This allows us to define a tuple: $\beth = (\boldsymbol{N}, \boldsymbol{M})$. This shows the association with every node $\boldsymbol{n}_{\mathrm{i}}$ and the corresponding model of the device, and thus, enables us to infer the topology and the brand. In addition, this tuple is very useful to help create relationships among the nodes, such as parental object relationships [40], etc. The first function helps to select the application. Generally, the application is requested during the query process. This can provide various services from the nodes, and also satisfies the queries. The applications in the network are defined below. When a new query is received by an object $\boldsymbol{o}_i$, at that time, application $\boldsymbol{A}$ is selected to handle the query, where application $\boldsymbol{A} = \{\boldsymbol{a}_1, \boldsymbol{a}_2, \ldots \boldsymbol{a}_{\mathrm{n}}\}$. The query is divided into the services: $\{\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots \boldsymbol{s}_n\}$. The services can be provided by objects in the network. It can also compose the applications. Application $\boldsymbol{A}$ is divided into two subsets. The first is $\boldsymbol{A}^{found} \in \boldsymbol{A}$ if the requested service is available. The second subset is $\boldsymbol{A}^{res} \in \boldsymbol{A}$ if the requested service is not found. The requirements and the needed services are specified in this model. The services are defined as $\boldsymbol{S} = \{\boldsymbol{S}_1, \ldots \boldsymbol{S}_{\mathrm{j}}, \ldots \boldsymbol{S}_{\mathrm{j}}\}$. These can be performed by a node in the network and can be used to compose the applications in $\boldsymbol{A}$. So, matrix $\boldsymbol{S}_1 = [\boldsymbol{S}_{ij}]$ where the element $\boldsymbol{S}_{ij}$ is equal to $\mathbf{1}$ if an object $\boldsymbol{n}_{\mathrm{i}}$ provides service $\boldsymbol{S}_{\mathrm{j}}$; otherwise, it is $\mathbf{0}$. To model an application that generates a query. We can model the query as a tuple: $\beth = \{\boldsymbol{Q}^{ser}, \boldsymbol{Q}^{req}\}$ where $\boldsymbol{Q}^{ser} = \{\boldsymbol{q}_1, \boldsymbol{q}_2, \boldsymbol{q}_3, \ldots \boldsymbol{q}_n\}$ demonstrates the individual services required to fulfill the application requirements using an object in the social network. On the other hand, $\boldsymbol{Q}^{req} = \left\{\boldsymbol{q}_1^{req}, \boldsymbol{q}_2^{req}, \ldots \boldsymbol{q}_k^{req}\right\}$ is the set of requirements. The objective of our query model is to generate specific query $\boldsymbol{Q}$. This query can be used to find multiple services at the same time.

3.4 Navigation in the Proposed Model

Based on Fig. 3, we first create a graph as shown in Fig. 4. This graph demonstrates a simple example of generic SIoT graph G; I = 9 and each of the objects is characterized as a tuple: $\beth = \{\mathbf{n}_i, \boldsymbol{m}_{xyz}\}$. From this, we can infer the topology $\boldsymbol{t}_x$ and brand $\boldsymbol{b}_{xy}$ in our proposed model. The application and the services are categorized into different classes, such as temperature, vehicle services, educational services, etc. In this example, three applications are installed, as indicated by the number in column matrix $\boldsymbol{O}$, and it is capable of providing different services. The user who owns the object $\boldsymbol{N}_1$ is interested in a temperature monitoring app that monitors and evaluates room temperatures and tasks that are installed on an object $\boldsymbol{N}_1$. The goal of our proposed model is to find all the services in $\boldsymbol{Q}^{ser}$ starting from1 selecting the temperature, and making use of its social relations to crawl the network. To provide the requested application to the user, which is shown in Fig. 4, at first, the Object $\boldsymbol{N}_1$ will generate the $\boldsymbol{\sigma}$ with $\boldsymbol{Q}^{serv} = \{\boldsymbol{Q}_1^{ser}, \boldsymbol{Q}_3^{ser}, \boldsymbol{Q}_4^{ser}, \boldsymbol{Q}_2^{ser}\}$. The first step is to generate a set of query requirements,$\boldsymbol{Q}^{req}$, which is applied to the set of atomic queries. And $\boldsymbol{Q}^{req} = \boldsymbol{\vartheta}$ looks for the requested service among its friends, i.e. $\boldsymbol{N}_{3,}\boldsymbol{N}_{4,}$ and $\boldsymbol{N}_{2.}$ The service search procedure is performed using Algorithm 1. In the beginning, we assume that each object in a social network computes a centrality score, *i*.e. ***influencei*** based on Eq. (1) (below):

$$\boldsymbol{influence\ i = D_i + Average\ Degree\ centrality\ of\ i\text{'}s\ neighbors + C_i * 3} \tag{1}$$

$$\boldsymbol{where;\ D_i = Node\ Degree,\ C_i = clustering\ coefficient,\ T = Number\ of\ friends}$$

Object $\boldsymbol{N}_1$ the request reaches the neighbors, i.e. $\boldsymbol{N}_3$ and $\boldsymbol{N}_4$. We examine that, the requested service $\boldsymbol{S}_{\mathrm{a}}$ is not available on both objects. Object $\boldsymbol{N}_4$ has high links as compared to the object $\boldsymbol{N}_3$ (based on Eq.(1)). Therefore, it is selected as a next-hop object based on the high centrality score. The same procedure is initialized from Object $\boldsymbol{n}_4$. In this time, the next-hop neighbors are $\boldsymbol{n}_2$ and $\boldsymbol{n}_5$. The object $\boldsymbol{n}_5$ has high priority as compared to object $\boldsymbol{n}_2$, because it has high links. Therefore, it is selected as a next-hop neighbor. We have used a maximum threshold, $\boldsymbol{T} = \mathbf{5}$. If the number of links is more than $\boldsymbol{T}$, it terminates immediately. Otherwise, it proceeds to the next hop. At every step, the path score is computed by adding the centrality of the next-hop node. This procedure is repeated on object $\boldsymbol{n}_5$. At this time it has only one neighbor, i.e. $\boldsymbol{n}_9$. Therefore, it is selected as the next hop. The requested service, i.e. $\boldsymbol{S}_a$, will be selected, and a permanent path is established between objects $\boldsymbol{n}_1$ And $\boldsymbol{n}_9$. Once the requested service has been accessed. The algorithm successfully terminates.

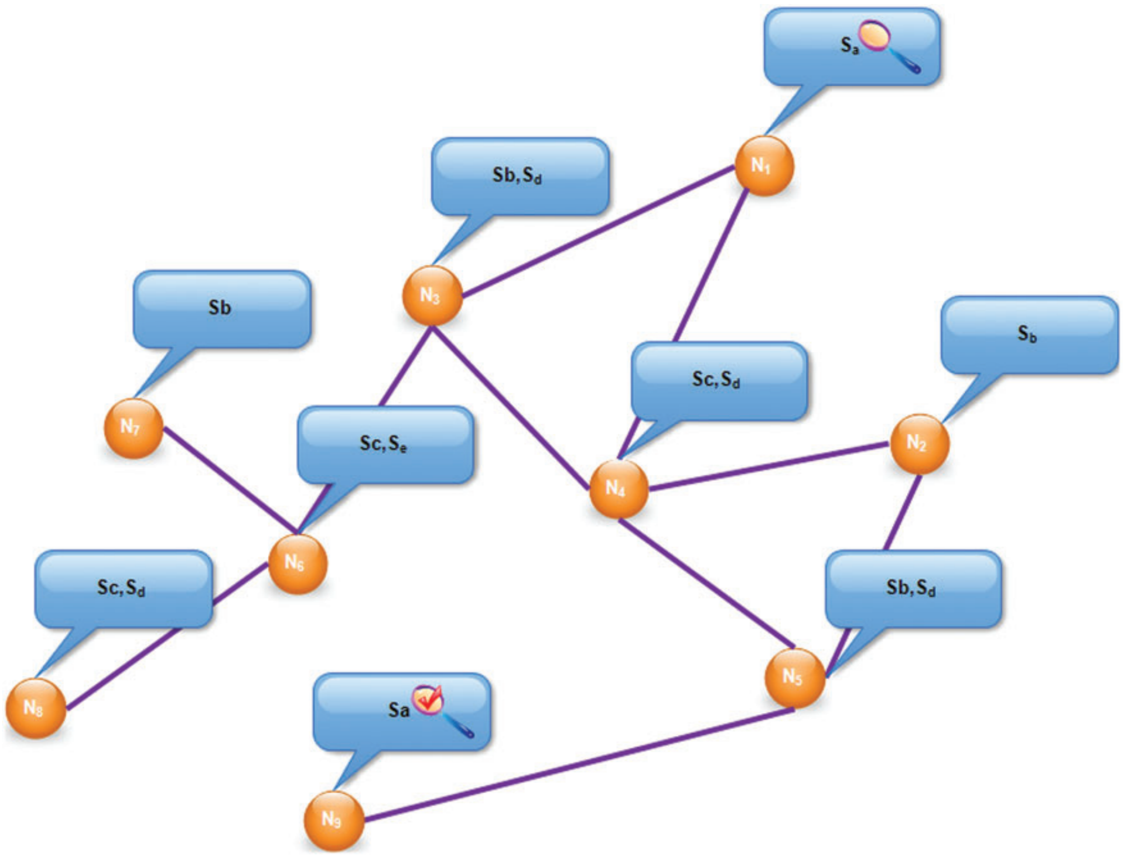

Figure 4: Automated service search model

Algorithm 1 Automated Service Search Model

Input: Send a Search request: Request query.
Output: Friendship circle: Service reply, desired service path, path score.
Start ()

(Continued)

Algorithm 1 Continued

Step 1) {Compute the centrality score of each object based on Eq. (1)}
Step 2) {Initial object sends query to neighbors}
Step 3) {Path [1] = Initial object}
Step 4) {Repeat}
Step 5) {Path score=centrality value of initial object}
Step 6) path length = 1
While path length <= T do
Step 7) path [path length] = next node is selected randomly from the graph
Step 8) path score=path score+ centrality value of next object
Step 9) path length=pathlength+1
End while
End ()

Fig. 5 demonstrates the 'TrafficApp' graph. This graph is part of our proposed query generation model and is used to describe the example of applications into the services. The services are shown in orange boxes, i.e. geolocation, speed and acceleration, sound, temperature, etc. The blue boxes show the processing of services that need the input provided by the sensing services to be executed. For instance, speed, acceleration, and temperature are the closest common ancestor services. Movement elaboration is one hop away from geolocation and one hop away from speed and acceleration. Therefore, the shortest distance between them is two hops.

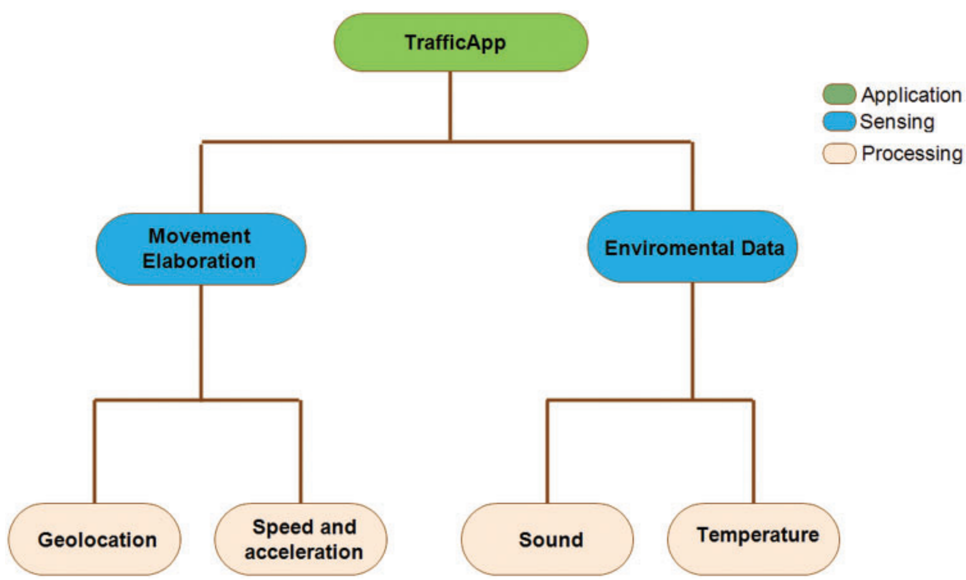

Figure 5: TraficApp: an example of applications into services

4 Results and Discussion

In this section, we have demonstrated the impact of our proposed algorithm. The SIoT is not completely deployed to date, so most of the experimentations are performed in an IoT environment by using different tools. For instance, we have used Network X in this study [8]. Network X is one of the famous tools that is widely used for fetching unstructured information. Network X is an independent platform used for the creation, manipulation, and identification of structures in complex networks [8]. In this section, the first part presents the details of the social IoT dataset and then performed visualization and social network analysis (SNA) of our proposed model. The subsequent section demonstrates the efficiency of our proposed model. We describe the efficiency of our proposed model in terms of service execution time, giant component and the path length.

4.1 The Visualization of our Proposed Model

In this section, we visualize our proposed model using giant components, path length, and the service execution time. The core objective of this section is to clearly understand the behavior of our proposed model. We have used a real social IoT dataset in our experiments [20]. This dataset is based on real IoT objects available in the city of Santander and contains a description of IoT objects. Each object is represented by fields such as (device_id, id_user, device_type, device_brand, device_model). The total number of IoT objects is 16,216. The 14,600 objects are from private users and 1,616 are from public services. The dataset includes the raw movement data of devices that are owned by users and the smart city. There are two kinds of devices: static devices and mobile devices. The static devices are represented by fixed latitudes and longitudes. On the other hand, mobile devices are represented by latitudes, longitudes, and timestamps. The latitude and longitude values of mobile devices are dynamic. In addition, the dataset includes an adjacency matrix for SIoT relationship produced with some defined parameters. Fig. 6, Illustrates the key features of the dataset [20]. The device types are listed in Tab.1. Fig. 7. Illustrates the social network analytics for the dataset using our proposed model. In this figure, we examine a huge network comprised of thousands of nodes. These nodes were connected with relationships. As the network size is very large, therefore we have used labels to represent this network. A relationship/link represents the connection between these objects. This dataset is publicly available to the researcher's community. It comprises various objects (from smartwatches to smartphones, to personal computers, and weather sensors). The information about IoT devices is based on real IoT objects located in Santander, Spain. Each object is represented with the following fields: user ID, device ID, device type, device model, device brand.

- id_user: It represents the device ownership.
- device_id: It is the identification of a device.
- device type: it shows the type of device.
- device_model: it is the model of a specific device.
- device_brand: it is the name of the device's brand.

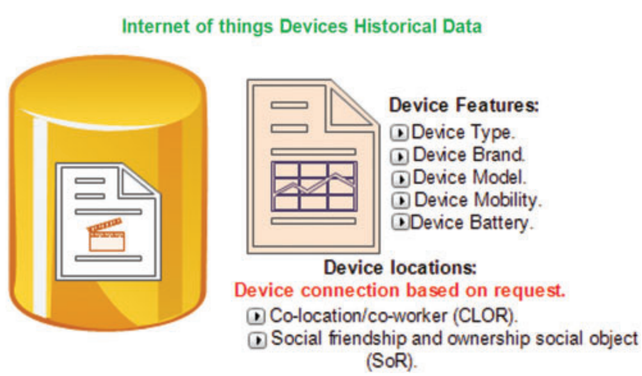

Figure 6: The real social IoT dataset

Table 1: Device type

Data model	Description
Point of interest	It designates a specific location. The user may find the useful information.
Environment and weather	It designates the collection of weather and environmental monitoring objects.
Transportation	It designates, Taxis, Buses and vehicles.
Indicator	It is used to display the information.
Garbage truck	These are containers used to collect the waste products and transport.
Street light	The collection of lights up a road in the city.
Parking	It is a specific location for vehicles.
Alarms	A device used to monitor the traffic.

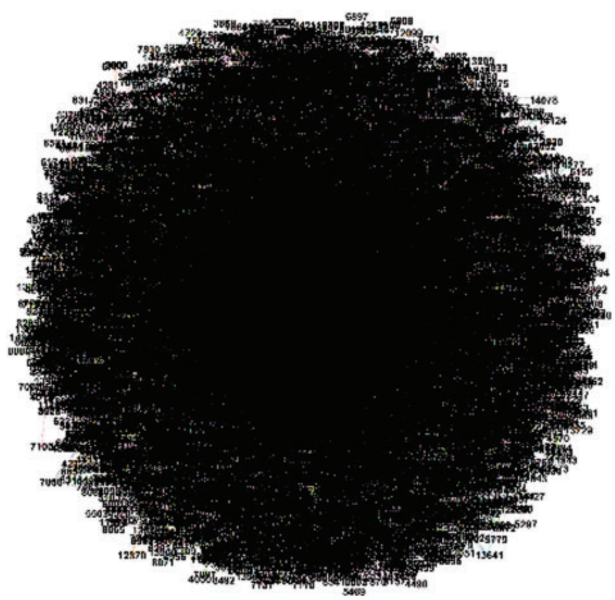

Figure 7: Social network analytics for the dataset

The first step of this section is to perform the visualization of our proposed model. For this, we have performed a social network analysis (SNA) of our proposed model. The SNA provides explanatory details and the hidden insights of objects and the relationships that coexist in the social network. It mainly focused on how individuals collaborate in the network.

4.1.1 Giant Component Visualization

The giant component means that the graph is connected or not. The objects can be accessed quickly via short paths. The giant component completely depends upon the number of objects, and if we have many objects then it results in terms of getting a large giant component. Usually, the giant component represents the group of objects. The giant component means that the graph is connected or not. The increase in giant components denotes that every object is directly or indirectly connected to all other objects in the network. If the giant component is 100% it means that the object can be accessed quickly via short paths. Fig. 8 illustrates the probability of connected nodes as a percentage by using a visualization of our proposed model. We show that the probability of connected nodes slightly increases by increasing the number of connections per node. At first, it starts from **0** and slightly increases to **100%**. The increase in the giant component denotes how every object is directly or indirectly connected to all other nodes in the network. The giant component for this experiment is 100%. This result indicates that our proposed model is completely connected. Therefore, the requested objects can be accessed quickly via short paths.

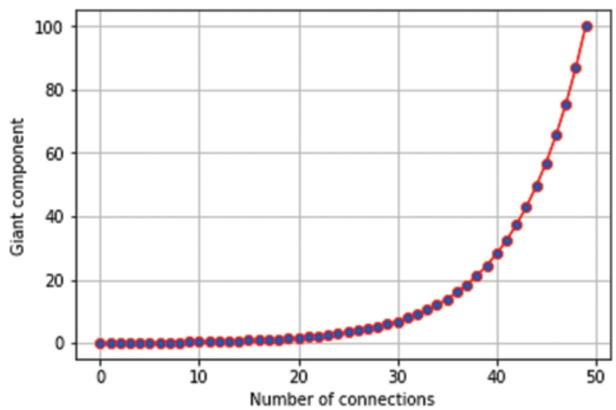

Figure 8: Impact on the giant component

4.1.2 Average Path Length or Hop Distance Visualization

Tab. 2 describes various parameters that we used for the experiments using state-of-the-art and our proposed models. Fig. 9 explains the hop distance especially when the objects request applications are located far from each other. In this comparison, we have used Barabási–Albert model (BA) [21], the current SIoT model [20], along with our proposed SIoT model. In this figure, the x-axis is the number of connections per node, and the y-axis is the average path length. In the x-axis the hop distance between different objects that are located, on average distance 0.5, 1.5, and 2.5 km from them. The path length in the current SIoT model [20], is measured based on the Euclidean distance between the service requester and the service provider. The average distance covered by the objects in our proposed model is less than the current SIoT model and other state-of-the-art models [21]. It is due to the utilization of neighbors or friends in the network. It indicates that our proposed model is efficient, especially in a case where a long-range path has been established between the service provider and service seeker. The distributed nature of our proposed model helps to discover the short paths between any pair of objects by using local information. Fig. 9 indicates the highest number of relations created with neighbor objects or devices. This fact is justified in Fig. 10, where the average number of friends is located at 1, 2, or 3 km from an object. We examine that our proposed SIoT model creates a larger number of relationships with nearby devices. The best results can be seen when the object looks for services in its vicinity. We examine that the current SIoT [20] and the BA [21] model is not performing well as compared to our proposed model. One important point is noted that with the increase of distance between the objects in the network, the efficiency of our proposed model is not affected. It remains the same. Briefly, we concluded from these graphical results that our proposed model is efficient as compared to the state-of-the-art models. The proposed SIoT model is highly navigable and we can use it to create a navigable network and find the short paths among any pair of objects by using only local information.

Table 2: Parameters for experiments

Parameters	Barabási–albert	Current SIoT	Proposed SIoT
Relationships	146,449	146,117	146,117
Average degree	18.06	16.1	18.02
Average clustering coefficient	0.02	0.03	0. 0.574
Average path length	3.17	3.6	4.22
Network diameter	5	6	8
Giant component	95%	96%	100%

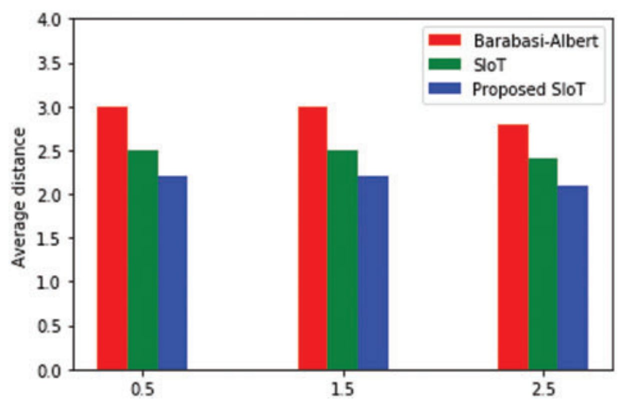

Figure 9: Average distance or path length

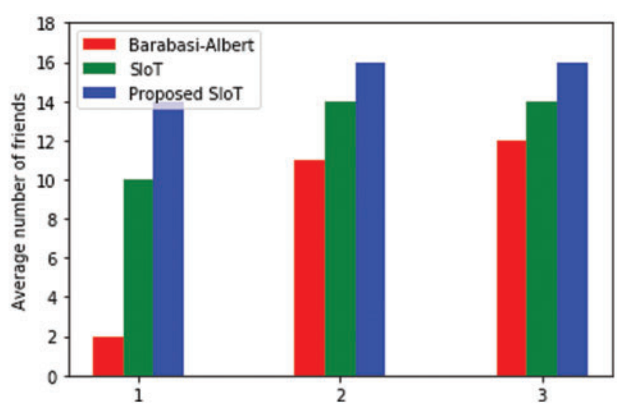

Figure 10: Average number of friends for objects within a an area of 1, 2, 3 km radius

4.2 Service Search

In this section, we discuss various simulation results related to our proposed and state-of-the-art models. In our network, each object is connected to several objects. We assume that:

1. Initially, when our model is created and later the structure of our network or topology is fixed.

4.2.1 Impact On the Degree Distribution

The degree distribution graph represents the frequency of objects in the network. For instance, to get the correct frequency distribution of objects, we have plotted a graph on a logarithmic scale, as shown in Fig. 11. In this graph, the x-axis is the degree, and the y-axis is the frequency of objects in the graph. We have used the logarithmic scale to show the large numbers of values; otherwise, they would not be visible to the reader. We have used red color to indicate the power law. The purpose of this experiment is to examine whether our proposed model follows the power law or not. The algorithm is considered efficient when it completely follows a power law. In this figure, blue stars indicate the objects in the network. We examine that the distribution of objects follows the power law, which indicates that our proposed model is highly navigable. Tab. 3 enlists the main parameters that we have used in this experiment. In this table, we also provide various network properties, such as the clustering coefficient, the network diameter, the average path length, etc.

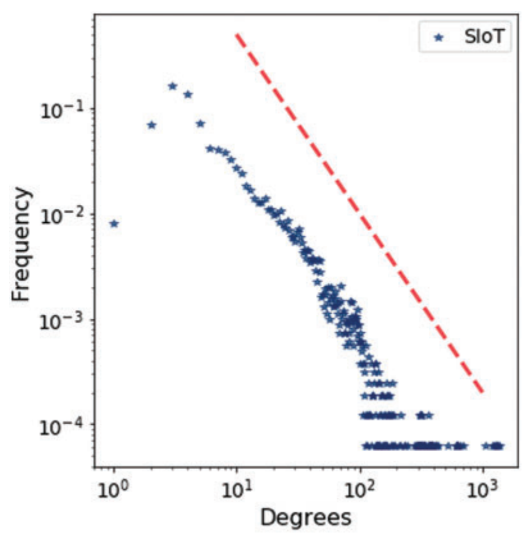

Figure 11: Impact on degree distribution

4.2.2 Impact on Service Execution Time

In this section, we discuss the impact of the service execution time of our proposed model *vs*. the current SIoT model. Usually, the time required for the search of a device is very important in service search algorithms. Generally, the execution time of an algorithm depends upon the objects and the hops required to reach destination objects [22].

Table 3: Parameters used in this experiment

Parameters	SIoT
Nodes	16,216
Edges	146,117
Average degree	18.02
Average clustering coefficient	0.574
Average path length	4.22
Network diameter	8
Giant component	100%

In Fig. 12, we compare our proposed SIoT model with the most recent SIoT model presented in [20]. The x-axis shows the number of objects, and the y-axis shows the execution time in seconds. These results indicate how the number of objects grows based on elapsed time. We had tested these models for different iterations and concluded that the efficiency of our proposed service search model increases in time intervals. In this chart, we see that the execution time of our proposed SIoT model is shorter than the most recent SIoT model. Our proposed SIoT model is more efficient because it requires less time to discover any object in the network as compared to the state-of-the-art models [20,21].

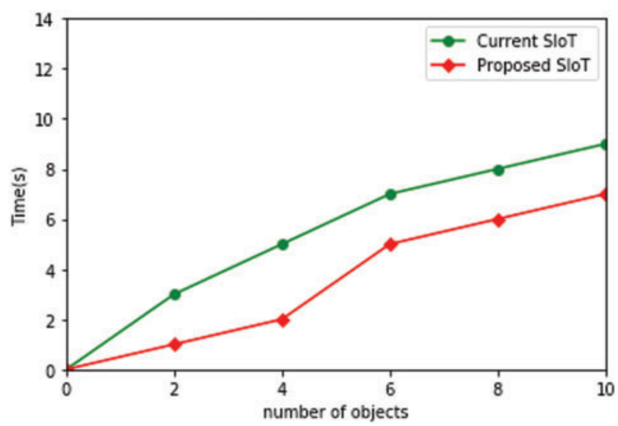

Figure 12: Impact on service execution time

5 Conclusion and Future Work

In a SIoT network, every object is connected with a large number of friends offering services that match the device requirements. This network facilitates the process of information resource retrieval and improves the network navigability and service composition. In this study, we propose an efficient, automated object service search model in SIoT based on local network navigability. The objects can use information from their friends or friends of their friends while searching for the desired services, rather than exploring a global network. We first presented the background of different concepts of SIoT devices based on their interest and relationships. We already presented an example scenario that shows the importance of service discovery and searches in SIoT environment. We found that clustering the

SIoT devices, is a relationship that improves service efficiency. Our simulation results demonstrate that it performs a service search efficiently owing to the local network navigability concept (i.e. centrality measures). Finally, our proposed model significantly improves network navigability and scalability. However, we did not discuss the trust-based neighbor discovery. In the future, we plan to build a trust-based query optimizer for the social IoT. The contents enclosed in this study propose a service search algorithm for the SIoT environment and provide a solid foundation for future research in this area.

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