DRCM: dynamic relationship creation and management in social internet of things

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Abstract: As internet of things (IoT) is overpopulated with a multitude of objects, services and interactions locating the most relevant object is emerging as a major obstacle. Over the last few years, the social internet of things (SIoT) paradigm, where objects independently establish social relationships with the other things has become popular as it provides several new characteristics to carryout reliable discovery approaches. Given a large scale deployment of socially connected objects, finding the shortest path to reach the service provider remains as a fundamental challenge. Most of the existing techniques, search for a specific object or service utilising its *friendship* or *friends of friends* connections. As a result, each object has to manage a large set of friends, thus slowing down the search process. In this paper, we propose similarity based object search mechanism that dynamically creates and manages relationships based on physical location proximity and social context of users in social communities. The result shows enhancement in the proposed method over the existing search techniques FSS, FSASV and LSFGA in terms of local cluster coefficients, the average degree of connections and average path length.

Keywords: object discovery; physical and social proximity; relationship creation and management; social internet of things; SIoT.

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1 Introduction

Internet of things (IoT) has been populated by a multitude of objects that are capable of interacting with heterogeneous objects, and have intensive communication capabilities to provide numerous services. With this, several applications can be built to provide support across different domains like smart cities, smart homes, healthcare, transportation, logistics, aviation, etc. These applications seek objects in the IoT network to offer particular service requested by either human user or objects in the network. Searching for the objects that provide desired service in the IoT network represents a critical issue due to heterogeneous object types, the dynamic topology, and varieties of data generated by objects in large volumes and at different velocities, etc. (Zhang et al., 2011). In this context, Yap et al. (2005) and Ostermaier et al. (2010) recommend a number of techniques for real-time search. Typically, these search engines are centralised and therefore cannot scale effectively with the multitude of objects and the search request. Thus, to handle the scalability issues, social aspects have been applied to the IoT. Integrating social networking principles into IoT has resulted in a novel paradigm called social internet of things (SIoT). In SIoT, objects establish new relationships based on social network properties and the present state of operations to improve the network navigability and thus aid in object discovery (Atzori et al., 2012).

Table 1 Object relationships

Notation	*Relationship type*	*Relationship establishment among objects*
POR	Parental object relationship	Created by the same manufacturer
CLOR	Co-location object relationship	Belonging to the same location or surrounding area
CWOR	Co-work object relationship	Associated to provide service for a common application
OOR	Ownership object relationship	Belonging to the same owner
SOR	Social object relationship	Come in contact with each other periodically
STGOR	Stranger object relationship	Encountered in the public surroundings or on the go
SVOR	Service object relationship	Fulfil the service request by coordinating with the same service composition
GSTOR	Guest object relationship	Possessed by the users in the guest appearance
SIBOR	Sibling object relationship	Belonging to a group of friends or family members

Accordingly, every object independently establishes different types of relationships in the SIoT network and uses the created connections to navigate in the network. The relationship can be of varied types such as friendship, community of interest, social contact, ownership, etc. Table 1 defines different types of user-object and object-object relationships depending on the type of the objects involved in a relationship (Roopa et al., 2019). These relationships progress as required in the direction of social structure and improve the object/service discovery in SIoT. SIoT system possesses the following properties and turns out to be a useful paradigm in peer-to-peer (P2P) communications:

1. *community of common interest:* the objects belongs to the same community as their owners often share similar interests
2. *encounter history:* the objects owned by users with similar interests often meet or encounter one another repeatedly
3. *mobility pattern:* the objects owned by users with similar interests often show similarity in their behaviour and movement patterns.

Computing social similarity among objects is quite significant to automate SIoT applications across different domains like smart industries and intelligent transportation (Roopa et al., 2020). For instance, in intelligent transportation system, social interactions exist among smart vehicles and roadside infrastructures to predict and reduce traffic congestion in urban roads. Also, manufacturing devices and assembly lines autonomously collaborate to self-diagnose and repair themselves to orchestrate the complete manufacturing operations in smart industries.

In SIoT, objects with similar characteristics or features exchange solutions among themselves to resolve issues that they experience, and thus social-driven concept improves the service search, selection, and composition. The most significant characteristic of the SIoT paradigm is to build connections between objects without human intervention and navigate inevitably to build more accessible solutions to discovery problems and provide scalability in the same way as seen in the social networks of humans. In the recent past, several research studies have interpreted the feasible strategies that initiate the objects to choose the relevant link to navigate in the overall network (Nitti et al., 2015; Militano et al., 2015). Although our previous study (Roopa et al., 2018) devised an algorithm to search social similar smart objects in SIoT by dynamically creating the relationships, the relationship management among the objects was not considered. However, the literature still lacks a friend selection operation and relationship creation and management technique that analyses the similarity of the objects in physical and social context. We summarise the major obstacles as follows:

1. Conventional friendship selection techniques only consider the structural characteristics of the network such as objects degree, social relationship diversity, local clustering coefficient and between centrality, etc. (Mardini et al., 2018; Nitti et al., 2015; Militano et al., 2016). Most of the related research work in SIoT defines the social relationships between objects. Still, it fails to quantify them and deficit to estimate the inferred relations among objects based on the objects encounters, which ultimately produces the friendship similarity values.
2. Existing cross-correlation and cosine similarity techniques are inappropriate to measure social similarity strength among objects for the spatiotemporal data (Pham et al., 2011).

To address the above mentioned issues, we propose an efficient friend selection procedure and relationship creation and management technique for a large scale Social IoT by capturing spatiotemporal features of an object. The contributions of the paper are summarised as follows:

1. to propose a friend selection procedure and to analyse a strategy for relationship creation and management
2. to improve the performance of the SIoT network in terms of average path length, average degree of connections and local clustering coefficient of objects.

The rest of the paper is organised as follows. Section 2 discusses the related works and existing techniques. In Section 3, we explain the background works. Section 4 contains the problem definition with the system model. The performance evaluation of the proposed search mechanism is analysed in Section 5. Finally, concluding remarks are presented in Section 6.

2 Related work

Recent research works carried out to efficiently choose an appropriate friend to create and manage relationships among objects that improves the overall network navigability is presented in this section. We present the state-of-the-art review for friendship selection and management techniques by classifying them into two categories based on structural connectivity and objects similarity.

Table 2 Evaluation of research publications: structural connectivity-based methods

Research contribution	*Year of pub.*	*Relationship model*	*Relationship management*	*Structural parameters*	*Dataset*	*Experimental environment*
Khamayseh et al. (2019)	2019	Dynamic weight-based heuristic algorithm	Naive Bayes classifier to classify each object into useful and non-useful friend	Number of services, number of mutual friends, number of friends, and QoS indicator.	Portion of the network with 2k nodes and 2k edges imported from Brightkite, Stanford Location-based Friendship Network Dataset (Leskovec and Krevl, 2014)	Gephi visualisation software (Bastian et al., 2009)
Amin et al. (2019)	2019	Network of friendship graph	Restricted the number of friends by ignoring the old friends or that has fewer connections.	Minimum number of mutual friends	Small portion of nodes from Brightkite and Facebook (Leskovec and Krevl, 2014)	Network X (Hagberg et al., 2008)
Mardini et al. (2018)	2018	Genetic algorithm	Computation of the fitness value	Number of direct friendships and number of common friends	First 2k nodes and 2k edges imported from Brightkite, Stanford Location-based Friendship Network Dataset (Leskovec and Krevl, 2014)	Gephi visualisation software (Bastian et al., 2009)
Militano et al. (2016)	2016	Game theoretic model	Approximated Shapley-value computation	Friend that offer the maximum marginal contribution	First 15k nodes and 60k edges obtained from Brightkite, Stanford Location-based Friendship Network Dataset (Leskovec and Krevl, 2014)	MATLAB simulation
Nitti et al. (2014)	2015	Social relationship graph	Heuristics based on local network properties such as local clustering and neighbourhood degree	Number of mutual friends and number of friends	12k nodes and 48k edges confined to Atlanta and Boston Region from Brightkite, Stanford Location-based Friendship Network Dataset (Leskovec and Krevl, 2014)	Gephi visualisation software (Bastian et al., 2009)

Table 3 Evaluation of research publications: behavioural similarity-based methods

Research contribution	*Year of pub.*	*Relationship model*	*Relationship management*	*Behavioural parameters*	*Performance metrics*	*Dataset*	*Experimental environment*
Xia et al. (2019)	2019	Restricted contact graph	Computation of correlation degree	Semantic similarity and semantic relativity	Average path length for searches, average number of relay nodes, and success rate of queries	Random network with 5,000 nodes	Network X (Hagberg et al., 2008)
Li et al. (2016)	2016	Virtual community construction	Computation of preference and movement pattern similarity	Interests, preferences, location and time	Search efficiency and average delay	Users social activities in the Jiangsu University Campus, China.	Opportunistic network environment (ONE) simulator
Jung et al. (2018)	2016	Weighted hypergraph-based network model	Profile and service similarity-based relatedness scores	Objects usage events	F-measure scores	Washington State University CASAS Dataset (http://ailab.wsu.edu/casas/datasets/)	Sensors and actuators used for smart home automation demo box
Nitti et al. (2016)	2016	Directed acyclic graph (DAG)	Semantic similarity between object and the services	Common interests	Average number of hops to discover each service	Nodes bound to the cities of Atlanta and Boston Region from Brightkite Stanford Large Network Dataset Collection (http://snap.stanford.edu/data/)	MATLAB tool
Kang et al. (2016)	2016	Social correlation group	Social interest similarity	Interest domains and social profiles	Resource hit ratio with interest domains	Facebook dataset from Stanford Network Analysis Platform (SNAP) (Leskovec and Krevl, 2014)	Simulation
Shen et al. (2015)	2015	Social-aware Bayesian network prediction model	Bayesian network parameter learning	Common interest, movement pattern at different location and time intervals	Prediction accuracy	Real trace data collected at the MIT Reality Group	NS2 simulation

2.1 Structural connectivity-based methods

Physical objects establish and manage relationships based on the structural characteristic of the network such as degree, diversity, clustering coefficient, betweenness centrality, closeness centrality, etc.

Khamayseh et al. (2019) have proposed a friendship management framework in SIoT to select, remove and update the friend list for multimedia services. It devises Naive Bayes classifier and weight-based mechanisms for friend selection.

Amin et al. (2019) have devised an advanced algorithm to achieve higher navigability of SIoT network using properties like path length, local clustering coefficient and giant component. It empowers navigability by dynamically adjusting the number of connections for objects in a network and removing old mutual friends that have fewer connections.

Mardini et al. (2018) have proposed a genetic algorithm-based technique for the link selection in the SIoT network. It shows an improvement in the network performance concerning local cluster coefficients, average path length and average degree of connections.

Militano et al. (2016) have designed a game theory-based distributed friendship selection method in SIoT using the Shapely-value-based algorithm. It reduces the computational complexity in the creation and management of the relationships between objects. It maintains the navigation in a SIoT network in terms of an average number of hops.

Nitti et al. (2014) have described heuristics for friendship selection in the SIoT network based on the local network properties. The network behaviour is analysed regarding average degree, average path length, giant component, and local cluster coefficient.

The above described methods use the structural clues on the network to select and manage friendship. Table 2 lists the summary of the reviewed research publications for structural connectivity-based methods.

2.2 Behavioural similarity-based methods

Objects in the physical world establish and manage relationships based on their behavioural characteristics such as preferences, common interests or habits.

Xia et al. (2019) have proposed a mechanism to discover the desired services using the ontology tree, based on OWL method. It utilises local network properties to select a suitable friend relationship that maximises the network navigation implementing an adaptive forwarding mechanism.

Li et al. (2016) have developed a resource discovery mechanism for SIoT network based on the objects movement pattern and preference similarity. It dynamically adjusts the radius of the searching process to reduce the system overheads and enhance search efficiency.

Jung et al. (2018) have proposed a hypergraph-based network model to discover smart objects. It forms communities by establishing inter-object social relationships and locates an ideal object that meets the user requirements and fairly manages the heterogeneous IoT objects.

Table 4 Summary of research background

Research contribution	*Relationship model*	*Relationship management*	*Network performance analysis*	*Dataset*	*Implementation tool*
Nitti et al. (2015)	Social relationship graph	Five heuristics are defined based on local network properties such as local clustering and neighbourhood degree	Average path length, giant components, local clustering and average degree of connections	12k nodes and 48k edges enclosed between Atlanta and Boston Region from Brightkite Stanford Large Network Dataset Collection (http://snap.stanford.edu/data/)	Gephi visualisation software (Bastian et al., 2009)
Militano et al. (2016)	Game theoretic model	Approximated Shapley-value computation	Average local clustering, group degree centrality and average path length	First 15k nodes and 60k edges from Brightkite obtained from Stanford Location-based Friendship Network Dataset (http://snap.stanford.edu/data/)	MATLAB simulation
Mardini et al. (2018)	Genetic algorithm	Computation of the fitness value	Average degree, average path length and local clustering coefficient	First 2k nodes and 2k edges imported from Brightkite Stanford Location-based Friendship Network Dataset (http://snap.stanford.edu/data/)	Gephi visualisation software (Bastian et al., 2009)

Nitti et al. (2016) have proposed an object discovery algorithm for specific application services. The SIoT establishes friendship connections among objects and creates a social network of objects and chooses the next hop based on internal characteristics of the network such as degree centrality and external characteristics such as object similarity. The intrinsic network characteristics based on object friendships, and the external characteristic resemblances among the objects and the query requirements.

3 Background work

Nitti et al. (2015) have proposed friendship selection strategies (FSS) that helps the object to discover friends exploiting the local information, such as their degree of connections. Militano et al. (2016) have proposed a distributed friendship selection algorithm based on Shapely-value (FSASV) that helps the objects to select an appropriate friend to improve the overall network navigability. Mardini et al. (2018) have proposed a link selection of friends using genetic algorithm (LSFGA) in the SIoT network. Table 4 provides a summary of the background work.

3.1 Friendship selection strategies

Nitti et al. (2015) have proposed object searching method using the key aspects of navigability characteristics of the SIoT network. It considers the degree centrality of an object to enable decentralised search using network hubs. Every object in the network is related as friends and has information about the nearby objects to find friends and to navigate in the network globally. Five heuristics are described to select an appropriate link in the network, and the network performance is analysed in terms of local cluster coefficient, average degree, average path length and giant component.

3.2 Friendship selection algorithm based on Shapely value

Militano et al. (2016) have proposed a distributed friendship selection approach based on a game-theoretic model using the Shapely-value-based algorithm. It defines a strategy to select friends that is efficient, distributed and dynamic. Further, a new utility feature such as average local clustering coefficient and group degree centrality for the objects is suggested, which improves the performance by reducing the computational complexity and ensure tractability in real problems.

3.3 Link selection of friends using genetic algorithm

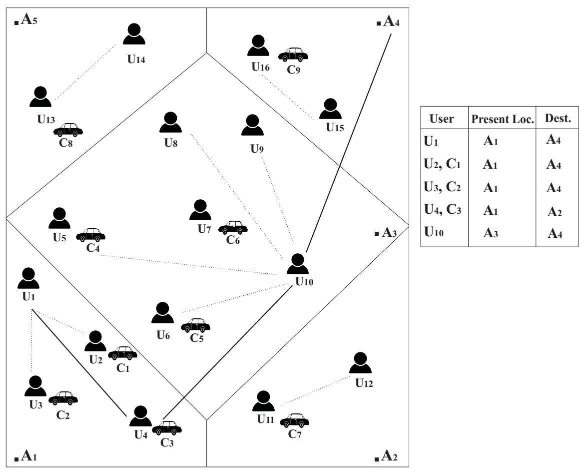
Mardini et al. (2018) have proposed a link selection strategy using a genetic algorithm to find the specific service in the SIoT. It achieves enhanced result over FSS (Nitti et al., 2015) search technique in terms of parameters such as average path length, average cluster coefficient and average degree.

However, it has been proved that friends often like to visit the same location (Cho et al., 2011) and jointly take part in some activities in real life and share similar interests bringing a homophily phenomenon (Bisgin et al., 2010). Therefore, it is highly probable to choose the objects with similar interest as a next-hop and reduce the average path length between all the pairs of objects in the network. In the existing search techniques, objects reach their destination using the intrinsic characteristic of the network such as object's degree, social relationship diversity, local clustering coefficient and betweenness centrality. Nevertheless, so far, object similarity property has not been considered for the search operation. In our approach, we use the spatiotemporal dimensions to measure the behaviour similarity of IoT objects.

4 Scenario description: a car pooling system

In this section, we illustrate the dynamic relationship creation and management approach with a carpooling use-case, where objects create relationships and groups, to provide several functionalities to the users. Assuming sensors, smartphones, laptops in the city campus, we exhibit an application that exploits their social relationships. The focus of this application is to provide useful information to the owners of the object type, typically the students with minimum human intervention. Suppose the student needs to go to a stadium to watch football World Cup soccer tournament after her class but unfortunately she does not own a car. Using an *app*, her smartphone can create *CLOR* with other students' smartphones at the school, to discover if any other student is going to the stadium. The application automatically sends messages asking for a ride to all the devices in the location proximity. The smartphone can connect up to a maximum of $N_{\max}$ devices. Upon entry of a new device, it computes the similarity score that meets the parameter such as frequency of meeting and terminates the relationship with the lowest similarity score. Likewise, by sensing the vicinity, we can find the students travelling towards the same place.

Figure 1 Search for social similar objects in SIoT: a scenario



For instance, in Figure 1 consider user U_1 present at location A_1 desires to go to A_4. U_1 establishes a relationship with other users U_2, U_3, and U_4 who owns a car in the proximity travelling to the same destination A_4 denoted as dotted links. Upon establishing the relationship, the application estimates the similarity score for the user, if U_4 is found higher it unites with it (represented as the bold line) and the user U_2 and

U_3 that has the lowest similarity score is detached from the relationship. En route to the destination at the location A_3 user U_{10} also wants to travel to the location A_4 creates a relationship with the nearby users and unites with U_1 that has higher similarity score. This process is repeated until U_1 reaches the destination. This strategy greatly improves the efficiency of the object discovery and reduces the traffic overheads incurred by the topological mismatch.

5 Problem definition and system model

5.1 Problem definition

Given a large set $O = \{o_1, o_2, ..., o_M\}$ of SIoT objects, the problem is to dynamically establish a social relationship with the nearby objects and infer the social similarity strength between each pair of the objects to manage relationships.

For a large scale of SIoT, our objective is:

1. To choose an optimal set of friends to scale down the intermediate objects required for the search operation and improve the overall network performance using objects physical and social context.
2. To evaluate the performance of SIoT network in terms of the parameters given below:
   a. *Average clustering coefficient:* It measures the closeness of objects to form a clique. The clustering coefficient for an undirected network is defined as:

   $$CC_n = \frac{2 * N_n}{K_n * (K_n - 1)} \tag{1}$$

   where N_n represents the connected links between neighbours of an object and K_n is the number of connections/degree of an object. The average clustering coefficient over all of the objects in the network is given below:

   $$Cn = \frac{1}{n} \sum_{i=0}^{N} CC_n \tag{2}$$

   where *n* represents the number of objects and CC_n represents local clustering coefficient.

   b. *Average degree of connections:* It measures the average number of direct connections of every object in the network.
   c. *Average path length:* It measures the average number of connections between all the pairs of objects in the network.

5.2 Assumptions

1. It is assumed that every user possess a set of smart objects connected to social IoT network, such as smartphone, iPad, etc.

2 Upon users contact with their friends their smart objects also come in contact with each other and then have the chance to establish relationships such as *SOR* and *CLOR*.

3 The objects are uniformly distributed throughout the space of interest.

4 An object is allowed to establish a relationship with a maximum of $N_{\max}$ friends.

5.3 Basic definitions

1 *Encounter:* We define two objects as encounter if these two objects check-in at the same location during the same time slice.

2 *Candidate friends (CFs):* Friends for the *object A* are defined as the nearby objects encounter in the proximity.

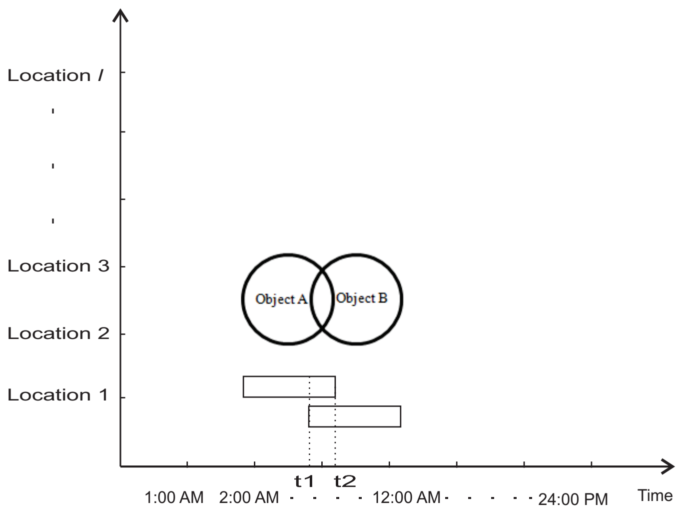
3 *Encounter frequency:* Number of encounter between *object A* and its CF at location *l* in the past.

4 *Social similarity strength:* It measures the weight associated with an edge or relation based on the physical encounters between objects (states how socially close the objects are).

5 *Absolute location:* Absolute location expresses the coordinates such as latitude and longitude, indicating a specific fixed point on the earth surface.

6 *Relative location:* Relative location refers to locations based on its proximity to the location of the *object A*.

Figure 2 Sojourn time of *object A* and *object B*



5.4 System model

In SIoT, objects develop a friendship with one another based on their common interests. Stating from *Bisgin* experiment, similar individuals associate with each other more often than others, bringing the homophily phenomenon (Bisgin et al., 2010) and therefore social features can be exploited to find the neighbouring object in the network. The proposed system model presented in Figure 2, illustrates that objects with similar interest meet more often at the same location at the same time slice.

Our proposed method offers two-fold contributions outlined in Algorithm 1. Initially, for the *object A*, we generate the nearby *CFs* who have similar preferences based on their physical contexts like locations and social interaction such as encounters or meetings in the real world and establish a co-location object relationship (CLOR). Then the relationship among the *object A* and its *CFs* are managed by computing the behaviour friendship similarity between *object A* and the candidates according to their encounter frequency and duration of stay.

Algorithm 1 DRCM: dynamic relationship creation and management

```
Step 1 : Friend Selection and Relationship Creation
Input: Target object A
Output: Set of Object A's Candidate Friends CF
for object A do
  | Extract the list of nearby objects in the physical
  | location proximity
  | Create a new CLOR or SOR relationship.
end
Step 2 : Relationship Management
Input: Set of Object A's Candidate Friends CF
Output: Friendship Similarity list for Object A, in the order of relevance
A new CF O_y is encountered in the vicinity
if the Number of Friends of Object A is less than N_max then
  | Create a new CLOR or SOR relationship
else
  | Compute Friendship Similarity between object A and O_y.
  | CF's are ranked in the decreasing order of their similarity score
  | if O_y is among the first N_max candidate friends then
  |   | Invoke a relationship with the first N_max Candidate Friends (CF)
  |   | Terminate the relationship with CF with the least score
  | else
  |   | Ignore Object O_y
  | end
end
Step 3 : Return the Friendship Similarity list.
```

5.5 Friend selection and relationship creation

This subsection describes the proposed friendship selection scheme to find the best set of friends to establish a new relationship among all possible friends.

5.5.1 Generation of nearby CFs

To instantly generate the nearby *CFs* for the *object A*, the prerequisite is to first locate the *object A* in the real-time. The current check-in location of the *object A* is obtained *via* Global Position System (GPS) coordinates at a specific timestamp, i.e.,

$$K = (location\ id,\ latitude,\ longitude). \tag{3}$$

From the current check-in location *k*, we find the set of nearest locations *L* in the vicinity within the range of *r* km radius, i.e.,

$$L = \{l_i \mid\mid D(l_i - l_k)| <= r\ and\ \forall_i, 1 \leqslant i \leqslant m\} \tag{4}$$

where *D* is the distance between two locations and *m* is the total number of locations in the range of *r* km radius for the *object A*. The cosine-haversine formula (Robusto, 1957) is used to measure the distance between two locations utilising their latitude and longitude values. It states that for any two locations on a sphere, the haversine of their central angle is:

$$hav\left(\frac{d}{r}\right) = hav(lat_2 - lat_1) + cos(lat_1)cos(lat_2)hav(lng_2 - lng_1) \tag{5}$$

where

- *hav* denotes haversine function:

$$hav(\theta) = sin^2\left(\frac{\theta}{2}\right) = \frac{1 - cos(\theta)}{2} \tag{6}$$

- *r* denotes the radius of sphere
- lat_1, lat_2 denotes latitude of location 1 and location 2 in radians
- lng_1, lng_2 denotes longitude of location 1 and location 2 in radians
- d/r denotes central angle in radians.

The presence of the objects that all have checked in the locations *L* are identified during $[t - \delta t, t]$ time interval, i.e., $O = \{o_1, o_2, ..., o_n\}$ to form a set of nearby *CFs* for *object A*, i.e.,

$$CFs = \{o_i \mid o_i\ is\ an\ Object \in O\ , \forall_i, 1 \leqslant i \leqslant nand\ [t - \delta t, t]\} \tag{7}$$

where *n* is the number of objects in Location *L* of l_i. An *object A* now establishes *CLOR* with the extracted *CFs* by capturing its spatiotemporal characteristics. Numerous design strategies as discussed in Roopa et al. (2019) can be applied to create relationships between objects.

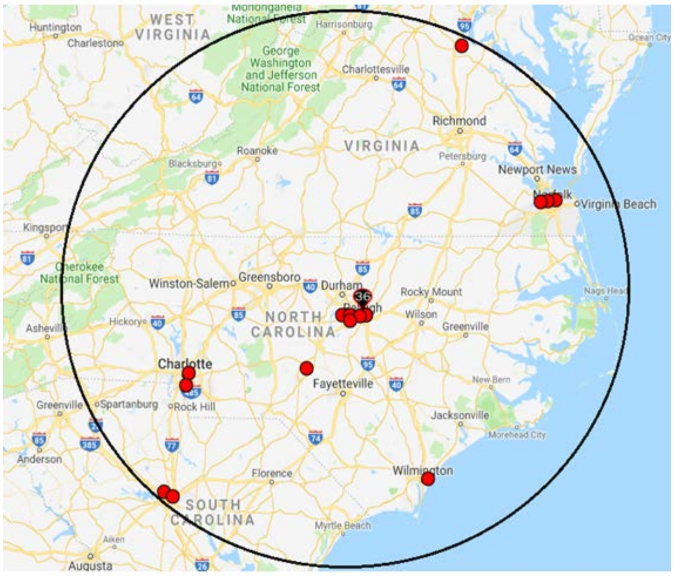
Example 1: Select *object 36* as the target object. *Object 36* has checked in the location *K = (location id =* $l_1{}^1$*, latitude = 35.787988, longitude = –78.634853) at 2009-01-30.* From the current check-in location we search the other nearby locations centred on location $l_1{}^1$ with *300* metre radius to form the nearest location set L. i.e., $L = \{l_2{}^2, l_3{}^3, l_4{}^4, ...\}$.

There are *116* spots within the radius of *300* metre of location $l_1{}^1$. We find that at the time interval *[01:00, 02:00]* on *2009-01-30* there are *16* other objects checked in these locations as shown in Figure 3. These objects are considered as the potential CFs for object *36*, i.e., CFs = {229, 1,890, 1,921, 2,030, 2,224, 2,365, 2,436, 2,523, 2,589, 3,368, 6,298, 1,0571, 21,699, 23,701, 25,299, 36,905}. This process can be applied to instantly generate nearby *CFs* for the other checkin locations of object *36* at different time intervals.

5.6 *Relationship management*

After completing the initial *CFs* selection and relationship creation process, a dynamic friendship management approach is needed. This subsection describes the proposed friendship selection strategy, to manage the relationship among objects when an object reaches the maximum friendship connections or upon arrival of a new friendship request.

Figure 3 Nearby CFs for *object 36* at a specific instance (see online version for colours)



5.6.1 *Friendship similarity computation*

For a given object A, many CFs are generated. When it arrives at maximum friendship connections or when a new friend is encountered in the vicinity, then the most relevant among these candidates must be ranked to establish a relationship. This ranking can be achieved by finding the behaviour friendship similarity between the object A and its friend $o_i \in CFs$. To measure this association, we construct a spatio-temporal encounter frequency vector for the *object* A and its CFs with reference to the absolute location and relative location.

Table 5 Spatio-temporal encounter frequency vector for object *A* and its *CFs* at absolute location

Object \ *Location and time*	*Location 1*					*Location 2*					*Location 3*					...	*Location l*				
	1	*2*	*3*	...	*t*	*1*	*2*	*3*	...	*t*	*1*	*2*	*3*	...	*t*	...	*1*	*2*	*3*	...	*t*
Object A	C_{11}^{a}	C_{12}^{a}	C_{13}^{a}	...	C_{1t}^{a}	C_{21}^{a}	C_{22}^{a}	C_{23}^{a}	...	C_{2t}^{a}	C_{31}^{a}	C_{32}^{a}	C_{33}^{a}	...	C_{3t}^{a}	...	C_{l1}^{a}	C_{l2}^{a}	C_{l3}^{a}	...	C_{lt}^{a}
o_1	C_{11}^{1}	C_{12}^{1}	C_{13}^{1}	...	C_{1t}^{1}	C_{21}^{1}	C_{22}^{1}	C_{23}^{1}	...	C_{2t}^{1}	C_{31}^{1}	C_{32}^{1}	C_{33}^{1}	...	C_{3t}^{1}	...	C_{l1}^{1}	C_{l2}^{1}	C_{l3}^{1}	...	C_{lt}^{1}
o_2	C_{11}^{2}	C_{12}^{2}	C_{13}^{2}	...	C_{1t}^{2}	C_{21}^{2}	C_{22}^{2}	C_{23}^{2}	...	C_{2t}^{2}	C_{31}^{2}	C_{32}^{2}	C_{33}^{2}	...	C_{3t}^{2}	...	C_{l1}^{2}	C_{l2}^{2}	C_{l3}^{2}	...	C_{lt}^{2}
o_3	C_{11}^{3}	C_{12}^{3}	C_{13}^{3}	...	C_{1t}^{3}	C_{21}^{3}	C_{22}^{3}	C_{23}^{3}	...	C_{2t}^{3}	C_{31}^{3}	C_{32}^{3}	C_{33}^{3}	...	C_{3t}^{3}	...	C_{l1}^{3}	C_{l2}^{3}	C_{l3}^{3}	...	C_{lt}^{3}
...			...					...					...			...			...		
...			...					...					...			...			...		
...			...					...					...			...			...		
...			...					...					...			...			...		
o_i	C_{11}^{i}	C_{12}^{i}	C_{13}^{i}	...	C_{1t}^{i}	C_{21}^{i}	C_{22}^{i}	C_{23}^{i}	...	C_{2t}^{i}	C_{31}^{i}	C_{32}^{i}	C_{33}^{i}	...	C_{3t}^{i}	...	C_{l1}^{i}	C_{l2}^{i}	C_{l3}^{i}	...	C_{lt}^{i}

Table 6 Spatio-temporal encounter frequency vector for object *36* and its CFs at absolute location

Object \ Location and time	l_1		l_2			l_3		l_4		l_5	l_6		l_7	l_8		l_9	l_{10}	l_{11}	l_{12}	l_{13}	l_{14}	l_{15}	l_{16}	l_{17}		l_{18}				l_{19}	l_{20}
	4	*24*	*1*	*2*	*3*	*18*	*22*	*23*	*24*	*15*	*2*	*3*	*13*	*21*	*22*	*24*	*24*	*4*	*5*	*3*	*24*	*12*	*21*	*1*	*2*	*13*	*16*	*20*	*21*	*3*	*20*
Object 36	3	2	2	2	3	6	6	2	1	2	2	4	1	1	1	2	1	2	1	4	2	1	1	2	2	1	2	1	1	1	1
1,890	0	0	3	3	3	1	0	2	4	0	2	1	2	2	1	3	1	2	2	2	2	1	2	2	5	2	1	1	1	2	2
229	0	0	0	0	0	0	2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2,224	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2,436	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2,365	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 7 Spatio-temporal encounter frequency vector for object *36* and its CFs at relative location

Object \ *Location and time*	l_1																		
	1	*2*	*3*	*4*	*5*	*6*	*8*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*
Object 36	17	32	23	11	5	0	0	0	3	1	7	2	8	8	3	8	8	10	10
229	15	24	20	9	3	0	0	0	1	2	5	1	7	5	3	10	11	17	12
Object 36	19	19	27	11	12	5	2	1	2	0	2	8	18	16	12	16	9	12	18
1,890	35	31	35	23	14	7	1	1	4	0	2	8	11	17	21	32	11	10	8
Object 36	25	15	17	10	6	3	0	1	0	5	4	4	1	4	1	6	0	5	18
1,921	21	12	12	12	5	3	0	1	0	3	5	4	1	6	1	5	0	6	15
Object 36	40	33	53	48	21	2	7	0	1	0	1	7	7	6	16	12	13	22	41
2,030	26	27	32	31	16	3	5	0	1	0	1	4	3	5	12	12	12	14	31
Object 36	27	20	17	7	3	0	0	0	0	0	6	10	3	8	6	5	14	7	18
2,224	29	24	14	6	2	0	0	0	0	0	3	6	6	7	6	4	8	9	17
Object 36	4	3	5	4	0	0	0	0	5	14	0	2	9	0	2	2	2	0	34
2,365	2	3	2	1	0	0	0	0	4	12	0	2	3	0	1	2	1	0	22
Object 36	3	4	8	9	2	1	0	0	0	0	0	1	4	2	2	0	1	4	0
2,436	1	4	3	4	2	2	0	0	0	0	0	1	3	1	2	0	1	2	0
Object 36	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0
2,523	0	2	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0

Note: l_1 = f477ff1835cf11de8972003048c0801e l_2 = 401f7284b5bf11dd8504003048c10834 l_3 = ec308a94a22411dda23b031f2d70f3a9
l_4 = 862b3838a62b11dda2dc003048c0801e l_5 = 3c8a6cac2c1e11deb4f2003048c10834 l_6 = 4716eef6230a11de921e003048c10834
l_7 = 47e785264b1311de95b5003048c10834 l_8 = 5f01fbe764e11deaaae003048c0801e l_9 = 6151b94b04111dd894c003048c10834
l_{10} = 68c55b181696a45775a2c691fee42576 l_{11} = 6b92ac4dc45a850b326177f8e654bae58a453f16 l_{12} = 97d6406ec771d5eceb8a77f1dd670abd7ecaf592
l_{13} = a7d2ae58231211deb3ec003048c0801e l_{14} = af1ac2567abe11dd8db80030487eb504 l_{15} = c93a745a2b4a11debd4a003048c10834
l_{16} = e27277f4fabe11dd896c003048c0801e l_{17} = e6b01838172b11de9c47003048c10834 l_{18} = e9f1efd0b8da11ddafa0003048c0801e
l_{19} = f79c99d28c2011dda29e003048c0801e l_{20} = fd9dae4ef3cb11ddb980003048c10834

Table 7 Spatio-temporal encounter frequency vector for object *36* and its CFs at relative location (continued)

Object / *Location and time*	l_1																		
	1	*2*	*3*	*4*	*5*	*6*	*8*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*
Object 36	1	1	1	3	0	0	0	0	0	0	0	2	0	0	0	0	1	0	0
2,589	1	1	1	3	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0
Object 36	6	10	1	5	0	0	0	0	4	1	1	5	1	0	0	2	4	4	9
3,368	5	8	1	7	0	0	0	0	1	1	1	3	1	0	0	1	4	3	7
Object 36	7	12	9	0	3	0	0	1	2	1	5	12	14	23	14	8	4	11	5
6,298	4	7	7	0	2	0	0	1	2	1	4	5	5	19	16	8	5	8	4
Object 36	17	17	18	23	4	3	1	0	0	1	10	12	13	15	13	12	10	20	20
10,571	20	15	10	13	3	3	1	0	0	2	14	13	14	19	19	9	10	20	18
Object 36	6	5	13	2	2	1	0	0	0	1	0	3	0	2	3	0	0	3	2
21,699	7	4	9	2	2	1	0	0	0	1	0	2	0	2	3	0	0	2	2
Object 36	0	1	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0
23,701	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Object 36	7	7	6	5	4	3	0	0	1	2	0	2	4	14	5	0	9	6	7
25,299	8	8	4	3	3	1	0	0	1	1	0	2	4	8	4	0	6	8	4
Object 36	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
36,905	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0

Note: l_1 = f477ff1835cf11de8972003048c0801e l_2 = 401f7284b5bf11dd8504003048c10834 l_3 = ec308a94a22411dda23b031f2d70f3a9
l_4 = 862b3838a62b11dda2dc003048c0801e l_5 = 3c8a6cac2c1e11deb4f2003048c10834 l_6 = 4716eef6230a11de921e003048c10834
l_7 = 47e785264b1311de95b5003048c10834 l_8 = 5f01fbe764e11deaaae003048c0801e l_9 = 6151b94b04111dd894c003048c10834
l_{10} = 68c55b181696a45775a2c691fee42576 l_{11} = 6b92ac4dc45a850b326177f8e654bae58a453f16 l_{12} = 97d6406ec771d5eceb8a77f1dd670abd7ecaf592
l_{13} = a7d2ae58231211deb3ec003048c0801e l_{14} = af1ac2567abe11dd8db80030487eb504 l_{15} = c93a745a2b4a11debd4a003048c10834
l_{16} = e27277f4fabe11dd896c003048c0801e l_{17} = e6b01838172b11de9c47003048c10834 l_{18} = e9f1efd0b8da11ddafa0003048c0801e
l_{19} = f79c99d28c2011dda29e003048c0801e l_{20} = fd9dae4ef3cb11ddb980003048c10834

1 *Absolute location:* with reference to the absolute location, Table 5 depicts the spatio-temporal encounter frequency vector for the *object A* and its *CFs*. Where n represents the total number of *CFs* for object A, t indicates the time interval of a day, here t is *24* (where time zone 0:00–1:00 is denoted as 1, 1:00–2:00 as 2, and so on) and l is the total locations checked in by the *object A* and its candidates. Where C_{lt}^{ai} represents the encounter frequency of the object A and its friend $o_i \in CF$ at location l during t^{th} time interval respectively.

   Example 2: The spatio-temporal encounter frequency vector of *CFs* that are encountered with the target *object 36* with reference to absolute location is shown in Table 6. There are only five *CFs* that are encountered with the *object 36* at absolute location i.e., 2,365, 2,436, 2,224, 229 and 1,890. An *object A* and its *CFs* are encountered with only a limited number at the absolute location, which makes the encounter frequency vector sparse. Therefore, we consider a relative location to check the objects encountered in the proximity.

2 *Relative location:* the spatio-temporal encounter frequency vector for the *object A* and its *CFs* are captured with reference to relative location in the range of r km radius.

   Example 3: The spatio-temporal encounter frequency vector of *CFs* that are encountered with the target *object 36* with reference to location *L1* in the range of *0.3 km* radius is shown in Table 7. All the sixteen CFs are encountered with *object 36* at the relative location.

Encounter frequency between *object A* and its friend $o_i \in CFs$ is the number of times A and o_i are associated with one another. More the number of times objects encounter one another, more similar their interests are. A similarity measure is a function which computes the degree of similarity and represents the similarity between two objects. To accurately measure the relevance between the objects and to rank the *CFs*, we use friendship similarity metric. Formula (7) is used to measure the similarity between the *object A* and its friend $o_i \in CFs$. The traditional similarity techniques such as Cosine similarity or Euclidean distance are inappropriate since they do not consider the spatiotemporal information. We use the concept of entropy (Cranshaw et al., 2010) in the spatial and temporal dimensions to compute the similarity between *object A* and its CF $o_i \in CF$. The friendship similarity between the *object A* and its CF $o_i \in CF$ is defined as follows:

$$Sim(A, o_i) = \sum_{l,t,C_{lt}^i \neq 0} \frac{C_{lt}^i}{f_{lt}^{ao_i}} \, log \, \frac{f_{lt}^{ao_i}}{C_{lt}^i} \tag{8}$$

where C_{lt}^i is the encounter frequency of the friend $o_i \in CFs$ and $f_{ao_i} = C_{lt}^a + C_{lt}^i$ is the total encounter frequency of both *object A* and $o_i \in CFs$ at location l and at time t.

The higher the friendship similarity score, the more similar the CFs are, so the friendship similarity is computed between the *object A* and all its *CFs* and are ranked in the decreasing order. Hence the CF with the highest similarity score is ranked in the first position and so on.

Table 8 Objects and their CFs

Object	*Location*	*Candidate friends (CFs)*	*CFs at absolute location with friendship similarity score*	*CFs at relative location with friendship similarity score*
0	L_1	2, 235, 1,067, 8,265, 9,724, 12,385, 17,155, 23,337, 28,547	2 (3.18)	2 (4.73), 1,067 (3.99), 235 (1.72), 8,265 (0.74), 23,337 (0.75), 17,155 (0.62), 9,724 (0.46), 28,547 (0.15)
19	L_2	246, 958, 965, 1,016, 1,067, 1,896, 2,841, 7,518, 8,112, 10,155, 13,201, 13,205, 13,230, 26,220	1,016 (0.84), 958 (0.30)	246 (4.37), 10,155 (3.79), 7,518 (3.71), 8,112 (2.14), 13,205 (2.00), 1,016 (1.59), 2,841 (1.00), 13,230 (0.91), 13,201 (0.54), 958 (0.45), 965 (0.39), 1,896 (0.15), 26,220 (0.15)
639	L_3	2,001, 2,069, 3,656, 5,638, 21,535, 22,911, 30,885, 31,653, 36,658, 48,370, 54,267, 54,269	54,267 (0.48), 2,001 (0.39), 30,885 (0.23), 31,653 (0.23), 22,911 (0.15)	2,069 (4.77), 3,656 (3.18), 2,001 (2.20), 21,535 (1.31), 36,658 (1.31), 5,638 (1.15), 54,269 (0.54), 54,267 (0.30), 30,885 (0.23), 31,653 (0.23), 22,911 (0.15), 48,370 (0.15)
2,001	L_4	236, 959, 961, 1,921, 2,165, 2,215, 2,227, 3,053, 3,081, 3,084, 3,767, 6,186, 6,776, 7,467, 7,579, 9,566, 10,238, 11,611, 14,276, 15,080, 20,531, 22,911, 23,148, 28,518, 29,731, 54,481	22,911 (2.14), 54,481 (1.36), 2,215 (0.45), 9,566 (0.16), 961 (0.15)	3,081 (25.57), 3,084 (24.19), 236 (21.98), 6,776 (18.65), 2,215 (18.38), 9,566 (17.43), 10,238 (16.48), 3,767 (14.89), 7,579 (14.06), 11,611 (12.66), 15,080 (11.14), 2,165 (9.51), 1,921 (9.18), 28,518 (9.02), 6,186 (6.14), 7,467 (4.30), 961 (3.54), 2,227 (3.29), 22,911 (3.17), 54,481 (2.88), 959 (1.84), 3,053 (1.28), 29,731 (0.85), 23,148 (0.61), 14,276 (0.46), 20,531 (0.23),
25318	L_5	537, 644, 652, 1,290, 1,897, 2,165, 2,841, 2,916, 5,207, 6,260, 7,546, 8,581, 11,926, 15,618, 17,046, 17,155, 19,870, 22,892, 24,409, 25,976, 27,783, 29,574	644 (4.29), 652 (4.51), 1897 (0.16), 2,165 (0.16)	644 (11.94), 2,841 (11.44), 25,976 (6.78), 652 (5.08), 2,916 (2.97), 17,155 (2.89), 5,207 (2.24), 2,165 (2.01), 1,290 (1.87), 17,046 (1.72), 22,892 (1.44), 11,926 (1.11), 8,581 (0.98), 27,783 (0.98), 537 (0.95), 6,260 (0.79), 29,574 (0.58), 1,897 (0.32), 7,546 (0.27), 15,618 (0.16), 19,870 (0.16)

Note: L_1 = 6822d481027f889e2b42050d5d311757 L_2 = f881d0e79a05a88549482b33a5503e8d L_3 = eb14b798a22411ddbf103b9d66732c0a L_4 = ece89cd8a22411ddaeb2eba49676acee L_5 = ede07eeea22411dda0ef53e233ec57ca

Example 4: The friendship similarity score between *object 36* and its friends generated in Example 2 at absolute location are: (*object 36, 2,365*) is 0.15, (*object 36, 2,436*) is 0.15, (*object 36, 2,224*) is 0.27, (*object 36, 229*) is 0.46 and (*object 36, 1,890*) is 3.66. As *1,890* has the highest friendship similarity score and hence it is ranked in the first position, while *229* and *2,224* are ranked in the second and third position respectively, *2,365* and *2,436* have the same friendship similarity score which implies that their similarity is same and can be ranked in any order.

Example 5: The friendship similarity score between *object 36* and its CFs, i.e., *229, 1,890, 1,921, 2,030, 2,224, 2,365, 2,436, 2,523, 2,589, 3,368, 6,298, 10,571, 21,699, 23,701, 25,299 and 36,905* generated in Example 3 at relative locations are *2.38, 2.51, 2.41, 2.63, 2.11, 1.85, 1.81, 0.42, 0.91, 2.13, 2.46, 2.51, 1.83, 0.30, 2.20, and 0.44* respectively. Table 8 lists the *CFs* at absolute and relation locations along with their friendship similarity score for different objects at a specific instance.

6 Performance evaluation

6.1 Evaluation of existing friendship techniques

In this section, we evaluate the performance of the existing friendship selection techniques.

6.1.1 FSS (Nitti et al., 2015)

It defines five strategies to select the best set of friends. The initial step in all the strategies is, an object can establish a friendly relationship with a maximum number of $N_{\max}$ objects. New object entry is managed by using one of the following five strategies.

1. *Strategy 1:* After reaching the $N_{\max}$ friends, an object rejects all the newly entered objects.
2. *Strategy 2:* When a new friendship request is received, each object arranges its friends in the decreasing order of their degree and procures relationship with the first $N_{\max}$ friends.
3. *Strategy 3:* When a new friendship request is received, each object arranges its friends in the increasing order of their degree and procures relationship with the first $N_{\max}$ friends.
4. *Strategy 4:* When a new friendship request is received, each object arranges its friends in the decreasing order of their common friends and procures relationship the first $N_{\max}$ friends.
5. *Strategy 5:* When a new friendship request is received, each object arranges its friends in the increasing order of their common friends and procures relationship the first $N_{\max}$ friends.

Average path length: Strategy 5, shows the best performance in terms of average path length based on the minimum local clustering that has more information on the neighbouring objects.

Average degree: Strategy 3, achieves the highest average degree, where the first $N_{\max}$ connections have the highest order of degree.

Local clustering coefficient: Strategy 4, exhibit the highest value for the average local clustering coefficient since the number of maximum connections is increasing.

6.1.2 FSASV (Militano et al., 2016)

It defines an efficient strategy using game theory approach to select the right friends. In the initial step, an object can establish a friendly relationship with a maximum of $N_{\max}$ objects.

1 *Strategy:* A new object entry is managed by computing the marginal contributions for every object using a cooperative coalitional game modelling and ranks them in the decreasing order of their shapely value.

6.1.3 LSFGA (Mardini et al., 2018)

It defines the strategy for link selection in the SIoT to find the near-optimal link using Genetic Algorithm.

1 *Strategy:* Link selection of friends is managed by computing the fitness function for every object in the SIoT network and measures the object that has the high number of common friends and friends, *i.e.* maximum clustering coefficient and maximum degree.

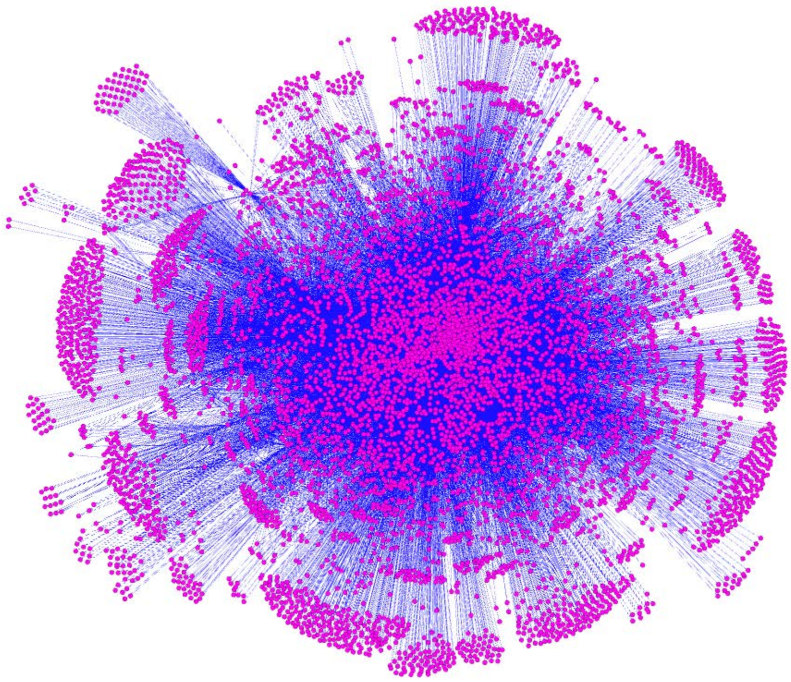
6.2 Proposed object similarity technique for friendship selection

To study the impact of applying object similarity technique for dynamic relationship creation and management in the SIoT network, we need information about the objects settings, profile and mobility patterns for a large number of real objects. Though, there are some existing SIoT platforms (Girau et al., 2013) to implement SIoT paradigm, this information is not feasible since no SIoT applications have been deployed in the real world till date. Therefore, we have relied on time and location information of check-ins made by users from Stanford Large Network Dataset Collection, Brightkite (http://snap.stanford.edu/data/) confined to Atlanta and Boston Region with 716k user check-ins. The SIoT network is visualised and analysed using a Gephi (Bastian et al., 2009), Open Graph *Viz* Platform and imported the dataset to NetBeans. Table 9 provides the summary of the dataset statistics prepared from the user check-ins at absolute and relative location of the nodes. Figure 4 shows the generated social network at the relative location. The proposed strategy is applied using the filtering plugin and evaluated the performance measures such as average clustering coefficient, average path length, and average degree of connections.

Table 9 Dataset statistics

Checkins	716,592
Nodes at absolute location	6,112
Edges at absolute location	56,008
Nodes at relative location	12,236
Edges at relative location	621,800

Figure 4 Social network at relative location (see online version for colours)



The proposed friendship selection technique utilises the object similarity property to find the best set friends in the SIoT network at absolute and relative locations. An object can establish a relationship with a maximum of $N_{\max}$ objects. New object entry is managed by the following strategy:

1 *Strategy:* When an object establishes a friendship relation with a new object, it computes the similarity between each of its friends and sorts them in the decreasing order of the similarity score and accepts the first $N_{\max}$ friends.

However, as discussed in Subsection 4.4, we are interested in using the external property with respect to network characteristics for object search. First, the nearby CFs are generated for an object based on encounter frequency and duration and then measure the association to choose the most relevant CF. The results of the proposed technique for relative location and the existing friendship techniques FSS (Nitti et al., 2015), FSASV (Militano et al., 2016), LSFGA (Mardini et al., 2018) using 12k nodes and 621k edges, connecting each node to a maximum of N_{max} = 50 friends are shown in Table 10 with reference to average path length, average degree and clustering coefficient.

Figure 5 Average path length (see online version for colours)

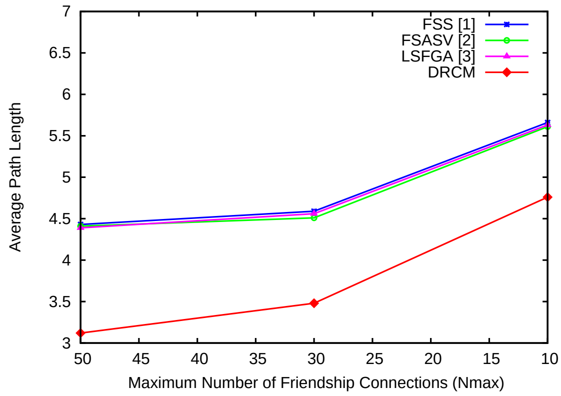


Figure 6 Average degree of objects (see online version for colours)

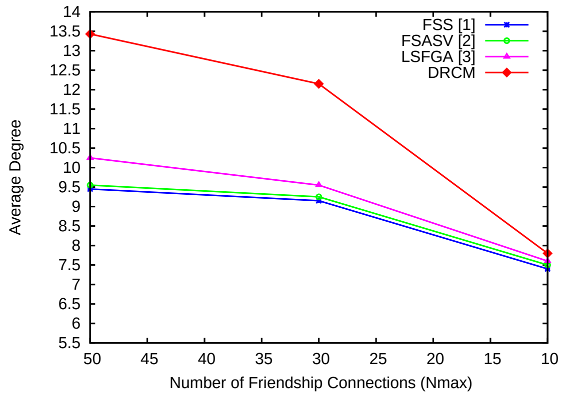


Figure 7 Average clustering coefficient (see online version for colours)

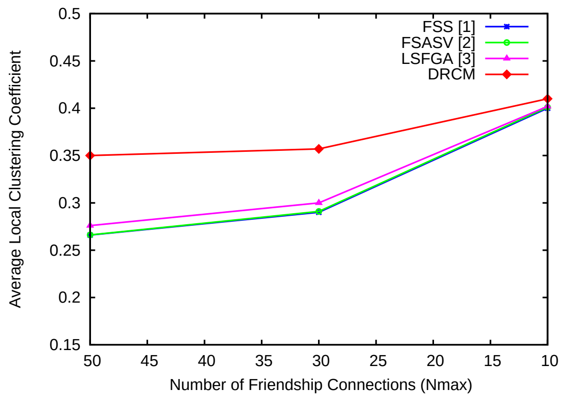


Table 10 Parameters of FSS (Nitti et al., 2015), FSASV (Militano et al., 2016), LSFGA (Mardini et al., 2018) and DRCM at relative location

	FSS (Nitti et al., 2015)	*FSASV (Militano et al., 2016)*	*LSFGA (Mardini et al., 2018)*	*DRCM*
Average path length	4.43	4.41	4.39	3.12
Average degree	9.45	9.55	10.25	13.43
Clustering doefficient	0.27	0.2661	0.276	0.35

1 *Average path length:* It is an important indicator that measures the average shortest path between any two objects in the network. The proposed object similarity technique shows better performance compare to the exiting friendship techniques (Nitti et al., 2015; Militano et al., 2016; Mardini et al., 2018) with an improvement of 34.7% approximately, where the average path length decreases rapidly to around 3.5 and gradually decreases to around 3.1 as shown in Figure 5. We observe that for the lower number of friendship connections when $N_{\max}$ is set to 10 friends, the network has too many clusters resulting with lesser average path length as the number of friendship connections are more i.e., when $N_{\max}$ is set to 50 friends, the performance is improved since objects with similarity characteristics in the SIoT network is highly associated with creating more number of relationships and thus reduces the number of local clustering.

2 *Average degree:* It measures the average number of friendship connections of every object in the network. As compare to FSS (Nitti et al., 2015), FSASV (Militano et al., 2016) and LSFGA (Mardini et al., 2018) techniques, the proposed methods gives better results with an average performance improvement of 34.93, 33.91 and 27.0% respectively as seen in Figure 6. The proposed object similarity technique maximises the average degree of objects in the network since the relationships are established between objects that are encountered in the proximity.

3 *Local clustering coefficient:* It is a measure of the degree to which the objects in the network tend to form a cluster together i.e., an object and its neighbour form a clique (Watts and Strogatz, 1998). The average clustering coefficient of the proposed object similarity scheme is higher than that of the existing friendship techniques, as shown in Figure 7. We observe that when $N_{\max}$ is set to 50, there is high connectivity of the objects, which indicates that there is a smaller number of clusters in the network and thus reduces the average clustering coefficient. At lower values of $N_{\max}$ there are fewer connections that exist between objects resulting with low average clustering coefficient.

7 Conclusions and future work

The object uses its *friends* or *friends of friends* relationships to search for the right object that provides the required service in social IoT (SIoT), resulting with large and complicated search space. In this paper, we have discussed the object similarity characteristic to experiment with the relationship management of SIoT network to overcome the limitations of the present state-of-the-art techniques. We first generate the nearby CFs for an object who have similar preferences based on their physical contexts like locations and social interaction such as encounters in the real world. The behaviour friendship similarity between objects according to their encounter frequency and duration of stay with reference to absolute and relative locations are evaluated. Our proposed object similarity technique DRCM, outperforms FSS (Nitti et al., 2015), FSASV (Militano et al., 2016) and LSFGA (Mardini et al., 2018) in terms of average path length, average degree and average clustering coefficient.

As a future enhancement to the object discovery, we will design a socially correlated secured routing technique considering the relay objects trustworthiness. We further propose to examine the performance of the object similarity technique for more realistic and heavily loaded data and investigate the effect of the proposed technique on the connectivity, scalability and navigability issues. We intend to employ machine learning technique that provides systems with the ability to automatically select friends by learning and improving from experience that is supposed to present an effective relationship creation and management strategies.

References

Amin, F., Abbasi, R., Rehman, A. and Choi, G.S. (2019) 'An advanced algorithm for higher network navigation in social internet of things using small-world networks', *Sensors*, Vol. 19, No. 9, p.2007.

Atzori, L., Iera, A., Morabito, G. and Nitti, M. (2012) 'The social internet of things (SIoT) – when social networks meet the internet of things: concept, architecture and network characterization', *Computer Networks*, Vol. 56, No. 16, pp.3594–3608.

Bastian, M., Heymann, S., Jacomy, M., et al. (2009) 'Gephi: an open source software for exploring and manipulating networks', *ICWSM*, Vol. 8, pp.361–362.

Bisgin, H., Agarwal, N. and Xu, X. (2010) 'Investigating homophily in online social networks', *2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, Vol. 1, pp.533–536.

CASAS Dataset [online] http://ailab.wsu.edu/casas/datasets/ (accessed June 2017).

Cho, E., Myers, S.A. and Leskovec, J. (2011) 'Friendship and mobility: user movement in location-based social networks', *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp.1082–1090.

Cranshaw, J., Toch, E., Hong, J., Kittur, A. and Sadeh, N. (2010) 'Bridging the gap between physical location and online social networks', *Proceedings of the 12th ACM international conference on Ubiquitous computing*, pp.119–128, ACM.

Girau, R., Nitti, M. and Atzori, L. (2013) 'Implementation of an experimental platform for the social internet of things', *Proceedings of Seventh International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS)*, pp.500–505.

Hagberg, A., Swart, P. and S Chult, D. (2008) *Exploring Network Structure, Dynamics, and Function Using Network X*, Technical report, Los Alamos National Lab.(LANL), Los Alamos, NM (USA).

Jung, J., Chun, S., Jin, X. and Lee, K.H. (2018) 'Enabling smart objects discovery via constructing hypergraphs of heterogeneous IoT interactions', *Journal of Information Science*, Vol. 44, No. 1, pp.110–124.

Kang, D.-H., Choi, H.-S. and Rhee, W.-S. (2016) 'Social correlation group generation mechanism in social IoT environment', *Proceedings of Eighth International Conference on Ubiquitous and Future Networks (ICUFN)*, pp.514–519.

Khamayseh, Y., Mardini, W., Atwood, J.W. and Aldwairi, M. (2019) 'Dynamic framework to mining internet of things for multimedia services', *Expert Systems*, p.e12404.

Leskovec, J. and Krevl, A. (2014) *SNAP Datasets: Stanford Large Network Dataset Collection* [online] http://snap.stanford.edu/data.

Li, Z., Chen, R., Liu, L. and Min, G. (2016) 'Dynamic resource discovery based on preference and movement pattern similarity for large-scale social internet of things', *IEEE Internet of Things Journal*, Vol. 3, No. 4, pp.581–589.

Mardini, W., Khamayseh, Y., Yassein, M.B. and Khatatbeh, M.H. (2018) 'Mining internet of things for intelligent objects using genetic algorithm', *Computers & Electrical Engineering*, Vol. 66, No. 1, pp.423–434.

Militano, L., Atzori, L., Nitti, M. and Iera, A. (2016) 'Enhancing the navigability in a social network of smart objects: a Shapley-value based approach', *Computer Networks*, Vol. 103, No. 1, pp.1–14.

Militano, L., Nitti, M., Atzori, L. and Iera, A. (2015) 'Using a distributed shapley-value based approach to ensure navigability in a social network of smart objects', *Proceedings of IEEE International Conference on Communications (ICC)*, pp.692–697.

Nitti, M., Atzori, L. and Cvijikj, I.P. (2014) 'Network navigability in the social internet of things', *IEEE World Forum on Internet of Things (WF-IoT)*, pp.405–410.

Nitti, M., Atzori, L. and Cvijikj, I.P. (2015) 'Friendship selection in the social internet of things: challenges and possible strategies', *IEEE Internet of Things Journal*, Vol. 2, No. 3, pp.240–247.

Nitti, M., Pilloni, V. and Giusto, D.D. (2016) 'Searching the social internet of things by exploiting object similarity', *Proceedings of 3rd World Forum on Internet of Things (WF-IoT)*, pp.371–376.

Ostermaier, B., Romer, K., Mattern, F., Fahrmair, M. and Kellerer, W. (2010) 'A real-time search engine for the web of things', *Proceedings of Internet of Things (IoT)*, Tokyo, pp.1–8.

Pham, H., Hu, L. and Shahabi, C. (2011) 'Towards integrating real-world spatiotemporal data with social networks', *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pp.453–457, ACM.

Robusto, C.C. (1957) 'The cosine-haversine formula', *The American Mathematical Monthly*, Vol. 64, No. 1, pp.38–40.

Roopa, M.S., Pattar, S., Buyya, R., Venugopal, K.R., Iyengar, S.S. and Patnaik, L.M. (2019) 'Social internet of things (SIoT): foundations, thrust areas, systematic review and future directions', *Computer Communications*, Vol. 139, No. 1, pp.32–57.

Roopa, M.S., Siddiq, A., Buyya, R., Venugopal, K.R., Iyengar, S.S. and Patnaik, L.M. (2020) 'Dynamic management of traffic signals through social IoT', *Procedia Computer Science*, Vol. 171, No. 1, pp.1908–1916.

Roopa, M.S., Valla, D., Buyya, R., Venugopal, K.R., Iyengar, S.S. and Patnaik, L.M. (2018) 'SSSSS: search for social similar smart objects in SIoT', *2018 Fourteenth International Conference on Information Processing (ICINPRO)*, pp.1–6, IEEE.

Shen, H., Liu, J., Chen, K., Liu, J. and Moyer, S. (2015) 'SCPS: a social-aware distributed cyber-physical human-centric search engine', *IEEE Transactions on Computers*, Vol. 64, No. 2, pp.518–532.

Stanford Large Network Dataset Collection [online] http://snap.stanford.edu/data/ (accessed December 2017).

Watts, D.J. and Strogatz, S.H. (1998) 'Collective dynamics of small-world networks', *Nature*, Vol. 393, No. 6684, p.440.

Xia, H., Hu, C-Q., Xiao, F., Cheng, X-G. and Pan, Z-K. (2019) 'An efficient social-like semantic-aware service discovery mechanism for large-scale internet of things', *Computer Networks*, Vol. 152, No. 1, pp.210–220.

Yap, K.-K., Srinivasan, V. and Motani, M. (2005) 'MAX: human-centric search of the physical world', *Proceedings of the 3rd International Conference on Embedded Networked Sensor Systems*, pp.166–179.

Zhang, D., Yang, L.T. and Huang, H. (2011) 'Searching in internet of things: vision and challenges', *Ninth International Symposium on Parallel and Distributed Processing with Applications*, pp.201–206.

Notes

1 l_1 = *4ec3d21dd7b43cd6ee85dfe75b472a50f4b35834*.

2 l_2 = *ec1a5daaa22411ddb0c0ab16b48fa536*.

3 l_3 = *4bae03f64add9bada5c9d326272431e454309f0f*.

4 l_4 = *2c8002cee6311ddbe0c003048c0801e*.