An Unsupervised Model for Detecting Passively Encountering Groups from WiFi Signals

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***Abstract*—In day to day life, people meet strangers while commuting in public transports, roaming around in a shopping mall, waiting at airport boarding areas etc., and thus form passively encountering groups. Detection and analysis of such groups are essential for providing services like targeted advertisements, supply chain management, information broadcasting and so on. However, identifying such groups is challenging because of the underlying dynamics, where an encounter between two subjects is entirely instantaneous without having a specific pattern. This problem has two steps – (a) identification of subjects in proximity and (b) detecting groups from the proximity information. In this paper, we develop an unsupervised model to identify subjects in proximity based on WiFi signal information and assign a proximity score to each pair of subjects based on a novel metric defining the degree of proximity. With the help of these concepts from network science, we then utilize a community detection mechanism to infer the passively encountering groups from the proximity score. The proposed model has been implemented and deployed over an academic institute campus. A study over 25 subjects for six months reveals that the proposed model can detect passively encountering groups with more than 90% accuracy, even with heterogeneous devices under various real-life scenarios.**

***Index Terms*—proximity sensing; WiFi signal gain; group detection**

I. Introduction

In daily life, people sporadically encounter strangers while commuting on public transport, waiting at the airport boarding gate, enjoying a movie in a multiplex etc. Albeit these group of people spend a considerable amount of time together at the same place, they hardly interact among themselves. We designate this kind of meetings as the *passively encountering group (PEG)*. Precisely, this is a group of (mostly) strangers who share proximity for a significant amount of time, with a little (if any) verbal communication. Notably, the formation of passively encountering groups is mostly instantaneous without any prior plan, and they hardly have any fixed pattern of formation.

Applicaiton Scenarios: Detection and analysis of the dynamics of *PEG* may lead us to multiple interesting services. Consider the following scenarios.

Scenario 1: Bob, Alice, Eve and John (each of them complete strangers to the other) went to a shopping mall and visited different sections of the mall. While roaming around the mall, Bob, Alice and Eve coincidently encountered with each other in the grocery and fabric sections, on the other hand, John and Eve passively met at the home decor section. Because they spent an appreciable amount of time together in these sections, the shopping mall administration can advertise messages to Bob, Alice and Eve on new arrivals and discounts on grocery and fabric related items, push notifications to John and Eve about discounts on home decor associated items. Developing this facility requires seamless detection of the *PEG* comprising {Bob, Alice, Eve} and {John, Eve}. This smart notification facility can substantially reduce the information overload for the customers.

Scenario 2: Consider that three strangers Bob, Alice and Eve drive from their residence to the office place every day. They (passively) share a significant stretch in the daily route which they cover almost at the same time of the day (say in the morning & in the evening). Hence, Bob, Alice and Eve can form a *PEG* while driving through that common route. Considering a service which can automatically detect this *PEG*, if one day Bob experiences a roadblock while returning to his residence, he can alert, in real time, Alice and Eve regarding this event.

Scenario 3: Alice and Bob spend a considerable amount of time in the same bus stop for a couple of days, and Bob also shares a portion of Alice's journey. Alice was infected by a germ during the shared journey with Bob and fall in sick after their meeting. Both Alice and Bob have their medical histories and medication charts uploaded to a digital health repository. Then, considering the disease history of Alice, a notification can be triggered to Bob regarding his chances of getting infected. For providing such kind of services, the seamless detection of the *PEG* comprising {*Alice, Bob*} is required.

Challenges: The above scenarios point to the fact that seamless detection of *PEG* may facilitate the development of a wide range of ubiquitous services. The penetration of sensor-equipped smartphones in society provides a unique opportunity for detecting the passive encounters. However, developing a framework for *PEG* detection comes with multiple challenges. First of all, in *PEG*, the encounter between the strangers are entirely instantaneous. Moreover, participants of *PEG* are mostly strangers without any prior history & pattern. Hence any supervised learning framework will be unsuitable to solve this problem. Secondly, the detection of *PEG* can be conceptualized as the localization problem. However, retrieving highly precise location information and identifying the passive encounters is challenging. As discussed in many related works, the energy-hungry GPS based solutions may fail or behave sporadically in the indoor environment and the presence of obstacles [1]. The indoor localization mechanisms based on WiFi or cellular signals use sophisticated hardware or device level information [2], [3], which is an overhead for proximity detection problem, as precise location information may not be necessary. Third, in real scenarios, subjects carry different make and model smartphone devices. Due to the different sensitivity of the sensors across models, differences in receiver gain and calibration offsets, a significant amount of error may get introduced in the *PEG* detection mechanism. Fourth, the uncontrolled churn of participants inside *PEG* and noisy indoor/outdoor environment further compound the problem of *PEG* detection.

Contributions & Paper Organization: Recently, there has been a plethora of exciting research exploiting the various characteristics of encounters to provide different services. However, the major portion of the literature primarily concentrated on the active encounters (say, physical interactions, verbal communications etc.) [4] and the conscious formation of meeting groups [5], [6]. In this paper, we focus on the population engaged in passive encounters and develop a smartphone-driven framework to detect passively encountering group *(PEG)*. This framework may work as a core for the development of various ubiquitous services. For providing various ubiquitous services in real time scenarios, our proposed framework addresses the problem of the stranger participants and device heterogeneity in unsupervised and lightweight manner. Proximity and location information may provide a major signature for detecting such passive encounters. In this line, GPS [7], Bluetooth [8], and WiFi [9] fingerprints apparently act as the most popular indicators for localization. We start by exploring the indicators mentioned above for proximity detection and expose their challenges with pilot experiments (§II). We show that albeit promising, vanilla WiFi fingerprint-based techniques fail to provide the accurate measure of proximity, especially in noisy environments. We propose a sophisticated technique which enhances WiFi fingerprint as a robust proximity indicator. Next, we borrow the concepts from network science and develop an unsupervised framework for *PEG* detection[1] (§III). We implement the framework in our Institute campus, and capture several passive encounters in places like classroom teaching, lab meeting, seminar presentation, and cafeteria gathering in indoor as well as the outdoor environments (§IV). We observe that our framework achieves more than 90% accuracy with lesser computation overhead as compared with the baseline approaches.

II. Background & Pilot Study

In this section, we first introduce the state of the art proximity indicators to detect passive encounters. Next, we launch a pilot experiment to identify the real-life challenges in proximity detection.

[1]This framework can be easily extended to detect actively encountering groups, involving verbal interactions, communications etc.

A. Proximity indicators and Prior Art

The population in proximity can be identified by recording their respective locations. In the following, we briefly illustrate the prime modalities in the literature for location-based proximity detection and highlight their limitations in PEG detection.

Global Positioning System (GPS): GPS [7], [6] is an important modality (albeit energy-hungry) for localization and detecting population within proximity. Although GPS performs well in outdoor environments, its accuracy sharply falls in indoor environments due to the interruption in the signal [1].

Bluetooth: Bluetooth-based study [10] is one of the earliest attempts for localization in indoor environments. Besides these, it is also useful for cooperation detection [11]. However, Bluetooth scanning is power hungry [9]. A recent work [8] addresses the group detection problem using iBeacon technology based on Bluetooth Low-Energy (BLE). Although many of the Android smartphones (starting from versions 4.4) have partial support for BLE, can detect other BLE devices only and cannot be discovered by others [5]. Additionally, the Bluetooth signal as a medium of information is considered to be unreliable and noisy.

WiFi: Many recent attempts have been made to detect proximity from WiFi fingerprint [9], [12]. WiFi-based localization is considered as an effective modality for identifying the population in proximity. The power consumption for WiFi is significantly less than Bluetooth and GPS. Though usage of BLE can act as an alternative to WiFi regarding power consumption, nevertheless BLE suffers from data loss and fluctuations with increasing distance [13]. Furthermore, the WiFi can work in any environment irrespective of the fact that whether the device location is indoor or outdoor. However, this is important to note that vanilla WiFi based localization techniques [5] are not suitable for detecting proximity.

Generic challenges: Recent study [1] claims that RSSI indicator sufficiently varies across smartphone devices (and models) due to the differences in receiver gain and calibration offsets[2]. Side by side, the contemporary Access Points optimize the transmitting power depending upon the surrounding channel conditions [2]. This automatic power adjustment strategy causes the fluctuation in the RSSI signal strength over the subject movement. Towards the line, a large number of works in the

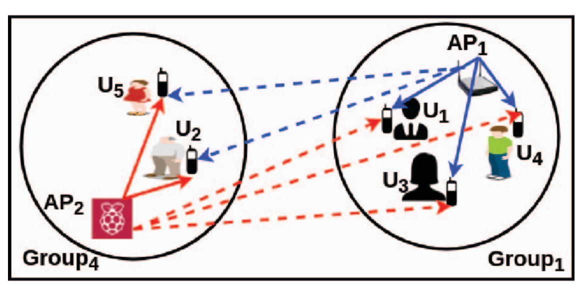
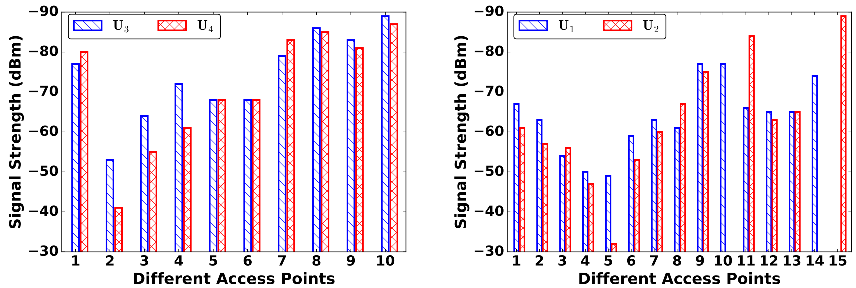


Fig. 1: Impact of WiFi Signal Strength in PEG

[2]Even if for same make and model, it may differ by $2-7dB$.

Group ID	Member IDs	Location
G_1	U_1,U_3,U_4	Lab
G_2	U_2,U_4	Class
G_3	U_1,U_3,U_4	Cafeteria
G_4	U_2,U_5	Lab
G_5	U_1,U_3,U_4	Corridoor

Fig. 2: Pilot Study Experimental Details



(a) WiFi Signal Similarity: U_3 and U_4 in G_3

(b) WiFi Signal Dissimilarity: U_1 in G_1 and U_2 in G_2

Fig. 3: Deviation of WiFi signals in various groups

current literature has focused on WiFi based localization [1], [2], [3], [14], [15]. Although such methods can be directly adopted for proximity measure; however, most of those works focus on high localization accuracy and therefore requires complex processing of WiFi signals as well as hardware or operating system level modifications. For PEG identification, we need an estimate of whether two subjects are in proximity, and do not require the exact distance between them. Therefore, we are interested to develop a lightweight WiFi fingerprint-based technique to estimate the proximity of two subjects, which can be implemented at the application level without any change in the hardware or operating system.

B. Pilot Experiment

We launched a pilot study to examine the potential of the WiFi fingerprints as an indicator of proximity in *PEG* detection. We developed an Android app for collecting the WiFi sensor log from the smartphones for conducting the pilot experiment. We recruited five subjects in this experiment for two weeks, installed the app on their smartphones (Moto X, Moto G 2nd Gen, OnePlus3, Samsung Note5) and instructed them to occasionally form pre-designed passively encountering groups (multiple time) for at least 15 minutes. They have been asked to record the passive group formation instances for validation manually. A brief overview of the passively encountering groups formed in this study is listed in Figure 2 (schematic view of the *PEG* G_1 and G_4 are shown in Figure 1). In Figure 1, AP_1 and AP_2 are the dominated WiFi access points for G_1 and G_4, respectively. In G_1, subjects U_1, U_3 and U_4 passively participated in the group, whereas in G_4, U_2 and U_5 are the passive participants. Notably, subjects U_1 and U_3 occasionally interacted with each other during the *PEG* formation period.

Observations: We investigate the behaviour of WiFi signal strengths of the subjects participating in a passively encountering group. This is comforting for us to observe in Figure 3a, which WiFi signal strengths exhibit similarity for subjects U_3 and U_4 belonging to the same passively encountering group G_3. Side by side, Figure 3b exhibits the signal strengths for two subjects U_1 and U_2 participating in two different groups G_1 and G_2, respectively. Notably, the differences in WiFi signal strengths between the members of two different groups are not strikingly visible. Moreover, Figure 4 reveals a wide variation in signal strength across smartphone models and devices, revealing the impact of device heterogeneity. We further examine the influence of access point signal strength of the subjects in mobility. Figure 5 shows the RSSI fluctuations of the subjects U_1 and U_4 over the time where the subjects are walking in a corridor forming the passive group G_5. Although both the subjects are following the same path, the RSSI value significantly differs due to the mobility of the subjects. Hence we conclude, albeit WiFi APs demonstrate a potential for detecting proximity, however, naive WiFi signal strengths show inadequacy to accomplish the task, specifically in the challenging environment.

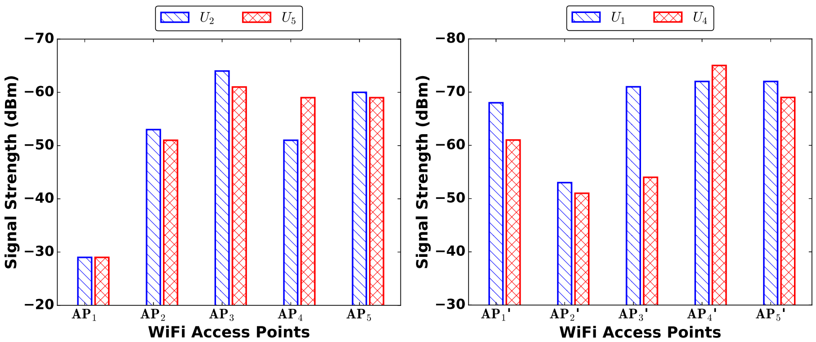
Lession Learnt: The outcome of the pilot study points to the fact that WiFi APs can be the potential channels to represent proximity. However, it is inadequate in its current form, especially in the heterogeneous mobile environment. Hence, significant preprocessing is required to make them suitable for group detection in practical scenarios.

III. PEG Detection Framework

From the pilot study, we conclude that WiFi centric proximity measure is the primal modality for identifying the passive encounters, although certain challenges need to be addressed. In this section, we first propose a sophisticated proximity feature generation methodology from WiFi fingerprints. Next, leveraging on this feature, we develop an unsupervised *PEG* detection framework. In this framework, every subject uses a smartphone to sense the WiFi APs in the vicinity and the signal strength from those APs. This sensed information is then forwarded to a central server, where the proposed model detects the subjects that form a *PEG*.

A. WiFi Centric Proximity Feature Generation

The broad idea for inferring proximity from WiFi signals is that the subjects in proximity should be under the similar set of WiFi APs and should show high similarity regarding signal property measures. The objective is to identify the population within the close proximity of a subject u_i from the collected WiFi AP log $p_i(\mathbb{B}_i, \mathbb{SS}_i)$. Precisely, $\mathbb{B}_i^t = \{\mathcal{B}_{i_1}^t, \mathcal{B}_{i_2}^t, \ldots, \mathcal{B}_{i_m}^t\}$



(a) Same Build: U_2 and U_5 in G_4

(b) Different Build: U_1 and U_4 in G_1

Fig. 4: RSSI values in devices of same and different builds

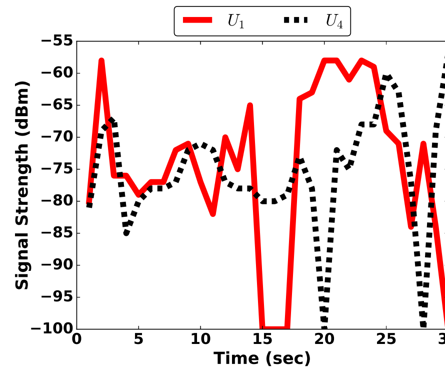


Fig. 5: Effect of mobility on RSSI U_1 and U_4 in G_5

is the vector of BSSIDs of WiFi APs scanned by the subject (smartphone) u_i at time t, and $\mathbb{SS}_i^t = \{\mathcal{SS}_{i_1}^t, \mathcal{SS}_{i_2}^t, \ldots, \mathcal{SS}_{i_m}^t\}$ represents their respective signal strength vector. We compute the proximity feature $\mathcal{F}_{ij}^t$ between a pair of subjects u_i and u_j. This is done in two steps; (a) first we detect the subjects exhibiting overlapping WiFi APs of u_i; (b) next, we further sophisticate the proximity measure considering WiFi received signal strength indicator (RSSI). The detail follows.

(a) Overlapping WiFi APs: Two subjects in proximity are likely to be within the range of the similar set of WiFi APs. Based on this intuition, we compute the measure of overlapping APs between a subject pair u_i and u_j at time t as Jaccard Coefficient [9] $\mathcal{J}_{ij}^t = \frac{|\mathbb{B}_i^t \cap \mathbb{B}_j^t|}{|\mathbb{B}_i^t \cup \mathbb{B}_j^t|}$. Intuitively, higher coefficient index depicts that the subjects are nearby. However, this is important to note that $\mathcal{J}_{ij}^t$ overlooks the signal strength. Hence the subjects staying apart (say, in two adjacent labs) but in the vicinity of the same set of WiFi APs, are incorrectly recognized as in proximity.

(b) WiFi Signal Strength: In the second step, we take the signal strength indicator RSSI into account to correctly measure the proximity. During the pilot study, we have shown that RSSI may not provide a good proximity indication when the devices are heterogeneous. To mitigate this problem, we compute the *relative gain* from RSSI and use that for a similarity measure. Considering a WiFi AP as the transmitter and two devices as the receivers, the relative gain indicates the relative difference of the receiver gains (measured from RSSI for the signals from the AP) between a pair of devices. If two devices are in proximity, then the relative gain between them is expected to be low. Consider two subjects u_i, u_j with signal strength vector $\mathbb{SS}_i^t$ and $\mathbb{SS}_j^t$ respectively, at time t. For eliminating the additive receiver gain from the RSSI feature computation, without loss of generality, the first AP RSSI $\mathcal{SS}_{i_1}^t$ is subtracted from rest of the scanned AP RSSI. This produces $\overline{\mathbb{SS}}_i^t = \{\mathcal{SS}_{i_m}^t - \mathcal{SS}_{i_1}^t : \forall \mathcal{SS}_{i_m}^t \in \mathbb{SS}_i^t\}$ and $\overline{\mathbb{SS}}_j^t = \{\mathcal{SS}_{j_n}^t - \mathcal{SS}_{j_1}^t : \forall \mathcal{SS}_{j_n}^t \in \mathbb{SS}_j^t\}$. Finally, the relative gain between the subjects u_i and u_j is computed as $g_{ij}^t = \frac{1}{|\mathbb{IS}_{ij}^t|} \sum_{(\mathcal{SS}_{i_k}^t, \mathcal{SS}_{j_k}^t) \in \mathbb{IS}_{ij}^t} ((\mathcal{SS}_{i_k}^t - \mathcal{SS}_{i_1}^t) - (\mathcal{SS}_{j_k}^t - \mathcal{SS}_{j_1}^t))$

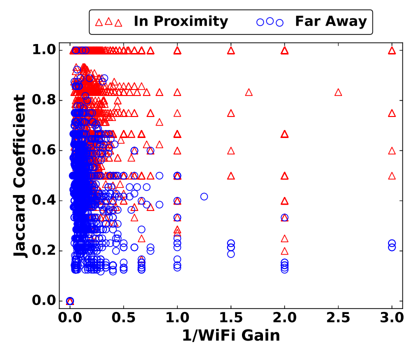


Fig. 6: Impact of WiFi fingerprints

where, $\mathbb{IS}_{ij}^t$ is the set of overlapping APs scanned by both the subjects u_i, u_j.

Computing Proximity Feature $\mathcal{F}_{ij}^t$: Finally, considering both overlapping APs and WiFi signal strength, we compute the proximity between subject u_i and u_j as $\mathcal{F}_{ij}^t = \frac{\mathcal{J}_{ij}^t}{g_{ij}^t}$. The Jaccard similarity improves with the higher degree of shared APs, whereas the gain factor reduces with the proximity of the subjects. In our pilot experiment, Figure 6 shows that the high values for Jaccard Coefficient and the inverse of WiFi gain mainly belong to the cluster where the devices are labelled as 'in proximity.'

B. Proximity Feature Refinement

We first compute the proximity feature between each pair of subjects u_i and u_j participating in a passive group for duration T by aggregating the feature $\mathcal{F}_{ij}^t$ in each timestamp $t \in T$. The simplest way of aggregating is computing the mean $\overline{\mathcal{F}}_{ij}$ for duration T. However, the WiFi signal may suffer from various sensitivity and fluctuations. Furthermore, for a few timestamps, the signal is missing due to the connectivity issues. For instance, multiple APs, with entirely different transceiver characteristics, may interfere with and distort the WiFi signal. The colluded mean features $\overline{\mathcal{F}}_{ij}^{init}$, computed from all the feature points $\mathcal{F}_{ij}^t$ for the time duration T, may not provide a clear indication of the proximity of the subject pair

u_i and u_j. Hence, we compute the refined mean features $\overline{\mathcal{F}}_{ij}$ by considering the maximally occurred feature points. Here we first construct two clusters set_h and set_l from the feature points $\mathcal{F}_{ij}^t$; $t \in T$ depending on if $\mathcal{F}_{ij}^t$ is above or below the mean feature $\overline{\mathcal{F}}_{ij}^{init}$, respectively. The higher cardinality of the cluster set_h (major cluster) signifies that the feature points are more likely to be distributed above the mean, whereas that of the cluster set_l (major cluster) indicates that the majority of the feature points are scattered below the mean. Hence, by considering the minority points as noise, we compute the aggregated feature from the majority cluster. Therefore, for the majority cluster set_h and set_l, we compute the mean $\overline{\mathcal{F}}_{ij}$ from the respective cluster as the final aggregated feature. In case of well-distributed feature points over the time span T, we favour all the feature values by considering the mean of that as the aggregated feature value $\overline{\mathcal{F}}_{ij}$. The overall feature aggregation mechanism is described in Algorithm 1. We populate the set $\overline{\mathbb{F}}$ with the aggregated feature points $\overline{\mathcal{F}}_{ij}$.

Algorithm 1 Feature Aggregation Method

Inputs: $\mathcal{F}_{ij}^t, t \in T$
Output: $\overline{\mathcal{F}}_{ij}$

$\overline{\mathcal{F}}_{ij}^{init} \leftarrow 1/|\mathcal{F}_{ij}^t, t \in T| \sum_{\forall \mathcal{F}_{ij}^t} \mathcal{F}_{ij}^t$
$set_h \leftarrow \emptyset, set_l \leftarrow \emptyset$
for $\mathcal{F}_{ij}^t, \forall t \in T$ **do**
  if $\overline{\mathcal{F}}_{ij}^{init} < \mathcal{F}_{ij}^t$ **then**
    $set_h \leftarrow set_h \cup \mathcal{F}_{ij}^t$
  else
    $set_l \leftarrow set_l \cup \mathcal{F}_{ij}^t$
  end if
end for
if $|set_h| > |set_l|$ **then** ▷ *Major Set set_h Scenario*
  $\overline{\mathcal{F}}_{ij} \leftarrow 1/|\mathcal{F}_{ij}^t \in set_h| \sum_{\forall \mathcal{F}_{ij}^t \in set_h} \mathcal{F}_{ij}^t$
else
  if $|set_h| < |set_l|$ **then** ▷ *Major Set set_l Scenario*
    $\overline{\mathcal{F}}_{ij} \leftarrow 1/|\mathcal{F}_{ij}^t \in set_l| \sum_{\forall \mathcal{F}_{ij}^t \in set_l} \mathcal{F}_{ij}^t$
  else ▷ Single Set Scenario
    $\overline{\mathcal{F}}_{ij} \leftarrow \overline{\mathcal{F}}_{ij}^{init}$
  end if
end if

C. Model Development

Finally, based on the aggregated proximity feature, we develop an unsupervised model for identifying *PEG*s using the community detection algorithm [16]. Community detection is a well-studied field in network science, aiming to extract the cohesive subgraphs from the sparse graph. First, we construct a weighted proximity graph $\mathcal{CG}(\mathbb{U}, \overline{\mathbb{F}})$ where the subjects $\mathbb{U}$ and aggregated feature points $\overline{\mathbb{F}}$ represent the nodes and the weighted links between the node pairs, respectively. This is evident that if the two subjects u_i and u_j belong to the same passive group, the proximity indicator $\overline{\mathcal{F}}_{ij}$ should be higher than if they participate in two different groups. However, the presence of the diverse set of devices generates a good variation in the aggregated feature. Therefore, it is inefficient to use any threshold based approach in real scenarios. Hence, we leverage on the community detection algorithm to design a model for passive group detection. Precisely, we apply random walk based community detection algorithm – Walktrap [17] on the proximity graph $\mathcal{CG}$ for measuring the similarity between the subjects. It initially computes the similarity between the subjects using the properties of random walk and then forms the community comprising of subjects with higher similarity. Then, it recursively measures the similarity between the communities and concludes the algorithm when the proportion of weighted links inside the community is high as compared with the proportion of weighted links between them. Hence, we finally achieve a partition $\mathbb{K}$ on population $\mathbb{U}$. We denote each detected community $\mathcal{K}_i \in \mathbb{K}$ as a *PEG*. We assume that all the subjects are connected to the central server (or cloud) where the model is being executed.

IV. Performance Evaluation

We evaluate the performance of the proposed *PEG* framework by developing a smartphone-based application and deploying it over IIT Kharagpur campus which is WiFi covered, with multiple hotspots for different stakeholders (such as administration, students, faculties, guests etc.). Additionally, the research labs have their WiFi setups. The available WiFi access points are of different makes and models like ASUS RT 3200AC, TP-link 1700, Dlink and Rasberry Pie3 working over different channels such as 2.4 GHz and 5 GHz. Further, the access points are also heterogeneous regarding supported capacity, antenna gains, transmission power etc., and therefore we test the proposed system under a realistic environment with broad WiFi coverage, where most of the time, devices can sense WiFi signals from multiple access points.

A. Experimental Design

For collecting the field data, we have developed an Android app which has been launched over smartphones of 25 subjects consisting of research scholars and faculties of the institute. We have considered that the set of subjects who remain in proximity for at least $T = 10$ minutes to be marked as a *PEG*. The data has been collected for approximately six months under different scenarios, like classrooms, cafeterias, laboratories etc. We have used Python3 in Linux operating system for processing the field data and finally computing the passive encountering groups. We have collected the ground truth information partially through GPS, and when GPS is not available, the same has been collected by interviewing the subjects on a daily basis by knowing their approximate locations (like in which classroom or in which laboratory) at different times of the day. Based on the field study collection, we have identified six typical scenarios where people have formed *PEG*. We have evaluated the performance of the proposed framework and compared it with the competing baseline algorithms using these typical scenarios as well as from the complete captured dataset. The scenarios are as follows.

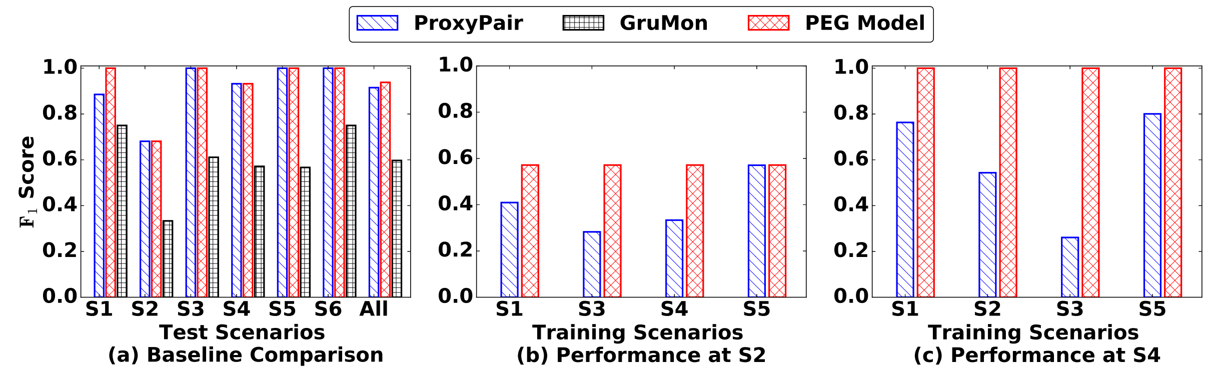


Fig. 7: Performance comparison with baselines

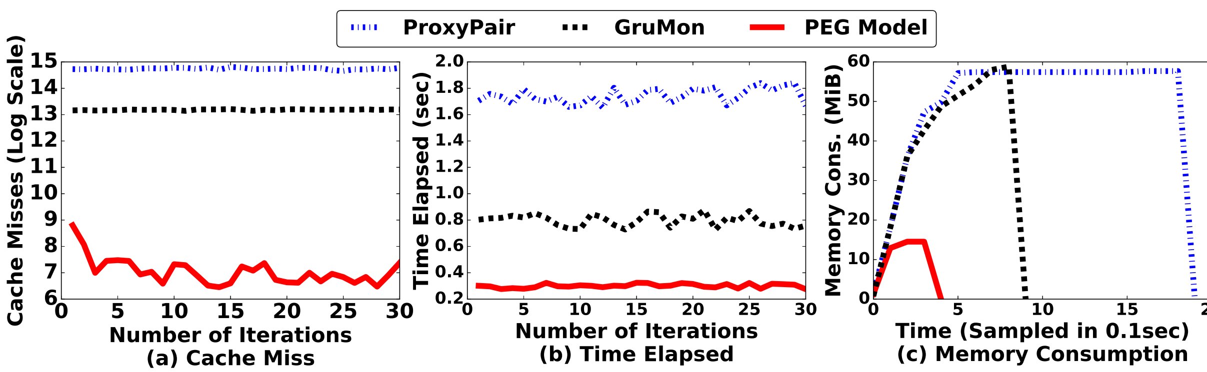


Fig. 8: Performance in terms of computational cost

S1: Subjects attend the lecture in two neighbouring rooms at the same instance of time, resulting two *PEG*s.
S2: Subjects attend meeting in the (i) faculty office on the second floor, (ii) the departmental library opposite to that faculty office, and (iii) the SMR Lab on the first floor, resulting three *PEG*s.
S3: Two different *PEG*s are formed at two different (outdoor) location of the cafeteria.
S4: Subjects attend a conference in the departmental conference room, resulting in a single *PEG*.
S5: Two different *PEG*s are formed within a large network lab.
S6: Subjects move from one room to another, forming two non-static *PEG*s.
Baseline Algorithms: We have implemented the following baselines to compare the performance of the proposed framework.
(a) WiFi based person-to-person proximity sensing (ProxyPair) [9]: Sapiezynski *et al.* developed a WiFi access point based *supervised* proximity detection mechanism, where Bluetooth data is considered as ground truth. We first implement this pairwise proximity detection model and apply the community detection algorithm on top of that for passive group identification.
(b) *GruMon* [5]: This is a real-time group monitoring system which leverages the similarity values of WiFi, accelerometer, compass and barometer readings from smartphones. They apply a decision tree based supervised learning approach to determine whether multiple persons follow the same travel trajectory together, and then the motion and location features are used to classify a group.

B. Results

We first evaluate the overall performance of the proposed *PEG* framework in terms of F_1-Score [18] which is defined as follows. Let $\mathit{\Gamma}$ and $\mathit{\Upsilon}$ be the sets of passive groups found in the ground truth data and by the model respectively. Then the F_1-Score is defined as $F_{1_{\kappa\nu}} = \frac{2\times|\kappa\cap\nu|}{|\kappa|+|\nu|}$ where ground truth group $\kappa \in \mathit{\Gamma}$ and detected group $\nu \in \mathit{\Upsilon}$. This parameter captures the accuracy of the detected group ν in terms of membership overlap with ground truth κ for the time duration T. Now, to obtain the final accuracy of the model considering all the detected groups, we compute the average F_1-Score as $F_1 = \frac{\sum_{\forall\kappa\in\mathit{\Gamma};\forall\nu\in\mathit{\Upsilon}} F_{1_{\kappa\nu}}}{|\mathit{\Upsilon}|}$. Figure 7a shows that the proposed *PEG* framework obtains overall accuracy more than 90% for most of the cases.

Figure 7a also compares the performance of the proposed *PEG* framework with *ProxyPair* and *GruMon*. We observe that *GruMon* performs very poorly as compared to the other two models, since *GruMon* primarily relies on the travel trajectory and motion details rather than proximity. Hence *GruMon* works well only in special cases like when a group of people roam around together in a shopping mall or airport (say, scenario $S6$). Moreover, there can be heterogeneity in motion within a *PEG*; for instance, in the case of $S1$, $S2$ and $S5$, one member may roam around during the presentation or classroom teaching while others are static. Our model can nicely capture those scenarios of *PEG* formation as well. Further, it is evident from Figure 7a that the *PEG* model, although an unsupervised approach in general, performs closely to a supervised approach such as *ProxyPair* when the complete training data is available for supervised learning. However, from Figure 7b and Figure 7c, we observe that *ProxyPair* performs poorly when the complete training data from all the scenarios are not available, which is indeed the limitation of a supervised learning based approach. In Figure 7b and Figure 7c, we train the *ProxyPair* model with the data from scenario $S2$ and $S4$ respectively and evaluate the scenarios except the trained ones. The proposed *PEG* framework mitigates this limitation by employing an unsupervised approach, and therefore performs significantly better than *ProxyPair* in realistic cases.

Finally, we evaluate the proposed framework regarding the computational resource requirements, as shown in Figure 8. We measure all these performance statistics in a standard Linux (Kernel version: 4.4.0) based workstation (Dell Precision Tower 7810) and obtain the primary memory consumption using the standard python memory profiling tool. We compute the number of cache misses, total execution time and the overall memory consumption during the execution of the three algorithms mentioned above. We observe that (i) the total cache misses are significantly lower for the *PEG* framework compared to other two baselines (Figure 8a); (ii) the proposed framework takes less computation time per iteration during the computation process compared to other two algorithms (Figure 8b); (iii) the memory consumption of the *PEG* framework is less than *GruMon* and *ProxyPair* (Figure 8c). Our framework enjoys the benefit of low resource consumption primarily because it is based on an unsupervised learning mechanism, whereas the other two algorithms rely on supervised learning based approaches and have the overhead of training. In a nutshell, we observe that the *PEG* framework can detect various passive groups generically and in a device independent way; moreover, the *PEG* framework can provide better group detection accuracy with less resource footprint, compared to the baseline mechanisms.

V. Conclusion

In this paper, we introduced a proximity-based *PEG* detection model leveraging on the WiFi signals sensed through smartphones. The significant contribution of the work is to design a novel feature extraction mechanism from WiFi signal strength and utilize the concepts from network science to detect a *PEG*. We defined the concept of relative gain from WIFi signal strength that can be utilized for measuring the degree of proximity, and this information is fed to a community detection mechanism for identification of *PEG*s among a set of subjects. We conducted real-life experiments in our institute campus over 25 subjects for six months, and the experimental results reveal that our model identifies the groups with good accuracy and also is significantly lightweight compared to other baselines. The proposed mechanism for *PEG* identification can be applied to design multiple services for the targeted audience, which can be a future direction of this work.

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