Linking People Through Physical Proximity in a Conference

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ABSTRACT
Past research has studied offline proximity such as co-location and online social connections such as friendship individually. People form social relationships based on certain characteristics they possess, called social selection. When people change their social behavior due to interaction with others, social influence is at work. However, few researchers have examined the relationship that exists between offline proximity and online social connection, and the transitions from offline to online and vice versa (O2O). To study this problem, we created a system for finding and connecting with people at a conference that uses offline proximity encounters in order to help attendees meet and connect with each other. Using data where our system was deployed at two conferences, we discover that for social selection, more proximity interactions will result in an increased probability for a person to add another as a social connection (friend, follower or exchanged contact). However, after the social connections are established, more online social interactions result in a decreased duration and frequency of offline interactions between the connected users and social influence is weak. These results are just the first step in understanding how O2O interactions can help link people together, improve friend recommendations, and improve overall user experience.

Categories and Subject Descriptors
H.5.3 **[Information Interfaces and Presentation]**: Group and Organizational Interfaces – Computer supported cooperative work;H.3.3 **[Information Search and Retrieval]** - Information filtering

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Algorithms, Measurement, Experimentation, Human Factors.

Keywords
Social selection, social influence, physical proximity, offline interactions, encounters, social linking, offline to online

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1. INTRODUCTION
In online social networks, social linking is accomplished through friend and follow requests. However, in real life, we make friends with others usually by meeting someone face-to-face and having a verbal conversation with them. These physical interactions are presently not captured automatically in online social networks, and do not have support for them.

As a result, physical proximity plays a significant role in making new friends because it helps you recognize how you know that person based on where and when you met. People tend to connect and form social links with others who share the similar intrinsic homophily and contextual factors, which is called social selection. Social influence describes that a person's social behaviors and activities may change and converge to be in accordance with the behaviors of their friends.

However, little work studies the social selection and social influence on daily life's physical proximity among individuals. In this paper, we try to understand whether physical proximity affects social connection formation (such as friendship and followship) and vice versa in physical environments, in particular in a conference. We hypothesize that: for social selection, more physical interactions will result in an increased probability for a person to add another as a social connection (friend, follower or exchanged contact)(H1), and for social influence, establishing these connections will result in an increased number of physical proximities between each other (H2).

In this paper, we address the following problem. Can physical proximity affect people to make connections and link to each other? To answer this question and test our hypotheses, we built an application and system and deployed it in two conferences, one at an academic conference and one at our internal conference. We used encounters to measure and record physical proximity between two people, then provided the number of encounters and the last time they encountered in the user's profile page as common information that can be used to assist whether a user wants to form a social connection with another user. First, one may argue that the encounters that we record may be spuriously recorded as proximity events and therefore may not be a true encounter. This is likely true, nonetheless, we believe that the encounter is more like a high probability that you may have encountered that person in order to record possible physical interactions that may have occurred, which is better to have rather than none at all. Second, the reason why we use encounters for facilitating social connections is the assumption that most people are disconnected and do not know each other before the conference. Note, this may not be a correct assumption since most people are connected to others in their research community, however, if we make this naive assumption, then people that already know each other before is just a simple base case so they can still decide to connect again within our application.

Through evaluating the system logs, we analyze the cumulative average total encounter duration and the frequency of encounter interactions between a pair of attendees A and B before A sends a connection request to B (friend, follow or exchanged contacts), and after the connection is made. For friend/follow requests, we consider whether they come from manual or recommendation, and whether the friend request is accepted or not.

Results show that for relationship between physical proximity and social connection, we discover that H1 is supported. However, contrary to our original hypothesis H2, after the above online connections are established, more online social interactions result in a decreased duration and frequency of offline interactions between the connected users and social influence is weak. These results are the same for both the academic and internal conferences, in other words, a user's social behavior is not dependent on the type of conference.

Our contribution is the following. We examine the relationship between physical proximity and online social connections in an indoor environment for a conference, where most researchers have only done for outdoor environments.

The paper is organized as follows. Section 1 is the Introduction, and Section 2 provides background and related work for the problem. In Section 3, we discuss about physical proximity and social linking in our system. In Section 4, we examine the relationship between physical proximity and social linking from the data obtained from our two conferences. Section 5 explains the results of our analysis for the relationships between encounters and social linking, and Section 6 concludes the paper along with future work.

2. RELATED WORK

2.1 Proximity and Offline Interactions

Consumer applications such as Foursquare, Path, and Google+ use location to allow users to check-in to find interesting friends and places, while research applications such as WhozThat [11] use sensors from the phone to help create context-aware mobile social networks. Nonetheless, these location-based applications do not exploit how location awareness offers facilities to users.

The position data collected by these location-based applications are now being used as an attempt to answer some sociological problems used to address the lack of efficient methodology or quantitative data. Among those studies, some promising results show that for those users of online social networks, underlying patterns emerge when combining their online behavioral interactions with properties of their offline behaviour before, during or after their online social connections are established.

For example, Eagle et al. [25] use GPS data on mobile phones to present the properties of users' offline location tracks. Cho et al [14] predict human location tracks based on Gaussian distribution and occasional influence of social network structure based from location-based social networks and cell phone dataset. Applications such as Aka-Aki [2] or Serendipity [19], use proximity encounters that can be detected using radio frequency identification technology (RFID) [13] or Bluetooth [27]. Proximity analysis has been studied at conferences. For example, Isella et al [26] and Catutto et al [13] studied face-to-face contact networks in a scientific conference using RFID to present network properties. Moreover, Barrat et al [10] utilize the Live Social Semantics application to collect and analyze data from both physical and virtual interaction networks, including friendship at online social network, co-authorship network, and face-to-face contact network during a conference. By defining scientific seniority, they find a clear assortative mix behavior, in which people tend to mix with others with similar seniority levels.

Considering that GPS positioning methods [16] have accurate limits (on the order of 50 meter error) that cannot omit the noisy proximities when no interaction is happening, outdoor co-location does not always infer the interaction. We believe that collected proximities through a WiFi-based positioning system such as in the work of [17] and our system [3, 4, 5,6] can better present or infer the offline interaction between users.

2.2 Linking People and Online Interactions

To understand social interaction, *social selection* [21,29] and *social influence* [21] are often used. Homophily principle [29] states that we tend to connect with similar people and are friends with them which contribute to our preferential ties. The fact that people form social ties based on similar characteristics they possess is often termed social selection [29]. In social selection, people may have more opportunities in the social environment to form friendships with other like-minded individuals, due to the shared characteristics [25, 33].

Work in [23] examines nine diverse information sources from three categories ("people", "things" and "places") to define user similarity, with which people form ties in social selection. Work in [8] utilities self-reported address data from Facebook users and their network ties to measure the relationship between geography and friendship. The authors find that in social selection, Facebook users' probability of friendship is roughly inversely proportional to their geographic distance at medium to long-range scale, while in shorter distance scale, the probability is less sensitive to the distance. Work in [19, 32] use Bluetooth technologies to define the relative physical closeness and infer the friendship in social selection through encounter duration and frequency.

In social environments, people not only tend to friend with like-minded individuals as indicated by the social selection principle, but they will adapt their activities and behaviors to be accorded with that of their friends, which is called social influence [21]. Social influence appears in consumer desires and behaviors [18] and technology adoption [34]. The probability of joining an online community, for example, in LiveJournal [9], editing a Wikipedia article and attending a conference listed in DBLP [9], increases linearly as the number of their friends who are already there increases. The social influence in these works is so strong that a set of friends is about 100 times more powerful in influencing a user to join a group than the same number of strangers. In addition, since individuals in networks affect one another, models of social influence can be built to model complex group dynamics such as the Dynamical Influence Model by Pan and his colleagues [30], where they capture and use human mobility data from sociometric badges worn by subjects in group discussions to study how influence changes over time.

Bluetooth technologies can be used to define the relative physical closeness and infer the friendship in social selection through encounter duration and frequency such as the work in [20, 32]. Recent social sensing systems such as [1,28] combine many sensing technologies such as accelerometer and compass, along with messaging and call logs, phone application usage, phone context, social media, surveys, financial status, and location technologies, to comprehensively measure and understand user behavior. These works, however, do not study social influence on physical proximity after social selection is committed. For example, does the physical proximity interaction in a physical environment affect two users in becoming friends? Cranshaw and his colleagues [16] study the diverse location measurements and propose location entropy to predict the friendship of two users by analyzing their GPS co-location traces, but not in indoor environments.

2.3 How Our Work Differs

Our system combines a user's location, social events and social context in the physical world, like in the workplace for managing workplace resources [3] or in the conference for enhancing conference participation [4]. We utilize a user's physical proximity in the form of encounters to broaden a user's social connections by creating an online social network service that suggests people to connect to, based on location and encounter history, and integrate it together with the conference schedule which is presented in a mobile user interface. Our work is most similar to Conferator [7] and Live Social Semantics [10], a system for enhancing social interaction at conferences [7], but differs in that we use WiFi and create an encounter algorithm for discovering potential contacts instead of using RFID tag interactions and direct face-to-face contacts. We also investigate the relationship between physical proximity interactions on online social interactions, which have been studied for outdoor environments (eg. GPS and Foursquare data) but not indoor environments, in order to determine if proximity affects users to have online social interactions.

3. PHYSICAL PROXIMITY AND SOCIAL LINKING IN A CONFERENCE

In this section, we explain about the physical proximity interactions and social linking that we used in our system for two conferences, one in an academic conference and one in an internal conference. Our system is a platform for providing social networking amongst attendees at a conference or meeting. Users can find where the room, session and people are on the map, then select them and view their profile to see who they are. If they want to connect with them, they can add them as a friend or follow them. In the academic conference, users can also connect with each other by sending messages or sharing items like which papers that they liked. In this paper, we do not describe about the user interfaces for the academic conference and the internal conference. Readers can refer to our previous papers in [4,5].

3.1 Physical Proximity

We encounter many people every day and the people that we encounter and meet could present opportunities to make new social connections. This is based on the concept of the 'familiar stranger' [31] where we repeatedly observe and are co-located with, but do not directly interact with a stranger. In our system, we record the position of every user (that participated in our trials) using WiFi technology. Each user's phone uploads the latest WiFi signal strengths from three nearest WiFi access points to our positioning server which compares the WiFi signal strengths to a positioning model (that has recorded all the WiFi signal strengths from the entire conference venue on the floor map), in order to estimate the real location (x,y) in pixels on the map. For our implementation, we used an off-the-shelf commercial WiFi positioning system [22]. We use encounter as the concept for defining a probable proximity interaction. We define an encounter if the distance between two people is within the encounter distance threshold and their distance lasts for at least the encounter duration threshold before they move away and are beyond the encounter distance threshold. From the individual's position, we calculate the distance between any two individuals on the same floor at the same time. We then create an encounter graph $G_{en}(V, E)$ where V is the set of nodes (v_i | $1 \leq i < N$), N is the number of nodes and E is the set of edges (e_{ij} | $1 \leq i<N, 1 \leq j<N, i \neq j$) and

- node v_i designates user i, node v_j is user j and the edge e_{ij} is a link when two users (v_i and v_j) encounter each other,
- edge e_{ij} has a timestamp attribute to define when the encounter happens called $T_{en\ start}(e_{ij})$ and when the encounter ends called $T_{en\ stop}(e_{ij})$, and
- edge e_{ij} is built only if the encounter distance $D_{en}(e_{ij})$ is less than the encounter distance threshold ΔD and the encounter duration $\Delta T_{en}(e_{ij}) = T_{en\ stop}(e_{ij}) - T_{en\ start}(e_{ij})$ is larger than ΔT (the time duration threshold that is defined to be an encounter)

We then record all the encounters between any two people at a frequency of f throughout the entire duration of the conference. The collection of all the encounters forms the *encounter network*. Note that the encounter is defined as a pairwise proximity interaction between two users, and since the WiFi positioning accuracy can be off by 5 meters (based on our experience), the encounter may not be a true encounter. Nonetheless, we assume that these encounters could be possible encounters, that is, there is a high probability that an encounter did occur. Therefore, we use this assumption for the remainder of our work.

3.2 Social Linking

In our system, people have opportunities to form relationships with other like-minded individuals, due to the shared characteristics that they have, such as common friends, similar profile, and common encounters. If you physically encounter a particular person more and have longer encounter duration, we hypothesize that this may increase the probability that you will follow this person and also become a friend. The reason why is because there is an attractive force of similarity between both of you, the similarities being that both of you are at the same place at the same time doing the same activity. In other words, *social selection* is at play which will influence your behaviour to want to establish a social connection with that person, which you also want to reflect online by following or becoming that person's friend.

In addition, *social influence* is at play where users adapt their activities and behaviors to be accorded with that of their friends. In the academic conference, we determine whether friendship will result in increased physical proximity encounters between each other and vice versa; whereas for the internal conference, we study whether users who have exchanged contacts or have followed, will result in increased physical proximity encounters between each other and vice versa. In other words, if I follow you, become your friend, or exchanged contact with you, will I encounter you even more because I want to have more offline social interactions with you? In order to encourage others to add people to be friends or to follow based on encounters, we also created a people recommendation algorithm based on common research interests, common friends/followers, common sessions, and shared encounters, which we do not discuss in this paper but can be found in [5].

From the adding of friends or followers, and the exchange of contacts, we construct the three networks described below.

Friend network: this is an undirected network where the edge means that the two people (A and B) are friends. In our system, A and B become friends when A selects B and then selects "Add as friend" from B's profile page. A can select B through the following user interactions: (i) viewing people on the map, (ii) results of a search for a person, (iii) viewing the list of people that A follows or list of people that follows A, or (iv) selecting a person recommended by our system. This sends a friend request to B, then B receives a notification in the Inbox where B can accept the friend request.

Following network: this is a directed network where a directed edge between two people (A and B) means that A follows B and can see the activities of B, similar to the following network in Twitter. In our system, A selects B to follow as a unidirectional link, which is different from the friend network which is bidirectional or undirected.

Exchange contacts network: this is an undirected network between two people (A and B) where both A and B receive the contact information of the other, when either A or B sent the exchange contacts request. This results in a vCard being sent as an SMS to both of them.

4. RELATIONSHIP BETWEEN PHYSICAL PROXIMITY AND SOCIAL LINKING IN A CONFERENCE

In this section, we address whether a relationship exists between physical proximity within a shared physical environment in the context of a conference, and social linking and social relationships among users. We use the data collected from our system deployed at the academic and internal conferences.

4.1 Trial and Dataset Description

4.1.1 Academic conference

Our system was developed for the academic conference (UIC/ATC 2010) for four days during October 2010. During the trial, we provided 50 Nokia X6 and 50 Nokia 5800 phones for the participants. A total of 112 people registered for the trial, of which 62 users were paper authors and 50 users were non-authors. We recorded friend and follow requests and exchanged contacts as well as the times of those requests. We also record if the friend requests are accepted. We discover that people mostly friend other people, rather than follow or exchanged contacts, because people want to establish strong social connections with others which is done through friendship and is a two-way strong social connection (from which they can decide to exchange contacts). Therefore, in the following analysis we concentrate on friendship as the mutual social link and study its relationship to physical proximity.

4.1.2 Internal conference

Our system was also deployed at an internal marketing event for one day on April 13, 2011 in Beijing at the main meeting room of a conference hotel with 8 WiFi access points placed in various locations in the room. The marketing event was single track and divided into 19 activities. Users were encouraged to download and use the Find & Connect client throughout the event, where a total of 76 users downloaded and used the client. For the event, we relaxed the social linking to be one-way follow instead of two-way friendship to allow more users to feel comfortable in using the social features of our software. Here, users connect only with people that are registered and the follow recommendations are only within the participants. We record the exchanged contacts, followers, and encounter information for each user, similarly to the UIC/ATC 2010 conference.

4.2 Network Properties

We record the user's position every 10 seconds and calculate the encounters with our encounter algorithm every 5 minutes for both conferences. We study the friend network for the academic conference and the follow and exchange contacts network for the internal conference, as the social links. The social network properties for each network are listed in Table I. Users connect only with people that are registered and the friend/follow recommendations are only within the participants. The friend/follow network includes also friendship/followship that was established from the friend/follow recommendations.

Table 1. Properties of Physical Proximity and Social Linking Networks in Our System from the Academic and Internal Conferences

Property	Friend (acad.)	Enc. (acad.)	Follow (int.)	Contacts (int.)	Enc. (int.)
Nodes	59	83	72	41	70
Links	221	1000	123	51	592
Avg. degree	7.49	24.1	1.71	2.5	8.46
Density	0.13	0.29	0.02	0.06	0.25
Avg. shortest path length	2.12	1.69	2.78	2.62	2.02
Diameter	4	3	6	6	4
Avg. cluster coeff.	0.46	0.82	0.22	0.20	0.68

For the encounter network, the encounter distance threshold is 4 meters. We choose 4 meters because according to Hall [24], he observed that proxemic behavior is anything between 1.2 m and 3.6 m, so the maximum rounds up to 4. The encounter networks have higher density, greater average degree, smaller average shortest path, smaller diameter and higher average clustering coefficient than the social linking networks (friend, follow and exchanged contacts). Therefore, as expected, encounters form a highly tight and dense network compared with social links. From the average shortest path length, all the networks follow the social influence theory that every other person can be reached within 3 degrees of separation [12].

4.3 Correlation between Physical Proximity and Social Linking

We now address whether there exists a relationship between physical proximity and social linking. From the trials, we want to see whether having greater encounter duration with a user will increase the probability of creating a social link with that user (ie. becoming a friend with that user, following that user or having an exchanged contact with that user).

The time when the social links are created (when the friend, follow, or exchange contact request is sent), are recorded and used as the origin point (time 0) of the time axis, with 30 minutes as the unit interval.

4.3.1 Cumulative Average Total Encounter Duration

For each of the user encounter pairs from the friend, follow and exchanged contacts networks, we sum out their cumulative duration value of their encounters in discrete time intervals before and after their respective behaviors were committed, and then average them by the number of this type of user pairs, which results in the Cumulative Average Total Encounter Duration for any pair of users.

Academic conference. Figure 1 shows the cumulative total encounter duration averaged per pair of encountered users in the academic conference at each discrete time unit (30 minutes) before and after the time 0 point when the friend request was sent, with the encounter distance threshold ΔD of 4 meters and 10 meters. We choose 10 meters because of the following. As mentioned earlier since the positioning error in our positioning system is 5 m, the maximum encounter distance error could be 10 m, meaning the encounter distance could range from 0 to 14 m. From examining the distribution of the total number of encounters defined by different encounter distance thresholds in the academic conference, we discover that the maximum total number of encounters occurs at 10 m, and then the encounter numbers decrease with increasing threshold, therefore we select 10 m as the encounter distance threshold.

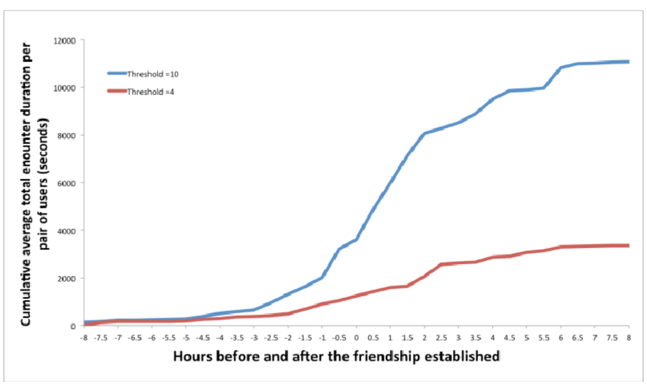

Figure 1. Cumulative average total encounter duration between any two users in the friend network in the academic conference

The distributions for encounter distance thresholds of 4 m and 10 m are similar and can be divided into four phases described below.

- *Phase I*. More than 2 hours before the friendship connection is established, the cumulative average total encounter duration is very small and rises very slowly. In the beginning, attendees do not know many people therefore there is no online social selection that occurs here.
- *Phase II*. Around 2 hours before the friend request is sent until time 0 when the friend request is sent, the cumulative average total encounter duration rises to be considerably large. As attendees begin to meet people, their encounters with that person increase as well as the encounter duration, thus causing attendees to know more about this person and add this person as a friend. Social selection on physical proximity in becoming friends is strong here.
- *Phase III*. Around 2 hours after the friend request has been sent, the cumulative average total encounter duration continues to rise but at a higher rate than before. After becoming friends, attendees want to know more about others' work so it is natural to continue to have more offline interactions, thus short-term social influence becomes strong.
- *Phase IV*. More than 2 hours after time 0 when the friend request is sent, the average cumulative total encounter duration continues to rise but the curve starts to stabilize and flatten out. The frequency of encounters are less and encounter durations are smaller, and since the social connection has been established, users spend less time being physically proximate to each other, causing long-term social influence to be weak.

The above behavior reflects the actual behavior of users at a conference where the intention is to meet more people. This agrees with our hypothesis (H1) that greater physical proximity encounter duration results in an increased probability for a person to add someone as a friend online. One may argue that these results are just a consequence of our friend recommendation algorithm which includes encounters as its feature [6]. However, it is up to the user to decide whether to add that person as a friend, therefore we just provide the awareness of encounters, which in our opinion do not influence the results. On the other hand, contrary to our original hypothesis (H2), after users have established a friendship, the probability of users being physically proximate to each other decreases. In addition, the cumulative average total encounter duration defined by a threshold of 10 meters is higher than the one defined by the threshold of 4 meters. This is because when we choose a bigger threshold value, more co-location will be included and this makes the total encounter duration longer.

Internal conference. Figure 2 shows the cumulative total encounter duration averaged per pair of encountered users in the internal conference at each discrete time unit (30 minutes) before and after the time 0 point when the friend request was sent, with the encounter distance threshold ΔD of 4 meters and 10 meters.

From the encounter defined by a threshold of 4 meters, we can see that exchanged contacts and follow have similar distribution, which can be divided into three phases described below.

- *Phase I*. More than 2 hours before any online social connection request (exchanged contacts or follow), the cumulative average total encounter duration is very small and rises very slowly.
- *Phase II*. Around 2 hours before the online social connection request until time 0 when the online social connection request is sent, the cumulative average total encounter duration rises sharply to be considerably large.

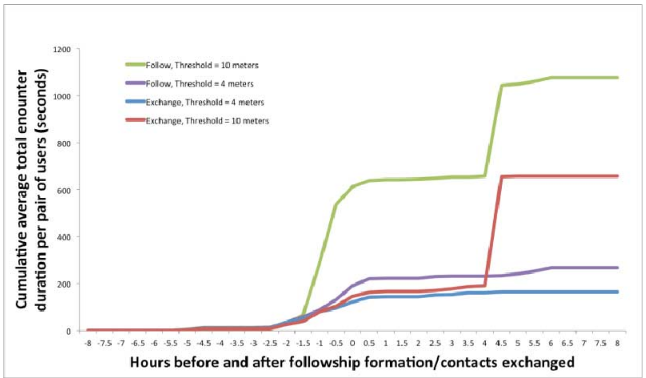

Figure 2. Cumulative average total encounter duration between any two users in the follow and exchanged contacts networks in the internal conference

- *Phase III*. After time 0 when the online social connection request is sent (exchanged contacts or follow), the average total encounter duration decreases which causes the cumulative average total encounter duration curve to stabilize and flatten out.

Since the trends are very similar to the academic conference, social selection on physical proximity in exchanged contacts and follow is also strong (Phase II), however social influence is weak (Phase III). This agrees with our hypothesis (H1) that more physical proximity encounter duration results in an increased probability for a person to follow another one, or exchange their contacts with. Again, similar to the academic conference, the results are not biased based on the follow recommendation algorithm which includes encounters. It is up to the user to decide whether to follow another person from the recommendation and the encounters are just used to make the user aware as to why she should follow this person. In addition, the follow requests that come from follow recommendations only account for 19% of the edges in the follow network. However, contrary to our original hypothesis (H2), after users have established an online social relationship, the probability of users being physically proximate to each other decreases. The reason for this behavior is similar to the academic conference results. If user X just wants to exchange contacts with user Y (get a business card of user Y), user X will spend less time in close proximity with user Y because once they have the business card, they have a means for contacting each other offline. However, people tend to follow others if they have spent more time in close proximity with them, therefore follow appears to be a much stronger link between users in a user pair than exchanged contacts.

However, this three-phase trend does not apply for those encounters defined by an encounter distance threshold of 10 meters, where there is a sharp rise in duration at around 4 hours after the social connection is established both for exchanged contacts and follow. We find that most follow and exchanged contacts activities occur shortly after the conference introduction, and the 4 hours corresponds to the one hour break during the internal conference where there was a demo session. As discussed previously, the choice of encounter distance threshold is important because too large of a threshold will include many co-locations into the encounter set. This perhaps can explain why the duration lines of encounters defined by threshold of 4 meters do not sharply rise around time point 4. Thus, we do not use a threshold of 10 meters in the next part of our analysis.

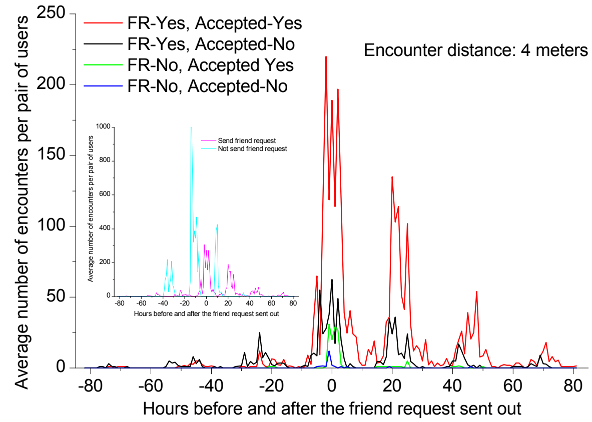

Figure 3. Average number of encounters per pair of users for manual friend requests and friend recommendations in the academic conference

4.3.2 *Average Encounter Frequency*

We now examine the average number of encounters per pair of users for each of the social linking types, to determine if users will encounter another person more often before, during and after the social linking type is established.

Academic conference. Figure 3 shows the graph for the effect of encounter frequency on friendship connection for the encounter distance threshold of 4 meters and for different types for establishing that friendship. *FR* indicates whether the friendship came from the friend recommendations and *accepted* indicates whether the recipient accepted the friend request. For encounter frequency and friendship connection establishment, we discover that there is an increasing number of encounters on average before the friend request is sent, and reaches its maximum at the time the friend request is sent and then dies off over time, as expected. We can also see that if a friend was recommended and the friend accepted the request, this results in the largest average number of encounters per pair of users. People that add friends from the friend recommendations will on average encounter their friends more than those that do not, thus demonstrating that social linking does indeed have an effect on the average number of encounters. Social selection on physical proximity appears to have a positive effect on the formation of online friendship. After establishing the friendship, the average encounter number per pair of users starts to decrease, showing that after people become friends they tend to encounter less than before.

Internal conference. Similar to the academic conference, aside from the duration of encounters, we also study the correlation between encounter frequency and online social connection establishment. We calculate the average number of encounters per user pair in discrete time intervals, before and after their respective behaviors are committed, for follow and exchanged contacts, and show this in Figure 4.

The results are similar to that of the academic conference, where social selection on physical proximity has a positive effect on the formation of online social connection, and social influence on physical proximity is weak after the connection is made. User pairs with followship have more encounters than user pairs with exchanged contacts, which agrees with the results from the cumulative average total encounter duration. As in the academic

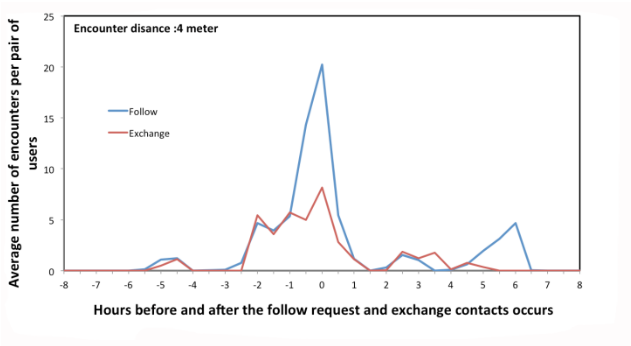

Figure 4. Average number of encounters per pair of users for Exchanged Contacts and Follow in the internal conference

conference, the average number of encounters per pair of users increases before the follow or exchanged contacts request is sent, then peaks at time 0 which is when the follow or exchanged contacts request is sent, and then gradually decreases. Therefore, physical proximity and friendship in our system are correlated in terms of both cumulative average total encounter duration and average encounter frequency.

5. CONCLUSION

In this paper, we presented work on examining the relationship between physical proximity and social linking. In particular, we investigated the roles of social selection and social influence in terms of physical proximity in the social linking formation process where social linking can be friendship, followship or exchanged contacts. Through defining encounters to measure the physical proximity interactions between people, we used our system deployed at two conferences (one academic and one internal) to analyze the distribution of cumulative encounter duration and encounter frequency averaged on per user pairs, for different types of user pairs. For the academic conference, we made a distinction between user pairs by considering whether they send out friend requests, where the friend request comes from (manual or friend recommendation) and whether the friend request is accepted or not (become friend or not). For the internal conference, we examined follow and exchanged contacts requests.

We discover that our first hypothesis is supported, that is, for social selection, more physical interactions will result in an increased probability for a person to add another as a social connection (friend, follower or exchanged contact). For the user pairs whose friend requests are from friend recommendations, generally there are more physical proximities than that for user pairs whose friend requests are manual, whether the friend request is accepted or not. However, our second hypothesis regarding social influence, that is, establishing these connections will result in an increased number of physical proximities between each other is not supported. After the social connections are made, more online social interactions result in a decreased duration and frequency of offline interactions between the connected users, therefore social influence is weak. Also, the results from the user study, survey and trial regarding user intent for adding social connections, demonstrate that offline interactions such as encounters can have an effect on whether a user wants to make a social connection with another person and helps to validate our previous claims.

The results need to be taken with a grain of salt, because as mentioned earlier, there could be some error in estimating the user's position in the conference due to the WiFi positioning inaccuracy, therefore this could cause spurious encounters that never occurred even though we recorded them. In addition, our dataset is much sparse compared to other online social networks and other proximity datasets that use GPS, Bluetooth or RFID (like the Live Social Semantics experiment [10]). Nonetheless, it is interesting to see how encounters might affect the decision for a user to add a friend, follower or exchange contact which the analysis demonstrates. For future work, we intend to collect longitudinal data from a longer time period to predict how repeated encounters at different venues predict social connection and how these social connections change over time, study the transitions between offline encounter interactions to online social connections and vice versa, in order to create a user behavior model, and create an algorithm for mining the encounters to discover encounter patterns for identifying groups of individuals that convene together to perform a particular type of activity at a specific point in time for a duration of time, which we call an ephemeral social network.

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