# Friend Recommendation Based on Mobile Crowdsensing in Social Networks

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***Abstract*—Online Social Network is booming with the development of the hardware and the popularity of the Internet in recent years. Users can invite friends through other users and become friends after consent of each other to share their living information. Here, crowdsensing is adopted by using Bluetooth Low Energy attached on mobile phones to collect proximity sensing information. The online social network data from users is extracted, such as expanding co-friend relationship, establishing a relationship chain through the interaction between friends. In this paper, a strategy is proposed to explore the co-friend's affinity incurring the relationship with common preferences for potential users. The friend recommended weighting strategy is derived to make a recommendation of friends among virtual and real communities. Moreover, the system is designed and implemented to realize in the actual environment and to analyze the data to prove the strategy which helps to find potential friends among users.**

***Keywords—Bluetooth Low Energy, Crowdsensing, Friend Recommendation, Online Social Networks, Proximity Sensing.***

## I. INTRODUCTION

Online social networking (OSN) has become a part of people's lives today [6]. The common friend recommendation strategy considers a variety of factors that may become friends to rank potential friends, and recommends users to become friends with friends who recommended. In Facebook, the number of mutual friends is the major consideration for providing a list of recommendations. The second consideration is whether the user joins the same Facebook community, interpersonal network relevance (such as school, college, or work experience), contact data, common interests, and so on.

The traditional friend recommendation system relies on the information obtained from online social network to recommend friends. Due to limited data, the accuracy rate is low and the interaction among people in real life is inadequate. Crowdsensing [2][3][12] is a proximity sensing technology used in mobile devices, such as mobile phones and wearable devices, that can sense and calculate, to analyze, estimate, or infer any content of interest. Here, the Bluetooth Low Energy (BLE) is used to collect data as a sensing technology.

In this paper, the friend recommendation strategy of crowdsensing integrated with online social network data is proposed. Users can discover potential users nearby, and then they with friendships become possible via the virtual contacts in a real environment. According to the Homophily Theory [1], everyone tends to like things similar to other users. The method proposed in this paper will calculate the common preference weights between users, analyze personal preferences from the behavior of users tracking and tracking fan page, and provide users with potential users who have the same preferences as themselves.

An Online Social Network Friend Recommendation-Crowdsensing strategy, named OSNFR-C for short, is proposed in this paper. OSNFR-C is in a cyberphysical environment as shown in Figure 1, where each person has his/her corresponding digital twin in the cyber social world. The crowdsensing-based data combined with the online social network data to acquire the friend recommendation weight for each potential user. According to the friend recommendation weights with the characteristics of the proximity friend's proximity perception and the number of the same interests explored, the potential friends could be explored and ranked. Furthermore, the system is designed and implemented. Finally, the experimental data is interviewed with the users, and the questionnaire is surveyed by users in the metric of Quality of Experience (QoE). By the reliability and validity analysis, the average opinion score, Mean Opinion Score (MOS), of each question was obtained. The major contribution of this paper is that the social sensing [9] can be realized in terms of OSNFR-C.

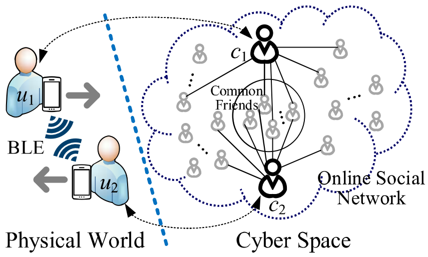


Fig. 1. OSNFR-C in a cyberphysical environment.

The rest of the paper is organized as follows. Section II presents the related work. In Section III, problem assumptions and statement are addressed. Section IV is to present the proposed method. Section V shows the system design and implementation. Experimental results are shown in Section VI. Finally, Section VII concludes this paper.

## II. RELATED WORK

The strategies of OSN friend recommendation are discussed in the cyber space [8]. The accuracy of recommending friends is not necessarily the same and each has its own advantages and disadvantages. They broadly divided the literature methods into three types: *Data Collection*, *Keyword Extraction*, and *Topic Finding*.

*Data Collection* refers to the method of data collection to estimate possible friends by analyzing the similarity to OSN user data. There are many other considerations such as locations [4][13], mobile device sensor [10], frequently viewed website [5]. *Keyword Extraction* refers to keyword analysis conducted by users in the OSN, and then recommends that users who discuss the same keyword to become potential friends, such as rule based [13] and learning based [4] methods. *Topic Finding* is to analyze user articles with Keyword Extraction, and then summarize the topic content of the discussion, and then recommend users who discuss the same topic to become friends. The main methods are LDA (Latent Dirichlet Allocation) model [4][10][14], in-degree and user based methods [6]. The proposed strategy here is similar to integration of data collection and topic finding categories, such as proximity sensing data collection, user friend affinity, and fan pages that users are interested in. The recommendation friend strategy research is combined with the social situation of physical world and cyber space.

Table I depicts the comparisons among several references using four kinds of features to propose recommendation strategy, common friends, common preferences, real environment, and proximity perception. The proposed strategy OSNFR-C here considers using proximity sensing features to capture the fate of passing.

TABLE I. CHARACTERISTICS COMPARISON OF RELATED WORK

| Reference | Common friends | Common likes | Physical Environment | Proximity Sensing |
|---|---|---|---|---|
| Chu, *et al.* [4] | ✓ | ✓ | ✓ | |
| Rashmi and Asha [5] | | ✓ | | |
| Tang, *et al.* [7] | ✓ | ✓ | | |
| Wang, *et al.* [10] | | ✓ | ✓ | |
| Yu, *et al.* [13] | | ✓ | ✓ | |
| Zheng, *et al.* [14] | | ✓ | | |
| OSNFR-C | ✓ | ✓ | ✓ | ✓ |

Note: ✓ refers that the proposed method has the corresponding characteristics.

## III. ASSUMPTIONS AND PROBLEM STATEMENT

In order to design a friend's recommended strategy algorithm, this paper needs to obtain certain permissions for users in experiments. Below are some assumptions in this paper:

1. Users agree to the program to obtain Facebook's post data, liked fan page and other permissions.
2. The user agrees to the program to obtain Bluetooth, network access, and Bluetooth program resident.
3. The user's mobile device has the capability of surfing the Internet.

To help users expand the social circle on the OSN, the strategy algorithm sorts all potential friends encountered by the proximity sensing in the way of friend recommendation weights, and provides user with a recommendation list to select new friends. It also indicates that the number of fan pages shared with potential friends related to the other party's relevant information such as gender, number of friends, most stable movement, closeness, and often encountered among potential friends. The friend's recommendation weight takes into account the close relationship between the user and the potential friend's mutual friend, the number of fan pages and the proximity perception record. The mutual friend affinity relationship indicates the two-step link between OSNs and reflects the six-degree separation theory of the small world phenomenon. The fan pages of the common praise symbolizes the degree of common interest with potential users, and the proximity perception represents the characteristics of potential friends who are very close to the user, often encounter, and are too far away.

The mass proximity sensing data comes from the Bluetooth sensing among users' smart device. In addition, information, such as Facebook user ID, are interchanged among them via Bluetooth low-power advertising and scanning functions. The set $U$ of users encountered for some user $M$ is defined after a period of collection by the smart device, $U = \{u_i | i = 1,2,\ldots,m\}$ where $m$ is the number of users encountered. A period of time window $w$ is defined to analyze the data of the period which is the time interval for the user to start collecting data to perform the friend recommendation function. After the friend recommendation function is performed, the data will be cleared and the proceeding data will be collected again.

For user $M$, the set $U$ of users is encountered within a period time $w$. The friend recommendation weight $Score_{u_i}$ for all users $u_i$ in $U$ is calculated as in Equation (1).

$$Score_{u_i} = \alpha_s \times Proximity_{u_i}^{score} + \beta_s \times CL_{u_i}^{score} + \gamma_s \times CF_{u_i}^{score},\ \ u_i \in U \quad (1)$$

where $\alpha_s + \beta_s + \gamma_s = 1, 0 \le \alpha_s, \beta_s, \gamma_s \le 1$, and

$$0 \le Proximity_{u_i}^{score}, CL_{u_i}^{score}, CF_{u_i}^{score} \le 1$$

$Score_{u_i}$ $0 \le Score_{u_i} \le 1$, composed of three parts is calculated by the ratios of $\alpha_s$, $\beta_s$, $\gamma_s$. The higher score indicates that the potential user $u_i$ is recommended to $M$. The first part is the proximity perception weight $Proximity_{u_i}^{score}$ representing the importance of proximity sensing. The higher the value indicates that $u_i$ is recommended to the user in the analysis of proximity perception $M$. The second and third parts are the weights in online social network. For $M$, the common preference weight $CL_{u_i}^{score}$ and, common friend weight $CF_{u_i}^{score}$ among $M$ and other users are calculated. The higher these two weights are, the similar interest and networking behavior between $u_i$ and $M$ are getting higher.

## IV. SOCIAL SENSING FRIEND RECOMMENDATION

In this section, we first introduce the strategy of proximity sensing weights, then describe the online community network weights, and finally combine them into recommend weights.

## A. Proxmity Sensing

In this section, we analyze the neighboring perceptual data used in this paper, and use statistical analysis methods and information entropy calculations to indicate closeness, stable situations and the amount of data that is often encountered. In terms of receiving signal strength, due to the weakening of the wireless signal, we use the Shannon formula to convert the received RSSI value $R_{u_i}$ into the social distance $D_{u_i}$ (in meters) and perform subsequent calculations as in Equation (2).

$$D_{u_i} = r_0 \times 10^{\frac{abs(R_{u_i})-A}{10*n}},\ \ u_i \in U \tag{2}$$

$r_0$ is the conversion magnification, here set to 1; $A$ set to 50 here is the absolute value of the RSSI value received when the two devices are one meter away. $n = 2.0$ is the environmental attenuation factor. $R_{u_i}$ is the RSSI value of $u_i$.

The Proximity Sensing Weight ($Proximity_{u_i}^{score}$) is determined by the distance variance weight $Var_{u_i}^{score}$, the information entropy weight $Entropy_{u_i}^{score}$ and the closeness weight $Closer_{u_i}^{score}$ in which the weights are normalized between 0 and 1, as in Equation (3). The higher the proximity perception weight indicates that *M* for $u_i$ has strong perception because $u_i$ is always nearby by *M*.

$$Proximity_{u_i}^{score} = \alpha_p \times Var_{u_i}^{score} + \beta_p \times Entropy_{u_i}^{score} + \gamma_p \times Closer_{u_i}^{score}, u_i \in U \tag{3}$$

where $\alpha_p + \beta_p + \gamma_p = 1, 0 \le \alpha_p, \beta_p, \gamma_p \le 1$, and

$$0 \le Var_{u_i}^{score}, Entropy_{u_i}^{score}, Closer_{u_i}^{score} \le 1$$

### 1) Distance Variance Weight

The signal received by a user $u_i$ in $U$ is converted to the distance variation $Var_{u_i}^{score}$ in the time of $w$. The higher the value indicates that the relative mobility of the user $u_i$ and $M$ is lower, that is, the distance is not too far, as in Equation (4).

$$Var_{u_i}^{score} = \begin{cases} 1, & if\ Var_{max} - Var_{min} = 0 \\ 1 - \frac{Var(D_{u_i}) - Var_{min}}{Var_{max} - Var_{min}}, & otherwise \end{cases},\ \ u_i \in U \tag{4}$$

where $Var(D_{u_i}) = E[(D_{u_i} - Avg_{u_i}^{D})^2],\ \ u_i \in U$,

$$Var_{max} = \max_{u_i \in U}\{Var(D_{u_i})\}, \text{ and } Var_{min} = \min_{u_i \in U}\{Var(D_{u_i})\}$$

$Var(D_{u_i})$ stands for the variation number of the signal received by the $u_i$ user in the time of $w$. $Var_{max}$ represents the maximum value of the distance variation of all other potential users in the $U$ set; $Var_{min}$ represents the minimum value of the distance variance. If $Var_{max}$ minus $Var_{min}$ is equal to 0, the distance variation of all potential users in the $U$ set is the same. At this time, set the value of $Var_{u_i}^{score}$ indicates the highest weight, otherwise it is expressed in inverse ratio after normalization. The higher the distance variability, the more unstable the distance variability $Var_{u_i}^{score}$ is lower, and the distance variability $Var_{u_i}^{score}$ value is larger, indicating that the signal of the user $u_i$ is higher stable.

### 2) Information Entropy Weight

For user $u_i$, the number of the frequency is multiplied by the information entropy ratio. The higher the information entropy weight $Entropy_{u_i}^{score}$, the more *M* often meet user $u_i$, as in Equation (5).

$$Entropy_{u_i}^{score} = \begin{cases} 1, & if\ p_{max}^e - p_{min}^e = 0 \\ \frac{p_{u_i}^e - p_{min}^e}{p_{max}^e - p_{min}^e}, & otherwise \end{cases},\ \ u_i \in U \tag{5}$$

where $p_{u_i}^e = \begin{cases} 1, & if\ Entropy = 0 \\ p_{u_i} * \frac{Entropy}{log_2(m)}, & otherwise \end{cases}$

$$p_{u_i} = \frac{|D_{u_i}|}{\sum_{i=1}^{m}|D_{u_i}|},\ \ u_i \in U$$

$$Entropy = -\sum_{i=1}^{m} p_{u_i} \times \log_2(p_{u_i}),\ \ u_i \in U$$

$$p_{max}^e = \max_{u_i \in U}\{p_{u_i}^e\}, \text{ and } p_{min}^e = \min_{u_i \in U}\{p_{u_i}^e\}$$

Here, $p_{u_i}$ represents the probability that the $u_i$ user appears within the period $w$, and $|D_{u_i}|$ represents the number of signals scanned by the $u_i$ user within $w$. The value of the information entropy *Entropy* will be between 0 and $log_2(m)$. The larger the value, the smaller the overall probability gap. If $Entropy$ is equal to 0, it means that there is only one user in the $U$ set, giving a maximum of 1. Otherwise, we divide the information entropy by the maximum information entropy $log_2(m)$ in a proportional way to obtain the proportion of the overall probability gap and multiply it by $p_{u_i}$ as $p_{u_i}^e$. The lower the ratio, the less probable the probability distribution. In this case, the probability values encountered are relatively small to reduce the information entropy weight difference of all users in the $U$ set. If $p_{max}^e$ minus $p_{min}^e$ is equal to 0, the user's $p_{u_i}^e$ in $U$ is consistent, giving the highest weight value of 1. Otherwise, normalization means that the information entropy weight of the $u_i$ user is $Entropy_{u_i}^{score}$, and the higher the information entropy weight, the more often it meets.

### 3) Closeness Weight

The closeness weight $Closer_{u_i}^{score}$ is defined as the distance average weight $Avg_{u_i}^{score}$ multiplied by the information entropy grading weight $EntropyRank_{u_i}^{score}$ as in Equation (6), both between 0 and 1. The close the overall average distance is to the user $M$, the higher the weight of the average value, and the more recommended the user. However, it is more difficult to compare the distribution of distances, so we classify the distances by far, moderate and near. The user information entropy grading weights of the closeness distance distribution will be higher, and the multiplication will reflect the overall closeness relationship between the user $u_i$ in the average distance and distance distribution.

$$Closer_{u_i}^{score} = Avg_{u_i}^{score} \times EntropyRank_{u_i}^{score},\ \ u_i \in U \tag{6}$$

where $0 \le Avg_{u_i}^{score}, EntropyRank_{u_i}^{score} \le 1$

#### a) Distance Average Weight

The average value $Avg_{u_i}^{score}$ of the distance of the encountered user $u_i$ is calculated. The higher the distance average weight is, the closeness of the average distance of user $u_i$ to $M$ is as in Equation (7).

$$Avg_{u_i}^{score} = \begin{cases} 1, & if\ Avg_{max} - Avg_{min} = 0 \\ 1 - \dfrac{Avg_{u_i}^{D} - Avg_{min}}{Avg_{max} - Avg_{min}}, & otherwise \end{cases}, \quad u_i \in U \qquad (7)$$

$$\text{where } Avg_{u_i}^{D} = \frac{\sum_{j=1}^{|D_{u_i}|} D_{u_i}^{j}}{|D_{u_i}|}, \quad u_i \in U$$

$$Avg_{max} = \max_{u_i \in U}\{Avg_{u_i}^{D}\}, \text{ and } Avg_{min} = \min_{u_i \in U}\{Avg_{u_i}^{D}\}$$

$Avg_{u_i}^{D}$ represents the average of the signal received by $u_i$ during $w$. $D_{u_i}^{j}$ is the time that the $j$-th scanned signal is converted to the distance $D_{u_i}$, and $|D_{u_i}|$ is the number of signals received within $w$. $Avg_{max}$ and $Avg_{min}$ represent the maximum and minimum values of the distance average of all users $u_i$, respectively. If $Avg_{max} - Avg_{min}$ is equal to 0, the average distance of users in $U$ is the same, and the maximum weight value is given to 1; otherwise it is represented by the inverse of the normalization operation. The larger the value of $Avg_{u_i}^{score}$, the closer the user $u_i$ is to $M$ in the average distance.

*b) Information Entropy Grading Weight*

The information entropy grading weight $EntropyRank_{u_i}^{score}$ is divided into the far, middle and near three levels. The information entropy weight $Far_{u_i}$, $Medium_{u_i}$, and $Near_{u_i}$ are calculated in individual intervals. Finally, the distribution ratios of $\alpha_r$, $\beta_r$ and $\gamma_r$ are integrated into information entropy grading weights. $\alpha_r$, $\beta_r$, $\gamma_r$ and information entropy weights are between 0 and 1. As in Equation (8), the closer the distance is, the larger the weight distribution is. The higher the information entropy grading weight value, the more the user $u_i$ meets the user $M$ in the nearer interval than the other users.

$$EntropyRank_{u_i}^{score} = \alpha_r \times Far_{u_i} + \beta_r \times Medium_{u_i} + \gamma_r \times Near_{u_i}, \quad u_i \in U \qquad (8)$$

$$\text{where } \alpha_r + \beta_r + \gamma_r = 1,\ 0 \le \alpha_r, \beta_r, \gamma_r \le 1, \text{ and}$$

$$0 \le Far_{u_i}, Medium_{u_i}, Near_{u_i} \le 1$$

The far, middle, and near grading calculations are as shown in Equation (9). $Var(D)$ takes the variance number of the overall distance data $D$. Then the standard deviation $\sigma$ of the overall distance data is made. The average distance $D_{avg}$ is added or subtracted as the far and near watershed in Equation (9) divides the overall distance data $D$ into three parts $D_{near}$, $D_{far}$, and $D_{medium}$.

$$D = \begin{cases} D_{near}, & if\ D \le D_{avg} - \sigma \\ D_{far}, & if\ D \ge D_{avg} + \sigma \\ D_{medium}, & otherwise \end{cases} \qquad (9)$$

$$\text{where } \sigma = \sqrt{Var(D)} \text{ and } Var(D) = E[(D - D_{avg})^2]$$

After classifying the three levels, the information entropy weights $Far_{u_i}$, $Med_{u_i}$ and $Near_{u_i}$ are calculated. Below derives the $Far_{u_i}$ only in Equation (10); the others $Med_{u_i}$ and $Near_{u_i}$ are the same derivation. The information entropy weight is calculated in the same way as in Equation (5) but one more judges whether the user $u_i$ is in the interval. If there is no user in the interval or the interval, the weight is 0. $p_{max}^{efar} - p_{min}^{efar}$ equals to 0 means that the probability of user encounter in the far interval is the same, $Far_{u_i}$ gives the maximum value 1, the middle and far interval and so on. Among them, $U_{far}$, $U_{med}$, and $U_{near}$ each represent a collection of users $u_i$ that are far away, moderate, and near, respectively. The probability that $p_{u_i}^{far}$, $p_{u_i}^{med}$, $p_{u_i}^{near}$ each represents the user $u_i$ of the three respective intervals. $Entropy_{far}$, $Entropy_{med}$, $Entropy_{near}$ each represents the respective information entropy of the three intervals.

$$Far_{u_i} = \begin{cases} 0, & if\ p_{u_i}^{far} = 0 \lor |U_{far}| = 0 \\ 1, & if\ p_{max}^{efar} - p_{min}^{efar} = 0 \\ \dfrac{p_{u_i}^{efar} - p_{min}^{efar}}{p_{max}^{efar} - p_{min}^{efar}}, & otherwise \end{cases}, \quad u_i \in U_{far} \subseteq U \qquad (10)$$

$$\text{where } p_{u_i}^{efar} = \begin{cases} 1, & if\ Entropy_{far} = 0 \\ p_{u_i}^{far} * \dfrac{Entropy_{far}}{\log_2(|U_{far}|)}, & otherwise \end{cases}, \quad u_i \in U_{far} \subseteq U$$

$$Entropy_{far} = -\sum_{i=1}^{|U_{far}|} p_{u_i}^{far} * \log_2(p_{u_i}^{far}), \quad u_i \in U_{far} \subseteq U$$

$$p_{max}^{efar} = \max_{u_i \in U_{far}}\{p_{u_i}^{efar}\}, \text{ and } p_{min}^{efar} = \min_{u_i \in U_{far}}\{p_{u_i}^{efar}\}, u_i \in U_{far} \subseteq U$$

## B. *Weighting on OSN*

In this section, we describe the online social networking weighting using Facebook's common favorite fan pages and mutual friend affinity as shown in Fig. 2.

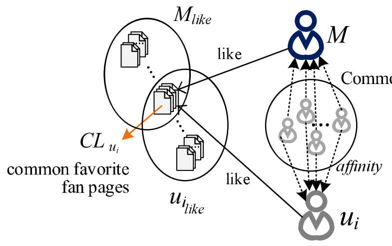


Fig. 2. OSN weighting relationship.

**Common Like Weight ($CL_{u_i}^{score}$):** At first, $CL_{u_i}$ stands for the common favorite fan pages among user $M$ and target $u_i$ where $M_{like}$ and $u_{i_{like}}$ represent their fan page collections, respectively. The common favorite weight $CL_{u_i}^{score}$ are expressed by Equation (11). $CL_{max} - CL_{min} = 0$ means that the number of fan pages shared by the users in the $U$ is the same, and the maximum weight value is given by 1. The greater the weight of the common preference, the more the same number of fan pages users $M$ and $u_i$ have, that is, the same interest as other users.

$$CL_{u_i}^{score} = \begin{cases} 1, & if\ CL_{max} - CL_{min} = 0 \\ \dfrac{|CL_{u_i}| - CL_{min}}{CL_{max} - CL_{min}}, & otherwise \end{cases}, \quad u_i \in U \qquad (11)$$

$$\text{where } CL_{u_i} = M_{like} \cap u_{i_{like}}, \quad u_i \in U$$

$$CL_{max} = \max_{u_i \in U}\{|CL_{u_i}|\}, \text{ and } CL_{min} = \min_{u_i \in U}\{|CL_{u_i}|\}$$

**Common Friend Weight** ($CF_{u_i}^{score}$) **:** A friend set $M_{friends}$ on the Facebook user's post for user $M$ is obtained firstly. The common friend weight $CF_{u_i}^{score}$ expressed in Equation (12) is to represent the importance for user $M$ to user $u_i$. The number of likes while user $A$ likes the posts for user $B$ is defined as $Affinity_{A,B}$. $A_{max}$ minus $A_{min}$ is equal to 0, indicating that the mutual friends in $U$ are intimately consistent, giving a maximum weight value of 1. The higher the weight of the mutual friend, the higher the affinity of the user $M$ and $u_i$.

$$CF_{u_i}^{score} = \begin{cases} 1, & if\ A_{max} - A_{min} = 0 \\ \dfrac{|A_{u_i}| - A_{min}}{A_{max} - A_{min}}, & otherwise \end{cases}, \quad u_i \in U \qquad (12)$$

$$\text{where } A_{u_i} = \sum_{k=1}^{|CF_{u_i}|} Affinity_{k,M} + Affinity_{k,u_i}, \quad u_i \in U$$

$$CF_{u_i} = M_{friends} \cap u_{i\,friends}, \quad u_i \in U$$

$$A_{max} = \max_{u_i \in U}\{|A_{u_i}|\}, \text{ and } A_{min} = \min_{u_i \in U}\{|A_{u_i}|\}$$

## V. System Design and Implementation

In this section, the system design and implementation are described. The overall system architecture is shown in Figure 3. The client application (Java program) is designed in mobile phones with Android 6.0 or higher version attached Bluetooth LE (BLE) version 4.0 or higher version. The mobile database uses SQLite to store user login information and scanned Bluetooth signals. The server program uses Node.js as the Web Service to receive the data uploaded by the mobile program, calculate the friend recommendation weight, and return the result to the mobile phone. The server database uses MongoDB in a non-relevant database (NoSQL) mode to store user Facebook data such as personal page links and Facebook API access tokens. The token is used to read the user's Facebook community information such as the fan page of the praise, and so on. In addition, the user history recommendation records are also stored, and the storage file format is in BSON.

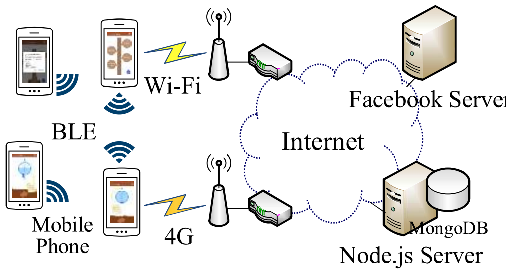


Fig. 3. System architecture.

Fig. 4. Design style of Look-for-Fate system.

The system is named "Look-for-Fate" and the design inspiration comes from a flowering tree of Chinese poet *Murong Xi* [11] as shown in Figure 4. This poem mentioned that in order to meet someone briefly, it turns itself into a tree and grows on the roadside where the person must pass. To looking forward to meeting him, we will make a tree theme, and design a fate image collector as shown in the upper left of Figure 4 as a symbolic container for receiving Bluetooth broadcast signals.

The fate collector (container) captures the incoming Bluetooth signal being converted from empty as in Figure 5(a) to half-full of water as in Figure 5(b). When the signal is received, the upper number shows the number of potential users encountered. The water is dripped down by the user clicking on the fate collector to cause the lower seed to germinate and grow into a tree as shown in Figure 5(c). The node, referred as a potential friend in the top has a high ranking to become a potential friend.

(a) (b) (c)

Fig. 5. Snapshots of Look-for-Fate APP.

## VI. Experimental Results

### A. Experimental Environment

Our field test considers the scope of proximity sensing and promotes programs in specific areas, requiring users to run programs for proximity sensing in the experimental area.

The main experimental area is at Main Campus and Rongyu Campus, National University of Tainan. 11 college and graduate students made an agreement to install and use the application in campus. Table II shows the field test parameters. Many weight ratio settings used in our experiments are depicted in Table III.

Table II. Experimental parameters

| Parameter | Value |
|---|---|
| $r_0$ | 1 |
| $A$ | 50 dbm |
| $n$ | 2 |

Table III. Weight ratios used in experiments

| Parameter | Value | Parameter | Value | Parameter | Value |
|---|---|---|---|---|---|
| $\alpha_r$ | 0.1 | $\alpha_p$ | 0.2 | $\alpha_s$ | 0.6 |
| $\beta_r$ | 0.3 | $\beta_p$ | 0.3 | $\beta_s$ | 0.3 |
| $\gamma_r$ | 0.6 | $\gamma_p$ | 0.5 | $\gamma_s$ | 0.1 |

## B. Experimental Analysis

A questionnaire is surveyed to explore the user's usage behaviors and comparisons between 'Look-for-Fate' and Facebook's "friends you may know" feature. The questionnaire uses the 5-point Likert scale to provide user-selected options. Data collection was conducted on the "Look-for-Fate" APP usage survey, Facebook's "You may know friends" feature survey, and basic data survey. The recovery rate of the questionnaire was 64%. After the partial analysis of the problem, the Clonbach's alpha was 0.854. The reliability of 0.8~0.9 is very good. The coefficient of this questionnaire is 0.854, which proves that the questionnaire has credibility.

To verify whether the user has successfully used the program, we investigated whether the user has successfully used a "look-for-fate collector to make the recommendation tree and "has successfully used the finder program to become a FB friend with potential users." In addition, about 43% of users have already used the Look-for-Fate search successfully and become friends with potential users.

In order to understand the user experience of using the program, the Mean Opinion Score (MOS) used in QoE is quantized for the survey. Users consider the factors that become friends, the function of finding a program, and the function of Facebook's "friends you may know" in the search function of Facebook. The MOS table related to the questionnaire results after the reliability and validity analysis is presented as follows.

Users generally believe that the recommended way of FB is recognized. In Table IV, compared to FB, MOS is 4.286, which means that most users like the recommended way for our designed system. In contrast, the MOS of FB is only 3.143. In terms of whether the recommended function is helpful to the user, MOS is 4.286, indicating that most users are helpful, and MOS of FB is only 3.429. It may be that the way FB's recommendation is adopted does not completely satisfy people requirements, and is only presented in a large number of recommended lists. Finally, in the use experience, the design of the search is easy to understand, so users generally agree that the use experience of the search is better than the recommended function of FB.

TABLE IV. MOS COMPARISONS BETWEEN LOOK-FOR-FATE AND FB

| Questions | MOS |
|---|---|
| I like the recommendation strategy of Look-for-Fate system. | 4.286 |
| I like the recommendation strategy of FB. | 3.143 |
| It is useful for me to use the recommendation of Look-for-Fate system to make friends. | 4.286 |
| It is useful for me to use FB recommendation to make friends. | 3.429 |
| I think the quality of experience of the Look-for-Fate system is better than that of FB. | 3.857 |

## VII. CONCLUSIONS

This paper has integrated the proximity sensing with the online community network including affinity among friends and common preferences to derive friend recommendation strategy for friend recommendation ranking. Using Bluetooth Low Energy broadcast and receive functions, a proximity-aware system is designed in considerations with proximity, stability, and frequent encounters to unknown friends. Finally, the experimental results showed that the method of this paper helps users to discover potential friends. To our 'Look-for-Fate' application, MOS is obviously superior to Facebook's recommendation. Users prefer our recommendation method to Facebook's "Friends you may know" feature, and users generally agree that our QoE is better than that of Facebook's recommendation scheme.

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