CircleSense: A Pervasive Computing System for Recognizing Social Activities

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Abstract—Social activities have great impact for human beings in psychological health and social relationship. The recognition of social activities can unobtrusively recognize and record users’ daily social activities, enabling users to better manage their life. Existing work of social activity recognition focus on recognizing a limited set of social activities and are mainly based on the patterns of individual user such as location pattern, vocal pattern, or others. However, social activities inherently exhibit the patterns with respect to multiple users rather individual user. In this paper, we introduce the concept of social circle, to extract social patterns associated with multiple users in a generic set of social activities. A social circle refers to a set of users frequently gathering to conduct certain social activities. Based on social circle, we design a system called CircleSense that supports accurate recognition of a generic set of social activities. We validate the effectiveness of CircleSense through the real trace collected by 10 volunteers. The result shows that CircleSense outperforms existing methods in terms of accuracy of social activity recognition.

Keywords-Pervasive computing; Social Activity Recognition; Social Circle;

I. INTRODUCTION

Social activities play a critical role in human’s well beings. The imbalance of human’s social activities may give rise to the problem of autism [1] and social relationship [2]. In this paper, we study the problem of recognizing social activities (e.g. meeting, seminar, religion service, dating, etc.) based on smartphones. The solution to the problem underpins the development of a variety of powerful pervasive computing applications. For example, recognition of social activity enables the automatic logs of users’ social activities, which can be used for the elderly to overcome cognitive decline [3] or delivering health intervention to motivate user behavior change [4]. Moreover, mobile applications like phone interruption management [5] can be augmented with the awareness of user’s current social activity to provide better service.

Prior Research has explored how to leverage the patterns of information obtained from various sensors in smartphone to perform activity recognition. Some work utilizes accelerometer or GPS to measure user’s locomotion state and then derive his/her physical activities based on locomotion pattern [6] [7]. Since social activities are more complex, which often involve mixed locomotion states, it is not adequate to simply use locomotion pattern for social activity recognition. Location pattern, which is attained by WiFi or GPS [8] [9], along with temporal pattern, have also been studied to infer certain kind of social activities. However, the aforementioned approaches only consider the patterns of an individual user, and thus it exhibits low accuracy when applied to social activities that inherently associate with multiple users.

In this paper, we develop techniques for recognizing social activities by introducing the concept of social circle, to extract social patterns with respect to multiple users in a generic set of social activities. A social circle is defined as a set of users frequently gathering to conduct certain social activities. This idea comes from the observation that a user’s social activities are often associated with the people he/she meets. As illustrated in Fig.1, a user normally encounters distinct set of people during different social activities, although some of the people may overlap among different sets. The social circle can be obtained by a user’s proximity information, which is captured using the Bluetooth module embedded a user’s smartphone to scan the nearby Bluetooth-enabled devices via collective sensing.

Based on social circle, we propose a system called CircleSense for social activity recognition. CircleSense first extracts social circle information from user’s proximity data and social circle is then used as the reference proximity information with respect to a social activity. In order to utilize proximity information, we need to classify it to the corresponding social circle correctly, so that the social activity can be recognized accordingly. However, a user’s proximity data with respect to the same social activities is quite dynamic and the proximity data across different social activities overlaps, making the accurate classification very challenging. In order to address the posed problem, we apply metric learning technique and design a fast gradient-based optimization algorithm to minimize the classification error. Furthermore, we incorporate temporal information to better differentiate social activities, by taking advantage of the temporal pattern of user’s social activities.

In summary, our paper has the following contributions: (1) We introduce the concept social circle to identify the social pattern with respect to a group of users. Compare with other patterns of individual user, social circle is more robust to characterize social activities; (2) Based on social circle, we propose a system called CircleSense that supports the accurate recognition of a generic categories of social activities; (3) We have evaluated the system with a 10-person dataset which is collected from deployed android phones, covering
seven kinds of social activities. The experimental results demonstrate that CircleSense outperforms existing methods with respect to accuracy of social activity recognition.

II. RELATED WORK

In general, existing phone-based activity recognition models can fall into three main categories: location-based model, motion-based model and hybrid model.

The location-based model attempts to infer the activity based on location pattern. In the Reality mining Project [8], Eagle et al. makes use of the GSM data obtained by mobile phones to determine users’ three simple activity states: home, work or elsewhere. Some researchers [9] propose the WiFi-based activity recognition model, using WiFi access points as location signatures to train the recognition model. However, the location-based model merely considers location and temporal patterns, but fails to recognize some activities that are held in unplanned and impromptu places.

Motion-based model focus on utilizing the locomotion pattern captured by accelerometer embedded in the mobile phone for activity recognition. In [7] [10], Emiliano et al. leverages the accelerometer data to infer users’ four simple physical activities: sitting, standing, walking or running. In the paper [11], the author targets a larger set of activities including walking, jogging, climbing stairs, sitting and standing. However, the method tends to capture coarse activities, which makes it difficult to recognize complex activities such as social activities with varying locomotion state.

Hybrid model make use of various sensors including GPS, microphone, accelerometer are used [12] to obtain location, vocal and locomotion pattern of user to recognize a set of activities. The activities are comprised of both simple activities such as walk, run, stationary and complex activities such as meeting, studying, exercising, socializing. Noticeably, their work only covers a small set of social activities such as meeting, studying, exercising, socializing.

In this paper, we targets at a generic set of social activities \( A = \{a_1, a_2, ..., a_n\} \), including meeting, seminar, classes, sports, religion service, dating, family time. We give our definition of social activity as follows.

Definition 1. A social activity is an event triggered by a set of users gathering on purpose and interacting in a place at some time.

We then formulate a social activity \( a_i \) for an individual user as \( a_i = (U_i, D_i) \), in which \( U_i = \{u_1, u_2, ..., u_m\} \) is the set of users who is involved in the activity, and \( D_i = \langle t^i_1, t^i_e \rangle \) is the time span of the activity starting at \( t^i_1 \) and ending at \( t^i_e \).

B. Social Circle

We take advantage of user’s proximity information to better characterize social activities. For a user \( u \), the proximity information is the list of the names of Bluetooth-modules in smartphones in proximity of his/her smartphone. Each user’s smartphone will be set with an unique name and the total set of users are represented as \( U = \{u_1, u_2, ..., u_m\} \) and the proximity information is represented in the format of \( f = [e_1, e_2, ..., e_m] \), where \( e_k \) represents the existence indicator of user \( u_k \), and \( e_k = 1 \) indicates user \( u_k \) has been detected, while \( e_k = 0 \) means user \( u_k \) did not appear during the data collection. Based on users’ proximity information, we can extract different social circles, which will be discussed in Session V. Social circle is defined as below:

Definition 2. A social circle of a user refers to a set of people of he encounters frequently in a social activity.

A social circle will serve as the reference proximity information of a social activity for the classification later.

C. Problem Formulation

Given a training dataset \( D = < U, A, F, T > \) collected from multiple users, in which a data record indicates a user \( u_i \in U \) is involved in a social activity \( a_i \in A \) at time \( t \in T \) and \( T \) means a set of time, while his/her proximity information is \( f \in F \) and \( F \) is the set of proximity information. We assume users bring their phones, indicating that when user \( u_i \)'s phone is detected, he/she is in the proximity. Our objective is to construct an accurate social activity recognition model through using the provided dataset, such that given a user’s proximity data at certain time, we are able to recognize the social activities that he/she is engaged in.
The system (see Figure 2) is composed of three components: data collection, offline training and online recognition.

In the data collection module, multiple users use their smartphones which deploy our system to collect the information including proximity information, time and the labeled social activities. Specifically, proximity information is obtained via scanning the nearby Bluetooth-enabled devices using the embedded Bluetooth module in smartphone. The collected data will be split into two parts, one part serves as training data and the other is used as testing data.

During the offline training module, the training data will be used to build the recognition model. Firstly, the data will be preprocessed into certain data format to facilitate the later process. Then social circle is extracted from the user’s proximity data and based on which, metric learning technique is applied to train social circle classifier. Besides, we utilize temporal information to further differentiate different social activities that are conducted by people belonging to the same social circle. Time is first segmented into different time slots and then a time classifier that associates time with social activities is trained. Finally, social circle classifier and time classifier are combined to construct the recognition model for online recognition.

In the online recognition process, the testing data is first preprocessed into certain data format and then act as the input for the recognition model. Finally, the recognized social activity of a user is outputted.

V. SOCIAL CIRCLE EXTRACTION AND CLASSIFICATION

A. Social Circle Extraction

We first focus on extracting the social circle from the training data. Social circle serves as the reference fingerprint of proximity information of a social activity. Firstly, we measure the degree of membership of a user with regard to a specific activity and then group of all users with high membership together as a social circle. A membership degree of user \( j \) to activity \( i \), denoted as \( r_{ji} \), is measured by frequency of attendance, which is computed as follows:

\[
r_{ji} = \frac{c(u_j,a_i)}{e(u_j)}, \forall u_j \in U, \forall a_i \in A\]

where \( c(u_j,a_i) \) is the number of records of activity \( a_i \) which involves user \( u_j \), while \( e(a_i) \) is the number of record of activity \( a_i \).

Then, a user is considered to be added to a social circle only if his/her membership degree to the associated activity is above a certain threshold. For a social circle \( c_i \), it can be obtained by: \( c_i = \{ u_j | r_{ji} > \beta, \forall u_j \in U \} \). The setting of threshold \( \beta \) will be discussed in the evaluation part.

B. Feature-Weighted Classification Problem Formulation

In order to classify the proximity data, we first choose cosine similarity [13] as distance measurement between proximity data and the reference fingerprint that is the social circle. Because the distance measured by cosine similarity is always within the range \([-1, 1]\), leading to a simple and effective objective function for problem formulation. The distance between data \( x \) and reference social circle \( y \) based on cosine similarity with transformation matrix \( W \) is denoted as:

\[
r(x, y, W) = 1 - \frac{(Wx)^T(Wy)}{\|Wx\|\|Wy\|}.\]

Dynamic property and overlapping property of user’s proximity data samples makes the data of the same social activities quite different and the data of different activities similar to each other, and thus causing classification error. Regarding the properties of the data, we apply the metric learning method to train the classifier. The key idea of metric learning [13] is learn a transformation matrix to make the data records of the same activities more similar while making the data records of different activities more distinguished.

The problem can be formalized as below: given a training dataset \( D_f = < U, A, F > \). The proximity data records of social activity \( a_i \) are denoted as \( F^i = \{ f_{j1}, f_{j2}, ..., f_{jN} \} \) and the corresponding social circle is represented as \( c_i, C = [c_1, c_2, ..., c_n] \) is the total set of social circles. \( W \) is the diagonal transformation matrix which we aim at training. The objective is to maximizing the classification accuracy by maximizing the margin [14]. Margin of a data record \( f_{ji} \) means the distance between \( f_{ji} \) and the nearest social circle \( c_j (j \neq i) \) minus the distance between \( f_{ji} \) and the corresponding social circle \( c_i \). The objective function is formulated as:

\[
\max \sum_{\forall f_{ji} \in F^i, F^j \in D_f} (D(c_{ne}, f_{ji}, W) - D(c_i, f_{ji}, W))
\]

s.t. \( \forall i \neq j, W_{ij} = 0 \)

where \( D(c_{ne}, f_{ji}, W) = \min_{k \neq j} D(c_k, f_{ji}, W) \) means the distance of \( f_{ji} \) to the nearest reference social circle of different social activity and \( D(c_i, f_{ji}, W) \) denotes the distance to corresponding social circle.

C. Social Circle Classification Algorithm Design

Since we use cosine similarity as the distance measure, we can compute the gradient of the formulated optimization problem.

The gradient of objective function is represented as:

\[
\nabla f(W) = \sum_{\forall f_{ji} \in F^i, F^j \in D_f} \left( \frac{\partial D(c_{ne}, f_{ji}, W)}{\partial W} - \frac{\partial D(c_i, f_{ji}, W)}{\partial W} \right).
\]

202
In order to compute the gradient of the objective function, without loss of generality, we redefine \( D(x, y, W) = \frac{u(W)}{v(W)} \), then we have \( \frac{\partial D(x, y, W)}{\partial W} = \frac{1}{v(W)} \frac{\partial u(W)}{\partial W} - \frac{u(W)}{v(W)^2} \frac{\partial v(W)}{\partial W} \). We further obtain \( \frac{\partial u(W)}{\partial W} = W(x^T - W^\top v) \) and \( \frac{\partial v(W)}{\partial W} = \sqrt{x^T W^T W x + W^T v v^T} \). Based on the computing gradient of the objective function, we can obtain the optimal result in a fast manner.

D. Social Circle Recognition

Given the detected proximity information \( f \), \( c_i \) is estimated to be the corresponding social circle only if \( c_i \) has the minimum distance to \( f \) among all the social circles. The decision rule for social circle recognition is formalized below:

\[
c_i = \begin{cases} \arg\min_{c_i} D(c_i, f, W) & \text{if } D(c_i, f, W) < \varepsilon \\ \text{Unknown otherwise} \end{cases} \tag{1}
\]

where \( \varepsilon \) denotes the distance threshold for decision. When the minimum distance is above the threshold, it would be treated as noise and discarded to reduce the recognition error. We will analyze the setting \( \varepsilon \) in the evaluation session.

VI. TEMPORAL INFORMATION CLASSIFIER

For a social circle, they can be involved in not necessarily one social activity. A motivating example would be on Wednesday from 9 a.m. to 10 a.m., a user engages in team meeting with colleagues while being found to play basketball with colleagues on Friday afternoon. Therefore, we attempt to leverage the temporal information to recognize users’s social activities. The underlying assumption in our use of temporal information is that the time when a user conducts specific social activities exhibit a consistent pattern.

A. Time Segmentation

Before we train the time classifier, we first segment the time and then associate it with social activities. In particular, we segment a day in the week into 24 time slots and each time slot has a 30-minutes period. It starts as time slot 0 at first hour of Sunday to time slot 335 at the final hour of Saturday. Then the conditional probability of \( a_i \), given detected circle \( c_k \) at time slot \( t_k \), can be calculated by using the Bayesian Theorm as follows:

\[
P(t_k | a_i) = \frac{P(c_k | a_i)}{c(a_i)}
\]

where \( P(c_k | a_i) \) is denoted as the number of data record of activity \( a_i \) that is conducted by people in social circle \( c_k \).

B. Addictive Smoothing Technique

Some of the activities may be conducted in a dynamic time slot. Therefore, the probability \( P(t_k | a_i) \) will be 0 if it occurs in a time slot different from before. As a consequence, it cancels out the effect of social circle classifier and thus increasing the false negative rate. To avoid this scenario and better make use of temporal information, we apply the additive smoothing technologies [15] to refine the equation. So we have:

\[
\int P(t_k | a_i) = \frac{P(c_k | a_i)}{c(a_i) + 1}
\]

where \( \mu \) will be set as the number of total number of time slots. Adding \( \mu \) means we consider all the possible time slots in the calculation.

With the refinement, we will hold \( P(t_k | a_i) \neq 0 \) for all \( t_k \).

VII. SOCIAL ACTIVITY RECOGNITION MODEL

We present the overall concept of the social circle recognition in this section. First, we determine the social circle of the user and then deduce the activity by considering the temporal feature.

After the extraction of both corresponding social circles and time slot, naive bayesian classifier is explored to merge social circle and time features to derive the social activity. We have:

\[
P(a_i | c_k, t_k) = P(c_k | a_i) P(t_k | a_i) P(a_i)
\]

Then we assume social circle and time are conditionally independent with respect to social activity. So that we obtain:

\[
P(c_k, t_k | a_i) = P(c_k | a_i) P(t_k | a_i) P(a_i)
\]

Finally, the activity will be derived based on maximum a posteriori decision rule:

\[
a = \arg\max_{a_i} P(c_k | a_i) P(t_k | a_i) P(a_i) \tag{2}
\]

where \( P(c_k | a_i) \) could be computed by following equation:

\[
P(c_k | a_i) = \frac{c_k(a_i)}{c(a_i)}
\]

and \( c_k(a_i) \) is denoted as the number of data record of activity \( a_i \) that is conducted by people in social circle \( c_k \).

VIII. EVALUATION

A. Experiment Setup

1) Datasets: In order to evaluate our proposed method, we collect the annotate users’ social activities trace by ourselves. Our dataset, as shown in Table I, covers four aspect of social activity: work, play, develop and connect. We develop the prototype software to collect Wi-Fi access points and nearby Bluetooth-enabled devices are filtered from the proximity information based on a mix of 2.3 and 4.0 versions. The data record is in a format of prototype software to collect Wi-Fi access points and nearby Bluetooth-enabled devices are filtered from the proximity information based on a mix of 2.3 and 4.0 versions. The data record is in a format of.

<table>
<thead>
<tr>
<th>Category</th>
<th>Specific activities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Work</td>
<td>Meeting, Research meeting, Report meeting, Seminar, Networking seminar, Bioinformatics seminar</td>
</tr>
<tr>
<td>Play</td>
<td>Sports, Frisbee, Basketball</td>
</tr>
<tr>
<td>Develop</td>
<td>Classes, Mobile computing, Research Ethics, etc.</td>
</tr>
<tr>
<td>Connect</td>
<td>Family time, Worship, Scripture Sharing, Lunch Gathering</td>
</tr>
</tbody>
</table>

We have collected two datasets. The first dataset is contributed by seven people from May to June, 2012. Three
of them are undergraduates, three are graduate students and one is a company employee. The data is recorded in half hour interval. In some case when some indoor places experiment subjects visit do not have WiFi access points or the nearby users does not open their Bluetooth-modules, the experimental subjects will record the nearby users’ names and the location directly. The second one is collected from 4 research students in Computing Department of PolyU in a 10-minute period for two weeks. Each of these students are distributed one deployed Android-based smartphone and the rest 5 lab colleagues are equipped with smartphones that open the embedded Bluetooth Modules periodically.

2) Methodologies: We examine our proposed methods based on supervised experiment and compare them with the baseline approaches which are implemented in the open source machine learning software Weka 3.6 [16]. In order to evaluate the recognition performance, we use Leave-one-out validation technique. We first split the collected dataset into two subsets based on the time-stamp. The first subset serves as the training set and the second subset is used as test set. The data amount percentage split for the training set will be set as 30%, 50% and 70% respectively. In order to measure the performance, we use three widely used evaluation metrics: precision, recall and F-measure.

3) Benchmarks: In order to demonstrate the effectiveness of the proposed methods, we compare the performance of proposed methods against a set of benchmarks. The benchmarks of social circle classification includes the popular classifier approaches widely adopted in activity recognition such as Naive Bayes, kNN and Support Vector Machine. The benchmarks of social activity recognition contain the conventional time-based, location-based, location and time-based approaches.

B. Performance

1) Classifier Performance: The objective of this experiment is to compare the proposed metric learning method for social circle classification against the conventional classification techniques including kNN, naive bayes and sector support machine. As illustrated in Figure 3.(a) and 3.(d), the metric learning method outperforms the other three baseline methods given a different training data amount. On average, the proposed method achieve a 17% higher precision rate and a 5% higher recall rate. Furthermore, it can be observed that, given a comparatively small amount (30%) of training data, the metric learning approach is able to achieve a quite high precision rate (90%), and thus lowering the burden of humans for providing labeled data.

2) Impact of parameter settings: This session aims at analyzing the impact of parameter β and ε to the system performance. The first experiment is to figure out the impact of parameter β for the accuracy of the social circle classification. Parameter β is the threshold of membership degree to determine whether a user should be considered as a member of a social circle. As seen in Figure 3.(b), when the training data amount is 30%, the optimal value of β is 0.5. If the value of β is set above 0.5, some users will be excluded from some social circles and thus the extracted social circles are inadequate to be the reference of the corresponding social activities. As a consequence, the classification accuracy will degrade. When the training data amount is 50%, we found that setting of β will not impact the classification accuracy. It is because when the amount of training data is considerable, the measurement of the membership degree of users are in line with the actual measurement with all the data.

The second experiment is to analyze the impact of parameter ε. Parameter ε is the threshold of distance measurement for decision making in social circle classification. Figure 3.(e) illustrates that the optimal value ε is 0.63 when the training data amount is 30%. The optimal value ε should be set to 0.65 given 50% amount of training data. When the parameter ε is set higher than the optimal value, many scenarios other than social activities will be mistakenly recognized as some social activities. Consequently, it will lead to a high false positive rate and degrade the precision. When the parameter ε is set lower than the optimal value, some occurring social activities would be treated as noise and falsely discarded, resulting in higher false negative rate and lower recall.

3) Recognition Performance: The objective of this experiment is to evaluate the recognition performance of the CircleSense method and other benchmarks using the collected dataset. We split the data based on time frame into two parts with equal amount. As illustrated in Figure 3.(c) and 3.(f), the proposed method is able to improve the performance against the second best by 15% in precision and 20% in recall and 18% in F-measure (see Table 3.).

From the evaluation, it is noted that location or time based approaches are effective most of the time in identifying some routine activities, while it is still unable to recognize the impromptu activities such as make-up classes or dating. Different from the baseline approaches, the proposed CircleSense method is able to recognize social activities more accurately.
IX. CONCLUSION

In this paper, we investigated the problem of social activity recognition based on patterns of multiple users. We first introduce the concept of social circle, which acts as a pattern of social activity. Based on the social circle, we develop a system called CircleSense for recognizing a generic set of social activities. The system utilizes the metric learning technique to train a classification model for social activity recognition. Finally, CircleSense is evaluated with the real trace contributed by 10 volunteers. The result demonstrates that CircleSense achieves higher accuracy than baseline methods in recognizing a variety of social activities.

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