Interactive Group Recognition Based on Mobile Phones

Jiaojiao Chen, Weiping Zhu*, Lin Xu, Zeyu Zhang and Yan Gu
International School of Software, Wuhan University, P. R. China
Email: jiaojiaochen@whu.edu.cn, wpzhu@whu.edu.cn
cathyxl_2013@whu.edu.cn, zhangzeyu@whu.edu.cn, billgoowhu@163.com

***Abstract*—People often participate in activities in groups, such as buying goods in a shopping mall, watching a show in a museum, and walking around in a public park. In the latest decade, recognizing people groups attracts great interests from both the industry and the academia. Interactive groups refer to the groups having intensive interactions such as shake hands, hook shoulder, put arm in arm and so on, which is not uncommon in our daily life. Existing group recognition approaches are based on the similarity of individuals' locations and actions; the interactions among people are regarded as not similar hence deteriorating the accuracy of group recognition. In this paper, we propose a Group Behavior Affiliation method called GBA for interactive group recognition. The acceleration data in mobile phones is collected and the behaviors of individuals are inferred based on the data. The disparity between two individuals is obtained by calculating the difference of their sequences of behaviors. Compared with DBAD and signal correlation algorithms, the average group affiliation accuracy of GBA can be improved at least by 7.6% and 11.05% based on the disparity of each pair of individuals. We further recognize the groups using majority voting-based method, our experimental results show that the average accuracy of the method can reach 98.8% when people's walking accounts for no more than 90% of the total execution time.**

***Index Terms*—interactive group; mobile phones; group recognition; GBA**

I. Introduction

Group recognition is to get the division of objects present in a spatial area such as shopping mall, museum, subway station, the library and so on. In daily life, about 70% of the time we spent with other people in public areas [1]. Therefore, the analysis of group recognition is of great significance.

Existing group recognition approaches are based on the similarity of individuals' locations and actions; the interactions among people is regarded as not similar hence deteriorating the accuracy of group recognition. In the real life, objects within one group not always follow the same pattern of movement, they are not just walking together in one direction, and keep almost same walking speed. There will be various kinds of interactions, verbal and non-verbal [2]. Therefore in the process of group recognition, join the interaction analysis is more applicable. Our goal is to identify the groups with interactions in the indoor environment through the mobile phones.

According to the figures [3], to 2016 smart phone users have reached 4.3 billion, accounting for 58.7 percent of the global population, by 2020, the number of smart phone users will reach to 4.78 billion. According to Strategy Analytics report [4], by the end of the third quarter of 2016, the global smart phone shipments were 375 million, of which 87.5% was the Android phone. At the same time sensor types in mobile devices are becoming richer, which have attracted great interests from both the industry and the academia to recognize people groups through the sensors in mobile phones.

At present, identifying the groups through the sensors of the mobile devices is based on the similarity of individuals' locations and actions [5],[6],[7], that is, members in the same group have similar physical behavior because group members often perform activities together, adopt behavioral norms of the group. Cross correlation analysis of a given time window of sensor data [5] or using the divergence of sensor data distributions as an indicator of similarity[6],[7] are the common used methods. In order to recognize interactive groups, we need to solve the following problems, because of the interaction, the acceleration orientation and positions of objects within the same group is not similar, thus we propose an algorithm called Group Behavior Affiliation (GBA) to recognize groups with interactions. The acceleration data in mobile phones is collected and the behaviors of individuals are inferred based on the data. The disparity between two individuals is obtained by calculating the difference of their sequences of behaviors. Compared with the exiting two algorithms, when using threshold iteration, the average group affiliation accuracy of GBA can be improved by 7.6% than DBAD and 11.05% than CC; when using joint density-based clustering, the group affiliation accuracy of GBA can be improved by 16.95% than DBAD and 36.68% than CC. We further recognize the groups using majority voting-based method, the average accuracy of three different classifiers: SVM, Random Forest and KNN are 97.2%, 100% and 100% respectively, compared with the 93.4% of DBAD and the 73.3% of CC. At the last part of the paper, we discuss the scope of our algorithm. The experimental results show that

*Corresponding Author. Email: wpzhu@whu.edu.cn

the average accuracy of the method can reach 98.8% when people's walking accounts for no more than 90% of the total execution time.

The rest of the paper is organized as follows: Section II reviews the related works; Section III describes the system models used in this paper. Our solution is illustrated in Section IV. The results for the proposed algorithm are reported in Section V. Section VI concludes the paper.

II. Related Works

At present, the research of group recognition can be divided into the following aspects: one is to calculate the signal correlation between the objects to determine the similarity. In [8] pointed that one can get better group affiliation results by calculating cross correlation of average or variance of the acceleration data rather than the original data. In [5], by calculating the cross correlation of the acceleration variance data to get the affiliation between objects, and proposed to predict individual behavior based on the parameters of the known behavior prototype. Calculate the variance of the acceleration[9],[10] to decide whether the objects are moving together. In [9], the changing time series of the objects moving orientation is obtained by making the orientation data into windows, and calculate the the cross correlation of the change value. The second is using the divergence of mobile phone sensor data distributions as an indicator of similarity [6],[7].

In [6],[8],[11], a uniform type of wearable sensor is fixed at the same location of all the objects to obtain the acceleration and orientation data. In [2] considered the vision based recognition of crow movement, but such method has limitation of placing cameras to get a proper view of the whole objects, while the privacy concern will be involved at the same time. In [12],[13], detect outdoor people groups from noisy urban GPS positions. However, most humans spent most of their day time indoor and many applications require indoor group recognition. The accuracy of GPS positions will be greatly affected in the case of obstacles, indoors or objects are close to each other. In [14] using the WIFI signal strength information to obtain spatial information to identify the groups appeared in the closed area using density clustering. The accuracy of spatial information will depends on the density of WIFI access points. In [15],[16], using the probability distribution of the received Bluetooth signal strength to predict the relative distance between objects. Objects are considered in a group when the distance between them is less than a certain threshold. In [9],[10],[17],[18], various data sources such as wireless data, kinds of sensor data, position data are used to recognize the groups. We proposed to recognize the interactive group only use the acceleration sensor embedded in smart phones. There are no restrictions of the infrastructure and environment and don't need to consider the fusion of different data, which can be used more widely.

III. System Model

In this section, we introduce the system models used in this paper.

A. Definition of Interaction Behavior

In this paper, we select several common interactions, such as wave hands, shake hands, hug, arm-in-arm, hook shoulder, walk, run, sit down, stand up and stay still.

B. Application Model

We assume that there is a larger spatial space, such as shopping malls, museums, subway station, etc. All objects equipped with Android phones and data acquisition application is installed on the phones, the acceleration data will be collected and sent to the server. Objects hold the mobile phones in hands, assuming that all objects are within the scope of the communication. During an experiment objects in one group will arm-in-arm or hook shoulder with each other, when they encounter obstructions or through narrow passages, they will stop the interactions. The interactions of a group are not exactly the same, some objects will stay away from the others and do different interactions, which is very common in daily life.

IV. The Solution

A. Process of Interaction Recognition

When collecting the sensor data, there are 4 persons holding android mobile phones and doing interactions: wave hands, shake hands, hug, arm-in-arm, hold shoulder, walk, run, sit down, stand up and stay still. Each interaction repeats for 3 minutes. Most of sensor-based behavior recognition research use sliding window while processing sensor data. Our chosen window size is two seconds and the overlap time is one second [19],[20]. Setting the overlapping area of adjacent sliding windows to half a windows size has been proved successful [21]. We select time domain and frequency domain features as eigenvalues [22]. In each window, features are extracted from the three axes of the acceleration and their resultant acceleration. Time domain features are mean value, standard deviation, maximum and minimum value. Frequency domain features are mean value, standard deviation, skewness and kurtosis [23],[24] obtained by Fast Fourier Transformation. So there are a total of 32 features extracted from one window and these features are processed into a single sample.

We use SVM [25], Random Forest [26], Decision Tree [27], KNN [27] respectively for training and testing samples gained from acceleration. When SVM is used, we choose the optimal parameter c and g by traversing all the values. As to other classifiers we use its default parameters of the package. To compare the accuracy of different classifiers, the training set and testing set for all classifiers remain the same. For each classifier, 10-fold cross-validation is used. Each interaction sample is divided into training set(80%) and testing set(20%). Detail results are shown in TABLE I. We can learn that for

TABLE I
ACCURACY OF EACH INTERACTION OF DIFFERENT CLASSIFIERS (100%)

Interactive Behavior	SVM	RF	KNN	DT
Wave hands	100	100	100	100
Shake Hand	96.5	94.32	97.37	89.51
Hug	97.97	95.94	93.91	85.81
Arm-in-Arm	92.69	87.67	94.06	85.84
Hold Shoulder	96.73	94.02	94.83	89.4
Walk	95.17	91.72	91.03	86.89
Run	100	100	100	96.29
Sit Down	96.29	87.65	87.65	81.48
Stand Up	92.3	93.4	97.8	93.4
Stay Still	98.92	98.92	99.46	98.38
Average Accuracy	96.67	94.52	95.88	90.86

our data set, the average accuracy of SVM, Random Forest and KNN can reach to 94% or even higher, so in the following experiments, we use these three classifiers to infer unknown interactions.

B. Behavior Sequence Window Partition

In the above, we propose a sliding window size for interaction recognition. To determine the affiliation among the objects, we also need to divide the behavior sequence into windows. If no special statement is made, the window size mentioned in the following paper is the window size of group affiliation.

Given a windowing function W(C, WINLEN) where C is the behavior sequence, WINLEN is the time interval. We compute the difference of behavior sequence C_A and C_B within the same time interval. The experiment result shows that when WINLEN is 15s can get higher group recognition accuracy.

C. Compute the Disparity Matrix

The disparity value computed from behavior sequences in a given window can reflect the similarity between two persons. The more similar of two objects behavior sequences, the more likely they belong to the same group. Here we use Edit Distance [28] to compute the disparity value. Edit Distance is a way of quantifying how dissimilar two strings are to one another by counting the minimum number of operations required to transform one string to the other. In general, the shorter the Edit Distance is, the more similar of behavior sequences. At a given window t, the behavior disparity of A and B is $M_{AB}^t = ED(C_A^t, C_B^t)$

Applying a low-pass filter to smooth behavior disparity over time [5],[6]. Parameter b denotes filter length. The behavior disparity value in current window t is the average value of b windows ahead of t and b windows after t and t.

$$\overline{M_{AB}^t} = \frac{1}{2b+1} \sum_{\tau=-b}^{b} M_{AB}^{t+\tau}$$

D. Group Affiliation Analysis

There are two ways to determine the affiliation of A and B according to the disparity matrix. One is setting threshold ϕ [6],[7]. If $\overline{M_{AB}^t} \leqslant \phi$ then $v_{AB}^t = 1$ that is at window t, object A and object B are considered within the same group, and if $\overline{M_{AB}^t} > \phi$ then $v_{AB}^t = 0$, that is at window t, object A and object B are considered not within the same group. The optimal value used for ϕ is dependent on the physical activity of the object. For practical purposes, the threshold can be experimentally obtained by maximizing the accuracy [6]. The other is to apply a joint density-based clustering algorithm based on the disparity matrix [7],[14],[9], and then get the affiliation of objects in this window.

E. Exiting Group Recognition Methods

After getting group affiliation of a given window, the methods of obtaining groups are as follows: In [7] determine the final groups when the grouping results are stable, i.e., groups remain for at least five group identification time windows. In [14], [9] temporal clustering is performed to combine highly similar clusters that existing for several successive time steps to get the groups.

The basic idea of these methods is that: A group is defined the number of its members stays unchanged within a period of time. In no interactive condition, this method perform well. Because in this condition, members in a group stay relative close to each other and have similar tendency of motion. In interactive condition, however, members in a group do not always stay close in an area and some of them may take activities separately. There are very often that one group or part objects of a group follow other groups, objects in one group perform different interactions. Experimental results show that the grouping results of consecutive identification windows are basically inconsistent under the interactive condition.

F. Majority Voting-Based Group Recognition

We use majority voting-based group recognition to solve the problem. The basic idea of this method is: If two objects are classified into the same group most of the experiment time, then we can regard them as one group. This method does not require consistency of grouping result in consecutive identification windows, which can avoid the demerit of the method mentioned above.

Given the number of total identification windows is NUMWIN, and $GWIN_{AB}$ denotes the number of windows in which person A and B are classified into the same group, if $GWIN_{AB} \geqslant \alpha*$NUMWIN, then we consider A and B are in the same group and set the affiliation matrix $v_{AB} = 1$; Otherwise, $v_{AB} = 0$. We eventually compute the accuracy on the final affiliation matrix. α is a constant that can set different values for different experimental environment. We set $\alpha = 0.7$ in our experiment.

The accuracy of group recognition is computed as follows: Suppose that the number of person A and person B who are

TABLE II
GROUP CONFIGURATIONS OF EXPERIMENTS

Exp No.	Group Members
Exp.1	{1,2,3,4,5} {6,7,8,9,10,11}
Exp.2	{1,2,3,4} {5,6,7,8} {9,10,11}
Exp.3	{1,2}{3,4} {5,6,7} {8,9,10,11}
Exp.4	{1,2,3,4} {5,6,7,8} {9,10,11}

TABLE III
GROUP RECOGNITION ACCURACY OF EACH CLASSIFIER(100%)

Classifiers	SVM	RF	KNN
Exp.1	1	1	1
Exp.2	0.972	1	1
Exp.3	1	1	1
Exp.4	0.916	1	1

classified into one group are actually in the same group is TP. The number of persons classified into different groups who are actually not in the same group is TN. And the number of possible affiliation of all objects is Q. Then the accuracy of group recognition is (TP + TN) / Q.

V. EXPERIMENT EVALUATION

A. Experimental Scene Design

The experiments were conducted in the laboratory hall of 10m*8m. Experimental phones were Samsung Galaxy S4/5.0, MI 5/6.0.1, MI 4/6.0.1, Redmi Note 2/5.0.2, MI 2A/4.4.4, MI 2/4.1.1, Redmi 3S/6.0.1, MI 3C/6.0.1, MI 5/6.0.1, MI 4C/6.0.1, MI 5/6.0.1. We developed a data acquisition application installed on all devices, set sensor sampling frequency at SENSOR_DELAY_NOMAL. Once an experiment was finished, these data were transferred to our server. 11 objects involved in the experiments in various group configurations were list at TABLE II. Each experiment lasted for about seven minutes.

During the experiments, mobile phones were held in hand but their positions were not restricted. Objects executed the interactions according to predefined scripts. The times and duration of the interactions were not limited. Two objects of one group may do arm-in-arm or hook shoulder while others don't have to, some objects of one group will separate and do some other interactions and then merge with other people.

B. Experiment Parameters Analysis

In this part, we will discuss the impact of window length and filter length on experimental results. The following figures are average values of four experiments.

Controlling the filter length to be 1, we change the window length from 0 to 30s. When the window length equals 0, all behavior sequences are computed at a time. From Fig. 1 we can see, group recognition accuracy obtained by Random Forest is slightly higher than SVM and KNN. For Random Forest, maximum accuracy is reached when window length equals to 10 and 14. As for SVM, when window length is 15, accuracy is maximum. For KNN, when the window length is 14 or 15, maximum accuracy is reached.

Controlling the window size to be 15s, we change the filter length from 0 to 3. From Fig. 2, we can see, for three classifiers, when filter length is 1, group recognition accuracy is maximum.

When window length is 15s and filter length equals to 1, we achieve relatively high group recognition accuracy. The results of three classifiers in four experiments are displayed in TABLE III. We can see that for each experiment, group recognition accuracy of three classifiers methods can reach over 90%, meanwhile, RF and KNN can reach 100% for four experiments.

C. Comparison of Different Methods

We choose the common used group affiliation algorithms DBAD [6],[7], and Cross-Correlation [8],[9] to compare the result with GBA. DBAD assess the group affiliation by modeling the data as a distribution and then calculating the disparity as the Jeffrey's divergence between models from different individuals. The second algorithm is used in [8],[9], acceleration variance as indicator of individual activity cues, a cross correlation analysis is conducted in a pair wise fashion, resulting in a disparity matrix in which indicates the strength of the correlation between the objects at a given window. Because behavior changes can be shifted in time between group members we compute the maximum cross correlation with a lag l between minus one to plus one second. After getting the disparity matrix of a window, one way is to set threshold to get the affiliation matrix of one window and calculate the average affiliation accuracy of all windows. The threshold was iterated to get the maximum average group affiliation accuracy, the other way is to apply joint density-based clustering to get the group affiliation, and then average accuracy of all windows is calculated.

We compare results of GBA obtained by threshold iteration and joint density-based clustering with DBAD and CC. The Random Forest is used to get the behavior sequences, the result showed in Fig. 3. Compared with the exiting commonly used algorithms, when using threshold iteration, the average group affiliation accuracy of GBA can be improved by 7.6% than DBAD and 11.05% than CC; When using joint density-based clustering, the group affiliation accuracy of GBA can be improved by 16.95% than DBAD and 36.68% than CC.

Combined with majority voting-based mentioned before. We get the final group recognition accuracy, as shown in Fig. 4. We can see that the average group recognition accuracy of GBA can be improved at by 6.5% than DBAD and 26.7% than CC.

D. Application Scope Analysis

Considering that walking account for most of our behavior in the real life, we select Exp.2 and Exp.4 to discuss the influence of walking's proportion on group recognition accuracy.

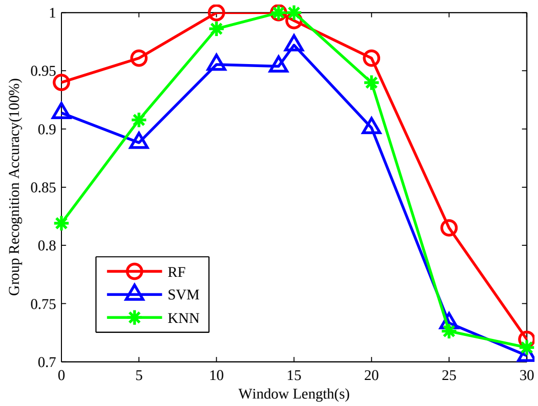

Fig. 1. Group recognition accuracy of different classifiers when varying the window length

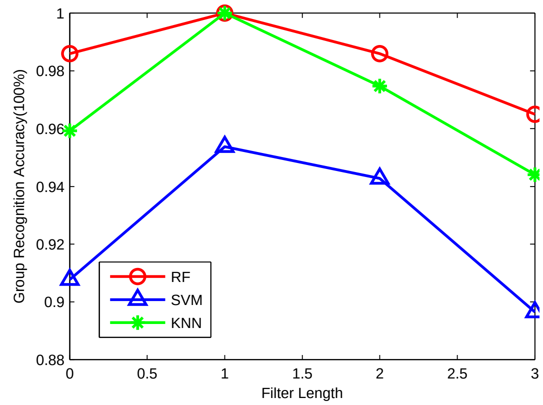

Fig. 2. Group recognition accuracy of different classifiers when varying the filter length

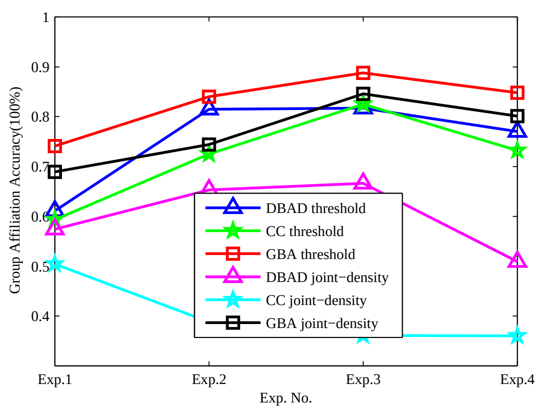

Fig. 3. Group Affiliation accuracy of different methods(100%)

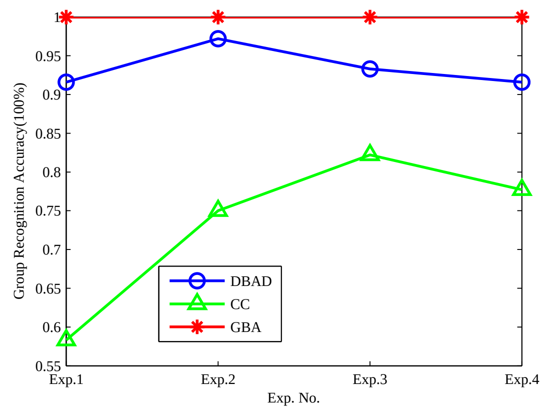

Fig. 4. Group recognition accuracy of different methods(100%)

For all objects, adding is to add walking data after behavior sequences, updating is to modify behavior sequences to walk from the tail to the head of the behavior sequence.

As you can see from Fig. 5, Fig. 6, when people's walking accounts for 70% of the total execution time, which is the proportion of added walking occupies the original data reach 233%, the proportion of updated walking occupies the original data reach 70%, the accuracy of the group recognition begins to fall. When we change majority voting-based threshold $\alpha = 0.9$, group recognition accuracy fluctuations in small ranges.

Therefore if people's walking accounts for more than 90% percent of the total execution time, the method could not achieve high group recognition accuracy, and may consider further classify the walk into fast walk and slow walk; and if the walking data of all the objects accounts for between 70% and 90% of all data, high group recognition accuracy can be reached when the constant threshold α is changed to 0.9; and if the walking data accounts for less than 70%, the average accuracy does not change too much.

VI. Conclusion

This paper focuses on more pervasive interactions scenes, we propose a Group Behavior Affiliation called GBA for interactive group recognition. The acceleration data in mobile phones is collected and the behaviors of individuals are inferred based on the data. The disparity between two individuals is obtained by calculating the difference of their sequences of behavior. Experimental results show that we can get higher accuracy when the windows length is 15s and filter length is 1. Compared with the exiting two algorithms, when using threshold iteration, the average group affiliation accuracy of GBA can be improved by 7.6% than DBAD and 11.05% than CC; when using joint density-based clustering, the group affiliation accuracy of GBA can be improved by 16.95% than DBAD and 36.68% than CC. We further recognize the groups using majority voting-based method, the average accuracy of three different classifiers: SVM, Random Forest and KNN are 97.2%, 100% and 100% respectively, compared with the 93.4% of DBAD and the 73.3% of CC. At the last part of the paper, we discuss the scope of our

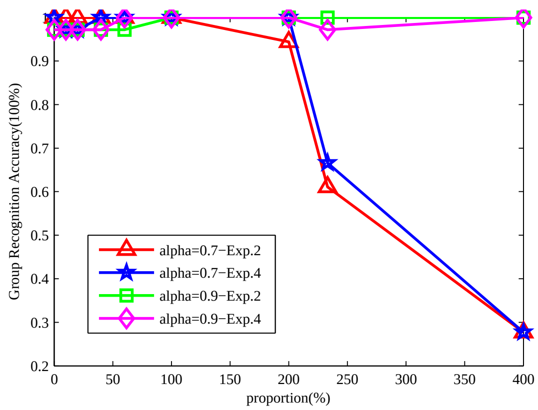

Fig. 5. Group recognition accuracy at different proportion of added walking sequence occupies the original data(100%)

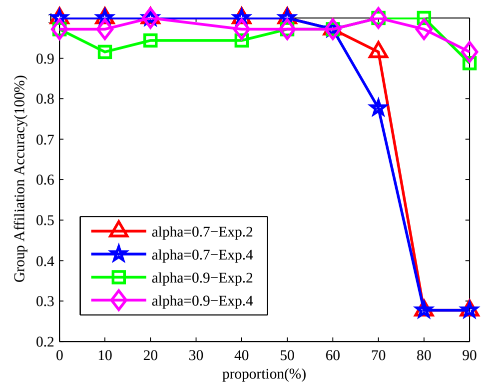

Fig. 6. Group recognition accuracy at different proportion of updated walking sequence occupies the original data(100%)

algorithm. The experimental results show that the average accuracy of the method can reach 98.8% when people's walking accounts for no more than 90% of the total execution time.

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