Indoor People Group Detecition Based on Trajectory

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***Abstract*—Most people in public tend to walk in group, which is composed by family, friends, couples and colleagues. As the rapid increasing of population, the management of crowd in public has raised great attention, such as crowd evacuation in shopping mall, group work like fireman's needing team coordination, large group of people advertising. All these activities need an effective division of groups due to that group possesses properties of consistency, cohesion, self-propagation and self-organization which contribute to most efficient information flow and work completion of coordination. Our paper proposed the implementation of real time graphical group and aligned trajectory interpolation algorithms to make the group recognition more executable and visible. The interpolated trajectory of original data's sample have achieved 97.8% group recognition accuracy while its counterpart of original trajectory is 97.4%, which explain the efficiency of our interpolation algorithm. The Frechet distance of these two trajectories is about 1.2.**

***Index Terms*—Flock, Density Clustering, Spatial-Temporal Group Recognition, Trajectory Interpolation, Trajectory Similarity**

I. Introduction

The grouping of the crowd in public places is very common, such as family, friends, colleagues, couples shopping in the mall and other tasks needing group cooperation. It has been researched that up to 70% people in crowd are moving in groups [1].With an increasing number of population, crowds management in public places turns out a critical issue. People are more likely to be attached to groups in dangerous situation [2]. Specifically, in evacuation process, people are willing to make group with familiar people rather than stay alone. In this situation, high cohesion in group dominates whole members behavior and information dissemination in group tends more rapid. If we send escape instructions to such a group based on their location, less divisions will appear, thus contributing a faster evacuation. Similarly, in some situation where teamwork is needed but no global vision of whole team, we can recognize their groups by trajectory data then direct whole team.

With the development of mobile device technology, almost every person possess a mobile device having locating function. And indoor locating technology also presents remarkable improvement [3]. More and more business activities also use indoor locating technology to promote sales, like Meow Street APP of Alibaba which can navigate shopping people in mall.

Nevertheless, human group recognition is not well applied in real life, no matter in emergency or business. This can be explained by that there are many imperfections in group identification technology, including equipment costs, technical difficulties and robustness and practicability of algorithms. For example, positioning trajectories are usually collected using smart devices. This causes two problems. First, with a different collecting start time, every persons locating time points are not aligned. Second is that the frequency of locating points cannot be too high considering the limited electricity and resource of mobile device thus a trajectory may not be accurate.

As a result, our work focuses on the group detection of trajectory data and how to make it more applicable in real life, more specifically is to make real-time graphical presentation of recognized group. Meanwhile, we also solves the low frequency and not aligned problem of trajectory data in order to realize effective group detection on such data.

The rest of the paper is organized as follows: Section II reviews the related works; Section III notes the real-time group detection algorithm and the realization of real time graphical group monitoring; Section IV explains the trajectory interpolation algorithm and Section V displays the experimental evaluation. Section VI presents some conclusions.

II. RELATED WORKS

There are many works involve trajectory group detection and a lot of patterns of data are used. The first is based on video stream. The general processing step of video stream is to process each frame of video to get trajectory data (i.e., position data, the direction of motion, etc.) of people and then calculate the degree of intimacy to get the group division. Masum [4] proposed a supervised learning algorithm based on PCA to identify the intimacy relationship of moving people flocks. Chen [5] obtained movement pattern of people based on video stream data and then assess the interaction intention to other people of each person. Sochman [6] applied Social Force Model to find the best group clustering. Video has the superiority that we can recognize more accurate location of each person, people actions and interaction with other people. However it also presents the limitation that overlap of people in frame and some environment influences like lights. Moreover, currently the insufficiently distributed camera monitoring in public places causes blind area, trajectory data will not be complete. Consequently, video is suitable for sparse crowds and small spaces.

Another used is sensor data. Feese [7-8] proposed to use ANT radio service and atmospheric pressure sensor in smartphone to determine the distance between each two firefighters and the current floor, so as to group the fire brigade in the firefighting mission. ANT radio service can only compute the relative distances between people but cannot give the specific location which is almost useless in evacuation process. Gordon [9] proposed DBAD group affiliation detection algorithm. It makes use of Gaussian mixture and Von Mises mixture model to get fitting function of accelerometer data and orientation sensor data and then compute affiliation by compute Jeffery divergence of fitting function. The method uses data get from sensor tied on peoples legs. Yet it is not suitable for people to tie anything on leg in real life and if we use sensor data of smartphone, the arbitrary placement of phone will also affect the sensor data thus same group member may presents different state. Brscic [10] designed method to detect location, moving direction and height based on 3D-range sensor and get relatively accurate trajectory data which base great foundation for group detection of trajectories.

Wirz [11] proposed "flock" such a spatial-temporal notion and develop a spatial-temporal flock detection algorithm by adopting Kalnis' [12] research on spatial-temporal clustering algorithms. Since then, Kj?rgaard's team has made a series of studies on flock detection [13-15]. First they researched on indoor flock detection based on wifi positioning data. Next, they developed a fusion model of multi-sensor and wifi positioning data to detect flocks. And later they focused on the detection of the following and influence of group members. The premise of these series of works is that trajectory data are synchronized (aligned) at each moment, thus making spatial-temporal algorithm applicable.
Considering the strength and shortcoming of above method, I use the trajectory data to detect group, making it much easier to monitor and will also solve unsynchronized trajectory data problem.

III. GROUP DETCTION AND REAL-TIME MONITORING

To implements the real-time group detection, I adapted Wirz's [11] spatial-temporal flock detection algorithm and make it perform real-time or online flock recognition.

A. Spatial-Temporal Flock Detection

First it is necessary to review the spatial-temporal flock detection algorithm.
Flock means a group of people who stay together sequentially. As for the steps of this algorithm, firstly it divides all the people into clusters by the density-based spatial clustering method DJ-Cluster [17] according to people's location at current time point, but what I used here is DBSCAN [16] due to it has faster dealing speed. Secondly, comparing with flock set of last time point, if the similarity between one flock and any cluster in current clusters reach a threshold value, then this flock is considered as continued temporally. Other clusters that is not a continuing of any flock of last time, it will form a new flock. Each time moment will produce a flock set. And current flock set is determined by past and present trajectory data. This provides real-time recognition of groups. Procedures of real-time Flock Detection are as follows:

B. Real-time Graphical Group Monitoring

The real-time graphical group monitoring asserts two requirements. First, to vividly display group division, each time moment different groups should differs obviously. Second, in terms of time, we have to show the graphics in real time by ensuring that graphics are changing with the updates on data. Equally important is recording the past grouping information so that dynamics of grouping, such as group fusion and splitting, can be presented.

Since we have realized the real-time group detection by spatial-temporal flock detection algorithm, graphical group monitoring needs to deal with the recognized results. Each time moment the detected results is like following, each flock has an id, duration is the number of continuing time moments and lastseen represents the number of moment since this flock hasnt continued. If lastseen exceed a predefined value, we will consider this flock as dissolved:
Timestamp, [flock_id1, duration, lastseen (id1, id2..., idn)], [flock_id1, ...], ... , [flock_idn, ...]
If we choose flock id for each flock at each time, we can get the following data form. Except for first column, the behind flock ids represent each flock id that each person belongs to.
Timestamp, flock_id1, flock_id2, ... , flock_id3
What we proposed to display the graphical group is using a hot map by assigning each flock one kind of color. Take the above data structure into consideration, at the same moment, people belong to the same group will presents same color while people of different group of course will be displayed in different color, thus satisfying the first requirements. Similarly, if a person always belongs to one flock temporally, then there will be a long bar in same color. If a group of people started in the same group but split after some, such situation shown on hot map will be same color bar turns out

to be two different long color bar. Fig.1 show a hot map of group detection. From which we can see, in the right hand, there is a color map bar. It indicates the color value of each flock id ranging from -2 to 42.

As the time goes by, the new group is constantly added, f the id of the group will continue to increase, which means larger value range of color map. For instance, if we use 44 kinds of color to represent different flocks, then they will demonstrate little color difference which is contrary to our second requirement. Actually, only 8 kind of colors are used in Fig.1Fig. This owes to color selection algorithm.

C. Color Selection Algorithm

Due to the flock formation and dissolution, even though the flock id accumulates, color needs is not that insufficient. We can recycling colors of which has been dissolved.

First of all, we have a set of colors that distinct a lot from each other. As new flock adding in, a random color assign algorithm is provided in algorithm 2.

Algorithm 1 Color Assign

Input: parameters $assigned$,$colors$

Output: $colorvalue$

$notAssgin$:= $colors$ $assigned$

return Random($notAssgin$)

The whole color selection algorithm is displayed in algorithm 3. Each time we record the largest flock id of last moment and by traversing the id values of current draw_array to obtain new added flock ids. Then assign colors for these new color according to algorithm 2. More importantly is the recycling of colors, color will be recycled if not appearing for longer than delta moment corresponding to the dissolution of flocks. Color selection updates the color list for each id by not affecting the past flock ids color, hence past graphics wont change only with new data being stitched behind.

D. Real-time Graphical System Model

Real-time graphical is based on real-time recognition and color selection. We combine the previous part of data with the new data. Each moment with the new data transferred, we will identify flocks based on context by flock detection algorithm, followed by a color selection which also depends on previous color list for each id. Then flock set and color list is going to be refreshed on the hot map. When horizontal axis exceeds certain length, the hot map will move left, showing a sliding form.

Fig. 2 is module diagram of the real-time graphical group system. First there is a user interface from where user can select parameter value and spatial clustering method like DBSCAN and DJ-Cluster, start the service which listens to remote data. Fig.3 shows the user interface.

The underlying protocol of data receiving module is TCP.

Algorithm 2 Color Selection

Input: $pointMatrix$, $draw_array$, $lastflockids$, $assigned$, $maxid$

Output:

$newcmap$:= []
for ($ti \in draw_array$) **do**
  // assign color for new added flock id
  for ($ui \in draw_array.height$) **do**
    x = $draw_array[ti][ui]$
    if ($x > newmaxid$) **then**
      $newmaxid$ = x
    end if
    $flockids$.append(x)
  end for
  for ($id \in flockids$) **do**
    if ($id > maxid$) **then**
      $newcmap[id]$:= assiggColor($assigned$)
    end if
  end for
  // if a flock id didnt appear longer than delta, then its color will be recycled.
  for ($id \in lastflockids$) **do**
    if ($idnot \in flockids$) **then**
      if ($id.lastseen > delta$) **then**
        $assigned[id]$ release
      else
        id.lastseen += 1
      end if
    else
      id.lastseen = 0 $lastflockids$.append(id)
    end if
  end for
end for

Specific data format is as following:

a. Participating people ids: “%id1,id2,...,idn%“

b. People location of each moment:

“#Timestamp;

People id1, location x, location y;

People id2, location x, location y;

......

People idn, location x, location y;#“

Received data comes as byte type and format a and b tend to stitch together, so data analysis is implemented in this TCP receiving module.

Next data is transferred to real-time group detection module and color selection to produce new color list and current flock set. Finally these two data will be refreshed on graphics.

IV. ALIGNED TRAJECTORY INTERPOLATION

As mentioned earlier, the spatial-temporal flock detection algorithm has a harsh requirement that all participants‘ trajectory is synchronized in order to get a snapshot of the location data at each moment. But due to the limitation of

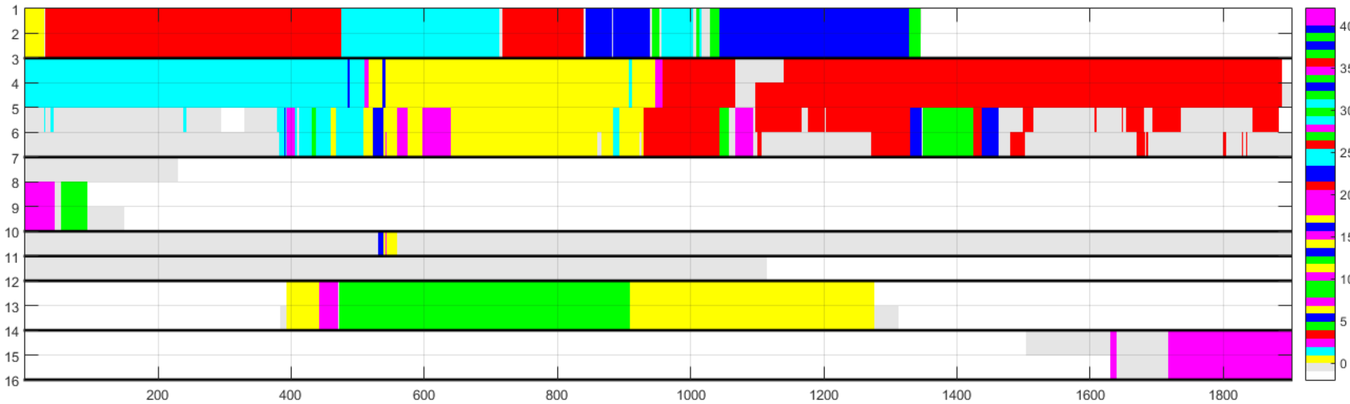

Fig. 1. Graphical Display of Flocks

data collecting frequency and unaligned start time, trajectories tend to be not accurate and unsynchronized. So next will introduce the aligned trajectory interpolation algorithm.

A. *Centripetal Catmull-Rom Spline*

Our interpolation is based on Catmull-Rom Spline. Just as we have outlined a curve from a few reference points in our lives, the Catmull-Rom Spline[18] algorithm is such a way to sketch curves in computer, which usually used to simulate path production of game roles. Catmull-Rom Spline interpolation algorithm is proposed by Catmull and Rom in 1974 by combining Lagrange Interpolation and B-Spline algorithm. Later it calculation was developed as a pyramid-type coefficient like in Fig.4 and recent years more researcher have explored its‘ improvement and parameter meaning.

The basic principle of the algorithm is based on four control points to get coordinates between the two middle points and all these points is on a Bezier curve. It has been proved that Centripetal Catmull-Rom Spline holds properties that control points is in the Bezier curve and also no cusp and intersection on the curve, which is consistent with the walking trajectory. That is why we choose Centripetal Catmull-Rom Spline.

B. *Aligned Trajectory Interpolation*

What is an unsynchronized trajectory data? Fig.5 displays such data. Left column is people‘s id. Where the longer black lines on the line segments are sample moment points and shorter red ones are interpolated time. We can see that sample points is not synchronized but after interpolation all users‘ time moments are well aligned. So next we will introduce the interpolation algorithm.

Assume the sample period is F, and target interpolation period is f. We have a sequence of sample points P0, P1, ...,Pn. The step is like following:

a. According to Catmull-Rom Spline we need four points each time but only area between two middle points is interpolated. So I add two points before and after the sampled data, which are defined as [2P0-P1], [2Pn-Pn-1].

b. Then each time slide the sample sequence to get four points and interpolate into the middle two points based on a interpolating moment sequence [t0,t1,tn]

c. Sample data are unsynchronized. Suppose we allocate time for each interpolation points according to the interval f, if the time offset of two person is a multiple of f, then all interpolated time moment will be aligned, however, if not ,all interpolated points will not be aligned. Say [1,2,3] and [1.3,2.3,3.3] two time sample sequence. If the interpolation period is 0.1, aligned sequence [1,1.1,1.2,1.3,1.4,... ,2.3,2.4,... ,2.9,3], [1.3,1.4, ... ,2.3,2.4,... ,3,3.1,3.2,3.3]. If period is 0.4, we get [1,1.4,1.8,2.2,2.6,3.0], [1.3,1.7,2.1,2.5,2.9,3.3], which is completely not aligned. Hence, our interpolation algorithm takes a starting time t0, 0¡= t0 ¡f and interpolating time later is defined as tn = t0+n*f. Therefore, if we make 1 as t0, the obtained aligned sequences turn out to be[1,1.4,1.8,2.2,2.6,3.0], [1.3,1.4,1.8,2.2,2.6,3.0,3.3]

C. *Trajectory Interpolation Assessment*

After interpolation, the original sample sequence became a movement trajectory, how to judge the error of this interpolated trajectory is an important part of judging the performance of the algorithm. Since the resulting trajectory is a list of discrete points in time, we can think of this sequence

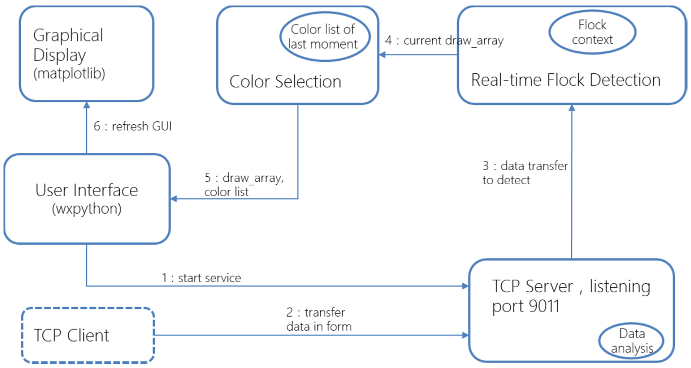

Fig. 2. Real-time graphical group monitoring System module

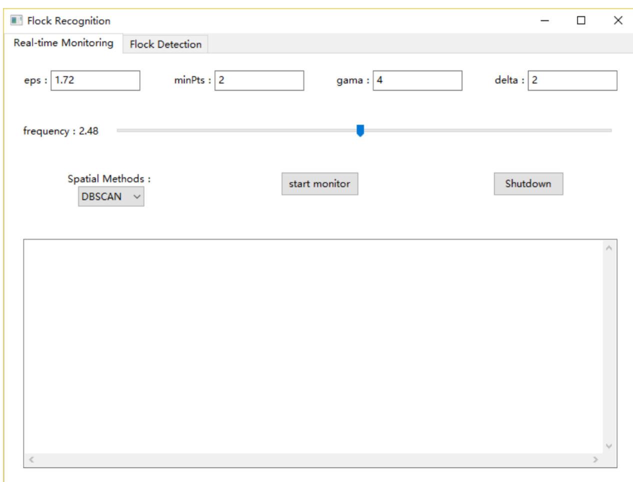

Fig. 3. User interface

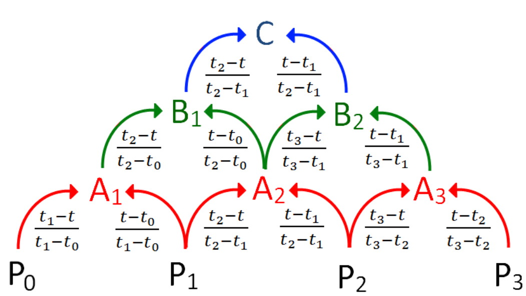

Fig. 4. Pyramid-type Catmull-Rom Spline

as a curve, and an effective method of calculating curve similarity is the Frchet distance [19]. This theory originated from the dog-man distance measurement model. A person hold a dog by a rope in an arbitrary speed the distance

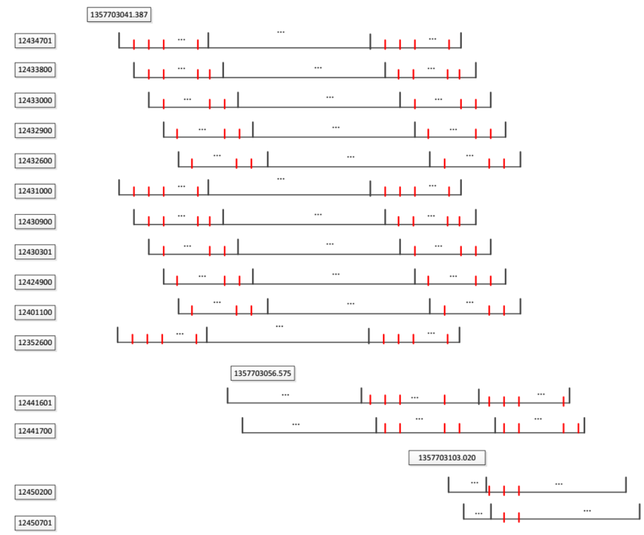

Fig. 5. Unsynchronized moment of trajectory

measure between them is the length of the rope.

Frchet distance calculation, simply to the two curves are sampled to get the sampling interval of the two curves at the same time on the corresponding distance of the maximum value, Frchet distance is the maximum distance to minimize the value of the sampling method.
Interpolation accuracy is bound to be affected by the period F of original sample sequence. And the their relation is displayed in Fig.6 and Fig.7. Clearly that interpolation error is increasing with an increasing F(also sparer location data).

In addition, there is a parameter t0 that determines the interpolating time moments. To explore the effects of different t0, we got such results in Fig.8 and Fig.9 where the sample period is 3s and target period is 0.04s. Fig.9 shows the trend of the error with the start time t0 more clearly. It can be seen from the figure that, as expected, the value of t0 will change the error periodically. In addition, in [0, f] interval, the error there is a certain ups and downs, changing like waves by decreasing at beginning and increasing later. Intervals 0.01-0.02 and 0.035-0.04 to present smaller error values.

V. EXPERIMENTAL EVALUATION

In order to test the results of the algorithm, we used the ATC [10] (Asia and Pacific Trade Center) pedestrian group data set. This data set was collected in Osaka, Japan‘'s commercial shopping center acquisition by 3D-range sensor. This data collection process continued for 6 days, 4 hours per day, each for an hour. The resulting human trajectory data format is:

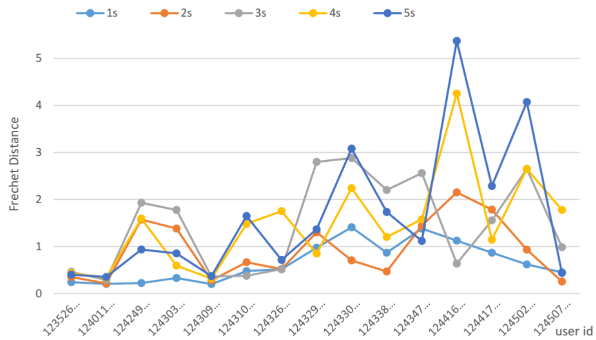

Fig. 6. displays each users Frechet distance trend with different

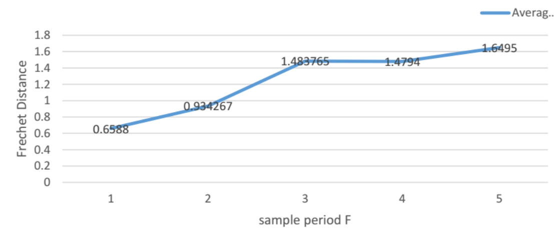

Fig. 7. shows the average Frechet distance of each F.

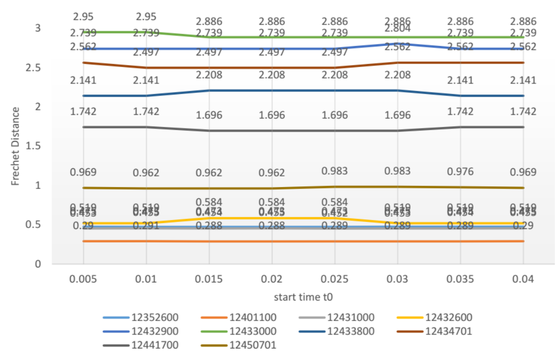

Fig. 8. shows each users Frechet Distance trend along with start time t0

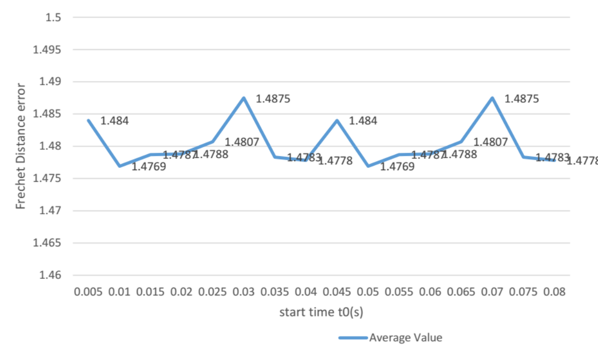

Fig. 9. displays their average value

Timestamp, person id, position x, position y, position z, speed, direction of movement, face orientation
In addition, each id is identified for all people in the collection area and records are made for the grouping of all participants and the interaction within the group. Therefore, this data set is well suited for validation of spatial-temporal clustering algorithms.

A. Parameters of Flock Detection

Final step of group detection is to calculate the recognition accuracy. Commonly used method of group identification accuracy is F1-measure. F1-measure is a comprehensive evaluation for accuracy Precision and recall rate Recall:
F1-Measure = (2 * Precision * Recall) / (Precision + Recall)
In our temporal detection methods, each each moment has a flock results so is a F1-Measure, so use the average of F1-measure at each moment. Wirz [11] named this value as FAA (Flock Assignment Accuracy), here we use it. Another Wirz evaluation method is NFDA (Number of Flocks Detection Accuracy), that is the proportion of moments when right number of groups are detected. To be precisely, if the number of groups at each time and the number of the original group is equal, if the equality is 1, the other is 0, the final accuracy is the average value of all moments.
In real-time spatial-temporal flock detection algorithm, density based clustering methods DBSCAN and DJ-Cluster are used. The two methods demands two parameters, epsilon the longest distance that two persons can be group together and minPoints the minimal number of points needed to form a cluster. Here we study the relation of different epsilon value and flock detection accuracy. From Fig.10 we can see, FAA and NFDA‘ s changing trends are almost the same. And when eps equals 3.5m, we got the largest accuracy with FAA equal to 97.4% and NFDA 84.4%.

B. Aligned Trajectory Interpolation Evaluation

The purpose of designing trajectory interpolation algorithm is to aim at making data that is unsynchronized and low sampling frequency into a denser trajectory that aligns at the same time, which is conducive to spatial-temporal flock detection. First, let’s look at the changes in the trajectory after interpolation. As shown in Fig.11, this is the trajectory

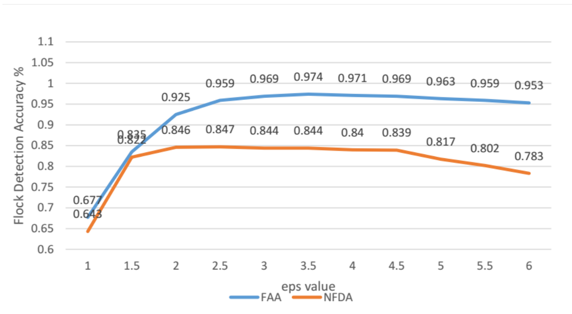

Fig. 10. FAA and NFDA with increasing epsilon value.

of a user in the ATC data set. It is shown that the trajectory after interpolation is smoother than the original data, and there is no rough corners. This is the characteristic of the Catmull-Rom spline algorithm that simulates trajectory by a smooth curve with control point on it. In addition, the movement trend of the graph is basically the same as the original data, which indicates the high restoration degree of our interpolation algorithm.

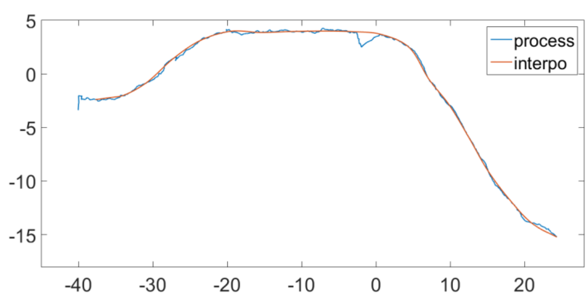

Fig. 11. Interpolated Trajectory and Original Trajectory

Of course, from the naked eye may not be able to observe the actual effect. Only when the interpolated trajectory can also play a great role in flock detection accuracy can verify its validity. The executed result is displayed in Fig.12 where we use the threshold eps = 3. The figure shows relation between the sampling period ranging from 1 to 5 and flock detection accuracy. We can see it reaches to 97.9%. Firstly, we can find that no matter for FAA and NFDA, interpolated accuracy is obviously higher than ones not interpolated. Secondly, the FAA accuracy of group identification is not much change but very high and in all sample period F, interpolated accuracy id higher than original data s accuracy. This can be explained by that the interpolated trajectory is smoother than original trajectory by ruling out some location noises. The accuracy is increasing at first and then a little declining later. When sampling period is 1, there are still a lot of noise into the sample data. When the sampling period is 4,5, large percent of original data are lost causing an unavoidable hard error for the reduction of the trajectory, so the group identification accuracy starts to decrease. When the sampling period reaches about 2,3, the sampling data and the interpolation algorithm are the most favorable for the track interpolation, and the group recognition is the most favorable. Comparing with original trajectory and sample data that is not interpolated, trajectory after interpolation reveals great superiority in flock detection.

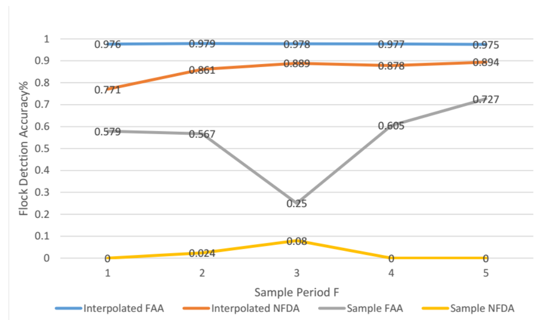

Fig. 12. FAA and NFDA accuracy of interpolated trajectories and sample data at different sample period F.

In daily life, people walking speed is generally at 0.5m/s-2m/s[20], which may be acceptable for 3 seconds sampling cycle. If the sampling period is up to 5 seconds, the person's walking distance is likely to reach 5m or so, this frequency of the positioning data indoor for group identification is too sparse. The interpolation algorithm proposed in this chapter can achieve 97.5% FAA accuracy, and accuracy of the number of identified groups is exactly 89%, which means that even in the 5-second sampling period, the trajectory obtained by using the trajectory interpolation algorithm can still performs well.

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C. Real-time Graphical Group Display

Fig.1 is a static group graphics drawn based on part of data that selected from ATC. The horizontal axis is time, and vertical axis represents peoples ids. Each line displays a persons group changes with time. The white area indicates no data for that person and light grey area means the person

doesnt belong to any group at that moment. It is clear that grouping is like this [1,2], [3,4,5,6], [7,8,9], [12,13], [14,15], and 10,11 were walking alone. In addition, 7 keeps relatively large distance to his partners 8 and 9, and they leave the monitoring area early at moment 100. Similar to 7, 8 and 9, 14 and 15 enter into area very late but most of the time they keeps together. 12 and 13 are divided into same group in the majority of time but be assigned to group [3,4,5,6] at moment 910 to 940. Observing the two group [1,2] and [3,4,5,6], from 0 to 480, 1,2,3 and 4 grouping normally, 5 and 6 no group. At interval 390-480 3,4,5 and 6 sometimes classified as one group and sometimes divided into two groups. In 480 to 500, these 6 person be classified into one group but split not long after. It is worthwhile to mention that there are a number of color changes on graphs of 1 and 2. The moment that they changed from red to light blue is because they were assigned to [3,4,5,6]. At other moments where color changes is due to the flock consisting of 1 and 2 is not continued longer than detla, thus leading the dissolution of flock. When such a flock composition appears again, its id changes and the same of color.
Fig.13 is the real-time graphical group monitoring screenshots.

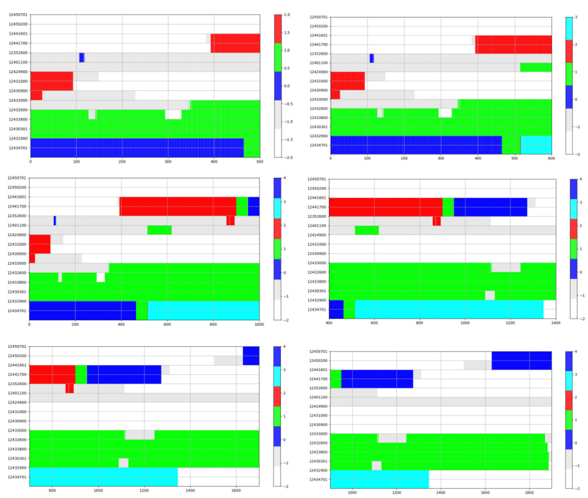

Fig. 13. Screenshots of real-time group graphical monitoring

VI. CONCLUSION

This paper mainly introduces the real-time spatial-temporal flock recognition algorithm, the method of real-time graphical group display, such as color selection, and the aligned trajectory interpolation algorithms. Through the spatial-temporal flock detection algorithm we get 97.4% of a grouping accuracy. Real-time graphical monitoring of group identification is realized by real-time calculation of group identification algorithm and color selection algorithm. It can not only see the current grouping situation, but also see the change state of the group with time. The aligned trajectory interpolation algorithm solves the problem of unsynchronized low frequency trajectory. The Frechet difference between interpolated trajectory and original trajectory is about 1.24m. And the interpolated trajectory achieves 97.9% accuracy in detecting flocks.

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