DETECTION OF CHANGES IN GROUPS OF MOVING OBJECTS

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ABSTRACT:

The analysis of moving objects is a rather challenging but also informative task. It provides important knowledge which is required in a large variety of research fields and applications. The same holds for the analysis of group movements, which, for instance, is able to provide knowledge that can support or contribute to social behavior studies of human beings or animals. In this work, we present an approach to identify changes in the group structure over time, which can support studies regarding an object's role or standing within the group. The presented methodology is based on the transformation to relative movements and a consecutive change detection algorithm. In order to evaluate our approach, we further conduct experiments by applying it to real data from different scenarios. The results obtained in these experiments demonstrate the functionality and its portability to different uses cases.

1. INTRODUCTION

Analyzing the behavior of moving objects is a challenging field. It provides important knowledge, which is needed for tasks from a large variety of research fields. For instance, it can support or contribute to social behavior studies of human beings or animals. However, the challenge with such analyses often lies in the fact that they are applied to pure trajectory data, which often only consists of the objects' time annotated location information. Although there certainly are further aspects, which have to be considered but are not present in the input data (such as the posture), an object's behavior has to be directly derived from its movements. The same holds for the analysis of group movements, which also play an important role when investigating the behavior of moving objects. Besides all the work aiming at the identification of groups in movement data there is a lot of work, which focuses on the detection or identification of pre-defined generic or behavioral movement patterns. A comprehensible overview is given by Dodge et al. (2008).

In this work, we assume to already have identified the objects, which move together and form a group. We focus on analyzing the intra-group behavior and, especially, we aim at the detection of changes in the formation of the objects during the observation period. This information can later be used by domain experts, for instance, to analyze the group structure or changes regarding an object's role or standing within the group. For this purpose, we have developed an approach, which consists of three consecutive steps and is applied to raw trajectory data. In the first step, the objects' movements are transformed to be relative to the movement of the whole group. While in the second step a change detection method is used to identify deviations from the usual group structure, in the third and last step the results are back transformed to the original movement space.

The presented approach requires the movement data to meet certain requirements. The position accuracy as well as the sampling rate should be high enough to preserve the details of the movement of the group members. If the uncertainty of the positions is too high, e.g., higher than the distances between the individual group members, or the sampling rate is too low, the results will be accordingly less meaningful. However, assuming that the movement data to be analyzed meets those requirements, possible application scenarios may be the observation of

- pedestrians walking through a pedestrian zone, mall, or bigger place as a moving cluster or flock,
- a group of animals like a flock of birds which usually fly together in a formation for certain amount of time or
- a team while doing sports like football, handball or any other team sport where unconstrained movement is usual.

The remainder of this paper is structured as follows: section 2 presents the related work in this research field. While in section 3 the proposed methodology is described in detail, in section 4 experiments are conducted, in which our approach is applied to real movement data. Afterwards, the results are discussed in section 5. This paper concludes with a summary and an overview of remaining open points and possible extensions of this work given in section 6.

2. RELATED WORK

The research field of group movement analysis is researched extensively. A lot of work focuses on the detection of the groups themselves, i.e., which objects belong to a group. Among others there are the works of Cheng et al. (2019a); Kjærgaard et al. (2012); Loglisci (2018); Kuntzsch and Bohn (2013); Buchin et al. (2013); Zaki and Sayed (2018). However, in our work we assume to already have identified the objects, which are part

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of a group. We aim at analyzing the behavior of the members within the group.

In this direction there is further work related to the identification of pre-defined generic or behavioral movement patterns (Laube et al., 2009; Benkert et al., 2008; Gudmundsson et al., 2012), which are described in Dodge et al. (2008). In addition, other related work aims at the analysis or the identification of patterns in group movements (Grunz et al., 2012; Feuerhake and Sester, 2013; Langrock et al., 2014; Wei et al., 2013). But all of those approaches deal with an evaluation of the movement of the group members, but they do not consider the group structure and its changes over time.

There are approaches to analyze the group movement behavior. While Buchmüller et al. (2019) propose an approach called "MotionRugs" for visualizing trends of moving groups, von Landesberger et al. (2014) focus on the automatic extraction of interesting events by exploring the feature space of a group behavior. Nagy et al. (2010) and Couzin et al. (2002) analyzed the grouping behavior of animals in terms of hierarchy and spatial sorting. While Bialkowski et al. (2016) discover team formations in football matches using clustering-based methods, Beernaerts et al. (2018) introduce the Static Qualitative Trajectory Calculus to describe the team formations in football. In this way, they can encode the relative movements of players during an epoch by a kind of matrix notation. The latter can then be compared to other epochs to find patterns or match a particular formation (Beernaerts et al., 2020).

The methodology presented in Andrienko et al. (2013, 2021) is very similar to our approach. They also applied a transformation to the movement space in order to analyze relative movements afterwards. The analyses they describe focus on the identification of trendsetting events. In Andrienko et al. (2021) they also applied their approach in a football context. Further, they show the possibilities enabled by a clustering analysis of the relative movements of the group members (Andrienko et al., 2013). However, the crucial difference to our work is that they cluster the movements with the help of feature vectors consisting of all members' positions. They are basically looking at repetitive constellations of the members. In contrast to that we analyze each object's intra-group movements individually and look for significant changes. After reviewing the literature we conclude that, to the best of our knowledge, there is no such approach for dealing with the given problem.

3. METHODOLOGY

The developed approach consists of three consecutive steps. In the first step, the movement data is transformed to relative movements with respect to the movement of the whole group. In the second step, a change detection method is applied to the resulting movements to identify significant changes over time. In the last step, the results are back transformed to the original movement data. To illustrate the description of the steps, we use the synthetic example shown in Figure 1, in which a group of four objects is observed for a time period of 16 epochs.

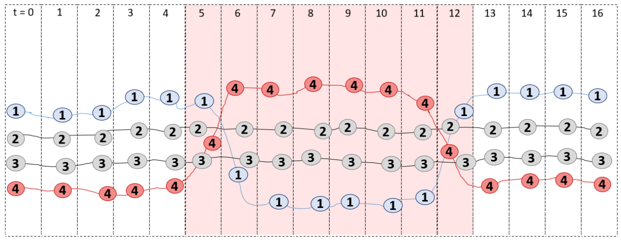

Figure 1. A synthetic example containing the trajectories of four group members (numbered dots). Objects 1 (blue) and 4 (red) change their positions within the group for a certain period of time before they return to their original positions.

3.1 Transformation to Relative Movements

Our approach assumes the objects' movements, which are the input data, to be represented by trajectories Tr_i in the form of

$$Tr_i = \{\begin{pmatrix} x \\ y \\ t=0 \end{pmatrix}, \begin{pmatrix} x \\ y \\ t=1 \end{pmatrix}, \ldots, \begin{pmatrix} x \\ y \\ t=T \end{pmatrix}\}. \tag{1}$$

According to Andrienko et al. (2013) we assume that the movement of an individual object in the observation space Tr_i can be represented as composition of two parts.

$$Tr_i = Tr_{group} + Tr_{rel,i}, \tag{2}$$

The first part given by Tr_{group} is the movement of the entire group, i.e., the translation of the group through the observation space. The second part denoted by $Tr_{rel,i}$ is the movement of the individual object, which might change its position in the group formation.

Since we are not interested in the way the group moves through the observation space, we use the mean group trajectory Tr_{group} to eliminate the part containing the translation of the whole group (see Figure 2, left). Tr_{group} is calculated by

$$P_{group,t} = \begin{pmatrix} x \\ y \end{pmatrix}_{group,t} = \frac{1}{n}\sum_{i=1}^{n}\begin{pmatrix} x \\ y \end{pmatrix}_{i,t}, \tag{3}$$

where $P_{group,t}$ is the center location of the group in epoch t, $\begin{pmatrix} x \\ y \end{pmatrix}_{i,t}$ is the location of the i-th object at t and n is the number of group members. If the trajectories are not equally sampled, a resampling or interpolation will be necessary.

To determine the relative trajectories $Tr_{rel,i}$, we follow Equation 2 and subtract Tr_{group} from objects' trajectories Tr_i. The resulting trajectories show the movements in relation to the whole group and are the input for the next step.

In the supporting example, which is shown in Figure 2 (right), object 1 (blue) and object 4 (red) show larger intra-group position changes.

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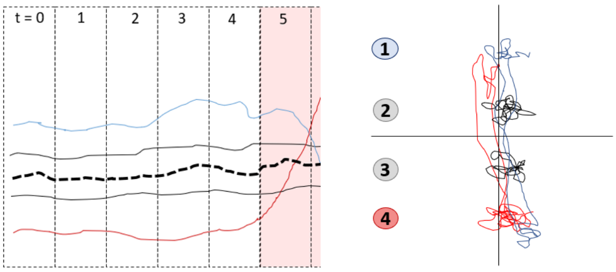

Figure 2. The objects' movements are transformed to relative movements. Left: a mean group trajectory is calculated (dashed black line). Right: the resulting relative trajectories.

3.2 Detection of Changes

In order to be able to detect changes over time there are at least two options we can apply to the relative movements.

The first option uses the a sliding window approach, e.g., the moving average. This rather simple method requires the two input parameters ϵ and $windowSize$. The latter defines size of the temporal sliding window, which is actually halved to get a preceding (first half of the window) and a succeeding value to compare to (second half). For each of these halves a mean position is determined and their distance is calculated. The parameter ϵ is then used as a threshold for the position change. A significant change will be detected, if ϵ is exceeded.

In the given example, this method is applied to object 1 (blue) exemplarily. Figure 3 shows that two position changes are recognized. In this example, position 1 (red), which stands for the original position of the object, and position 3 (orange) are very close to each other. So, the object more or less returns to its previous position. However, using this detection method we are not able to recognize this situation automatically. Each of the resulting "new" positions are handled individually, which might not be a problem, if the following analysis of the group behavior does not require this information.

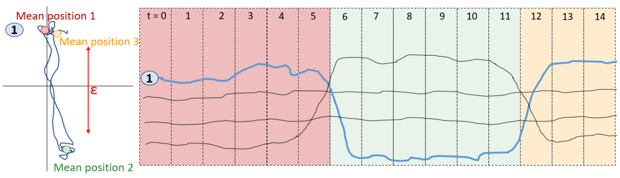

Figure 3. A sliding window-based detection method is applied to find intra-group position changes. Three resulting mean positions (left) indicate that object 1 (blue) changes its position twice.

To consider the issue of recognizing previous positions, the second option is based on a clustering method. In this case, we apply the DBSCAN algorithm introduced by Ester et al. (1996) to the locations of each object's trajectory individually. The temporal component is ignored here for the first. Depending on the choice of the required input parameters ϵ, $minPts$, which control the significance of the detected changes, we obtain position clusters for each object. By re-integrating the temporal information to the clustered motions, we are able to obtain a sequence of distinct clusters for each object. Each of these clusters represents an intra-group position. Thus, as soon as there is more than one cluster in this sequence, the object has changed its position. The choice of the parameters ϵ and $minPts$ depends on the actual scenario. As ϵ describes the required spatial density, it controls the significance of spatial changes, which can be detected. Since we apply the clustering on point objects, we can use the Euclidean distance as metric. A reasonable value can therefore be directly derived from typical object distances in the corresponding scenario. $minPts$ is the minimum number of points to be in a cluster. This way it distinguishes between significant position changes and random short-term changes, which can be considered as outliers.

This method is also applied to our supporting example, in particular to object 1 (blue) exemplarily. Figure 4 shows that there are two resulting clusters (red, green). Taking into account the temporal sequence of these clusters (1, 2, 1), we still detect two position changes. But in contrast to the previous method, we are able to notice that the object returns to its original position, represented by cluster 1 (red).

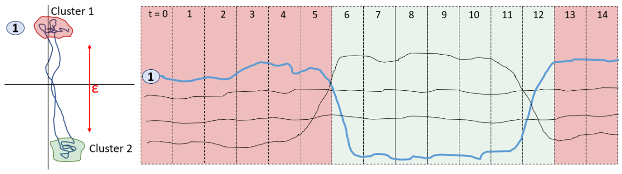

Figure 4. A clustering-based change detection method is applied to find intra-group position changes. Three resulting clusters (left) indicate that object 1 (blue) changes its position twice.

As there is temporal information available in both presented options, we can also determine the duration the object spent on each intra-group position. This may be additional and helpful information, when interpreting the scenario afterwards.

3.3 Backtransformation to Original Movement

To revert the transformation to relative movements, which is done in the first step, we add Tr_{group} to $Tr_{rel,i}$. In this way, we are able to show the information about the changes of the group members in the original trajectory data (see Figures 3 and 4, right).

4. EXPERIMENTS

In order to evaluate our presented approach, especially with regard to its portability, we have conducted two experiments. Trajectory datasets, which contain movement data from different scenarios, provide the data basis for each case. While the first scenario is based on the observation of pedestrians, some of whom cross the scene together, two other datasets come from sports tracking, namely football and handball. The experiments are presented in the following sections.

4.1 Experiment: pedestrians

The first experiment is based on a pedestrian tracking dataset created and published by Cheng et al. (2019b). It has been acquired with the help of a video-based tracking approach presented in Cheng et al. (2019a) and contains the trajectories of different traffic participants (pedestrians, cyclists and vehicles) in a shared-space. The observation time is nearly 20 minutes. The sampling rate is 2 Hz. Thus, the mean visibility of each object is about 30 seconds. It additionally provides information about which pedestrians walk together as group. Figure 5 gives an overview over the data.

In our experiment we only consider the first of three parts of the datasets. In this subset there are 48 distinct groups. While

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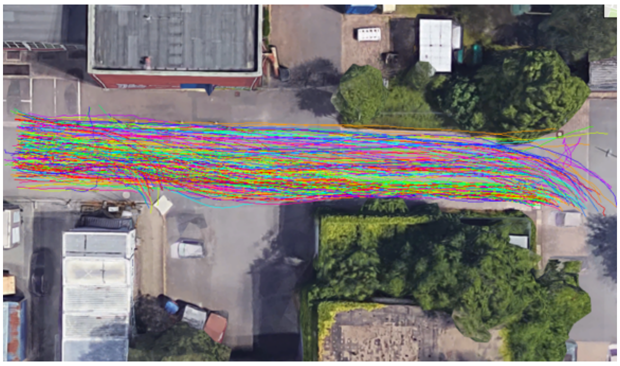

Figure 5. The trajectories of pedestrians are analyzed in our first experiment. The colors encode the different objects. (Basemap: imagery ©2019 Google, map data GeoBasis-DE/BKG ©2009)

38 of them only have a group size of 2 o 3 members, there are also 5 of size 4, 2 of size 5 and 6 as well as 1 of size 9. We especially focus on the groups with at least 4 objects as we expect more and more meaningful changes there. However, we have noticed that the members of many groups constantly stay on their positions within the group. A reason for this can be the rather short observation time.

In order to analyze a group of 5 persons, we applied our approach to their trajectories. During the second step, we use both possible options with the sliding window and the clustering-based method, so that we can compare the results afterwards. We use $windowSize = 5\ s$ and $\epsilon = 0.5\ m$ as input parameters. In Figure 6 the results of the analysis of a group of 5 persons is visualized. In the left part of the Figure, the results of the first and second step of our approach, which are the relative trajectories and the detected changes, are visualized. On the right, the original trajectories together with the position changes are shown, i.e., the results of the last step. In this scenario, we can observe that the red person changes its position for a short time, while the other members (encoded by colored dots) stay on their positions.

Comparing the results of the sliding window and clustering methods, we find a different number of distinct positions for the red person. While the sliding window method outputs three positions, denoted by 1, 2 and 3 in the Figure, the clustering-based method only provides two positions (1 and 2). The reason for this is the capability of the latter to recognize the return to the original position of the red person.

However, in this example, the reason for this change is the avoidance of an obstacle and has less to do with a change of the intra-group role of the person.

4.2 Experiment: football

In the next experiment the movement of a football team is analyzed. As in common football analyses often the real tactical line-up (RTL) of a team is presented to visualize and reveal its tactics, this type of analysis provides an illustrative example of the problem addressed in this paper. The RTL consists of the mean positions of the players during a certain observation period. It can be used to evaluate the team's tactical performance by comparing it to the formation given by the coach. However, if only one mean position is determined for the complete match, temporal changes in the formation could remain unnoticed. The changes are averaged out (Figure 7, red marked player). Furthermore, the need for working with relative movements becomes clear, as we do not want to consider the movement of the entire team, which is characterized by a permanent alternation between defense and offense.

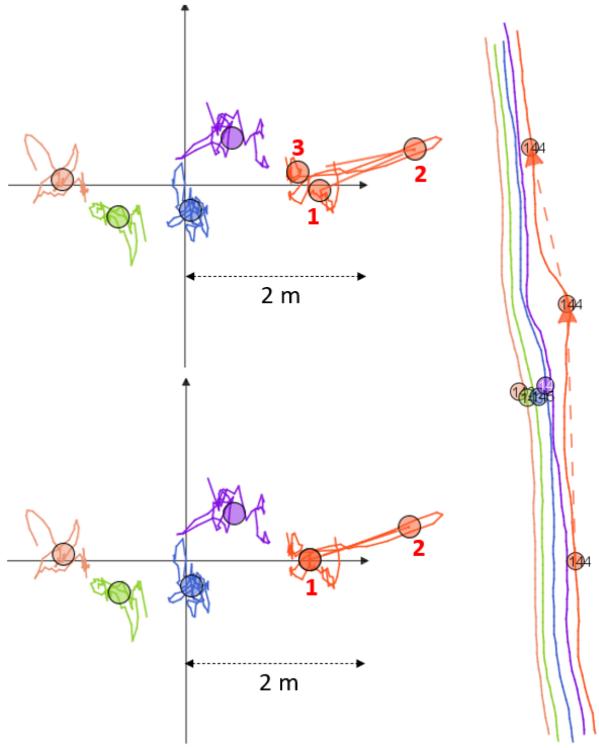

Figure 6. A group of 5 pedestrians is analyzed. The red colored person changes its position twice (back and forth). Left: the resulting relative movements and intra-group position changes by the sliding window (top) and the clustering variant (bottom). Right: The backtransformed changes into the original movement data.

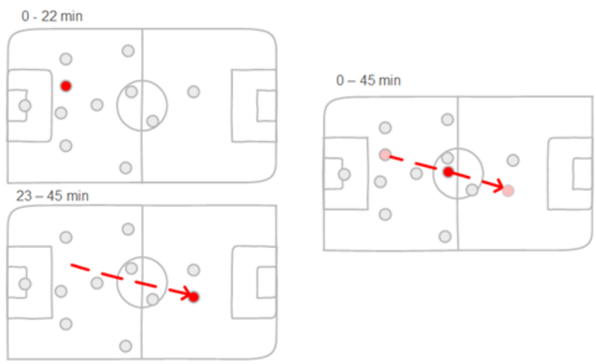

Figure 7. Left: the RTL of one team (grey dots) for two consecutive time periods of the first half of the match. The highlighted player played in different positions in each of them. Right: a single RTL for the complete half is not able to show the change in position.

The underlying dataset of this experiment contains the trajectories of the team's players. The data has been collected by using GPS trackers and is sampled with a frequency of 5 Hz. Figure 8 shows the data and makes clear that it is hardly possible to identify interesting situations by visually inspecting it. We have selected only the second half of the match (45 - 94 min). We have additionally discarded the trajectory of the goalkeeper because we assume that he does not change his role during the match and does not move across the field like his team mates. In this scenario, we use apply the sliding window-based method in step 2 of our approach. We further use $windowSize = 5\ min$ and $\epsilon = 25\ m$ as required input parameters.

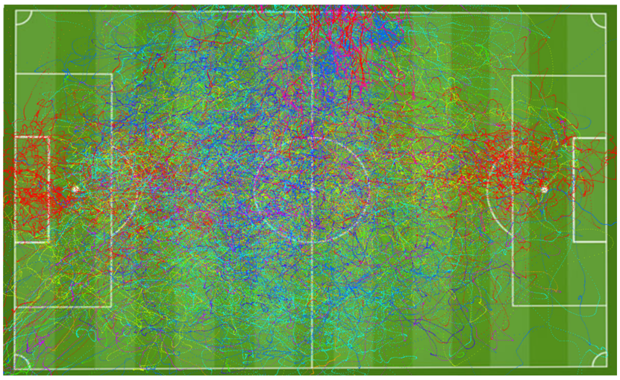

Figure 8. The data basis for the football experiment: the trajectories for the players during the full match are encoded by colors.

The result is shown in Figure 9. The colored and numbered markers encode the players' mean positions for the annotated time period (black numbers below markers). Changes of positions are visualized by several markers of same color and number. They are connected by an arrow to show the direction of the change. The playing direction of the team is from right to left. We can observe that are two significant changes in this example. While player 8 (light green) moves from a typical "defensive midfielder" to an "offensive midfielder", the change of player 8 (violet) is even more dramatic as he has started as "defender" and becomes a "forward" at the very end of the match. Since we also have the official game history including all major events (goals, substitutions, yellow and red cards, etc.), we are able to somehow interpret and verify this result. In this match the analyzed team was behind 1:0 since the first half. In the second half, analyzed here, the team tried to equalize by a successively more offensive orientation.

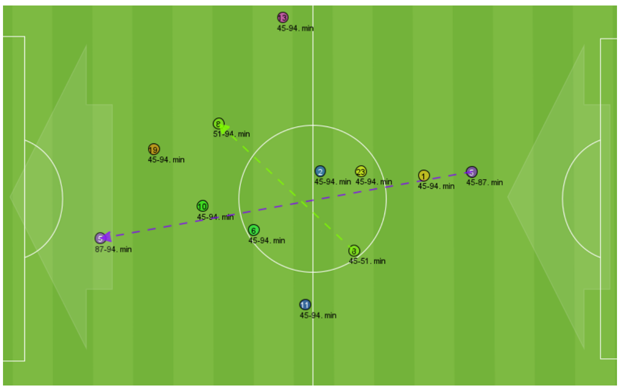

Figure 9. The identified formation changes of the observed team (except the goal keeper). The changes are visualized by arrows connecting the different player mean locations (colored dots, time annotated) during the match. The playing direction of the team is from right to left.

4.3 Experiment: handball

In our last experiment we change from football to handball. This time, we apply our approach to the trajectories of 7 players during a 10 minute scene. The sampling rate is 1 Hz. The dataset shown in Figure 10 has been published by Janez Pers et al. (2006) in the context of the CVBASE '06 workshop.

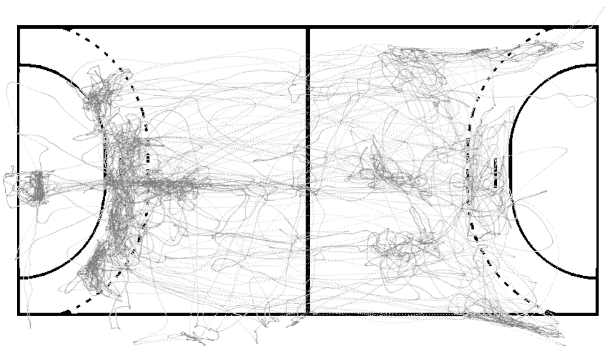

Figure 10. The dataset for the last experiment: the trajectories of 7 handball players are analyzed.

In contrast to football, handball has game situations with the attack, in which the team has possession of the ball, and the defense, which are clearly different from each other. Accordingly, the team formation also differs in these phases. Figure 11 shows an example. In addition, the attack phases are limited in time by the referee to avoid a passive game of a team. Luck (1996) state that an attack lasts on average about 15 seconds. Because of that we again face the issue of having alternating movements on the field. Furthermore, the movements of the players are constrained as they are not allowed to enter the goal area. Therefore, they form around this area, which, obviously, is mirrored on both sides. Based the previous reasons and especially on the last fact, changes in the formation are to be expected with an appropriate choice of parameters.

Figure 11. Often used defense (blue) and offense (red) formations in handball. (Source: https://en.wikipedia.org/wiki/Handball#/media/File:6-0-Deckung.svg)

Determining the RTL, as described in the previous experiment, for the handball team leads to the result shown in Figure 12. Obviously, such type of analysis is not useful here. The alternations between attack and defense leads to player positions close to the center of the field. However, as described before, this does not match the reality and is just another reason for applying our approach.

When applying the approach to the dataset, we try to consider the aforementioned domain knowledge in terms of the field size and the usual attack duration. Thus, we use $windowSize = 20\ s$ and $\epsilon = 3\ m$ as input parameters. Compared to the football

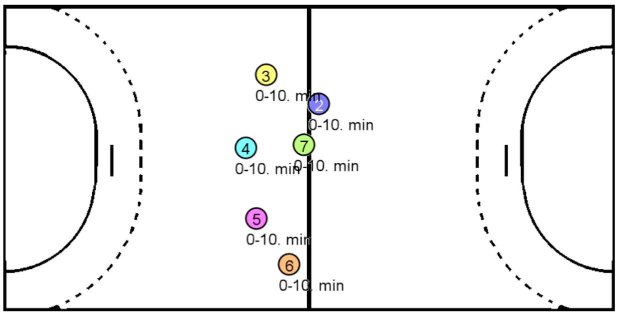

Figure 12. The RTL of the handball team. The constant change between offense and defense locates the players (colored dots) in the middle of the field.

scenario the value ϵ is significantly smaller. The result shown in Figure 14 is the comparison of the two options of the second step: sliding window (left) and clustering (right). As expected, there are many intra-group position changes. Although the Figure is quite overloaded, especially the changes of player 6 (orange) show that he or she is mainly alternating between two position clusters in the very left (defense situations) and the very right (during attacks). If we use the sliding window approach, the alternation between those clusters will not be recognized. Each change leads to a new position within the group. However, if use the clustering-based variant, there will be only two different intra-group positions for this player.

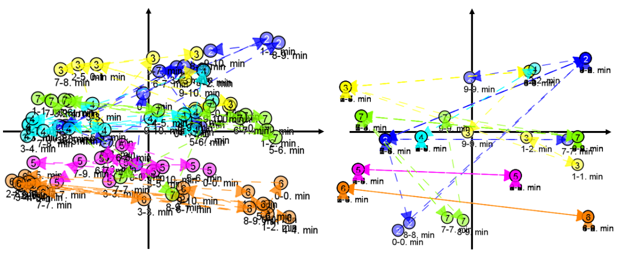

Figure 13. The detected changes using two different parameter settings. The changes are given in the group movement frame (black arrows). Left: many changes are found by using $windowSize = 20\ s$ and $\epsilon = 3\ m$. Right: less but more significant changes remain using $windowSize = 40\ s$ and $\epsilon = 10\ m$.

Increasing the values for both parameters to have $windowSize = 40\ s$ and $\epsilon = 10\ m$ leads to the results shown in Figure 14 (right). The changes become less and only the more significant ones remain. Looking at the players 7 (green) and 2 (blue) we can observe that they tend to be more offensive during the last part of the observation time.

5. DISCUSSION

In order to evaluate our approach, we conducted the previously presented experiments. The obtained results reveal the capabilities and limits.

The experiments demonstrate that the presented approach is able to detect changes in the structure of groups over time. The different data bases show that this also works in different application areas. Moreover, with the help of the required parameters, we can adjust the significance of the detected changes. Nevertheless, the choice of values requires a certain understanding or prior knowledge of the scenario. Either domain experts have

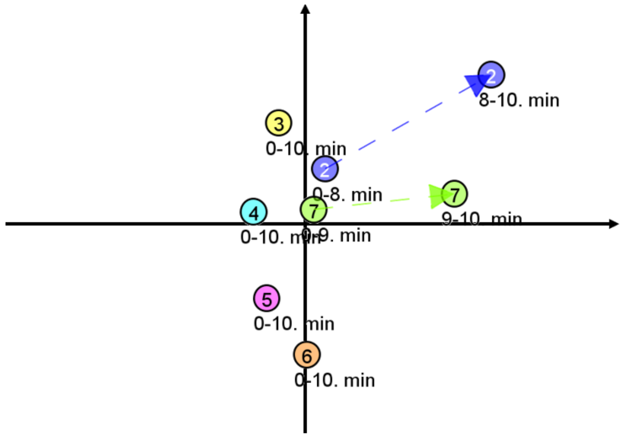

Figure 14. The detected changes using a less sensitive parameter setting. Only more significant changes remain.

to give input or additional analyses with respect to the normal behavior of the group have to be conducted first. For instance, an investigation of typical object distances during the observation period or the general extends of the observation space, e.g., the dimension of a football field, could provide a useful hint to reasonable parameter values.

Additionally, the football experiment shows the capability of our approach to identify formation changes during the match, which are not visible by just determining the RTL. Further, this type of analysis provides the possibility to reveal an important part of the team tactics in significantly less than a minute. This is a major time saving compared to watching one or multiple videos of the matches and manually searching for those changes. However, in the current state it does not consider interactions among the team members or with the members of the opponent team. Usually, the movements of the players are strongly influenced by the movements of their direct opponents. So, it does not explicitly consider the current game situation.

The other two experiments are also affected by this problem as we have not taken external influences into account there either. Besides considering the movement space including static obstacles and the movement of other dynamic objects, which are interacting with the observed group, approaches of e.g., Helbing and Molnar (1995) dealing with the interactions of human beings during those encounters could be used to explain the group members' behavior.

With respect to the previous problem, the experiments also reveal another limitation of this approach, as it generally does not provide an interpretation of the analyzed scenarios. For instance, in the first experiment, a change in the group structure is detected (see Figure 6). However, this is more likely to be caused by external influences, such as obstacles or other moving objects. Since these influences are not taken into account in our approach, as mentioned above, a reasonable interpretation becomes difficult. This means that either additional data to model the scenario completely or expert knowledge is required. However, the approach helps to point out potentially interesting situations that are worth being interpreted afterwards.

6. SUMMARY AND OUTLOOK

In this paper, we presented an approach to detect changes in groups of moving objects. The approach consists of three steps in which the motions are first transformed to relative motions and then searched for changes in these with respect to the intra-group object positions. In three experiments with data of different domains we evaluated our approach and demonstrated its functionality and portability. However, we also noticed limitations in terms of the consideration of the given environment and other interacting dynamic objects with the observed group and the missing reasoning of the changes.

The found limitations and further open points can be addressed in future work. As discussed in the previous section, approaches to model the general movement behavior of interacting human beings could be integrated in the analyses. The same holds for the movements of the other interacting objects. While we focused on moving human beings in this work, another open point is the application to data of further domains, e.g., the observation of animals. In addition to that, the application of the approach to movements in other spaces than the Euclidean space, e.g., the network space, where movements are more constrained, could be investigated.

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