Procedia Computer Science
Volume 71, 2015, Pages 85–91
2015 Annual International Conference on Biologically Inspired Cognitive Architectures

Model-based Behavioral Causality Analysis of Handball with Delayed Transfer Entropy

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Abstract

In goal-type ball games, such as handball, basketball, hockey or soccer, teammates and opponents share the same field. They switch dynamically their behaviors and relationships based on other players' behaviors or intentions. Interactions between players are highly complicated and hard to comprehend, but recent technological developments have enabled us to acquire positions or velocities of their behaviors. We focus on handball as an example of goal-type ball games and analyze causality between teammates' behaviors from tracking data with Hidden Semi-Markov Model (HSMM) and delayed Transfer Entropy (dTE). Although 'off-the-ball' behaviors are a crucial component of cooperation, most research tends to focus on 'on-the-ball' behaviors, and relations of behaviors are only known as tacit knowledge of coaches or players. In contrast, our approach quantitatively reveals player's relationships of 'off-the-ball' behaviors. The extracted causal models are compared to the corresponding video scenes, and we claim that our approach extracts causal relationships between teammates' behaviors or intentions and clarifies roles of the players in both attacking and defending phase.

Keywords: Goal-type Ball Game, Handball, Causality Analysis, Group Behavior, Hidden Semi-Markov Model, delayed Transfer Entropy

1 Introduction

Goal-type ball games, such as handball, basketball, hockey or soccer include complex dynamics of multiple experts' behaviors and their interaction. These are unpredictable and hard to comprehend. However, fine-grained data like tracking data are assumed to help us to understand their cooperative group behaviors. We focus on handball and analyze causality between players' behaviors in their cooperation using video, tracking and annotation data in a match. Here we note that this paper mentions 'causality' based on predictive relationships of behaviors. The term is used for emphasizing the time-asymmetric relations. Tracking data are segmented with Hidden Semi-Markov Model (HSMM) and causality are extracted with delayed Transfer Entropy (dTE). The combination of HSMM and dTE flexibly handle the behavioral difference relationships with multiple time delays. While 'off-the-ball' behaviors are a crucial component

Selection and peer-review under responsibility of the Scientific Programme Committee of BICA 2015

doi:10.1016/j.procs.2015.12.210

of cooperation, most research tends to focus on 'on-the-ball' behaviors, and behavioral relationships are only known as tacit knowledge of coaches or players. On the other hand, our approach quantitatively reveals player's relationships of 'off-the-ball' behaviors. We have verified the validity of our approach by comparing the video scenes and the analysis result. The results suggest that our approach likely reveal causal relations and infer intentional communications among players from their trajectories.

2 Related Work

Recent technological developments have enabled us to acquire various kinds of data in sports games, and many types of analysis are conducted. For example, the relationships of player events and scores in football[12], passing networks[19], and player's decision-making processes in basketball[10] are investigated. Video data analysis are conducted for more than a decade[18, 4], additionally more fine-grained data are currently collected[1]. In particular, player trajectories of tracking data are beneficial to grasp real-time behaviors of players in games and used for analysis of their positions, distances, and velocities[5, 9].

In particular, there are several kinds of handball research based on player trajectories or raw video data [2, 6, 15]. Most of their motivations are activity recognition of a team and use HMM-like coupled or hierarchical method to model their dynamic structures. Although these types of research are similar to our research, our motivation is based on not predicting the team activities, but extracting player's relations in group behaviors.

3 Dataset

We use CVBASE06 handball video dataset[11], and it includes video, tracking and annotation data of a handball model match. The video data is recorded 10 minutes long in 25 fps. The tracking data includes trajectories of seven players belong to one team, i.e., six field players and a goalkeeper (also recorded in 25 fps). They do not include tracking data of the opponent team or the ball, and our analysis is conducted on the recorded team. The annotation data of group behaviors are written down by a handball coach every one second based on the included video. The group behaviors are classified into 9 classes (Table 1).

Annotation	Meaning
ovpp	defense, returning, preventing fast break
ovpc	defense, slowly returning
obg	defense, basic defense, defense against preparation of an offense
obz	defense, basic defense, defense against ending offense
t	break or time-out
nks	offense, fast break
nfpn	offense against set-up defense, setting up an offense
nfan	offense against set-up defense, ending an offense
npp	offense, slowly going into offense

Table 1: Group Behavioral Annotations

4 Analysis Methods

4.1 Hidden Semi-Markov Model

HSMM (Hidden Semi-Markov Model) is used to segment tracking data into discretized players' behaviors. A lot of research use HMM-like models to cope with time series segmentation problems[16, 8]. The joint distribution of HSMM can be written

$$p(\mathcal{X}, \mathcal{D}, \mathcal{Y}) = p(x_0)p(d_0)\prod_{t=1}^{T} p(y_t|x_t, \theta)p(x_t|x_{t-1}, d_{t-1}, A)p(d_t|x_t, d_{t-1}, \lambda) \tag{1}$$

where $\mathcal{X} = \{x_0, x_1, \ldots, x_T\}$, $\mathcal{D} = \{d_0, d_1, \ldots, d_T\}$, and $\mathcal{Y} = \{y_1, y_2, \ldots, y_T\}$ denote the hidden, duration, and observation sequence, respectively. θ, A, and λ denote the emission, transition, and duration parameter of each distributions[3]. In particular, $x_0, x_1, \ldots, x_T$ is assumed to be a homogeneous semi-Markov process with initial state probability $p(x_0)$ and transition probability $p(x_t|x_{t-1}, d_{t-1}, A)$. Each hidden state have state duration drawn from $p(d_t|x_t, d_{t-1}, \lambda)$ and emit observation based on the probability $p(y_t|x_t, \theta)$. HSMM has three advantages to segment players' behaviors. First, efficient learning method enables us to acquire unknown behavioral segments from data in a completely unsupervised way. Second, HSMM explicitly models duration of hidden states[3] and deals with duration variability of each behavior. Third, Hierarchical Dirichlet Process (HDP) prior on states and state transitions automatically determine the optimal number of hidden states for explaining data through the learning process[17, 8].

4.2 delayed Transfer Entropy

dTE (delayed Transfer Entropy) is used to extract causality between the players' behavioral sequences. Transfer Entropy (TE) is a model-free measure which infer information flow between sequences[13] and recently applied to analyses of spiking neurons or behavioral analysis[7, 14]. dTE is proposed as an extension of TE and able to extract causality including multiple time delays[7]. dTE is defined as follows

$$TE_{J\to I}(d) = \sum p(i_{t+1}, i_t, j_{t+1-d}) \log_2 \frac{p(i_{t+1}|i_t, j_{t+1-d})}{p(i_{t+1}|i_t)} \tag{2}$$

where d denote time delay of interest. i_t and j_t denote the states of the discrete sequences I and J at time t. TE and dTE are time-asymmetric which consider causal directions compared to correlation or mutual information. Since this metric reflect the decrease of uncertainties of a sequence by considering the information of the other sequence, this value represents predictive relation. dTE extracts players' behavioral causality with multiple time delays by changing the parameter d. Therefore, this method deals with several timings of changing behavior based on other behaviors. We simply select a peak of dTE in multiple d and construct a matrix by calculating dTE between the combinations of whole players in a group. It shows the strength of behavioral relationships in a group. We refer the causality matrix as delayed Transfer Entropy Matrix (dTEM) below.

5 Behavioral Causality Analysis in Handball

5.1 Player Behavioral Sequence Segmentation

We segment the 10 minutes handball tracking data in CVBASE06 by using HSMM. We hypothesize that players' intentions appears on their turns or sudden accelerations, thus players' behaviors are defined as five dimensional time series, i.e., velocity $(\dot{x}, \dot{y})$, acceleration $(\ddot{x}, \ddot{y})$ and amount of directional changes θ. Amounts of directional changes are defined as internal angles of velocity vectors. The emission distributions of HSMM is defined with multivariate Gaussian distributions which represent their average behavioral dynamics. Duration of the behaviors are discrete time frames and modeled with Poisson distributions. The hyperparameters are determined based on their conjugacy. We use weak-limit approximation on HDP for efficient parameter inference based on forward-backward sampling algorithm[8].

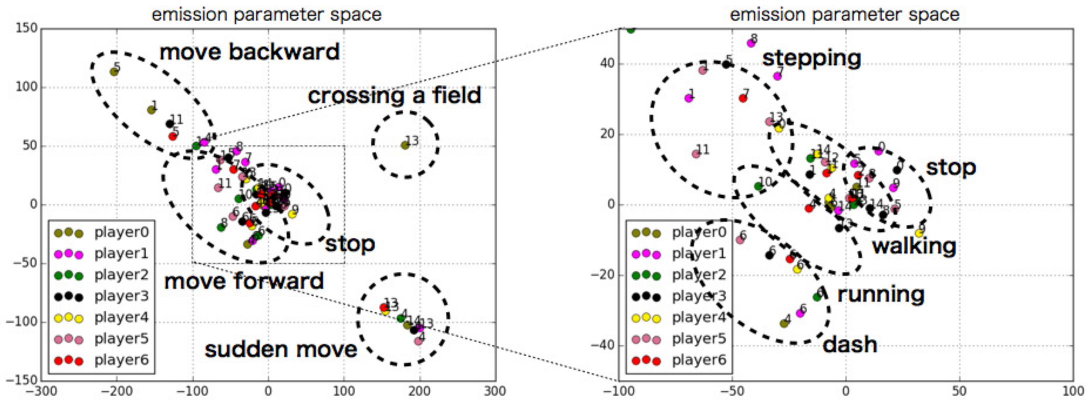

Figure 1: Each emission distributions in the parameter space. The upper right character of each colored points represents a number of player's HSMM hidden states.

As a result of segmentations, the number of player's hidden states (player 0 to 6) are each determined with the estimated distribution; 8, 10, 8, 9, 7, 9, 8 (total 59). We evaluate the validity of the segmentations by checking the positions of the emission distributions of each learned HSMMs in their parameter space. Player's behaviors are different in each game, but they are assumed to be classified into common or uncommon behaviors. Hence, we project the parameters of the emission distributions to low dimensional space and check their distribution pattern. The distance matrix is defined by Kullback-Leibler (KL) divergence and projected with Multi-Dimensional Scaling (MDS). Since behaviors of players are modeled with distributions based on their average and covariance parameters of their dynamics, similarity of distributions indicates the similarity of behaviors.

Ellipses of a black dashed line represent rough groups in the parameter space determined based on our visual judgment with the video. These groups are softly clustered into several groups, for example, "stop", "walking", "running" or "dash", and the more or less the number of emission distributions almost correspond to the number of common or uncommon behaviors. The segmentations with the HSMMs are assumed to be close to the segmentation of human judgment and we consider that these results support their validity.

5.2 Causality Analysis between Behaviors in each Group Behaviors

dTEM are constructed through the whole combinations of each change point sequences. These are calculated from hidden state sequences in each group behavior classes, e.g., fast break, setting defense. To extract causality for 1 second (25 frames), we calculate dTE with 25 delays and select the peak value. That is because ball game players often have to change their behaviors based on the other players' behaviors or intentions in very short times. For the visibility of analysis, we use directed graphs which show relationships of players. These graphs are constructed by assuming dTEMs as adjacency matrices.

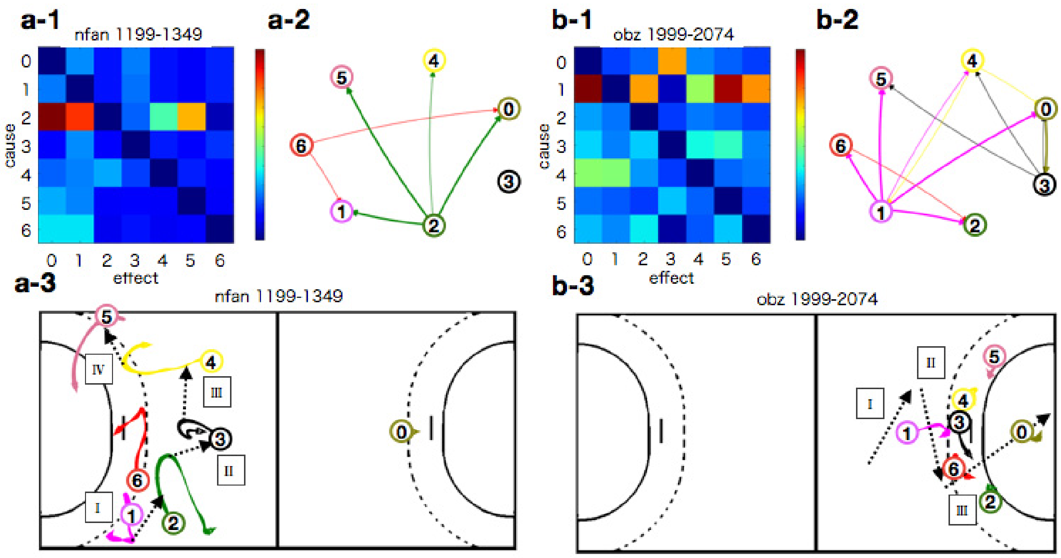

Figure 2: dTEM, Directed graphs of dTEM, and player trajectories of (**a**) attacking phases and (**b**) defending phase. The edges of the graphs are quantized with k-means by the amount of causality (the thick edges represent strong relation, the thin edges represent weak relation, and the non-edge represent almost no relation). The dashed arrow on the field plot denotes passings (of (**a**) teammates/ (**b**) opponents) and the Roman numbers are the orders. According to their formations, player 0: keeper, player 6: pivot, player 1/5: left/right wing, player 2/4: left/right back, player 3: center back in attacking phases. The player 4, 5 and the player 1, 6 change their positions in defending phases (a-3, b-3).

Fig. 2 shows a few examples of the results. Fig. 2a shows an end of attacking behaviors and includes one passing sequence and one shot. This attacking behavior starts from a pass of the player 1, and the pass sequence continues as player 2 $\rightarrow$ 3 $\rightarrow$ 4 $\rightarrow$ 5. According to the extracted causality, the player 2 has strong effects to the other players in the right side. Fig. 2b shows an end of defending behaviors. In this scene, the opponents attack in the right side and then change to attack in the left side. The extracted causality strongly appears from the player 1 in the front of the opponents to the other teammates. These also appear on the player 6 and 3 who have moved to cover spaces of the defense in the left and center position.

6 Discussion

In attacking and defending phases of handball, whole field players participate in same group behaviors. In attacking phases, they surround opponents and pass around within teammates or take shots. Since the opponents crowd in front of their goal, the attackers ought to break down the defense by their passes. In the scene of Fig. 2a, the ball was moved from the left side to the right side. The left back player 2 went to the opponents' crowd, pulled the opponents to him, and finally pass to the receiver. This behavior indicates that the player has intended to disrupt the defense, and then become the central role of the attacking. The other players are assumed to change their behaviors by the intention of the player 2, and the relations are expressed on the dTEM. The pivot player locates at the center and has a role in disrupting the opponents' defense or assist the teammates passings. The causality of the pivot player 6 is assumed to correspond to the role.

In defending phases, on the other hand, they are surrounded by the opponents and block the opponents' passes or shots. They make a defensive wall and need to cover spaces of passes or shots. In Fig. 2b, the center player 1 stands front of the opponents and tries to block their attacks. We consider the analysis target team have intentions to keep their defensive wall, and the other players exclude the frontal player 1 move to defend based on the player 1. The dTEM explicitly shows causality between the players in the both side of the player 1, i.e., the player 4 and 5 in the right side, and the player 6 and 2 in the left side. Moreover, we consider the causality from the player 3 to 4, 5 corresponds to defending behaviors to cover the defensive wall in the right side, and the causality from the player 6 to 2 show the relationship in the left side defense.

Our method is useful to detect the central players whose behaviors affect many teammates' behaviors or hidden relations in cooperative behaviors. In the future, we will verify the validity of relationships by cooperating with experts in goal-type ball games.

7 Conclusion

The results of the analysis are as follows: (1) Handball players' behaviors are segmented based on their velocities, accelerations and direction changes with HSMM. The validity of segmentation has been verified by checking the parameter space and the video scenes. (2) Causality between the segmented behaviors is extracted with dTE. As a result, differences of the players' roles and relationships of 'off-the-ball' behaviors or intentions are clarified on the extracted causality in both attacking and defending phases from their trajectories.

Our approach has several limitations. First, although our method infers player's relationships based on the behavior changes, it might detect spurious relations based not on their perceptions. To solve this problem, we consider to model not only their output behaviors but also their input perceptions. Second, since our method extract relations from behavioral changes in multiple time delays, it can deal with fast and slow behavioral changes caused by other behaviors through setting the delay parameter. However, extracted relation with long time delays may reflect indirect relation which mediated by several players. These problems can be avoided by conditioning Transfer Entropy based on behaviors of whole other players, but considering more and more other players to infer relations between two players needs a lot of data of each group behaviors. We have future works for solving these problems.

In this analysis, the dataset does not include tracking data of opponents and a ball. We will analyze additional dataset and verify the validity of our analytical method. Moreover, we plan to discuss goal-type ball game experts' evaluations of our approach.

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