Trajectory Based Assessment of Coordinated Human Activity*

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Abstract. Most approaches to detection and classification of human activity deal with observing individual persons. However, people often tend to organize into groups to achieve certain goals, and human activity is sometimes more readily defined and observed in the context of whole group, where the activity is coordinated among its members. An excellent example of this are team sports, which can provide valuable test ground for development of methods for analysis of coordinated group activity. We used basketball play in this work and developed a probabilistic model of a team play, which is based on the detection of key events in the team behavior. The model is based on expert coach knowledge and has been used to assess the team performance in three different types of basketball offense, based on trajectories of all players, obtained by whole-body tracker. Results show that our high-level behaviour model may be used both for activity recognition and performance evaluation in certain basketball activities.

Keywords: human motion, group activity, activity analysis, sport analysis

1 Introduction

Observation and analysis of human motion by the means of computer vision strives to answer several questions [6]: *where* (the position), *who* (the identity) and *what is he/she doing* - the activity the observed person is engaged in.

Fair amount of work [1, 13, 15, 16, 9, 3] has been devoted to human activity recognition in the past years. Nevertheless, most of the related research has been focused on the problem of recognizing the activity of a single isolated subject, with several exceptions, for example [8] and [4].

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It is known that people tend to organize into groups to achieve certain goals. The activity of such group, especially the *coordinated activity* is in the center of our work. Although group consists of individuals, their actions are not isolated. The group activity should be observed in the context of the group and group goals. Moreover, relations between members of the group become important if we want to answer the question "What are *they* doing?"

Team sports are excellent example of coordinated group activity: the teams have clearly defined goals, which need cooperation between individual players. Outcome of the particular group activity (offense and defense, for example) depends both on cooperation of the team and individual skills of team members. Team sports have well defined rules, which form the foundation of the play. Actions of the team members are coordinated in space and time. All this increases complexity of the play, and interference from the opposing team severely impacts its course. This makes the team sports the ideal test ground for developing and testing the algorithms for group activity detection, recognition and evaluation. Our research is based on the game of basketball.

This paper is structured as follows: first, we present the way the data has been obtained for our study. Next, we present the important properties and rules of the basketball play, which have been used to develop the model of the play, which is presented next. The model has been adjusted and tested using the real data. An expert (basketball coach) comments are used to interpret the results.

2 Tracking

During the past several years we have witnessed rapid advancement in video and computer technology. This enabled many ways of acquiring human motion that previously have not been possible. We used the computer-vision based system for tracking players in the sport matches, which is described in detail in [11]. The calibrated system is permanently installed in sports hall and available for experiments. The tracking has been performed automatically using the methods described in [12], under human supervision. Human supervision guarantees that the obtained data is consistent and contains no major errors. The output of the system are smoothed trajectories of all the players on the basketball court, for the whole duration of the experiment. The error of the tracking system has been previously measured by the means of field tests [11] and has been found to be 0.3-0.6 m RMS (court center - boundary) for position and 0.2 m/s for velocity measurements.

Therefore, our approach is based entirely on player trajectories, obtained by tracking of whole body. Position of the player is represented by a pair of coordinates in the 2D coordinate system of the court, and can be seen as an approximation of the 2D position of player gravity center.

3 Basketball

Basketball is the team sport, played by two opposing teams on a court, measuring 28×15 meters and divided into two equal halves, as shown in Fig. 1. Teams score points by throwing a ball in the opponent's basket, and the team with the highest score wins. Baskets of both teams are placed at the opposite ends of the court, and teams play in opposite direction. The ultimate goal of each team is to get a ball, come to a throwing range by outsmarting the opponent's defense and score a point. When the opposing (other) team gets the ball, team goes to defense mode and tries to prevent opponents from achieving the previously described goal.

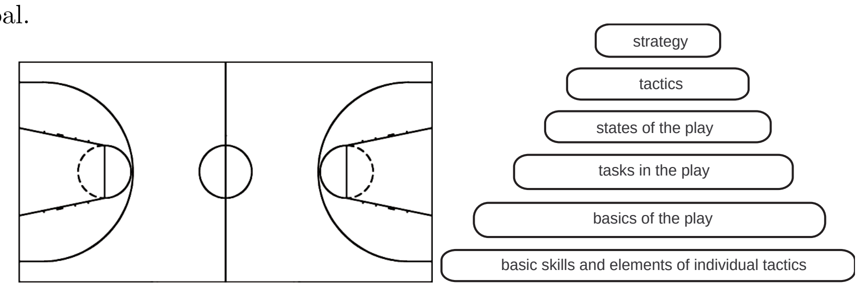


Fig. 1. Left: basketball court. The direction of the play is left to right for one team and right to left for the other. Right: hierarchical structure of the basketball play.

3.1 Basketball offense and its properties

Basketball play consists of two interchanging phases (from the viewpoint of one team): offense and defense. In this work, we focused on basketball offense. Therefore, our model of the play includes only the players from one team, and is, as presented, limited only to offensive play. The structure of a basketball play can be decomposed hierarchically, as shown in Fig. 1. The basic building blocks of team play are *basic skills (technical elements)* and *elements of individual tactics*. We call these elements, defined in Table 1 the *key events*.

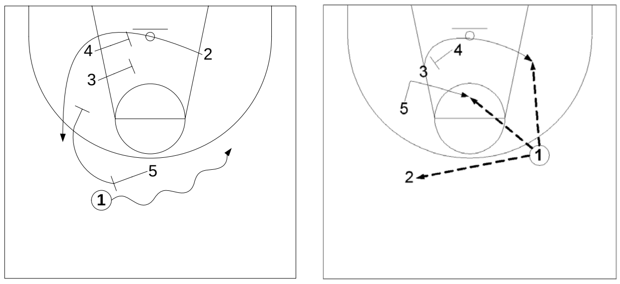
Table 1. Key events as manifestation of tactical basketball elements in offensive play.

move	Smooth motion of a player, without rapid direction changes.
getting open	Conclusion of a move; before stopping or before a rapid change in direction and/or velocity.
cutting	Rapid, nearly straight motion towards or over particular court region.
pick, screen	Meeting of two players, where first one sets the block (standing still) and the second one exploits it by running as close as possible to the first one.

These events may be grouped according to certain spatio-temporal relations to describe a particular *type* of offensive play. We focused on three types of basketball offense ("52", "Flex" and "Moving stack"), shown schematically in Figs. 2, 3 and 4.

4 Recognition system and model of the play

We mainly followed the approach by Intille and Bobick [8] in development of the recognition system. The system is given a set of trajectories of individual



Player 1 uses the high screen on the ball by 5. Player 2 runs off the staggered triple screen by 4, 3 and 5.

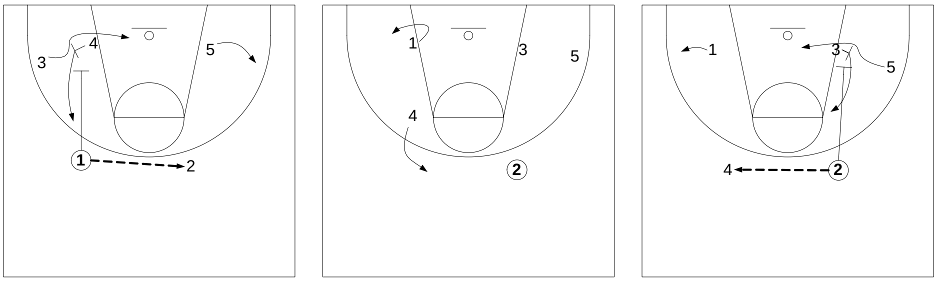
Player 4 then turns and backscreens for 3. Player 3 pops to the ballside wing. 5 ducks into lane. 1 looks for 2, 3, or 5.

Fig. 2. Basic motion of players in the "52" offense. Numbers denote players. Adapted from [5].

players, and its objective is to establish whether they correspond to a particular type of the team play. The type of the play is defined by its model. Our approach has the following stages:

- The position, velocity, acceleration, angle and angular velocity of the players are fed into probability estimation functions, which assign the grades in the interval [0,1] to the predefined scenarios, which describe relations between different players, and players and the playing court, e.g. "player A is on the right side of player B". In this example, the highest grade means that players A and B are *exactly* at the modeled positions, while lower grades indicate certain amount of discrepancy between the predefined and observed positions.
- Graded descriptions are then grouped according to the definition of *key events*, as defined in Table 1. In our case, key events are strongly related to the elements of the basketball tactics and technique, therefore expert (coach) knowledge becomes essential. The output of this stage are numerical grades in interval [0,1] which describe the probability that a certain key event has been observed.
- Since the actions of the players are coordinated, the sequence of observed key events is graded according to their temporal relationship [2] (for example `before`). Finally, probability that certain type of play has been observed is calculated using `NoisyAnd` and `NoisyOr` models [10]. For example, let us model certain action by the set of weights that correspond to the key events A, B and C, weighted as (A, 0.9), (B, 0.5) and (C, 0.4). Invoking `NoisyAnd` when only B and C (but not A) have been observed will result in probability of 0.1 (1 - 0.9).

Our main contribution is the use of properly defined high-level *key events*, which simplifies the descriptions of the actions and allows for easy formalization

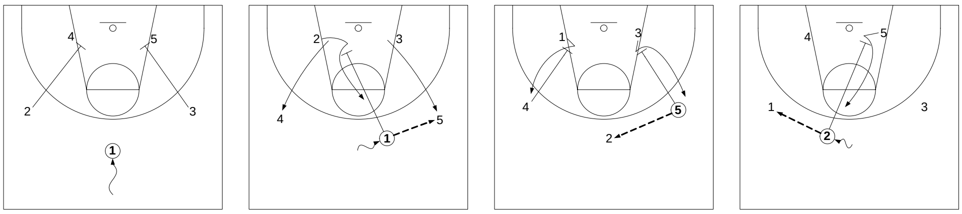


The floor is balanced, with the players filling five positions on the court. There is a basic overload on the ball-side before the motion begins. One initiates the offense by passing the ball to 2. 3 uses the 4's screen and cuts to the basket.

1 then screens for 4 who comes up the lane and replaces 1 in his original position. 2 has the option to either pass to 3 cutting to basket or to 4 looking for the jump-shot. If 2 passes to 4 the offense is initiated to the other side of the floor.

The rotation is the same, 5 uses the screen by 3 to cut to the basket. 2 sets the screen for 3 who opens up on the wing. 1 moves away from the basket and the rotation is complete.

Fig. 3. Basic motion of players in the "Flex" offense. Numbers denote players. Adapted from [14].



Player 1 should be the team's top ball-handler because he controls the ball until the inside players in the stack, 4 and 5, pop out of the down-screens set by 2 and 3, and an entry pass can be made.

1 chooses to pass to 5. After the pass, 1 screens down for the offside post player 2, who moves to the point. This motion takes away the off-side help's primary helper (X2) and permits 3 to play one-on-one in the ball-side post area.

5 may pass the ball to 2, and the basic motion may be repeated.

If 3 doesn't have a shot and 5 is not open the next pass option is to 2 on the high post after which the offense is effectively reset.

Fig. 4. Basic motion of players in the "Moving Stack" offense. Numbers denote players. Adapted from [7].

of expert (coach) knowledge about *how* does particular action (offense) looks like. Figure 5 shows the diagram of temporal relations for the offense "52", defined in Fig. 3. Three different models have been built by translating expert knowledge about basketball offense (provided by one of the authors) into the logical structure. This knowledge includes certain thresholds (for example, the definition of "fast" motion), above mentioned weights in the NoisyAnd and NoisyOr models and the specification of temporal relations (sequence, allowed intervals) between the events. The accuracy of the underlying tracking system was also taken into the account in model design, by choosing the appropriate threshold values.

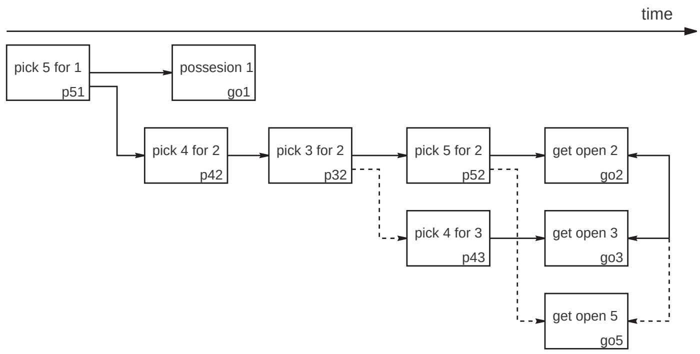


Fig. 5. Diagram of temporal relations for the offense "52".

The procedure to calculate an estimate of probability that the execution of offense "52" was observed can be derived from such diagram. As an illustration, sample algorithm for the offense "52" is provided below. Players are marked `s1` through `s5` and uppercase labels denote regions of the court. For the purpose of our experiments, all algorithms were implemented in the the C++ code.

```
is_52L(Group S={s1,s2,s3,s4,s5}) {
   p51 = is_picking(s5,s1, WING_LB)
   p42_1   = is_picking(s4,s2, POST_LO_L)
   p42_2   = is_picking(s4,s2, CORNER_LB)
   p32_1   = is_picking(s3,s2, POST_LO_L)
   p32_2   = is_picking(s3,s2, CORNER_LB)
   p43_1   = is_picking(s4,s3, POST_LO_L)
   p43_2   = is_picking(s4,s3, CORNER_LB)
   p52 = is_picking(s5,s2, WING_LB)

   go1 = is_gopen(s1, WING_LT, WING_LB)
   go2 = is_gopen(s2, POST_HI_L, CORNER_LT)
   go3 = is_gopen(s3, CORNER_LT, POST_LO_L)
   go3c    = is_cutting(s3, POST_LO_L)

   or_p42  = OR(p42_1, p42_2)
   or_p32  = OR(p32_1, p32_2)
   or_p43  = OR(p43_1, p43_2)
   or_go3  = OR(go3, go3c)

   bgo1p51 = before(go1, p51)
   bp42p51 = before(or_p42, p51)
   bp32p42 = before(or_p32, or_p42)
   bgo3p43 = before(or_go3, or_p43)
   bp52p32 = before(p52, or_p32)
   bgo2p52 = before(go2, p52)

   wgo2go3 = within(bgo2p52, bgo3p43, 25)
   n_and   = NOISYAND(0.0,
       (bgo1p51, 0.9),
       (bp42p51, 0.9),
       (bp32p42, 0.7),
       (bp52p32, 0.9),
       (bgo2p52, 0.9),
       (wgo2go3, 0.4))

   is_52L := n_and
}
```

5 Experiments and results

The experiments were performed in the sports hall under the guidance of two experienced basketball coaches. Ten students of the basketball class were participating in the experiments. We divided them into two teams, the "green team" (experienced players) and the "yellow team" (less experienced players). The coaches instructed players how to play particular type of offense.

All three types of offense were played with numerous repetitions, both with and without the presence of the defensive team. The number of test video sequences totaled 74, and tracking of players with subsequent analysis was performed on all of them.

Since we built the model with the expert knowledge alone, some model adjustment was needed. In the process of adjustment, we used the trajectories of several flawlessly executed offensive actions (the training set). The structure of the model and several parameters were adjusted, until the model yielded high probability of particular type of offense for the training trajectory set. This way, the model is fitted to the knowledge of a particular expert, which may be desirable in some circumstances and undesirable in others.

In some instances the algorithm was unable to infer the type of offense that is about to be played from the starting formation. In these cases, we manually initialized the algorithm for the particular type of offense. These video sequences are marked by italic text in the remainder of the section.

The results are structured as follows: the offense type, number of particular sequence and team color is specified in the first column. In the second column the roles of the players are specified (e.g. P1, P5, P2 ... means that the person P1 was playing in the role of player 1 from Fig. 3, person P5 was playing in the role of player 2, etc.) The third column shows the probability that particular type of offense was observed by the system, and last column contains expert coach observations and explanations about particular action and explanation why particular probability has been assigned. Applying inappropriate descriptions to the test video sequences (confusion analysis) yielded low results (around 0.1). Therefore, those results are not presented here.

Table 2. Results for the green team offense of the type "52". "green" denotes the trials without the defense team, "play" denotes trials with passive defense present. "/" sign means "Comment not necessary".

sequence:	roles:	probability:	remarks:
52-01-green	P1,P5,P3,P4,P2	0,9254	/
52-02-green	P1,P5,P3,P4,P2	0,7482	unclear relation before(p32, p42)
52-03-green	P1,P5,P3,P4,P2	0,9088	/
52-04-green	P1,P5,P3,P4,P2	0,0573	2 does not open at the right place
52-05-green	P1,P5,P3,P4,P2	0,9417	/
52-06-green	P1,P5,P3,P4,P2	0,7392	unclear relation before(p32, p42)
52-07-green	P1,P5,P3,P4,P2	0,8454	/
52-08-green	P1,P5,P3,P4,P2	0,9840	training sequence
52-09-green	P1,P5,P3,P4,P2	0,9079	/

sequence:	roles:	probability:	remarks:
52-01-play	P1,P4,P2,P3,P5	0,4181	p51, 1 too far from screen
52-02-play	P1,P5,P3,P4,P2	0,3135	p43, 3 too far from screen
52-03-play	P1,P5,P3,P4,P2	0,0394	poorly performed screens
52-04-play	P1,P5,P3,P4,P2	0,2472	poorly performed screens
52-05-play	P1,P5,P3,P4,P2	0,1957	poor p51, taken into account several times? different before needed?
52-06-play	P1,P5,P3,P4,P2	0,9368	/
52-07-play	P1,P3,P5,P4,P2	0,2555	poor p51
52-08-play	P1,P5,P3,P4,P2	0,3383	poor p51 and p42
52-09-play	P2,P5,P3,P4,P1	0,8847	/
52-10-play	P1,P5,P3,P4,P2	0,1786	poor p51
52-11-play	P1,P3,P5,P4,P2	0,5903	poor p51
52-12-play	P1,P3,P5,P4,P2	0,1016	poor p51 and p42

Table 3. Results for the offense of the type "flex". "green" denotes the trials by green team without the defense team, "play" denotes trials by both teams with passive defense present. TOP and BOTTOM denote the two possible directions of the basic motion.

sequence:	roles:	probability:	remarks:
flex-01-green	BOTTOM,P4,P5,P3,P2,P1	0,9928	/
	TOP,P5,P2,P1,P3,P4	0,6817	4 does not open, poor p53
flex-02-green	BOTTOM,P2,P1,P3,P4,P5	0,9000	/
	TOP,P1,P4,P5,P3,P2	0,1187	/
flex-03-green	BOTTOM,P1,P2,P5,P4,P3	0,9697	/
	TOP,P2,P4,P3,P5,P1	0,9488	/
flex-04-green	TOP,P2,P1,P5,P4,P3	0,8842	/
	BOTTOM,P1,P4,P3,P5,P2	0,2795	no p15
flex-05-green	TOP,P1,P2,P5,P4,P3	0,8464	/
	BOTTOM,P2,P4,P3,P5,P1	1,0000	/
flex-06-green	BOTTOM,P1,P2,P5,P4,P3	1,0000	/
	TOP,P2,P4,P3,P5,P1	0,1495	5 does not open, poor p35, p13
	BOTTOM,P4,P5,P1,P3,P2	0,4692	unfinished
flex-07-green	BOTTOM,P2,P1,P3,P4,P5	0,9985	/
	TOP,P1,P4,P5,P3,P2	0,7932	poor p13 (both moving)
flex-08-green	BOTTOM,P2,P1,P3,P4,P5	0,9809	/
	TOP,P1,P4,P5,P3,P2	0,2366	3 opens poorly, poor p35
flex-09-green	BOTTOM,P2,P1,P3,P4,P5	0,9989	/
	TOP,P1,P4,P5,P3,P2	0,5928	2 does not open, poor p13
flex-10-green	BOTTOM,P2,P1,P3,P4,P5	0,9725	/
	TOP,P1,P4,P5,P3,P2	0,9688	/
flex-11-green	TOP,P1,P2,P5,P4,P3	1,0000	/
flex-12-green	BOTTOM,P2,P1,P3,P4,P5	1,0000	/
	TOP,P1,P4,P5,P3,P2	0,5372	poor p13 and opening of 2
	BOTTOM,P4,P3,P2,P5,P1	0,6917	poor screens
sequence:	roles:	probability:	remarks:
flex-01-play	BOTTOM,P2,P3,P1,P5,P4	0,3355	green offense
	TOP,P3,P5,P4,P1,P2	0,9912	/
	BOTTOM,P5,P1,P2,P4,P3	0,1344	/
	TOP,P1,P4,P3,P2,P5	0,1079	/
flex-02-play	TOP,P1,P2,P5,P4,P3	0,9733	green offense
	BOTTOM,P2,P4,P3,P5,P1	0,9434	/
flex-03-play	TOP,P1,P2,P5,P4,P3	0,9293	green offense
	BOTTOM,P2,P4,P3,P5,P1	0,4000	/
flex-04-play	TOP,P1,P2,P5,P4,P3	0,8498	green offense
	BOTTOM,P2,P4,P3,P5,P1	0,1756	/
flex-05-play	TOP,P1,P2,P5,P4,P3	0,8178	green offense
	BOTTOM,P2,P4,P3,P5,P1	0,1565	/
flex-06-play	TOP,P1,P2,P5,P4,P3	0,9928	green offense
	BOTTOM,P2,P4,P3,P5,P1	0,3562	/
flex-10-play	BOTTOM,P1,P2,P5,P4,P3	1,0000	green offense
	TOP,P2,P4,P3,P5,P1	0,2500	/
flex-11-play	*BOTTOM,P2,P1,P3,P4,P5*	1,0000	yellow offense
	TOP,P1,P4,P5,P3,P2	0,8850	/
flex-12-play	*BOTTOM,P1,P2,P3,P4,P5*	0,3600	yellow offense
	TOP,P2,P4,P5,P3,P1	1,0000	/
flex-13-play	TOP,P1,P2,P4,P5,P3	0,3621	yellow offense
flex-14-play	TOP,P1,P2,P3,P4,P5	0,3016	yellow offense
	BOTTOM,P2,P4,P5,P3,P1	0,1419	/
flex-15-play	TOP,P1,P2,P5,P4,P3	0,2471	yellow offense
	BOTTOM,P2,P4,P3,P5,P1	0,5242	/

6 Conclusion

Results show strong correlation between the quality of the performance of the particular action and the probability that particular action has been observed.

Table 4. Results for the offense of the type "moving stack". "green" and "yellow" denote the trials by green and yellow team without the defense team, respectively, "play" denotes trials by both teams with passive defense present.

sequence:	roles:	prob.:	remarks:
motion-01-green	P1,P3,P2,P5,P4	0,9753	/
	P3,P5,P4,P1,P2	0,9834	/
motion-02-green	*P1,P3,P2,P4,P5*	0,9304	/
	P3,P4,P5,P1,P2	0,9564	/
motion-03-green	P1,P3,P2,P4,P5	0,9866	/
	P3,P4,P5,P1,P2	0,9132	/
motion-04-green	P1,P3,P2,P4,P5	0,9750	/
	P3,P4,P5,P1,P2	0,9862	/
motion-05-green	P1,P3,P2,P5,P4	0,9673	/
	P3,P5,P4,P1,P2	0,6648	simultaneous screens p54, p32 absent
motion-06-green	P1,P3,P2,P5,P4	0,9914	/
motion-07-green	P1,P2,P3,P5,P4	0,9770	/
motion-08-green	P1,P3,P2,P4,P5	0,9549	/
	P2,P4,P5,P3,P1	0,6742	p51 on wrong position, out of sync
motion-09-green	P1,P3,P2,P4,P5	0,9968	
	P3,P4,P5,P1,P2	0,8850	/
motion-10-green	P1,P3,P2,P4,P5	0,9351	/
	P2,P4,P5,P3,P1	0,7404	/

sequence:	roles:	prob.:
motion-01-yellow	P1,P3,P2,P4,P5	0,9925
	P3,P4,P5,P1,P2	0,8272
motion-02-yellow	P1,P2,P3,P5,P4	0,6397
	P2,P5,P4,P1,P3	0,6375
motion-03-yellow	P1,P3,P2,P4,P5	0,9115
	P3,P4,P5,P1,P2	0,3612
motion-04-yellow	P1,P3,P2,P4,P5	0,9878
	P3,P4,P5,P1,P2	0,9392
motion-05-yellow	P1,P3,P2,P5,P4	0,9703
	P3,P5,P4,P1,P2	0,5756
motion-06-yellow	P1,P2,P3,P5,P4	0,8073
	P2,P5,P4,P1,P3	0,5554
motion-07-yellow	P1,P2,P3,P5,P4	0,9637
	P2,P5,P4,P1,P3	0,5669

sequence:	roles:	probability:	remarks:
motion-01-play	*P1,P3,P2,P4,P5*	0,7683	green offense
	P3,P4,P5,P1,P2	0,4280	/
motion-02-play	P1,P3,P2,P4,P5	0,4701	green offense
	P3,P4,P5,P1,P2	0,5000	/
motion-03-play	*P1,P2,P3,P5,P4*	0,9834	green offense
motion-04-play	P2,P3,P1,P4,P5	0,8886	green offense
	P3,P4,P5,P2,P1	0,4057	/
motion-05-play	P1,P3,P2,P4,P5	0,2857	green offense
	P2,P4,P5,P3,P1	0,3095	/
motion-06-play	P1,P2,P3,P5,P4	0,6198	green offense
	P3,P5,P4,P2,P1	0,4529	/
motion-07-play	P1,P3,P2,P4,P5	0,9738	green offense
	P3,P4,P5,P1,P2	0,7690	/
motion-08-play	P1,P2,P3,P5,P4	0,9275	green offense
	P3,P5,P4,P2,P1	0,5667	/
motion-09-play	P1,P3,P2,P4,P5	0,6666	green offense
	P3,P4,P5,P1,P2	0,8341	/
motion-12-play	P1,P2,P3,P5,P4	0,8352	yellow offense
	P2,P5,P4,P1,P3	0,6733	/
motion-13-play	P1,P2,P3,P5,P4	0,6883	yellow offense
	P2,P5,P4,P1,P3	0,3803	/
motion-17-play	P1,P2,P5,P3,P4	0,8653	yellow offense
	P2,P3,P4,P1,P5	0,6971	/

This is due to the use of key events, which are closely tied to the key events of the basketball play. Therefore, our system could be used in automated assessment of team performance, monitoring players' progress in the course of training. The concept of key events enables the expert to obtain explanations, why the particular performance received low grades, by inspecting the grades of each individual key event, and thus learning the reasons for the poor performance of the team. This is demonstrated by expert comments on presented results.

It is not surprising that the existence of the defensive team greatly reduces the performance of the team; players are obstructed by the sole presence of the defense players, even with passive defense.

The presented results show adequate sensitivity of our model to improperly executed actions. Additionally, extremely low grades are assigned to the types of the play which do not match the model used.

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