

# Dependencies on Player Formation in Event-driven Hybrid Learning Classifier Systems for Soccer Video Games

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## ABSTRACT

In this paper, we discuss dependencies on player formation when using a classifier system in a decision algorithm for agents in a soccer game. Our aim is to respond to the changing environment of video gaming that has resulted from the growth of the Internet, and to provide bug-free programs in a short time. We have already proposed a bucket brigade algorithm and a procedure for choosing what to learn depending on the frequency of events with the aim of facilitating real-time learning while a game is in progress. We have also proposed a hybrid system configuration that combines existing algorithm strategies with a classifier system, and we have reported on the effectiveness of this hybrid system. In this paper, we pit players in several different formations against each other and show that the proposed system is able to learn regardless of the differences in formation. We also show that by performing simulations ahead of time, it is possible to investigate formations that will be effective against an opponent's formation. Finally, by investigating changes in frequency and success rates for each type of play due to changes in formation, we show that it is possible to acquire a team strategy for the current formation through learning.

## Categories and Subject Descriptors

D.3.3 [Programming Languages]: General

**General Terms:** Design, Experimentation, Verification.

**Keywords:** Learning classifier systems, Event-driven, Real-time learning, Soccer game, Video-game.

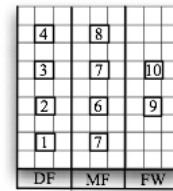
## 1. FORMATIONS AND LEARNING

In previous research [1] we used fixed formations for each team to study effective learning techniques. However, in actual play, each team can assume various formations, so it is important to study how learning effectiveness is dependant on these formations. Accordingly, here we focus on how the behavior of the agents changes when the formation is changed, and look at what effect this has on learning effectiveness and acquisition of new strategies.

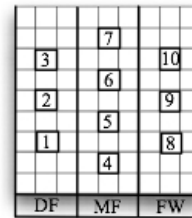
Figure 1 shows the formations that were examined in this study. F1 is the basic formation that we have used in previous experiments. F2 is balanced formations that distribute forwards, mid-fielders and

defense players more evenly. F3 is a defensive formation emphasizing the defensive players, and F4 formations use the midfield players more, emphasizing passing the ball. F5 is offensive formations, emphasizing the forwards more. Formations F1 to F4 are widely used formations in actual soccer game play, while F5 is the rarely-used and risky “four top” formations, that are only used to break through weak points in the opponent’s defense when points are desperately needed.

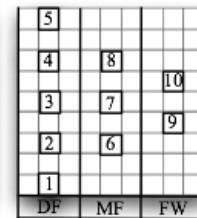
In this study, we examine our proposed event-driven hybrid classifier system to determine whether it can learn practically, independent of the formations used, whether the level of learning effectiveness changes due to formation, and how frequency and effectiveness of various types of play differ by formation.



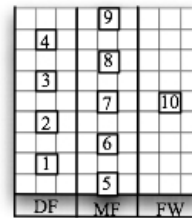
(a) Formation F1



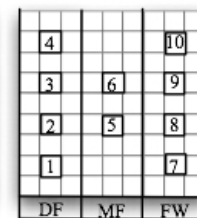
(b) Formation F2



(c) Formation F3



(d) Formation F4



(e) Formation F5

Fig. 1. The formations that were examined in this study.

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 GECCO'08, July 12–16, 2008, Atlanta, Georgia, USA.  
 ACM 978-1-60558-130-9/08/07.

## 2. EVALUATION AND DISCUSSION

Figure 2 shows the relationship between number of games played and win rate for each different formation. Figure 2 shows the results using algorithm A, which tries to balance offensive and defensive play. Examining Figure 2 shows that the hybrid system learns and is able to achieve a greater-than-50% win rate, whichever formation, F1 to F8, was used. However, win rates for the “4-top” formations, F7 and F8, were slower to rise than the other formations, and did not reach a final level comparable to the others. This is likely because these strategies so emphasize winning points that defenses are left weak and there is also a tendency for the other team to score points more easily. While these strategies can be effective for short periods of time they are probably not appropriate to be used for an entire game. We can also see that, for the game strategies used here, the balanced formation, F2, was the most effective, increasing in win rate most quickly and reaching the highest final win rate against the basic formation, F1.

Figure 3 shows changes in pass success rate respectively. The actual values for number of passes and success rate are somewhat scattered, but for all formations, success rate started to show an increasing trend after about 200 matches. This seems to show that learning is progressing and a trend is evolving to recognize impossible passing situations and increase the certainty of successful passes. Figure 4 shows success rates for dribbling. Actual values for dribbling occurrences and success rate are scattered, but for all formations, dribbling success rate tended to converge after several tens of matches. From this it appears that the strategy is evolving to be able to keep the ball for longer periods of time as the number of games increases and learning progresses. Figure 5 shows the success rates for shooting. Actual values for number of shots and shot success are scattered, but for all formations the success rates converged after several tens of matches, and showed an increasing trend after about 200 matches. This seems to indicate that as learning progresses with more matches, the strategy evolves to be able to gain a higher total number of points.

From the preceding trial results, we can deduce that the proposed event-driven hybrid classifier system is effective independent of the formation used, and as learning progresses its strategy evolves to keep the ball by dribbling when a pass is not possible, to increase the number of shots taken, and effectively increase the number of points won.

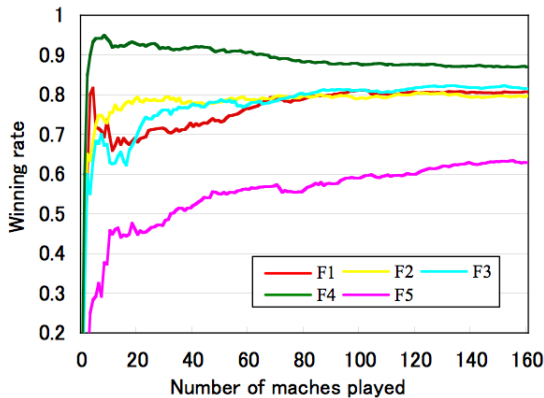


Fig. 2. Relationship between the number of games played and winning rate against for formation F1.

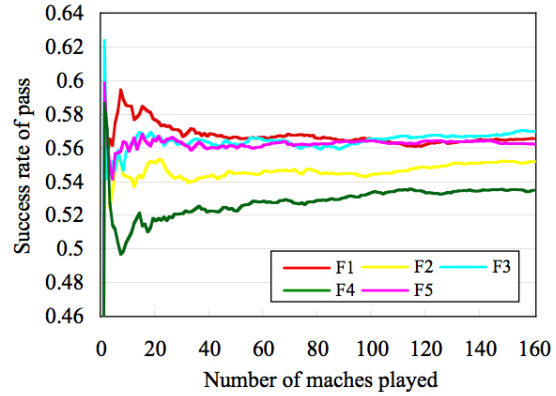


Fig. 3. Relationship between the number of games played and success rate of passing.

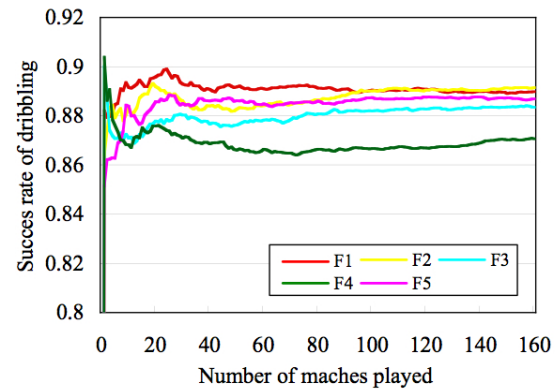


Fig. 4. Relationship between the number of games played and success rate of dribbling.

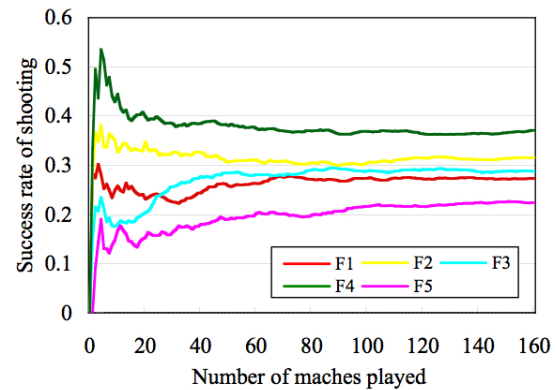


Fig. 5. Relationship between the number of games played and success rate of shooting.

## 3. REFERENCE

- [1] Sato, Y., Akatsuka, Y., and Nishizono, T. Reward Allotment in an Event-driven Hybrid Learning Classifier System for Online Soccer Games. In *Proceedings of the 2006 Genetic and Evolutionary Computation Conference*, ACM Press, Seattle, 2006, pp. 1753-1760