YuShan2024 Team Description Paper for RoboCup2024

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Abstract: This team description paper describes the direction and methods of team optimization over the past year at YuShan2024. There are two main parts of the work, which are the analysis and optimization of the shooting module and the analysis of physical strength and running distance. In a lot of tests in the past, we found that the team has the situation that even though the player is in front of the goal and has a chance to shoot, but there is no shooting action, and missed some good chances, so we hope to find the main direction to optimize the shooting module by analyzing the shooting data from multiple perspectives. At the same time, in the test with some strong teams, we found that YuShan's stamina maintenance has a big problem, often around 500 cycles before the end of the half, the player's stamina has been exhausted, resulting in the defense out of position, so we hope that through the method of data analysis, we can find the difference in the stamina maintenance of the players between us and the strongest teams, so as to further make optimization of the team's stamina maintenance.

1 Introduction

Team YuShan belongs to the Institute of Artificial Intelligence, School of Computer Science, Anhui University of Technology, and has participated in 9 RoboCup competitions since 2012, and won the third place for three consecutive years in the Online World Cup 2021, the World Cup 2022 in Thailand, and the World Cup 2023 in France. We have also won 6 championships and 4 runner-ups in RoboCup China Open in the last 11 years.

In recent years, the YuShan team has reorganized its engineering and launched the YuShan_Base base layer based on Agent-2D 3.1.0 [1] and a new version of librcsc [2]. Based on YuShan_Base for R&D, the characteristics of the team were analyzed using data mining techniques, and in 2019, we proposed to use the digital twin framework to find the focus direction of the team's R&D. Based on this, we analyzed and improved the directions of the team's formation, offensive and defensive state transitions, the players' running strategies, and shoveling and passing strategies.

2 Previous Work

As a regular participant in 9 RoboCup World Cups, YuShan's team has done a series of work around various directions of the team with the technology accumulated over the years. Initially, YuShan developed AutoPlay, an automated testing tool that avoids the tediousness of manually loading teams and helps teams conduct multiple tests without manual supervision. Considering that the scores between teams will visually present the strength of the teams, modeled after the human soccer scoring rules, YuShan also developed a score analysis tool called RcgAnalysis,which outputs a variety of information such as a team's winning percentage and goals scored based on the score result files of multiple matches. Based on the secondary development of the fedit2 tool, YuShanfedit2 tool was developed, which can open 2 sets of formation files (such as offensive and defensive formations) at the same time, so as to view the distribution of the home position points under different formations. YuShan also proposed a digital dual framework [3] and continuous modeling and analysis of teams through machine learning algorithms, which mainly include density clustering analysis of key areas of offense and defense[4] to adjust the team's defensive strategy; identification of different passing patterns of a team using the KNN algorithm[5]; and use of negative example learning to identify and classify the types of passes, and analyze the variability of the types of passes of different teams in different regions [6].

3 Team Shot Analysis and Optimization

3.1 Problem Overview

The goal shooting module is one of the important modules of the team, and the act of shooting is one of the important behaviors for scoring in a soccer game. In the past matches, we found that YuShan team has the situation that the attacking player is in front of the goal, has a good chance to shoot, but has not issued the command to shoot, which will greatly affect the team's performance in the critical moment, so we hope to find the optimization direction for the shooting module.

Unlike CSU's research on shooting, which focuses on using reinforcement learning techniques to improve shot paths and shot times[7], the methodology proposed in this paper focuses more on data imbalance, hoping to be inspired by the data analysis, and then working with the developers to make specific modifications.The existing data analysis work for the goal kicking module is mainly carried out by extracting and analyzing various kicking data such as passes, interceptions, and field goals, etc. This method reflects the influence of more pitch information on the goal kicking, but the data generated from the game is too large, and the extracted data will have the problem of the distribution of goal kicking events on all kicking data and its imbalance, which seriously affects the ability of some classification algorithms to recognize the goal kicking events. event recognition ability of some classification algorithms. We hope to reduce the imbalance rate of the datasets to achieve a better classification effect through the category balancing process, and analyze the features that have the most influence in identifying the field goal data through the interpretive analysis of the classification model.

In addition to this, we also wanted to adjust the running position and shot spotting of offensive players in more detail by comparing the difference in shot preference between YuShan's team and other strong teams, so we chose to extract shot spots from multiple games and perform density clustering on them, to find the difference in shot spotting preference between our team and other strong teams, so that we can further adjust our shot module.

3.2 Experiments

Shot Scoring Event Classification

In the goal scoring event classification experiment, we selected YuShan_2023 as the benchmark team and conducted round-robin tests with MT2022, Miracle2D, HfutEngine2022, and FRA-UNIted to extract features from the game logs. We used a total of 12 features, as shown in Table 1, which were manually selected and are actually player information and ball information generated by YuShan_2023 during the game.

Table1. Feature used in our model

ID	Feature Description	Feature Name
0	X-coordinate of the player's position	player_x
1	Y-coordinate of the player's position	player_y
2	Partial velocity of the player in the X-axis	player_vx
3	Partial velocity of the player in the Y-axis	player_vy
4	X-coordinate of the ball position	ball_x
5	Y-coordinate of the ball position	ball_y
6	Partial velocity of the ball in the X-axis	ball_vx
7	Partial velocity of the ball in the Y-axis	ball_vy
8	Angle of rotation of the player's body	turn
9	Angle of rotation of the player's neck	turn_neck
10	Players' kicking power	kick_power
11	Players' kicking angles	kick_angle

Since there are some cases of missing information generated by the game, and the missingness is more serious after integrating the data from multiple games, we choose to filter out the data with empty kick actions as our experimental data, and the amount of integrated data is 20,805 pieces.

The distribution of scoring sample data in the integrated data is and its unbalanced. Among these data, we choose to take the data samples of final successful scoring as positive samples, otherwise as negative samples. After labeling, the positive samples only account for 0.59% of the total number of samples, and there is a serious imbalance.

The original dataset is divided into training set and test set according to the ratio of 4:1, SVM-SMOTE oversampling[8] is performed on the training set, and the sampling ratio is set to 1. After the training set is oversampled, the positive example samples account for 36.66% of the total number of samples, which weakens its imbalance rate. Figure 1 shows the comparison between the original shooting score data distribution and the augmented sample data after performing SVM-SMOTE oversampling.

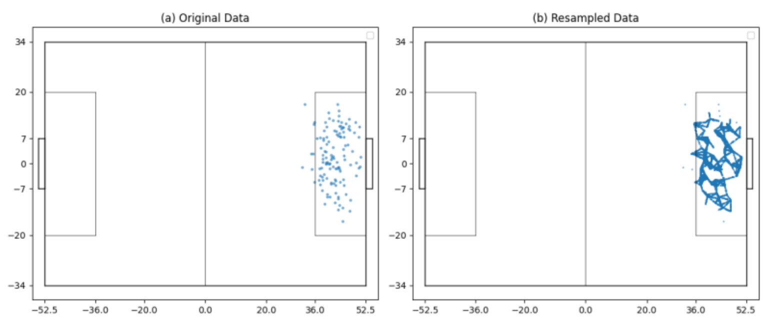

Fig. 1 Comparison between original shot points and SVM-SMOTE augmented shot points

In some prevalent machine learning algorithms, we have observed that decision tree algorithms hold an advantage in handling imbalanced data. Therefore, in this experiment, we aim to construct XGBoost and random forest models for classification experiments, and try to assess their performance by employing evaluation metrics suitable for imbalanced datasets. Additionally, recognizing the limited interpretability of ensemble algorithms, we seek to enhance the interpretability of our models by utilizing SHAP values[9].XGBoost model and RandomForest model were constructed for the augmented dataset respectively, and the best model was obtained by comparing with the results without sample equalization process.The final classification effect of the shot scoring events is as follows, and we used G-mean, F-value, and AUC as the evaluation indexes.

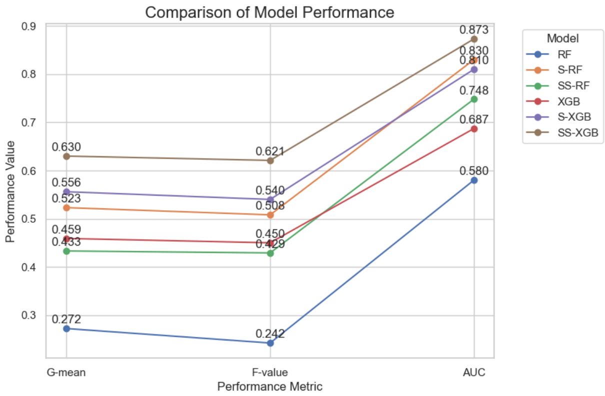

Fig. 2 Comparison of different models

As can be seen in Figure 2, the XGBoost classification model constructed using the SVM-SMOTE algorithm achieves better results in all evaluation metrics.

Since the XGBoost model is an integrated model with poor interpretability, we analyze its feature importance using the SHAP framework, and the top 5 metrics that significantly affect the ranking of the model output are: ball_x, ball_y, kick_power, ball_vx, and kick_angle.

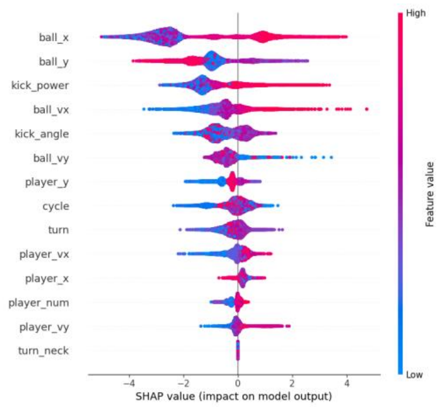

Fig. 3 Graph of SHAP feature variable analysis

In the SHAP feature importance plot, each row represents a feature, the horizontal coordinate is the SHAP value, a point represents a sample, and the color indicates the high or low value of the feature (red means high, blue means low), as can be seen in Figure 3, a low value of the ball_x feature (the blue part) is a negative impact on the predictive classification, and a higher value of the ball_x feature (the red part) improves the model's predictive classification of the scored events.Meanwhile, lower values of ball_y and higher values of kick_power also have a positive effect on goal scoring events.

Therefore, we can get some inspirations from the feature importance graph, for example, we can adjust the logic of the attacking players in front of the goal, and adjust the position of the shot appropriately. Subsequent adjustments and modifications to the team code are made in the following areas:

1. Adjust the team's attacking formation to appropriately adjust the striker's target point in the penalty area forward.

2. Adjust the kick action of the attacking players, for special scenarios, modify the 3-step kick shot to a faster and simpler 1-step kick shot.

3. Adjust the evaluation module to adjust the score high when shooting action is taken to encourage players to shoot.

Shot Points Clustering

In the shot point clustering experiment, we chose several different teams for round robin testing and extracted the shot point information from the logs and analyzed them by defining the K-means clustering algorithm for clustering, we hope to find out the different clustering results from different teams to find out their shot point selection preference area, so that we can earn to analyze and study the strongest team's preference areas to learn their offensive strategy and adjust our defense strategy.

We chose the Day4 executable of RoboCup 2D World Cup YuShan2023 as the benchmark team, and CYRUS, Helios2023 of World Cup Day4, as well as Maricle and MT of 2023 China ladder tournament as the test teams, and we filtered out the unscored matches after conducting multiple rounds of 400 matches.

In the process of conducting the experiment, we set the n_clusters parameter to 3. We wanted to observe the shot point selection preference of each team on the left, center, and right side of the goal, and by extracting the shot data and performing outlier detection, we ultimately presented the clustering effect as shown in Figure 4. Due to the different strengths of each team, resulting in different amounts of shot data, we use the ratio of the total number of samples accounted for by each cluster sample in the end to react to the shot preference of each team.

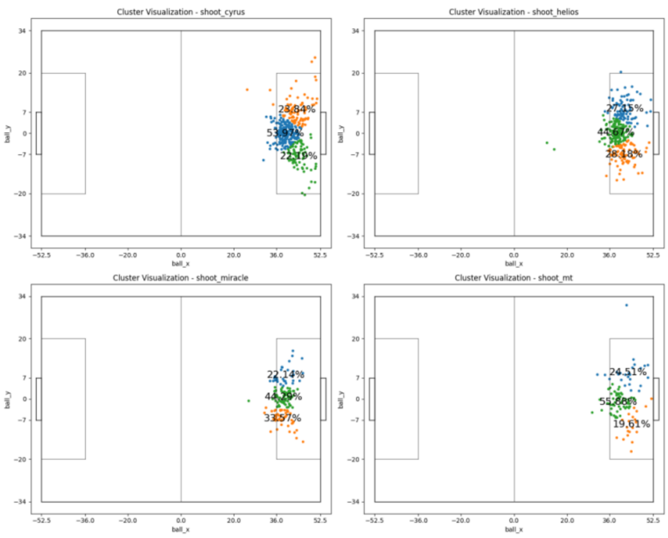

Fig. 4 Clustering results of different teams' shot data

From Fig. 4, we can see that the above four teams all have the most shots before the goal, with Cyrus and MT choosing the center position as the goal position more often, and Helios and Miracle choosing the left and right side of the goal spot a little more.

We hope to gain some inspiration from these analyses for adjusting our attacking and defensive strategies to deal with different teams. Currently, we are still exploring our existing attacking strategies, which still have situations such as losing long balls and crosses, and have great problems dealing with opponents' breakthroughs in the midfield and in front of the goal.

Result

In order to evaluate the effectiveness of the proposed strategy, we modified the code of YuShan_NB according to the above strategy and chose Cyrus_Base, MT2023 and Chord as the opposing teams. Subsequently, we played 10 games against each opponent and recorded the total number of goals scored in each game. The results are summarized in Table 2.

Table2. Results before and after improvement

Different Teams		Total goals
YuShan_NB vs Cyrus_Base	Before_Improvement	5
	After_Improvement	12
YuShan_NB vs MT2023	Before_Improvement	9
	After_Improvement	12
YuShan_NB vs Chord	Before_Improvement	2
	After_Improvement	6

From Table 2, it is evident that after modifying the shooting logic of the forward players, YuShan_NB achieved an improvement in the total number of goals scored. The simulation experiment demonstrates the effectiveness of optimizing the team's shooting logic.

The data analysis work on the shot module has led us to recognise what factors have the greatest impact during a shot, but all of this work has only scratched the surface and has not been analysed in depth in conjunction with a number of other factors, such as the generation and evaluation of the action chain. And the modifications specific to shooting are only effective for the bottom layer and do not result in a generalised module.The research on the shooting module needs to be explored continuously, and we hope that in the subsequent work, a deeper understanding of the shooting actions and decisions can be analysed and a generalisable module can be formed, which will be a great challenge.

4 Analysis of Players' Physical Strength and Running Distances

4.1 Problem Overview

In our daily testing of teams, we found that YuShan's midfielders are often the most physically exhausted players, usually running out of stamina 300-500 cycles before the end of a half, and thus unable to resist the attacks of opposing players and being scored on by the opposite side. Comparing to some international teams, Cyrus' midfielders have more transmission between each other but do not consume energy as fast; Helios has a more refined movement chain, is better in running position and movement selection, and consumes less energy than us. Therefore, we would like to find out the differences between YuShan's team and theirs by extracting the physical strength corresponding to each cycle of the players, defining the running distance of the players in the adjacent cycles through Euclidean distance, visualizing the physical strength and running distance of different types of players in different teams, and similarity analysis, so as to modify the strategy to keep the players' physical strength in a better way.

4.2 Experiment.

In the physical strength and running distance analysis experiments, we choose Day4 of RoboCup 2D World Cup YuShan2023 as the benchmark team, and Cyrus, Helios, FRA-UNIted, and Oxsy of World Cup Day4 as the test team.

The physical strength information of all players of different teams per cycle is extracted in the RCG log file by regular matching method, the running distance of players in adjacent cycles is defined by Equation 1, and the numerical difference between adjacent elements, i.e., the physical strength consumption of players and the running distance of players per cycle, is calculated by the .diff() method.

$$distance = \sqrt{{ball_x}^2 + {ball_y}^2} \quad (1)$$

After extracting the players' physical information and running distance per cycle, we chose to calculate the players' physical exertion and running distance at every interval of 300 cycles, and we chose to visualize and analyze the strikers and midfielders, and by displaying the physical exertion and running distance of players of each team in a graph with two coordinates, we can intuitively observe the differences of the players of different teams in these two indexes. Figures 5 and 6 show the relationship between physical exertion and running distance of the forward and midfielder players of different teams. The farther a player runs, the greater the physical exertion of the player, but the complexity of the field, the physical collision between players, shoveling, and other events will lead to a rapid loss of physical strength of the player. From Fig. 5 and Fig. 6, it is easy to see that there are cases of high stamina consumption but not much running distance, and cases of low stamina consumption but much running distance, which are both relatively abnormal cases. In the case of high physical exertion but not much running distance, we can assume that the player is being watched by the opponent in the process of controlling the ball, resulting in the inability to run widely or the player has a physical collision and other events. For the case of small physical exertion and large running distance, on the one hand, there may be a situation where the player is physically exhausted and replaced, and on the other hand, because this experiment does not exclude the situation where the player's physical strength is recovered after the end of the half of the game. However, through the information presented in the picture, we can get the cycle interval of the abnormal situation, so as to further review and analyze with the match video.

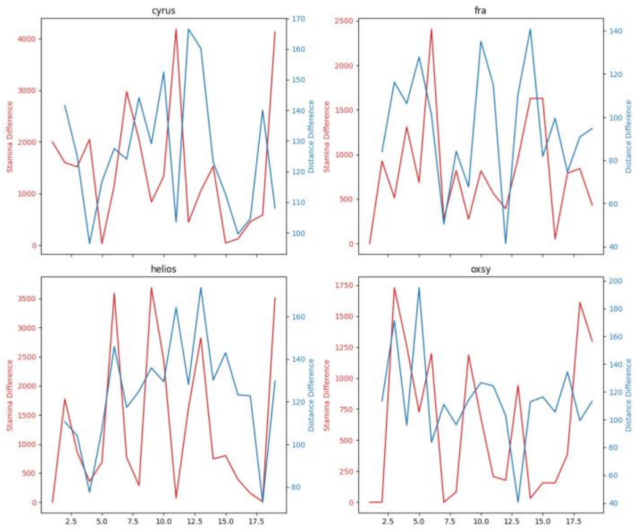

Fig. 5 Joint comparison of physical exertion and running distance of forward players of different teams

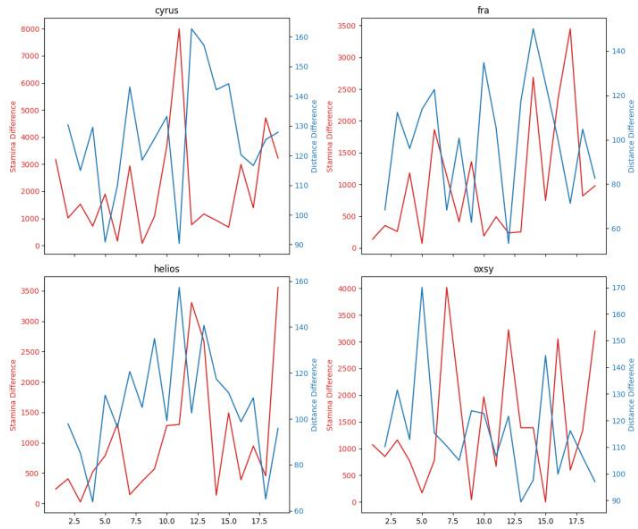

Fig. 6 Joint comparison of physical exertion and running distance of midfielders in different teams

Meanwhile, we calculated the average values of running distance and physical exertion of forward players and midfielders of different teams and visualized them. Figures 7 and 8 present the comparison graphs of the average values of running distance and physical exertion of forward players and midfielders of different teams, respectively. From the graphs we can see that there is a small difference between the mean values of running distance of the forward players and midfielders of CYRUS and Oxsy, but a larger difference in the physical exertion of the midfielders, because CYRUS conducts more in the midfield and often finds opportunities to break through the attack by passing in the midfield, while Oxsy, by keeping an eye on the whole field, makes it impossible for the opposing players to break through the midfield often, and has a more defensive strategy in the midfield. FRA-UNIted's style is also a full-court defense, but its physical consumption is the lowest among all the teams. Helios2023 is the team whose strikers' physical consumption is greater than that of the midfielders, because Helios2023 has done a very good job in the players' basic movements and formations, and it is very difficult to break through its defense. Helios2023 mostly controls the ball in the opponent's half of the field to attack, and frequently runs to look for opportunities, which leads to the situation that the forward players consume more physical strength and run a long distance.

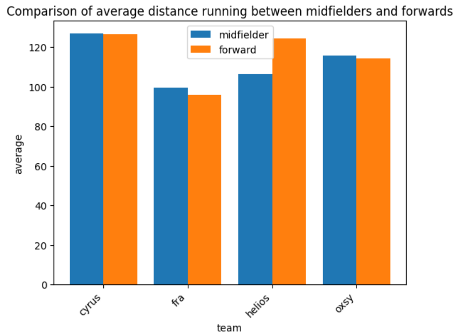

Fig. 7 Comparison of distance run by strikers and midfielders in different teams

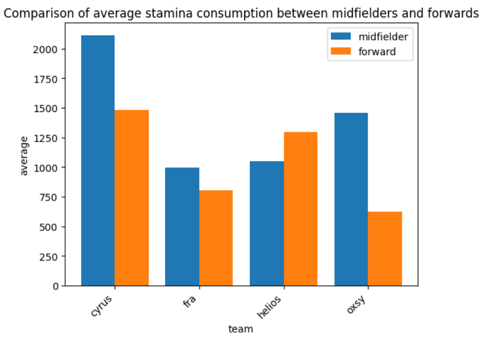

Fig. 8 Comparison of stamina consumption of strikers and midfielders in different teams

5 Summary and Outlook

In this paper, we investigate two aspects under the digital twin framework, namely, the player's goal kicking problem and the player's running distance and physical exertion problem. We processed the kicking data through the unbalanced data processing method, which greatly improved the correctness of the machine learning model in classifying the goal scoring events, as well as the K-means method to find out the differences of different teams in the preference of goal point selection.However, there are significant challenges in translating the work done into a concrete code implementation and a generalisable module.In the player stamina exertion and running distance experiment, we visualize and analyze the stamina exertion information and running distance information, we hope to find the gap in stamina management between us and the world's strongest teams, and we also hope to find out the anomalies of the rapid stamina exertion during the game more easily, which can help our team to better review and analyze the game.

In future work, under the digital twin framework, YuShan would like to put more focus on the research of action chain selection and evaluators, and we hope to refine our basic actions (e.g. running, intercepting, kicking, etc.) to further enhance the execution efficiency. At the same time, we will also try to implement the work done on the data analysis in this paper into the team code, which will be a long process considering its adaptability.

Thanks to open source technologies like Helios[1], CYRUS[10] and Glider[11], we wish the 2D League better and better and look forward to 2050 soon.

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