Game-Watching Should be More Entertaining: Real-Time Application of Field-Situation Prediction to a Soccer Monitor

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Abstract. This paper describes an extension to a soccer monitor used in the RoboCup Soccer Simulation 2D League. The aim of the extension is to make the experience of watching games more entertaining. The audio effects and the visualization are focused on this purpose. The extended soccer monitor simulates the supporters' excitement in watching a game by estimating the time cycle until the next goal, which is called *SituationScore*. This paper describes how *SituationScore* is obtained using a machine learning model and also describes the resulting soccer monitor.

- github : `https://github.com/rinmunagi/spectator_app`
- YouTube demo : `https://youtu.be/J_NgcwcFtQI`

1 Introduction

Soccer is a sport as well as an entertainment. RoboCup soccer should have the same characteristics as the real soccer has. The current version of the official soccer monitor [1] shows only the status of the soccer field. This is a simple monitor just for watching games. *soccerwindow2* [2] is an extended soccer monitor which is mainly for promoting a team development. For the team developers, *soccerwindow2* is one of the most useful tools to analyze games and perceive about the thinking process of the players. Although the monitor is sufficient for the team developers to watch the games. If there were an additional effects in accordance with the field status, such effects would make the spectator possible to enjoy the game more. For example, the audio narration would be helpful for the spectator to understand what is happening the ongoing game. For instance, Caspian monitor [3] has a function of on-line commentary that utters in the real time when passes and shoots are made. Another audio information is the sound from the virtual supporters inside the soccer monitor. The cheering and booing could have non-verbal effect to enjoy watching the game. In this paper, we define "the supporters" as the virtual supporters inside the soccer monitor, and "the spectator" as the real-world people who watching the soccer monitor.

In this paper, we propose an application that extends *soccerwindow*2 in the way the spectator does not miss the important scenes such as scoring. A prediction model is built by learning the field situation from a set of log files. Nakashima et al.[4] proposed a machine learning method to evaluate the game situation quantitatively from field images. We also use the same method in our application to express the excitement of the supporters. The prediction model takes the current field situation as an input and produces the number of expected time steps until the next goal, which is called a *SituationScore*. We have enhanced *soccerwindow*2 so that it produces a sound effect and the visualization according to the *SituationScore*.

2 Soccer Simulation 2D League

Since the games in the Soccer Simulation 2D League happen on a virtual soccer field constructed within a computer, every piece of information regarding the games can be digitally stored. This stored information can be easily utilized for analysis purposes by team developers. Such logs contain, for example, the coordinates of the ball and all players' positions, the velocity of the ball and the players, and the players' body and neck angle for every cycle of a game. Therefore, it is not surprising that the log files play an important role when analyzing games and designing strategies.

Games can be visualized on computers even after the games are finished by using tools such as *soccerwindow*2 [2] that displays the position of the ball and all players for every cycle of the game, with one computational cycle corresponding to one frame on it. A game consists of 6,000 cycles and one cycle is discretized in 0.1 second, which means a game consists of 6,000 frames. Figure 1 shows the example screen of the ongoing game on *soccerwindow*2. *soccerwindow*2 is a component of HELIOS Base package [5]. This tool not only allows spectators to watch games, but also allows researchers to replay the same game, the same actions, in order to easily analyze them.

3 *SituationScore* Evaluation

In the RoboCup Soccer Simulation 2D League, there are various ways to define the degree of dominance in an ongoing game. Example metrics would be the number of those players who are on a specific part of the field, the target place and the partner teammate of passes, and the position and the player of the current ball holder. While such analysis can be easily conducted using numerical data from log files, it would be much more complicated to work only with field images that are provided by the soccer monitor. Therefore, another metric was defined in [4], which is called a *SituationScore*, that asseses the situation of a game without numerical data.

In this paper, we also employ *SituationScore* of a frame f_r as the value of a field situation, which is defined by the following equation:

$$SituationScore(f_r) = \pm(100 - n), \tag{1}$$

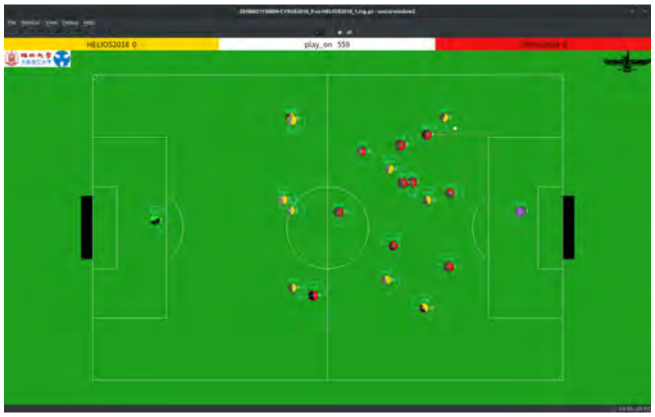
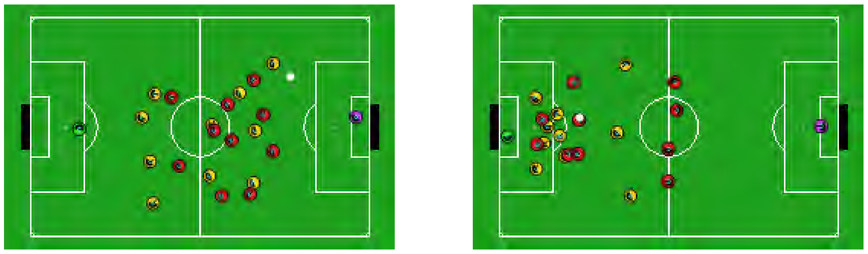


Fig. 1: Running a game on $soccerwindow2$.

where n is the number of frames between f_r and the one corresponding to the next goal. It is assumed in this paper that the considered frames are at most 100 cycles away from the next goal. Therefore, in this formula, n should be lower than 100. The range of $SituationScore$ is $-100 \leq SituationScore \leq 100$. The sign of $SituationScore$ is determined by the team that will score the next goal. A positive value is assigned when the next goal is scored by the left team. On the other hand, a negative value is assigned when the next goal is scored by the right team. An example of soccer field images and its corresponding score is provided in Figure 2.



(a) 35 frames before the left team scores. The corresponding $SituationScore$ is $+65$.

(b) 17 frames before the right team scores. The corresponding $SituationScore$ is -83.

Fig. 2: The example of soccer field images and $SituationScore$.

The definition of the $SituationScore$ in this paper brings us two main merits. The first merit is easy to assign $SituationScore$ to newly produced images, as it does not require any complex computation. The second merit is inherent to our objective, which is to work only with images. $SituationScore$ does not take into account the state of the field itself at all, but only the number of frames before next goal. Therefore, all situations or formations can be automatically covered by this model.

Using the defined $SituationScore$, a prediction model is built. that model estimates the value of $SituationScore$ for any given frame. The next section talks about a prediction model.

4 Prediction Model

Nakashima et al. [4] showed high prediction accuracy of $SituationScore$ by using a CNN model that handles image data. Therefore, we also employ a CNN for the prediction model of the $SituationScore$. This section first describes the CNN model in detail, and then describes the dataset used for training the model.

4.1 The CNN Model

The CNN model is trained with Python scripts and based on the images generated by $soccerwindow2$ during matches. We decided to use the TensorFlow library [6] for use the CNN model. A CNN architecture as well as its appropriate hyper-parameter values leading to satisfactory results have been determined by our preliminary experiments. Our architecture is illustrated in Fig. 3. The network structure is similar to the VGG architecture [7]. This structure has four convolutional blocks (blue boxes), four max-pooling layers (orange boxes), and a four-layered fully-connected block. ReLU (Rectified Linear Unit) is used as an activation function. Adam algorithm [8] is used as the optimizer. Our CNN was trained with an initial learning rate of 0.0001, then it was decreased by 5% every 1500 steps. The size of the mini batch was 16. It should be also noted that our CNN takes a 160×256 image as input and the dropout rate is 15% at the last layer of each convolutional block, as well as after each fully-connected layer.

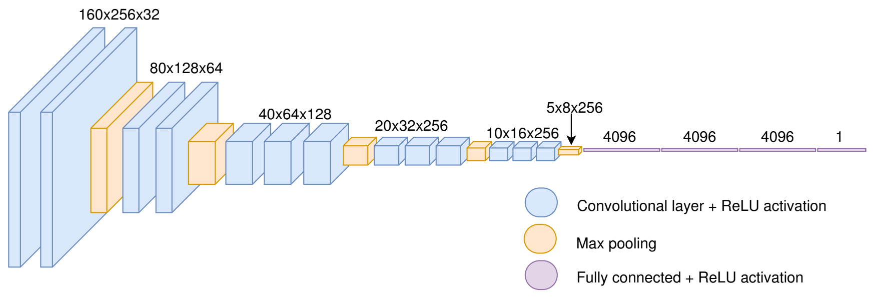


Fig. 3: Architecture of our CNN, composed of four convolutional blocks as in VGG, but with another fully-connected layer at the end of the network.

4.2 Dataset for Training The Model

In order for our dataset to cover as many situations and formations as possible, games between several 16 different teams have been simulated.

Dataset-creation process is decomposed into the following five steps:

1. Games between each possible pair of teams are performed.
2. Log files of games without any goals are deleted.
3. For each game, every frame is saved using $soccerwindow2$.
4. Their corresponding log files are analyzed by using Python scripts to determine at which cycles goals have been scored.
5. The field situations of $0 \sim 100$ frames before each of these goals are captured, and the value of $SituationScore$ for these frames is computed. These frames are saved as an image data, and the name of the image file is specified so as to include their $SituationScore$ value.

When using $soccerwindow2$ in this procedure, some graphic options have been specified, mainly to enhance the frames' quality, to remove superfluous information, and to enlarge the players and the ball. These options include hiding score board, player numbers, view area, stamina and potential yellow card, as well as setting player size to 2.0, and ball size to 1.3. The size of the saved images has also been specified in these options, but because the minimum size from $soccerwindow2$ is 280×167, captured frames have been then cropped to be of size 256×160. Soccer field images such as in Figure 2 offers a good insight of frames contained in our dataset.

A dataset containing about 1.02 million soccer field images taken from 5,215 games was constructed. This dataset was then split into three parts: a training set containing ∼720,000 images, a validation set containing ∼156,000 images and a test set containing ∼135,000 images. Images from a specific game are all included in only one of these sets. In other words, each of these sets contains images from different games. The CNN model trained by this dataset, and the performance to the test data was as high as $MeanAbsoluteError = 14.00$.

5 Application of the Prediction Model to Soccer Monitor

We developed a spectator application by extending $soccerwindow2$ in order to pursue the entertaining aspect. This application expresses the supporters' excitement by sound effects and visualization.

First of all, this application calculates the $SituationScore$ by using the trained CNN model described in 4.2. And then, the $SituationScore$ is displayed on the window with color changing and sound effects like as supporters' cheering.

The CNN model in the spectator application was trained the dataset as described in 4.2. The $SituationScore$ only have to be evaluated at the end of the match in the previous work [4]. This is because we could only take images after finishing the game. To use the trained model in real time, we need to capture images from the ongoing game in real time. This paper proposes to permit this score to be evaluated during a match, in real time. We store images from *soccerwindow*2 in real time and pass them into the already trained CNN model. Figure 4 shows the architecture of the spectator application. The application performs the following procedure:

The first procedure is to take the images from extended *soccerwindow*2 in real time using the Qt library. Then, *soccerwindow*2 sends the directory name of saving images to the Python server. And, the python server evaluates the saved images by using the trained CNN model. Finally, the application expresses the supporters excitement by sound effects and color display according to the *SituationScore*. We use socket connection by TCP/IP protocol to connect between *soccerwindow*2 and the server, and the first one was coded in C++ and the second one in Python.

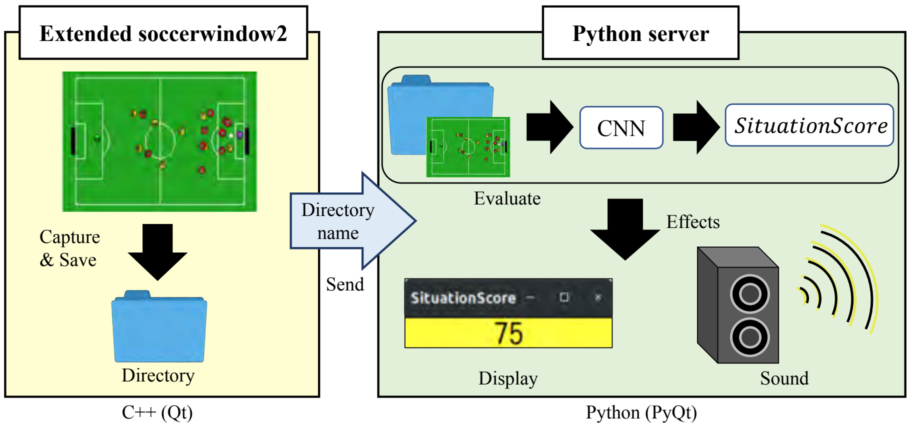
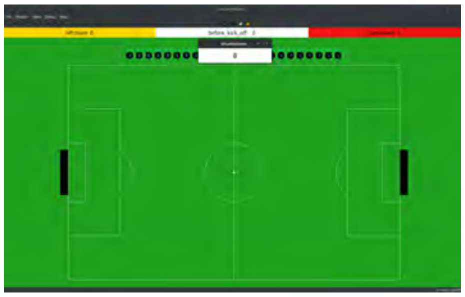


Fig. 4: The architecture of the spectator application.

Once we begin a game between two teams, the images of the game in progress are stored every five frames in a local directory. Then, whenever an image is stored, *soccerwindow*2 sends the saved directory name as a signal to the Python server for evaluating the image. The trained CNN model calculates the *SituationScore* of the image in the directory when the Python server receives the signal. What is more, the Python server add sound effects and display the colored window according to the *SituationScore*. The image already used is sequentially moved to the other directory that store images of the past.

Figure 5a shows the window displays the *SituationScore* using PyQt library. This window's background is colored and changes the color according to the *SituationScore* as shown in Figure 5b. If the situation is good for the yellow team, the window gradually changes to yellow. And if the situation is good for the red team, the window gradually changes to red. It's shown in Figure 6.

In addition, the application has the sound effects in order to make the game-watching experience more entertaining during a whole game. We employed


(a) The *SituationScore* displayed.

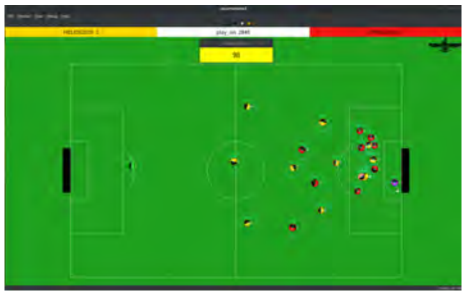

(b) The good situation for the yellow team.

Fig. 5: Example images displaying the *SituationScore*.

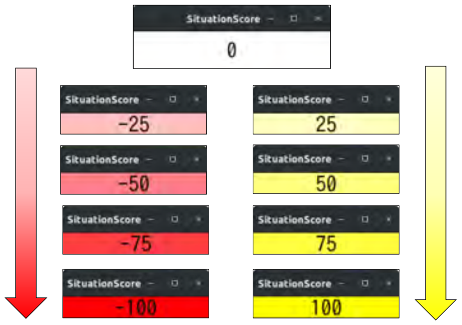
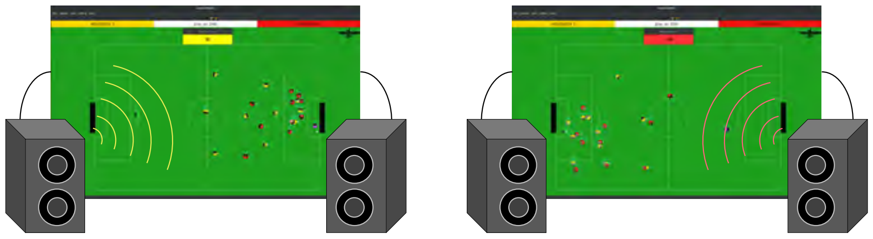


Fig. 6: The background color of the window gradually changes to red or yellow according to the *SituationScore*.

the sounds library called Freesound [9]. The application implements real soccer game's supporters sound that is included in the Freesound library. The sound effects are changed according to the *SituationScore*. There are three kinds of sound effects : murmuring sounds (in stereo), cheering sound from the side of the dominating team (in monaural), and excited cheering sound from both sides of the teams (in stereo). Figure 7 shows the image of the sound effect. The choice of the sound out of the three is defined by using two thresholds $T1$ and $T2$ ($0 < T1 < T2 < 100$) of *SituationScore*. When the *SituationScore* is higher than $T1$, which means it is a great opportunity for the yellow team (left team) to score, the sound volume from the left speaker is turned up. On the other hand, if the *SituationScore* is lower than $-T1$ which means the field situation is in favor for the red team (right team), the sound volume from the right speaker is turned up. Furthermore, if the *SituationScore* is greater than $T2$ or less than $-T2$, the sound is changed to more excited cheering. For the other cases, the sound is set to the murmuring noise from both sides. The thresholds are set as $T1 = 70$ and $T2 = 90$ in the demo movie[1].



(a) The good situation for the yellow team. (b) The good situation for the red team.

Fig. 7: Sound effects of the supporters.

The spectator application is available at our code repository[2]. This contains the already-trained CNN prediction model. This application works on Ubuntu OS, and requires rcssserver[3] and soccerwindow2-screenshot[4] as tools. The other required libraries include Python 2.7, Tensorflow 1.12.0, PyQt4 and opencv2. After preparing the above, the application called soccerwindow-screenshot should be put in *spectator_app* directory. If *librcsc* [5] is not installed in the system directory (default path), it is necessary to change the library path in the script called *execute*. If the shell script *execute* is executed, three windows are launched: two $soccerwindow2$ and the window for display the $SituationScore$. One of the launched $soccerwindow2$ is the main window for watching games and the other generates the images in order for the CNN to predict $SituationScore$. Next, the both soccerwindows should be connected to the rcssserver and run the team scripts to start a game. Lastly, a game is started with a 'KickOff' option.

The demonstration, the tutorial, and detailed information are described in the demo movie[5].

6 Conclusions

In this paper, we described an extension to a soccer monitor that is used in the RoboCup Soccer Simulation 2D League. The extension is achieved by using $SituationScore$ and a machine learning method. The extension involves visualization and sound effects by using the $SituationScore$ that make the experience of watching games more entertaining.

1 https://youtu.be/J_NgcwcFtQI
2 https://github.com/rinmunagi/spectator_app
3 https://github.com/rcsoccersim/rcssserver
4 https://github.com/rinmunagi/soccerwindow2-screenshot
5 https://youtu.be/J_NgcwcFtQI

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