DATA VISUALIZATION FOR ANALYZING SIMULATED ROBOTIC SOCCER GAMES

Brígida Mónica Faria[1,2], Beatriz Sousa Santos[1], Nuno Lau[1] and Luis Paulo Reis[3]

[1]*DETI/UA – Departamento de Electrónica, Telecomunicações e Informática, Universidade de Aveiro*
IEETA – Instituto de Engenharia Electrónica e Telemática de Aveiro, Aveiro, Portugal
[2]*ESTSP/IPP – Escola Superior de Tecnologia de Saúde do Porto, Instituto Politécnico do Porto, Porto, Portugal*
[3]*DEI/FEUP – Departamento de Engenharia Informática, Faculdade de Engenharia da Universidade do Porto*
LIACC – Laboratório de Inteligência Artificial e Ciência de Computadores da Universidade do Porto, Porto Portugal

Keywords: Data Visualization, Visual Data Mining, RapidMiner, RoboCup Soccer, Simulation.

Abstract: RoboCup is an international cooperative research project aimed at promoting research in Artificial Intelligence and Robotics. It includes a simulation league where two teams of 11 players compete in a robotic soccer game very similar to real soccer. Teams exhibit very complex strategies in these games that are very difficult to analyze by conventional observation methods. This paper presents an approach to the visualization of simulated robotic soccer games using the RapidMiner software package. Various visualizations were developed using Andrew´s Curves, Survey Plots, several types of Parallel Coordinate visualizations and Radial Coordinate Visualizations. These visualizations enabled to take some interesting conclusions about the differences between games of FC Portugal robotic soccer team using different formations and against distinct opponents.

1 INTRODUCTION

RoboCup is an international cooperative research project aimed at promoting Artificial Intelligence, Robotics and related fields (Lau et al., 2007) (Robocup, 2009). There are different leagues divided in two main groups: robotics and simulation. The first group involves physical robots with different sizes and different rules based on the competition that they integrate. The second one has the goal of, without the necessity to maintain any robot hardware, enable to research on artificial intelligence, coordination methodologies and team strategy (Robocup, 2009) (Reis et al., 2001).

RoboCup Simulation League has been one of the pioneer competitions integrated on the RoboCup international project. It is subdivided into three distinct fields of simulation (Lau et al., 2007): 2D and 3D Simulation League and mixed reality using the Eco-Be Citizen Robots. In the 2D Simulation League two teams of eleven autonomous agents (software programs) each play soccer in a two-dimensional virtual soccer stadium represented by a central server, called SoccerServer. This server knows everything about the game, the current position of all players and the ball and is responsible for updating the world state executing the players' commands and sending the perception information to the players (Reis et al., 2001). The football games are recorded to a log file that holds all actions that took place at every moment in each game. Studying the other team's code and binaries is not an easy task since most teams don't publish their code and the binaries change throughout the competition. So, a possible alternative is to visualize the recorded data in previous games logfiles to get a general understanding of other teams' techniques.

This work involves a simple case study using visualizations of a data set containing robotic soccer games of the FC Portugal simulation 2D team developed by the Universities of Aveiro and Porto (Reis et al., 2001). The data set contains the coordinates of the players and ball and the information concerning the opponent team as well as the formation that was being used by the FC Portugal team.

This paper is organized as follows. Section 2 includes an initial explanation about theoretical concepts concerning Information Visualization and Visual Data Mining. Next a simple comparison

Faria B., Sousa Santos B., Lau N. and Paulo Reis L.
DATA VISUALIZATION FOR ANALYZING SIMULATED ROBOTIC SOCCER GAMES.
DOI: 10.5220/0002851301610168
In *Proceedings of the International Conference on Computer Graphics Theory and Applications (VISIGRAPP 2010)*, page
ISBN: Not Available

study about some software available and more specialized for developing this kind of analysis is presented. The explanation is focused on the RapidMiner software (RapidMiner, 2009) since it is suitable for applying Data Mining techniques and to produce visualizations with multi-dimensional data. Finally, the experimental developments and results are presented along with some conclusions and future work.

2 DATA VISUALIZATION

The term visualization may serve several areas (Chen et al., 2008) with their own specificity. Data visualization, information visualization and visual data mining are some examples of fields intimately connected to the multidimensional data with high dimensionality (Keim, 2002). In fact, information visualization and visual data mining are areas of research that are gaining increasing attention due to the huge importance of extracting information of vast volumes of data produced everyday (Keim, 2002) (Card et al., 1999) and as stated by Edward Tufte (Tufte, 1983): “often the most effective way to describe, explore and summarize a set of numbers – even a very large set – is to look at pictures of those numbers”. More scientific research about data visualization and visual data mining has been published and can be found in (RapidMiner, 2009) (Hansen et al., 2005) (Tan et al., 2006) (Young et al., 2006) (Sebillo et al., 2008) (Rao et al., 2005).

Nowadays several simple functions for generating complex images from abstract data are available. The objective is to provide a way to understand and get insight into non trivial agglomeration of data (Rao et al., 2005). Therefore the main goal is to communicate information without discarding the design and simplicity of images (or animations) in order to produce and be able to extract the most significant knowledge.

The development concerning data visualization techniques is occurring in a very fast way in the last years. Some examples are the development of a variety of highly interactive computer systems, new paradigms of direct manipulation for visual data analysis such as linking, brushing, selection or focusing. New methods for visualizing high dimensional data and the invention of new graphical techniques for discrete and categorical data are other examples of the fast progress on this domain (Rao et al., 2005).

The advances in theoretical and technological infrastructure such large-scale software engineering, extensions of classical linear statistical modeling to wider domains, the increase of computer processing speed or even capacity and access to huge and variable data accelerate the advances in order to solve the new challenges.

Another goal of visualization is the interpretation of the visualized information by an individual and the creation of a mental model of information (Tan et al., 2006). Every day visual techniques such graphs and tables are used to display simple information like weather forecasts or sports results. With the same importance visual techniques represent an significant role in data mining and are usually known as Visual Data Mining.

3 VISUAL DATA MINING

Using visualization techniques it is possible to absorb large amounts of visual information and find patterns in it. However, it is important to include the individuals in the data exploration process to draw conclusions and directly interact with the data (Keim et al., 2002). The definitions proposed for Visual Data Mining (Simoff et al., 2008) have in common that visual data mining relies on human visual processing channel and uses human cognition. However, there are some variations in the understanding of this concept. In fact, it is defended that “the objective of visual data mining is to help an individual to get a feeling for the data, to detect knowledge and to gain a deep visual understanding of the data set” (Simoff et al., 2008) or, as it is proposed by Niggemann (Simoff et al., 2008), that visual data mining is a visual presentation of the data close to the mental model.

Data visualizations can provide the verification of the initial hypotheses and may be accomplished by automatic techniques from statistics and machine learning. Nevertheless it is important to mention that using visual data exploration, allows identifying rather homogeneous and noisy data and, obviously, it is more intuitive and does not require understanding complex mathematical or statistical algorithms (Keim et al., 2002).

There are three phases (Keim et al., 2002) that should be followed to process visual data exploration according to Keim (Keim et al., 2002). First it is necessary to get an overview of the data to find patterns and outliers. Next it is important to zoom and filter the data. The final step consists in interactively selecting parts of data to be visualized in more details known as details-on-demand (Keim et al., 2002).

The type of data to be visualized can be 1D (e.g. time-series); 2D (e.g. geographical maps); multidimensional data (e.g. relational tables); text and hypertext; hierarchies and graphs (e.g. telephone calls). Closely to the type of data are the visualization techniques used. The techniques can be classified as standard 2D/3D displays (e.g. scattered plots, histograms); geometrically transformed (e.g. parallel coordinates); icon-based display (e.g. Chernoff faces); dense pixel display and stacked displays (e.g. treemaps). More detailed explanations of these techniques can be found at (Chen et al., 2008) (Keim et al., 2002) (Hansen et al., 2005) (Young et al., 2006) (Ware et al., 2004) (Tan et al., 2006).

To implement Data Mining (DM) techniques there are several options (RapidMiner, 2009) (Eibe et al., 2002) (Miner3D, 2009) (Moebes, 2009), all incorporating some of the visual components previously described. In this work three software options were chosen for a comparative analysis:

- Weka (Eibe et al., 2002) for historical reasons since it is one of the oldest and one of the most used software in this field;
- 3D Miner is a data visualization software for multidimensional exploratory data analysis (Miner3D, 2009). Recently it has been receiving attention due to its capacity to support visual data analysis, visual data mining and visual creativity, speed and freedom to analyze and explore data;
- RapidMiner (RapidMiner, 2009) provides solutions for data mining, text mining and data analysis.

The choice of the RapidMiner software has to do with several points (RapidMiner, 2009). First the number of operators related with data mining and visual data is higher in this package than in the others, second its usability, since the data flow is always the same in a tree based structure. The tree-based layout with a modular concept also enables breakpoints and re-using building blocks. Another important aspect is concerned with the efficiency because of the layered data view concept, many data transformations are performed at run-time instead of transforming the data and storing the transformed data set. The scalability of RapidMiner has improved and in the last versions algorithms were optimized for speed and the internal data handling of RapidMiner allows the application of a large amount of data mining and learning methods directly on an external database. The Weka toolkit is easy to integrate into other software products. However, to integrate different data mining processes into the same product based on Weka it is necessary to re-transform the data. In RapidMiner the layered data views allow the integration of different lines of analysis into a single product without copying and re-transform repeatedly (RapidMiner, 2009). 3D Miner has developed the visualization structure for analyzing the data, however in RapidMiner visualization techniques for 1D, 2D and multivariate are also available and allow the best choice of visual data. Another aspect that separates these two software packages is that RapidMiner is Open Source and has a quick response for questions, since the Rapid-forum is maintained by several full members. On the other hand, 3D Miner provides information, demos, videos, support on the official web page, however it is not Open Source.

For the abovementioned reasons RapidMiner was chosen for this study.

4 EXPERIMENTAL TASKS

This section describes the importance of the visualizations and the problem context. Therefore it establishes several steps to perform the data acquisition, visualization and a preliminary evaluation with the target users of the visualizations, as well as external experts in design and visual statistics.

4.1 Visualization and User's Objectives

Visualizing Robotic Soccer games and gathering adequate information from them is a key issue to the performance of a robotic soccer team. However, most of the information needed is not easy to gather or visualize from the games. The information gathered along in the games contains the coordinates of 22 players and the ball throughout time. Even simple information like the team formation (spatial distribution of the players of the team) is hidden in the data and some global analysis and visualization is needed in order to correctly detect it.

Although in the data used for developing the visualizations in this work, information regarding the team formation was manually added in the log files, in real games this information is not directly available in these log files. Thus, the formations must be inferred from the (x,y) coordinates of the opponent team players prior to using it in the team strategic decisions.

The users for visualizations of RoboCup simulated soccer games are mainly the team developers that need information about the opponent's teams in order to define their team strategy for a given game.

Sometimes, very simple strategical decisions like playing in a 4-3-3 or 4-4-2 formation may be of crucial importance to win a given game.
SoccerMonitor (RoboCup, 2009) is an application that generates visual representations of the log files as can be seen in Figure 1. Although it provides information about all variables of each player, at every moment of a single game, it does not analyze or summarize the global motion of the players and the team. This motion reflects the group's strategy and coordination capacities. However, the software only gives consecutive snapshots of the positions of the players and ball at a given moment in time.

Figure 1: Frame of a game in Soccer Monitor.

The objective of this study is to generate visualizations that can gather information about the global motion of the FC Portugal team (RoboCup, 2009) (Reis et al., 2001) against different teams and with different formations.

4.2 Data Set Description

The dataset was constructed using the log files of a very basic version of FC Portugal team playing with three teams that historically participate in the Simulation League (Almeida, 2009): AT Humbolt (GermanTeam, 2009), Hellios and Brazil (Bahia, 2009). These teams were chosen since one of them is a very strong team (Hellios), other is a good team (AT Humboldt) and the other is a very weak team (Brazil). Thus, the games against these teams are very different from each other.
The dataset was produced with the x, y positions of eleven players of FC Portugal Team in six distinct games (two with each of the abovementioned teams) without dynamic positioning and role exchange for the players. The attributes are the positions and the class is the formation that the team was playing or the team against which FC Portugal Team was playing. The field coordinate x had the range [-52,5;52,5] and the coordinate y varies between [-34,0;34,0] (corresponding to a typical real soccer field of 105x68m).
The games were executed in Linux and the log files are converted in text files with a simple application getWState (Almeida, 2009) written in C++ for this purpose. The information that can be extracted from the games are the position as well as velocity of the ball and the eleven players of the two teams and other particular characteristics such as stamina, kicks, head and body angles.

The final data set had the positions of the players, the position of the ball, the formation that the team was playing and the name of the opponent team. Thus the global data base has 24 numerical and continuous attributes (R^{24}) and two nominal attributes. The nominal attributes are the team formation (10 formation options) and the name of the opponent team (3 opponent options in this data set). With this 26 attributes the visualizations can be perceived as a multivariate problem. Table 1 displays the possible formations that the team could play.

Table 1: Formations of FC Portugal Team.

Classes	One	Two	Three	Four	Five
Formation	433	442	343	352	541
Classes	Six	Seven	Eight	Nine	Ten
Formation	532	361	451	334	325

4.3 Visual Techniques

RapidMiner incorporates several options for analyzing multivariate data. The first objective was to give a general view of the three games on the database and let three groups with different experience: RoboCup experts, designers and statisticians decide which of the visualizations better represent the data set. Five visualization methods were selected: Andrew´s Curves (Hardle, 2007), the Survey Plot Parameter (Orange, 2009), two types of Parallel Coordinate Parameters (Young et al., 2006) and the RadViz (Hoffman, 1999).

Andrews' Curves. Andrews' Curves were first suggested in 1972 (Andrews, 1972) and the idea was mainly to code and represent multivariate data by curves. Each multivariate observation $X_i=(x_{i1}, x_{i2}, \ldots, x_{ip})$ is transformed in a curve using:

$$f_i(t)=\begin{cases}\frac{x_{i1}}{\sqrt{2}}+x_{i2}\sin(t)+x_{i3}\cos(t)+\ldots+x_{ip-1}\sin\left(\frac{p-1}{2}t\right)+x_{ip}\cos\left(\frac{p-1}{2}t\right) & \text{for } p \text{ odd}\\ \frac{x_{i1}}{\sqrt{2}}+x_{i2}\sin(t)+x_{i3}\cos(t)+\ldots+x_{ip}\sin\left(\frac{p}{2}t\right) & \text{for } p \text{ even}\end{cases} \quad (1)$$

where the observation represents the coefficients of the Fourier series and $\left(t\in\left[-\pi,\pi\right]\right)$.

The visualization of the database with distinct formations and with diverse opponents was produced and in Figure 2 it is possible to observe the Andrews' curves coloured by formation. The curves are different for each formation.

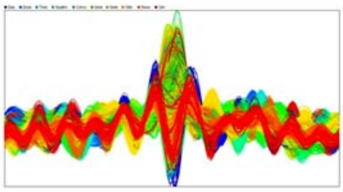

Figure 2: Andrews' Curves coloured by formations.

Survey Plot. The survey plot is a multi-attribute visualization technique that can help to find correlations between any two variables especially when the data is sorted according to a particular dimension (Orange, 2009). Each horizontal line in a plot corresponds to a particular data example. The data on a specific attribute is shown in a single column, where the length of the line corresponds to the dimensional value. When data includes a discrete or continuous class, the data examples are colored likewise (Orange, 2009). This diagram enables, naturally, to observe the different formations and the different opponents since they are depicted with different colours (Figure 3).

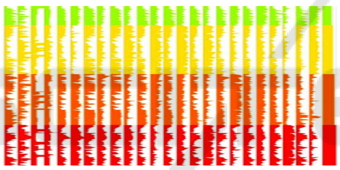

Figure 3: Survey Plot fragment with 3 distinct formations.

However, a more detailed analysis is necessary and certainly the opinion of the experts could help understand important spots in this kind of visualization.

Parallel Coordinates. Parallel coordinates (Tufte, 1983) (Hoffman, 1999) represent multidimensional data using lines and was first introduced by (Inselberg, 2009). A vertical line represents each attribute and the maximum and the minimum values of those attributes are usually scaled to the upper and lower points on these vertical lines. Therefore for representing a N-dimensional point N-1 lines are connected to each vertical line at appropriate value. Figure 4 represents the dataset using the formation information.

An alternative for this kind of visualization is also available in RapidMiner and is called a deviation plot were the examples are not so marked as in these two previous visualizations. The plots for formations and games may be observed in Figure 5 and 6.

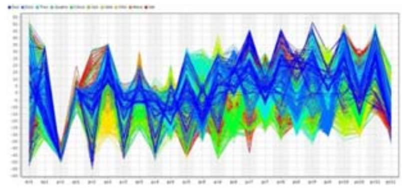

Figure 4: Parallel coordinates plot with formations.

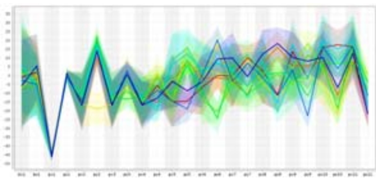

Figure 5: Parallel coordinates plot (Deviation)-formations.

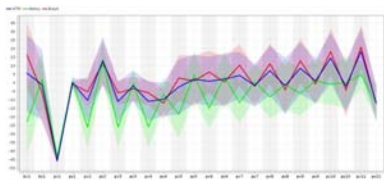

Figure 6: Parallel coordinates plot (Deviation) – teams.

It is interesting to see on this diagram that the x coordinates of the team players in games against Hellios (green line) are lower than the x coordinates of the games against the other teams. Also the x coordinates of the players in games against Brasil (red line) are higher than in the other games, indicating that the FC Portugal Team attacked more on the games against this team.

Radial Coordinate Visualization (RadViz). Radial Coordinate Visualization (Andrews, 1972) is an N-dimensional radial visualization in which N lines originate radially from the center of the circle and terminate at the perimeter where the points called Dimensional Anchors (DA) are. One end of a spring is attached to each DA and the other end of each spring is attached to a data point. The visualized attributes correspond to points equidistantly distributed along the circumference of the circle. The spring constant has the value of the i-th coordinate of the data point and each point is then displayed at the position that produces a spring force sum of zero. The attribute with larger magnitude than the others will dominate the spring visualization. Therefore this approach maps a set of N-dimensional points into a 2D space.

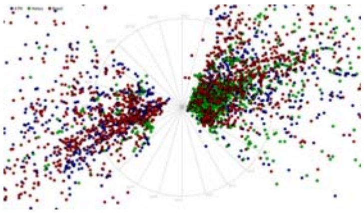

Figure 7: RadViz with teams.

Some characteristics of this kind of visualizations are described at (Andrews, 1972) and can be summarized as: points with equal values, after normalization, lie on the center; points with similar dimensional values, whose dimensions are opposite to each other on the circle lie near the center; points which have one or two coordinate values greater than the others lie closer to the dimensional anchors of those dimensions; the position of a point depends on the layout of a particular dimensions around the circle. Figure 7 show the RadViz by opponent teams.

4.4 Results' Evaluation

Visualizations were performed using RapidMiner [5] in a Pentium dual-core processor T2330 (1.60 GHz, 533 MHz FSB L2 Cache) and 2 GB DDR2.

The first preliminary evaluation of the visualization were performed with the help of personal interviews/inquiries to three groups of individuals: the first group was constituted by four experts on simulated robotic football; the second included seven teachers of Statistics of Escola Superior de Tecnologia de Saúde do Porto and the third was formed by two web designers.

The questions that were asked had to do with: Q1) which visualization conveys more information; Q2) which visualization shows more intuitively the differences of formations and opponents; and the third point was Q3) the evaluation on an esthetics' point of view. The answers were analyzed by a voting system inspired in Borda Count (Taylor et al., 1996). The Borda count determines the winner of a preference by giving, in this case, each visualization a certain number of points corresponding to the position in which it is ranked by each voter. Once all votes have been counted the visualization with fewer points is the winner. Sometimes the broadly acceptable visualization is chosen, rather than those preferred by the majority.

Concerning the results obtained for question Q1 users think that Deviation and Parallel visualizations are the ones that convey more information. Andrew's curves are believed to convey less information (although some statisticians disagree on this result). For question Q2, most users believe that Deviations are the visualizations enabling to better see the differences between formations and opponents. Concerning aesthetics of the visualizations it is interesting to see that RadViz and Andrew's Curves were preferred, although most of the experts and designers didn't like the latter.

Visualizations are very important tools to understand patterns in data, although the advices given by Keim (Keim, 2002) concerning zooming and filtering the data must be followed. Moreover, parts of the data should also be interactively selected to be visualized in more detail. To perform this kind of analysis two experts contributed with their specific domain knowledge.

Figure 8 shows a display of the x positions of players 2, 7 and 10 of the team (defender, midfielder and attacker of the right wing of the team) depending on the x coordinate of the ball. It is interesting to see that there is a strong correlation of the positions of the players with respect to the ball. However, there are several deviations that are higher in the attacker player (red in figure 9). These deviations correspond to active situations in which a player has control of the ball and thus abandons his formation position, for example dribbling the ball towards an empty space. Other deviations, corresponding to vertical lines in the figure, are caused by playoff situations like throw-ins. In these situations, the ball is stopped but players move towards their playoff positions for that situation. This is more evident for player 2 (defender represented in blue) that sometimes goes to the attacking field in order to perform a thrown in

Figure 9 shows a display of the team attacking players y coordinates in a 4-3-3 formation (players 9, 10 and 11) depending on the ball y coordinate. It is interesting to see that the y coordinates of the players vary with the ball y coordinate. However, the correlation seems higher for player 9 (the central attacker).

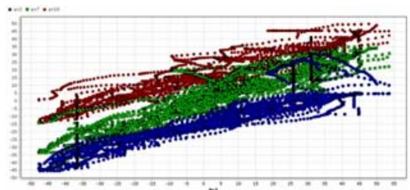

Figure 8: Scatter Plot with right wing x coordinates.

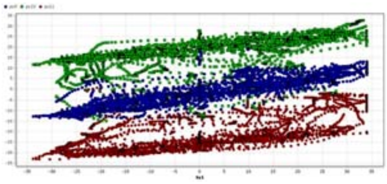

Figure 9: Scatter Plot with team attackers y coordinates.

This is due to the fact that the winger players are more often in active play than the central forward. Thus, their y positions change in a less correlated way with the ball y position.

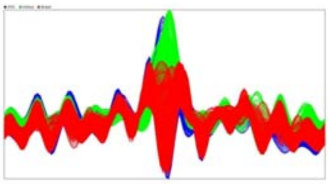

Figure 10: Andrew´s Curve for formation One.

Figure 10 shows an Andrews' curve for formation One with colour depending on the opponent. An interesting result is that the game against Brasil (displayed in Red) is a lot different than the other two games. The justification is that in this game, FC Portugal Team was always attacking with the ball controlled by its players while the other games were not so unbalanced.

Figure 11 shows a Parallel Curve for the x coordinate of the ball and players of formation One depending on the opponent. The diagram enables to see that in the games against Hellios (displayed in green) the team had a lot more defensive positions while in the game against Brasil the positions were a lot more offensive.

Figure 12 shows a RadViz of the right wing players (2, 7 and 10) for FC Portugal Team, in formation One against the three distinct opponents (identified by colors). It is interesting to see that in the games against Brazil (represented in red) players 7 and 10 (midfielder and attacker) have equal weight during the game, while player 2 has a very low weight. In the games against Hellios (green points) player 2 (defender) has greater weight attracting most of the points, while the weight of player 10 is very reduced.

Figure 13 enables to take the same conclusions showing that the points are attracted towards the attacking side (left side of the image) for the games against Brasil and towards the defender players (right side of the image) against Hellios.

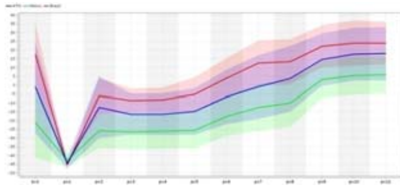

Figure 11: Parallel Curve for formation One.

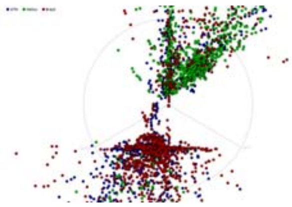

Figure 12: RadViz with right wing players.

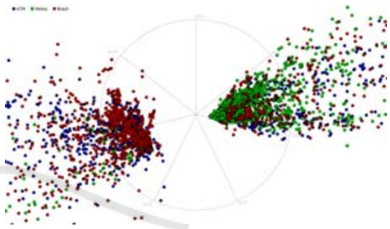

Figure 13: RadViz with defending and attacking players.

Another important issue is the problem of colour, since most visualizations use different colours to separate the cases by classes. So, and since one of the members of the group of experts is colour blind, he was truly helpful to understand which visualizations are more easily readable by colour blind people. By using the filter available in (Dougherty et al., 2009) the images were transformed in PhotoShop (Adobe et al., 2009) into images that let us perceived how a colour blind sees. Those images are represented in the annex. By analyzing them it is very interesting to conclude that most of the default colours used by Rapid Miner are almost indistinguishable for colour blind people.

5 CONCLUSIONS

Several visualizations for robotic soccer games were created, using Andrew´s Curves, Survey Plot, two types of Parallel Coordinate and Radial Coordinate Visualizations. These visualizations allowed some interesting conclusions concerning the differences among games of FC Portugal Team using different formations and against distinct opponents. The visualizations were developed using the freely available RapidMiner software package. Although the visualizations were very simple, they enabled to spot several characteristics not easily detectable by a normal visualization.

A simple inquire was conducted to several users showing that, independently of the expertise, users prefer simpler visualizations as parallel plots (Deviation) to explain and analyze the data.

Future work will be concerned with testing games of other robotic soccer teams and other robotic soccer leagues, the small or middle size leagues. Other future development of the work could include producing visualizations using high-level information previously extracted from the log files. Finally the development of a color blind safe palette for RapidMiner, as well as tests with color blind individuals are planned.

ACKNOWLEDGEMENTS

We would like to acknowledge to FCT – Portuguese Science and Technology Foundation: PhD Scholarship FCT/SFRH/BD/44541/2008 and FCT/PTDC/EIA/70695/2006 – Project ACORD - Adaptative Coordination of Robotic Teams.

REFERENCES

Adobe, 2009. *Adobe Photoshop Family*. Available at [http://www.adobe.com/products/photoshop/family/?promoid=BPDEK/] Consulted June 2009.

Almeida, R., 2009. *Análise e Previsão das Formações das Equipas no Domínio do Futebol Robótico*, Tese de Mestrado, FEP, Porto, May.

Andrews, D.F., 1972. *Plots of high dimensional data*, Biometrics, 28:125-136, Bell Telephone Laboratories, New Jersey, Princeton University, March.

Bahia Robotics Team, 2009. *Futebol Simulado 2D.* Avail. at [http://www.acso.uneb.br/]. Cons. May 2009.

Card, S.K., Mackinlay, J.D., Shneiderman, 1999. *Readings in Information Visualization using Vision to Think*.

Chen, C., Hardle, W., Unwir, A., 2008 *Handbook of Data Visualization*, Springer Handbooks of Computational Statistics, Springer.

Dougherty, B., Wade, A., 2009. *Vischeck*, Univ. British Columbia. Available at [http://www.vischeck. com/]. Cons. July 2009.

Eibe, F., Mark, H., Len, T., 2009. *Weka 3: Data Mining Software in Java*, Available at [http://www.cs.waikato. ac.nz/~ml/weka/index.html]. Consulted on June 2009.

GermanTeam, 2009. *GermanTeam.* Available at [http://www.germanteam.org/]. Cons. May 2009.

Hansen, C. D., Johnson, C. R., 2005. *The Visualization Handbook*, Elsevier, Academic Press.

Hardle, W., Simar, L. 2007. *Applied Multivariate Statistical Analysis.* 2nd Edition, Springer Verlag, Berlin-Heidelberg-New York, pp. XVIII/486.

Inselberg, A., 2009. *Parallel Coordinates: Visual Multidimensinal Geometry and Its Applications*. Springer 2009.

Keim, D., 2002. *Information Visualization and Visual Data Mining*, IEEE Trans.Visualization and Computer Graphics, Vol. 7, No. 1, pp. 100-107, Jan – Mar.

Hoffman, P. E., 1999. *Table Visualizations: A formal model and its applications*, Institute for Visualization and Perception Research, Department of Computer Science, University of Massachusetts Lowell, Lowell.

Lau, N., Reis, L. P., 2007. *FC Portugal - High-level Coordination Methodologies in Soccer Robotics*, Robotic Soccer, Book edited by Pedro Lima, Itech Education and Pub., Vienna, Austria, pp. 167-192.

Miner3D, Inc., 2009. *Visual Data Analysis Software for Business Intelligence and Science.* Available at [http://www.miner3d.com/]. Consulted on June 2009.

Moebes, T., 2009. *Data Mining Software for Windows and Solaris|Insighful Miner.* Available at [http://www. insightful.com/products/iminer/]. Cons. June 2009.

Orange, 2009. *Survey Plot.* Orange: Data Mining Fruitful&Fun. Available at [http://www.ailab.si/ orange/]. Consulted on June 2009.

Rao, C.R., Wegman, E.J., Solka, J.L., 2005. *Data Mining and Data Visualization*, Elsivier, England.

Rapid|Miner, 2009a. *RapidMiner Report the Future* Available at [http://rapid-i.com/]. Cons. June 2009.

Reis, L. P., Lau, N., 2001. *FC Portugal Team Description: RoboCup 2000 Simulation League Champion*, in P. Stone et al. eds, RoboCup-2000: World Cup IV, Springer LNAI, Vol. 2019, pp.29-40.

Robocup, 2009, *Robocup 2009*, Available at [http://www.robocup2009.org/]. Cons. June 2009.

Rhyne, T.M., 2003. *Does the Difference between Inform. and Scientific Visualization Really Matter?* IEEE Comp. Graphics and Apps, pp. 6-8, May/Jun.

Sebillo, M., Vitiello, G., Schaefer, G., 2008. *Visual Information Systems: web-based visual information search and management.* Proc. 10th Int. Conference, Visual 2008, Salerno, Italy, September.

Simoff, S., Bohlen, M., Mazeika, A., 2008. *Visual Data Mining: Theory, Techniques and Tools*, State-of-the-Art, Springer, London.

Tan, P., Steinback, M., Kumar, V., 2006. *Introduction to Data Mining*, Pearson Education, Inc.

Taylor, A.D. Brams, S.J., 1996. *Fair Division: From cake-cutting to dispute resolution*, Univ.Press, Cambridge.

Tufte, E., 1983. *The Visual Display of Quantitative Information*, Graphics Press, pp. 9-10.

Ware, Colin, 2004. *Information Visualization: Perception for Design*, Morgan Kaufmann, 2nd Edition.

Young, F. W., Valero-Mora, P. M., Friendly, M., 2006. *Visual Statistics: Seing Data with Dynamic Interactive Graphics*, Wiley-Interscience, John Wiley&Sons, Inc.