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Abstract

Over the last decades Information and Communication Technologies (ICTs) are increasingly being used in sports, especially in professional football, aiming to improve the athletes training and results. However, training systems for young and amateur athletes are not available. Most available systems, lack learning abilities in order to adapt, evolve and find new training recommendations, designed specifically for each athlete. In this paper we introduce the *Smart Coach* architecture and user adaptation model and present our information system to help young athletes evolve.

Keywords: Recommender systems; User modelling; Personalized coaching; Reasoning

1. INTRODUCTION

Information and Communication Technologies (ICTs) are increasingly being used in the world of sports, especially in football, aiming to enhance athletes training methods, improve the team results or support sports decisions and refereeing.

However, training systems for young (semi)amateur athletes do not, for the most part, consider their performances and accomplishments in training and competition, regarding the young athletes' characteristics, technique, tactics, physical and mental status, in the training selection and recommendation process.

On the other hand, these systems do not have learning capabilities in order to adapt, evolve and find new training recommendations for each young person. These limitations, make the results of these systems, not adapted, and not focused on the players specificities.

It is in this context that the *Smart Coach* recommendation system, intends to innovate and to make impact, using artificial intelligence technology and techniques, to support coaches and technical staff, allowing them to analyse better their young athletes skills and to enhance their development and training (Matos et al., 2019).

In this paper we introduce the user adaptation model of *Smart Coach*, targeting the evolution of young athletes. In summary, *Smart Coach* will allow to represent technical, tactical, physical and/or psychological characteristics of young athletes, and adapt a Dynamic Training Model, defining a training schedule to improve a young sportsman performance, targeting is evolution as a player.

In section 2 we make a brief description of User Modelling and Recommendation Systems.

In section 3 we describe in detail the *Smart Coach* proposed architecture and in section 4 we take some conclusions and talk about the future work.

2. STATE-OF-THE-ART

In this section we make a resume of the current state-of-the-art of user modelling and recommendation systems. There is also a review of five football coaching applications.

2.1. User Modelling

User modelling is normally implemented with two sets of techniques, the behavioural and the knowledge-based (Kobsa, 2001). Knowledge-based adaptation typically result from the information gathered using forms, queries and other user studies, with the purpose to produce a set of heuristics. Behavioural adaptation is related with user monitoring during his daily tasks and activities (Santos, Almeida, Martins, de Oliveira, & Gonçalves, 2017).

In a historical approach, one of the first research's related with user modelling appears in literature in the 70's was conducted by Allen, Choen, Perrault and Elaine Rich. During this state-of-the-art, became clear that Rich and more recently Kobsa (Kobsa, 1993; Rich, 1979) are two of the most important researchers in this field (Martins, Faria, De Carvalho, & Carrapatoso, 2008). In the last decades, several different systems were developed to store various kinds of user information. Some of those applications were analysed and reviewed in works done by Morik, Kobsa, Wahlster and McTear in 2001.

Different user modelling techniques and methodologies were used to represent knowledge, some of them are data representation oriented and others data inference oriented (Santos, Almeida, Martins, Oliveira, & Gonçalves, 2017).

The User Modelling techniques (linear models, decision trees, neural networks, text mining, Bayesian networks and data mining) are all forms of predictive statistical models, since they are applied in areas with thousands or millions of items (from products, clients, actions, etc.) and can also benefit from recent machine learning evolution (Zukerman & Albrecht, 2001). Finally, not all of them might actually be applied in some domains, due to their specific characteristics (Santos, Almeida, Martins, Oliveira, et al., 2017).

Linear models is probably the most common techniques, and it can probably even be said that almost all systems uses linear models, one way or another, although there are systems that are entirely based in linear models. These models are easy to build and understand; they are efficient and assume probabilistic data as believable effects, which has been a successfully employed theory so far (Zukerman & Albrecht, 2001). They generally use weighted sums or means of frequently accessed items to conclude user interests, in the case of the product applications described previously, and, therefore, infer the likelihood for new unknown items (Santos, Almeida, Martins, Oliveira, et al., 2017).

2.2. Recommendation Systems

A Recommender System can be characterized as a collection of different techniques used by different systems to filter and organize its items in order to select either the best ones or the most suitable ones for presentation, according to the user (Porter, 2006). Although the most common scenario is when the system has to choose the best items from a certain group which otherwise (without the filtering) would be randomly selected, there are other more important cases where certain items or types of items just can't be shown to the user at a given moment, for example, due to player field position. A complete recommender system should therefore be prepared to handle both types of situations. The mode of operation normally used by recommender systems is to use a knowledge base (the user model) as the basis for a series of calculations to infer which are going to be, amongst all the items available, the ones that will better please the user, according to a wide variety of theories or approaches (Santos, Almeida, Martins, de Oliveira, et al., 2017). In this work is considered that the best way to please users is to suggest trainings that can improve their abilities and their in game-play insufficiencies.

Recommend something to someone carries an implicit responsibility to whom does that because it is fundamental to assure accuracy and quality in the recommendation results in order to gain users confidence. These systems are basically based in three types of paradigms (content, collaborative and knowledge-based) and all their possible combinations (Berka & Plößnig, 2004; Felfernig, Gordea, Jannach, Teppan, & Zanker, 2007; Kabassi, 2010; Schafer, Konstan, & Riedl, 1999). Content-based filtering tries to capture information from within the content of unstructured or disorganized item data elements, such as textual or descriptive attributes, generally includes powerful text mining algorithms from the information retrieval area. Collaborative filtering (also called social-filtering) is one of the currently most used techniques and was greatly influenced by the Web 2.0 ("social web") phenomenon. It relies on other user's information for recommending items to the current user (Berka & Plößnig, 2004). Knowledge-based filtering is almost inevitable to use, because it means using any form of domain knowledge in a recommender system (Santos, Almeida, Martins, Oliveira, et al., 2017).

In some systems the referred techniques are combined to take advantage of each approach characteristics and also mitigate limitations. The systems are characterized as hybrid approaches.

These two fields, user modelling and recommender systems, are the base used to develop this work, complemented with a tool used to collect important athlete's performance data during matches.

3. PROPOSED APPROACH FOR *SMART COACH*

This paper proposes the creation of a training recommendation system, for young football players, based on the athlete's performance during matches. This performance information is collected using a web responsive application, by friends/family and stored in a database for future use by the recommendation system. The system architecture (Figure 1) consists of three levels. The first level, clusters the information in three groups, and associate it to models used by the recommendation system. The second level, the recommendation and learning module, uses data from the knowledge and interface levels and recommends the skills the player should improve, and the exercises suited to improve those skills. The Interface level allows the input/output of data to the system, namely the player statistic collection (Matos et al., 2019).

User profiles will be created based on players position, physical characteristics (*e.g.* height, weight, speed, jumping height, etc.) and match performance. The Table 1shows the most important attributes collected for each young player during matches. Some of these attributes are more or less important, depending the position the athlete plays during matches (Matos et al., 2019).

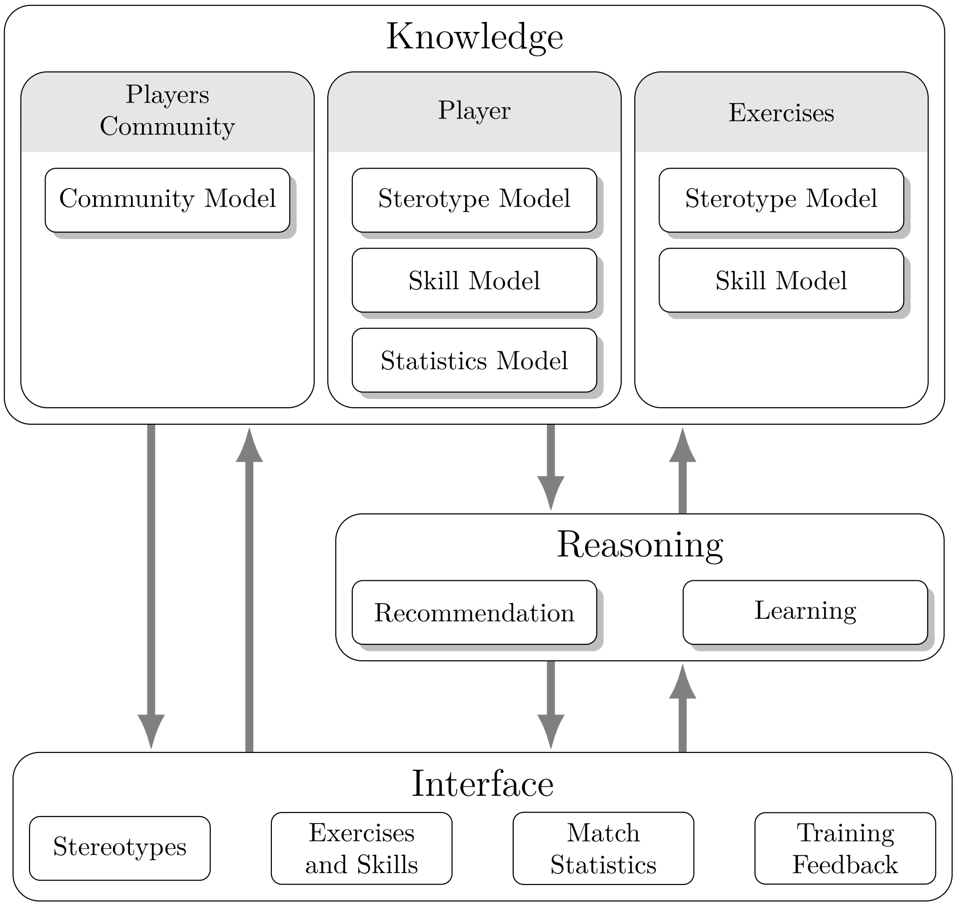

Figure 1 - Diagram of Proposed Architecture

The player modelling module, presented in section 3.1, creates a player profile based on all data previously collected and in conjunction with the training recommendation module, filters and selects the recommended training for that specific athlete. This recommendation process is presented at the end of section 3.1.

3.1. Smart Coach User Profile Modelling

This section presents the characteristics that allow concepts modelling. These concepts are then applied, to define the young athletes' profiles and recognize their different characteristics. Finally, the athlete profile is used, to pinpoint the most appropriate training to fulfil young athlete needs.

Attribute	Goalkeeper	Centre Back	Full-back/Wing-back	Defensive Midfielder	Centre midfielder	Attacking midfielder	Winger	Centre forward
(In)Complete saves	●	–	–	–	–	–	–	–
Passing accuracy	●	●	●	●	●	●	●	○
Clearances	○	●	●	●	●	○	○	○
(In)Complete interception	○	●	●	●	○	○	○	○
Ball recovery	–	○	○	●	●	●	○	○
(In)Successful tackles	–	●	●	●	●	●	○	○
Fouls committed	●	●	●	●	●	●	●	●
Fouls suffered	○	○	○	○	●	●	●	●
(In)Successful dribbles	–	○	○	○	○	●	●	●
Duels won/lost	–	●	●	●	●	●	●	●
(In)Successful crosses	–	○	●	○	○	●	●	○
Shots/Shots on target	–	○	○	○	●	●	●	●
Offsides	–	○	●	○	●	●	●	●
Assists	–	●	●	●	●	●	●	●
Goals	–	●	●	●	●	●	●	●

● Major attribute ○ Minor attribute – Not applicable

Table 1- Performance attributes collected during matches for players, classified by position

The *Smart Coach* young athletes User Modelling solution to be implemented, involved initially the definition of stereotypes for the athletes. These stereotypes, were defined during interviews with several football coaches, and the K-Means (Anderberg, 1973) clustering algorithm application to data obtained during matches of two football academies in Portugal, collected according to attributes defined in Table 1. Each cluster was classified with a set of attributes, with diverse weights and mapped according to their relevance in training, and their influence in a football team performance. The clustering outcome are the young football players profiles, *e.g.*, goalkeeper, defender, midfielder, striker. Each cluster has a user type, which is classified with several types of attributes/tasks that typically has to perform during a football match.

In the proposed solution, some domain-independent data was not considered in player modelling, but is stored, since it may have future importance and can be used to produce better reports. Thus, domain-independent data stored in Smart Coach defines characteristics that are common to most user profiles and are generally referred to as generic profiles (see Table 2).

CHARACTERISTIC	DESCRIPTION/EXAMPLES
Personal information	Name, email, password
Demographic	Age, gender, etc.
Education	Academic degree, Technological versus Social studies
Life Experience	Jobs (current and past), hobbies (sports or others), etc.
Disabilities	Hearing, visual, other

Table 2 - *Smart Coach* Domain-Independent Data

The characteristics that define each young athlete's particularities and his/her origins, has influence in is performance during a football match and can define is kind of game-play approach (*i.e.* a more or less aggressive posture, a technical or a physical player, etc.). These goals are extracted directly from the domain model and define the user domain-dependent data for the user. Each of these stereotypes corresponds to a set of objectives, tasks or functions.

The athletes goals are reached, when they successfully complete a set of actions, necessary to the conclusion of certain training.

In the user model, each training (regardless of granularity) has associated a performance percentage that allows the confirmation of successful training completion. The player also gives feedback on trainings and exercises, allowing the system to adjust the recommendations. As a result, based on his personal performance/training history, the user experience is improved with suggestions for specific workouts.

4. EVALUATION AND CONCLUSION

The first version of the data collection prototype has been evaluated in two football clubs' academies, which we will designate by club A and club B.

However, it already was possible to observe with the data obtained, that the innovative solution developed to implement the young athlete model, seems to be valid (Matos et al., 2019). The represented young athlete characteristics definition and the hybrid solution using the overlay method technique and the use of stereotypes, for the representation of the player's knowledge and to suggest what training/activity should be performed at some point, appear to be getting positive results. This validates our conviction that the present work allows the definition of a new model and process for young athletes modelling to be used in recommendation systems to support sports training in football (Matos et al., 2019).

This model enables young athletes to enhance their attributes in order to accelerate their evolution as a football player.

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