

A Collective Director for Highly Interactive Viewing of Live Sports Events

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ABSTRACT

New forms of personalised and interactive viewing experiences are being developed that enable spectators to act as directors of their own customised live sports videos. Scalability concerns for such systems dictate that group-based streaming rather than individual streaming can be realized in practice. In this positional paper, the application of the group personalisation model to enable social groups of possibly distributed individuals to collectively direct and share a common viewing experience of a live sports event is proposed. The design of this platform, developed as part of the My-e-Director 2012 project, is described and a discussion of a prototype system is given.

Categories and Subject Descriptors

H. Information Systems; H.5 Information Interfaces and Presentation (I.7); H.5.3 Group and Organization Interfaces; H.5.3 Group and Organization Interfaces.

General Terms

Design, Experimentation, Human Factors, Theory,

Keywords

Personalised, interactive, video streaming, group interfaces.

1. INTRODUCTION

Sports events are becoming increasingly instrumented, both actively by attaching tags to objects of interest, e.g., athletes, balls etc, and passively via vision based systems, enabling these objects of interest to be detected and tracked. Sports events can also be recorded from multiple perspectives using multiple cameras. Together these provide professional directors with a richer variety of content from which they can then select, schedule and broadcast a set of interlined views that they deem appealing to viewers.

However, different viewers may have different preferences and perspectives of what they find appealing in contrast to what is presented by the broadcast director. For example, different viewers may only be fans of and prefer only to track particular athletes based upon nationality or based upon recent performance, supporting, for example, only in form athletes. Multiple viewer preferences cannot all be accommodated by the director's cut of the event. Currently, sports events are not able to be directed and broadcast to match different preferences of different users.

The My-e-Director Project¹ [Poslad et al, 2009] is creating a new video delivery platform to offer viewers much greater choice and freedom to interact with live sports video content delivery. This platform improves social communication and belonging by putting the spectator in the director's seat. This enables spectators to choose amongst a wide range of camera streams, tracked objects and athletes, to use personal preferences, and for content to be delivered over a range of network infrastructures and access devices. Multiple views of the sports events with different tracked objects selected can be multicast over IP based networks.

The outline of this paper is as follows. First, related work is discussed. Next, the design and implementation of the platform is presented. Finally, conclusions and further work are presented.

2. RELATED WORK

Many projects have researched and developed personalised and interactive broadcast multimedia content delivery and access. ELIN focuses on personalisation of newspaper content. ePerSpace [Danet et al., 2006] focuses on building unified virtual personal environments and mCDN [Sokol and Eckert, 2007] focuses on personalisation to enhance the content retrieval process. IST-LIVE [Williams and Wages, 2008] also supports the concept of a future video conductor and user participation in real-time by allowing users to feedback to a director their choices for which parallel Olympic sports event they wish to view, enabling these to form 'non-linear stories' of events. Although IST-LIVE uses a similar concept to My-E-Director 2012, that of a director, the director concepts is used very differently. IST-Live seeks to support manual viewer feedback to schedule future events whereas My-e-Director 2012 focuses more on automated personalised viewing with respect to tracked objects of interest, on multi-camera use during live sports events that match personal profiles, and on the use of multicasts in addition to broadcasts.

3. MODEL OVERVIEW

The My-e-Director 2012 system consists of the following main components: video acquisition, video processing, camera selection, security, metadata generation and streaming, personalisation and terminal applications [Poslad et al. 2009]. Here the focus is on the personalisation component of the system. This acquires the individual personal preferences and clusters these to form group profiles.

The personalisation component is located between the video (and their associated metadata) stream server and terminal applications

¹ See also <http://www.myedirector2012.eu/>

within the overall system. It is used to direct the personalised video streams to multi-platform user terminals. This is achieved by clustering social group preference for sports event incidents (things of interest during sports events).

In My-e-Director 2012, sports event streams can be either manually or automatically switched. Streams can be predefined with respect to content focus (see Section 3.1), e.g. camera views of the pit in a long jump event defined as a stream focusing on a result change phase. Streams can be captured by a single camera or a set of cameras collectively. Spontaneous switches among these streams by spectators can generate personalised streams. The group personalisation processes forms two stages, i.e. **learning** and **inferencing**. *Learning* occurs after each viewing session if stream manual switch mode is enabled and *inferencing* occurs before each viewing session if user preferences for event incident types are given and the stream auto switch mode is enabled.

In inference stage, existing knowledge infers default rules for this user's preferences for event incidents and the system directs the associated user group preferred streams to that user. In the learning stage, a learning process updates the existing knowledge of user clustering. Figure 1 shows the workflow of the method.

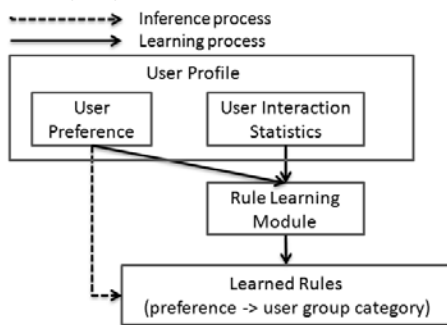


Figure 1 Social group preference clustering workflow

3.1 ACQUISITION OF USER PROFILES

Individual personal profiles are created and maintained via a mix of both explicit user input and through observations of user interaction.

User can explicitly express the preferences for a given set of predefined incident types for one particular sports event. The incident types are further grouped into three groups, namely **non-competition phase**, **competition phase** and **result change phase**. The defined phases are used to describe the content focus for the video stream and provide consequence vocabularies of clustering rules. Table 1 shows the defined incident types in corresponding groups. In practice, this allows users to select the interested incident types before viewing the sports event. Each incident type selected as assigned a value 1 or 0 if not selected.

Event	Non Competition phase	Competition phase	Result Change phase
Athletic Jump	Preparation, warm-up phases	Running, Take-off, Flying, Landing, On-your-mark	Distance announcement; Ranking announcement
100m	See above	Set, Running, Cross-finish-line,	Ranking announcement
Swimming	See above	On-your-mark,	One turn time

		Set, Jump, Swimming, Turn, Finish	announcement; Ranking time announcement
Football	See above	Kick off, Handball, Penalty kick, Offside, Red card, Yellow card	Score; Winner announcement

Table 1 Predefined incident types grouped in three phases

The system observes user interaction during viewing of a recorded sports event. Associated video streams are defined and associated with incident type groups. Users are allowed to switch to any interested recorded streams. The viewing duration for each defined phase is obtained with reference to the content focus of the stream and is recorded in an XML file (Table 2).

<Measure PName="Viewing Event" PDurationCounter="18" ClipTime = "00:00:12.000" RecordingTime="28/03/2009 12:49:56" />
<Measure PName="Viewing Event" PDurationCounter="12" ClipTime = "00:00:17.372" RecordingTime="28/03/2009 12:49:29" />
<Measure PName="Viewing Event" PDurationCounter="14" ClipTime = "00:00:00.000" RecordingTime="28/03/2009 12:49:07" />
<Measure PName="Viewing Event" PDurationCounter="0" ClipTime = "00:00:00.000" RecordingTime="28/03/2009 12:48:53" />

Table 2 Partial recorded viewing duration for a user

3.2 SOCIAL GROUP CLUSTERING

Social group clustering is done within the relationship learning module. A fuzzy neural network (FNN) framework is used to achieve this. Three social groups are defined, i.e. *non-competition process*, *competition process*, and *results prone*.

The motivation to use FNN is to address two critical issues concerning representing user preferences and group preference determination (i.e. rules determination). A neural network's leaning capability and a fuzzy system's fuzzy quantization power are both utilized. As a result, the constructed FNN for a social group clustering can be further decomposed into two major parts, namely a fuzzy membership function and the neural network.

People often use fuzzy labels such as "like", "not like" etc. to describe their preferences for one particular event incident. These labels can be quantized in a fuzzy system.

Another issue is that user interaction could reveal a preference that may not be directly reflected in explicit preferences. For example, two users may choose exactly the same incident type but the recorded viewing duration could be different. User A may be more result prone whereas user B may be more competition process prone. To solve this problem, different weights are assigned to each fuzzy label, e.g. 80% similar to a goal. A supervised learning neural network can do this by adjusting the expected weight of each fuzzy label given a training set, i.e. user profiles.

In order to produce the rules that cluster user social groups, the REFuNN [Kasabov, 1996] algorithm is used. Four modified steps are required to produce rules. They are user profile *fuzzification*, *FNN training*, *extracting initial set of weighted rules* and *aggregating the initial weighted rules*.

3.2.1 FUZZIFICATION

The user explicit preferences are fuzzified in this step, triangular membership functions ($0 \leq f(x) \leq 1$) are applied to determine the degree of interest on certain incident group. And three fuzzy sets (i.e. low, mediate and high) are defined for each fuzzy variable (i.e. non-competition interest degree, competition process

degree and result interest degree). The user chosen preferences within each incident category are summed and divided by the number of predefined incidents in that phase, i.e.

$$IGroup_i = \frac{\sum(Incident_{i, k})}{N} \cdot k, \text{ where } 1 \leq i \leq \text{group number}, 1 \leq N \leq \text{Incident number in phase } i \text{ and } k = \frac{N}{\text{Total Incidents No.}}$$

As a result, when the $IGroup_i$ is fed into the function, three membership degree are produced, e.g. if $IGroup_2 = 0.5$, where $0 \leq X \leq 1, 0 \leq Y \leq 1$, THEN membership degree for “low interest” would be 0, membership degree for “mediate interest” would be 1, and membership degree for “high interest” would be 0 (Figure 5).

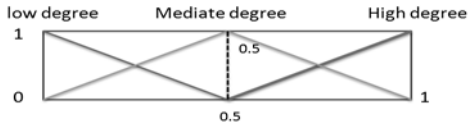


Figure 2 Fuzzification Example

Since user interaction data are expressed as crisp values already, they can be used directly as the expected results, associated with the explicit user preferences. A simple normalisation is performed by the following formula.

$$Duration_{max} = MAX\left(\frac{Duration_{group}}{Duration_{total}} k\right), k = \frac{Default Duration_{group}}{Default Duration_{total}}$$

3.2.2 FNN TRAINING

The previous step constructs the input vector and output result for the neural network. In this step, supervised learning is performed. The training set (i.e. user profiles) would be trained by a backpropagation training algorithm until convergence occurs.

The neural network is constructed with three layers. A number, e.g., nine, of input neurons are fully connected to the hidden layer neurons. The number of hidden layers (rule layers) is three which is the same number as output decisions (social groups). In this model, the sigmoid function with an alpha value of 1 is used to for each hidden neuron.

The following figure partially shows a trained network with 8 pseudo user profiles with a learning rate of 0.25, and trained for 1000 epochs. (Note that not all weights are labelled).

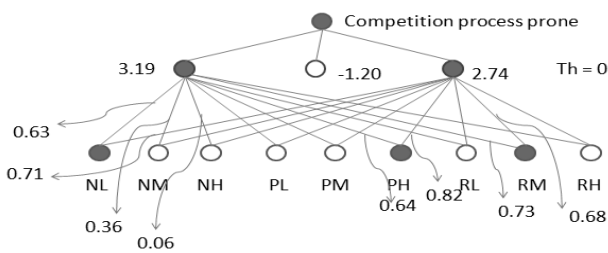


Figure 3: a partially trained neural network (ep =100, lr =0.25, n =8)

3.2.3 EXTRACTING & AGGREGATING RULES

Initial sets of rules are extracted from the trained network. Those connections from a hidden layer to the output neurons that significantly contribute to their activations are chosen. For each of these, its connections (those above a threshold, e.g., 0 in Figure 6) to a set of input neurons used in the antecedent part of expected rule. The connection to its output neuron is the initial value for the certainty degree. The partially trained network in Figure 6

demonstrates how rules can be extracted. Two initial rules obtained are:

R1: NL (0.63) & PH (0.64) & RM (0.73) → Competition process prone (N, P, R stand for non-competition, competition and results; L, M, H stand for low, mediate and high interest degree)

R2: NL (0.71) & PH (0.82) & RM (0.68) → Competition process prone

Note that the relationship for input variables is defined as synergism (collectively contributing to rule activation) in the network.

The last step is to aggregate the initial weighted rules with the same condition and consequent elements. The two rules obtained in step two can be aggregated by normalising the sum of initial degrees of importance of each condition element. i.e. $(R1+R2) / 2 \Rightarrow NL (0.67) \& PH (0.8) \& RM (0.71) \Rightarrow$ “More Interested in the Competition process”. Therefore, new user explicit preferences after fuzzification with fuzzy values can activate the rules that meet this rule.

4. DISCUSSION AND FUTURE WORK

This paper presents an approach to fulfil a collective director by grouping user preferences for event incident types. The proposed methodology can effectively learn the group preference clustering rules given the user preferences and user interaction data. The modelled neural work self explains the scalability of the system. Existing learned rules could effectively be updated once new set of user instances are added to the training set. Initial testing on the system shows that rules are produced as expected.

Future work could improve the current work by investigating issues such as multidimensional grouping, e.g. users can be grouped by other dimension such as athlete orientation, event type orientation etc. Issues concerning learning frequency and learning speed would also be investigated.

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