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Personalising Live Sports Video Zooming

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***Abstract*— An innovative Internet streaming video player, called ePlayer, oriented to live events, has been researched, developed and evaluated. This supports a personalised zoomable user interface. The main novelty of the system is first that it is designed to optimise the zoomed video quality when viewing live events via adaptation of the streamed video quality across multi-video streams with a differing network quality of service. Second, it also personalises the live video zooming with respect to users' zooming preferences, easing the user interaction needed for the zooming task. The experimental results indicate that the system is not only able to zoom effectively but that it can also maintain the visual quality of the video at the same time. ePlayer is also able to infer a user's zooming preferences via dynamically clustering a user's zooming regions of interest when viewing live sports video content.**

Keywords- HCI, Video zoomable interface, adaptive zooming, visualization

I. INTRODUCTION

A major innovation for next generation Internet streaming video players when used with live events and where multiple views of an event may be available, is to put the spectator in the director's seat, enabling them to choose amongst a range of available camera streams, tracked objects and athletes, offering personalised user interactions such as zooming even when content is delivered over a range of different network bandwidths and access devices [20]. We have researched, developed and evaluated such a player, we call ePlayer. This allows spectators to smoothly and adaptively zoom in and out on athletes, referees, spectators and other objects of interest. Within the context of live video such as live sports events, zooming normally occurs when a cameraman changes between a far and near field view. A human director rather than the spectator controls if and how these zoomed views are seen by spectators. An alternative zooming approach is soft zooming at the video terminal. This allows spectators to zoom in on a display whenever and wherever they choose to. Using a ZUI (zoomable user interface), spectators can view objects of interest in different modes, e.g. viewing an extreme long shot on a larger screen and viewing video on a small screen device. However, challenges arise when applying existing ZUI techniques to support a range of viewing modes. One such challenge is reduced visual quality that can result from zooming when there is an over magnification of the video frame. [18].

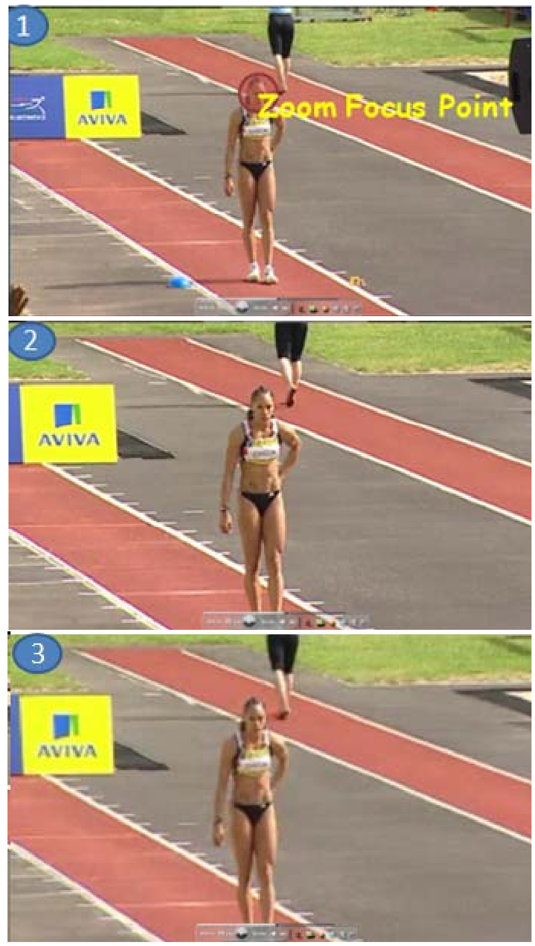

Figure 1 ePlayer's Zoomable user interface allows users to view the objects of interest in much more detail. The upper part (#1) of the figure shows the screen without zoom, the lower part of the figure shows two zooming cases: one (#2) with network adaptation and one (#3) without

In the context of zooming on live sports video content, zooming (in and out) may occur frequently as a sports event progresses. This turn can become a mentally demanding user task. In a typical use case for soft zooming using an Internet streaming player, a viewer needs to locate the zooming target of interest using a cursor, and then trigger the actual zoom in. In order to ease this task, a system needs to be able of infer a user's zooming preferences and adapt these to the task

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interaction, e.g. automatically doing a zoom in and out. Personalisation involves tailoring applications and services specifically to an individual's needs, interests, and preferences [20]. A user's zooming preferences during a live event can depend upon the event content such as incidents, the progress of athletes in a competition, and on the types of and use of the camera, i.e., the shot angle. Obtaining user preferences is a challenging task particularly when used in a live broadcast scenario. Metadata that describes live video stream content can be used to help personalise on-demand video content, e.g., [6]. However, metadata based annotation of highly dynamic events can be computationally costly and complex to generate and process in real-time.

In this paper, a personalised zoomable interface is proposed (see Figure 1). To achieve this goal, existing ZUI theories and the state of the art are examined to identify best practice and to identify the limitations of current approaches (Section II). Next, the design of a framework to meet the resulting challenges, to dynamically personalise zooming, is offered (Section III). A method to evaluate the personalisation and adaptation elements in this framework is proposed (Section IV). Then, the application and results of the evaluation of the video ZUI scheme and personalisation model are given (Section V). Finally, conclusions are drawn and future work is outlined (Section VI).

II. RELATED WORK

A. *Zoomable User Interface*

Zooming techniques have been widely used in multimedia content browsing applications. These enable users to view multimedia content at different levels of granularity. A zoomable user interface (ZUI) enables users to more easily access spatially organized information and to view video that is larger than the device screen [13]. A ZUI can be used on different types of target such as images, texts, and documents. ZUI techniques also vary in terms of presentation. In general, four types of presentations are often used: focus + context where zooming is immediately triggered based upon a focus (e.g., Apple Mac OS X Dock) [21]; overview + detail where both an overview and a zoomed content are provided at the same time (e.g., Google map street view) [5]; cue-based interfaces where a cue is used to lead to more detailed information (e.g. outlook calendar) [19]; temporal separated zooming where each zooming is sequentially separated (e.g. Microsoft's' deep zoom) [8]. The presentation of a ZUI usually depends on the zooming targets. For live video content, a focus + context presentation is not a suitable solution as a rapid zoom-in and zoom-out can cause dizziness and visualization distortion[7][12], e.g., image distortion may make the athlete in live sports events less identifiable or even unidentifiable. The Overview + detail presentation is also not suitable for dynamic content as it requires an additional overview of the live video stream to be generated at run-time [19]. This can reduce the available bandwidth which in turn can reduce both the live and overview stream visual quality. Cue-based zooming is promising to enrich the live video content, e.g. a zoom-in on a moving athlete could trigger an additional GUI showing the detailed information of that athlete. However, live video content metadata must be descriptive enough so that the system can tag and then parse the content frame by frame which is very challenging to achieve reliably. Another downside of cue based presentation is it can increase the visual working memory where only one graphical object is often held [4]. For temporal separated zooming, when it is applied to live video content, its only pitfall is that it can require an additional cognitive load in order to understand the relationship between pre- and post-zoom states. This work proposed a ZUI that leverages the temporal separated zooming but requires less cognitive load while zooming in and out.

B. *User Preference Acquisition Techniques*

The definition and acquisition of user preferences are crucial to a personalisation system to enable it to make decisions on how to tailor the personalised service to specific users. User preferences can be defined as a function of how much a user likes a given item [10]. User preferences may be temporal [14][22][2][24]. Historical user data can be used to build a more accurate and realistic model of user preferences. In principle, there are two main approaches to acquire user preferences. An implicit model utilises monitoring and learning algorithms to collect user preferences indirectly such as in [23]. An explicit model allows a user to input preferences directly such as in [15]. The advantage of using an implicit model is that it is unobtrusive [2][16]. However, the main drawback of this approach is that a lack of user's understanding of the system adaptation behaviour can confuse or frustrate users [17]. An explicit model has the benefit that it potentially provides more accurate data describing user preferences, e.g., in a Web-based information retrieval application [2]. However, a system relying on user input of preference information may result in minimal sets of user preferences being defined [9]. Studies also find that users are often unable to accurately state their preferences beforehand [3]. The explicit model used in some video rating systems is often not that explicit. For example, in systems such as YouTube, it is difficult to tell how consistent the user preferences really are. This is because neither an objective rating standard from the user side nor explicit preferences from system side are defined. This work allows an implicit system adaptation to the user's preferences based upon individual user's interactions with system.

III. EPLAYER ZUI

A. *System Overview*

Our personalised video ZUI Internet streaming video player system (ePlayer) consists of the following two integrated and implemented key components: a ZUI for live video content, a personalisation zooming control. The player is networked to a video streaming server. Two designs were considered to execute the zooming process: a terminal centric design versus a network centric design. A network centric approach was chosen as this avoids the use of a high-performance user terminal to implement the zooming processing and can be used on lower specifications PCs and on mobile phones.

The streaming server transmits multi-bitrate video streams to the video ZUI control which delivers the visual content to an ePlayer client or terminal. A personalised zooming control located at a remote server analyses a user's historical interactive data related to past zooming tasks and builds up an implicit user profile representing a user's zooming preferences linked to specific zooming regions of interest. It can then generate a predicted zooming region position based upon the user profile, matched to the current content.

B. ZUI for Live Video Content

Video ZUI is a critical element in the video ZUI control that implements the proposed Video ZUI scheme. It has three interlinked functions, namely, video quality adaptation, time-shift playback and zooming animation.

The video quality adaptation adapts the right video streaming bit rate per second to the right zooming levels and also takes account of access network's available bandwidth. The video quality adaptation requires the source video content to be encoded with different quality levels in terms of bit rates per second. An algorithm is proposed (see Table 1) to enable video quality adaptation.

Table 1 Video quality adaptation algorithm

```
Input: Available video stream bitrates Bs={ B1, B2,..., Bn} where
Bn> Bn-1,
        Terminal screen height Ts in pixel,
        Video screen height Vs in pixel,
Output: Adaptive Bitrate Badp
BEGIN
Recursion begin
for each individual item in Bs
If Bi is supported by terminal
Bsupport ← add Bi to a supported bitrates collection
Recursion end

BiP←Supported Bitrate per Pixel = Max(Bsupport) / Ts
Init MaxB= 0← Maximal Bitrate for current video screen;

Recursion begin
for each item in Bsupport
MaxB← Min(Abs(BiP*Vs- Bsupporti))
Recursion end

 RETURN Badp ← MaxB
END
```

The Time-shift playback process allows the current video to playback past video frames before the zoom-in animation begins and to catch up with live video frames after a zoom-out. This helps a viewer to better zoom on a moving object. Therefore, the ideal time-shift should be the duration of animation, i.e. if the zoom-in occurs at time $\boldsymbol{T_n}$ then the playback timeline will be at $\boldsymbol{T_n} - \boldsymbol{T_{ani}}$. If the zoom-out occurs at time $\boldsymbol{T_n}$ then the playback timeline will be $\boldsymbol{T_n} + \boldsymbol{T_{ani}}$ where $\boldsymbol{T_{ani}}$ is the animation duration.

Zooming animation can support a gradual zoom in/out effect, this helps a viewer to remember the pre-zooming state after a zooming. The animation duration is the key parameter. The determination of the animation duration T_{ani} depends on the time spent doing the video quality adaptation T_{apt}. T_{ani} is required be greater than T_{apt} as it is envisioned that users should always be shown the adapted video quality after each zooming animation.

C. Personalising Zooming Control

The personalised zooming control allows the system to automatically distinguish the zooming regions of interest and rank them based upon an analysis on the user profile containing the zooming usage information. The personalisation consists of two processes, user profile processing and the areas of interest clustering.

1) User Profiling

User profiling is the process to access, parse and extract a user's zooming task information. In the proposed approach, the user profile contains the following usage information which constitutes the user zooming preferences including normalized coordinates of the zooming target's central position, sport event name and camera IDs.

The normalized coordinates of the zooming target central position is extracted from the parsed user profile. It is used to infer the boundaries of the zooming regions of interest through a clustering process given that the sports event and camera ID match the current viewing properties. The clustered zooming regions are then ranked in order of a user's preferences in a prediction process.

2) Region of Interest Clustering and Future Zooming Prediction

Clustering is a function that identifies groups within a set of unlabelled data. Data within the same group are similar with respect to a measurement metric, e.g. the Euclidean distance. There are different types of clustering techniques (Hoppner et al., 1999). From these, the fuzzy type clustering was chosen in our design. One benefit of using a fuzzy clustering technique is that it enables one data value to belong to more than one cluster. Clustering is based upon the strength of membership of that data in each cluster. Each cluster then has a soft boundary rather than a crisp one.

Here, clustering a user's area of interest in a particular camera view is a tricky issue as these regions cannot always be absolutely located. The boundaries of these regions can change. Hence, they can only be roughly estimated. The cluster membership feature of fuzzy clustering is useful for this case when data boundaries are not clearly defined. The fuzzy C-means (FCM) algorithm [11] is a well-known fuzzy algorithm that allows data to become a partial member of different clusters defined by a membership value between 0 and 1. By using FCM, *N* zooming focus points can be divided into *C* fuzzy groups and identifies the cluster centre in each group via the minimization of the following objective function:

$$J_m(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{C} \mu_{ji}^{m} ||X_i - C_j||^2 \qquad (1)$$

Where:

U a matrix of [μ_{ji}]

V vector of cluster centres $\{Vi\ (i = 1, 2 \ldots c)\}$

μ_{ji} membership of *i*th data in the *j*th cluster

X_i coordinate of ith zooming focus point
C_j the jth cluster centre
$||X_i - C_j||^2$ distance of X_i from C_j
m (≥ 1) the degree of fuzzification
c (≥ 2) the cluster number

For the area of interest clustering process, the cluster number and initial cluster points can be determined by the algorithm (see Table 2). The number of clusters is determined by the magnification level, e.g. a 1.3 magnification (i.e. enlarge 1.3 times) could produce 4 clusters. The initial clustering centres are obtained by a counter clockwise rotation of the farthest point about the centroid for the zooming points coordinates extracted from the user profile.

Table 2 Personalised zooming control initial cluster centres generation algorithm

Input: Zooming focal points coordinates $Z_c = \{ Z_1, Z_2, \ldots, Z_n \}$
Magnification level M>1, Cluster number N_c
Output: initial cluster coordinate $C_i = \{ C_1, C_2, \ldots, C_n \}$
Cluster number N_c

BEGIN
initialise *cnum* =0;
initialise *zcentroid* =0;
cnum= *round*((*M*-1)*10);
zcentroid=*Point*(*Mean*($\sum Z_{cx}$), *Mean*($\sum Z_{cy}$))

intialize maximum distance *maxdis* = 0;
intialize maxiumum number of points *maxpoint* =null;
Recursion begin
for each point Z_i in Z_c
if *distance*(Z_i , *zcentroid*) > *maxdis*
update *maxdis;*
maxpoint =Z_i
Recursion end

Initialise Collection of points, *CP* =null
Recursion begin
repeat N_c times
CP +={
$C_n = \begin{pmatrix} zcentroid_x \\ zcentroid_y \end{pmatrix}^{-1} \begin{pmatrix} \cos\partial & -\sin\partial \\ \sin\partial & \cos\partial \end{pmatrix} \begin{pmatrix} zcentroid_x \\ zcentroid_y \end{pmatrix} \begin{pmatrix} maxpoint_x \\ maxpoint_y \end{pmatrix} \}$
Recursion end

N_c = *cnum*
C_i = *CP*
END

In some situations, a user may change his or her zooming preferences, e.g. a user becomes more or less interested in specific athletes. This can be due to several factors such as a significant video content change, e.g. an incident happened during a critical phase of an event or zooming action mistakes. The consequence of this change will directly reduce the precision for future zooming regions of interest prediction. In order to mitigate such noise data, the amount of training data (i.e. recorded zooming centres) used for zooming region of interest clustering is adjusted in relation to the prediction rate changes. The amount of training data will be decreased to allow the system predicted zooming preferences to align better to a user's recent zooming preferences.

IV. EVALUATION

A. Experimental Setup

The experiments here were carried out in both a laboratory setting and a real setting. In a laboratory setting, the broadband connection limit is capped. In a real setting, the ePlayer is downloaded to different users at different locations with different network contexts. In order to collect experimental data from both settings an overall experimental setup is modelled (see Figure 2).

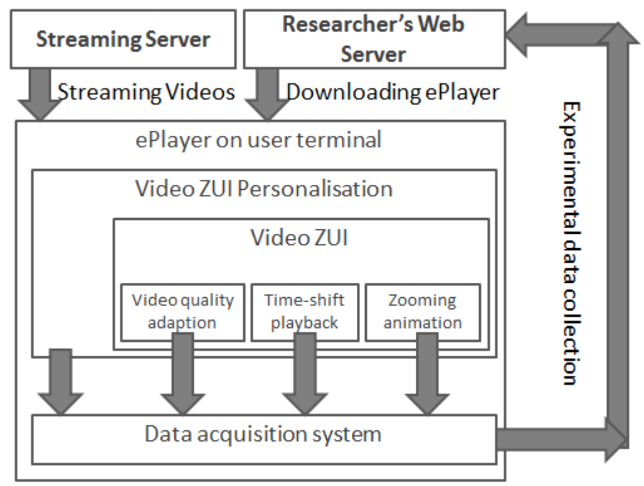

Figure 2 Experimental Setup

The functional requirements for the video ZUI components were first tested in a laboratory setting where the network bandwidth can be better monitored and controlled. The personalisation aspect of the video ZUI is evaluated in a real setting where human users interacted with the prototype system. An additional data acquisition system is hooked into the ePlayer so that evaluation data can be acquired from a terminal, exchanged via Web services, with server-side processes.

For the personalised zooming evaluation, two athletic sports events video streams including a long jump (360 seconds) clip and a 400m athletics video (180 seconds) clip are used are served at any one time due to limited high definition sports videos resources. In order to simulate live sports event viewing and to investigate adaptive streaming, videos from the 2008 Aviva European Trials and UK Championships with an original resolution of 640 X 480 and a frame rate of 25fps were encoded in different bitrates versions: 230Kbps, 305Kbps, 403Kbps, 543Kbps, 708Kbps, 937Kbps, 1241Kbps and 1644Kbps. The video is streamed in a looped live mode so that video content, unicast from a streaming server and each of the ePlayer terminals, is synchronised. The default viewing session uses a default video screen of 951 x 500, and a zooming factor of 1.3. The zooming animation duration is by default set to be 300 milliseconds with the zooming factor increasing or decreasing by 0.06 per 50 milliseconds.

A user test approach is used to evaluate the personalisation of the video ZUI. The tests are to assess whether or not the personalisation mechanism can infer a user's zooming preferences in terms of zooming cluster PP (prediction precision) which is defined by the following equation.

$$PP = \frac{Number\ of\ true\ prediction}{Number\ of\ true\ prediction + Number\ of\ false\ prediction} \quad (2)$$

The prediction consistency inherits the consistency definition by Dix et al [1] that is termed as likeness in system's input-output behaviour arising from similar situations. A usability survey of four questions is also conducted after each individual user testing.

50 users took part in the personalisation experiments; this group includes both expert and novice users, the gender distribution for these users is 28% female and 72% male, 62% of users are aged 26-35 and 38% of users aged 18-25. Among them, 50% of users use Internet video streaming applications frequently on a daily basis, 12% of users use it less frequently, i.e. on a weekly basis, and the rest of the users are in between these frequencies. In these experiments, the most recent 60% of a user's historical data in profile are used as the training data by default. Four clusters are initially set with corresponding zooming magnification level of 1.4. Participated users were asked to use the system for at least 15 zooming sessions. A session starts by zooming in and finishes by zooming out. The personalisation mechanism was executed before and after a user's manual zooming so that the accumulated prediction precision value could be obtained after each zooming session. The true prediction here is defined for the predicted zooming cluster being zoomed. The system randomly generated a zooming centroid based upon the screen size to represent the results from using system without personalisation. The PP value of this system can be generated by checking if the random centroid falls within the actual cluster representing the zooming region of interest.

B. *Results*

The zooming animation timestamps from begin to end and video bitrates changes are monitored by the data acquisition system. Given the adaptation time cost is the time difference between each zooming animation finish and the consequential video bitrates changes, the collected adaptation time cost samples are further analysed. The WSR (Wilcoxon signed-rank test) test reveals that the population median time cost ranges from 79.90 to 92.60 milliseconds ($p \geqslant 0.05$). This implies that given a frame rate of 25fps, video quality adaptation can effectively occur within three sequential video frames after zooming.

The collected data also show that there is a time-shift cost associated with each time-shift playback. The shift time cost in this experiment is defined as the difference between the ideal shifted time and real shifted time. A further WSR test reveals that the population median time cost is between -20.02 and 20.07 milliseconds ($p \geqslant 0.05$). This result implies the time-shift playback used in this experiment, is able to effectively allow users zoom on a particular image frame containing the zooming target.

The performance of personalisation was tested in terms of consistency. The consistency test is based upon testing a predesigned hypothesis:

a) H1 (for multiple users): if the mean PP does not tend to decrease across user sessions, then personalisation is consistent

This hypothesis is tested with the 50 participating users. A Spearman's rank correlation coefficient test is used to test specific correlations. The correlation of the number of uses (i.e. 15 zooming sessions) and the prediction precision of each use is obtained. The correlations are classified as: [0.5~1]: strong positive correlation, [-1~-0.5] strong negative correlation), (0~0.5) weak positive correlation, and (-0.5~0) weak negative correlation. Overall 80% of users have a positive correlation coefficient. 44% of users (i.e. 22 out of 50 users) have a strong positive correlation coefficient. Another 36% of users have a weak positive correlation coefficient. The remaining 20% of users have a weak negative correlation coefficient.

After each individual user testing, the user is asked to finish an online survey of 4 questions with respect to different user experience and usability criteria: the perceived user enjoyment, learnability, video quality and smoothness, and ease of use. These questions are designed in accordance of the approach used in the My-e-Director 2012 project [6]. For each question, a Likert scale is used to qualify an answer where a score of '1' represents 'Not at all' and a '5' represents 'Very much'). Table 3 summarises usability testing results which have an above average score in terms of these usability aspects.

Table 3 Usability questions and answer stats

Questions	Answer Stats
1. How much did you enjoy using ePlayer zooming feature?	84% of the users enjoyed using the ePlayer (score 4 and 5)
2. I needed to learn a lot of things before I could get going with eDirector	92% of the users thought they did not need to learn a lot things beforehand (score 1 and 2)

3.	I felt that video playback was smooth	74% of the users felt the video was smooth (score 4 and 5)
4.	How easy do you think the zooming control	78% of the users thought the zooming control was easy to use (score 4 and 5)

V. Conclusion and Further Work

An innovative Internet streaming video player has been researched developed and evaluated. The experiment results show that the proposed video ZUI can effectively capture and zoom in on regions of interest and support simultaneous time-shifted playback. Our approach can effectively preserve an adaptive visual quality based upon a proposed video quality adaptation algorithm. In addition, the Fuzzy clustering technique is used to personalise the user zooming task in term of zooming preferences. The experiments results show that the personalisation mechanism is able to adapt to a user's zooming target preferences in the tested athletic events in terms of inferred zooming focuses. The usability test also indicates the ePlayer ZUI is usable with respect to user experience and usability criteria.

In the future, we plan to extend the personalised zooming that will allow the system to zoom in on multiple regions of interest or targets when a user is interested in more than one zooming region. This can effectively improve the viewing experience in a sense that a single user input such as a mouse button click can result in zooming in on multiple regions. In order to achieve this, multi-target highlights animation that switches in turn between targets is required. The ZUI for video can also be extended through introducing more advanced playback controls, e.g. slow motion can be used in a zoomed state, followed by the use of fast forward back to the live mode. For patterns of slow motion and fast forward, the latency caused by switching from the normal playback rate between these needs to be investigated to ensure the performance of the video ZUI. Second, the approach used to acquire user preferences for the zooming task can also facilitate the personalisation of related services, e.g. in order to recommend a different camera view of the current event to users. The known zooming cluster positions can be used to infer which camera views a user may be interested in.

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