Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Quality of Experience for Adaptation in Augmented Reality

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***Abstract*—Augmented Reality enhances the user perception by overlaying real world information with computer-generated information. In this paper, we study the user experience in Augmented Reality for the deployment of real-time adaptation. In the context of thin-client mobile Augmented Reality, the rate is often constrained due to limitations in the transmission link. End-to-end delay, frame rate, image size and head motion speed have been identified as important variables impacting the user experience. We propose a model to link the effect of these variables with the Quality of Experience metrics. Using this model, we present an adaptation scheme that adapts, in real time, the frame rate and the image size to maximize the Quality of Experience according to the context while satisfying the given rate constraint. Simulation shows the efficiency of the proposed scheme which achieves a better Quality of Experience than without adaptation. The adaptation still performs better than a solution with a fixed frame rate set to its maximum value.**

***Index Terms*—Augmented Reality, Quality of Experience, adaptation scheme, model, mobile thin-client, rate constraint.**

I. Introduction

Augmented Reality (AR) is mainly applied to the sense of sight by displaying 3D virtual objects onto the real vision [1]. In a near future, AR would eventually be applied to many common tasks, such as museum visit, home maintenance, domotics and marketing. In order to give the illusion that virtual objects are parts of the reality, tracking, processing and display are needed. The tracking system measures user position and orientation to define the viewpoint. The virtual scene is generated and an image is rendered for the particular viewpoint. This image is then displayed to the user, for example on an optical see-through Head Mounted Display (HMD). The user vision is thus enriched with an aligned virtual scene.

Most of today's AR applications aim at providing a given user experience. The setup parameters such as frame rate, image resolution or transmission delay may not be modified over time even if a feasible compromise would improve the user experience. In this paper, we propose to adapt, in real time, the variables that can be controlled. The user experience is therefore improved by adjusting some variables according to the context.

In mobile AR the virtual scene can be generated and rendered at the server side and then sent as a video stream to the mobile client for display [2]. If the images are transmitted to the display using a wireless communication link, the transmission rate might be constrained [3]. The rate constraint for wireless transmission is taken as illustrative example along the paper, but other constraints such as processing limitation or mobile client energy can be managed in a similar manner. With rate constraint, the image size (resolution or compression) and the frequency (frame rate) at which the images are generated must be controlled in real time. For a better user experience, the adaptation consists of feedback mechanisms where measurements, such as head motion speed, are used to determine the values to apply to the AR system. Intuitively, frame rate should be high for fast head motion, while high resolution seems more important for slow motion.

The proposed adaptation scheme requires a model to adequately control these encoding parameters. The model gives the relation between frame rate, image size, delay, head motion speed and the user experience. The effect of some of these variables on user experience has been studied [4]–[6] but was not used for adaptation. In AR, adaptation is mainly used by mechanisms for real-time video transmission [7], [8].

In this paper, we first identify the variables that have an impact on user experience and present an objective model suitable for adaptation. This model links the above variables to the Quality of Experience (QoE) metrics for user experience. Based on the model, an adaptation scheme which maximizes the QoE by adjusting the input variables regarding constraint and other variables measurements is presented. Finally, the model is identified for a specific setup and the adaptation scheme is illustrated in simulation.

II. Model

In Augmented Reality (AR) like in other Man-Machine Interaction applications, user experience plays a key role. To maximize the user experience, the *variables* impacting the subjective user experience should be known and understood. The variables have been classified in three main groups, namely the design variables, the encoding parameters and the contextual variables. The design variables correspond to mechanical and ergonomic aspects. The screen dimension, the weight of the system, the communication infrastructure choice or the static tracking error are included in this group. They are determined at the design stage and are generally fixed. The encoding parameters are related to the realism of virtual scene

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generation, or its representation as image. It could correspond to the number of polygons of a virtual objects, the color depth, the image resolution or the number of images rendered per second. Contextual variables have also an important impact on user experience. In a stress situation, for example when a security alarm occurs, the user will not appreciate the AR application the same way as during his usual work. AR is also appreciated differently depending on previous knowledge or expertise level. Other contextual variables such as user health, visual acuity, the task difficulty or the moving speed also impact user appreciations. Some of these variables can be quantified and their impact on user experience too.

Another important variable impacting the user experience is the end-to-end delay. The end-to-end delay corresponds to the time difference between the instant when the virtual objects should be displayed and the instant when the AR image is displayed. If this delay is zero, virtual and real worlds are perfectly aligned; if it is not, virtual objects might seem to swim around and lag behind their supposed position in the real world. The higher the delay, the lower the coherence between virtual and real worlds is. The delay can be classified either as a design variable if it is fixed over time, or as a contextual variable if it is subject to variation. In this paper, since information is transmitted over a wireless link, delay varies and is therefore taken as contextual variable. Since they are static, design variables that do not change over time are not taken into account in this study for real-time adaptation. Only encoding parameters and contextual variables are considered since their evolution modifies instantaneously the user experience.

A. Model variables for mobile Augmented Reality

In the case of data transmission from a server to a mobile client through a wireless link, user experience is affected by the video quality and by the dynamic registration error [9] (static registration error is assumed to be negligible). The video quality depends on the encoding parameters, namely the image size and the frame rate. The dynamic registration error depends mainly on the end-to-end delay. The head motion speed can be taken as another contextual variable that has a coupled impact with frame rate and delay on the user experience. Therefore, we consider the image size, the frame rate, the end-to-end delay and the rotational head motion speed as variables for characterizing the user experience.

End-to-end delay and image size effects are illustrated in Fig. 1, where a virtual object is placed on a table. The real table is emulated to represent the see-through user view. Figure 1b shows the dynamic registration error due to the end-to-end delay for a given relative speed between real and virtual worlds. Figure 1c shows the same virtual scene rendered in different image resolution and scaled to the display resolution. A lower resolution gives a smaller image size but also a poorer user experience. The frame rate determines the frequency of new rendered images. In the case of head movement with no end-to-end delay, the virtual object is perfectly aligned with the real world only when the new image has just been displayed. While waiting for the next image to be displayed, the misalignment between real and virtual worlds grows. This additional delay is barely noticeable at high frame rate but is annoying at lower frame rate.

The adaptation scheme proposed in Sec. III requires a model to represent the impact of the selected variables on the user experience. Experience evaluation can be either subjective or objective [10]. Subjective evaluation is a reliable but time consuming quality measurement method. Subjective testing is generally done by asking users to vote for the experiences perceived with different operating conditions. However, subjective evaluation cannot provide real-time quality monitoring. Objective evaluation is not as accurate as subjective evaluation, but can be used in real time without intruding the end user. For video quality assessment, the Peak Signal to Noise Ratio measure has been widely used. However it does not correlate well subjective results. Other objective measures are more suitable to replace subjective measures [11] for video quality assessment, but there is not such a measure for AR.

We define the *Quality of Experience* as the objective metrics of the user experience for a specific application. This metrics is based on a *model* which links the impact of the selected variables on the Quality of Experience (QoE). The model is identified with subjective user experience evaluation.

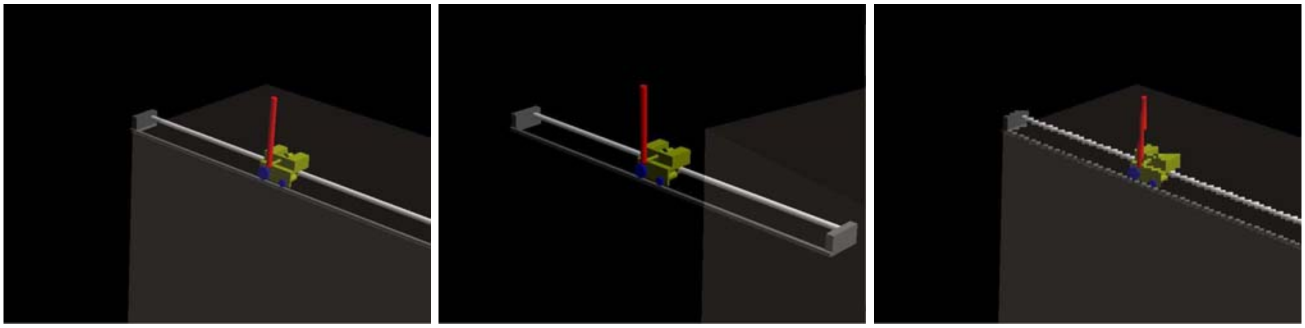
B. Mathematical representation

The adaptation scheme requires a model represented in an adequate mathematical form. An hypersuface is chosen to link the selected variables to the QoE. An hypersurface is an higher-dimensional generalization of the surface concept. It consists of a n-dimensional topological manifold represented in a $n+1$ Euclidian space, where n corresponds to the number of variables. With 4 variables, this is a 4D hypersurface in a 5D space, which is not graphically displayable in the usual 3D space. B-splines have been arbitrarily chosen to define the model in a smooth way and with a low error sensitivity.

C. Model identification

The model is fully defined when the hypersurface function coefficients are known. These coefficients are identified using subjective testing with a finite set of variables combinations covering the range of all possible variables values. Subjective testing is performed on a group of test users. The model hypersurface aims at fitting the measured user experience answers. The coefficients are chosen to minimize the square distance on the QoE axis between measurements and the hypersurface.

Subjective testing is performed according to International Telecommunication Union recommendation [12], [13]. A user is equipped with an AR application and is faced with different variables combination trials. The trials last about 10 seconds and are interleaved with pauses, during which the user is asked to give a grade between 0 and 1 for his appreciation. The end-to-end delay, the frame rate and the resolutions are manually set at different values. For the head motion, the user is asked to turn naturally his head between two target points within a specified period of time to get a quasi-triangular head yaw



(a) The virtual object is placed on the real world table. The table is emulated here with grey box and is rendered without delay and with maximal frame rate and image resolution.

(b) Illustration of the dynamic registration error with a 100 ms end-to-end delay for a 20 degrees per second relative speed.

(c) The virtual scene is rendered at a 179x134 resolution and scaled to the 800x600 resolution for display. The real world table is still rendered at the 800x600 display resolution.

Fig. 1: Illustration of the effect of end-to-end delay and image size on the user experience.

motion [14]. An audio digital metronome is used to give this period of time to the user. As the speed is not constant during the yaw motion, the virtual object are in the field of view only during the period of time where the head motion speed can be measured as almost constant.

The model coefficients are derived from the measurements. The hypersurface order is chosen for the best compromise between model complexity and measurement fitting precision. Although an high order model would probably gives a lower error, it requires significantly more coefficients. B-splines of order 3 (quadratic) have been selected as the balanced choice between the number of coefficients and the fitting error. The curve fitting process is done using least-square approximation of the data for a quadratic B-spline with multiple knots at the variables range bounds.

The model identification procedure specific to the considered context is described in Sect. IV. The adaptation scheme presented in Sect. III assumes that the model is known and valid to capture the user experience at the appropriate level of details.

III. Adaptation

In the considered case of thin-client mobile Augmented Reality (AR), wireless transmission constraints are the most important since their variation impacts greatly the Quality of Experience (QoE). For example, the communication link might be partially of fully saturated resulting in a lower available bandwidth. If these limitations are ignored, unpredictable behavior may appear. For example if the available bandwidth is exceeded, transmitted data can be lost or strongly delayed. We propose to quantify these limitations and take them as *constraints* to follow, in order to avoid unpredictable behavior and to maximize the QoE.

The rate constraint corresponds to the maximal amount of data over time that flows wirelessly between a server and the mobile client. For example, a typical 802.11g wireless network has a theoretical 54 Mb/s bandwidth (half in practice), and the rate of a raw 800x600 pixels resolution image with 24 bits color depth without compression at 25 images per second is 288 Mb/s. If this video is sent as it is, the network will not be able to handle this flow of data. Packets will be lost and/or delayed and as a result, images will not be usable by the client application. In other words, the rate constraints should not be exceeded and the sending rate must be adapted in real time to the network capabilities for adequate usage of the available bandwidth.

Encoding parameters, namely the frame rate and the image size, can be controlled and have a direct impact on the output rate: they are called the *input variables* of the encoder. These input variables must be adapted to follow the provided rate constraint reference, which is represented as a product between the frame rate and the image size. The end-to-end delay and the head motion speed are only estimated. In the presented adaptation scheme, the image size is proportional to its resolution. A more advanced scheme that considers both temporal and spatial compression is hinted in the conclusion.

The proposed QoE model is used to determine the optimal inputs variables combination; by optimal we mean the maximal instantaneous QoE. Figure 2 shows the adaptation scheme that adapts the input variables $u_e(k)$ (frame rate and image size) in real time. These input variables modify the behavior of the whole AR system, the encoder being the actuator. The QoE MODEL has been determined offline based on subjective user experience (UX) testing and is not updated in real time. The general context varies over time according to its surrounding and the current operating conditions. It is represented as a perturbation on the AR system. Although the notion of context encompass many aspects, a picture of its current state is estimated. These estimations are the contextual variables $v_c^{est}(k)$ of the QoE model presented above, namely the end-to-end delay and the head motion speed. These contextual variables are estimated based on specific measurements $m_c(k)$ such as current head position and orientation. The reference rate $r_r(k)$ is derived from the available bandwidth and assumed to be known [15].

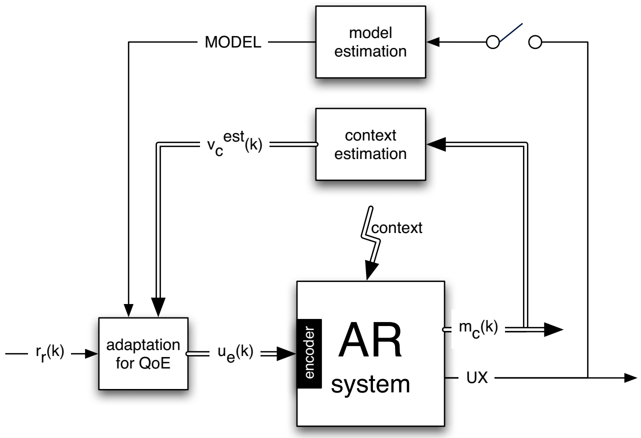


Fig. 2: Adaptation scheme that adapts, in real time, the input variables $u_e(k)$ (frame rate and image size) of the AR system to maximize the QoE. The model is estimated offline, while the contextual variables $v_c^{est}(k)$ are estimated in real time.

The *adaptation for QoE* uses the QOE model as well as the estimated contextual variables and the rate reference to determine the optimal input variables (encoding parameters) in real time. The reference rate is represented as a surface in the same space as the QOE model. The intersection of the two surfaces gives a curve that represents all possible input variables combinations following the reference rate. The maximum of this QOE curve represents the optimal combination for frame rate and image size.

IV. Preliminary results

The concept of adaptation for Quality of Experience (QOE) is validated using the following procedure. We identify the model for a user wearing an Head Mounted Display (HMD). The virtual scene is static and its position is fixed in the real world. This model has been built without taking the end-to-end delay into account. This model is not directly generalizable to all Augmented Reality (AR) applications.

In the considered experimentation scenario, the AR scene consists of a virtual inverted pendulum located on a table. The user can freely move his head and looks at the pendulum displayed in his optical see-through HMD. The monocular HMD (Liteye 750) displays full SVGA (800x600) images using OLED technology. Its field of view of 22 degrees gives the user a good sensation of immersion. An hybrid inertial-optical tracker (Intersense IS-1200 VisTracker) is fixed on the HMD. A constellation of markers is placed on the ceiling over the test area. The position and orientation are computed based on the images acquired by the camera and the inertial platform measurements. The orientation is represented as quaternion. Based on the measured user's viewpoint, the virtual scene is generated on a computer. The image is then displayed in the HMD connected to the computer.

Four inter-frame periods have been chosen in the feasible range: 33 ms (30 Hz), 50 ms (20 Hz), 83 ms (12 Hz) and 133 ms (7.5 Hz). Three image resolution has been selected: 400x300, 219x164 and 126x95 (correspond to an image size of a tens of the base 400x300 resolution). The resulting image are scaled at to the 800x600 display resolution. Three head motion speeds have been selected: quasi-static, 0.2 rad/s and 0.4 rad/s. The angular head motion speed was computed based on the discrete measured orientations using the following formula:

$$\omega(k) \quad = \quad \frac{2}{\Delta(k)} \left\| Im\big(q(k) \circ \bar{q}(k-1)\big) \right\|$$

where $\Delta(k)$ is the time between the conjugate of the past measured quaternion $\bar{q}(k-1)$ and the current quaternion $q(k)$. The variables values have been scaled between 0 and 1, the highest frame rate, the highest resolution and the lowest speed corresponding to 1. The 36 variables combinations (4 frame rates, times 3 resolutions, times 3 speeds) are presented to the user in a random order.

The user seats on a fixed chair at 140 cm from the table where the virtual objects was set. Two markers were physically placed on the table on both end of the 70 cm pendulum rail structure to refer the exact location of the pendulum. The user looks at the real table augmented with the generated pendulum. The head motion was imposed by asking the user to turn his head between two predefined points on the table. This motion corresponds to a 40 degrees yaw angle. After each trial, the user was asked to give a grade for a scale between 0 and 1, where 1 means the best user experience. The quadratic 3D-hypersurface B-spline has been computed by a least-squares spline approximation algorithm, with knots of multiplicity of three at 0 and 1 in each dimension. The 27 coefficients of the resulting B-spline are not presented here. Figure 3 illustrates the surfaces for the three tested head motion speeds. It can be seen that the maximal QOE is achieved for the highest frame rate and the highest resolution for quasi-static motion. This confirms the intuition presented in Sect. I. The QOE decreases as the frame rate decreases or as the resolution decreases, independently of the head motion speed. On the other hand, increasing the head motion speed results in lowering QOE. This is due to the dynamic registration error which becomes annoying as the head motion speed increases.

The evaluated QOE model is then used by the adaptation scheme to determine in real time the optimal input variables (frame rate and image resolution) for achieving the best possible QOE. Figure 4 illustrates the intersection between the model for the current context estimation (measured head motion speed) and a given rate constraint. The rate constraint (r_r) is scaled between 0 and 1, where 1 corresponds to the maximal achievable rate with both the highest frame rate and the highest image size. This intersection gives a curve linking the input variables to the QOE. This curve is also approximated with a B-spline using computed intersection points. Its maximum has been computed with an algorithm for minimizing a function. The optimal input variables can be directly read on the XY axis of the figure.

The adaptation to find the optimal input variables in function of the context and the constraint is performed in real time.

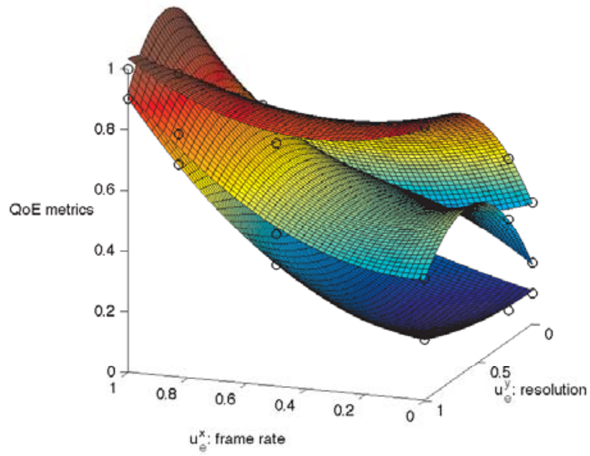


Fig. 3: The QoE model depends on three variables (delay is omitted) and is represented as B-spline. The quadratic 3D-hypersurface B-spline is displayed as surfaces in the 3D space for three different head motion speeds: quasi-static, 0.2 rad/s and 0.4 rad/s (displayed from top to bottom). The points correspond to the subjective testing measurements. The adaptation will select the surface corresponding to the current head motion speed ($v_c^{est}(k)$).

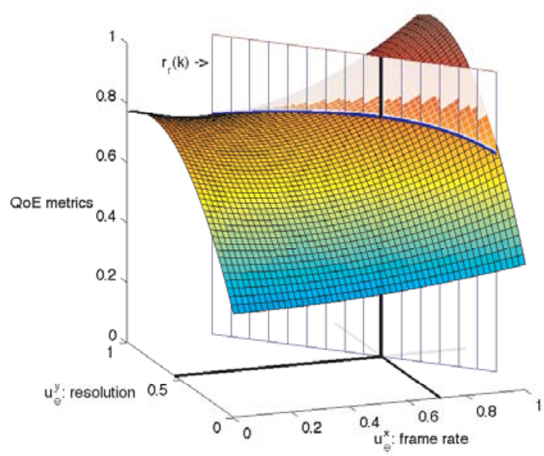


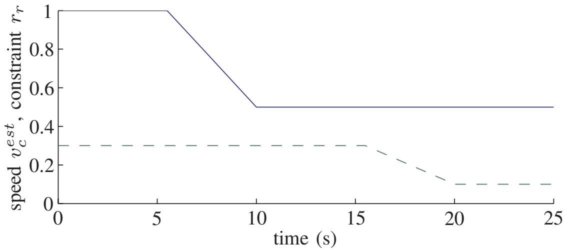
Fig. 4: Intersection between the QoE model given for the current low head motion speed (0.9) and the rate reference constraint ($r_r(k) = 0.3$). The maximal QoE is obtained for the next input variables to apply $u_e^x(k) = 0.71$ and $u_e^y(k) = 0.55$.

Figure 5 illustrates the simulated adaptation for varying head motion speeds and varying rate references. Figure 5a shows the motions and the rate constraint profiles. The head is static from time t=0 to 5 s, then its speed increases to 0.5 from time t=5 to 10 s and remains until t=25 s. The rate is constrained to 0.3 from t=0 to t=15 s and then decreases to 0.1 during the period from time t=15 to 20 s and it remains to 0.1 until t=25 s.

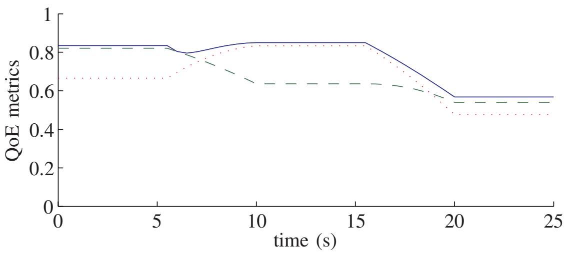
Figure 5b shows the evolution of the QoE metrics over time for different conditions. The QoE values are only computed to analyze the efficiency of the adaptation scheme, but are not used in real time for adaptation. The difference between QoE for the fixed input variables (the frame rates are set to 0.6 (dashed green) and 1 (dotted red); the image sizes are set according to the rate constraint) and the optimal input variables computed in real time. This shows that the adaptation scheme results in higher QoE than with fixed input variables. The adaptation still better performs than with a fixed frame rate set to its maximum value of 1. Figure 5c show the evolution of the optimal input variables. For quasi-static head motion, the maximal QoE is obtained with an high resolution and a low frame rate. This QoE is much higher than with frame rate fixed to its maximal value at 1. As the head motion speed increases (t=8 s), the image resolution decreases while the frame rate increases resulting in much higher QoE than with the frame rate fixed to 0.6. This is due to the fact that the QoE model has captured that the user prefers to have a good dynamical representation of movements than a detailed image. The user is less sensitive to the image resolution during head motion. The higher the head motion speed is, the higher the ratio between frame rate and resolution becomes. When the rate constraint decreases (t=15 s), both the frame rate and the resolution decrease but the QoE is still higher that both measurements without adaptation. The proposed real-time adaptation scheme permits to achieve the maximal QoE for any measured head motion speed compared to different fixed variables conditions. Studies show similar results for short video scene displayed on a computer screen [16], [17], but without considering the head motion which greatly improves the QoE.

V. Conclusion

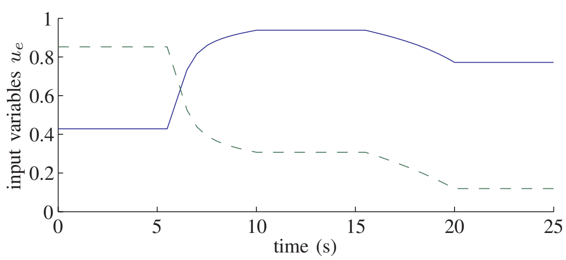
This paper presents an adaptation scheme that aims at maximizing the user experience in the context of mobile Augmented Reality (AR). The user experience is characterized with the help of the Quality of Experience (QoE) model. This model links the identified variables, namely the frame rate, the image size, the end-to-end delay and the head motion speed, to the QoE metrics. The model is represented as a 4D-hypersurface B-spline. The coefficients of the B-spline are identified using subjective testing with users performing specific given AR tasks. In the context of thin-client mobile AR, the data transmission through the wireless link is constrained by the available bandwidth. The proposed adaptation scheme maximizes the user QoE in real time by adapting the encoding parameters (frame rate and image size) to follow the rate constraint, this according to the QoE model, the end-to-end delay and the head motion speed measurements. The intersection between the model and the rate constraint gives the set of encoding parameters that follows the constraint. For a given constraint, the maximal QoE is achieved when the encoding parameters are optimal. The optimal input variables values are determined using an optimization algorithm on the curve intersection between the model and the constraint.



(a) Profile for head motion speed (solid blue) and rate constraint reference (dashed green) used in the simulation. Head is quasi-static at the beginning and then its motion speed is increased. The rate constraint is then decreased.



(b) Comparison between QoE with adaptation (solid blue) and QoE without adaptation with fixed frame rate at 0.6 (dashed green) and with maximal frame rate at 1 (dotted red). Adaptation results in higher QoE than with a fixed frame rate and the corresponding image size.



(c) Optimal encoding parameters resulting from the adaptation. The frame rate (solid blue) is lower than the resolution (dashed green) for low head motion speed, but is higher for faster movements.

Fig. 5: The adaptation scheme for QoE is illustrated through a 25 s simulation.

The QoE model is identified using subjective testing. This model mainly shows that the user prefers an higher frame rate when the head motion speed increases, even though the resolution must be reduced to follow the rate constraint. Based on this model, the adaptation scheme computes the encoding parameters according to head motion speed. The adaptation results in higher QoE than with fixed encoding parameters. The adaptation still better performs than with a fixed frame rate set to its maximum value.

The proposed model needs to be extended to consider the end-to-end delay. If known, this delay could be compensated by generating the AR scene ahead of time. Using the proposed modeling and adaptation methodologies, a broader range of users and scenarios should be considered to improve the QoE model. In the presented adaptation scheme the rate constraint is satisfied by varying the frame rate and the image resolution (and thus its size). Both spatial and temporal compression should be considered to reduce the image size. In this case, the QoE model values will be different and an adequate rate control [2] should be deployed to follow the reference rate independently from the image content.

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