A Nonlinear Quality of Experience Model for High Dynamic Spatio-Temporal Mulsemedia

Lana Jalal
Department of Electrical and Electronic Engineering
University of Cagliari
Cagliari, Italy
lana.jalal@diee.unica.it

Maurizio Murroni
Department of Electrical and Electronic Engineering
University of Cagliari
Cagliari, Italy
murroni@diee.unica.it

***Abstract*—In multimedia, quality of experience (QoE) accounts for the degree of delight or annoyance of the user of an application or service. Although humans have five senses, only two of these senses (i.e., sight and hearing) are stimulated by traditional multimedia contents. Therefore, the research efforts try to provide realistic media contents to the users. Realistic media contents are media with multiple sensorial effects, called mulsemedia, aimed at increasing user's experience through the five senses representation. This introduces a number of new issues like the evaluation of the QoE for audiovisual sequences enriched with additional sensory effects such as light, wind, vibration, scent. QoE evaluation is based on mean opinion score (MOS) subjective tests measurement campaigns, which are time consuming, although allowing for the definition of statistical prediction models. This paper proposes a nonlinear model for predicting the QoE for high dynamic spatio-temporal mulsemedia. The parameter estimation relies on metaheuristic particle swarm optimization (PSO) which has been efficiently applied to optimization of nonlinear problems. A comparative analysis of the performance of the proposed model with other state of the art model for the QoE has been carried out to assess the effectiveness of the former with respect to the latter. Results show that the QoE estimated by the proposed model is more accurate and therefore the proposed model can enhances the estimation accuracy.**

Keywords: Quality of Experience, Sensory Effects, Mulsemedia, Particle Swarm Optimization

I. INTRODUCTION

Multimedia content is increasingly used in every area of our life. Usually multimedia contents only stimulate the visual and/or the hearing system of the end user. Researchers try to simulate the other human senses by enriching multimedia with additional effects such as light, wind, vibration, scent, and so on, to increase the user's quality of experience (QoE). QoE can be defined as the degree of delight or annoyance of the user of an application or service. It results from the fulfilment of his/her expectations with respect to the utility and/or enjoyment of the application or service in the light of the user's personality and current state [1]. The main point of adding effects is to give the user the sensation of being part of the multimedia content, so achieving a better user experience. The enhancement of multimedia content using additional light effects has been demonstrated in [2, 3].

The existing approaches for predicting the QoE aim to map quality of service QoS to QoE [4, 5] or to predict the QoE with a main focus on audiovisual services [6, 7] and do not take in to account additional assets such as sensory effects. Exponential interdependency of QoE and QoS (IQX hypothesis) was introduced by [8]. The IQX hypothesis is formulated with QoE and QoS parameters, thus, providing an exponential function. That is, if the level of satisfaction decreases, the level of disturbance increases. The authors defined this function as an exponential because a small disturbance drastically decreases the satisfaction. These models allow us to get a rough understanding on how specific QoS parameters impact the QoE for audiovisual services.

Additional QoE models such as the one presented in [9] are based on perception, emotion, and sensation and mainly address adaptation and presentation issues without explicitly addressing sensory effects. A pseudo subjective quality assessment (PSQA) was presented in [10], which is a hybrid approach between objective and subjective evaluations. The results of the subjective assessment are used to train a learning tool that provides the relation between the parameters causing the distortion of the video sequences and the perceived quality. A linear utility model for sensory experience was introduced by [11] based on mean opinion score (MOS) [12] quality assessment. The aim of this model is to enable an estimation of the QoE of multimedia content with sensory effects (Q_OE_{eff}) from the multimedia content without sensory effects. The model proposed in [11] has been validated on three highly dynamic spatio-temporal multimedia sequences enriched with three sensory effects, namely wind, vibration and lights. From the results, the authors conclude that there a linear relationship between the number of effects and the actual Q_OE_{eff}.

This paper proposes a nonlinear model for the estimation of QoE with sensory effects, based on MOS subjective quality assessment, and compares the nonlinear model with the linear model presented in [11].

Estimation of parameter values is one of the crucial steps in the modeling process. Parameter estimation helps to determine the appropriate numerical parameter values that can convert the symbolic model into a numerical model and makes the latter consistent with experimental observations [13]. Parameter estimation procedures are very important for development of mathematical models, since all the process depends on model parameter values obtained from experimental data. Difficulties in estimation of parameter and the statistical analysis of parameter are due to the large number of parameters and multi modal nature. As to parameters estimation metaheuristic methods have been successfully applied in engineering design and optimization. In [14, 15], authors proposed a modified particle swarm optimization (PSO) for intelligent mobile robot navigation. PSO and simulated annealing (SA) were used in [16, 17] to optimize the coverage of television broadcasting single frequency network (SFN) while minimizing the interference degree. The results show that PSO algorithm, increase the overall coverage and reduce interference in critical directions. Reliable parameter estimation approach based on PSO algorithm for nonlinear regression model was developed in [18] and tested on the well-known 28 nonlinear regression models. The results show that PSO is an efficient method for handling the problems of parameter estimation of the nonlinear regression models. Therefore, in this work PSO is used as to parameter estimation of the proposed nonlinear model to enhance the estimation accuracy.

Results of the present study show that the proposed nonlinear model outperforms the performance of the linear model presented in [11] in terms of means square error (MSE) and square of multiple correlation coefficient (R^2) between actual and the predicted MOS values. The remaining contents are organized as follows: section 2 presents linear and nonlinear models, section 3 presents test and results. Finally, section 4 concludes the study.

II. MULSEMEDIA QUALITY OF EXPERIENCE MODEL

Enriching traditional multimedia with additional effects, introduces a number of new issues like the evaluation of the QoE for video sequences enriched with additional sensory effects, also called mulsemedia. Mulsemedia is a multiple sensorial media, which is a combination of traditional media with multiple sensory effects that aim to stimulate other human senses [19]. The resulting QoE is referred to as mulsemedia QoE. The concept of receiving sensory effects with audiovisual content is shown in Fig. 1. The processing terminal is responsible for managing the actual media audiovisual resource associated with sensory effect metadata (SEM). SEM is a description of supplementary effects based on sensory effect description language (SEDL) which is an XML Schema-based language that can be used to describe sensory effects. Media and effect renders are used to reproduce audiovisual media and supplementary effects, respectively.

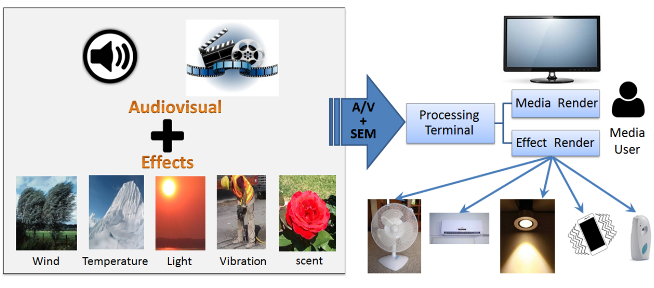

Fig. 1. Schematic of mulsemedia scenario.

A. Basic Utility Model

A linear utility model for sensory experience was proposed in [11] to estimate the Q_OE_{eff} from the Q_OE of multimedia content without sensory effects (Q_OE_{av}) i.e., only considering audio and video contents. According to the results from the study presented and discussed in [11] there is a linear relationship between the number of effects and the actual Q_OE_{eff}. In this model, three sensory effects were taken into account (i.e., light, wind, and vibration). Equation (1) shows the utility model.

$$Q_oE_{eff} = Q_oE_{av} * \left(\delta + \sum w_i b_i\right) \qquad (1)$$

where w_i represents the weighting factor for a sensory effect of type i, where $i \in$ {light (L), wind (W), vibration (V)}, b_i is a binary variable used to identify whether effect is present or not, and δ is used for fine-tuning. The instantiation of the model was according to the studies described in [11, 20].

Multiple linear regression (MLR) with the least square (LS) estimator method [21] was employed to validate the model and to estimate the weights w_i and δ. This model has been validated using the subjective test data MOS performed on some opportune test video sequences. The light (L), wind (W) and vibration (V) effects were also combined, thus creating seven different test cases: *L, W, V, L+W, L+V, W+V, L+W+V.*

B. Proposed Mulsemedia Quality of Experience Model

This work proposes a nonlinear mulsemedia QoE model. Equation (2) shows the proposed nonlinear model

$$Q_oE_{eff} = Q_oE_{av} * \delta + \left(\sum b_i * QoE_{av}^{w_i}\right) \qquad (2)$$

where w_i, b_i and δ are as in section II *A*. The model has been validated according to the subjective test experiments used to validate the linear model. This allowed performing a fair comparison between the performance of the linear and nonlinear model. The objective of choosing this model is that, it's the best and simplest model that adequately fits the dataset in [11].

Nonlinear regression (NLR) [22] was employed to validate the models. NLR is characterized by the fact that the prediction equation depends nonlinearly on one or more unknown parameters. NLR usually arises when there are physical reasons for believing that the relationship between the response and the predictors follows a particular functional form.

Parameter estimation procedures are very important in the many scientific fields for development of mathematical models, since all the process depends on model parameter values obtained from experimental data. Nonlinearity model makes the estimation of parameter and the statistical analysis of parameter estimates more difficult and more challenging. Minimizing sum of squared of errors function using analytic optimization techniques is not trivial when not possible at all. In order to overcome these difficulties, the use of metaheuristic methods such as PSO algorithm may be considered [18]. According to that, the parameter estimation of the proposed model has been based on PSO algorithm, which was introduced in 1995 by Kennedy and Eberhart [23]; based on the idea of swarms in the nature such as birds, fish, etc. PSO is a metaheuristic method that finds a solution of a problem within a population of candidate solutions, by moving particles composing the swarm around in the search space according to simple mathematical formulas.

III. TEST AND RESULTS

Test has been performed according to [11], when 32 students were invited to participate in the subjective quality assessment, 6 female and 26 male students. The age of the participants is between 20 and 47 years with both technical and nontechnical background. Three highly dynamic spatio-temporal audiovisual sequences, i.e., 2012 from the action category, Pastranas, and Berrecloth from the sports category, with 720p resolution and with duration of 10s are showed to the participants. The duration of the individual sequences was chosen according to the recommendation of the ITU-R Rec BT.500-13 [12]. The assessment was performed in an isolated room, the details of the hardware and software components that used to perform the assessment are presented in [11]. The duration of the subjective quality assessment for each participant was around 15 minutes. The hardware and software components used for the subjective quality assessment are [11]

- amBX Premium Kit (Fan, Vibration Panel, Light, Sound)
- 24" Monitor with a resolution of 1400 × 1050
- Mozilla Firefox 6 & 8 in full-screen mode
- Ambient Library 1.5 & Web browser plug-in 1.5
- amBX Software (amBX System 1.1.3.2 and Philips amBX 1.04)
- Dell Optiplex 655: Pentium D 2.8 GHz w/1 GB RAM & ATI Radeon HD 5450

Fig. 2, 3 and 4 show snapshots of the three highly dynamic spatio-temporal audiovisual sequences, presented during the subjective quality assessment.

Fig. 2. Snapshot of the action sequence "2012".

Fig. 3. Snapshot of the sport sequence "Pastranas".

Fig. 4. Snapshot of the sport sequence "Berrecloth".

To estimate the parameters of the proposed models PSO algorithm has been implemented in MATLAB and run on a computer with a processing unit of 2.50 GHz Intel (R) Core i5 with 6 GB of RAM. At first, we run prelaminar test on the convergence of PSO, the PSO parameter setting is summarized in Table 1. This choice of parameters setting ensured the algorithm to achieve convergence.

TABLE I. PSO PARAMETERS SETTING FOR THE EXPERIMENTS

PSO Parameters	**Setting**
Swarm size, p	15, after running preliminary tests and based on trial and error approach
Maximum number of iterations, t_max	300, after running preliminary tests and based on trial and error approach
Self-confidence factor, c_1 and swarm-confidence factor, c_2	2, as suggested by [24] and [25]
The inertia weight, I	0.02, was selected by running preliminary tests on the selected use case

The estimated parameters for the proposed model are shown in (3)

$$Q_oE_{eff} = Q_oE_{av} * 1.212 + b_L * QoE_{av}^{0.404} + b_W * Q_oE_{av}^{0.418} + b_V * Q_oE_{av}^{0.742} \quad (3)$$

The resulting δ and the weights w_i for the linear model proposed in [11] are shown in (4).

$$Q_oE_{eff} = Q_oE_{av} * 1.1 + Q_oE_{av} * 0.16 * b_L + Q_oE_{av} * 0.17 * b_W + Q_oE_{av} * 0.44 * b_V \quad (4)$$

Fig. 5, 6 and 7 shows the data used to conduct the proposed model, and also show the estimated response of the model for the three sequences. Each of the estimated responses according to the proposed model are almost within the confidence interval CI (95%) of the responses of the subjective quality assessment, and close to the means of the assessed MOS of each configuration which show that the proposed model can provide satisfactory estimation accuracy.

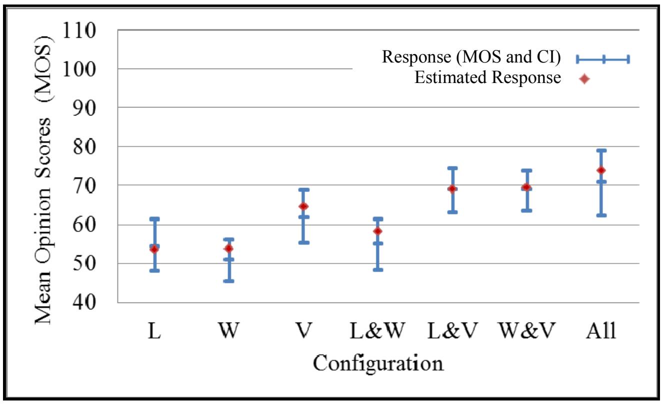

Fig. 5. The estimated response by the proposed model compared to the MOS for the action sequence “2012”.

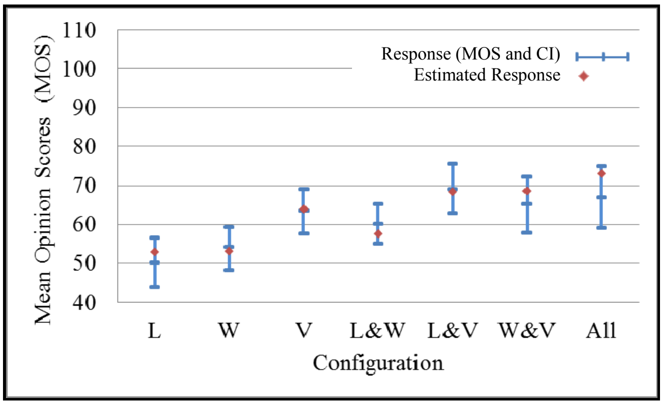

Fig. 6. The estimated response by the proposed model compared to the MOS for the sport sequence “Pastranas”.

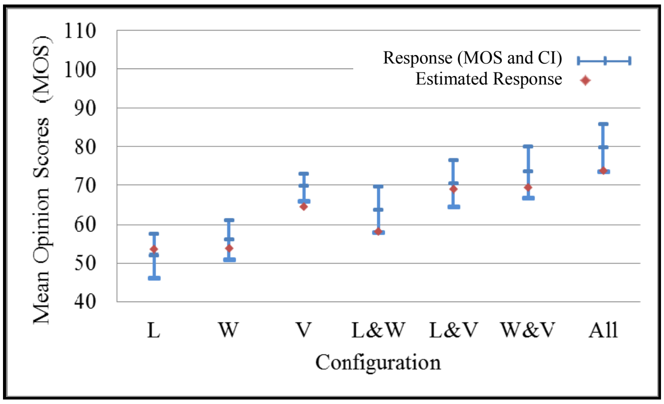

Fig. 7. The estimated response by the proposed model compared to the MOS for the sport sequence “Berrecloth”.

In order to show the improvement of the proposed model a comparison has been made a with the linear sensory experience model proposed in [11]. The performance comparison is in term of MSE as given in Fig. 8. The MSE is between the response estimated by the model and the MOS obtained by the subjective quality test, it shows how much the estimated response differs on average from the MOS values.

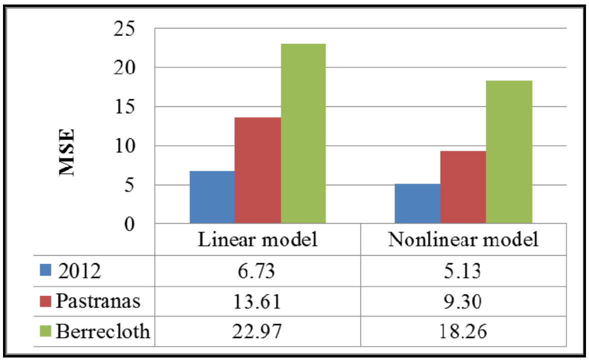

Fig. 8. Comparison between the linear and nonlinear model in term of MSE.

According to the results shown in Fig. 8, it can be concluded that the proposed model give improved results compared to the linear model for all the three test sequences. The proposed nonlinear model allows obtaining an improvement of 11.27% with respect to the linear model presented in [11].

Furthermore, the models prediction accuracies are compared by using the value of the square of multiple correlation coefficients (R^2), where R^2 is the correlation between the actual values and the predicted values. As shown in Table 2, the achieved value of R^2 for the proposed model is higher than the value of the linear model presented in [11]. Therefore, evaluation using the proposed model is more accurate and enhances the estimation accuracy.

TABLE II. COMPARISON BETWEEN THE LINEAR AND NONLINEAR MODEL IN TERM OF R^2

Model	Linear model [11]	Nonlinear model
R^2	0.782	0.836

IV. CONCLUSIONS

In this paper, a nonlinear model for high dynamic spatio-temporal mulsemedia quality of experience evaluation has been presented. The model has been validated using subjective test data based on mean opinion score and nonlinear regression. Due to the nonlinearity of the problem, as to the model parameters estimation, a meta-heuristic approach, based on particle swarm optimization algorithm, has been implemented. In order to show the effectiveness of the proposed nonlinear model a comparison has been made with a linear multi sensorial quality of experience model presented in literature, in case of high dynamic spatio-temporal mulsemedia. Results show that the estimations provided by the proposed model offer a basic step towards an objective quality measurement for sensory effects, which will reduce the necessity for subjective quality assessments in this domain.

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