Robust Optimization in Non-Linear Regression for Speech and Video Quality Prediction in Mobile Multimedia Networks

Charalampos N. Pitas, Apostolos G. Fertis, Athanasios D. Panagopoulos, and Philip Constantinou

Abstract Quality of service (QoS) and quality of experience (QoE) of contemporary mobile communication networks are crucial, complex and correlated. QoS describes network performance while QoE depicts perceptual quality at the user side. A set of key performance indicators (KPIs) describes in details QoS and QoE. Our research is focused specially on mobile speech and video telephony services that are widely provided by commercial UMTS mobile networks. A key point of cellular network planning and optimization is building voice and video quality prediction models. Prediction models have been developed using measurements data collected from live-world UMTS multimedia networks via drive-test measurement campaign. In this paper, we predict quality of mobile services using regression estimates inspired by the paradigm of robust optimization. The robust estimates suggest a weaker dependence than the one suggested by linear regression estimates between the QoS and QoE parameters and connect the strength of the dependence with the accuracy of the data used to compute the estimates.

1 Introduction

Contemporary mobile networks have been based on WCDMA (Wideband Code Division Multiple Access) radio access technology. UMTS (Universal Mobile Telecom-

C. N. Pitas · A. D. Panagopoulos · P. Constantinou
Mobile Radiocommunications Laboratory, School of Electrical and Computer Engineering, National Technical University of Athens.
9, Iroon Polytechniou Str., Zografou, GR 15773, Athens, Greece.
e-mail: {chpitas, thpanag, fkonst}@mobile.ntua.gr

A. G. Fertis
Institute for Operations Research, Department of Mathematics (D-MATH), Eidgenössische Technische Hochschule Zürich, (ETH Zürich).
Rämistrasse 101, HG G 21.3, 8092, Zürich, Switzerland.
e-mail: afertis@ifor.math.ethz.ch

munication System) networks have been widely deployed to deliver circuit switched (CS) speech and video telephony services [8]. Both network monitoring systems as well as extended drive-test measurement campaigns are useful tools in radio network planning, performance evaluation and optimization [6,7,14]. While radio coverage prediction models have been developed and widely used in network planning processes, quality prediction is assumed of the recent research areas. Advanced statistical analysis, usually linear and non-linear regression modeling, has been used in order to build prediction models [11] in a simulation environment of a mobile network. The quality of the predictions is affected by the ability of the considered models to represent reality as well as the accuracy of the data used to estimate their parameters.

Robust optimization has been increasingly used in mathematical optimization as an effective way to immunize solutions against data uncertainty. If the true value of a problem's data is not equal to its nominal value, the optimal solution computed using the nominal value might not be optimal or even feasible for the true value. Robust optimization considers uncertainty sets for the data of a problem and defines solutions that are immune to such uncertainty. In linear optimization problems, box-type uncertainty sets [10], and ellipsoidal uncertainty sets have been considered. In linear, as well as mixed integer optimization problems, robust counterparts with budgeted uncertainty sets that connect the uncertainties developed by the coefficients of the constraints have been efficiently solved [2,3]. The robust optimization paradigm has been successfully applied to regression and classification problems to deal with uncertainty in the statistical data and has been connected with regularized regression models [1,15].

In this paper, we apply robust optimization in order to refine the accuracy of quality prediction models. More specifically:

1. We use measurements data that acquired by a drive-test campaign of a live 3G network in Switzerland. Test mobile speech and video calls were performed by experimental equipment.
2. We focus on speech, video as well as on audio-visual quality prediction modelling based on live-network measurements.
3. We compute the linear and non-linear regression estimates that connect QoE with QoS, as well as the linear regression estimates that follow the robust optimization paradigm. The estimates depend on the size of the uncertainty set that is considered.

The robust estimates suggest a weaker dependence than the one suggested by linear regression between QoE and QoS. Our approach enables the choice of the strength of the dependence based on the accuracy of the data used to compute the estimates. The remaining of the paper is organized as follows: Section 2 is devoted to UMTS network architecture, radio KPIs as well as to QoE aspects regarding speech and video transmission. Followingly, we present regression analysis and robust optimization for speech and video quality prediction in Section 3. Finally, a general discussion of our contribution on QoE estimation is placed in Section 4.

2 Quality in Mobile Multimedia Networks

2.1 *QoS in UMTS networks*

A UMTS network consists of a radio access network (RAN) and a core network (CN). RAN basically consists of RNCs (Radio Network Controllers) and NodeBs (base stations) that are connected with UEs (User Equipments). The CN can be interconnected to various backbone networks like IP-networks (Internet) public fixed telephone networks (ISDN/PSTN). The report in [5] presents details for a UMTS coverage measurements methodology in order to characterize the quality of radio network coverage, specifically:

RSCP (Received Signal Code Power) is the received power on one code measured, in *dBm*, on the pilot bits of the P-CPICH (Primary Common Pilot Channel).

RSSI (Received Signal Strength Indicator) is the wideband received power, in *dBm*, within the relevant channel bandwidth.

E_c/N_0 is the ratio, in *dB*, of received pilot energy, E_c, to the total received energy or the total power spectral density, I_0.The received energy per chip, E_c,divided by the power density in the band. The E_c/N_0 is identical to $RSCP/RSSI$. We note that E_c/N_0 is the most crucial radio quality parameter.

2.2 *QoE of Mobile Multimedia Services*

Commercial UMTS networks provide both mobile speech and video telephony services. Specifically, a 64 kbit/s (speech is coded at 12.2 kbit/s and video at 50 kbit/s respectively) transport channel is dedicated for video communication. On the one hand, an objective method for end-to-end (E2E) narrow-band speech telephony quality is PESQ described in ITU-T P.862. Besides, a mapping function for transforming PESQ raw result scores to MOS (Mean Opinion Score) scale is presented in ITU-T P.862.1. On the other hand, video quality algorithms shall be eligible and applicable for end-to-end mobile applications and predict the perceived quality by the user-viewer according to the ETSI TR 102 493. J.247 is recommended by ITU-T for objective perceptual video assessment in the presence of a full reference. Audio-visual quality can be computed by speech, MOS_{SQ}, and video, MOS_{VQ}, quality parameters according to the formula of the ITU-T P.911: $MOS_{AVQ} = \lambda + \mu \cdot MOS_{SQ} \cdot MOS_{VQ}$, where $\lambda = 0.765$ and $\mu = 0.1925$.

2.2.1 QoE Evaluation

The assessment of a QoE indicator, either MOS_{SQ} or MOS_{VQ}, is made by comparing the original speech/video samples transmitted by the calling party, A-side, $S(\tau) =$

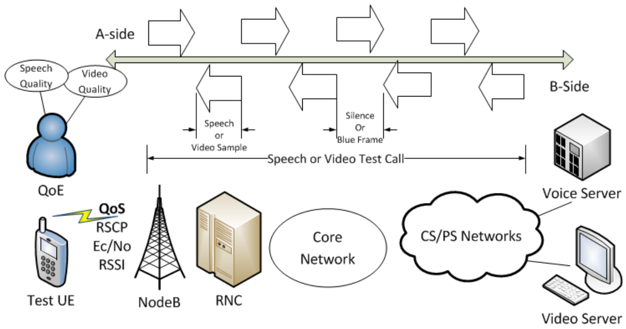

Fig. 1 UMTS architecture and Measurement Campaign configuration.

$\{s_1(\tau_1),\ s_2(\tau_2),\ \ldots,\ s_n(\tau_N)\}$, with the corresponding degraded received samples, $\tilde{S}(\tau) = \{\tilde{s}_1(\tau_1),\ \tilde{s}_2(\tau_2),\ \ldots,\ \tilde{s}_N(\tau_N)\}$, at the called party, B-side, by applying the objective assessment algorithm, φ. The objective QoE indicator, $MOS_{i\to j}$, varies between 1 (bad/very annoying) and 5 (excellent/imperceptible) and $(i,j) \in \{(A,B), (B,A)\}$:

$$MOS_{i\to j} = \frac{1}{N}\sum_{\nu=1}^{N} \varphi(s_{\nu,i}(\tau_\nu), \tilde{s}_{\nu,j}(\tau_\nu)) \tag{1}$$

Fig.1 presents a measurement campaign configuration for E2E QoE assessment with a "*Diversity Benchmarker*" [12]. Besides, we conducted post-processing analysis with *NetQual NQDI* on a measurements database managed by *MS SQL Server* and we used MATLAB for regression and optimization modelling.

3 Robust Optimization in Regression Analysis

In order to predict QoE from QoS, a non-linear regression method can be performed for speech and video quality estimation from E_c/N_0, $QoE = \exp(\alpha \cdot E_c/N_0 + \beta)$. A log-linear model can be derived, $ln(QoE) = \alpha \cdot E_c/N_0 + \beta$. The estimates for α and β can be computed through non-linear regression or linear regression and are almost the same. The estimates of linear regression are the optimal solution to

$$\min_{\alpha,\beta} \sqrt{\sum_{i=1}^{n} (ln(QoE_i) - \alpha \cdot (E_c/N_0)_i - \beta)^2}, \tag{2}$$

where QoE_i, $(E_c/N_0)_i$ denotes the i-th samples of QoE, E_c/N_0 respectively.

The accuracy of the data used to compute them is limited. To deal with this problem, we propose to follow a robust optimization approach. We assume that that data $(E_c/N_0)_i$ incorporate errors and that their true value resides in a ρ-sized interval centered at $(E_c/N_0)_i$, $\rho \geq 0$. The robust estimates are the optimal solution to the min-max problem

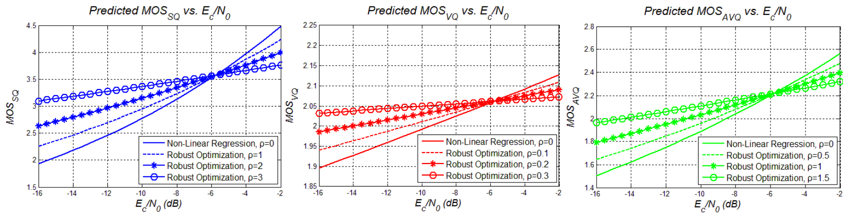

Fig. 2 Robust optimization in non-linear regression for QoE prediction models.

$$\min_{\alpha,\beta} \max_{\forall i:\ |x_i-(E_c/N_0)_i|\leq\rho} \sqrt{\sum_{i=1}^{n}(ln(QoE_i)-\alpha x_i-\beta)^2}. \tag{3}$$

The constraint $\forall i: |x_i-(E_c/N_0)_i| \leq \rho$ is equivalent to $\|\boldsymbol{x}-(\boldsymbol{E_c/N_0})\|_\infty \leq \rho$, where $\|\cdot\|_\infty$ is the infinity norm and $\boldsymbol{x}$, $(\boldsymbol{E_c/N_0})$ are the vectors which contain the x_i, $(E_c/N_0)_i$ respectively. Problem (3) is equivalent [15] to

$$\min_{\alpha,\beta} \sqrt{\sum_{i=1}^{n}(ln(QoE_i)-\alpha(E_c/N_0)_i-\beta)^2}+\rho|\alpha|, \tag{4}$$

which defines an l_1-regularized regression estimator [13]. Using our data and SeDuMi [9], we computed the robust estimates for α and β for various values of the size ρ of the uncertainty set. The results can be seen in Fig. 2.

We observe that as the size of uncertainty ρ increases, α drops, namely the robust estimates suggests a weaker dependence between QoE and E_c/N_0. This weaker dependence is compensated by a smaller fixed term β, as seen in Fig. 3. Thus, in the presence of errors, one should be more conservative in the prediction of QoE for a given E_c/N_0. The rate of change for QoE with respect to E_c/N_0 estimated by linear or non-linear regression is too optimistic in the presence of errors. The regularized estimator of Eq. (4) takes this phenomenon into consideration by adding the trade-off term $\rho\ |\alpha|$. Our method connects the impact ρ of this trade-off with the size of the uncertainty sets for the data $(E_c/N_0)_i$. In this way, we can use the information

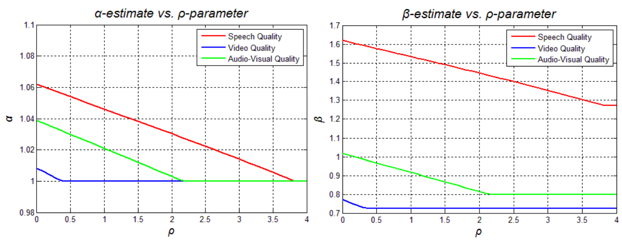

Fig. 3 Robust estimates of α and β parameters for various values of the size ρ of the uncertainty set.

on the accuracy of the data to assess the strength of the dependence between QoE and E_c/N_0.

4 Conclusions

The use of robust optimization to deal with uncertain data in regression-based speech, video, and audio-visual quality prediction was addressed in our paper. Indeed, our method suggested a weaker dependence between QoS and QoE parameters than the one suggested by linear regression estimates. In particular, it explicitly connected the strength of this dependence with the accuracy of the measurements data used to compute the estimates. The used QoE empirical models for mobile video telephony have been extracted from live 3G multimedia network measurements. Our models can be applied in quality-centric network planning and optimization processes to tackle the effect of errors in a measurement campaign.

Acknowledgements We would like to thank Mr. Arthur Tollenaar from SwissQual AG, Switzerland, for providing to us measurements files regarding mobile video-telephony.

References

1. Ben-Tal, A., El Ghaoui, L., Nemirovski, A.: Robust Optimization. Princeton University Press (2009).
2. Bertsimas, D., Sim, M.: Robust Discrete Optimization and Network Flows, Mathematical Programming **98**(1-3), 49-71 (2003).
3. Bertsimas, D., Sim, M.: The price of robustness. Operations Research **52**(1), 35-53 (2004).
4. Boyd, S., Vandenberghe, L.: Convex Optimization. Cambridge University Press (2004).
5. ECC Report 103: UMTS Coverage Measurements. Electronic Comm. Committee (ECC), European Conf. of Postal and Telecomm. Administrations (CEPT), Nice (2007).
6. Malkowski, M., Claßen, D.: Performance of Video Telephony Services in UMTS using Live Measurements and Network Emulation. Wireless Personal Communications, Springer, **46**(1), 19-32 (2008).
7. Goudarzi, M., Sun, L., Ifeachor, E.: PESQ and 3SQM measurement of voice quality over live 3G networks. 8^{th} Int'l Conf. on Measurement of Speech, Audio and Video Quality in Networks (MESAQIN), Prague (2009).
8. Holma, H., Toskala, A.: WCDMA for UMTS - HSPA Evolution and LTE. 4^{th} Ed., John Wiley & Sons Ltd. (2007).
9. SeDuMi 1.3: A Matlab toolbox for optimization over symmetric cones. Available [On Line] http://sedumi.ie.lehigh.edu/
10. Soyster, A. L.: Convex Programming with Set-Inclusive Constraints and Applications to Inexact Linear Programming. Operations Research, **21**(5), 1154-1157 (1973).
11. Sun, L., Ifeachor, E.: Voice Quality Prediction Models and their Applications in VoIP Networks. IEEE Transactions on Multimedia **8**(4), 809-820 (2006).
12. SwissQual AG: Diversity Benchmarker. [On Line]: http://www.swissqual.com/
13. Tibshirani, R.: Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society, Series B (Methodological) **57**(1), 267-288 (1995).
14. Vlachodimitropoulos, K., Katsaros, E.: Monitoring the end user perceived speech quality using the derivative mean opinion score (MOS) key performance indicator. 18^{th} Annual IEEE Int'l Symp. on Personal, Indoor and Mobile Radio Comm. (PIMRC'07), Athens (2007).
15. Xu, H., Caramanis, C., Mannor, S.: Robust Regression and Lasso. IEEE Transactions on Information Theory **56**(7), 3561-3574 (2010).