Predicting the Quality Level of a VoIP Communication through Intelligent Learning Techniques

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***Abstract*—This paper presents a method for determining the quality of a VoIP communication using intelligent learning techniques. The proposed solution uses historical values of network parameters and communication quality in order to train the intelligent learning algorithms. After that, these algorithms are able to find the quality of the VoIP communication based on network parameters of an specific period of time. The intelligent learning algorithms take as input a baseline file that contains some values of network parameters and voice coding, associating an index quality for each scenario according to the ITU-T Recommendation G.107. The tests were performed in an emulated network environment, totally isolated and controlled with real traffic of voice and realistic IP network parameters. The quality ratings obtained for the learning algorithms in all scenarios were corroborated with the results of the algorithm of ITU-T Recommendation P.862. The results show the reliability of the three learning algorithms used on the tests: Decision Trees (J.48), Neural Networks (Multilayer Perceptron) and Bayesian Networks (Naives). The highest value of reliability in determining the quality of the VoIP communications was 0.98 with the use of Decision Trees Algorithm. These results demonstrate the validity of the method proposed.**

***Keywords*-QoS; VoIP; Machine Learning; Decision Tree; E-Model; PESQ.**

I. INTRODUCTION

The quality of a VoIP (Voice over IP) communication does not have the quality levels of the conventional circuit-switched telephony, thus, users who do not have an acceptable user experience with VoIP calls continues using the traditional telephony. For this reason, the study of methods for evaluating quality of VoIP communication is very important because it allows that network resources can be reallocated to improve the communication quality.

Initially, determining the quality of a VoIP communication was done by subjective tests, resulting in a quality score called MOS (Mean Opinion Score), the ITU-T Recommendation P.800 [1] describes the requirements and methodology followed in these tests. After, some objective methods was performed: such as ITU-T Recommendation P.862 [2] or PESQ (Perceptual Evaluation of Speech Quality), which determines an index named MOS-LQO MOS-Listening Quality Objective which is the result of the comparison of the original voice or reference signal and the degraded speech signal. Also, nonintrusive methods were developed, such as the ITU-T P.563 [3], where the algorithms do not need a voice signal reference.

Other metrics of voice quality [4] - [6] do not consider the voice signal, for determining the quality index are employed models based on network parameters such as the E-Model [23], used in network planning and to configure the rate of communication VoIP MOS.

Machine Learning algorithms have been used to determine the quality of multimedia services, thus trying to ensure a better quality of service [7], [8]. For the case evaluation of voice quality in VoIP service, the works [9] - [12] show how neural networks are used for monitoring this service, but are not studied other learning techniques and do not detail how the training file used was built. The E-Model is not sufficient to predict the Quality Level, because sometimes a parameter is missing and it is not possible to measure the QoS with the E-Model, but with the machine learning if one parameter is missing it is possible to measure the QoS. This paper uses as a training file wich has been built based on ITU-T Recommendation G.107, more knowledge as E-Model, considering some network scenarios that have been extracted from real traffic and the results was achieved high levels of reliability.

Algorithms used in this study come from different approaches in sub-area of artificial intelligence, devoted to the study of learning by machines to predict the quality level of a service, these algorithms are: Decision Tree (J48 - C4.5 algorithm), Bayesian networks (Naive Bayes) and Neural Networks (Multilayer Perceptron) to determine the quality of a VoIP communication in a sample interval of 8 seconds; so, the reliability of the specified algorithms on this application was measured. Network training was performed using a file of 650 cases, which were prepared by the E-Model algorithm, each line of the file contains the network parameters: transmission rate, delay and probability of packet loss, and the value of quality (MOS), which is the result of the E-Model algorithm.

This work considers the encoding rates of 64 kbps for ITU-T G.711 [13] codec and rate of 8 kbps for ITU-T G.729 [14], respectively, and also consider the intrinsic values that these encoders have in the scenario with packet loss.

The tests were performed in a scenario of IP network emulation, where it is established a VoIP communication and is programmed different network parameters, in order to study the quality degradation of voice communication for each scenario tested. For purposes of network emulation, the

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software named NETEM (Network Emulator) [20] was used, where the parameters of packet loss probability and delays point in an IP network can be changed. This article is divided as follows:

Section 2, where it is made a theoretical revision of machine learning algorithms used in this work; Section 3 deals with the E-Model algorithm; Section 4 presents briefly the PESQ algorithm, Section 5 presents the test scenario, the methodology followed on the tests and the parameters evaluated; Section 6 shows the results and discussions, and finally, Section 7 presents the conclusion and future work.

II. ALGORITHMS USED IN THE DETERMINATION OF COMUNICATION QUALITY

This section is presenting the different algorithms used in training of the network to determine the quality of VoIP communications.

A. Decision Tree Classification

Decision Trees [24] are tools that can be used for giving to the agent the ability for both learning and making decisions.

The decision tree takes as input a situation described by a set of attributes and returns a decision, which is predicted by the value of the input attribute. The input can be both discrete or continuous values. In this paper, only discrete values are used. The learning of discrete values is called classification.

B. Bayesian Classification

The Bayesian classification [25] algorithm has its name because it is based on probability of Bayes' Theorem. It is also known as Naïve Bayes classifier or only Bayes algorithm. The algorithm aims to calculate the probability that an unknown sample belongs to each of the known classes. This type of prediction is called the statistical classification; it is completely based on probabilities.

A feature of this algorithm is that it requires a data set that is already classified previously. Based on this preliminary data set, which is also called the training set, the algorithm takes as input a new unknown, i.e., this has no classification, and returns as output the most likely class for this sample according to probabilistic calculations.

C. Multilayer Perceptron

Rosenblatt [26] introduced the perceptron as the simpler architecture of neural network capable of classifying linearly separable patterns. The operation of a perceptron (artificial neuron) shows that:

- The neuron is responsible for calculating the combination of inputs and weights, and then applies an activation function that determines the effective output of the neuron.
- The training is done through the presentation of known inputs and outputs (supervised learning) and adjusting the weights with specific algorithms.

Multilayer Perceptron Networks (MLP) are computationally more powerful than networks without hidden layers. The MLP can handle data that are not linearly separable.

The processing performed by each neuron is defined by the combination of the processing performed by the previous layer of neurons that are connected to it. From the first hidden layer to output layer, implemented functions become increasingly complex. These functions define how the division is made of space-making.

There are several algorithms to train the MLP networks. Among these, the most popular learning algorithm for training these networks is the back propagation [27]. This is a supervised algorithm that uses the desired output for each input provided to adjust the parameters, called weights of the network. In addition, the adjustment weights use the method of backpropagation gradient to define the corrections to be applied.

III. ITU-T G.107 RECOMENDATION

This recommendation, better known as E-Model [23], is a computer model that measures the effects of the parameters of a transmission signal and the transmitted voice quality. The E-Model is defined by the following equation:

$$R = R_o - I_s - I_d - I_e + A \tag{1}$$

where:

- R: determination factor of the transmission rate that has a correspondence with the MOS score ITU-T P.800.
- R_o: ratio - signal to noise.
- I_s: simultaneous degradation factor, which represents all the degradations that occur simultaneously with the speech signal.
- I_d: quality degradation due to the delay.
- I_e: degradation of the quality by effect of the device (encoder).
- A: improvement factor.

The default value of R_o is 93.2, which is obtained by putting all the inputs of the model with their default values, for example, the parameter of quality degradation due to delay (I_d), and the parameter corresponding to the degradation of equipment, i.e., for this calculation.

The parameter is not considered in the calculations of this work, since it describes conditions that are related to the signal, not depending on the transport network.

The factor A has the value 0 [15] for cable networks and is the scenario that matches the emulation of this work.

The delay factor I_d is defined by composition:

$$I_d = I_{dle} + I_{dte} + I_{dd} \tag{2}$$

The parameters I_{dte} and I_{dle} correspond to delays due to echo, both the sender and receiver. These factors are not considered for the test scenario to assume perfect echo suppression.

The I_{dd} represents the delay (T_a) produced in the encoder and the network, including an echo cancellation. The network delay is set according to the type of test on the network emulator.

The I_{dd} is defined as:

For $T_a \leq 100ms$: $I_{dd} = I_d = 0$

For $T_a > 100ms$:

$$I_{dd} = I_d = 0.024d + 0.11(d - 177,3)P(d - 177,3) \quad (3)$$

with: $P(k)$ = 0, if $k < 0$, $P(k)$ = 1, if $k \geq 0$

With these considerations, one can calculate the parameter R as a function of the parameters that correspond to the value of R_o, the delay (I_d) and the factor corresponding to the encoder (I_e).

$$R = R_o - I_d - I_e \quad (4)$$

The R factor is related to the MOS index, according to the following equation:

$$R = 3,026 \times M^3 - 25,314 \times M^2 + 87,06 \times M - 57,336 \quad (5)$$

IV. RECOMENDAÇÃO ITU-T P.862

The ITU-T Recommendation P.862 [16], known as PESQ (Perceptual Evaluation of Speech Quality) is an objective evaluation method that compares an original signal with a degraded signal, resulting from the passage of the signal through a communication system. The output is a PESQ predicting the perception of quality that would be felt by an individual in a subjective listening test. This prediction is related to a score, called an index MOS (Mean Opinion Score), and the methodology PESQ, this estimate is called LQO-MOS (MOS-Listening Quality Objective) and scores ranging from 1 (poor) to 4.5 (excellent).

PESQ only measures the effects of one-way speech distortion and noise on speech quality. The effects of delay, sidetone, echo, and other impairments related to two-way interaction are not reflected in the PESQ scores.

According to this recommendation, PESQ had demonstrated acceptable accuracy on the following scenarios:

- Speech input levels to a codec.
- Transmission channel errors.
- Packet loss and packet loss concealment with CELP codecs.
- Transcodings.
- Effect of varying delay in listening only tests.
- Short-term and long-term time warping of audio signal.
- Coding Technologies: Waveform codecs, e.g. G.711; G.726; G.727; CELP and hybrid codecs .4 kbit/s, e.g. G.728, G.729, G.723.1; Other codecs: GSM-FR, GSMHR, GSM-EFR, GSM-AMR, CDMA-EVRC, TD-MAACELP, TDMA-VSELP.

In the test scenario was used the codecs G.711 and G.729, and the network suffer degradation due packet loss and delay, the audio input was isolated to avoid voice impairments. Only delay is not included on tested scenarios of recommendation P.862. To be possible include this factor on test scenarios were delay is present, it was converted the MOS index to R index value using equation (5); this way, we obtained the quality index in these type of scenarios.

V. SCENARIO AND TEST METHODOLOGY

The tests were conducted in emulation of IP network shown in Figure 1, which consists of three computers, two of them (PC-A and PC-C) establish VoIP communication point to point, and the third (PC-B) emulates the transmission channel, which are programmed different degradations of network such as: packet loss and delay. The audio inputs used belong to the set of validation tests that are included in ITU-T P.862, the algorithm of this same recommendation (PESQ) is used to assess the level of quality of voice signal in reception. The second quality index is determined by machine learning algorithm, these algorithms are: decision trees, neural networks and Bayesian networks.

The first step is to build the algorithm used in machine learning or training file, which has built considering 650 scenarios where QoS has been obtained using the E-model algorithm. Each test scenario is represented in the training file as a line, that will be presented later in more detail.

In the emulator network are programmed different scenarios, with different parameter values of probability of packet loss and delay inserted in the training file in order to better validate the reliability of results.

The sample period for assessing the quality of VoIP communications is 8 seconds, this time was chosen, in addition to the original size of the audio file, due to the number of packets sent by the transmitter (PC-A) during this time period thus considering an encoding rate of 64 kbps are sent 400 packets of 160 bytes, for a shorter time the number of packets sent is smaller and therefore the percentage of packet loss has a lower resolution.

The software and tools, in each PC, used to build the test scenario are the following:

- PC-A, PC-C: clients using softphone MyPhone 0.2b10 [17], packet analyser Wireshark [18] and software to record audio file of extension .wav - VRS Recording System [19].
- PC-B: router using the network emulator NETEM [20], to simulate packet loss, delay, jitter and bandwidth; the software ITU-T P.862 was used to find the MOS index for the voice quality.

The sound transmitted was generated by a player of file .wav that is connected to the microphone input of PC1 by an audio cable, and as mentioned previously, this file has a duration of 8 seconds and was sampled at 8 kHz and 16 bits.

The methodology followed in the tests to get the value using the tool PESQ MOS is as follows:

- Initially, it starts a communication between the PC-A and PC-C by softphones installed in the PCs, and lets you choose the voice coder used to each VoIP call, where it is made of computer to computer.

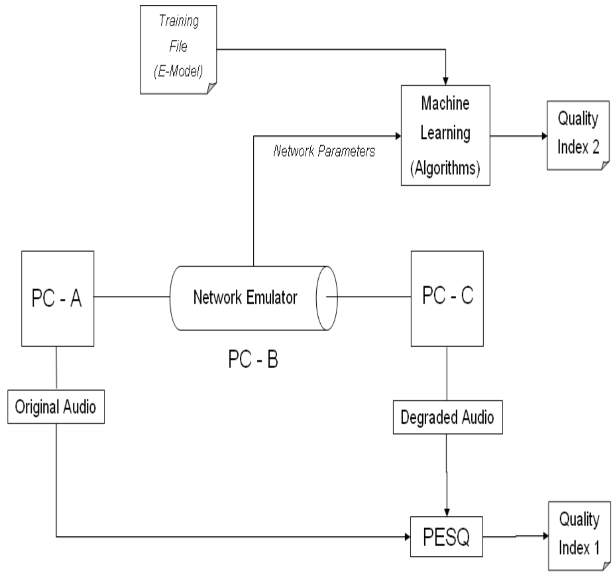

Fig. 1. Test scenario.

- For each scenario the network emulator is configured with parameters required to perform the test.
- The player transmits the audio (arq-orig.wav) to PC-A where this sound is recorded (arq-orig2.wav), as the call is active, and the voice is transmitted to the PC-C through the PC-B.
- While data are transmitted, the program Wireshark that is running on the PC-A and PC-C, it is saved the network information such as: the signaling messages for establishing, maintaining and finalizing calls, messages from the RTP, the average size of the package (bytes), average number of packets transferred per second and average bandwidth.
- In the PC-C, the received audio is recorded in a file (arq-deg.wav). This file and the original file are compared by PESQ software, which runs on PC-B, resulting in a MOS-LQO score.

A. Implementation of the input file for training algorithms

As mentioned before, the preparation of an initial database of network parameters and the quality score for each scenario was performed considering the ITU-T Recommendation G.107. This mathematical model provides an R value of quality ranging from 0 to 93.2, where the highest value corresponds to a higher quality. The different scenarios were constructed leaving the default parameters fixed and varying the following parameters:

- The Mean One-Way Delay.
- The Packet-loss Probability.
- The type of encoder is related to the parameters: encoding rate, I_e (Equipment Impairment Factor) and Bpl (Packet-loss Robustness Factor).

The values of I_e and Bpl are dependent on the vocoder used, Table I represents values for the encoders have been tested by the ITU-T G.107 and presented the recommendation. In the test scenario were employed coders G.711 and G.729.

TABLE I
VALUES OF I_e AND Bpl FOR VOICE CODERS

Codec	I_e	Bpl
G.723.1+VAD	15	16.12
G.729A+VAD	11	19
GSM-EFR	5	10.03
G.711	0	4.3
G.711+PLC	0	25.14

To obtain the value of quality index R were used the parameters described in Table II.

TABLE II
PARAMETERS OF THE E-MODEL ALGORITHM

Parameter	Default Value	Units
Noise Referred to at 0 dBr point - Nc	-70	dBm
Noise Floor - Nfor	-64	dBm
Room Noise (Send) - Ps	35	dB
Room Noise (Receive) - Pr	35	dB
Send Loudness Rating - SLR	8	dB
Receive Loudness Rating- RLR	2	dB
D-factor (Receive) - Dr	3	-
Listener's Sidetone Rating - LSTR	21	dB
D-factor (Send)	3	-
Mean One-Way Delay - T	100	ms
Absolute Delay from (S) to (R) - Ta	100	ms
Round-Trip Delay - Tr	200	ms
Talker Echo Loudness Rating - TELR	65	dB
Weighted Echo Path Loss - WEPL	110	dB
Quantizing Distortion Units - QDU	1	-
Equipment Impairment Factor - Ie	0	-
Packet-loss Robustness Factor - Bpl	1	-
Packet-loss Probability - Ppl	1	%
Expectation Factor - A	0	-

As a result it was obtained a file with 650 lines, for a better understanding Table III presents the 10 first cases or network scenarios:

In order to group ranges of R values and define categories of QoS, we took as reference model the classification drawn from ITU-T Recommendation G.107, which is presented in Figure 2, where it is presented the limit values for both R and MOS index.

The quality levels of classification used in this work only consider five categories, where the last two categories, Nearly All Users Dissatisfied and Not Recommended at Figure 2 were grouped into one.

These five categories are presented in Table IV:

With this categorization it is obtained the file that will works as training file to the algorithms that determines the quality of the communication. The sample lines from this file is presented on Table V.

TABLE III
VALUES OF I_e AND Bpl FOR VOICE CODERS

Rate (kbps)	Delay (ms)	Bpl (%)	Ie	R (Value)
64	0	4.3	0	93.2
64	50	4.3	0	91.8
64	100	4.3	0	90.7
64	150	4.3	0	89.5
64	200	4.3	0	85.8
64	250	4.3	0	79.2
64	300	4.3	0	72.5
64	350	4.3	0	67
64	400	4.3	0	62.2
64	450	4.3	0	58.2

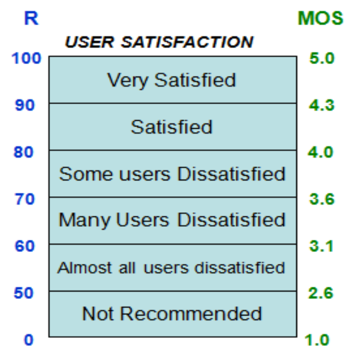

Fig. 2. Levels of User Satisfaction of a VoIP communication.

TABLE IV
QOS LEVELS USED IN THE TEST SCENARIO

Categories	R (Min. value)	R (Max. Value)
Very Satisfied (QoS_1)	90	94
Satisfied (QoS_2)	80	90
Some Users dissatisfied (QoS_3)	70	80
Many Users dissatisfied (QoS_4)	60	70
Nearly all Users Dissatisfied and Not Recommended (QoS_5)	0	60

TABLE V
CODEC AND NETWORK PARAMETERS AND QOS

Rate (kbps)	Delay (ms)	Bpl (%)	QoS
64	0	0	QoS_1
64	50	0	QoS_1
64	100	0	QoS_1
64	150	0	QoS_1
64	200	0	QoS_2
64	250	0	QoS_2
64	300	0	QoS_3
64	350	0	QoS_4
64	400	0	QoS_4
64	450	0	QoS_5

B. *Determination of QoS using the tool Weka*

In order to determine the QoS using the learning algorithms, the software Weka-version 3.7.4 [21] was used as a tool for data analysis method. This tool supports several algorithms, based on related works, it was decided use the following three algorithms :

- Desicion Tree J48 - algorithm C4.5;
- Bayesian networks - Naive Bayes;
- Neural Networks - Multilayer Perceptron.

With the training file, it was analyzed the cross-validation and obtained the values of the factor 'F' (F-measure) for each algorithm tested, as shown in Table VI.

TABLE VI
VALUES OF FACTOR F FOR EACH ALGORITHM

Algorithm	F-measure
Trees J.48	0.98
Multilayer Perceptron	0.92
Bayes (Naives)	0.78

The values reached for the F factor were very high, whereas values greater than 0.7 are enough for network training. As the decision tree algorithm it was obtained the best results, having the same results determining the QoS for all tests.

VI. EXPERIMENTAL RESULTS

In this work, 300 tests were conducted following the methodology explained, where in each test was considered a scenario configured with different parameters on network emulator. The higher the number of tests in learning techniques greater the validity of the results.

The results obtained are presented in Figure 3, where it can be seen the highest value of successes in determining the quality of service of VoIP communication for each learning algorithm used, where the Decision Trees algorithm reach 294 test results concordant with the results obtained by PESQ.

Also, the Multilayer Perceptron and Naives-Bayes algorithms reached high values, these were 282 and 243 hits respectively.

It is important to note that these results were obtained considering the range of MOS values of each QoS category and not a single value of index MOS.

VII. CONCLUSION AND FUTURE WORK

The test results obtained show that machine learning is a valid method to determine the quality of a VoIP communication in several network conditions and using different voice codecs, for this work the codecs: G.711 and G.729. The good performance of the learning algorithms definitely depend of the initial file used to training these algorithms, in this work was used parameters values from a real IP network, and the test was performed in network with realistic parameters. Also, it was tested the confidence of the E-Model algorithm to determine the values of quality index for each scenario included in the training file. The best result was obtained

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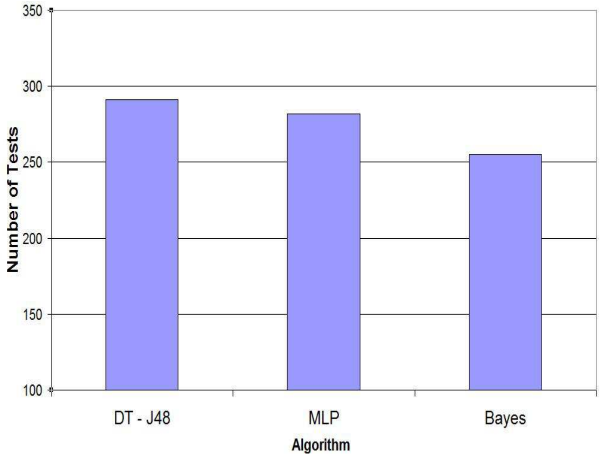

Fig. 3. Algorithms results

by the Decision Tree algorithm that reach 98% of accuracy, this is a very high degree of reliability to determine the quality category of VoIP communication in relation to other works. The Multilayer Perceptron algorithm had high number of success too, reaching 94% of accuracy. The Bayes Naives algorithm obtained a less number of success and reached 85%. The tests were performed in an emulated network and all the software used are free, for this reason the implementation of the same scenario for other works is possible. As future work, we intend to evaluate the quality of video services, for example, streaming video, creating a training file based on ITU-T Recommendation P.930 [22]. Also, it will be studied different techniques of network resource allocation based on predictions of quality services of a future period of time, being the goal of this idea improving the quality of an specific service.

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