Medical QoS Provision Based on Reinforcement Learning in Ultrasound Streaming over 3.5G Wireless Systems

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***Abstract*—The design of an efficient mobile healthcare system using 3.5G and 4G wireless networks is a challenging problem especially for bandwidth demanding telemedical applications.**

In this paper, we focus on the concept of medical Quality of Service (m-QoS) applied to a typical bandwidth demanding m-health application. Based on this concept, we propose a novel multiobjective rate-control mechanism for the optimized delivery of diagnostically acceptable ultrasound video images over 3.5G wireless networks.

The performance of the proposed algorithm has been evaluated via both simulations and experimental studies. The proposed optimal rate control algorithm achieved performance improvements that are compatible with the medical QoS requirements.

***Index Terms*—Q-learning; medical video streaming; wireless telemedicine; m-health; rate-control; medical QoS; robotic ultrasonography.**

I. Introduction

MOBILE healthcare (m-health) is a new paradigm that brings together the evolution of emerging wireless communications and network technologies with the concept of 'connected healthcare' anytime and anywhere [1] [2]. However, there are two critical issues affecting the successful deployment of m-health applications from the wireless communications perspective. First, wireless connectivity issues and mobility requirements of real-time bandwidth demanding m-health applications. The recent advances in 3.5G and 4G systems are addressing some of these challenges that require advanced and efficient telemedical multimedia content delivery. Second, the Quality of Service (QoS) issues from the healthcare perspective and their required levels to guarantee robust and clinically acceptable healthcare services. Hence, the need to introduce a new sub-category of the traditional QoS that is customized for such medical applications and critical wireless telemedical scenarios. In this paper we focus on the concept of medical Quality of Service (m-QoS) that can be defined as the *augmented requirements of critical mobile healthcare applications with respect to traditional wireless Quality of Service requirements*. Providing end-to-end QoS in real time medical video delivery in wireless networks is becoming an increasingly important requirement in mobile communications and wireless multimedia systems [3] [4]. Medical QoS issues are also addressed from a different perspective in [6] in this special issue.

In particular, supporting robust video communications over wireless networks is a significant problem, primarily because of two factors: low bandwidth and the time varying characteristics of the transmission channel. Therefore, adaptation schemes have to be applied in order to overcome these challenges.

The recent deployment and introduction of 3.5G systems (High Speed Downlink Packet Access (HSDPA)) [7] [8] represents an enhancement of W-CDMA networks with higher data transfer speeds, improved spectral efficiency and greater system capacity with a theoretical downlink data-rate peak of 14.4 Mbps (typically around 1.4 Mbps) and with uplink data-rate of 384 kbps. Although the downlink data rate in 3.5G networks provides improved connectivity conditions for robust m-health applications and scenarios, the uplink data rate still constitutes a major challenge for different wireless multimedia telemedical systems.

The main contribution of this paper is the proposition of a novel adaptive rate control algorithm for medical video streaming in bandwidth demanding m-health applications. Such rate-control algorithm - QoS Ultrasound Streaming Rate Control (Q-USR) - based on the concept of reinforcement learning leads to fulfilment of the m-QoS definition.

To validate the concepts introduced in this paper, we adopt an advanced wireless robotic tele-ultrasonography system [2] as an example of a bandwidth demanding m-health system with different m-QoS requirements. The advanced medical robotic system (mObile Tele-Echography using an ultra-Light rObot - OTELO) is a fully integrated end-to-end mobile tele-echography system for population groups that are not served locally, either temporarily or permanently, by medical ultrasound experts [9]. It comprises a fully portable tele-operated robot allowing a specialist sonographer to perform a real-time robotised tele-echography to remote patients. Fig. 1 shows the main operational blocks of the system over a 3.5G communication network. Further details of this system and related work are described in [10] and [9].

The paper is structured as follows. Section II presents the details of the m-QoS concept. Following the rate-control problem statement in Section III, Section IV introduces the new rate control method. Section V details the system im-

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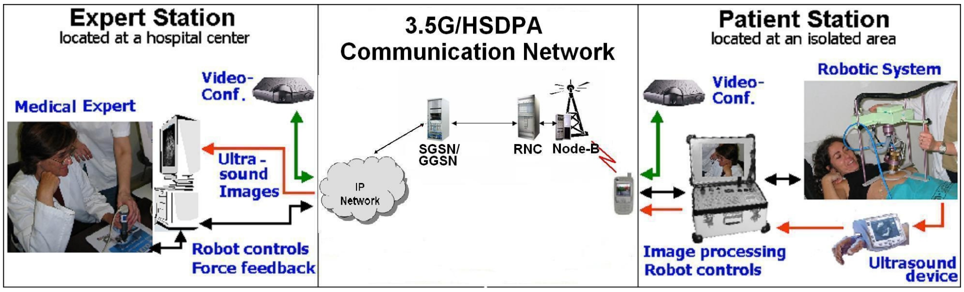

Fig. 1. The OTELO mobile robotic system over a 3.5G (HSDPA) communication network.

TABLE I
MEDICAL QOS (M-QOS) FOR A MOBILE ROBOTIC TELE-ULTRASONOGRAPHY SYSTEM (OTELO)

m-QoS metrics	*Functional Bounds*
Image quality (PSNR)	$> 36dB$ (QCIF - 144×176) $> 35dB$ (CIF - 288×352)
Image quality (SSIM [12])	> 0.9
Frame Rate	$> 5fps$ (QCIF - 144×176) $> 7fps$ ($CIF - 288 \times 352$)
End-to-End Delay	$< 350ms$

plementation and validation results. Finally, conclusions are drawn in section VI.

II. MEDICAL QUALITY OF SERVICE

The main quality of service metrics in video streaming environments are summarized in the following:

- Utilization;
- Packet Loss;
- End-to-End delay;
- Delay jitter.

These QoS metrics need to be guaranteed by the delivering network in order to provide satisfactory wireless multimedia services [11]. We assume that for medical QoS in the considered bandwidth demanding m-health application, extra bounds and functional metrics need to be added to the traditional QoS metrics outlined above. Table I shows an example of m-QoS metrics for teleultrasound streaming in the OTELO system. The functional bounds reported are specified by previous clinical evaluation studies of such a system [9], where abdominal ultrasound scan was considered. Bounds on the video quality are reported in terms of the classical peak signal-to-noise ratio (PSNR) metric and in terms of the structural similarity (SSIM) index, a quality assessment method focusing on the structural similarity between the original and the distorted image [12].

The relationship between the m-QoS metrics reported in Table I and the generic wireless QoS metrics is reported below.

1- Utilization: The main two data types that can be transmitted simultaneously by the OTELO Patient station (Fig. 1) are the ultrasound streaming data and the robotic control data. However, due to the low generated data rate by the robotic control data (5-6 kbps), we consider in this study the ultrasound streaming (US) data only. To achieve an optimum utilization within the available bandwidth, data need to be within the available bandwidth with good link utilization. This is implied in the image quality index and the frame rate metrics shown in Table I. In the Q-USR algorithm, we assume the link utilization factor as the constraint of the extent we can increase or reduce the image quality and the relevant frame rate to utilise the available bandwidth optimally.

2- Packet loss: Transmission impairments, such as packet loss, will impact differently on the medical expert's perception depending on where the loss occurs within the video clip. Measuring the average packet loss cannot predict the impact on an expert viewer's perception since the same packet loss rate can produce a wide range of different qualities [13]. Therefore, the effect of packet loss is implied in the image quality index metrics (PSNR and SSIM) shown in Table I.

3- End-to-End delay: This is an important issue that is explicitly identified in Table I. Streaming video requires bounded end-to-end delay so that packets arrive at the receiver in a timely fashion, in order to be decoded and displayed correctly. If a video packet does not arrive on time, the play out process will pause, which is annoying to human eyes. For this robotic m-health application the end-to-end delay is the round trip response to the hand movement of the expert that controls the robot and, in the mean time, is receiving continuous ultrasound stream in real time. The end-to-end delay for the OTELO system should be lower than 350 msec.

4- Delay jitter: This is represented by the arriving frame rate metrics in Table I. The recommended delay jitter for normal video streaming applications is within 2 sec. This is also acceptable for the current medical platform. The delay jitter effect has been mitigated by the decoder buffer as shown in the following.

III. RATE CONTROL FOR WIRELESS (US) VIDEO STREAMING

Rate control is an important issue in video streaming. Rate control attempts to optimally match the rate of the video application to the available network bandwidth. Two important factors are considered here: maximizing the utilization of the bottleneck and minimizing the congestion of a network. A class of rate control approaches is model based or TCP friendly (TFRC) approach based [14]. In TFRC the TCP friendly rate is determined as a function of packet loss rate, round-trip time (RTT), and packet size, to mimic the long-term steady performance of TCP algorithm [15]. For the estimation of the RTT, in general there is a large variation in end-to-end delay in wireless Internet [16]. Sending only a single acknowledgment to measure the RTT during a predefined period of time may be inaccurate and variable. Furthermore, in wireless networks the end-to-end packet loss can be caused by either congestion loss due to buffer overflow or the bit errors occurred in the wireless link. Efforts to improve the performance of TFRC in wireless environments include [17] [18] [19] [20] [21]. Since the TCP-friendly rate calculation depends on the value of packet loss reported by the receiver, these approaches either hide end hosts from packet loss caused by wireless channel error, or provide end hosts with the ability to distinguish between packet loss caused by congestion and that caused by wireless channel errors. Therefore there is a need for some sort of end-to-end packet loss differentiation and estimation. Some examples can be found in [20] and [22]. In such rate control approaches (probe and model based rate control) measuring the packet loss requires this extra stage of packet loss differentiation.

The work we present in this paper uses the probe-based approach based on probing the wireless network to measure the available bandwidth instead of measuring the packet loss.

We propose a novel technique to estimate the available bandwidth based on the linear prediction approach (LPC) [23]. Linear Prediction is a mathematical operation in which future values of a discrete-time signal are estimated as linear functions of current and previous samples. The current available bandwidth is estimated from previous bandwidth readings.

In particular, the focus of this work is on rate control at the application layer for quality maximisation. From previous research, rate control algorithms for media transmission optimisation are mainly based on either Lagrangian optimization or dynamic programming (DP) [24] [25]. Although the Lagrangian multiplier based optimal rate control methods are less complex than rate control methods based on DP [24], the Lagrangian multiplier methods may suffer from two main problems, such as having negative bits and real numbers [26]. In the rate control algorithm proposed in [24], the optimization methods used to solve the rate control problem are based on dynamic programming and Lagrangian multipliers. This work assumes a two-state channel model and it shows the effect of feedback delay and of the mismatch between the underlying channel behaviour and the assumed channel model at the encoder. The approach proposed in [25] uses the dynamic programming method. It is based on the rate-distortion optimized application-level retransmission scheme presented in [27]. The downlink scenario is considered, where the available bandwidth is not a major issue as compared to the more problematic wireless uplink bandwidth scenario that is addressed in our work. The work in [4], [5], and [28] is based on a network-aware joint source channel coding and decoding (JSCC/D) approach, based on two controller units at the physical and the application layers. The two controllers work together to provide control for both the source encoder and the physical layer parameters to satisfy user requirements. A cross-layer rate control strategy is adopted.

In this paper we focus on the application layer: we assume that the physical layer is addressed by the wireless standard (HSDPA) and we cannot modify physical layer parameters.

We propose a new application layer rate control algorithm that adjusts the sending rate of the source encoder according to partial knowledge about the mobile link throughput and leave the error control issues to the lower layers.

New directions in the design of wireless systems do not necessarily attempt to minimize the error rates in the system, but to maximize the end-to-end quality. The non-stationary behaviour of the channel is exploited such that in case of good channel states significantly higher data rate is supported compared to bad channel conditions. In addition, reliable link layer protocols with persistent Automatic Repeat reQuest (ARQ) are typically used to guarantee error-free delivery. For example, in HSDPA systems ARQ, adaptive modulation schemes, and multi-user scheduling considering the channel states are combined to significantly enhance the throughput [29]. It should be noted that different network technologies might implement rate control in different levels, such as hop-to-hop level or network level. Nevertheless, for IP-based networks involving multiple networking technologies, it is common to rely on rate control performed by the end-hosts application layer [11].

The approach presented here, targeting at dynamic, multi-objective rate control optimisation in 3.5G wireless medical video streaming applications, is based on modelling the rate-control problem as a Markov Decision Process (MDP).

We propose a scheme using a form of real time reinforcement learning known as 'Q-Learning' [30]. Q-learning has been used previously to solve several network control problems [31] [15], but it has never been used, to the authors' knowledge, for the purpose of optimising rate-control for wireless video transmission.

The main advantage of this method is that it allows dynamic adaptation and it does not require a-priori knowledge of the state transition probabilities, which are very difficult to estimate due to the large fluctuations in the bandwidth and channel conditions of mobile networks. Furthermore, our method does not require an explicit model for the underlying wireless channel.

IV. The Q-USR Control Algorithm

In this section we describe the proposed Q-USR algorithmic approach: in order to match the data rate resulting from medical video acquisition with the network available bandwidth, a trade off among the different m-QoS requirements described in Section II has to be considered and rate control can be used to control the transmitting rate of the ultrasound data in a way that satisfies both the network requirements in terms of available bandwidth and the medical QoS requirements.

In the Q-USR algorithmic approach, the rate control policy of wireless video streaming is regarded as a discrete-time Markov Decision Process (MDP) problem.

A discrete Markov decision process is a stochastic process represented by a finite number of states $\mathcal{S}$. For each state $s \in \mathcal{S}$ a finite set of actions $\mathcal{A}$ is possible. By selecting the action $a_k \in \mathcal{A}$ at the time step k, we incur a cost $c(s_k, a_k)$. A policy π consists of the assignment of an action a_k in correspondence of the state s_k at each time step k.

In our scenario, we assume the adaptive controller is the decision maker, known as agent, that monitors the environment state and accordingly assigns actions. When the agent realizes this action, the environment's state changes, the agent receives the new environment's state and signals of immediate reward

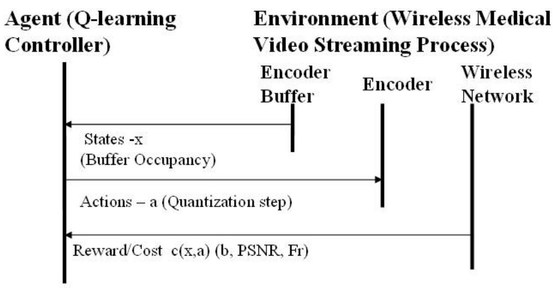

Fig. 2. Schematisation of the (Q-USR) algorithm

or cost, as a consequence of the previous action. Based on this information the agent updates its knowledge base. The process is repeated until the agent reaches an optimal policy π that assigns optimal actions leading the environment to a state that satisfies the control constraints.

The congestion in the network is sensed via the encoder buffer occupancy as shown in Figure 2. We assume the buffer occupancy represents the status s of the system. Actions a consists of modifying the source encoding parameters in terms of quantisation step.

We define the system state x_k at time step k as the buffer occupancy state b_k.

We assume the buffer occupancy b_k can assume values in a finite set $\mathcal{B} = \{b^{(1)}, b^{(2)}, ..., b^{(L_b)}\}$. In the simulation set-up in Section V, 10 buffer occupancy percentage states in the range of 10% to 100% are considered ($L_b = 10$).

Based on the system state x_k and on the evaluation of the reward/cost for each possible action, the video streaming rate controller will determine an action a_k, which is defined as the scaling factor that affects the quantization parameters and eventually affects the quality of the compressed image. The values used for the scaling actor (actions a_k) belong to a discrete set $\mathcal{A} = \{a^{(1)}, a^{(2)}, ..., a^{(L_a)}\}$. In this work 10 values of actions - corresponding to ten values of the video encoder quantisation parameters have been chosen ($L_a = 10$). The value of the action will be either an increase in the value of quantisation step (QS) or a decrease in the value of the QS. The video frame rate (variable in our approach) and the video quality are affected by the selection of such an action.

If the state-action pair (x, a) has been determined, an immediate cost is defined as:

$$c(x,a) = \max\left\{\max\left\{\frac{\epsilon_1 - b}{\omega_1}, 0\right\}, \max\left\{\frac{QI - \epsilon_2}{\omega_2}, 0\right\}, \max\left\{\frac{F_r - \epsilon_3}{\omega_3}, 0\right\}\right\} \quad (1)$$

where $\epsilon_1 = 80\%$, $\epsilon_2 = 36dB$ (if we use PSNR as quality index) and $\epsilon_3 = 5fps$ are the bounds set by the authors for the buffer occupancy b, the quality index QI and the frame rate F_r respectively. The ϵ_2 and ϵ_3 values were chosen to reflect the m-QoS bounds shown in Table I. ω_1, ω_2 and ω_3 are positive weights set by the authors; their values are 0.1, 0.5 and 10 respectively. Such values have been selected with the goal to give a higher weight to buffer occupancy and a lower weight to F_r.

In (1), the value of $c(x, a)$ assesses the immediate cost incurred due to the assignment of the action a at state x. The basic idea is to assign a lower cost to the actions resulting in a lower buffer occupancy, higher quality (QI) and higher frame rate F_r. We have three objective functions, so it is a multiobjective design problem. An approach to solve a multiobjective design problem is to formulate the problem as set of algebraic inequalities that must be satisfied for a successful design [32]. In this work we use the method of MINMAX [33] in order to combine the three objective functions together as shown in (1) above. The objective of the learner is then to find an optimal policy resulting in the action a for each x, which satisfies a cumulative measure of the cost defined in (1) over time. An evaluation function, denoted by $Q(x, a)$, which is referred as the total expected discounted return from the initial state-action pair (x, a) over an infinite time horizon, is given by [30]:

$$Q(x,a) = \mathbb{E}\left\{\sum_{k=0}^{\infty} \gamma^k c(x_k, a_k) | x_0 = x, a_0 = a\right\} \quad (2)$$

where $\mathbb{E}$ is the expectation operator and γ, $0 \leq \gamma < 1$, is a discount factor (in this work we assume $\gamma = 0.8$).

The rate control algorithm consists of determining the optimal action, denoted by a^*, which minimizes the Q-function represented in (2). The minimization of the Q-function represents the fulfilment of the defined m-QoS requirements.

Based on Bellman's theory in Dynamic Programming [34], there is at least one optimal policy that satisfies the minimization of the Q-function represented in (2), which is $Q^*(x, a)$. Hence, from (2) we can write [15]:

$$Q^*(x,a) = C(x,a) + \gamma \sum_y P_{xy}(a) \min_{b \in \mathcal{A}}\{Q(y,b)\} \quad (3)$$

where $C(x, a) = \mathbb{E}\{c(x, a)\}$. Equation (3) indicates that the Q function of the current state-action pair can be represented in terms of the expected immediate cost of the current state-action pair $C(x, a)$ and the minimum Q-function of the next state y and action b. $P_{xy}(a)$ is the state transition probability from state x with action a to the next state y, i.e.:

$$P_{xy}(a) = Prob(y|x,a). \quad (4)$$

However, it is hard to find the $C(x, a)$ and $P_{xy}(a)$ to solve (3). Based on the Q-learning approach, we can find the optimal rate control without a priori knowledge of $C(x, a)$ and $P_{xy}(a)$ [30]. To find the optimal $Q^*(x, a)$, the Q-learning algorithm computes the Q value recursively, using the available information $x, a, c(x, a)$. The Q-learning rule is defined as [15]:

$$Q(x,a) = \begin{cases} Q(x,a) + \alpha \Delta Q(x,a) & \text{if} \quad a = a^* \\ Q(x,a) & \text{otherwise}. \end{cases} \quad (5)$$

where α, $0 \leq \alpha \leq 1$, is the learning rate. In this work we selected $\alpha = 0.5$.

$$\Delta Q(x,a^*) = C(x,a^*) + \gamma \min_{\mathcal{A}}\{Q(y,b)\} - Q(x,a^*) \quad (6)$$

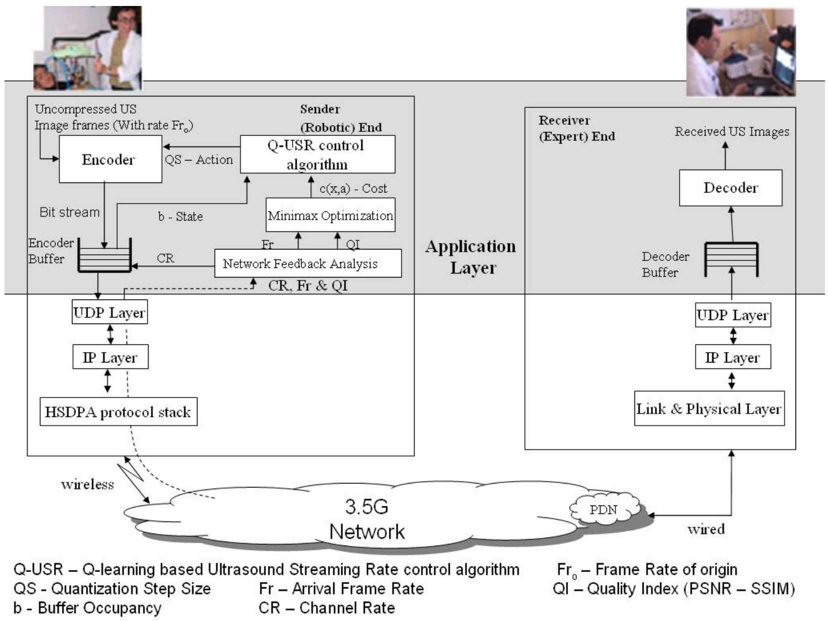

Fig. 3. Implementation and architecture of the Q-USR algorithm at the application layer, on the top of a 3.5G mobile network.

Since only one state-action pair is chosen for evaluation in each learning epoch for the Q-learning rule, only the Q value of the chosen action pair is updated, whereas the others are kept unchanged. In (6) the operation of $\min_{\mathcal{A}}\{Q^*(y,b)\}$ is executed by comparing the Q-values of all the possible action candidates for state y and then choosing the desired action b with minimal Q-value.

Figure 2 shows the state model of the Q-USR algorithm. It shows the timing sequence between the Q-learning controller and the wireless medical video streaming environment in terms of states, actions and relevant reward/cost.

Note that, although the controller action consists of the selection of the source coding quantisation parameters, such action also results in determining the video frame rate at the output of the source encoder and the next buffer status.

The frame rate (F_r) estimation is performed using the following equation:

$$F_r = CR/Fs \tag{7}$$

where CR and Fs are the channel rate and estimated frame size. Given the estimation of the channel rate (performed through linear predictive coding based on previous measurements received as feed-back) and the estimation of the frame size resulting from the selected quantisation parameters, the frame rate selected by the controller is determined by (7).

The encoder buffer model used here to measure the buffer occupancy b is based on the following equation [35]:

$$b_k = \frac{F_{s,k} - (CR/F_r)}{B} + b_{k-1} \tag{8}$$

where $F_{s,k}$ and b_k are the size of the frame at the input of the buffer in bits and the buffer occupancy respectively. B is the buffer size; CR and F_r are the channel rate and the frame rates respectively. With this implementation of encoder buffer model, we ensure that decoder buffer underflow will not occur, since it occurs when all the bits corresponding to a given frame are not present in time to be decoded.

At each learning epoch, an action is selected according to the table of Q-values and the table of Q-values is updated.

V. Implementation and Results

In order to validate the algorithmic concept introduced above, a simulated OTELO system set-up was developed to validate the performance of the proposed Q-USR control algorithm. The relevant algorithmic implementation was carried out using LabVIEW and MATLAB. 3.5G/HSDPA network connectivity using the Vodafone/UK system was used for the experimental data transmission with a data rate of 1.8 Mbps on the downlink and 384 kbps in the uplink.

As shown in Figures 2 and 3, the feedback information that the Q-USR controller requires consists of the channel rate (CR), the Frame Rate (F_r) and the image Quality Index (QI). In this case we use the Peak Signal to Noise Ratio ($PSNR$) as the quality evaluation index. The feedback information is received by the network feedback analysis block and the CR value is fed to the encoder buffer management in order to calculate the buffer occupancy b which will be used as the state of the environment in Q-USR control algorithm. The F_r and the QI parameters are used by the Q-USR block to calculate the cost function (1), to obtain the resultant optimal actions that will be used by the encoder to adapt its rate.

The encoded video stream passes through the encoder buffer and is then packetized and delivered via the UDP transport protocol to the lower IP based layers. The ultrasound scanner data stream used is at a rate of 10 fps and at a resolution of (320x240). It has been captured using a video card and fed to the laptop at the patient station. The captured images are then re-sampled to the QCIF (176X144) format and then encoded using the H.264/AVC JM12.3 AVC video codec test model [36]. Due to the mismatch between the generated rate at the encoder/decoder and the available communication bandwidth,

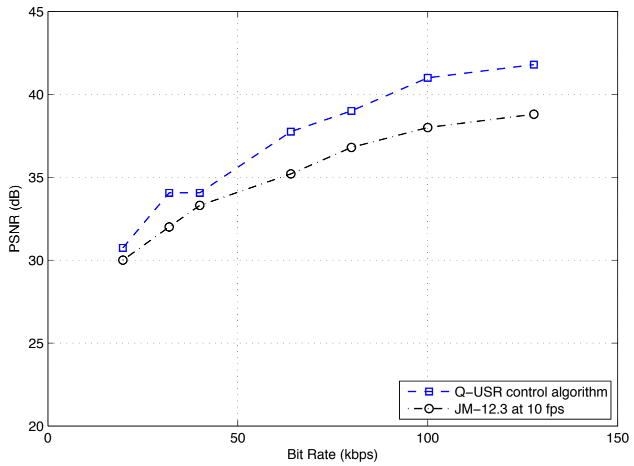

Fig. 4. Quality of the received ultrasound images (PSNR) at different bit-rates, with and without the Q-USR control algorithm.

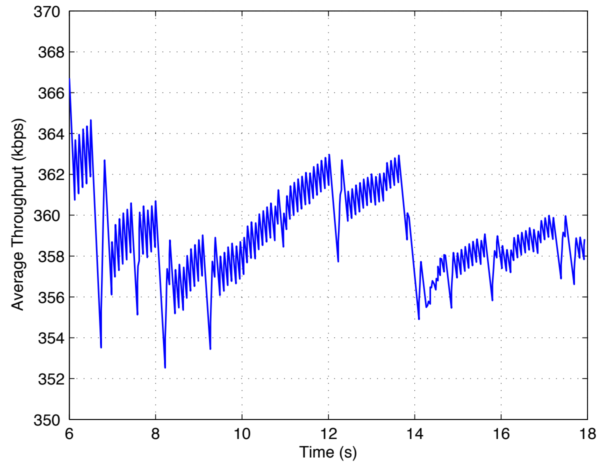

Fig. 5. 3.5G uplink bandwidth capability measured during the experiments.

we use the encoder/decoder buffer management structure shown in Fig. 2. The experimental tests were carried out at different real 3.5G network loading conditions, especially at peak working hours and the 3.5G testing results reflect these network conditions.

At the stage of UDP packetization shown in Fig. 3, each encoded ultrasound frame is divided into a number of UDP packets. Depending on the video codec used, the choice of the packet size in video streaming communication is a challenging issue [37]. Choosing small UDP packet size means generating more packets per frame and hence larger frame size due to the added headers. On the other hand, choosing large packet size is not feasible in wireless communication, as those packets can be dropped if the wireless link suffers bit errors due to noise and fading. When the packet size is large, dropping a packet means losing a large amount of information that will affect the decoding process. In 3.5G wireless communication, one of the uplink physical channels used to transmit data is the Dedicated Channel (DCH). This channel can have bit rates from a few kbps to 384 kbps depending on the maximum link power and the cell capacity. However selecting the DCH channel for transmission requires a long setting up time. Therefore other transmission channels are used for example Forward Access Channel (FACH) and Random Access Channel (RACH) that require less set-up time but can carry lower bit rate. The choice between these channels (DCH, RACH/FACH) depends on the packet scheduler buffer threshold in the Medium Access Control (MAC) layer, if the packet size is low then RACH/FACH is used, otherwise DCH is used [38]. The recommended packet size to use in DCH is in the range of (128-512) Bytes [38]. Experimentally in this work, using the packet size range above, it was found that the best reliable connectivity in this application can be achieved by choosing a packet size of 300 Bytes.

The Q-USR rate control algorithm described above was applied. At each decision time step an action is selected based on the table of Q-values obtained according to (5) in the previous step, and the table of Q-values is updated.

Fig. 4 shows the comparative performance of the system using the Q-USR algorithm and using the rate control of JM12.3 test model. In this test, the same encoding parameters have been set in both cases in order to have a fair comparison. Only quantization parameters and frame rate are modified in our algorithm, by keeping the same total bit-rate as in the reference case. The group of pictures (GOP) structure selected here is of IPPPP... type with 10 frames per group. The figure shows that the proposed algorithm achieves improved PSNR with an average gain of 2.5dB. This is at the expense of a variable frame rate: the frame rate is kept constant in JM12.3 rate-control, whereas with our algorithm the frame rate varies with time, with the lower constraint given by the mQoS requirements in Table I. In the example reported in the figure, the frame rate is 10fps in the JMmodel, whereas in our case it varies between 8fps and 10fps. Even for the cases where the frame rate for both the Q-USR controller and the existing JM12.3 rate control algorithm are the same, the achieved PSNR is still better in the case of Q-USR controller. The figure also shows that for the proposed rate controller the achieved PSNR and frame rate for bitrate of over 50kbps was within the acceptable m-QoS functional bounds in Table I.

Fig. 5 indicates that the achieved data rate (for PSNR of 36dB and frame rate of 5 fps) is within the available bandwidth of the 3.5G uplink of approximately 360 kbps. The experiments to test the 3.5G uplink available bandwidth were carried out by uploading files with large sizes and measuring the average throughput achieved at the receiver. The proposed algorithm adapts the sending rate according to the available bandwidth. In this work the available bandwidth was measured based on measuring the average throughput for the ultrasound stream over time at the receiver using the bottleneck capacity estimation described in [39]. The measurement of this average throughput is then sent from the expert station to the patient station. At the patient station the current average throughput is predicted via Linear Predictive Coding (LPC) [38].

Fig. 6 shows the comparative visual results for one of the tested ultrasound video sequences. The original frame no. 4 is shown in Fig. 6(a). The corresponding video frame received with the Q-USR controller is shown in Fig. 6(b), presenting a high visual quality, also reflected in diagnosis accuracy. Fig. 6(c) reports the corresponding received video frame without the Q-USR controller; evident artefacts are visible, affecting the correctness of the diagnosis. In order to evaluate these images from a medical perspective, a subjective measure evaluation based on Mean Opinion Score (MOS) was also used: three expert observers have been asked to evaluate the quality of the processed test images and to provide a score from 1 to 5. The average MOS values (in percentage) achieved by these tests have shown that the image transmitted with the Q-USR controller attains a better score (60%) as compared to a 20% score for the image transmitted without Q-USR controller.

Considerations in terms of delay have been performed, in order to verify the compliance with the defined m-QoS parameters. The transmitter buffer size has been selected in our experiments taking into account the delay requirements of the described telemedical application. In the results shown above, the buffer size B is assumed to be twice the average frame size.

The performance analysis of the packet delay at the Expert station shows an average packet delta time T_{us} (time difference between two consecutive packets) of 0.12 s and standard deviation T_{sd} of 0.063 s. The time delay for the expert side to request the ultrasound images T_{rc} is measured as 0.07 s, which is based on the transmission of 16 Bytes robotic control data. The total end-to-end delay of the system can be estimated as $T = T_{us}+T_{sd}+T_{rc} = (0.12+0.063+0.07)s = 0.253s$ which is within the acceptable medical requirements for robotic diagnostic quality, that are quantified as 0.35 s. The delay variation (jitter) in this experiment was found as 0.063 s (which is the standard deviation of the delta time).

VI. Conclusion

In this paper we proposed a new rate control algorithm (Q-USR), based on the Q-learning approach, that satisfies medical quality of service requirements in bandwidth demanding ultrasound video streaming. A comparison of the proposed Q-USR controller and the "standard" H.264 rate control algorithm is also provided, showing the better capability of the proposed scheme to dynamically satisfy the medical QoS requirements. Simulation results show that the proposed algorithm keeps both the image quality (PSNR) and the frame rate above the minimum m-QoS requirements, also fulfilling delay requirements. An improvement in PSNR is achieved with an average gain of 2.5dB. Real-time 3.5G network and simulation tests with H.264 compressed medical ultrasonography video show the successful implementation of the proposed algorithm that allows the selection of the suitable rate in order to satisfy the proposed m-QoS metrics. In addition, the end to end delay was 253 ms which is within the m-QoS of 350 ms. Visual results of the received images show the better diagnostic image quality of the received images under Q-USR controller. Further work is ongoing to develop a cross layer based m-QoS requirement control system and to consider next generation wireless communications systems like HSUPA and beyond.

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(a) (b) (c)

Fig. 6. Visual results of a sample ultrasound image of abdomen, acquired by the OTELO system. Frame no. 4. [a] Original image; [b] After transmission, Q-USR applied; [c] After transmission, Q-USR not applied.

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