Cognitive Approaches for QoS Enhancement of Medical Image Transmission over LTE Network

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Abstract - Advancements in healthcare services demand reliable transmission of immense medical data across various topographical locations for obtaining expert opinion and tele-consultation. The medical data include high resolution images like CT, MRI, Ultrasound, surgical videos, patient records, prescriptions and so on. The Quality of Service (QoS) provided by the transmission network is a primordial factor for better diagnosis and treatment. Bandwidth optimization and QoS requirements can be achieved greatly in 4G-LTE networks by employing effective image compression and resource allocation techniques. This work proposes three separate cognitive approaches (three modules) to enhance the QoS of image transmission in LTE networks. First, an intelligent resource scheduling algorithm for the fair scheduling of Real Time (RT) and Non real Time (NRT) Traffic is examined. Second, a pre-trained Convolutional Neural Network (CNN) for denoising the compressed images is explored and finally, a machine learning (ML) based lossless image coding is executed. Combination of the proposed three cognitive schemes can be employed for the effective transmission of the medical data over the fourth generation LTE networks for bandwidth optimization in Telemedicine Applications.

Keywords—Long Term Evolution (LTE), Compression, Denoising, QoS, Throughput, PLR, Delay. PSNR and SSIM

I. INTRODUCTION

Sophisticated clinical healthcare has become very much essential nowadays. Advanced medical technologies need to handle huge amount of patient data such as laboratory test results, radiological images (CT, MRI, EEG, ECG, X-RAY, and Ultrasound) and prescriptions. Lossless transmission of medical images and surgical videos from remote areas to city hospitals for tele-consultation is a challenging task in Telemedicine. Equipment for the acquisition and analysis of medical signals uses technical advancements in a greater way for better quality diagnosis and accurate treatment. CT and MRI are the popularly used imaging modalities with high resolution [25]. The recent pandemic COVID -19 disease also diagnosed with CT. These types of images require higher bandwidths while transmitted over wireless networks.

An extremely higher data rates and radically newer applications are expected from Next Generation Wireless Communication Networks. This expectation requires a novel radio technology paradigm. Traditional compression techniques aid the optimum spectrum utilization in LTE-networks through reduction in the original data size. In case of medical image transmission over these networks a careful selection of suitable compressing technique is very much crucial as any loss of data will have adverse effects in the medical diagnosis.

Long Term Evolution (LTE) Proposed by Third Generation Partnership Project (3GPP) is a packet based mobile network with higher data rates, varying bandwidths from1.4MHz to 20 MHz and little suspension. It was introduced by the Third Generation Partnership Project (3GPP). Elementary modules of the LTE system are eNodeB (eNB) and numerous User Equipment (UE). The eNB location pools with the central system by numerous regular complex procedures. Orthogonal Frequency Division Multiple Access (OFDMA) is used in LTE network for downlink services. This gives a flexibility in bandwidth usage. QoS providing has been definite as a chief aim in 4G LTE radio access systems. Conversely, as said by the 3GPP, there are no stable conditions for planning method in LTE system. One of the most significant components of package planning is Radio Resource Management (RRM) which selects customers that would transfer their data on the air border. The package planning should assimilate justice regarding output and also the facility strategies to which customers contribute [1].

For any wireless technology to be successful its resource allocation strategy plays a vital role. The Long Term Evolution (LTE) network uses Carrier Aggregation based resource allocation techniques. The overall objective of the proposed work is to optimize QoS in LTE network through effective resource allocation and compression techniques. Our previous works related to the objective involved applying the state of art image compression algorithms to test the efficiency and suitability for bandwidth optimization [29, 30]. Machine Learning is emerging as an important enabling technology for Artificial Intelligence (AI). A numerous ML algorithm have explored and implemented in radically new applications. The application areas of ML include Medical Diagnostics, Wireless Networks and Communication, Computer vision and Image and Video Processing. ML in 4G and 5G networks
solves many complex problems like radio resource management, Networking and Mobility Management [31]. Incorporating ML algorithms for bandwidth optimization in LTE networks is a new area of research. Image Compression techniques are capable of processing volumetric set of images and help in optimizing the memory size for storing and bandwidth requirements for transmission. The main objective of any compression technique is to assure reduction in image size, provide acceptable levels of visual quality and little or no loss of information. There are three types of image compression techniques Lossy, Lossless and Hybrid. Many literatures have proposed compression algorithms for medical images. [36]. The following issues and research challenges are identified from the literature.

Open Issues/ Research Challenges:

a. In LTE-Networks
   1. The unique challenges such as rate adaptation, quality assurance for optimal resource allocation for the heterogeneous traffic (Real time and Non-Real Time) in the existing wireless networks needs to be considered.
   2. Bandwidth starvation of the low priority users with acceptable quality of service (QoS) needs to be contemplated.
   3. The exploding number of users in cellular networks which has exponentially increased the volume and variety of multimedia content flowing across the network needs to be examined.

b. In image compression:
   1. Efficiency and optimization issues is to be addressed.
   2. Preserving the quality of the images is important.
   3. Large amount of compression time needs to be considered.
   4. Background noise reduction in compressed images needs to be explored.
   5. AutoShaping is done by physicians in ROI based compression which will lead to errors needs more focus.
   6. Restricted image types for compression needs to be examined.

   Problem statement: The challenges experienced by 4G-LTE Wireless Networks for providing optimum bandwidth for the lossless transmission of exponentially increasing multimedia traffic and compressed medical data is taken as the major issue. Addressing this issue with acceptable levels of quality of service in fourth generation LTE networks is a key issue to be addressed.

A. Rationale/ Motivation

   1. The exploding number of users in cellular networks which has exponentially increased the volume and variety of multimedia content flowing across the network. This results in huge traffic congestions for real time non real time users which needs attention.
   2. Background noise problems in compressed medical images. When these images are used for critical diagnostic purposes, it may lead the physicians to interpret wrongly.
   3. Lack of intelligent (AI, ML,DL, NN-based) lossless image coding which combats for computation time needs to be addressed as well.

B. Research Questions

   1. How far the state-of-the-art compression algorithms can aid in loss less coding and transmission of the medical images?
   2. How to effectively reduce background noise in compressed medical images?
   3. Is there an effective intelligent algorithm to address the complete lossless coding?

C. Aim of the Work

   To design and develop a collaborative algorithm for the lossless coding and transmission of medical Images over the fourth generation Long Term Evolution Network to improve telemedicine services with the acceptable level of Quality of Service.

D. Objectives

   1. Designing and developing an intelligent Resource scheduling algorithm for the fair scheduling of RT and NRT traffic in LTE.
   2. Removing Noise artifacts in the compressed medical images (CT, MRI, Ultrasound and Angiogram) using a pre-trained Neural Network in order to enhance the diagnostic quality.
3. Lossless coding of medical images using an ML to enhance CNN over 4G-LTE network for Telemedicine applications which will help medical experts for better diagnosis and treatment.

This paper is organized as follows. Section II discusses the related work based on resource scheduling methods, algorithms and techniques for LTE, Section III explains the proposed methods with their results and Section IV concludes the work with future enhancements.

II. RELATED WORK

This section presents various literatures on medical image compression, resource scheduling for LTE networks and the application of Machine learning in Next Generation networks for improving the radio performance.

A. Resource Scheduling

Experts have proposed a number of traditional resource scheduling methods and modern algorithms and techniques in various research articles, like QoS aware [4], Delay and Quality aware [5], content based [6,7], to address the bandwidth optimization problems in LTE-network. Recently Game Theory (GT) based algorithms [8]-[21] contribute significantly in addressing the resource allocation problems in LTE-network. Most of the GT based algorithms consider one or few of the QoS parameters like Delay, Throughput, Data rate, Queue size, Priority and Channel conditions. The Bandwidth starvation of low priority users are very rarely considered in literatures.

B. Compression Techniques

Various traditional and modern compression algorithms suggested in literatures [22]-[28] were proven to contribute a major role in the effective utilization of available channel resources. Compression algorithms are categorized as Lossy, Lossles and Hybrid. Selvi et.al [22] proposed a lossy compression technique for the compression of 2-D MRI and CT images. This technique uses Binary array technique (BAT combined with wavelet-based contourlet transform (WBCT). This approach generate precise output results requires less processing time. Denis et.al [23] proposed a novel compression algorithm for effective transmission of graphical data obtained from CT scanner. After Hounsfield scaling the compression is done. The efficiency of the algorithm is evaluated by prototyping. Ibraheem et. al. [24] proposed cognitive lossless compression techniques based on logarithmic computation. Enhanced image quality is obtained compared with conventional DWT. Claude Labit et.al.[25] presented a resolution scalable algorithms to compress the CT and MRI images. The efficiency and scalability are improved using this algorithm. Chandrasekar et.al. [26] Proposed a thresholding based Set Partitioning in Hierarchical Tree (SPIHT) algorithm for Region of Interest (ROI) Compression. It produces higher values of PSNR. Jianji Wang et al [27] developed a Fractal Image Compression (FIC) technique based on Structural Similarity Index (SSIM). Perumal and Rajasekaran [28] presented a Discrete Wavelet based Back Propagation (DWT-BP) compression for the medical images better compression ratio and PSNR.

The major limitation of compression algorithms is the tradeoff between the qualities of reconstructed image at the receiver end. If we prefer to choose high compression ratio, then quality will be reduced to a considerable amount and vice versa. This is a critical issue in employing compression techniques. The quality metrics may vary for various imaging modalities (CT, MRI, Ultrasound and Angio). Therefore, a careful selection of suitable compression method becomes essential. Denoising of compressed medical images is a open challenge in the area of image processing.
C. Machine learning in next generation networks and image processing

In recent days, the contribution of machine learning networks for improving the performance of wireless networks has become vital. Machine learning have explored and implemented radically new applications in next generation networks and image processing. An extremely higher data rates and radically newer applications are expected from Next Generation Wireless Communication Networks. This expectation requires a novel radio technology paradigm. Traditional compression techniques aid the optimum spectrum utilization in LTE-networks through reduction in the original data size. In case of medical image transmission over these networks a careful selection of suitable compressing technique is very much crucial as any loss of data will have adverse effects in the medical diagnosis. In this proposed work, an attempt is made to use of Machine Learning for lossless coding of medical images. [31]-[35].

Opportunities identified:

1. There is a need for designing an algorithm that considers all the QoS parameters like delay, throughput, queue size, priority, channel conditions and all types of traffic (discussed in Module 1).
2. Denoising of compressed images are to be addressed in an effective way (discussed in Module 2).
3. Employing Machine learning techniques in next generation networks may enhance this performance significantly (discussed in Module 3).

III. METHODOLOGY

The research questions, objectives and aim of the proposed work are addressed and attained through three work modules.

1. A Game Theory Based Resource Scheduling Scheme (GTBS) for RT and NRT traffic.
2. A Pre-trained Convolutional Neural Network for denoising the compressed images.
3. A ML based method for lossless coding of medical images.

The modules are discussed below with their results.

WORK MODULE 1: GTBS RESOURCE SCHEDULING:

In this phase of work, an intelligent game theory based resource scheduling (GTBS) algorithm is developed and implemented for RT and NRT Multimedia traffic over LTE network. Figure 1 depicts process of the algorithm flow. This method addresses the low-priority user’s resource requirements without affecting the top user’s throughput.

![Fig. 1 The intelligent GTBS algorithm](image-url)
The Game theory model is applied for the low priority users for allocation of resources meeting their Guaranteed Bit Rate (GBR). Since the utility function is formed in terms of throughput degradation and delay increment, it ensures that the throughput is not degraded, and delay is not increased for other higher priority classes.

**Results and Discussions:** The performance is evaluated in terms of end-to-end delay, throughput, packet loss rate (PLR), fairness index, SINR and CQI. For RT traffic, VoIP, Video and CBR are used. For NRT traffic, Best Effort (BE) model is used.

![Video-Delay](image1)

Fig. 2 Users Vs Delay

Figure 3 shows the delay measured for DQAS, PF and GTBS schemes when the users are varied. As we can see from the figure, GTBS achieves the least delay around 0.00636 seconds followed by DQAS and PF. The delay of GTBS is 30% lesser than PF and 19% less than DQAS.

![Video-PacketLossRatio](image2)

Fig. 3 Users Vs Packet Loss Ratio (PLR)

Figure 4 shows the packet loss ratio measured for DQAS, PF and GTBS when the users are varied. As we can see from the figure, GTBS has the least PLR around 0 followed by DQAS and PF. Hence the PLR of GTBS is 51% lesser than PF and 47% less than DQAS.
Figure 5 shows the throughput measured for DQAS, PF and GTBS when the users are varied. As we can see from the figure, GTBS attains the highest throughput around 8.2Mb followed by DQAS and PF. Hence the throughput of GTBS is 10% higher than PF and 5% higher than DQAS.

Figure 5 shows the delay measured for DQAS, PF and GTBS when the users are varied. As we can see from the figure, the GTBS has the least delay around 0.0015 seconds followed by DQAS and PF. Hence the delay of GTBS is 8.5% lesser than PF and 4% lesser than DQAS.
Figure 6 shows the throughput measured for DQAS, PF and GTBS when the users are varied. As we can see from the figure, GTBS achieves the highest throughput around 0.84 Mb followed by DQAS and PF. Hence the throughput of GTBS is 42% higher than PF and 33% higher than DQAS.

Figure 7 shows the throughput measured for DQAS, PF and GTBS schemes when the users are varied. As we can see from the figure, the GTBS attains the highest throughput around 5.12Mb followed by DQAS and PF. Hence the throughput of GTBS is 22% higher than PF and 12% higher than DQAS.

Figure 8 shows the PSNR values measured for PF, DQAS and GTBS for different frame numbers. As we can see from the figure, DQAS achieves PSNR around 14, PF achieves PSNR around 13 and GTBS achieves PSNR in the range of 35. From the simulation results, it is shown that the proposed technique reduces the delay and improves the throughput for both category of flows.

WORK MODULE 2: DENOISING OF COMPRESSED MEDICAL IMAGES USING PRE-TRAINED NEURAL NETWORK.

The main objective of any compression technique is to assure reduction in image size, provide acceptable levels of visual quality and little or no loss of information. Experts have proposed several algorithms, mechanisms and techniques for the compression medical images. Preserving the image quality, computational time, background noise in the compressed images are some of the challenges still need to be addressed effectively [36]. Medical images are subjected to many types of noises like Random noise, Electronic noise and statistical noise. CT images are mainly prone to this type of noise components [37].

Results and Discussions: In our previous work we have tested two state of the art image compression algorithms on medical images to optimize the resources in LTE-network [29, 30]. In this phase of our work a denoising method using pre-trained neural network for removing the noise artefacts in the compressed images is carried out. PSNR and SSIM are taken as the quality measures. The values of these parameters are compared for noisy and
denoised images. Figure 9 shows the images used in the simulation. These images are modelled with Gaussian noise. A pre-trained convolutional neural network is used to denoise the compressed images.

Table 1. PSNR and SSIM values of noisy and denoised images

<table>
<thead>
<tr>
<th>Image Type</th>
<th>PSNR</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Noisy Image</td>
<td>Denoised Image</td>
</tr>
<tr>
<td>CT</td>
<td>21.638</td>
<td>28.0662</td>
</tr>
<tr>
<td>MRI</td>
<td>20.202</td>
<td>30.0716</td>
</tr>
<tr>
<td>ULTRASOUND</td>
<td>20.250</td>
<td>26.618</td>
</tr>
<tr>
<td>ANGIO</td>
<td>21.415</td>
<td>26.000</td>
</tr>
</tbody>
</table>

The Peak Signal to Noise Ratio (PSNR) and Self Similarity Index (SSIM) are the popular metrics used to evaluate the image quality. When an image is affected with noise its reconstructed image is severely affected. This reduces the values of PSNR and SSIM values. It can be seen from Table 1 that the values of PSNR and SSIM are improved after denoising the images.

![Fig. 9. Input and output of the Denoising network](image-url)
The value of SSIM is greatly improved after denoising.

SSIM between two images $X$ and $R$ is expressed as

$$SSIM(X, R) = \frac{(2\mu_X\mu_R + C_1)(2\sigma_{XR} + C_2)}{(\mu_X^2 + \mu_R^2 + C_1)(\sigma_X^2 + \sigma_R^2 + C_2)}$$

(a)

Where

$\mu_X, \mu_R, \sigma_X^2, \sigma_R^2$ are the averages and variances of $X$ and $R$ respectively.

$\sigma_{XR}$ is the covariance between $X$ and $R$, $C_1$ and $C_2$ are predefined constants.

The PSNR is expressed as

$$PSNR = 10 \times \log_{10}\left(\frac{255 \times 255}{MSE}\right)$$

(b)

Where,

MSE-Mean Square Error between $X$ and $R$.

**WORK MODULE 3: A MACHINE LEARNING METHOD FOR LOSSLESS CODING OF MEDICAL IMAGES.**

In this phase of work a multi paradigm machine learning algorithm is designed and tested for the lossless coding of medical images. Machine Learning plays a vital role in modern Image analysis. Use of Machine Learning techniques to infer useful information from visual data is a promising one for the physicians. A set of CT-COVID images are used to train and test the proposed algorithm. A total of multi-iterated epochs is carried out. From the simulation results, it can be inferred that when the noise artefacts are removed the quality of the image is enhanced. The higher values of PSR and SSIM are the evidence. Similarity index is the measure of perceptual quality measure of an image.

![Fig. 10 ML Enhanced System for Image Transmission](image-url)
Algorithm Analysis:

The value function estimates how good it is to be in a given state. Value function approaches attempt to find a policy that maximizes the return by maintaining a set of estimates of expected returns for optimal policy.

A relation between the value function, reward and states are analyses in terms of the equations below. The equations are derived with the efforts of finding the mathematical relationship between the salient features in the images along with the values to improve the efficiency of the entire process

a. Computing Estimates Incrementally:

Let

\[ R = \text{Reward} \]

\[ V_T = \text{Value of iteration} \]

\[ T = \text{Time} \]

\[ S = \text{State} \]

\[ R_T(S) = \text{Rewward in state 1 at time } T \]

\[ \alpha = \text{Learning rate} \]

\[ V_T(S) = \text{Value of iteration in state 1 at time } T \]

\[ V_{T-1}(S) = \text{Value of iteration in previous state} \]

The value of iteration in state 1 is expressed as

\[ V_T(S) = (T - 1)V_{T-1}(S) + (R_T(S)) \quad (1) \]

\[ V_T(S) = (T - 1)V_{T-1}(S) + \alpha(T_R(S) - V_{T-1}(S)) \quad (2) \]

Where

\[ \alpha = \frac{1}{T} \]
b. Properties of learning rate

The following two properties are assumed for the learning rate.

1. \[ \sum_{T} \alpha_T = \infty \]  

2. \[ \sum_{T} \alpha_T^2 < \infty \]  

\[ \text{With the above mentioned properties eqn (1) can be written as} \]
\[ \lim_{T \to \infty} V_T(S) = V(S) \]  

(c) Temporal Difference Analysis:

It is a prediction process used to predict the next state value. It is a supervised learning process. This can be used to predict the total amount of reward expected in the future.

\textbf{TD (1) Rule:}

For every episode ‘T’

For all \( S \), \( e(S)=0 \) at the start of episode,

When \( S_{t-1} = S_t \)  

\textbf{Eligibility Criteria:}

\[ e(S_t - 1) = e(e_t - 1) + 1 \]  

For all \( S1 \)

\[ V_T(S_t) = V_T(S) + \alpha_T(r_T + \delta V_{T-1}(S_t) - V_{T-1}(S_t - 1)) \]  

\[ e(S) = \delta e(S) \]

\textbf{TD (0) Rule: (if finite data repeats infinitely often)}

The value in the next iteration is expressed as

\[ V_T(S_{t-1}) = V_T(S_{t-1}) + \alpha_T(\delta_T + \gamma V_T(S_t) - V_T(S_t - 1)) \]

\( \delta_T - \text{Reward} \)

\( \gamma - \text{Discrete value of the estimate} \)

\[ V_T(S_{t-1}) = E[\delta_T + \gamma V_T(S_t)] \]

\textbf{TD (\lambda) Rule:}

Both TD (0) and TD (1) have updates based on differences between temporal successive predictors.

This will be same as TD (1) rule except

\[ e(S) = \lambda \delta e(S) \]
\[ E_1 = (1 - \lambda) \] (14)

\[ E_2 = \lambda (1 - \lambda) \] (15)

\[ E_3 = \lambda^2 (1 - \lambda) \] (16)

\[ E_\infty = \lambda^\infty (1 - \lambda) \] (17)

**Results and Discussions:** The proposed ML algorithm is implemented using Python. A set of CT-COVID images [40] are used for Training, Testing and Validation. It is inferred that the Training, Testing and validation accuracy increases with increasing epochs and the loss for the same getting reduced.

![Fig.12 Model Efficiency for various pooled pixels](image)

![Fig.13 Training Vs Validation Accuracy](image)

Fig 12. shows the model efficiency for various pooled pixels of the images. The graph signifies the importance of image resolution that depends upon the model’s parameters and its influence on Training and Testing. A total of multi-iterated epochs is carried out. It is inferred Fig.13 that the Training and validation accuracy increases with increasing epochs which means the loss for the same getting reduced. It can be inferred from the results that for every values of the neighborhood pixels taken into account separated by the Euclidean distance the accuracy of the model gets aggregated which in turn compensates for any losses the transmitted data endures along the communication channel.
Contribution of the Research Work:
From the discussions on the above three work modules, the following contributions of the research work can be understood.

1. The GTBS scheduling algorithm provide fair scheduling for all type of multimedia traffic and improve the QoS in LTE-network.
2. Suggests the optimum selection of compression method for a targeted medical image (CT, MRI, Ultrasound or Anglo) to be transmitted over LTE-Network. [29][30]
3. The combination of image denoising of compressed medical images and ML based lossless image coding may help the physicians for better diagnosis and treatment
4. When all the proposed algorithms are combined, it will be addressing the implantation challenges and help in evaluating the QoS parameters of Telemedicine over 4G and 5G network.

IV. CONCLUSIONS AND FUTURE WORK

This work proposed three separate cognitive approaches (three modules) to enhance the QoS of image transmission in LTE networks such that the emerging technologies constitute a ubiquitous healthcare system. In the module 1, an intelligent resource scheduling algorithm for the fair scheduling of Real Time (RT) and Non real Time (NRT) Traffic was examined. In the module 2, a pre-trained Convolutional Neural Network (CNN) for denoising the compressed images were explored and in the module 3, a machine learning (ML) based lossless image coding was executed. Combination of the proposed three cognitive schemes can be employed for the effective transmission of the medical data over the fourth generation LTE networks for bandwidth optimization in Telemedicine Applications. When the proposed work is completely incorporated in a healthcare service module it will aid a huge community of physicians in the quality diagnosis of remote patients during emergency/pandemic/epidemic periods.

The proposed approaches can be implemented for medical image and video transmission for telemedicine applications in 4G and 5G networks with different real time parameters and constraints. We will further improve the cognitive approaches by integrating all the approaches together, also introducing new techniques to get better efficiency. We will focus on quality-of-experience (QoE) / quality-of-service (QoS) in video telephone consultations (two-way communication), as achieving higher quality of streaming video in an IP network is highly challenging, so suitable methods/techniques/approaches are required to enhance the overall performance . We will focus on building a conceptual framework to provide ubiquitous teledmedicine services using disruptive technologies as an enabler by addressing various challenges listed out. We will be closely working with the hospitals and tech industries to tackle real-time implementation, so the new paradigm of healthcare becomes significant for the community.

REFERENCES


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