Wavelet-Based Compression With ROI Coding Support for Mobile Access to DICOM Images Over Heterogeneous Radio Networks

Ilias Maglogiannis, Member, IEEE, Charalampos Doukas, Student Member, IEEE, George Kormentzas, Member, IEEE, and Thomas Pliakas, Student Member, IEEE

Abstract—Most of the commercial medical image viewers do not provide scalability in image compression and/or region of interest (ROI) encoding/decoding. Furthermore, these viewers do not take into consideration the special requirements and needs of a heterogeneous radio setting that is constituted by different access technologies (e.g., general packet radio services (GPRS)/universal mobile telecommunications system (UMTS), wireless local area network (WLAN), and digital video broadcasting (DVB-H)). This paper discusses a medical application that contains a viewer for digital imaging and communications in medicine (DICOM) images as a core module. The proposed application enables scalable wavelet-based compression, retrieval, and decompression of DICOM medical images and also supports ROI coding/decoding. Furthermore, the presented application is appropriate for use by mobile devices activating in heterogeneous radio settings. In this context, performance issues regarding the usage of the proposed application in the case of a prototype heterogeneous system setup are also discussed.

Index Terms—Digital imaging and communications in medicine (DICOM) images, heterogeneous radio networks, image compression, mobile telemedicine, ROI coding, wavelets.

I. INTRODUCTION

VARIOUS types of mobile devices (e.g., Pocket personal computers, personal digital assistants (PDAs), etc.) support applications used by medical personnel for retrieving and examining patient data [1], [2]. Most of these applications deal with medical images, such as computed tomography (CT) scans, computed radiography (CR) scans, and magnetic resonance (MR) images, stored in picture archiving and communication systems (PACS) and/or hospital information systems (HIS). The visual quality of the medical images/scans is required to be high, in order to ensure correct and efficient assessment resulting in correct diagnosis. In this context, a mobile device has to handle medical images of significant sizes, while also taking into account its own limitations concerning memory and processing resources. For reducing the size of medical images, the discrete wavelet transform has been widely used in various applications for medical image manipulation. Indicative examples include wavelet-based applications for medical images compression [3], [4], for MR and ultrasound images denoising [5], [6], and for medical images features’ extraction [7], [8].

A plethora of medical image file viewers can be found in international literature (for a collection of them, see [9]). Most of them include functionalities that allow image and header information extraction (in case of DICOM compliant images), as well as partial image manipulation. The digital imaging and communications in medicine (DICOM) standard launched by the National Electrical Manufacturers Association (NEMA) facilitates the distribution and viewing of medical images. DICOM defines a special file format that contains a header (that stores information about the patient’s name, the type of image, image dimensions, etc.), and the rest of the image data. Fig. 1 shows a DICOM-compliant image file representation including the header section.

Commercial versions of medical image file viewers appropriate for mobile devices are “RemotEye” [10], “DicomViewer” [11], and “ReviewMD PDA” [12]. Most of the aforementioned applications do not provide any means of scalability in image compression and/or region of interest (ROI) encoding/decoding. Furthermore, the current medical image viewers do not take into consideration the special requirements and needs of an heterogeneous radio access environment composed of different radio access technologies (e.g., GPRS/UMTS, WLAN, and DVB-H).

In the aforementioned context, this paper presents a medical application, which enables scalable compression, retrieval, and decompression of medical images on mobile devices, enhanced with ROI coding for advanced image examination of specific areas within the image. The proposed application can be used for accessing medical images at a healthcare center, where the electronic medical record system resides, at a medical treatment/care center established at a sports facilities center, at a...
A major drawback, however, of the JPEG2000 standard is the fact that it does not support lossy-to-lossless ROI compression. In [15], a lossy-to-lossless ROI compression scheme based on set partitioning in hierarchical trees (SPIHT) [16] and embedded block coding with optimized truncation (EBCOT) [17] is proposed. The input images are segmented into the object of interest and background and a chain code-based shape coding scheme [18] is used to code the ROI’s shape information. Then, the critically sampled shape-adaptive integer wavelet transforms [19] are performed on the object and background image separately to facilitate lossy-to-lossless coding. Two alternative ROI wavelet-based coding methods with application to digital mammography are proposed by Penedo et al. in [20]. In both methods, after breast region segmentation, the region-based discrete wavelet transform (RBDWT) [21] is applied. Then, in the first method, an object-based extension of the set partitioning in hierarchical trees (OB-SPIHT) [16] coding algorithm is used, while the second method uses an object-based extension of the set partitioned embedded block (OB-SPECK) [22] coding algorithm. Using the RBDWT, it is possible to efficiently perform wavelet subband decomposition of an arbitrary shape region, while maintaining the same number of wavelet coefficients. Both OB-SPIHT and OB-SPECK algorithms are embedded techniques, i.e., the coding method produces an embedded bit stream which can be truncated at any point (in the context of bit-plane level), equivalent to stopping the compression process at a desired quality. The wavelet coefficients that have larger magnitude are those with larger information content. In a comparison with full-image compression methods as the SPIHT and JPEG2000, the OB-SPIHT and OB-SPECK exhibited much higher quality in the breast region at the same compression factor [20]. A different approach is presented in [23], where the embedded zerotree wavelets (EZW) coding technique is adopted for ROI coding in progressive image transmission (PIT). The method uses subband decomposition and image wavelet transform to reduce the correlation in the subimages at different resolutions; thus, the whole frequency band of the original image is divided into different subbands at different resolutions. The EZW algorithm is applied to the resulting wavelet coefficients to refine and encode the most significant ones. Compression scalability is also supported in the HS-SPIHT [24], where the SPIHT is enhanced to support spatial scalability providing a bit stream that can be easily adapted (reordered) to given bandwidth and resolution requirements by a simple transcoder. Another approach using wavelet localization for ROI-specific scalable compression is presented in [25]. The wavelet coefficients at each level are correlated to weighting factors allowing scalability based on the received peak SNR (PSNR). Apart from compression scalability for the whole image or a specific ROI, additional rate scalability can be introduced during network transmission of the image. The latter technique, however, applies mostly on cases of video transmission [26], [27].

The proposed application adopts the distortion-limited wavelet image Codec (DLWIC) algorithm [28]. In the DLWIC, the image to be compressed is first converted to the wavelet domain using the orthonormal Daubechies wavelet transform [29]. The transformed data is then coded by bit-levels and the output
is coded using the QM-coder [30], an advanced binary arithmetic coder. The algorithm processes the bits of the wavelet-transformed image data in decreasing order concerning their significance in terms of MSE. This produces a progressive output stream enabling the algorithm to be stopped at any phase of the coding. The already coded output can be used to construct an approximation of the original image.

The aforementioned feature is useful when a user browses medical images using slow-bandwidth connections, where the image can be viewed immediately after only few bits have been received; the subsequent bits then make it more accurate. DLWIC uses the progressivism by stopping the coding when the quality of the reconstruction exceeds a threshold given as an input parameter to the algorithm. The presented approach solves the problem of distortion limiting (DL) allowing the user to specify the MSE of the decompressed image. Furthermore, this technique is designed to be as simple as possible consuming less amount of memory in the compression–decompression procedure, being thus suitable for usage on mobile devices.

Fig. 3 depicts the RMS error results concerning the application of the DLWIC algorithm for both lossless (quality factor equal to 1) and lossy compression (quality factor smaller than 1) for CR, CT, and MR medical images of sizes 262 KB, 525 KB, and 1 MB, respectively. The medical image data sets used in this study were collected at Sotiria General Hospital of Athens, Greece. The data set included 117 CT scans, 90 CR, and 112 MR images in the upper chest (thorax) and the abdominal area. The numerical data presented in this paper are average values from experiments executed on images from the specific data set. A second study has also been conducted using the structural SIMilarity (SSIM) index found in [31] as an image quality indicator of the compressed images. The specific metric provides a mean of quantifying the perceptual similarity between two images. Perceptual image quality methods are traditionally based on the error difference between a distorted image and a reference image, and attempt to quantify the error by incorporating a variety of known properties of the human visual system. In the case of the SSIM index, the structural information in an image is considered as an attribute for reflecting the structure of objects, independent of the average luminance and contrast, and thus the image quality is assessed based on the degradation of the structural information. A brief literature review [32]–[34] has shown clear advantages of the SSIM index against traditional RMS and PSNR metrics and a high adoption by researchers in the field of image and video processing. Average SSIM index values for different compression factors are presented in Table I.

As derived by the similarity comparison experiments using the SSIM, the quality degradation even in high compression ratios is not major (i.e., 88.4% and 99.04% for compression factors 0.1 and 0.7, respectively, in case of the MR image data set). This fact proves the efficiency of the proposed algorithm.

At this point, it should be noted that concerning lossy compression, the DLWIC performs better in case of medical images of large sizes; Lossy compression is performed by multiplexing a small number of wavelet coefficients (consisting of the base layer and a few of additional layers for enhancement). Thus, a large number of layers are discarded, resulting in statistically higher compression results concerning the file size. However, lossy medical image compression is considered to be unacceptable for performing diagnosis in most of imaging applications, due to quality degradation. Therefore, in order to improve the diagnostic value of lossy compressed images, the ROI coding concept is introduced in the proposed application to improve the quality in specific regions of interest only by applying lossless or low compression in these regions, maintaining the high compression in none of the interest regions of the image. The wavelet-based ROI coding algorithm implemented in the proposed application is depicted in Fig. 4 (block diagram). A dyadic decomposition is used that repeatedly divides the lower subband into four subbands. Let \( D \) denote the number of decomposition level, then the number of subbands \( M \) equals \( 4 + 3(D − 1) \). Assuming that the ROI shape is given by the client as a binary mask form on the source image, the wavelet coefficients on the ROI and on the ROI of none interest (RONI) are quantized with different step sizes. For this purpose, a corresponding binary mask is obtained, called the WT mask, on the transform domain. The whole coding procedure can be summarized in the following steps:

1) The ROI mask is set on the source image.
2) The mask and the requested image are transferred to the application server.
3) The corresponding WT mask \( B \) is obtained.
4) The DWT coefficients are calculated.
5) Bit allocations for the ROI and RONI areas are obtained.
6) The DWT coefficients are quantized with the bit allocation from the previous step for each subband of each region.
7) The resulting quantized coefficients are encoded.
8) The WT mask \( B \) is encoded.

The entropy-coded coefficient and WT mask are multiplexed in order to create the bit stream.

<table>
<thead>
<tr>
<th>Image Type</th>
<th>Compression Factor</th>
<th>0.1</th>
<th>0.3</th>
<th>0.5</th>
<th>0.7</th>
</tr>
</thead>
<tbody>
<tr>
<td>MR</td>
<td>88.3975</td>
<td>96.0845</td>
<td>97.3111</td>
<td>99.0466</td>
<td></td>
</tr>
<tr>
<td>CT</td>
<td>81.2853</td>
<td>91.1986</td>
<td>94.2828</td>
<td>97.6702</td>
<td></td>
</tr>
<tr>
<td>Type</td>
<td>CR</td>
<td>90.2179</td>
<td>94.5156</td>
<td>96.0221</td>
<td>96.8969</td>
</tr>
</tbody>
</table>

The SSIM index provides an indication of perceptual image similarity between original and compressed images.
The decoding process follows the reverse order at the client side. The major advantage of the proposed ROI coding method is that it produces a progressive output stream; thus, the ROI is decoded progressively at the receiver. The user has the capability to stop the transmission at any phase of the coding, while the already transmitted output can be used to construct an approximation of the original image. The specific feature is especially desired for browsing medical images in low-bandwidth mobile networks. In comparison to the JPEG2000 standard, the proposed scheme is preferable since it supports lossy-to-lossless ROI compression. When compared to the rest of the methods discussed in Section II, the proposed method has superior characteristics in terms of complexity and simple implementation, enabling this way its application in portable and mobile devices with limited computing power. The mobile computing paradigm is quickly entering the electronic healthcare sector since it supports the moving and commuting physician; therefore, technical solutions aligned with this concept are extremely desirable. The performance of the proposed method in terms of subjective and perceptual metrics (MSE and SSIM) was comparable to ROI-coding methods found in literature. Finally, mean opinion score (MOS) tests have been conducted by two medical experts, which reflects the feasibility of diagnosis on a number of 20 medical images in total. The score ranges between 1 and 5; 1 corresponds to unfeasible assessment, and 5 corresponds to the best image quality and highest accuracy for assessment. As indicated, an average compression factor (0.5) can still result in high image resolution and clearance (MOS 4.75 for both whole image and ROI assessment), resulting thus in high assessment accuracy.

**II. DESIGN AND NETWORK IMPLEMENTATION DETAILS OF THE PROPOSED MEDICAL APPLICATION**

As depicted in Fig. 5, the proposed medical application follows three-tier architecture, consisting of the client part, the DICOM server, and the electronic medical record system—remote database management system (EMR-RDBMS). The client requires a Java-enabled Web—browser and communicates using the HyperText Transfer Protocol (HTTP) and remote method invocation (RMI) protocols with the server. The transactions between the server and the database are performed through the JDBC [35]. Generally, the client’s operations may be divided into two categories according to whether they are performed locally or through the server. Image manipulation (e.g., brightness, contrast, negative adjustment, drawing annotations, etc.) are handled by appropriate Java applets at the client’s side. User authentication, image and header retrieval, as well as compression and encryption are performed through the server.

The proposed medical application supports lossless and lossy image compression through scalable wavelet-based transforms with ROI support that provides the user the ability to select desired regions on the compressed DICOM image. The medical personnel using the application can draw annotations on the images and store them through the DICOM header as comments. The DICOM header can be extracted and presented separately. Furthermore, it can be parsed into the XML format providing in this way interoperability with other medical file standards (e.g., HL7 [36]). Concerning security features, the proposed application supports user authentication through credentials (i.e., username and password) and data encryption using a symmetric key of 128 bits length. Additionally, various helping image manipulation functions (such as brightness and contrast adjustment) accompany the basic image retrieval feature of the discussed application.

Fig. 6 presents the sequence of messages exchanged between the client and server entities. The messages can be grouped according to their functions into four categories: user authentication, DICOM image retrieval, ROI coding, and XML parsing. Most of the messages concern, either RMI lookup calls for initializing communication, or procedure calls for data exchange.

<table>
<thead>
<tr>
<th>Table II</th>
<th>AVERAGE MEAN OPINION SCORE (MOS) OF IMAGE QUALITY FOR THREE DIFFERENT IMAGE TYPES USING DIFFERENT COMPRESSION FACTORS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Image Type</strong></td>
<td><strong>Compression Factor</strong></td>
</tr>
<tr>
<td>MR</td>
<td>0.1</td>
</tr>
<tr>
<td>CT</td>
<td>1</td>
</tr>
<tr>
<td>CR</td>
<td>2.75</td>
</tr>
</tbody>
</table>

**B) MOS FOR REGION OF INTEREST ASSESSMENT**

<table>
<thead>
<tr>
<th><strong>Image Type</strong></th>
<th><strong>Compression Factor</strong></th>
<th><strong>Average Mean Opinion Score (MOS)</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>MR</td>
<td>0.3</td>
<td>0.5</td>
</tr>
<tr>
<td>CT</td>
<td>4</td>
<td>4.5</td>
</tr>
<tr>
<td>CR</td>
<td>3</td>
<td>4.75</td>
</tr>
<tr>
<td>CR</td>
<td>4</td>
<td>4.5</td>
</tr>
</tbody>
</table>

Table A) presents the MOS score for assessing the whole image, whereas Table B) presents the MOS score for assessing a specific region of interest compressed with different factors. The background is compressed using the highest lossy compression factor.
The procedure calls differ according to the action triggered by
the user. Between server and EMR-RDBMS, appropriate mes-
sage queries are exchanged.

Closing this section, Fig. 7 depicts three screenshots from
the proposed medical application in use. The first screenshot
refers to a Tablet PC, the second one to a PDA, and the last
one illustrates basic functions of compressed medical image
retrieval and ROI coding.

### III. PERFORMANCE AND RELIABILITY ASPECTS OF THE
PROPOSED MEDICAL APPLICATION

This section discusses performance and reliability issues of
the proposed medical application offering wavelet-based com-
pression and ROI coding support, in the context of both an actual
prototype heterogeneous system and an emulated one using the
National Institute of Standards and Technology emulation tool
with the parameters depicted in Table III [37].

The prototype includes a DICOM server and an EMR sys-
tem, which have been installed on a single machine (further
referred to as server), a Tablet PC (Acer TravelMate C100, Mo-
bile Pentium 800 MHz processor, 256 MB RAM), and a Pocket
PC (Compaq iPAQ 3955, Intel X-Scale 400 MHz processor, 64
MB SDRAM), with a Java-enabled Web browser (both further
referred as clients).

The server and client modules are connected through, either a
802.11b WLAN (in a mode of theoretical 11 Mb/s bandwidth),
or a commercial GPRS segment [see Fig. 8(a)].

The first set of measurements concern the application’s re-
sponse time (i.e., time $T_R$ of Fig. 6) for different types of DI-
COM images (CR, CT, and MR of sizes 262 KB, 525 KB,
and 1 MB, respectively) for different types of compression (no
compression, JPEG compression (with a quality factor of 0.75),
lossless and lossy discrete wavelet compression), for the cases
where either the GPRS or WLAN is the access network. The
corresponding results are depicted in Table IV.

As expected, discrete wavelet compression reduces the actual
medical image downloading time thus improving the response
time for the proposed application.

The aforementioned set of measurements is repeated in the
context of the emulated heterogeneous system [see Fig. 8(b)].
The emulated system is enriched with a DVB-H segment, which
constitutes an emerging access standard for handheld mobile
devices [38]. For the DVB-H radio network, both WLAN and
GPRS have been emulated as return channels separately, and
the corresponding performance results are also separately doc-
umented in Fig. 9.
A first important remark is that the behavior of the emulated system is very close to the actual one for both the cases of GPRS and WLAN networks, indicating both the reliability of the emulation tool and the correctness of the adopted emulation parameters. For example, in the case of an MR image, the overall response times with lossless discrete wavelet compression for emulated GPRS and WLAN networks (see Fig. 9) are 21.2 s and 5 s, whereas in the actual testbed are 22 s and 5.1 s, respectively. Commenting on the rest of the performance results of Fig. 9, the GPRS produces the highest response time (lowest performance) in both cases. The WLAN and DVB-H networks perform much better providing lower response times, whereas the return channel for DVB-H (GPRS and WLAN) does not seem to affect the performance of the latter network.

An additional performance metric of the proposed medical application concerns the ROI transmission time (time $T_{ROI}$ of Fig. 6) for different types of DICOM images (CR, CT, and MR of sizes 262 KB, 525 KB, and 1 MB, respectively) for the three emulated radio access networks (i.e., GPRS, WLAN, DVB-H). The corresponding results are depicted in Table V.

As is expected, again the bandwidth of the access radio network plays the most important role for the specification of the coding time.

The last set of performance measurements concern the signaling overhead produced due to simultaneous user requests. The overhead refers to the “protocol lookup” messages of Fig. 6 (i.e., the sum of times TS). The corresponding results for the three radio access networks (i.e., GPRS, WLAN, DVB-H) are depicted in Fig. 10. The referred experiments have been conducted in order to assess the efficiency and resistance of the picture archiving and communication system platform in simultaneous user requests for image compression and transmission, as in a realistic healthcare environment. The illustrated average time delay for the user request processing increases as the number of requests increase. The depicted signaling delay threshold refers to a level where the server cannot handle all user requests, resulting in time outs and connection errors. This threshold can, however, be increased by using a server with better computing power and memory capabilities.

For GPRS, which is the low-bandwidth network, the signaling overhead per session initialization can reach 1.5 s for 20 simultaneous user requests, whereas the corresponding overheads for WLAN and DVB-H are 1.0 s and 0.9 s, respectively. It is also important to note that a delay larger than 1 s can cause a session initialization timeout. This has to be taken into account for the proper setup of the proposed medical application in the context of heterogeneous radio network settings.

The RMI and HTTP protocols used in the presented platform are Transmission Control Protocol-based; thus, network issues,
like dropped packets during data transmission in the mobile networks, are already addressed. However, additional data error correction or prevention techniques might be applied, either in the application layer (i.e., during image coding) or in lower network levels, depending also on the mobile network technology used. Error control coding is often introduced to reduce the error rates encountered during the transmission of images through a wireless channel. The most common means by which channel coding is accomplished is through equal error protection (EEP) schemes. With EEP, an error control code belonging to a single class is used to protect the entire input data stream. These schemes are suitable in the cases where all the information bits are of equal importance. The hierarchical nature of the proposed wavelet ROI coding suggests the use of an unequal error protection (UEP) scheme that provides a varying amount of error protection according to the importance of transmitted data. In [39] and [40], the UEP is achieved by using rate-compatible punctured convolutional (RCPC) codes and Reed Solomon (RS) codes with different rates, respectively. The authors in [41] propose an alternative UEP scheme, in order to improve the quality of the ROI and to reduce the computational complexity. This method employs two or more codes belonging to two or more different classes, chosen according to the error sensitivity of the compressed multimedia file. A stronger code may be applied on critical data and a weaker code may be applied on the remaining data [42].

The process of estimating the lost piece of data from the received ones is called error concealment. A major advantage compared to the forward error correction (FEC) and Automatic Repeat-request techniques is that it does not require any additional bandwidth. However, error concealment introduces additional computational complexity at the receiver side, and in addition, missing data may not be reconstructed exactly. Significant work performed on image error concealment techniques may be found in literature. The authors in [5] propose an adaptive bicubic error concealment method for subband-coded images. This method can be applied very well to uncompressed images, but there is a need to apply them more realistic experimental scenario. A method for recovering missing blocks for block-based image coders, such as the JPEG is presented in [6]. The authors in [7] present an adaptive maximum a posteriori (MAP) error concealment algorithm for dispersive packetized wavelet-coded images. According to the authors, this method gives PSNR advantages of up to 0.7 dB compared to the competing algorithms. In conjunction to the UEP schema applied during image coding, error resilience may be applied in the network layers.

In the proposed application, different techniques are adopted depending on the utilized underlying network interface (i.e., DVB-H, GPRS/UMTS, WLAN). Regarding DVB-H transmission, an additional stage of FEC, prior to encapsulation, has been added in contrast with conventional DVB transmission systems, named after multiplexing environment (MPE)-FEC [43]. This method allows the streamer to apply a different level or protection on each stream, depending either on the importance of the service, and/or on the reception conditions of the terminal(s) to which the service is targeted. The latter organizes the Internet Protocol (IP) datagrams in a table, and then protects each row of the table with a Reed Solomon overhead. Then, the IP datagrams are encapsulated and transmitted separately from the FEC data.

In the GPRS, a specific QoS profile can be associated to every subscriber on his attachment to the network. This profile contains information like: traffic precedence class, delay class, reliability class, peak throughput, and Mean throughput. Traffic precedence class may be of high, normal, and low priority. Four delay classes and five reliability classes are defined. Nine peak throughput (i.e., 8, 16, 32, 64, 128, 256, 512, 1024, 2048 kb/s) and 19 mean throughput classes (best effort defined at 111 kb/s) are defined. The GPRS QoS profile can either be requested by the mobile user, during a phase known as the PDP context activation, or if no profile is requested, a default one, assigned to the user on his subscription to the network, is being activated [44]. Finally, for the case of the WLAN network interface, in the 802.11b protocol, to our best knowledge, no means of guaranteeing quality of service have been introduced so far. However, the IEEE 802.11e wireless network infrastructure may be used instead, achieving QoS classification between image ROIs and RONIs and achieving faster and more reliable data delivery. The media access control (MAC) protocol of 802.11e uses the hybrid coordination function (HCF), which supports both connection-based and controlled channel access. Contention-based access is supported by the enhanced distributed channel access (EDCA) mechanism, which is an extension of the traditional 802.11b mechanism that enables distributed differentiated access to wireless channel with the support of multiple access categories (ACs). A higher priority access category has a smaller minimum contention window $CW_{\text{min}}$, and thus, has a higher probability to access the channel. Additionally, different access categories can have different maximum contention windows $CW_{\text{max}}$ and interframe spacing intervals (IFSs). The aforementioned parameters ($CW_{\text{min}}$ and $CW_{\text{max}}$) affect clearly the packet transmission time between the intercommunicating wireless nodes.

IV. CONCLUSION

This paper discusses a medical application that enables scalable wavelet-based compression, retrieval, and decompression of DICOM medical images and also supports ROI coding/decoding. The benefits of the proposed image compression
algorithm based on discrete wavelet transformation can be summarized into the following:

1) The algorithm provides low complexity that enables the integration of the decoding process into low processing resources devices, e.g., mobile devices.

2) The algorithm exhibits better compression results (in terms of image size reduction) are produced in case of larger image files [e.g., MR images].

3) Evaluation results indicate low image quality degradation even in the case of lossy image compression, based on RMS, SSIM quality metrics, and perceptual assessment conducted by medical experts.

4) The algorithm provides progressive output stream that enables the reconstruction of the original image at any phase during the encoding and transmission of images.

In addition, the application takes into consideration the special requirements and needs of heterogeneous radio settings constituted by different access technologies [e.g., GPRS/UMTS, WLAN, and DVB-H]. Performance results regarding the usage of the proposed application in the case of a prototype heterogeneous system setup validate both the design and the efficiency of the deployed application. Appropriate error-resilient and error-concealment methods are proposed for each underlying network infrastructure.

The discussed results are quite encouraging for our future plans, where we target to evaluate the proposed application in real-life situations for both measuring actual user acceptance and satisfaction and for also identifying possible improvements. One emerging technical issue can concern the application’s upgrade in order to enable roaming between different radio access networks, improving in this way its performance in terms of response times.

ACKNOWLEDGMENT

The authors wish to thank Dr. C. Michail from Sotiria General Hospital of Athens for the provision of the medical image data sets used in this study, Dr. G. Panagi, Department of Radiology, General Hospital of Chios “Skilitsion,” Chios, Greece, and Dr. G. Karachristos for performing the visual assessment of the compressed images.

REFERENCES


[34] Z. Y. Mai, C. L. Yang, and S. L. Xie, “Improved best prediction mode(s) selection methods based on structural similarity in H.264 I-frame en-
Ilias Maglogiannis (M’00) received the Diploma in electrical and computer engineering and the Ph.D. degree in biomedical engineering and medical informatics from the National Technical University of Athens (NTUA), Athens, Greece, in 1996 and 2000, respectively. From 1996 to 2000, he was a Researcher in the Biomedical Engineering Laboratory, NTUA. Since 2001, he has been a Lecturer in the Department of Information and Communication Systems Engineering, University of the Aegean, Greece. Since 2008, he has been working as a Assistant Professor in the Department of Computer Science and Biomedical Informatics, University of Central Greece, Lamia, Greece. He has been Principal Investigator in many European and national research programs in biomedical engineering and informatics. He has served on program committees of national and international conferences and is a reviewer for several scientific journals. His scientific activities include biomedical engineering, image processing, computer vision and multimedia communications. He is the author of more than 100 publications in the above areas.

Dr. Maglogiannis is a member of the Association for Computing Machinery (ACM), the SPIE, and the Hellenic Association of Biomedical Engineering.

Charalampous Doukas (S’04) received the Diploma in information and communication systems engineering from the University of Aegean, Karlovasi, Samos, Greece, in 2005, where he is currently working toward the Ph.D. degree. He is currently with the Department of Information and Communication Systems, University of Aegean, and is associated with the Information Technology Institute, Athens, Greece, as an External Researcher. His current research interests include video and image processing of medical data, medical ontologies and semantics, and medical data classification and data transmission over heterogeneous networks.

George Kormentzas (A’04–M’04) received the Diploma in electrical and computer engineering and the Ph.D. degree in computer engineering from the National Technical University of Athens (NTUA), Athens, Greece, in 1995 and 2000, respectively. He has been actively working for many years in the area of network management and quality of service of computer and communication systems. He is currently an Assistant Professor in the Department of Information and Communication Systems Engineering, University of Aegean, Karlovasi, Samos, Greece.

His current research interests include the concept of abstract information model, an ancestor of next generation networking middleware.

Dr. Kormentzas is a member of pronounced professional societies, an active reviewer for several journals and conferences, and an EU-Independent Expert for Marie Curie Actions.

Thomas Pliakas (S’03) received the B.Sc. degree from the Department of Electronics, Technological Educational Institute of Crete, Crete, Greece, in 1999, and the M.Sc. degree in electronics engineering from the Department of Electronic Systems Engineering, University of Essex, Colchester, U.K., in 2001. Currently, he is working toward the Ph.D. degree in the Department of Information and Communication Systems Engineering, University of Aegean, Karlovasi, Samos, Greece.

He is also a Research Fellow at the Informatics and Telecommunications Institute, National Centre for Scientific Research “Demokritos,” Athens, Greece. His current research interests include mobile and wireless networking, scalable video coding and transmission, and end-to-end quality of service provisioning.