Joint, Image-Adaptive Compression and Watermarking by GA-Based Wavelet Localization: Optimal Trade-Off between Transmission Time and Security

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Abstract

Teleradiology using internet can offer patients in remote locations the benefit of diagnosis and advice by a super specialist present in a metropolis. However, exchange of vital information such as the clinical images and textual facts in the public network poses challenges of transmission of large volume of data as well as prevention of the distortion of the images. In this paper, a novel application system to jointly compress and watermark the medical images in a near-lossless, image-adaptive adaptive fashion is proposed to address these challenges. The system design uses genetic algorithm for adaptive wavelet coding to generate compressed data and integration of dual watermarks to realize the security and authentication of the compressed data. The GA-based image adaptive compression provides feasible way to obtain optimal compression ratio without compromising the image fidelity upon subsequent watermarking. A multi-gene approach, with one gene coding for the embedding strength of the robust watermark and the other for the number of bits for embedding the semi-fragile watermark is used for optimal image-adaptive watermarking. A multi-parameter fitness function is designed to address the conflicting requirements of image compression, authenticity and integrity associated with teleradiology. Experimental results show the ability of the system to detect tampering and to limit the peak error between the original and the watermarked images. Moreover, as the watermarking is performed on the compressed image, the overhead for watermarking gets reduced.

Keywords: Adaptive Compression, Dual Watermarking, Multi-gene Genetic Algorithm, Multi-objective Fitness Function, Teleradiology.

1. INTRODUCTION

Within the expanding paradigm of medical imaging and wireless communications, there arises an ever increasing demand of fast transmission of diagnostic medical imagery over error-prone wireless communication channels such as those encountered in cellular phone technology. The mobile transmission of such images is prohibitive without the use of image compression to reduce the image size [1]. Therefore, medical images must be compressed to minimize transmission time, and robustly coded to ensure security [2]. This is especially favorable if the end application is teleradiology, because rural areas do not have high bandwidth communication network. The primary challenge of medical image compression is to reduce the data volume and to achieve a low bit rate in the digital representation of radiological images without perceived loss of image quality [3].

To control the amount of information lost during the compression process, a class of algorithms capable of strictly controlling the compression loss has been devised and grouped under term

Near-Lossless Compression, whose main requirement is that of ensuring that the maximum error between the original and the compressed image does not exceed a fixed threshold. In the same line, the concept of near-lossless watermarking has been introduced recently to satisfy the strict requirements for medical image watermarking [4]. Moreover, these techniques do not adaptively arrive at an optimal compression ratio. A single compression technique might not be suitable for all medical images because of their differing noise characteristics. A high compression ratio is preferable for reducing transmission time. But, it is difficult to attain the same compression ratio for an image with low PSNR, because it might degrade the original image, making it difficult for clinical reading. Hence it is necessary to find an optimal trade-off between the image quality and compression ratio. In addition, it is also essential to ensure that the compressed image has sufficient bandwidth to accommodate the watermark payload. This work attempts to investigate, for the first time, the application of GA in achieving an optimal compression ratio for dual watermarking in wavelet domain without degrading the image.

2. GA-BASED IMAGE ADAPTIVE COMPRESSION

Discrete wavelet transform (DWT) has gained extensive interest as a method of information coding [5, 6], due to its ability to decorrelate data effectively. Due to their inherent multiresolution nature, the coefficients of DWT are localized in both spatial and frequency domains, which is highly desired because HVS functions as a bandpass filter with the localization property [7-10]. In contrast to the conventional wavelet transform, the lifting scheme (LS) allows faster implementation of the wavelet transform [11]. In addition, it is better matched to the HVS characteristics. In the context of image authentication through joint coding and watermarking is highly desirable, since otherwise the fragile nature of the watermark will identify image compression as an unwanted manipulation, and will eventually fail to distinguish between compression (allowed) and tampering (not allowed). On the other side, tying the watermarking system to a particular coding format limits the flexibility of the authentication scheme, since the watermark is likely not to survive lossless format changes. It is one of the goals of the algorithm developed in this paper to embed the watermark in the compressed image, while still allowing the recovery of the watermark.

Optimal compression can be measured as sufficient fidelity (~37 dB) of medical images given that an appropriate amount of compression is used [12]. To calculate the error value in the compressed image various parameters like mean square error (MSE), root mean square error (RMSE) may be used. These parameters help to measure the trade-off between image quality and compression ratio (CR), defined as , is used as a relative measure. Here I and IC correspond to the input and compressed images, respectively. CR performs as a good measure for all images, independent of the way they are encoded, because it is only a ratio of the respective image sizes. The activity diagram of the novel joint GA algorithm for optimal compression and watermarking is presented in Fig. 1.

In a general wavelet compression algorithm, an image is decomposed using wavelet transform to obtain LL, HL, LH and HH sub-bands. In the wavelet quantization context, the decorrelation property suggests that processing the coefficients independent of each other and the sparseness (or “heavy-tailedness”) property pave a way to use threshold estimators aimed at removing coefficients that are “small” relative to the noise. The classical choices for performing thresholding of lifting wavelet transform (LWT) coefficients are the hard and soft thresholding functions [6]. However, most of the wavelet thresholding methods suffer from the drawback that the chosen threshold may not match the specific distribution of signal and noise components in different scales.

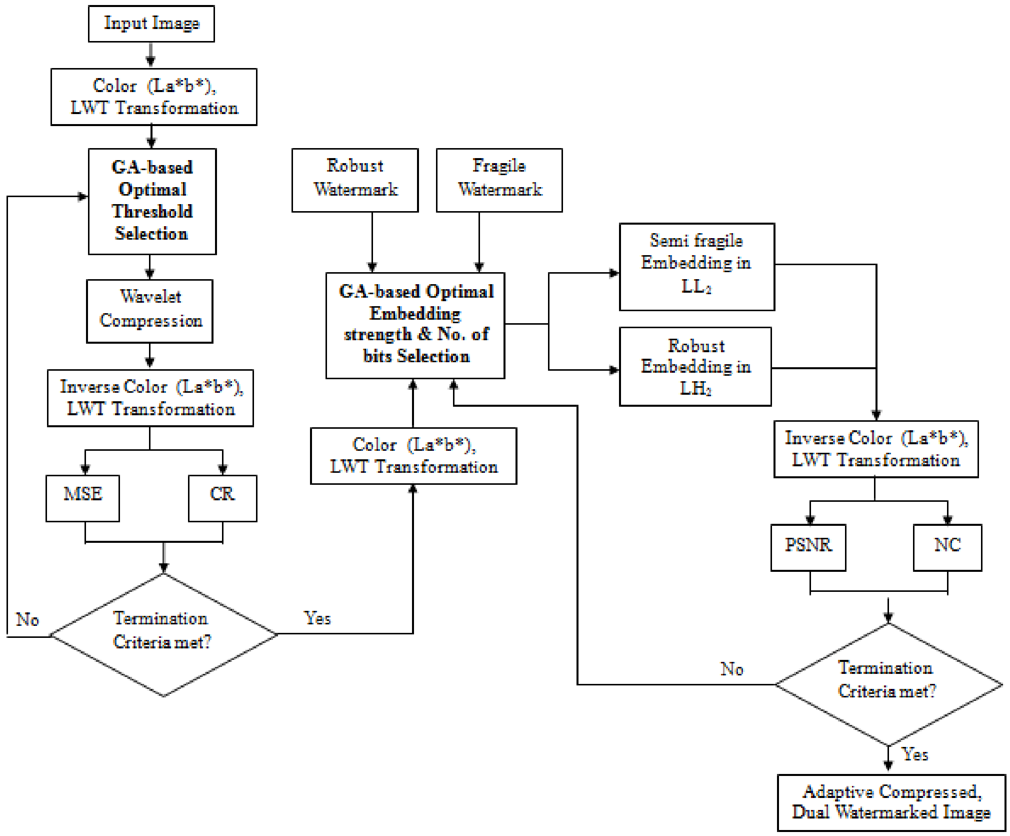


FIGURE 1: Activity Diagram

This is especially so, for medical images where both the PSNR and compression ratio are equally important. To address this problem, adaptive thresholding based on statistical priors of the noise models may be applied as it is done in denoising [13]. But, success of these methods depends upon the exact knowledge of the spectral SNR relationship, which varies with the type of imagery, leading to a case-by-case basis investigation. This motivates the development of robust and versatile compression methods that are capable of universal application, rather than being optimal under very specific condition. An ideal method should perform quantization by intelligently arriving at the level of compression from the images themselves without a priori input information. One such innovative approach is to use GA to optimize the threshold of each sub-band across different scales. Hence, an optimal trade-off between the MSE and compression ratio of medical images forms the basis for the fitness function used in the algorithm developed here..

2.1 Chromosome Encoding

The basic structure of GA revolves around the concept of encoding a solution and evolving successive solutions according to their fitness. In the present work, the genes of a chromosome represent the threshold for a given image. Wavelet threshold values were represented by real-coded chromosome to offer a number of advantages in numerical function optimization over the binary encoding. Efficiency of the GA is increased as there is no need to convert chromosomes to phenotypes before each function evaluation; less memory is required as efficient floating point internal computer representations can be used directly. There is no loss in precision by discretization to binary or other values; and there is greater freedom to use different genetic operators. The chromosome encoding adopted in this work is presented in Fig. 2.

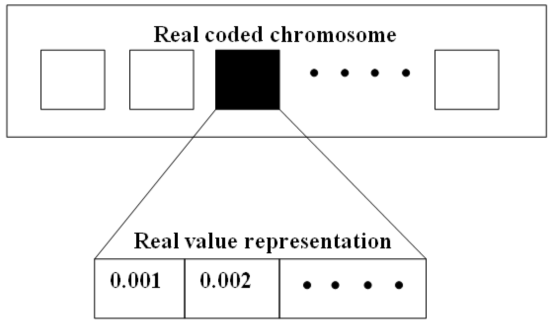


FIGURE 2: Real-coded chromosome for GA-based image adaptive compression.

2.2 Fitness Function

The desired compression of medical images not only aims at achieving a higher compression ratio but also to retain the image quality. Hence the correct choice of threshold is crucial to the performance of a LWT-based compression algorithm. Hence, a multi-objective fitness function may be designed. In the present study, the fitness function is designed to maximize CR while keeping the error metric, MSE low. Such a function is given in Eqn. 1.

$$f = CR - wt * MSE \quad (1)$$

Similarly a multi-objective fitness function for adaptive dual watermarking is designed to maximize PSNR while keeping the NC low. The function is given in Eqn. 2.

$$f = \max(PSNR(I, I_W) - (wt * avg(NC(W_r, W_r^{'}), NC(W_f, W_f^{'})))) \quad (2)$$

Here I_W refers to the watermarked image. Two watermarks W_r (robust) and W_f (semifragile) are embedded in I. The recovered watermarks are represented as $W_r^{'}$ and $W_f^{'}$.

3. RESULTS AND DISCUSSION

For validation of the algorithm, the six test images (Lena and five medical images as shown in Column 1 of Fig. 5) were used. To provide data integrity, an image containing patient name, physician name, hospital logo, date and remark of diagnosis was used as a robust watermark. The size of the semi-fragile watermark was kept small. Hence, a binary image containing the physician's signature was used as the semi-fragile watermark. The watermarks used in this work are presented in Table 1.

	Semi-fragile	Robust
Watermarks		Cadiologist: Dr. Rathinavel Patient Name: Sathish kumar Date: 29/07/07 Remarks: Rheumatic Heart Disease 
Size	64 x 65	56 x 28

TABLE 1: Watermarks Used

The efficiency of GA depends upon tuning of the GA-parameters for specific application. Hence several trials were performed to select optimal GA-parameters. Roulette wheel method was used for selection of chromosomes to the next generation. From extensive experiments, we found the proposed GA-based approach to work well with a single point crossover with a random crossover probability of Pc = 0.4 and a single point mutation with a mutation probability of Pm = 0.05.

3.1 Influence of Population Size on Convergence

To arrive at a suitable population size, experiments were performed using different population sizes with the above mentioned fixed crossover and mutation rates. Experiments were carried out with population sizes ranging from 10 to 150. There is a gradual increase in the fitness function with increase of population size up to 90. Further increase in population size does not show any significant improvement in the fitness function. The computational overhead of different population sizes was also investigated. There is a fast increase in execution time when the population size increases above 50. Based on these results, a population size of 50 was selected as an optimal trade-off

3.2 Halting Condition

The termination condition adopted here is based on both evaluating the progress made by the algorithm in a predefined number of generations (100) or arriving at the average distance between the individuals to be less than 0.01. Similar experiments were done to estimate the GA parameters for dual watermarking of medical images. The various GA parameters thus estimated are collected in Table 2.

Genetic Operator	GA parameters for adaptive compression	GA parameters for adaptive watermarking
Initial population	90 chromosomes	60 chromosomes
Encoding	Real encoding scheme	9 bit encoding scheme
Fitness function	CR and MSE values as in Eqn. 1	PSNR and NC values as in Eqn. 2
Selection	Roulette wheel selection	Roulette wheel selection
Crossover	Single-point crossover with probability 0.4	Two-point crossover with probability 0.5
Mutation	Single-point mutation with probability of 0.05	Single-point mutation with probability of 0.062
Convergence	Convergence to single result or 100 generations	Convergence to single result or 100 generations

TABLE 2:GA Parameters

The compressed images obtained using the GA-based image-adaptive compression is presented for visual evaluation in column 2 of Fig. 3. The quantitative parameters computed are presented in Table 3. The threshold values for different images clearly bring out the scope of the adaptive nature of the proposed algorithm. The threshold value obtained by the proposed algorithm is larger for the standard Lena image. Due to its high image quality, the Lena image is able to withstand a high compression ratio of 80.2:1. Since, medical images are of relatively low PSNR, a higher threshold value may lead to more information loss. The GA-based image adaptive compression algorithm automatically selects a lower threshold when the PSNR of input image is low, thus finding an optimal solution for the two conflicting objectives of fidelity and compression.

3.3 Performance Evaluation

The compressed images should be evaluated for their fitness to watermarking, because our overall aim is speed as well as secure transmission of medical images. Hence, the compressed images were tested whether they can withstand the dual watermarking process without suffering loss of clinical diagnostic reading. Hence, the multi-gene, multi-objective GA-based dual watermarking algorithm was used to watermark the compressed images, given in column 2 of Fig. 3. The visual results (the watermarked images) presented in column 3 of Fig. 3 reveal that, the image fidelity is retained even after compression and dual watermarking.

Image	CR	MSE	RMSE	PSNR	Threshold
Lena	80.2 : 1	4.26	2.06	41.84	20.17
Echo-A	63.7 : 1	3.86	1.96	42.26	9.06
Echo-B	63.2 : 1	3.58	1.89	42.59	8.96
Echo-C	40.2 : 1	4.82	2.20	41.30	5.23
Fundus	62.1 : 1	3.27	1.81	42.99	7.83
fMRI	61.8 : 1	4.21	2.05	41.89	7.21

TABLE 3: Optimal threshold adaptively arrived by the GA-based algorithm.

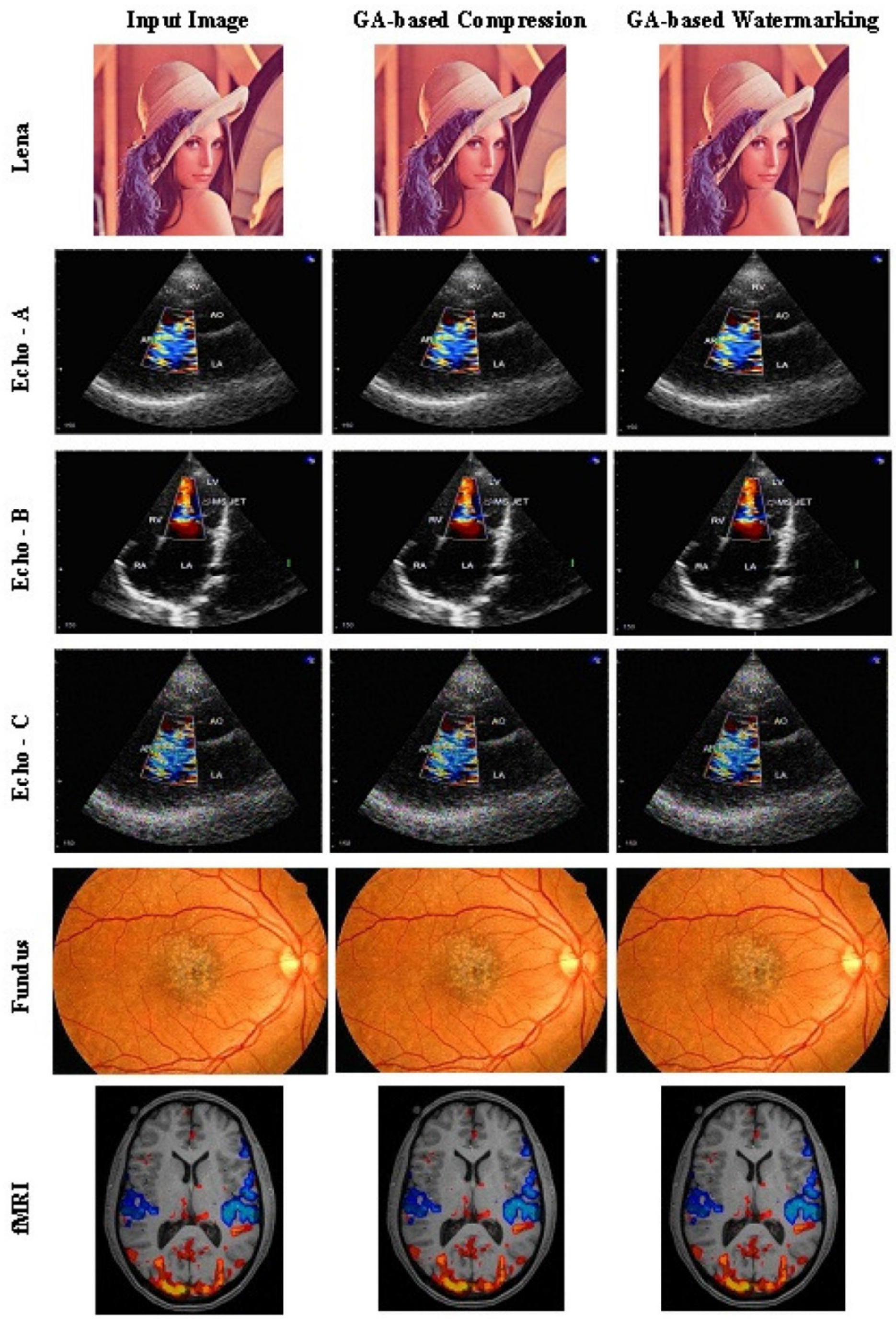


FIGURE 3: Visual comparison of input, compressed and watermarked images

The optimal embedding strength and the number of bits selected by the multi-gene, multi-objective GA are collected in Table 4. The CR values in Table 4 correspond to the compression ratio achieved by GA-based compression approach.

The PSNR values obtained for all images, given in column 3 of Fig. 3 are greater than 37 dB, satisfying the fidelity requirement of medical image watermarking. At the same time, the recovered watermarks from these images result in correlation above 0.85, satisfying the conflicting requirements of fidelity, robustness and image size.

Image	α	No. of bits	PSNR	NC	CR
Lena	0.46	3	39.21	0.92	80.2 : 1
Echo-A	0.22	2	38.62	0.89	63.7 : 1
Echo-B	0.25	2	39.45	0.9	63.2 : 1
Echo-C	0.11	1	37.02	0.85	40.2 : 1
Fundus	0.17	2	39.45	0.89	62.1 : 1
fMRI	0.27	2	38.86	0.89	61.8 : 1

TABLE 4: Watermarking and image quality parameters.

The common approach followed in reducing the transmission time in teleradiology is to compress the watermarked image. But, in this paper, for the first time, a novel algorithm which initially compresses the image by multi-objective GA, and then embeds the watermarks in the compressed image by a multi-gene, multi-objective GA is implemented. It would be of interest to compare these approaches in terms of fidelity and robustness. Such a comparative evaluation is presented in Table 5. Row (a) corresponds to the recovered watermarks (robust and fragile) from the proposed GA-based joint, image-adaptive compression and watermarking algorithm developed in this chapter. Row (b) shows the recovered dual watermarks from the common approach of compressing the watermarked images.Row (a) reveals high NC value for the recovered watermarks and good image fidelity (PSNR > 37dB). But, for the same compression ratio (63.7:1), the recovery of the watermark fails, when the other widely used approach of compressing the watermarked image (Row b).

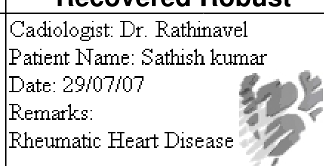
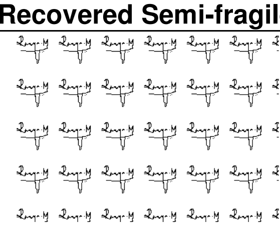
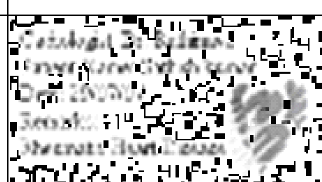
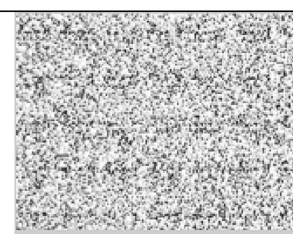
	CR	Recovered Robust	Recovered Semi-fragile	PSNR	NC
(a)	63.7:1			38.62	0.96
(b)	63.7:1			27.64	0.61

TABLE 5: Recovered watermarks (robust and semi-fragile)

These results prove the superior performance and wide ranging significance of the algorithm presented here. There is also an added advantage. Since the watermarking is performed on the compressed image, the overhead for the watermarking process becomes less due to the compactness of the compressed image.

3.3.1 Robustness to Attacks

Five different types of attacks were used to evaluate the robustness of the GA-based algorithm for adaptive watermarking of the adaptively compressed image. The watermarks recovered after various attacks, shown in Table 6, reveal the robust watermark to withstand the attacks like copy, rotation and noise addition. However, the robust watermark does not withstand compression, since further compression of a compact image leads to more information loss, and thus making it difficult for the detector to recover the watermark.

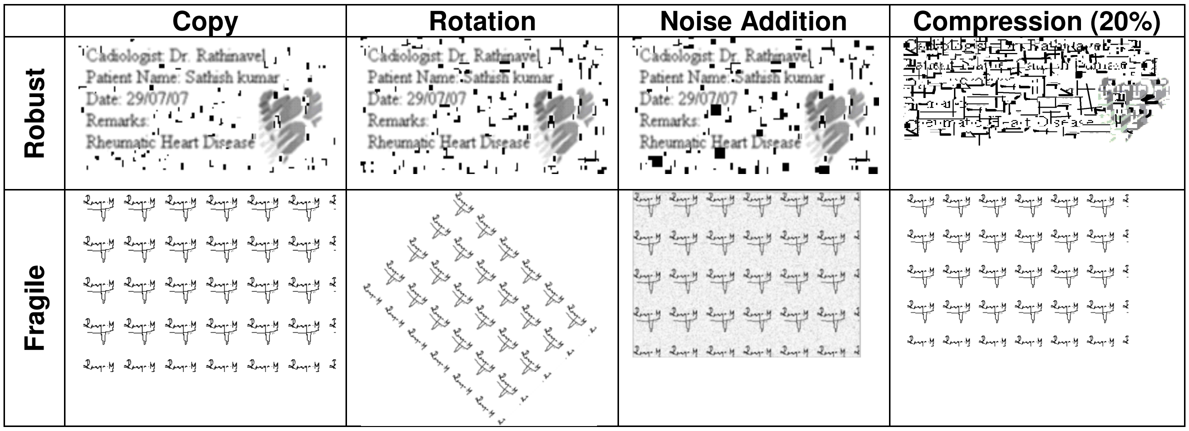


TABLE 6: Recovered watermarks after attacks

3.3.2 Tamper Localization

The semi-fragile watermark embedded in the compressed image can be used to spy the malicious tampering of the watermarked image. The results of tamper localization are shown in Table 7. The three tampering operations (Columns a-c) correspond to malicious drawing, copy paste and cropping attacks. The non-malicious compression (10%) is shown in (d). Rows 1, 2, 3 of columns a-d of Table 7 show the tampered images, recovered watermarks and the tamper localization results, indicating the efficiency of the algorithm for joint compression and dual watermarking. It is interesting to note that the image compression of 10% is not seen as tampering. Thus, the algorithm presented here satisfies many demands of medical image watermarking.

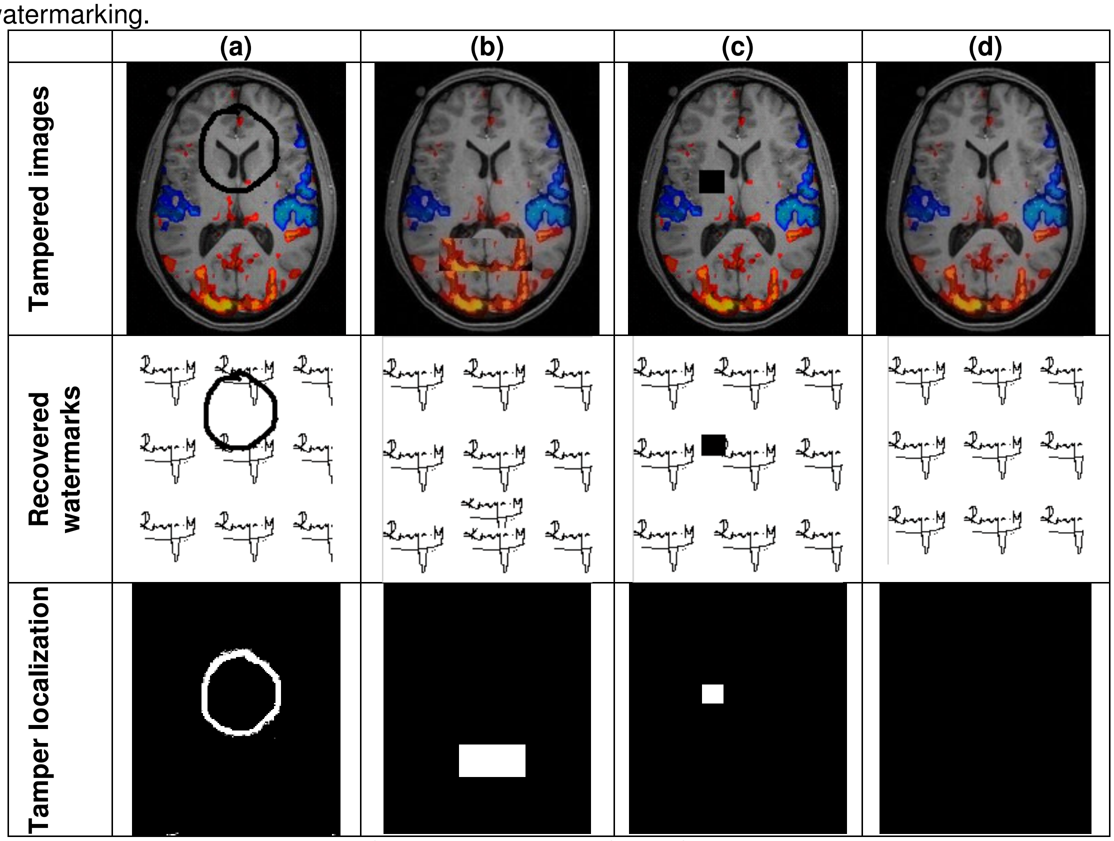


TABLE 7: Performance evaluation of semi-fragile watermarking

3.4 Computational Time

The computational time required for the joint, image-adaptive compression and watermarking algorithm was estimated on an Intel dual core 2 GHz processor with 1 GB RAM. The time taken for compression and watermarking is presented in Table 8. It is interesting to note that, the time required for GA-based dual watermarking algorithm to embed in the uncompressed image is 12.36 min. But, the time taken for the same dual watermarking on the same image after adaptive compression is only 8.58 min. Since the joint image-adaptive compression and watermarking algorithm embeds the dual watermarks in the compressed image, the computational time required for embedding is reduced by 4 min. Though, there is an additional computational overhead of 4.82 min for GA-based image compression, the reduction in size can help improving the transmission time.

Modules	Time taken (min)
GA-based dual watermarking	12.36
GA-based dual watermarking after adaptive compression	8.58

TABLE 8: Computational time

4. CONCLUSION

This paper presents a novel algorithm to enhance the potential of teleradiology by integrating GA-based image adaptive compression with GA-based color image dual watermarking. Two image processing applications, compression and watermarking are coupled to enhance the potential of watermarking in teleradiology, by exploiting the localization property of wavelet transform, using genetic algorithm. The algorithm permits to jointly compress and watermark medical images and at the same time to maintain fidelity of the image. The algorithm is designed in such a way that the compression ratio and watermarking error can be controlled (near lossless compression and optimal watermarking). The results show that the GA-based system can automatically and image-adaptively arrive at optimal compression and watermarking parameters. The application system can readily detect any tampering in the images. While the developed system is tested to work on telemedicine imagery, its use may be extended to other sensitive areas such as remote sensing, military application, video surveillance etc.

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5. REFERENCES

1. J. Strom, P. Cosman. “Medical Image Compression with Lossless Regions of Interest”.Signal Processing.vol. 3, pp.155-171, 1997.

2. M. J. Zukoski, T. Boult, T. Lyriboz. “A Novel Approach to Medical Image Compression”.*Bioinformatics research and applications*, vol. 2, pp. 89-103, 2006.

3. T. Iyriboz*et al.*“A Comparison of Wavelet and JPEG Lossy Compression Methods Applied to Medical Images”. *Journal of Digital Imaging*, vol. 12, pp. 14-17, 1999.

4. K. Chen, T. V. Ramabadran. “Near-Lossless Compression of Medical Image through Entropy-Coded DPCM”.*IEEE Transactions on Medical Imaging*.vol. 13, pp. 538-548, 1994.

5. J. Froment, S. Mallat. “Second Generation Compact Image Coding with Wavelets”.*Wavelets: A Tutorial in Theory and Applications*, New York: Academic Press, 1992.

6. S. Lewis, G. Knowles. “Image Compression Using the2D Wavelet Transform”. *IEEE Transactions on Image Processing*, vol. 1, pp. 244-250, 1992.

7. S. Bhattacharjee, M. Kutter. “Compression Tolerant Image Authentication”.In Proc. of ICIP, 1998, pp. 435-439.

8. M. M. Ramya, R.Bhaskran, R. Murugesan. “GA-based Image Adaptive Watermark Embedding for Optimal Fidelity and Robustness in Medical Images”. *In Proc.of ICICOT*, 2007, pp. 47-52.

9. Y. Ester, T. Kai-Shiang.“HDWT-based Grayscale Watermark for Copyright Protection”.*Expert Systems with Applications*, vol. 35, pp. 301–306, 2008.

10. W. Lin*et al.*“A blind watermarking method using maximum wavelet coefficient quantization”. *Expert systems with Applications*, vol. 36, pp. 11509-11516, 2009.

11. W. Sweldens. “The Lifting Scheme: A Custom-Design Construction of Biorthogonal Wavelets”. *Applied Computational Harmonic Analysis*, vol. 3, pp. 186-200, 1996.

12. F. A. P. Petitcolas. “Watermarking Schemes Evaluation”.*IEEE Signal processing*, vol. 17, pp. 58-64, 2000.

13. M. Vetterli, C. Herley. “Wavelets and Filter Banks: Theory and Design”. *IEEE Transactions on Signal Processing*, vol. 40, pp. 2207-2232, 1992.