System for Efficient and Secure Distribution of Medical Images on the Internet *

James Ze Wang, M.S. and Gio Wiederhold, Ph.D.
Medical Informatics, Stanford University, Stanford, California

Because of the high compressibility of the medical images, data compression is desirable for digital storage despite the availability of inexpensive hardware for mass storage. A progressive transmission algorithm with automatic security filtering features for on-line medical image distribution using Daubechies' wavelets has been developed and is discussed in this paper. The system is practical for real-world applications, processing and coding each 12-bit image of size 512×512 *within 2 seconds on a Pentium Pro. Besides its exceptional speed, the security filter has demonstrated a remarkable accuracy in detecting sensitive textual information within current or digitized previous medical images. The algorithm is of linear run time.*

INTRODUCTION

As more and more advanced medical equipment is used in diagnosis and management of disease, it is becoming increasingly difficult to maintain and retrieve health care information manually. Besides the traditional textual data such as patient reports, health care records are being filled with X-ray images, MRI scans, CT scans, 3-D volume reconstructions, and video streams. Efficient data compression and progressive transmission with security filtering for digital medical images is desirable because of the high compressibility of the medical images and limited bandwidth of the network.

In this paper, we present a wavelet-based lossless medical image compression and progressive transmission algorithm that also detects textual information (including identifying information) from some current or digitized previous medical images. Textual terms not known to be innocuous are eliminated [17]. The resulting processed images can then be made available to medical researchers, second-opinion physicians, students, and other legitimate users after being processed by our algorithm. Such a system may be used by health care institutions and other repositories of medical images as part of a real-time medical image distribution system.

* *Correspondence to:* wangz@cs.stanford.edu

BACKGROUND

Currently, there are many compression and progressive transmission algorithms available. Interested readers are referred to [3, 11, 18]. Progressive transmission algorithms rapidly provide successively better approximations to the input image as the digital data arrives from the network. The progressive property allows users to truncate an image data sequence and still get a reasonably good recovery of the image under this bit rate. Fully embedded compression algorithms generate image data sequences that can be truncated anywhere. Because successive approximation of images solves the conflict of different requirements on image qualities, it is valuable in many applications, especially for medical images because of the wide range of quality requirements in retrieval and diagnosis. GIF89a, a predominant graphics format on the Web, has build-in interlaced progressive transmission and lossless compression algorithms. It is not suitable for medical image transmission due to the high blocky effect introduced in images prior to the last frame.

Since wavelet transforms decompose images into several resolutions, the coefficients, in their own right, form a successive approximation of the original images. Because of this property, wavelet transforms are naturally suited for progressive image compression algorithms. As a result, many current progressive compression algorithms use wavelet transforms as an initial step [12]. This trend became stronger after Shapiro's [12] invention of the zerotree structure for wavelet coefficients. Much subsequent research has taken place based on the zerotree idea, including a very significant improvement made by Said and Pearlman, which is referred to as the S & P algorithm. This algorithm was applied to a large database of mammograms [1, 10] and was shown to be highly efficient using real clinical-quality evaluations. An important characteristic of the S & P algorithm and many other progressive compression algorithms is the encoding and decoding simplicity from the decorrelation of images into different frequency bands brought by the wavelet transforms. No training is needed since trivial scalar quantization of the coefficients is applied in the compression process. However, by sacrificing simplicity, recent research [5] has made improvements on the S & P algorithm by tuning the zerotree structure to specific data.

Before digital medical images in computer-based patient record systems can be distributed online, it is necessary for confidentiality reasons to eliminate patient identification information that appears in the images.

Face and eye detection algorithms [2, 8] are at a mature stage of development in the computer vision community. For photographic medical images, it is necessary to use such an algorithm to detect and eliminate human eyes in order to protect patient privacy. Since the system we are developing deals with radiological images, such an algorithm is not necessary.

With the DICOM standard, it is easy to eliminate textual information such as patient name and ID. However, for digitized films or previous history images, a computerized detection and elimination algorithm is needed. The problem of text identification [9, 13] arises in many applications other than medical security. Document understanding systems locate text and figure captions on a page for processing by optical character recognizers. The detection of text in scanned maps and mechanical, electrical, and piping drawings is important for converting the paper form to computer-analyzable form. Work done by University of Maryland [4, 6] uses neural network, texture and multiresolution analysis to segment the documents into areas of text and areas of image or graphics. However, the algorithms used in such systems are not designed to handle superimposed text because it is difficult to differentiate the edges of text from the edges of the medical objects in the image.

OVERVIEW

In this project, we have developed a wavelet-based progressive lossless compression and transmission algorithm that takes advantage of the Daubechies' wavelet transforms we used in the textual information detection and elimination (TIDE) module of the system. The current implementation of this algorithm is much simpler and hence faster than that of the top-of-the-line algorithms mentioned above. The tradeoff is the recovering image quality at a given bit rate. The quality loss in terms of PSNR (Peak Signal Noise Ratio) compared with the S & P algorithm is within $2dB$. However, our purpose of presenting it is mainly to explain the basic ideas of progressive transmission based on wavelet transforms and to demonstrate an efficient combination of text detection and progressive lossless compression and transmission of digital medical images in our TIDE system.

The TIDE module in the system consists of an efficient and accurate algorithm to distinguish areas with and without textual information in digital or digitized medical images. Areas with text can then be blurred or striped. Because variations in the diagonal directions can be found in almost all Roman characters or Arabic numbers, we use Daubechies' wavelets and analysis techniques to detect the high frequency variation in the diagonal direction that is indicative of text. A mask is used to preserve the losslessness of non-textual areas. With some basic knowledge of the machine used to create the image, we are able to eliminate only sensitive patient identification information while retaining the medical information in the image. Excellent results have been obtained in experiments using a large set of real-world medical images, many with superimposed text.

SYSTEM

We have developed a new progressive transmission algorithm with textual information detection and elimination for digital medical images using Daubechies' wavelet transforms. Figure 1 shows the basic structure of the algorithm.

We apply an N-level fast wavelet transform (FWT) with Daubechies-4 wavelet to each medical image, where N is determined adaptively by the image size. If the image is of DICOM standard, we may eliminate the patient identification information without processing the image content. The wavelet transform code can be directly passed to the progressive transmission and lossless compression coding routine.

For non-DICOM images, we extract and analyze the lower right-hand corners of each level of the transform matrix, where the diagonal directional high frequency information is located, to obtain a mask containing only the areas with textual information. Once such a mask is computed, we apply it to all the high-frequency bands to eliminate the text within areas with textual data. Or, we may apply the mask selectively to all the frequency bands to block the areas with text. Knowledge of the rough location (e.g., which one of four corners) of the critical patient identification information of certain type of medical images or the TIHI (Trusted Interoperation of Health care Information) system [17] is used to eliminate only information needed to be deleted while preserving the rest. When we do not have knowledge of the rough location of patient identification information, we may apply the mask to eliminate all textual information within the medical image.

Then we pass the processed wavelet transform code to a new adaptive progressive transmission and lossless compression coding routine. To achieve progressive secure transmission, we may also apply a PGP encryption [7] to the code segments before sending the data to the TIDE client via public network.

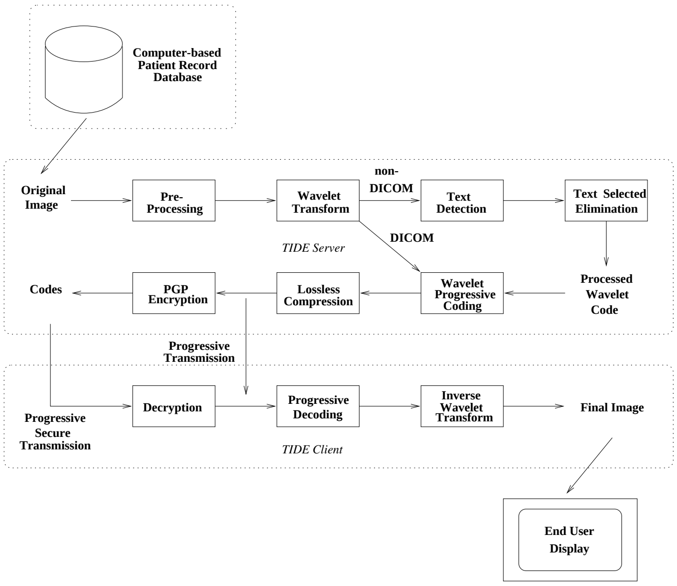


Figure 1: **Basic structure of the algorithm used in TIDE.**

Our text detection algorithm has several immediate advantages.

1. Unlike traditional approaches, such as the neural network, our algorithm does not depend on the actual font size, font type and style of the text in the medical image. Experiments indicate that the algorithm is capable of handling images with superimposed hand-written text and even foreign languages. Figure 5 shows one example with hand-written text.

2. We used Daubechies' wavelets rather than a traditional edge detector to capture the high frequency information in the images. This reduced the dependence of the results on the quality or the sharpness of the images.

3. The algorithm does not rely on the color of the image or the text. It also has minimum dependence on the contrast between text and background objects.

4. It is faster than other algorithms due to our adaptive multiresolution approach.

5. Wavelet-based algorithm using Daubechies' wavelets can be easily integrated with cutting-edge image compression, compressed-domain indexing and processing algorithms.

6. Our wavelet-based compression and progressive transmission algorithm does not have edge artifacts found in many non-wavelet-based compression algorithms.

We compared the performance of the current implementation of our algorithm with one of the best available image compression algorithms on a few common benchmark images. We have achieved comparable results, and we expect the performance to be improved if we take into consideration the cross-band correlation of wavelet coefficients.

Our coding algorithm at the server side are outlined in [14, 15]. The encoding stopping criterion at the server can be specified by the client. Some examples are the number of output bits exceeding a threshold and the distortion of the lossy compressed image being less than a threshold. Because floating point operations are involved in the encoding process of the wavelet transform, we usually cannot get a perfect reconstruction of the original image, although we can make the distortion as small as we want. In the case that perfect reconstruction of the image is required, we can calculate the error image and compress the error image losslessly and transmit it at the end. As the errors are small, the error image is much more losslessly compressible than the original image.

RESULTS

This algorithm has been implemented on a Pentium Pro 200MHz workstation. We have tested about 100 medical images of different modalities, collected from different sources. Some of them are downloaded from the world-wide web and medical imaging newsgroups, while others are provided by the Stanford Medical Center.

Lossless Compression and Progressive Coding Module

The encoding and decoding programs are both very fast. It takes less than 2 seconds of CPU time to fully encode a 512×512 CT scan. The decoder takes about 2 seconds of CPU time to recover to the original image with Mean Squared Error (MSE) less than 3. To fully recover the original image without loss, it takes about 3 seconds of CPU time.

The efficiency of the lossless compression and progressive transmission module in the TIDE system is summarized in Table 1 and Figure 2. Since we used Daubechies continuous wavelet for compression, edge artifact is minimized. When MSE is lower than 3 for an 8-bit image, the distortion is barely noticeable to the human eye.

Modality	CT scan	X-ray	Mammogram	MRI
size/img (bits)	$512^2 \times 8$	$2048^2 \times 8$	$4096^2 \times 12$	$256^2 \times 8$
img/exam	40	2	4	60
size/exam	10 MB	8 MB	128 MB	4 MB
$MSE < 10$	0.07MB (0.7%)	0.10MB (1.3%)	8.65MB (6.7%)	0.22MB (5.5%)
$MSE < 3$	0.56MB (5.6%)	0.61MB (7.6%)	18.6MB (14%)	0.64MB (16%)
$MSE = 0$	4.00MB (40%)	3.73MB (47%)	47.2MB (37%)	1.68MB (42%)

Table 1: Performance of progressive coding in TIDE.

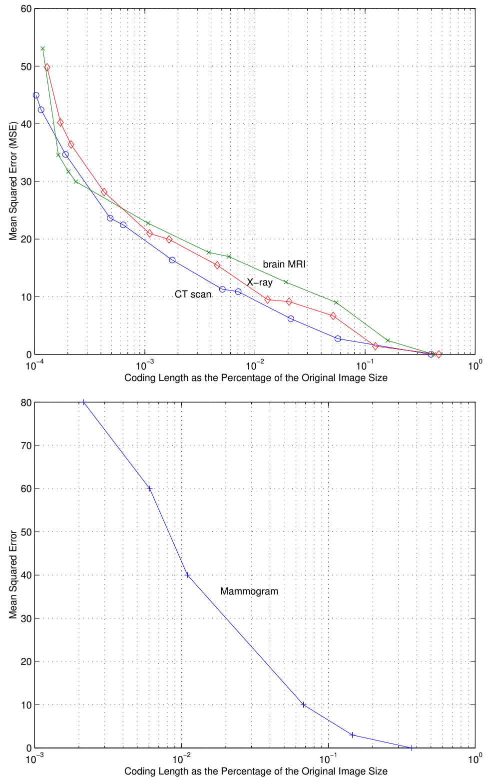
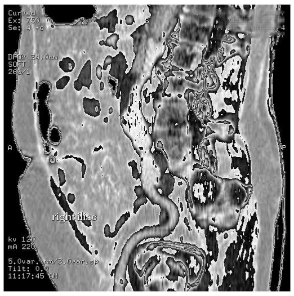
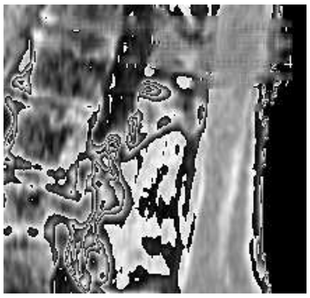


Figure 2: **Progressive lossless compression coding efficiency.** CT scan, chest X-ray and brain MRI images are 8-bit images. Mammogram images are 12 bit images.

Textual Information Detection Module



Full image



Upper-right corner

Figure 3: **Final images after wavelet reconstruction.** After text detection, we use the TIHI process or some other basic knowledge of the location to eliminate any text not known to be innocuous.

The textual information detection and elimination module takes about 1 second of CPU time to process a 12-bit medical image of size 512×512. The algorithm is a linear algorithm with respect to the size of the image. Besides the fast speed, the algorithm has achieved remarkable accuracy. It successfully detected and eliminated all of the critical textual information within the corners of the medical images.

Figure 3, Figure 4 and Figure 5 show some sample results on gray scale medical images processed by the TIDE system. The areas without text are maintained without loss. The alsorithm can also be applied to color medical images.

CONCLUSION

In this paper, we have demonstrated an efficient wavelet-based progressive transmission algorithm with security filtering features for on-line medical image distribution. The algorithm uses Daubechies' wavelets to

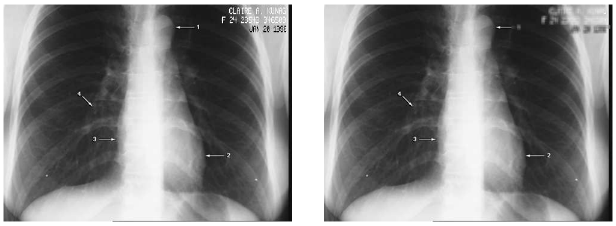


Figure 4: **A chest X-ray image processed by the TIDE system.** Note that patient identity information on the upper-right corner is eliminated while the arrows and annotations within the image are preserved. Text Information simulated.

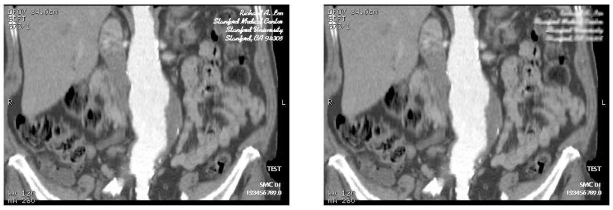


Figure 5: **A medical image with hand-written text processed by the TIDE system.** Text Information simulated.

detect and eliminate textual information within digitized medical images, while maintaining non-textual areas lossless.

The system is practical for real-world applications, processing and coding each 12-bit image of size 512×512 within 2 seconds on a Pentium Pro. Besides its exceptional speed, the security filter has demonstrated a remarkable accuracy in detecting sensitive textual information within digital medical images.

Acknowledgments

We would like to thank Oscar Firschein and Michel Bilello of Stanford University, and Steve Wong of University of California at San Francisco for valuable help and discussions.

References

[1] C. N. Adams et al., Evaluating Quality and Utility of Digital Mammograms and Lossy Compressed Digital Mammograms, *Proc. of the 3rd Int Workshop on Digital Mammography*, Elsevier, pp. 169-176, 1996.

[2] V Bruce and M Burton (eds), *Processing Images of Faces*, Ablex Pub. Corp., N.J., 1992.

[3] C. Chrysafis and A. Ortega, Efficient Context-based Entropy Coding for Lossy Wavelet Image Compression, *Data Compression Conference*, IEEE, UT, March, 1997.

[4] David Doermann, Document Understanding Research at Maryland, *DARPA Image Understanding Workshop Proc.*, 2:817-826, Science Applications, Inc, 1994.

[5] M. Effros, Zerotree Design for Image Compression: Toward Weighted Universal Zerotree Coding, *Proc IEEE Int Conf on Image Processing*, Santa Barbara, Nov 1997.

[6] K Etemad, D Doerman, R Chellappa, Page Segmentation Using Decision Integration and Wavelet Packet Basis, *Proc Int Conf on Pattern Recognition*, IEEE, 1994

[7] Simson Garfinkel *PGP : Pretty Good Privacy*, O'Reilly & Associates, Inc., CA, 1995.

[8] V Govindaraju, Locating Human Faces in Photographs, *Int Journal of Computer Vision*, 19(2):129-146, 1996.

[9] AK Jain et al., Text Segmentation Using Gabor Filters for Automatic Document Processing, *Machine Vision and Applications*, 5:169-184, 1992.

[10] SM Perlmutter et al., Image Quality in Lossy Compressed Digital Mammograms, *Signal Processing, Special Issue on Medical Image Compression*, Elsevier, pp. 189-210, 1997.

[11] A Said and WA Pearlman, An Image Multiresolution Representation for Lossless and Lossy Image Compression, *IEEE Trans. on Image Processing*, 5:1303-1310, 1996.

[12] Jerome M. Shapiro, Embedded Image Coding Using Zerotrees of Wavelet Coefficients, *IEEE Trans. on Signal Processing*, 41(12):3445-3462, 1993.

[13] Yuan Y. Tang et al., Quadratic Spline Wavelet Approach to Automatic Extraction of Baseline from Document Images, *Proc. 4th Int Conf on Document Analysis and Recognition*, IEEE, August 1997.

[14] James Ze Wang et al., Texual Information Detection and Elimination System for Secure Medical Image Distribution, Proc. 1997 AMIA, Tennessee, October 1997.

[15] James Ze Wang et al., Wavelet-based Progressive Transmission and Security Filtering for Medical Image Distribution, *Advances in Biomedical Image Databases*, S. Wong (Ed.), Kluwer, to appear, 1998.

[16] Gio Wiederhold, Interoperation, Mediation, and Ontologies, *Workshop on Heterogeneous Cooperative Knowledge-Bases*, Vol.W3, pages 33-48, ICOT, Tokyo, Japan, Dec. 1994.

[17] Gio Wiederhold, Michel Bilello, Vatsala Sarathy, XiaoLei Qian, A Security Mediator for Health Care Information, *Proceedings of the 1996 AMIA Conference*, Washington DC, Oct. 1996, pp.120-124.

[18] STC Wong, L Zaremba, D Gooden, HK Huang, Radiologic Image Compression, *Special issue of Proc. IEEE on Image and Video Compression*, 83(2):194-219, 1995.