Symmetry-Based Biomedical Image Compression

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Abstract Image compression techniques aim at reducing the amount of data needed to accurately represent an image, such that the image can be economically transmitted or archived. This paper deals with employing symmetry as a parameter for compression of biomedical images. The approach presented in this paper offers great potential in complete lossless compression of the biomedical image under consideration, with the reconstructed image being mathematically identical to the original image. The method comprises getting rid of the redundant data and encoding the non-redundant data for the purpose of regenerating the image at the receiver section without any observable change in the image data.

Keywords Symmetry · Biomedical image compression · Redundancy · Diagnostic ability

Introduction

The area of medical imaging involves a vast amount of data which is generated at a very rapid pace and has to be handled with utmost care because of the importance associated with a medical image. The problem with medical images is that they are large in size, so large amount of bandwidth is required to send and receive images. Large amount of data is generated by a total of 20 scanners of different types such as nuclear, magnetic resonance imaging (MRI), computed tomography (CT),

positron emission tomography (PET), computed radiography (CR), etc. A medium scale hospital with the above facilities produces on an average 5 to 15 GB of data per day [1–3]. To meet the demand for high-speed transmission of images, efficient image storage, and remote treatment, an efficient image compression technique is essential.

The importance of medical images increases in manifold when one needs to consider the case of telemedicine wherein the doctor is not present to treat the patient but has to rely on the medical image in front of him/her to make the right decision for the patient. Compression in case of medical images is thus a sensitive issue where loss of data cannot be tolerated at any cost. Thus, it is a challenging task to achieve satisfactory amount of compression without losing any content of the image and maintaining the diagnostic ability of the image.

Motivation was drawn from the fact that applications of biomedical image compression can be tremendous in Telemedicine. They can further help in providing medical facilities to people who are not able to access proper medical help directly but which can be made available to them through Telemedicine. The amount of medical data is huge, and the transmission of huge amounts of data is both costly and time-consuming. To remove these bottlenecks and to make the Telemedicine system efficient, it is necessary to compress this data using a lossless compression technique, which is presented in this paper.

The limitations of the transmission media in Information and Communication Technology (ICT), especially for rural areas, present a challenge to the success of telemedicine. Lossless compression ensures complete data fidelity after reconstruction, but the compression ratio (size of the output stream/size of the input stream) (Cr) is limited in general from 0.5 to 0.35. The lossy techniques can provide less than 0.10 compression ratio (more compression as compared with lossless technique), but are not generally used. This is due to the possible loss of useful clinical information which may

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adversely influence diagnosis. In addition to these reasons, there can be legal issues [4].

DICOM (Digital Imaging and Communications in Medicine) is a standard for handling, storing, printing, and transmitting information in medical imaging. It includes a file format definition and a network communications protocol. DICOM format has a header which contains information about the image, imaging modality, and information about patient [5, 6]. To compress such a DICOM file, special attention should be given to header information that contains vital data.

Compression used for DICOM format is JPEG, JPEG-LS, RLE, and JPEG 2000, depending on the requirement, i.e., image type [5]. It is distinct from lossless JPEG, ISO 14495–1/ITU T.87, based on HP LOCO-I (“Low Complexity Lossless Compression for Images”) used in Mars Spirit Rover [3].

Symmetry Concept and Compression

In geometry, symmetry is exact similarity of position or forms about a given point, line, or plane. From the above definition, it can be concluded that the extraction of symmetry axis is possible only for intrinsically symmetrical objects. In fact, even for symmetrical objects, perfect symmetry is impossible to obtain in digital imaging due to imperfect lighting, digitization, or occlusion [7]. Human body naturally has approximate mirror symmetry. There are some examples of human body organs which possess bilateral symmetry like axial view of brain, pupil, labia, cervical, lumbar, chest, thorax, larynx, lungs, etc. All the above mentioned body parts exhibit more or

less symmetry. An example of the symmetry exhibited in human brain is as shown in the Fig. 1.

The above medical image, which is symmetric about vertical axis (by crude observation), presents an opportunity to compress it, using symmetry as a parameter. The image data present in both halves of this image is almost equal, barring a few pixels. Thus, if data from only a single half along with differential information of other half is transmitted, instead of transmitting both halves, then substantial amount of compression can be achieved. The first task is to obtain the dominant axis of symmetry for any kind of image. The axis will act as a differentiating detail between the two halves of the medical image.

As seen in Fig. 2, it is clear that if symmetry is used as a parameter most of the redundancy is removed. Note that for complete lossless compression process one needs to preserve the residual part of the subtraction process. The first task is to obtain the axis of symmetry for any kind of image and that too without any error. This axis will act as a differentiator between the two halves of the medical image.

Proposed Work

The algorithm used in this case is compatible with medical images having any rotation, i.e., orientation. The biomedical image in any format, preferably DICOM format, is applied to the algorithm. There is a need to find the axis of symmetry for further processing, for compressing the image using symmetry as a parameter. The main challenge is to find the axis of symmetry (as shown in blue color in Fig. 3) of actual image object (the main informative part excluding background) and not the geometrical axis (as shown in red color in Fig. 3). The actual object of image may not lie on the central geometrical axis, also it may have small angle with respect to the central geometrical axis. The Huffman coding is used for the purpose of source encoding. The block diagram is as shown in the Fig. 4.

Encoding Stage

Algorithm

1. Read the image and check for size, if odd*odd keep it as it is else make it odd*odd. This step is necessary because one needs to extract the axis of symmetry and align it along the diagonal which will be present only if the dimensions are odd.
2. Apply image to symmetry module to get axis of symmetry. The SIFT (Scale Invariant Feature

Fig. 1 Symmetric biomedical image of human brain. **a** actual left part, **b** actual right part, **c** flip of left part, **d** right-flip of left, **e** symmetry processed image

Fig. 2 The concept of symmetry processing

Transform) [8] operator is used here and based on the feature points obtained from this algorithm, the axis of symmetry is determined. It is not necessary to use scale invariant techniques however they can be employed if need be. The scale-based technique basically is used to limit the number of symmetric matches for a particular feature vector. A set of feature points p_i are determined using any rotationally invariant method, such as SIFT [8], which detects distinctive points with good repeatability. The point vector $p_i = (x_i, y_i, i, s_i)$ is assigned to each feature and stores the information such as the location coordinates, orientation, and scaling data. A set of mirrored feature descriptors is generated. Here, m_i describes a mirrored version of the image patch associated with feature vector k_i .

The mirrored feature descriptors m_i can be generated in one of two ways. The simplest way, which allows the feature detection and matching to be treated entirely as a “black box”, is to flip the original image about the y (or x) axis and compute the feature point descriptors for the mirrored image.

Each mirrored feature point can then be assigned to the corresponding feature point in the original image, so that m_i is the mirrored version of the vector K_i . The second, more efficient yet slightly more involved, approach requires knowledge of the configuration of the feature descriptor k_i and generates the mirrored feature points m_i by directly modifying this feature descriptor. For example, in the case of Lowe’s SIFT descriptor [8], this can be achieved simply by reordering the elements of the descriptor vector so they represent the original image patch flipped about the axis aligned with the dominant orientation. Matches are then sort between the features k_i and the mirrored features m_i to form a set of (p_i, p_i) pairs of potentially symmetric features. Figure 5 shows a schematic of the process of extracting and matching a pair of symmetric features from an image. Each pair of symmetric features generates two matching pairs, but as these matches are equivalent, only one need be recorded. The symmetry of each pair is quantified as a function of the relative location, orientation, and scale of p_i and p_i .

$$\Phi_{ij} = 1 - \cos(\Phi_i + \Phi_j - 2\theta_{ij}) \quad (1)$$

Where the angles are defined as shown in Fig. 6. A scale weighting $s_{ij} \in [0, 1]$ quantifying the relative similarity in scale of the two vectors is computed as

$$S_{ij} = \exp\left(\frac{-|S_i - S_j|}{\sigma_s S_i - S_j}\right)^2 \quad (2)$$

Where σ_s controls the amount of scale variation accepted,

Fig. 3 Geometric axis and object symmetry axis

Fig. 4 Block diagram of proposed work

$\sigma_s = 1$ was used in our experiments.

There might be multiple axes possible in single image, but only one will be accepted as a major axis of symmetry. Matching pairs that are closer to the symmetry axis are taken in to consideration. This agrees with psychophysical findings that symmetric features close to the symmetry axis contribute more to human symmetry perception than features further away.

There are numerous ways to measure the similarity between feature vectors, the Euclidean distance between the SIFT descriptors has been used for this purpose.

3. After getting axis of symmetry, calculate slope of symmetry axis so that the inclination of axis from x -

axis in terms of angle “theta” can be found. It would then be possible to calculate angle X by which the image is to be rotated, so that the axis of symmetry can be aligned with the diagonal of matrix, i.e., at 45 degree. The need for aligning the axis along the diagonal is to apply the zig-zag algorithm (vertical raster scan within the lower triangle and upper triangle is scanned with a conventional horizontal raster scan) to the image and to store the two halves of the image in separate vectors. Also, the effect of interpolation effect while rotating the image at particular angle is minimum. Since the image is processed in matrix form where columns and rows are used to describe the image, the processing of subtraction of one symmetric part from other will be much difficult if the axis of

Fig. 5 Schematic illustrating the extraction and matching of a pair of symmetric features [8]

Fig. 6 A pair of point vectors p_i and p_j under scrutiny for mirror symmetry [8]

symmetry is inclined. Further steps will shed more light on this aspect.

4. Lets us see how the arraignment of pixels is done after detecting the axis of symmetry, let A the image with 5 pixel in row and 5 pixel in Colum (5×5 Pixel Image).
5. Zig-zag technique is used for the conversion of an image-matrix to a vector. The zig-zag encoding is vital for this algorithm because the basis of this algorithm is the separation of image into two halves based on the axis of symmetry and storing these two halves into different vectors can be achieved through zig-zag encoding. Figure 7 given below shows how a matrix is mapped into a vector by using zig-zag encoding technique. Keeping lower triangular elements as it is in Fig. 7 and subtracting upper triangular elements from lower triangular elements the subtracted vector is obtained. The lower triangular elements are traced as 6-11-16-21-12-17-22-18-23-24. Also, upper triangular elements are traced as 2-3-4-5-8-9-10-14-15-20.
6. Array 1 containing lower half elements and diagonal. Array 2 containing subtraction elements are obtained. The one dimensional vector is rearranged to form an image matrix as shown in Fig. 2e to form symmetry processed image. The choice of encoding technique is of utmost important when implementing any of the

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

Fig. 7 5×5 matrix representing image Now axis is 1-7-13-19-25

compression algorithms. The encoding method should be elegant, less complex and fast, and should give accurate results [9]. In case of medical images, the required feature is that the technique must be lossless and optimized for the removal of symmetric redundancies, as is presented in this algorithm. Initially, the arithmetic encoder is implemented which suits the needs of the above task at hand. Any other encoding technique may be used, as the compression ratios for different techniques are different for various formats [10].

Arithmetic encoder is used which is more efficient than normal encoders like RLE in terms of higher compression ratios. For medical images, Huffman is comparable in terms of compression ratio as compared with Arithmetic encoder. But now data is changed as seen in Fig. 2e (compared with Fig. 1), the half part of image along with residual part of rest half after subtraction. So, comparison between Huffman and Arithmetic encoder is done to find the better method among them.

7. At the decoding stage, the same steps are reversed and the original biomedical image is reconstructed without any loss.

The first step is to find out the feature points from the medical image using the Scale Invariant Feature transform and compute the axis of symmetry from the feature points.

Experimental Results

The Fig. 8a shows the sample MRI scan of the human. It is a DICOM image in unit 16 (16 bit). All the processing however is done considering unit 16 format. Figure. 8b shows all the feature points that have been detected in the sample MRI images. The number of feature points is large and it is necessary to filter out the matching feature points from them

The mirrored feature points are as shown in the Fig. 8c. These are extracted from the complete set of feature points found out by using the SIFT algorithm. The feature vectors which are having similar orientations [8] are noted down or observed as being matched pair of vectors. The orientations of the feature points are compared considering the values stored in the feature vectors.

A number of axes are computed from the matching key feature points and are displayed in the above Fig. 8d. Further, the major axes are extracted from the set. This can be done by using a straight line passing through major number of axes. The Hough transform is used for the purpose of finding out the strongest axis from the complete set of axes found out from the matching set of features. Each symmetric pair (P_i ,

Fig. 8 Various stages of symmetry processing. **a** MRI sample image, **b** Feature points, **c** mirrored feature points, **d** axes of symmetry, and **e** major axis of symmetry

Table 1 Compression ratio comparison between symmetry-based compression and other encoders

(Ten images in each type)		Average compression ratio			
Sr No	Name of type	Only arithmetic encoder	Symmetry+Arithmetic	Only Huffman	Symmetry+Huffman
1	CT-abdomen	0.64357	0.56761	0.485414	0.42882
2	CT-head	0.74669	0.64839	0.562288	0.49331
3	CT-neck	0.75135	0.67035	0.563801	0.50961
4	CT-spine	0.77232	0.67635	0.582679	0.51519
5	MR-abdomen	0.57283	0.5366	0.426529	0.42240
6	MR-head	0.4750	0.4475	0.35847	0.31028
7	MR-pelvic	0.55055	0.52208	0.415903	0.39943
8	X-lumber	1.06	0.9423	0.7103	0.54493

P_j) casts a vote in Hough space weighted by its symmetry magnitude m_{ij} . The resulting Hough space is blurred with a Gaussian and the maxima extracted and taken to describe the dominant symmetry axes. Once the major axis is computed as shown in Fig. 8e, the further processing is done on the image considering the two halves formed by the major axis of symmetry.

Result Table

The algorithm is tested and verified on more than 500 MRI/CT/Ultra Sound/X-Ray, DICOM images (available from private domain database as well as from public domain images) [11–13], few of the representative images from database are shown in Fig. 10. The developed method is used as one of the pre-processing blocks along with standard compression algorithms like Huffman coding, Arithmetic coding, and JPEG-lossless (LS), and the results are presented in Tables 1 and 2.

Observations

- From Fig. 2, it is clear that using symmetry as a parameter one can get lossless compression up to 50 %. From Table 1, it is clear that for CT images using symmetry as a pre-processing block, compression ratio of traditional arithmetic concoder is enhanced by 12 % and compression ratio of Huffman encoder is enhanced by 11 %. Also, for MRI images, an average of 7 % improvement (decrease) is observed. It is clear that even after symmetry processing the Huffman encoder is better than arithmetic encoder. Hence, Huffman encoder is selected as source encoder hereafter.
- From Table 2, it is observed that using symmetry as a pre-processing block, compression ratio is enhanced by 47 % as compared to traditional JPEG lossless encoder and by 81 % as compared to JPEG 2000 LS standard.
- The enhancement in performance of well-known standard algorithm with the use of symmetry pre-processing block is due to the fact that, by using symmetry pre-processing

Table 2 Compression ratio analysis for symmetry processed image

Sr No	Image type	Size of original image (KB)	Compression ratio			
			Only JPEG-LS	Symmetry+JPEG-LS	Only JPEG –2000-LS	Symmetry+JPEG2000-LS
1	CT_Abdomin	520	0.3211	0.2288	0.2519	0.1040
2	CT_Head	520	0.4980	0.2096	0.4423	0.0934
3	CT_Spine	520	0.4576	0.1857	0.3807	0.0815
4	MRI_Pelvic	130	0.3969	0.2792	0.3353	0.1476
5	MRI_Brain	130	0.3846	0.3515	0.3530	0.1461
6	CT_Chest	514	0.3287	0.1488	0.2704	0.0647
7	MRI_Dental	514	0.5797	0.3073	0.5175	0.1459
8	MRI_Chest	563	0.4280	0.0563	0.3300	0.0266
	Average	0.4243	0.2209	0.3602	0.1012	

Fig. 9 Major axis of symmetry for rotated images. **a** Original image and **b** dominant symmetry axis

nearly 50 % of the image portion is carrying lower intensity pixels (near to “0”).

Discussion

The results show that the symmetry-based compression approach gives better compression ratios as compared to the standalone Huffman compression method. The technique is completely lossless and hence the diagnostic ability of the image is fully retained. The compression ratios are approximately 11 % enhanced as compared to those achieved when only the encoding technique (Huffman) is applied. The timing complexity is somewhat increased; however, as compared to that of a standalone encoding technique, where an Huffman algorithm takes 15 s for execution, the symmetry plus

Huffman algorithm takes 18 s approximately (for 512×512 size, 16 bit images). Thus, higher compression ratios are obtained but at a cost of slightly higher time of processing.

The symmetry hence proves to be an important parameter which can be exploited for achieving greater compression while at the same time not compromising with the data quality. The symmetry-based technique can be further used with other encoding schemes for higher compression ratios. In case of this algorithm, half of the image is compressed directly if it is completely symmetric and due to application of encoding technique further compression is achieved. The more the symmetric elements in an image, the higher is the compression. The algorithm mentioned in this paper is better as it works for any orientation of the medical image, i.e., even if the image is slightly rotated as in Fig. 9, it is possible to find the axis of symmetry and then use it to achieve compression. As wavelet transform is not used anywhere in this algorithm as is the case

L1: Abdomen MRI, L2: Brain MRI, L3: Other Organ CT, L4: Brain, L5: Ultra Sound, L6: Brain Bmp, L7: Other Organ, L8: Other Organ, L9: Hand X-Ray, L10: Chest X-Ray

Fig. 10 Few representative images in database. L1; abdomen MRI, L2; brain MRI, L3; other organ CT, L4; brain, L5; ultra sound, L6; brain Bmp, L7; other organ, L8; other organ, L9; hand x-ray, L10; chest x-ray

with some other similar algorithms (Fig. 10) [14, 15]. The complexity of developed method is less as compared to algorithm mentioned in [15].

Conclusions

This approach provides a practical tool for efficiently compressing an image based on the symmetry redundancy present in the image. The algorithm has been modified in such a way that the symmetry redundancy removal and the encoding both complement each other and thus the entire image is stored in less than 10 % of the memory requirement of the original image. The use of the presented method can also be extended for application in volumetric medical images. Study of medical image data available from various hospitals and improvement in algorithm to accommodate as many types of medical images as possible can be further work possible.

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References

1. Miaou S-G, Ke F-S, Chen S-C: A lossless compression method for medical image sequences using JPEG-LS and interframe coding". *IEEE Trans Inform Technol Biomed* 13(5):818–821, 2009
2. Giuseppe Placidi, "Adaptive Compression Algorithm From Projections: Application On Medical Greyscale Images", *Journal of Computers in Biology and Medicine*, Elsevier Publication, Vol 39, pp 993 – 999, 2009
3. 'DICOM Traffic Performance and WAAS Application Deployment Guide', <http://www.cisco.com> accessed on Dec 2011.
4. David S, Giovanni M: "Handbook of Data Compression", 5th edition. Springer, London, 2010, pp 1–51
5. Digital Imaging and Communications in Medicine (DICOM), Part 5: Data Structures and Encoding PS3.5, 2014 b, <http://medical.nema.org/standard.html> as accessed in October 2014.
6. V K Bairagi, A M Sapkal, "Texture Based Medical Image Compression", *Springer Journal of Digital Imaging*, Vol 20, No 1, pp 65–71, Jan 2013
7. Schmid-Saugeon P: Symmetry axis computation for almost-symmetrical and asymmetrical objects: application to pigmented skin lesions". *Med Image Anal* 4(3):269–282, 2000
8. Gareth Loy and Jan-Olof Eklundh, "Detecting Symmetry and Symmetric Constellations of Features", *Proc. Intl Conf. ECCV*, Part II, LNCS 3952, pp. 508–521, 2006.
9. V K Bairagi, A M Sapkal, "Automated Region Based Hybrid Compression for DICOM MRI Images for Telemedicine Applications", *The IET Science, Measurement & Technology*, Vol 6, No 4, pp. 247 – 253, July 2012
10. V K Bairagi, A M Sapkal, M S Gaikwad, "The Role of Transforms in Image Compression", *Springer Journal of Institute of Engineers (India)*, Series B., Vol 94, No 2, pp 135–140, June 2013
11. The Whole Brain – Atlas [Online]. Available, <http://www.med.harvard.edu/AANLIB/home.htm>. accessed Dec 2011
12. Computer vision group [Online]. Available, <http://decsai.ugr.es/cvg/index2.php>. accessed Aug 2011
13. The National Library of Medicine (NLM) [Online]. Available, <http://www.nlm.nih.gov>. accessed Jul 2011.
14. Sanchez V, Abugharbieh R, Nasiopoulos P: Symmetry-based scalable lossless compression of 3D medical image data". *IEEE Trans Med Imaging* 28(7):1062–1072, 2009
15. V. Sanchez, R. Abugharbieh and P. Nasiopoulos, "3D scalable lossless compression of medical images based on global and local symmetries", *Proc. 16th IEEE Intl Conf. ICIP*, pp. 2525–2528, Nov 2009.