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Contour extraction for medical images using bit-plane and gray level decomposition

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ABSTRACT

In this paper we have implemented a contour extraction and compression from digital medical image (X-ray & CT scan) and is proposed by using the most significant bit (MSB), maximum gray level (MGL), discrete cosine transform (DCT), and discrete wavelet transform (DWT). Transforms depend on different methods of contour extraction like Sobel, Canny and SSPCE (single step parallel contour extraction) methods. To remove the noise from the medical image the pre-processing stage (filtering by median & enhancement by linear contrast stretch) is performed. The extracted contour is compressed using well-known method (Ramer). Experimental results and analysis show that proposed algorithm is trustworthy in establishing the ownership. Signal-to-noise ratio (SNR), mean square error (MSE), and compression ratio (CR) values obtained from MSB, MGL, DCT & DWT methods are compared. Experimental results show that the contours of the original medical image can be extracted easily with few contour points at high compression exceeded to 87% in some cases. The simplicity of the method with accepted level of the reconstruction is the main advantage of the proposed algorithm. The results indicate that this method improves the contrast of medical images and can help with better diagnosis after contour extraction. This proposed method is very useful for real time application.

Keywords: bit-planes and Gray level decomposition; contour edge extraction and compression; image compression; DCT; DWT;

1. INTRODUCTION

In the recent years, a huge amount of digital information is circuiting through all over the world by means of the World-Wide Web. Most of this data is exposed and can be easily forged or corrupted. The need for intellectual property rights protection arises. Use of multimedia technology and computer networking is all over the world. Image resolution enhancement is the process of manipulating an image so that resultant image is good quality image. Image enhancement can be done in various domains. The conventional method using Bit-plane decomposition [1], gives an image that is better in visual quality and PSNR parameters. For much better resolution of an image, a new proposed method, which uses Gray-level decomposition, is employed and the result will be compared with the existing methods. Medical image contour extraction based on most significant bit / maximum gray level has been proposed as one of the possible ways to deal with this problem, to keep information safe. Feature extraction approach in medical imaging (i.e. magnetic resonance imaging MRI, computed tomography CT, and X-ray) is very important in order to perform diagnostic image analysis [2]. Edge detection reduces the amount of data and filters out useless information, while protecting the important structural properties in an image [3]. The extraction contours of digital data have become very popular approach for reduction data. Several contour compression techniques were developed and a large amount of methods were proposed, but still the most of known methods to compress the contours is Ramer [4] which is has high quality compared with others like Centroid [5], Triangle [6, 7], and Trapezoid [8, 9] methods. The contour can be extracted from binary image using single step parallel contour extraction (SSPCE) method [10, 11], or simply used Sobel & Canny edge detectors [12-14].

2. THE ANALYSED ALGORITHM

Figure 1 shows a sequence of steps which are to be followed before contour compression from the CT /X-ray images. When CT / X-ray images are viewed on computer screen, they look like black and white but in actual they contain some primary colors (RGB) content. So, for further processing of these image, it must be converted to perfect grayscale image in which the red, green and blue components all have equal intensity in RGB space. The pre-processing step is required for Gray-level decomposition for efficient and accurate calculation of edges from the medical images. This step is carried out to improve the quality of the image to make it ready for further processing. This improved and enhanced image will help in detecting edges and improving the quality of the overall image. Edge detector step is using for contour extraction. Finally, the extracted contours can be compressed using well-known method Ramer with different threshold values.

3. PRE-PROCESSING STAGE

This stage is very necessary when the gray level decomposition has been used. Usually the medical images are captured with some undesired components and hence the median filter can remove it. In this work the medical images (CT scan or X-ray) captured in foggy weather conditions get highly degraded due to suffering from poor contrast and loss of color characteristics [15]. This task uses a contrast enhancement algorithm for such degraded medical color images to obtained the contour extraction with high quality and later with good compression. Besides proposed method being simple, experimental results show that the proposed method is very effective in contrast and color of image after resizing to 256 X 256 medical pixels to be given in 8bit/pixel (bpp) precision. Each pixel has a gray value between 0 and 255 For example, dark pixel may have a value of 10 and a bright pixel might have a value of 230.

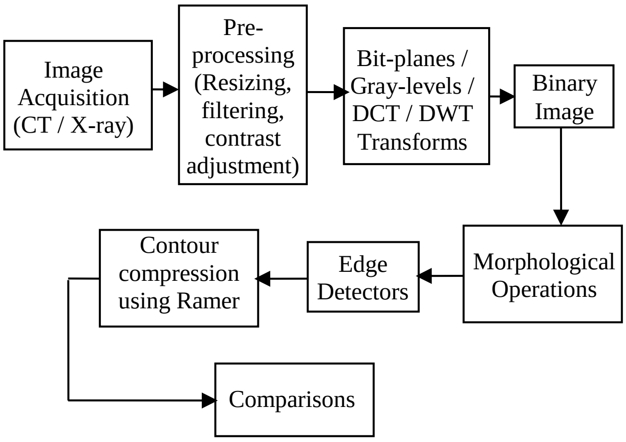
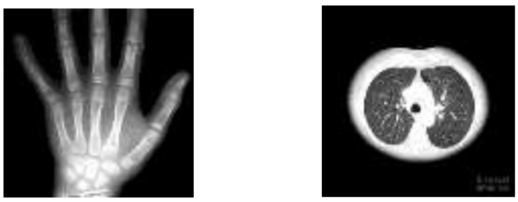


Figure. 1 Block diagram analysed algorithm

4. BIT-PLANE DECOMPOSITION

We assume a 256 X 256 medical pixels image to be given in 8bit/pixel (bpp) precision. The entire image can be considered as a two-dimensional array of pixel values. We consider the 8bpp data in the form of 8-bit planes, each bit plane associated with a position in the binary representation of the pixels. 8-bit data is a set of 8 bit-planes. Each bit-plane may have a value of 0 or 1 at each pixel, but together all the bit-planes makeup a byte with value between 0 to 255. Given below (as shown in Figure 3 & 4) are the most significant bit-planes of two tested images (as shown in Figure 2).



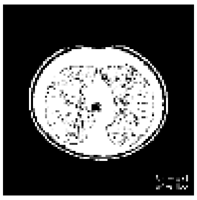
(a) (b)

Figure. 2 Test Images: (a) X-ray, and (b) CT scan

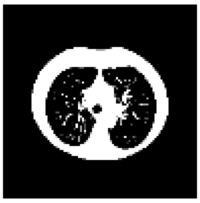
(a) (b)

(c)

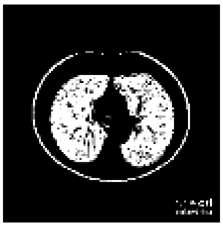
Figure. 3 X-ray Hand Skel Images: (a), (b), and (c) Bit-planes no. 7, 8, and (7 & 8) respectively



(a)



(b)

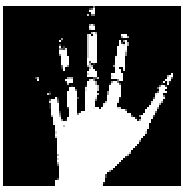


(c)

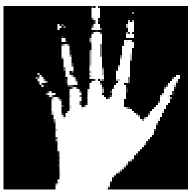
Figure. 4 CT scan Images: (a), (b), and (c) Bit-planes no. 7, 8, and (7 & 8) respectively

5. GRAY-LEVEL DECOMPOSITION

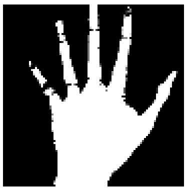
The idea consists on that given a set of gray-level patterns to be first memorized: (1) Decompose them into their corresponding binary patterns, and (2) Build the corresponding binary associative memory (one memory for each binary layer) with each training pattern set (by layers). A given pattern or a distorted version of it, it is recalled in three steps: (1) Decomposition of the pattern by layers into its binary patterns, (2) Recalling of each one of its binary components, layer by layer also, and (3) Reconstruction of the pattern from the binary patterns already recalled in step 2. The proposed methodology operates at two phases: training and recalling. Conditions for perfect recall of a pattern either from the fundamental set or from a distorted version of one they are also given. Figures 5 and 6 represent the gray level decomposition.



(a)



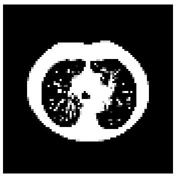
(b)



(c)

Figure. 5 X-ray Hand Images: (a), (b), and (c) Gray-level decomposition using maximun gray level, quarter gray levels, and half gray levels respectively

(a) (b)



(c)

Figure. 6 CT scan Images: (a), (b), and (c) Gray-level decomposition using maximun gray level, quarter gray levels, and half gray levels respectively

This paper compared this zonal method with another zonal sampling method consists in selecting one block of the spectral images (i.e. shadow region) as LPF for image compression and the other coefficients will be taken into account in the contour reconstruction stage. This algorithm is referred as algorithm II and is shown in Figure 2 [16].

6. SINGLE STEP PARALLEL CONTOUR EXTRACTION

Detection of edge points (pixels) of a 3-dimensional physical object in a 2-dimensional image and contour is one of the main research areas of computer vision. The extraction of object contours and object recognition depends on the correctness and completeness of edges [17]. Edge detection is required to simplify images and to facilitate image analysis and interpretation [18]. Edge detection extracts and localizes points (pixels) around which a large change in image brightness has occurred. Edge detection is based on the relationship a pixel has with its neighbors. If the grey-levels around a pixel are similar, the pixel is unsuitable to be recorded as an edge point. Otherwise, the pixel may represent an edge point.

- Sobel Metric

It is defined as the square root of the sum of squared and squared, where and are obtained by convolving the image with a row mask and column mask respectively.

The Sobel operator performs a 2-D spatial gradient measurement on an image. Typically, it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The Sobel edge detector uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows). A convolution mask is usually much smaller image than the actual image. As a result, the mask is slid over the image, manipulating a square of pixels at a time.

The Sobel operator performs a 2-D spatial gradient measurement on an image and so emphasizes regions of high spatial gradient that correspond to edges. Typically, it is used to find the approximate absolute gradient magnitude at each point in an input grey-scale image. In theory at least, the operator consists of a pair of 3×3 convolution masks as shown in Figure 7. One mask is simply the other rotated by 90°.

-1	**0**	**+1**
-2	**0**	**+2**
-1	**0**	**+1**

G_x

+1	**+2**	**+1**
0	**0**	**0**
-1	**-2**	**-1**

G_y

Figure. 7 Sobel Cross convolution masks

- Canny Metric

It is optimal for step edges corrupted by white noise. In evaluating the performance of various edge detectors, Canny has defined three criteria [19-22] for optimal edge detection in a continuous domain:

- ✓ Good Detection: the maximum of the ratio of edge points to non-edge points on the edge map.
- ✓ Good Localization: the detected edge points must be as close as possible to their true locations.
- ✓ Low-responses Multiplicity: the maximum of the distance between two non-edge points on the edge map.

The Canny operator was designed to be an optimal edge detector (according to particular criteria, there are other detectors around that also claim to be optimal with respect to slightly different criteria). It takes as input a grey scale image and produces as output an image showing the positions of tracked intensity discontinuities.

- SSPCE Metric

The SSPCE (single step parallel contour extraction) method is applied to the binary image which is obtained by suitable threshold value applied to the noisy digital watermarked image [10, 11]. The eight rules of edge extraction are applied and are coded using 8-directional chain-code as shown in Listing (1).

LISTING (1): IMPLEMENTATION OF THE EIGHT RULES FOR CONTOUR EXTRACTION (3X3 WINDOWS)

```
a(i,j) ⟵ 0; i = 1,2,…..,N; j = 1,2,…..,N;
for i = 2,3,…..,N-1; j = 2,3,…..,N-1;
{
if b(i,j) and b(i+1,j) and [b(i,j+1) or b(i+1,j+1)] and  [ not [b(i,j-1) or b(i+1,j-1)]]
then a(i,j) ⟵ a(i,j) or 2^0
{ edge 0 }
if b(i,j) and b(i+1,j) and  b(i+1,j-1) and [ not [b(i,j-1)]]
then a(i,j) ⟵ a(i,j) or 2^1
{ edge 1 }
if b(i,j) and b(i,j-1) and [b(i+1,j) or b(i+1,j-1)] and  [ not [b(i-1,j) or b(i-1,j-1)]]
then a(i,j) ⟵ a(i,j) or 2^2
{ edge 2 }
if b(i,j) and b(i,j-1) and  b(i-1,j-1) and [ not [b(i-1,j)]]
then a(i,j) ⟵ a(i,j) or 2^3
{ edge 3 }
if b(i,j) and b(i-1,j) and [b(i,j-1) or b(i-1,j-1)] and  [ not [b(i,j+1) or b(i-1,j+1)]]
then a(i,j) ⟵ a(i,j) or 2^4
{ edge 4 }
if b(i,j) and b(i-1,j) and  b(i-1,j+1) and [ not [b(i,j+1)]]
then a(i,j) ⟵ a(i,j) or 2^5
{ edge 5 }
if b(i,j) and b(i,j+1) and [b(i-1,j) or b(i-1,j+1)] and  [ not [b(i+1,j) or b(i+1,j+1)]]
then a(i,j) ⟵ a(i,j) or 2^6
{ edge 6 }
if b(i,j) and b(i,j+1) and  b(i+1,j+1) and [ not [b(i+1,j)]]
then a(i,j) ⟵ a(i,j) or 2^7
{ edge 7 }
```

Morphological filters [18] are used for sharpening medical images. In this method, after locating edges by gradient-based operators, a class of morphological filter is applied to sharpen the existing edges. In fact, morphology operators, through increasing and decreasing colors in different parts of an image, have an important role in processing and detecting various existing objects in the image. Locating edges in an image using morphology gradient is an example that has comparable performance with that of classic edge-detectors such as Canny and Sobel [23, 36].

7. DISCRETE COSINE TRANSFORM

Spectral domain transforms like Karhonen-Loeve [24], Fourier, Haar [25], Pieodic Haar Piecewise-Linear (PHL) [26], Walsh-Hadamard [27, 28], Discrete Cosine (DCT) [29], and recently, wavelets [30, 31] can be used to extract the medical contours points and image compression using low-pass filter (LPF) and high-pass filter (HPF) are investigated and compared with Sobel and Canny detectors in this section. The algorithm uses Discrete Cosine Transform (DCT). Effectiveness of the contour extraction for different classes of images is evaluated. The main idea of the procedure for both contour extraction and image compression are performed. To compare the results, the mean square error and signal-to-noise ratio criterions were used. The simplicity and the small number of operations are the main advantages of the proposed algorithms.

A high pass filter is a filter that passes high frequencies and attenuates low frequencies. In high pass filtering the objective is to get rid of the low frequency or slowly changing areas of the image and to bring out the high frequency or fast changing details in the image. This means that if we were to high pass filter the box image we would only see an outline of the box. The edge of the box is the only place where the neighbouring pixels are different from one another. Contour representation and compression are required in many applications e.g. computer vision, topographic or weather maps preparation, medical images and moreover in image compression. The results are compared with Sobel and Canny edge detectors for the contour extraction [12, 18, 32-34].

8. DISCRETE WAVELET TRANSFORM

The Wavelet analysis is an exciting new method for solving difficult problems in mathematics, physics, and engineering, with modern applications as diverse as wave propagation, data compression, signal processing, image processing, pattern recognition, computer graphics, the detection of aircraft and submarines and other medical image technology [31, 35].

Wavelets allow complex information such as music, speech, images and patterns to be decomposed into elementary forms at different positions and scales and subsequently reconstructed with high precision. Wavelets are obtained from a single prototype wavelet called mother wavelet by dilations and shifting using the equation (1).

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi(\frac{t-b}{a}) \qquad (3)$$

9. ZONAL SAMPLING METHOD

A lot of zonal sampling methods which was described in [16], shows that the best scheme for compression and contour extraction is as illustrated in Figure 8. Fit criterion of the algorithm consists in selecting one of the squared block of the spectral images (e.g. shadow region) as LPF filter for image compression and the other coefficients will be taken into account in the contour reconstruction stage as shown in the Figure 2. This method is mainly used in this work using DCT transform.

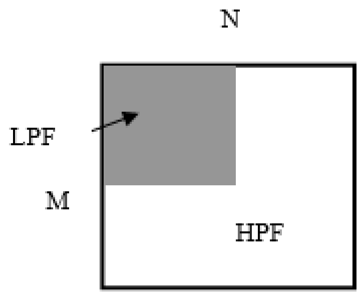


Figure. 8 LPF & HPF filters zonal method for the spectral image using the algorithm I

10. RAMER METHOD

The Contour is represented as a polygon when it fits the edge points with a sequence of line segments. There are several algorithms available for determining the number and location of the vertices and also to compute the polygonal approximation of a contour. The well-known is Ramer method which is based on the polygonal approximation scheme [4]. The simplest approach for the polygonal approximation is a recursive process (Splitting methods). Splitting methods work by first drawing a line from one point on the boundary to another. Then, we compute the perpendicular distance from each point along the segment to the line. If this exceeds some threshold, we break the line at the point of greatest error. The idea of this first curve approximation is illustrated in Figure 1.

We then repeat the process recursively for each of the two new lines until we don't need to break any more. For a closed contour, we can find the two points that lie farthest apart and fit two lines between them, one for one side and one for the other. Then, we can apply the recursive splitting procedure to each side. First, use a single straight line to connect the end points. Then find the edge point with the greatest distance from this straight line. Then split the straight line in two straight lines that meet at this point. Repeat this process with each of the two new lines. Recursively repeat this process until the maximum distance of any point to the poly-line falls below a certain threshold. Finally draw the lines between the vertices of an edge of the reconstructed contour to obtain the polygonal approximating contour as shown in Figure 9.

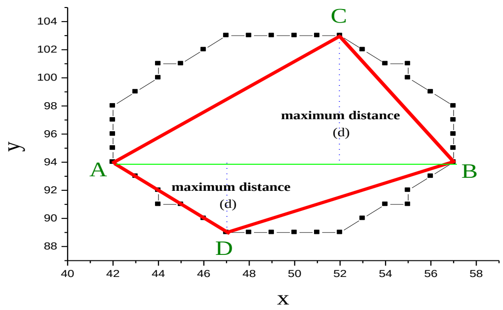


Figure. 9 Contour compression using Ramer Algorithm

11. APPLIED MEASURES

The compression ratio of the analyzed methods is measured using the equation (4).

$$CR = [(L_{CC} - L_{AC}) / L_{CC}] \cdot 100\% \tag{4}$$

where L_{CC} is the input contour length, and L_{AC} is the approximating polygon length.

Quality measuring of a contour approximation during the approximating procedure uses mean square error (MSE) and signal-to-noise ratio (SNR) criterions by the relations (5) and (6) respectively [11, 35].

$$MSE = (1/L_{CC}) \cdot \sum_{i=1}^{L_{CC}} d_i^2 \tag{5}$$

where d_i is the perpendicular distance between i point on the curve segment and straight line between each two successive vertices of that segment.

$$SNR = -10 \cdot \log_{10}(MSE / VAR) \tag{6}$$

where VAR is the variance of the input sequence.

The mean square error (MSE) and peak signal-to-noise ratio (PSNR) criterions were used to evaluate the distortion introduced during the image compression and contour extraction procedures. The MSE criterion is defined by the following equation:

$$MSE(I, \tilde{I}) = \frac{1}{(n*m)} \sum_{i=0}^{n} \sum_{j=0}^{m} (I(i,j) - (\tilde{I}(i,j))^2 \tag{7}$$

Where I and I are the grey-level and reconstructed images respectively.

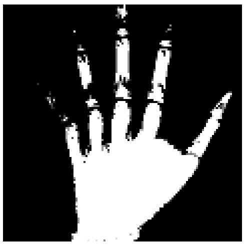
The PSNR is defined by the following formula:

$$PSNR(I,\tilde{I}) = 10\log_{10}\frac{(L-1)^2}{MSE(I,\tilde{I})} \tag{8}$$

where *L* is the grey-level number.

12. RESULTS OF THE EXPERIMENTS

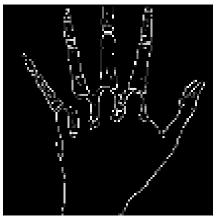
To visualize the experimental results a CT scan Hand image & X-ray image. Selected images are shown in Figure 2. Some selected results of the tested images are shown in Figure (10 to 19) (Related results are in Tables (I to X)). Where CE is contour extraction; BP is bit plane; GL is grey level; PN is contours points number.



(a) Binary image using MSB

(b) CE using Sobel

(c) CC using Sobel



(d) CE using Canny

(e) CC using Canny

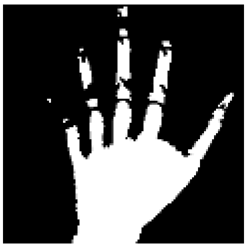
(f) CE using SSPCE

(g) CC using SSPCE

Figure. 10 Contour extraction & compression using Most significant bit (MSB) and Sobel, Canny, and SSPCE respectively

Table. 1 Results of hand medical image contours extraction & compression using msb and ramer and sobel, canny, & sspce methods with threshold =0.1

Measures / Contour Extraction Methods	*Original Contour Points (MSB)*	*Compressed Contour Points Using Ramer*	*MSE*	*SNR*	*CR [%]*
Sobel	1865	401	0.0337	14.7248	78.4987
Canny	2079	443	0.2467	6.0782	87.1054
SSPCE	1759	1399	0.0155	18.1044	20.4662



(a) Binary image using MGL

(b) CE using Sobel

(c) CC using Sobel

(d) CE using Canny

(e) CC using Canny

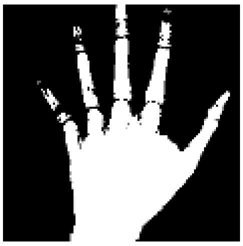
(f) CE using SSPCE

(g) CC using SSPCE

Figure. 11 Contour extraction & compression using maximum gray level (MGL) with adjust input image intensity values [0.3 0.5], based on Sobel, Canny, and SSPCE respectively

Table. 2 Results of Hand Medical Image Contours Extraction & Compression using MGL and Ramer and Sobel, Canny, & SSPCE Methods with threshold =0.1

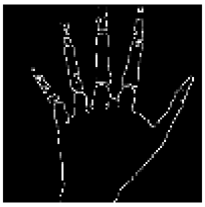
Measures / Contour Extraction Methods	*Original Contour Points (MGL)*	*Compressed Contour Points Using Ramer*	*MSE*	*SNR*	*CR [%]*
b) Sobel	1379	365	0.0155	18.1044	73.5315
c) Canny	1662	366	0.0198	17.0387	77.9783
d) SSPCE	1392	701	0.0109	19.6339	49.6408



(a) Binary image using DCT

(b) CE using Sobel

(c) CC using Sobel



(d) CE using Canny

(e) CC using Canny

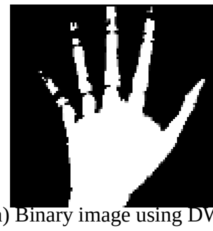
(f) CE using SSPCE

(g) CC using SSPCE

Figure. 12 Contour extraction & compression using DCT with zonal block 150 & threshold=33, and Ramer based on Sobel, Canny, and SSPCE respectively

Table. 3 Results of hand medical image contours extraction & compression using dct and ramer and sobel, canny, & sspce methods with zonal sampling block=150

Measures / Contour Extraction Methods (Threshold)	*Original Contour Points (DCT)*	*Compressed Contour Points Using Ramer*	*MSE*	*SNR*	*CR [%]*
b) Sobel (0.1)	1623	415	0.0184	17.3441	74.4301
c) Canny (0.1)	1881	416	0.0224	16.5064	77.8841
d) SSPCE (0.5)	1667	672	0.0154	18.1259	59.6881



(a) Binary image using DWT

(b) CE using Sobel

(c) CC using Sobel

(d) CE using Canny

(e) CC using Canny

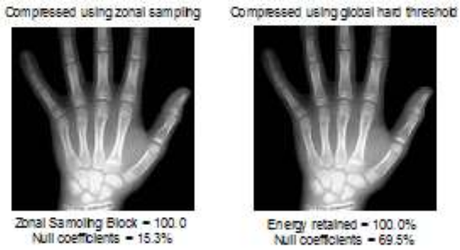
(f) CE using SSPCE

(g) CC using SSPCE

Figure. 13 Contour extraction & compression using DWT with threshold=10, and Ramer based on Sobel, Canny, and SSPCE respectively

Table. 4 Results of hand medical image contours extraction & compression using dwt (haar) details coefficients and sobel, canny, & sspce methods with threshold =10

Measures / Contour Extraction Methods	*Original Contour Points (DWT)*	*Compressed Contour Points Using Ramer*	*MSE*	*SNR*	*CR [%]*
b) Sobel	1454	562	0.0282	15.5025	61.3480
c) Canny	1800	696	0.0271	15.6753	61.3333
d) SSPCE	1521	696	0.0126	19.0003	54.2406



a) b)

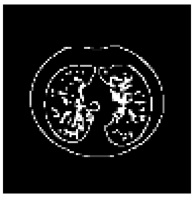
Figure. 14 Image compression using a) DCT (zonal sampling), and b) DWT (Haar)

Table. 5 Results of hand medical image comptression using dct and dwt

Measures / Image compression	*MSE*	*PSNR*	*CR [%]*
a) DCT	19.1210	35.3157	34.30
b) DWT	255.40.64	24.0585	69.50

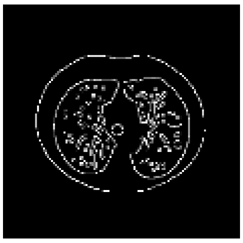
(a) Binary image using MSB

(b) CE using Sobel

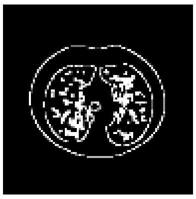


(c) CE using Sobel after Morphological

(d) CC using Sobel



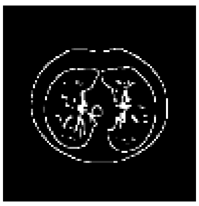
(e) CC using Sobel



(f) CE using Canny after Morphological

(g) CC using Canny

(h) CC using SSPCE



(i) CE using SSPCE after Morphological

(j) CC using SSPCE

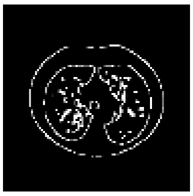
Figure. 15 Contour extraction & compression using Most significant bit (MSB) and Sobel, Canny, and SSPCE respectively

Table. 6 Results of chest medical image contours extraction & compression using msb and ramer and sobel, canny, & sspce methods with threshold =0.1

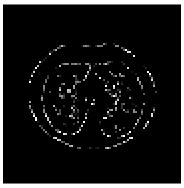
Measures / Contour Extraction Methods	*Original Contour Points (MSB)*	*Compressed Contour Points Using Ramer*	*MSE*	*SNR*	*CR [%]*
Sobel	2039	1649	0.0331	14.8082	19.1270
Canny	2705	1729	0.0430	13.6685	36.0813
SSPCE	1427	1664	0.0261	15.8323	14.2428

(a) Binary image using MGL

(b) CE using Sobel

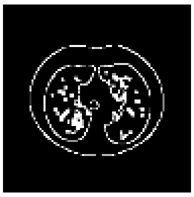


(c) CE using Sobel after Morphological



(d) CC using Sobel

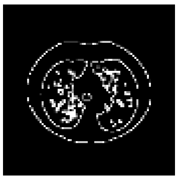
(e) CE using Canny



(f) CE using Canny after morphological

(g) CC using Canny

(h) CE using SSPCE



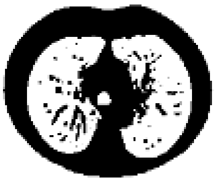
(j) CE using SSPCE after morphological

(j) CC using SSPCE

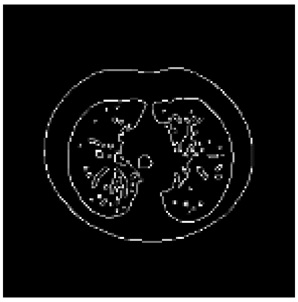
Figure. 16 Contour extraction & compression using maximum gray level (MGL) with adjust input image intensity values [0.4 0.44], based on Sobel, Canny, and SSPCE respectively

Table. 7 Results of chest medical image contours extraction & compression using mgl and ramer and sobel, canny, & sspce methods with threshold =0.1

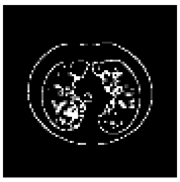
Measures / Contour Extraction Methods	*Original Contour Points (MGL)*	*Compressed Contour Points Using Ramer*	*MSE*	*SNR*	*CR [%]*
b) Sobel	1681	1450	0.0263	15.7969	13.7418
c) Canny	2258	1490	0.0123	19.1176	35.5624
d) SSPCE	1720	1525	0.0299	15.2400	11.3372



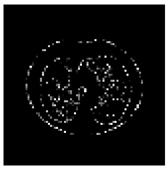
(a) Binary image using DCT



(b) CE using Sobel

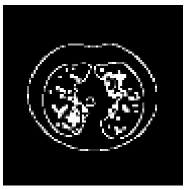


(c) CE using Sobel after morphological



(d) CC using Sobel

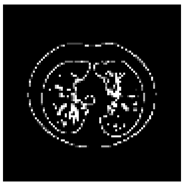
(e) CE using Canny



(f) CE using Canny after morphological

(g) CC using Canny

(h) CE using SSPCE



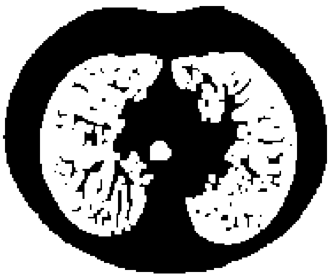
(i) CE using SSPCE after morphological

(j) CC using SSPCE

Figure. 17 Contour extraction & compression using DCT with zonal block 150 & threshold=33, and Ramer based on Sobel, Canny, and SSPCE respectively

Table. 8 Results of hand medical image contours extraction & compression using dct and ramer and sobel, canny, & sspce methods with zonal sampling block=100

Measures / Contour Extraction Methods (Threshold)	*Original Contour Points (DCT)*	*Compressed Contour Points Using Ramer*	*MSE*	*SNR*	*CR [%]*
b) Sobel (0.1)	1874	1640	0.0307	15.1242	12.4867
c) Canny (0.1)	2501	1640	0.0418	13.7921	34.4262
d) SSPCE (0.5)	1758	1510	0.0280	15.5213	14.1069



(a) Binary image using DWT

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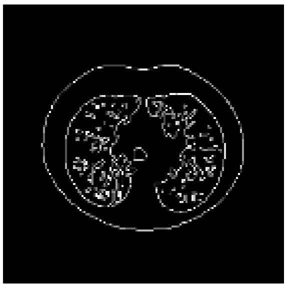
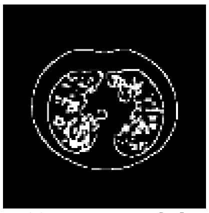


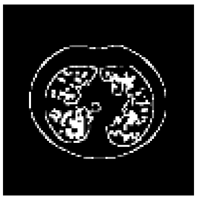
(b) CE using Sobel



(c) CE using Sobel after morphological

(d) CC using Sobel

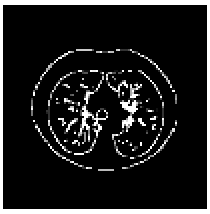
(e) CE using Canny



(f) CE using Canny after morphological

(g) CC using Canny

(h) CE using SPCE



(i) CE using SSPCE after morphological

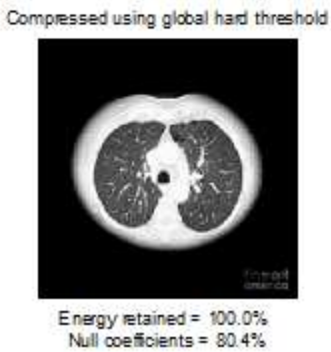
(j) CC using SSPCE

Figure. 18 Contour extraction & compression using DWT with threshold=10, and Ramer based on Sobel, Canny, and SSPCE respectively

Table. 19 Results of hand medical image contours extraction & compression using dwt (haar) details coefficients and sobel, canny, & sspce methods with threshold =10

Measures / Contour Extraction Methods	*Original Contour Points (DWT)*	*Compressed Contour Points Using Ramer*	*MSE*	*SNR*	*CR [%]*
b) Sobel	2233	1847	0.0365	14.3772	17.2862
c) Canny	2817	1847	0.0453	13.4372	34.4338
d) SSPCE	1943	1551	0.0294	15.3182	20.1750

(a)



(b)

Figure. 19 Image compression using a) DCT (zonal sampling), and b) DWT (Haar)

Table. 10 Results of hand medical image comptression using dct and dwt

Measures / Image compression	*MSE*	*PSNR*	*CR [%]*
a) DCT	72.4032	29.5332	15.30
b) DWT	70.9038	29.6241	80.40

13. CONCLUSIONS

Medical image enhancement technologies have attracted much attention since advanced medical equipment was put into use in the medical field. Enhanced medical images are desired by a surgeon to assist diagnosis and interpretation because medical image qualities are often deteriorated by noise and other data acquisition devices, illumination conditions, etc. We have implemented of CT / X-ray sample images. Sobel and Canny edge detection operators & single step parallel contour extraction (SSPCE) have been implemented on that image. The contours of the tested images can be also extracted using (DCT) high pass filter coefficients during zonal sampling methods; and single level of (DWT) within high pass filter details coefficients. Enhanced medical images are desired by a surgeon to assist diagnosis and interpretation because medical image qualities are often deteriorated by noise and other data acquisition devices, illumination conditions, etc. For these reasons we use pre-processing stage (filtering & enhancement) before the main processing. The results show that this kind of algorithms has a satisfactory performance. The extracted contours are compressed using well known Ramer method. Simulation results using MATLAB programming show that this kind of algorithms has a satisfactory performance with good compression ratio exceeds to 87% (see Table I) for Hand X-ray. By using DWT, the compressed image can be obtained during approximation coefficients (low pass filter) by compression ratio exceeds to 80% with good quality approaches to 30 decibels (see Figure 19 & Table X). In the feature we can used the proposed strategy is to detect, analyze and extract the tumor from patient's CT scan images.

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