Improve Method for Processing Dental Images with Fast Spatial Filter and Shearlet Transform

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Abstract— **Dental caries is one of the biggest problems in human health, in the whole world. Methods of detection are usually complex and in most cases are invasive. A non-invasive method may be using image processing.**

With the help of an optimized algorithm, developed in matlab, using the shearlet transformation, 2D images are processed from dental X-ray samples.

The results show the efficiency of the method and the precision with which it is possible to detect the contours of the caries in all the planes that are required to analyze.

For edge detection used Shearlet transform and compared with classic filters: Sobel, Prewitt, Roberts, Canny, LoG and for quality evaluation used SSIM measure, for accelerated time process for reduce noise used fast 2D Gauss filter.

Index Terms— **dental images, medical image, contour detection, shearlet transform, classis filters, SSIM measure, fast 2D Gauss filter.**

I. INTRODUCTION

In the modern times, caries is one of the most prevelent disease of the teeth in the very large population throughout the world. Dental caries are, clearly visible in the x-ray changes and it can be detected from the caries lesion present in the radiographs. This work shows how image processing techniques using shearlet transform will help to find contour of caries lesion present in the dental radiograph. Dental caries are very common. They begin with acid on the tooth. The acid is made from the bacteria in dental plaque and form a cavity. [1-4]

Medical images are often contaminated by impulsive, additive or multiplicative noise due to a number of non-idealities in the imaging process. For remove noise we used fast 2D Gauss filter [5-9].

To find contour of cavity used shearlet transform. Shearlet transform have emerged in recent years as one of the most successful methods for the multiscale analysis of multidimensional signals [10-16]. Shearlets are obtained by translating, dilating and shearing a single mother function. Thus, the elements of a shearlet system are distributed not only at various scales and locations - as in classical wavelet theory - but also at various orientations. Thanks to this directional sensitivity property, shearlets are able to capture anisotropic features, like edges, that frequently dominate multidimensional phenomena, and to obtain optimally sparse approximations.

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Moreover, the generalization to higher dimensions and to treat uniformly the continuum and the discrete realms, as well as fast algorithmic implementation [10-16].

Show the optimization of the control algorithm for medical image processing, performed previously, using shearlet transforms.

II. DIGITAL PROCESSING OF IMAGES

The digital processing of images consists of algorithmic processes that transform an image into another in which certain information of interest is highlighted, and/or the information that is irrelevant to the application is attenuated or eliminated [5-9]. For remove noise we used fast 2D Gauss filter, for contour detection used shearlet transform and classic filter: Sobel, Prewitt, Roberts, Canny and LoG, and to evaluate quality used SSIM measure. Following we describe these methods.

Classic and fast 2D Gauss filter

Gauss 2D classic filter calculate kernel Gauss bell G(x,y), take pixels from gray value image A in kernel area and add to sum considering Gaussian coefficient, and put obtained value in study pixel in image B.

The Gaussian filter uses a Gaussian function (which also expresses the normal distribution in statistics) for calculating the transformation to apply to each pixel in the image.

The equation of a Gaussian function in one dimension is

$$G(x) = \frac{1}{\sqrt{2\pi} \cdot \sigma} e^{-\frac{x^2}{2\sigma^2}}$$

In two dimensions, it is the product of two such Gaussians, one in each dimension:

$$G(x, y) = \frac{1}{2\pi \cdot \sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution.

Since the image is represented as a collection of discrete pixels it is necessary to produce a discrete approximation to the Gaussian function before perform the convolution. Depends on kernel size and σ some of coefficients can be out range of kernel. Theoretically the Gaussian distribution is non-zero everywhere, which would require an infinitely large convolution kernel. In practice it is effectively zero more than about three standard deviations from the mean. Thus it is possible to truncate the kernel size at this point. Sometimes kernel size truncated even more. Thus after computation of Gaussian Kernel, the coefficients must be corrected that way that the sum of all coefficients equals 1. Once a suitable kernel has been calculated, then the Gaussian smoothing can be performed using standard convolution methods. The

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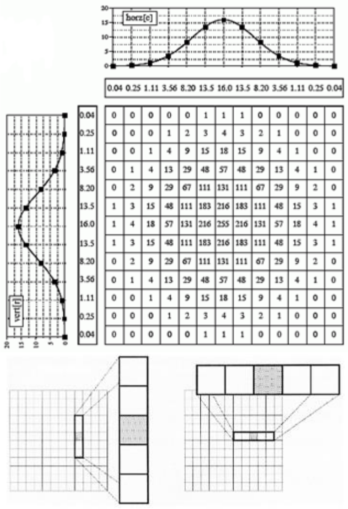
convolution can in fact be performed fairly quickly since the equation for the 2-D isotropic Gaussian is separable into y and x components. In some cases the approximation of Gaussian filter can be used instead of classic version [5-9].



Difference in processing time of classical 2D and double 1D implementations of Gaussian filter shown on Figure 1.

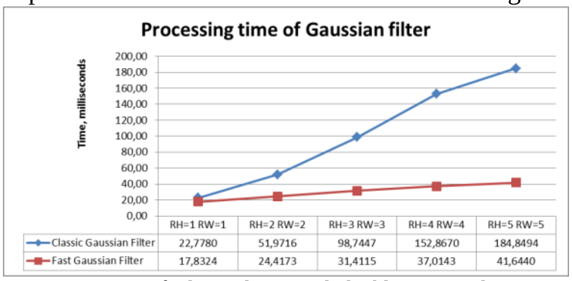


Fig. 1. Comparison of classical 2D and double 1D implementation of Gaussian filter [17] owned by author.

Filters for edge detection.

Used following filters to edge detection: Shearlet transform, Prewitt, Sobel, Roberts, LoG and Canny, and compared its by measure SSIM. Following describe Canny edge detector and Shearlet transform.

The Canny edge detector is the first derivative of a Gaussian and closely approximates the operator that optimizes the product of signal-to-noise ratio and localization. The Canny edge detection algorithm is summarized by the following notation. Let $J[i,j]$ denote the image. The result from convolving the image with a Gaussian smoothing filter using separable filtering is an array of smoothed data,

$$S[i,j] = G[i,j;\sigma] * I[i,j]$$

where σ is the spread of the Gaussian and controls the degree of smoothing.

The gradient of the smoothed array $S[i,j]$ can be computed using the 2×2 first-difference approximations to produce two arrays $P[i,j]$ and $Q[i,j]$ for the x and y partial derivatives:

$$P[i,j] \approx (S[i,j+1] - S[i,j] + S[i+1,j+1] - S[i+1,j])/2$$
$$Q[i,j] \approx (S[i,j] - S[i+1,j] + S[i,j+1] - S[i+1,j+1])/2$$

The finite differences are averaged over the 2×2 square so that the x and y partial derivatives are computed at the same point in the image. The magnitude and orientation of the gradient can be computed from the standard formulas for rectangular-to-polar conversion:

$$M[i,j] = \sqrt{P[i,j]^2 + Q[i,j]^2}$$

$$\theta[i,j] = \arctan(Q[i,j], P[i,j])$$

where the arctan function takes two arguments and generates an angle over the entire circle of possible directions. These functions must be computed efficiently, preferably without using floating-point arithmetic. It is possible to compute the gradient magnitude and orientation from the partial derivatives by table lookup. The arctangent can be computed using mostly fixed-point arithmetic with a few essential floating-point calculations performed in software using integer and fixed-point arithmetic [18].

Shearlet transform

Let $\Psi = (\psi i)i \in I \subset L^2(R^2)$ be a normalized frame for $L^2(R^2)$, then Ψ is said to provide optimally sparse approximations of cartoon-like images if the N-term approximations associated with the N largest coefficients fulfill [10-16].

$$\|f - f_N\| \lesssim N{-}1$$

for all cartoon-like images $f \in L^2(R^2)$.

In the case for 1D Fourier Analysis, we decompose signals into sen and cos waves of varing frequency.

The Simple reconstruction for $f \in L^2\{[0,2\pi]\}$ (up to normalization) is

$$f = \sum_{n\in\mathbb{Z}} < f, e^{in\cdot} > e^{in\cdot} \qquad (1)$$

In the case of wavelets 1D and 2D, the problems solved by using localized generator functions.

The generator functions are scaled isotropically $\psi \in L^2(R^2)$ and índices $\Gamma \subset R^+ \times R^2$ and the 1D and 2D wavelets system is given by

$$\Psi = \{\psi_{a,t} = a^{1/2}\psi(a \cdot - t) : (a,t) \in \Gamma\} \qquad (2)$$

$$\Psi = \left\{\psi_{a,t} = a^{1/2}\psi\left(\begin{pmatrix} 2^j & 0 \\ 0 & 2^j \end{pmatrix} \cdot - t\right) : (a,t) \in \Gamma\right\} \quad (3)$$

Shearlets solve the problem by using directionally sensitive analyzing functions, and adding another necessary degree of freedom for changing the orientation – shears.

The problem arises when high frequency wavelets, which are very tight, can not adapt to the shape of the discontinuity. In this case the solution is to generate a different scale in the xy direction, which is anisotropically.

The signals that exhibit anisotropic singularities as cartoon images require the analysis of these elements consist of waveforms that extend over various scales, orientations and locations with the ability to become very elongated. . This requires a combination of an appropriate scale operator to generate elements at different scales, an orthogonal operator to change its orientations, and a translation operator to displace.

To build a shearlet system is necessary to have a shearlet generator, anisotropic scaling, and shear matrices.

The shearlet system is given by

$$\Psi = \left\{\psi_{a,s,t} = a^{((1+\alpha)/2)}\psi\left(\begin{pmatrix} 1 & s \\ 0 & 1 \end{pmatrix}\begin{pmatrix} a & 0 \\ 0 & a^{\alpha} \end{pmatrix}(\cdot - t)\right) : (a,s,t) \in \Gamma\right\} \qquad (4)$$

Where the $\psi \in L2(R2)$, is the shearlet generator and the parameters $a \in R+$, $s \in R$. The parameter $a \in (0,1]$ defines the degree of anisotropy of the system.

Discrete Shearlet Transform is detailed in [13], in Figure 2 show discrete shearlet action in last scale in 0º, 45º, 90º and 135º

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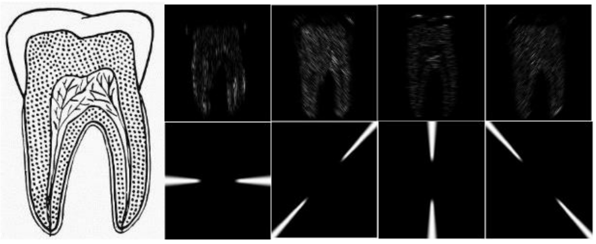

Fig. 2. The discrete shearlet in last scale in 0º, 45º, 90º and 135º

Cavity detection in dental image

To detection contour of the cavity in dental X-ray image used and modify algorithm FFST[11-12] and found that the contours of objects can be obtained as the sum of the coefficients shearlet transform a fixed value for the scale and the last of all possible values of the shift parameter as follow:

$$f_{cont} = \sum_{k=0}^{k_{max}} \sum_{m=0}^{m_{max}} sh_{\psi}\big(f(j*, k, m)\big), \qquad (5)$$

where shψ assigns the coefficients of the function fshψf(j *, k, m), obtained for the last scale j*, orientation k and displacement m, where kmax - the maximum number of turns, mmax - the maximum number of displacements.

Measure SSIM

The structural similarity (SSIM) index is designed to improve on traditional methods such as peak signal to noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human visual perception.

Structural information is the idea that the pixels have strong interdependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene. Luminance masking is a phenomenon whereby image distortions (in this context) tend to be less visible in bright regions, while contrast masking is a phenomenon whereby distortions become less visible where there is significant activity or "texture" in the image.

The mean structural similarity index is computed as follows:

Firstly, the original and distorted images are divided into blocks of size 8 x 8 and then the blocks are converted into vectors. Secondly, two means and two standard derivations and one covariance value are computed from the images as:

$$\mu_x = \frac{1}{T}\sum_{i=1}^{T} x_i \qquad \mu_y = \frac{1}{T}\sum_{i=1}^{T} y_i$$

$$\sigma_x^2 = \frac{1}{T-1}\sum_{i=1}^{T}(x_i - \bar{x})^2$$

$$\sigma_y^2 = \frac{1}{T-1}\sum_{i=1}^{T}(y_i - \bar{y})^2$$

$$\sigma_{xy}^2 = \frac{1}{T-1}\sum_{i=1}^{T}(x_i - \bar{x})\,(y_i - \bar{y})$$

Thirdly, luminance, contrast, and structure comparisons based on statistical values are computed, the structural similarity index measure between images x and y is given by:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

where c_1 and c_2 are constants [19-20].

III. EXPERIMENTAL RESULTS

Methodology

This work propose follow algorithm to select cavity in the X-ray dental image.

1.- Find shearlet coefficients using FFST algorithm.
2.- Find contour using formula 5.
3.- Show all possible contours.
4.- Select cavity contour from color scale.
5.- Contour compare with classic filters: Sobel, Prewitt, Roberts, Canny and LoG, and SSIM measure.
6.- Result can see in figures 3-22.

For the experiment used Notebook ACER Aspire ES15 AMD A4, Quad Core, 12Gb RAM, graphic card Radeon R3, software Matlab 2015 (The MathWorks) [21].

The figure 3-6 show the process to obtained the cavity for the dental images.

Fig. 3 Model image for experiment.

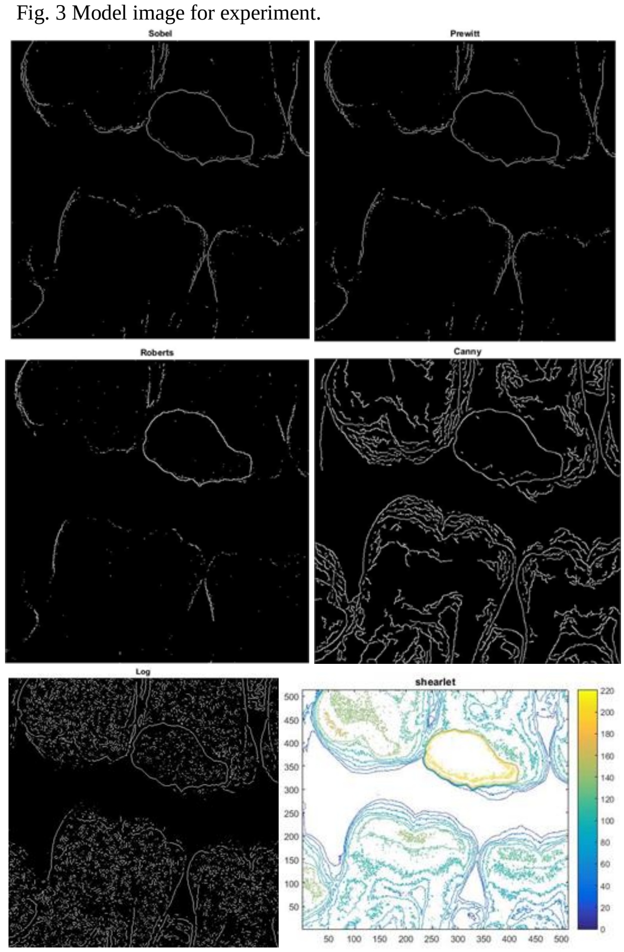

Fig. 4 Results contour detection with filters: Sobel, Prewitt, Roberts, Canny, LoG, Shearlet transform.

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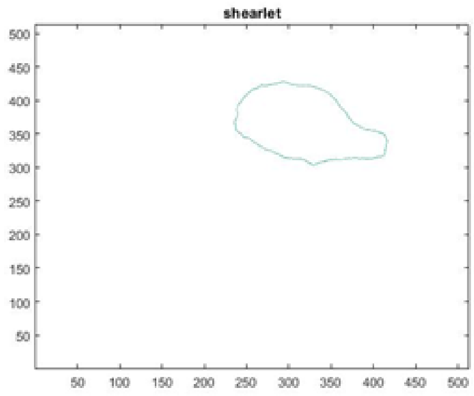

Fig. 5 Result cavity from Shearlet transform contour detection.

Evaluation edge filters Shearlet transform, Sobel, Prewitt, Roberts, Canny and LoG with the SSIM metric and the results are show in Table I and Figure 7.

TABLE I.
SSIM MEASURE IMAGE QUALITY FOR CONTOUR IMAGES

	Shearlet	Sobel	Prewitt	Roberts	Canny	LoG
Shearlet	1.0000	0.8715	0.8715	0.8711	0.8807	0.8823
Sobel	0.8715	1.0000	1.0000	0.9997	0.9975	0.9978
Prewitt	0.8715	1.0000	1.0000	0.9997	0.9975	0.9978
Roberts	0.8711	0.9997	0.9997	1.0000	0.9974	0.9978
Canny	0.8807	0.9975	0.9975	0.9974	1.0000	0.9970
LoG	0.8823	0.9978	0.9978	0.9978	0.9970	1.0000

Fig. 6 Result SSIM by Shearlet transform and Canny value 0.8807

Following results from processed another dental model images

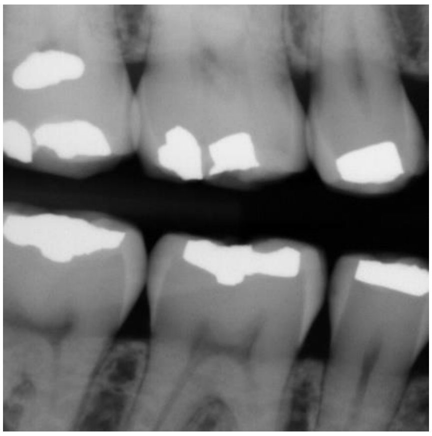

Fig. 7. Model image for experiment.

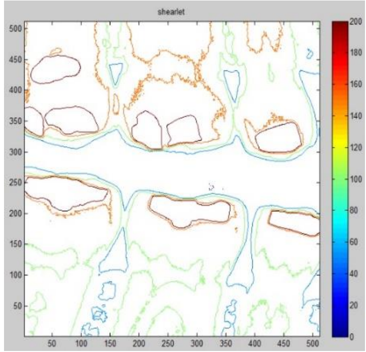

Fig. 8. All contours processed by shearlet transform

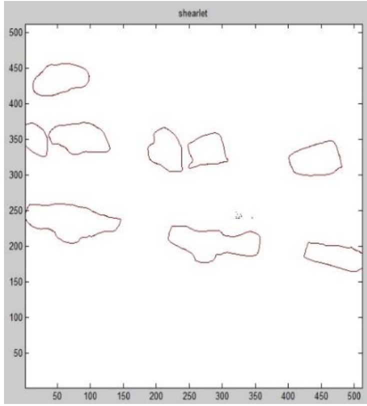

Fig. 9. Result cavities selection

TABLE II.
SSIM MEASURE IMAGE QUALITY FOR CONTOUR IMAGES

	Shearlet	Sobel	Prewitt	Roberts	Canny	LoG
Shearlet	1.0000	0.9113	0.9113	0.9118	0.9163	0.9137
Sobel	0.9113	1.0000	1.0000	0.9997	0.9982	0.9991
Prewitt	0.9113	1.0000	1.0000	0.9997	0.9982	0.9991
Roberts	0.9118	0.9997	0.9997	1.0000	0.9982	0.9990
Canny	0.9163	0.9982	0.9982	0.9982	1.0000	0.9983
LoG	0.9137	0.9991	0.9991	0.9990	0.9983	1.0000

Fig. 10 Result SSIM by Shearlet transform and Canny value 0.9163

Fig. 11. Model image for experiment.

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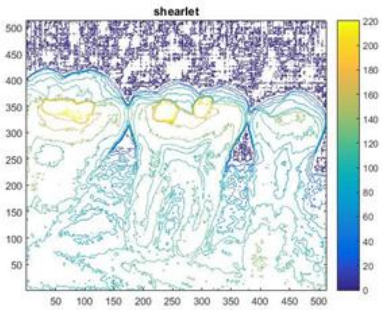

Fig. 12. All contours processed by shearlet transform

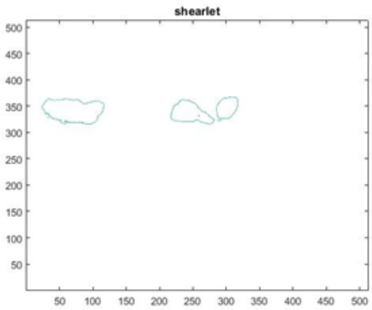

Fig. 13. Result cavities selection

TABLE III.
SSIM MEASURE IMAGE QUALITY FOR CONTOUR IMAGES

	Shearlet	Sobel	Prewitt	Roberts	Canny	LoG
Shearlet	1.0000	0.9462	0.9462	0.9462	0.9502	0.9492
Sobel	0.9462	1.0000	1.0000	0.9997	0.9972	0.9984
Prewitt	0.9462	1.0000	1.0000	0.9997	0.9972	0.9984
Roberts	0.9462	0.9997	0.9997	1.0000	0.9971	0.9983
Canny	0.9502	0.9972	0.9972	0.9971	1.0000	0.9974
LoG	0.9492	0.9984	0.9984	0.9983	0.9974	1.0000

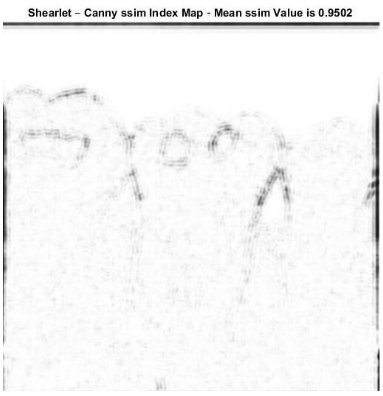

Fig. 14 Result SSIM by Shearlet transform and Canny value 0.9502

Fig. 15. Model image for experiment.

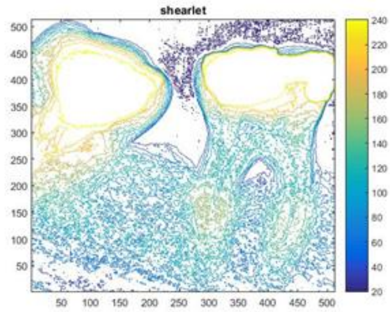

Fig. 16. All contours processed by shearlet transform

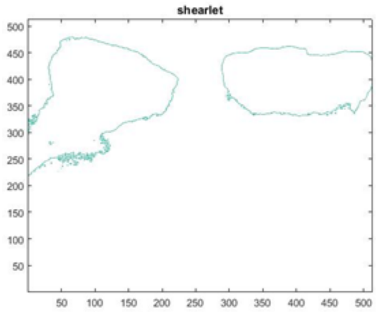

Fig. 17. Result cavities selection

TABLE IV.
SSIM MEASURE IMAGE QUALITY FOR CONTOUR IMAGES

	Shearlet	Sobel	Prewitt	Roberts	Canny	LoG
Shearlet	1.0000	0.7766	0.7764	0.7757	0.7993	0.7958
Sobel	0.7766	1.0000	1.0000	0.9997	0.9956	0.9969
Prewitt	0.7764	1.0000	1.0000	0.9997	0.9956	0.9969
Roberts	0.7757	0.9997	0.9997	1.0000	0.9955	0.9968
Canny	0.7993	0.9956	0.9956	0.9955	1.0000	0.9966
LoG	0.7958	0.9969	0.9969	0.9968	0.9966	1.0000

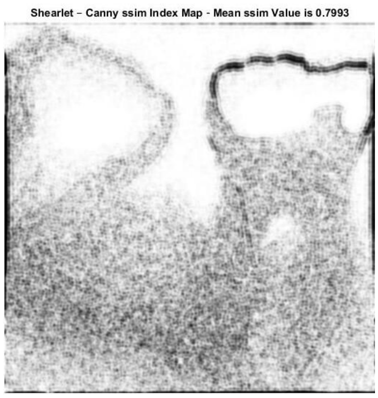

Fig. 18 Result SSIM by Shearlet transform and Canny value 0.7993

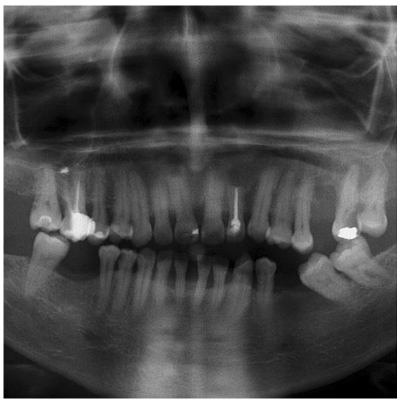

Fig. 19. Model image for experiment.

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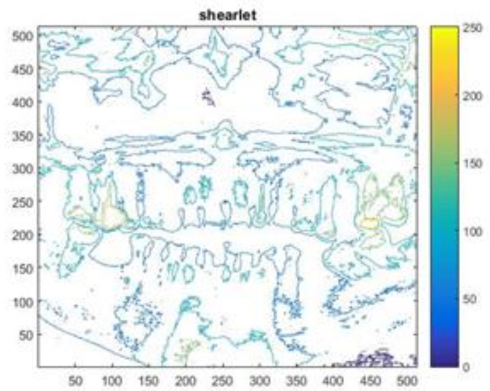

Fig. 20. All contours processed by shearlet transform

TABLE V.
SSIM MEASURE IMAGE QUALITY FOR CONTOUR IMAGES

	Shearlet	Sobel	Prewitt	Roberts	Canny	LoG
Shearlet	1.0000	0.7893	0.7892	0.7880	0.8040	0.7992
Sobel	0.7893	1.0000	1.0000	0.9995	0.9967	0.9980
Prewitt	0.7892	1.0000	1.0000	0.9995	0.9967	0.9980
Roberts	0.7880	0.9995	0.9995	1.0000	0.9966	0.9978
Canny	0.8040	0.9967	0.9967	0.9966	1.0000	0.9970
LoG	0.7992	0.9980	0.9980	0.9978	0.9970	1.0000

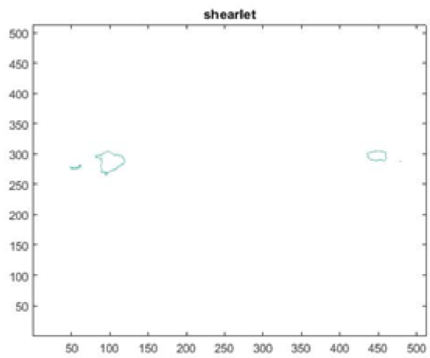

Fig. 21. Result cavities selection

Fig. 22 Result SSIM by Shearlet transform and Canny value 0.8040

IV. CONCLUSIONS

In our experiment for reduce noise of image we used fast 2D Gauss filter with good acceleration time of process.

The algorithm, based on the shearlet transform, is optimized to find the edges of the caries in X-ray images of dental samples. With the shearlet transform it is possible to define the area (contour) of affectation of the caries with a high degree of precision.

For quality contour detection used SSIM measure with good result which showed in tables I-V.

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