Diagnostics of Complex Phenomena on the Basis of Geometrical Analysis Images

Luis Cadena, Franklin Cadena, Alexey Kruglyakov, Konstantin Simonov, Feodor Kapsargin

Abstract— **A review of the basic concepts shearlet transform spatial data observations. The possibilities of the new approach for the geometric analysis of complex medical images. The proposed method can improve the radiological diagnosis of urological diseases by detailing changes of tissues.**

On the basis of the developed method of spectral data decomposition is performed solution of filtration problem and isolating contour studied medical target. The task of image contrast is also solved for the better understanding of the found geometric features and patterns.

Index Terms— **image processing, medical image, contour, denoising, wavelets, shearlet, analysis of medical images, urolithiasis, ureteroscopy.**

I. INTRODUCTION

The problem of separating an image into morphologically different components has recently been given much attention in the scientific community because of its significance for mission-critical applications. Successful techniques to efficiently and accurately solve this problem may be in fact be applied to a much wider range of areas, including medical imaging, imaging for diagnosis of complex phenomena.

In the diagnosis of urolithiasis, until recently, X-ray method of study was the only one. However, with the introduction of modern technologies of treatment beyond the capabilities of X-ray studies and sufficiently frequent erroneous conclusions, forced to look for other methods of diagnosis. To date, only enough to identify the localization of calculus, but it is necessary to determine the density and configuration of the calculus, to evaluate the functional condition of the urinary tract obstruction below and above [1-3].

In patients with urolithiasis, during the initial survey who were unable to identify stones in the urinary tract by routine imaging techniques, only multislice computed tomography (MSCT) with multiplanar reconstruction, can accurately determine their location, even when roentgen stones, without the use of contrast agents [4-6].

Manuscript received December 08, 2016; This work was supported by Universidad de las Fuerzas Armadas ESPE, Av. Gral Ruminahui s/n, Sangolqui Ecuador

L. Cadena is with Electric and Electronic Department, Universidad de las Fuerzas Armadas ESPE, Av. Gral Ruminahui s/n, Sangolqui Ecuador. (phone: +593997221212; e-mail: ecuadorx@gmail.com).

F. Cadena is with College Juan Suarez Chacon, Quito, Ecuador (e-mail: fcfc041@gmail.com)

A. Kruglyakov is with Siberian Federal University, 79 Svobodny pr., 660041 Krasnoyarsk, Russia (e-mail: piggsyy@gmail.com)

K. Simonov is with Institute of Computational Modelling of Siberian Branch of Russian Academy of Science, 50/44 Akademgorodok str., 660036 Krasnoyarsk, Russia (e-mail: simonovkv50@gmail.com)

F. Kapsargin is with Krasnoyarsk State Medical University, 1 Partizana Geleznyaka str., 660022 Krasnoyarsk, Russia (e-mail: kapsargin@mail.ru)

The use of modern methods of diagnosis significantly improved outcomes in patients with urolithiasis. This is a refinement of prognostic criteria (location, size, structure, stone density functional state of the upper urinary tract, etc.) in the preoperative period.

The use of modern methods of computer tomography allows detailing readings and predict the effectiveness of various methods of treatment [2, 6-7]. For example, long distance calculus in the ureter leads to the presence of the development ureterita hypergranulation ureteliya. Carrying ureteroscopy and lithotripsy contact in this situation, due to the infiltration of tissues and poor visualization, fraught with high risk of damage to the wall of the ureter.

We believe that multislice computed tomography (MSCT) with discrete shearlet transform by image detail reveals radiological signs of these changes. The use of laser in ureteritis, presence of granulation makes it possible to produce them coagulation, increasing visualization of calculus.

Thus, the investigation focuses on the use of shearlet transform for processing of spatial data [7-19]. It provides an improved method of geometrical analysis of complex medical images. The proposed approach is adapted in relation to the processing of images in urology.

II. SHEARLET TRANSFORM

Directional multiscale representation of images to address curved singularities has received much attention in harmonic analysis in the last 25 years. In particular, shearlets provide an optimally sparse approximation of carton-like images, that is [6-19].

$$||f - f_N||_{L_2}^2 \leq CN^{-2}(\log N)^3 \text{ as } N \to \infty$$

where f_N is the nonlinear shearlet approximation of a function f from this class obtained by taking the N largest shearlet coefficients in absolute value. Shearlets possess a uniform construction for both the continuous and the discrete setting. They further stand out since they stem from a square-integrable group representation and have the corresponding useful mathematical properties.

For the shearlet transform we use the dilation matrix A_a and shear matrix S_s for $d = 2$ and $\gamma = \frac{1}{2}$ they read [6-18]

$$A_a = \begin{pmatrix} a & 0 \\ 0 & \sqrt{a} \end{pmatrix}, a \in R^+, S_s = \begin{pmatrix} 1 & s \\ 0 & 1 \end{pmatrix}, s \in R.$$

The shearlets $\psi_{a,s,t}$ emerge by dilation, shear and translation of a function $\psi \in L_2(R^2)$ as before

$$\psi_{a,s,t}(x) = a^{-\frac{3}{4}}\psi\left(A_a^{-1}S_s^{-1}(x-t)\right) = a^{-\frac{3}{4}}\psi\left(\begin{pmatrix} \frac{1}{a} & -\frac{s}{a} \\ 0 & \frac{1}{\sqrt{a}} \end{pmatrix}(x-t)\right).$$

We assume that $\hat{\psi}$ can be written as

$$\hat{\psi}(\omega_1, \omega_2) = \hat{\psi}_1(\omega_1)\hat{\psi}_2\left(\frac{\omega_2}{\omega_1}\right).$$

Consequently, we obtain for the Fourier transform

$$\hat{\psi}(\omega) = a^{-\frac{3}{4}}F\left(\psi\left(\begin{pmatrix}\frac{1}{a} & -\frac{s}{a}\\ 0 & \frac{1}{\sqrt{a}}\end{pmatrix}(\cdot - t)\right)\right)(\omega) =$$

$$a^{-\frac{3}{4}}e^{-2\pi i\langle\omega,t\rangle}F\left(\psi\left(\begin{pmatrix}\frac{1}{a} & -\frac{s}{a}\\ 0 & \frac{1}{\sqrt{a}}\end{pmatrix}\cdot\right)\right)(\omega) =$$

$$a^{-\frac{3}{4}}e^{-2\pi i\langle\omega,t\rangle}\left(a^{-\frac{3}{2}}\right)^{-1}\hat{\psi}\left(\begin{pmatrix}a & 0\\ s\sqrt{a} & \sqrt{a}\end{pmatrix}\omega\right) =$$

$$a^{\frac{3}{4}}e^{-2\pi i\langle\omega,t\rangle}\hat{\psi}\left(a\omega_1, \sqrt{a}(s\omega_1 + \omega_2)\right) =$$

$$a^{\frac{3}{4}}e^{-2\pi i\langle\omega,t\rangle}\hat{\psi}_1(a\omega_1)\hat{\psi}_2\left(a^{-\frac{1}{2}}\left(\frac{\omega_2}{\omega_1} + s\right)\right).$$

The shearlet transform $SH_\psi(f)$ of $f \in L_2(R)$ is given as

$$SH_\psi(f)(a, s, t) = \langle f, \psi_{a,s,t}\rangle = \langle \hat{f}, \hat{\psi}_{a,s,t}\rangle =$$

$$\int_{R^2}\hat{f}(\omega)\,\overline{\hat{\psi}_{a,s,t}(\omega)}d\omega = a^{\frac{3}{4}}\int_{R^2}\hat{f}(\omega)\,\hat{\psi}_1(a\omega_1)\hat{\psi}_2\left(a^{-\frac{1}{2}}\left(\frac{\omega_2}{\omega_1} + s\right)\right)e^{2\pi i\langle\omega,t\rangle}d\omega = a^{\frac{3}{4}}F^{-1}\left(\hat{f}(\omega)\hat{\psi}_1(a\omega_1)\hat{\psi}_2\left(a^{-\frac{1}{2}}\left(\frac{\omega_2}{\omega_1} + s\right)\right)\right)(t).$$

The same formula is derived by interpreting the shearlet transform as a convolution with the function $\psi_{a,s}(x) = \bar{\psi}(-A_a^{-1}S_s^{-1}x)$ and using the convolution theorem.

The shearlet transform is invertible if the function ψ fulfills the admissibility property

$$\int_{\mathbb{R}^2}\frac{|\hat{\psi}(\nu_1,\nu_2)|}{{\nu_1}^2}d\nu_1 d\nu_2 < \infty.$$

We consider digital images in $R^{M\times N}$ as functions sampled on the grid $\left\{\left(\frac{m_1}{M}, \frac{m_2}{N}\right): (m_1, m_2) \in G\right\}$ with $G \coloneqq \{(m_1, m_2): m_1 = 0, \dots, M-1, m_2 = 0, \dots, N-1\}$ and assume periodic continuation over the boundary.

The discrete shearlet transform is basically known, but in contrast to the existing literature we present here a fully discrete setting. That is, we do not only discretize the involved parameters a, s and t but also consider only a finite number of discrete translations t. Additionally, our setting discretizes the translation parameter t on a rectangular grid and independent of the dilation and shear parameter [6-7].

Let $j_0 \coloneqq \left\lfloor\frac{1}{2}\log_2\max\{M, N\}\right\rfloor$ be the number of considered scales. To obtain a discrete shearlet transform, we discretize the dilation, shear and translation parameters as

$$a_j = 2^{-2j} = \frac{1}{4^j}, j = 0, \dots, j_0 - 1$$

$$s_{j,k} = k2^{-j}, -2^j \le k \le 2^j$$

$$t_m = \left(\frac{m_1}{M}, \frac{m_2}{N}\right), m \in G.$$

With these notations our shearlet becomes $\psi_{j,k,m}(x) \coloneqq \psi_{a_j,s_{j,k}t_m}(x) = \psi(A^{-1}_{a_j,\frac{1}{2}}S^{-1}_{a_j,k}(x - t_m))$.

III. DENOISING AND CONTOUR DETECTION OF MEDICAL IMAGES BY SHEARLET TRANSFORM

The spectral decomposition of data - a solution the problem of filtration and separation contour studied medical object using wavelet transform and shearlet is the most reliable method of spectral decomposition of the spatial signal characterizing the analyzed medical object and allows you to select a fundamental frequency, which characterizes its geometric features.

On the basis of the method of use of algorithms shearlet transform [8-19] solved the problem of contrast image for a clearer representation of geometrical features found and studied patterns of health care facilities. It is proposed to perform the following method contrast images after wavelet and shearlet transforms:

- Conversion are carried out element by element to highlight interesting parts of the studied medical object;
- Performed the exception of minor features in the image (background);
- Is performed to bring the image to the form, which is convenient for visual interpretation and further analysis;
- The estimate calculation of required parameters (the solution of problems in the selection contour and filtering noise reduction).

Next, the experimental study application of the developed computational methods for the treatment of various medical imaging in urology. Figures 1-2 show examples of treatment of complex medical images based on the developed technique.

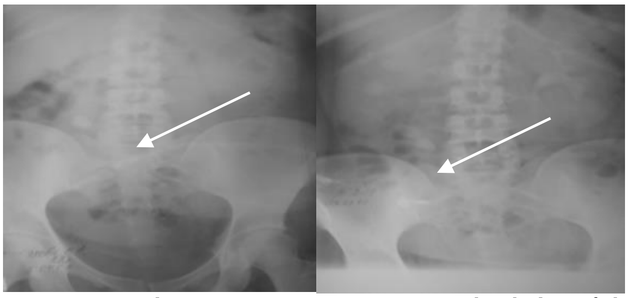


Fig. 1. Review and excretory urogram urinary tract: the shadow of the calculus at the level of intervertebral space L4 - L5 right.

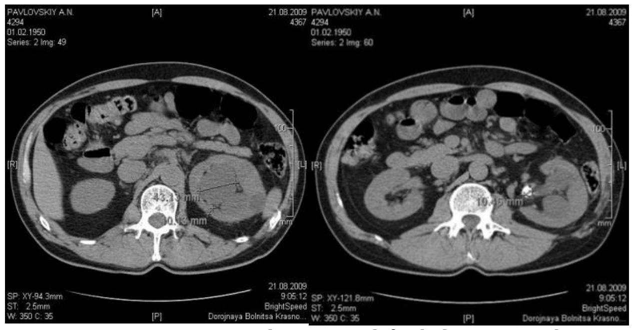
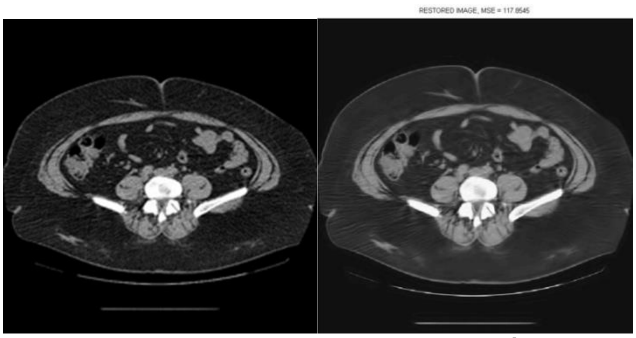


Fig. 2. Computer Tomography scan: left kidney parenchyma is homogeneous with clear smooth contours, the right renal pelvis system is expanded: pelvis to 4.3 cm to 2.5 cm cup, a parenchyma non-uniform thickness in some places up to 0.5 cm, in the lumen v/3 right ureter is determined by the size of the shadow of the calculus of 1.5 cm, a density of 1163 HU.

Solve problems involving noise reduction (image quality improvement Fig. 1) and the selection of the desired contour of the medical object (Fig. 2).

Analysis calculated image obtained as a result of shearlet transform, contrast images on the basis of algorithms: A – algorithm FFST (Hauser, 2013); B – algorithm Shearlet toolbox (Easley, Labate, 2013); C – algorithm Shearlab (Kutyniok, Lim, 2011); D – algorithm TGVSHCS (Jing, 2013).

To solve the problem of noise reduction performed research of algorithms B, C and D for images from a variety of subject areas (spread of fire, medical imaging, geo-ecology and Geodynamics). Figure 3 shows the noise reduction problem solution on the basis of algorithms for the image in relation to the urology.



a. b.

Figure 3. Solution noise reduction objectives, based on B algorithms, original (a) and denoised (b).

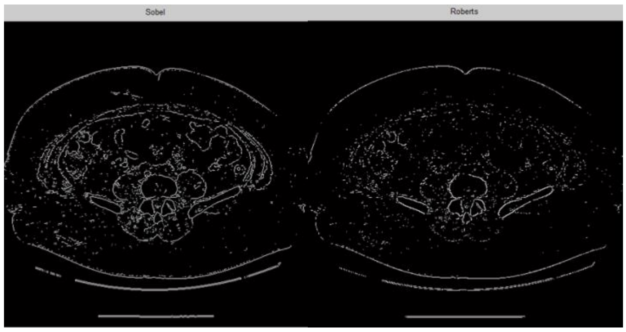
The contours of objects can be obtained as the sum of the coefficients shearlet transform fixed parameter values for the last shift of scale and various parameter values.

$$f_{cont} = \sum_{k=0}^{k_{max}} \sum_{m=0}^{m_{max}} \mathcal{sh}_{\psi}\big(f(j*, k, m)\big).$$

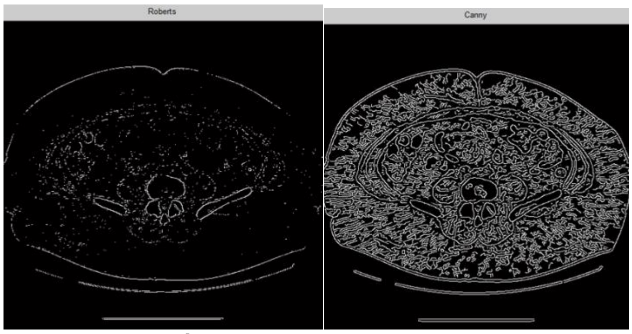
Where $\mathcal{sh}_{\psi}$ assigns the study of the function f coefficients $\mathcal{sh}_{\psi} f(j*, k, m)$, obtained for the last scale $j*$, cornering (orientation) k and displacement m, where k_{max} - the maximum number of turns, m_{max} - the maximum amount of displacement [16-22].

The following are the results of treatment of urology image (a) and Figure 4 show results of the find contour with Sobel (b), Prewitt (c), Roberts (d), Canny (e), LoG (f) and shearlet transform (g).

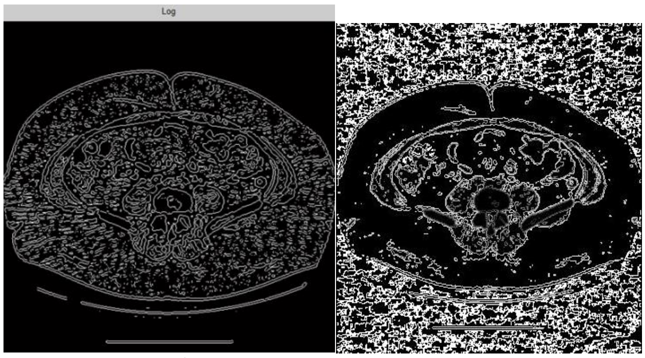
a,



b. c.



d. e.



f. g.

Figure 4. Results of the find contour: original (a): Sobel (b); Prewitt (c); Roberts (d); Canny (e); LoG (f) and shearlet transform (g).

IV. CONCLUSIONS

A computational method of calculating the contrasting results for a clearer separation of detected patterns in the test image data.

The studies addressed the problem of complex image processing in urology: the selection contour and filtering for contrast studied medical objects.

Showed the possibilities of spectral decomposition based on shearlet transform of medical imaging for analysis of complex phenomena in the studied domain.

REFERENCES

[1] Teodorovich O.V., Borisenko G.G., Shatohin M.N., etc. Complications of percutaneous surgery staghorn nephrolithiasis // First Russian Congress on endourology: Proc.; June 4-6, 2008, Moscow. – M., 2008. – P. 256-257.

[2] Alyaev Y.G., Rudenko V.I., Gazim M.A., etc. Types of stenting after contact ureterolithotripsy // First Russian Congress on endourology: Proc.; June 4-6, 2008, Moscow. – M., 2008. – P. 126-127.

[3] Veshkurtsev V.V. Endoscopic treatments ureterolitiaza in providing emergency medical care // First Russian Congress on endourology: Proc.; June 4-6, 2008, Moscow. – M., 2008. – P. 148-149.

[4] Emelyanov S.I., Panfilov S.A., Fomichev O.M. Three-dimensional reconstruction and virtual endoscopy of the abdominal cavity // Endoscopic surgery. – 1999. – № 3. – P. 22-29.

[5] Kitaev B.M., Kovynev A.V., Dubrovskikh S.N. Predicting the effectiveness of ESWL ureteral stones using ultrasound in triplex mode // First Russian Congress on endourology: Proc.; June 4-6, 2008, Moscow. – M., 2008. – P. 181-183.

ISBN: 978-988-14047-3-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

[6] Dzeranov N.K., Lopatkin N.A. Kidney stones: a wedge. Recommended. – M.: Publishing House of the "Overlay", 2007. – 296 c.
[7] Filimonov G.P., Alyaev Y.G., Vasiliev P.V., etc. The treatment of nephrolithiasis: the role of spiral CT // Radiology Practitioner. – 2001. – № 4. – P. 34-35.
[8] Donoho D. L., Kutyniok G. Geometric separation using a wavelet-shearlet dictionary // SampTA'09 (Marseille, France, 2009), Proc., 2009.
[9] Guo K., Kutyniok G., Labate D. Sparse multidimensional representations using anisotropic dilation and shear operators // Wavelets and Splines (Athens, GA, 2005), Nashboro Press, Nashville, TN, 2006. P. 189-201.
[10] Guo K., Labate D. Optimally Sparse Multidimensional Representation using Shearlets // SIAM J Math. Anal., 2007. V. 39. P. 298-318.
[11] Guo K., Labate D. Optimally sparse 3D approximations using shearlet representations // Electronic Research Announcements in Mathematical Sciences. 2010. V. 17. P. 126-138.
[12] Guo K., Labate D., W.-Q Lim, Edge analysis and identification using the Continuous Shearlet Transform // Appl. Comput. Harmon. Anal., 2009. V. 27. P. 24-46.
[13] Hauser S. Fast Finite Shearlet Transform. Available: http://www.mathematik.uni-kl.de/fileadmin/image/haeuser/software/FFST.zip
[14] Kutyniok G., Labate D. Construction of regular and irregular shearlet frames // J. Wavelet Theory and Appl., 2007, N 1, P. 1-10.
[15] Kutyniok G., Labate D. Introduction to shearlets. In Shearlets. Multiscale analysis for multivariate data. – Boston, MA: Birkhauser, 2012. P. 1-38.
[16] Kutyniok G., Sauer T. From wavelets to shearlets and back again // In Approximation theory XII. Proceedings of the 12th international conference (San Antonio, TX, USA, March 4-8, 2007). Brentwood, TN: Nashboro Press, 2008. P. 201-209.
[17] Labate D., Easley G., Lim W. Sparse directional image representations using the discrete shearlet transform // Applied Computational Harmonic Analysis, 2008. V. 25. P. 25-46.
[18] Labate D., Lim W.-Q., Kutyniok G., Weiss G. Sparse multidimensional representation using shearlets // Wavelets XI (San Diego, CA, 2005). SPIE Proc. 5914, SPIE, Bellingham, WA, 2005. P. 254-262.
[19] Lim W.-Q. The discrete shearlet transform: a new directional transform and compactly supported shearlet frames // IEEE Trans. Imag. Proc., 2010. V. 19. P. 1166-1180.
[20] Luis Cadena; Nikolai Espinosa; Franklin Cadena; Ramiro Rios; Konstantin Simonov; Alexey Romanenko. Contour detect in the medical image by shearlet transform // International Conference on Optical and Photonic Engineering (icOPEN 2015), Proceedings of SPIE Volumen 9524 ISSN 1996-756X; doi:10.1117/12.2189725.
[21] Luis Cadena, Nikolai Espinosa, Franklin Cadena, Svetlana Kirillova, Daria Barkova, Alexander Zotin, "Processing Medical Images by New Several Mathematics Shearlet Transform ," Lecture Notes in Engineering and Computer Science: Proceedings of The International MultiConference of Engineers and Computer Scientists 2016 Vol I, IMECS 2016, 16-18 March, 2016, Hong Kong, pp369-371. ISBN: 978-988-19253-8-1 ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)
[22] Luis Cadena, Franklin Cadena, Daria Barkova, "Processing Dental Caries Images by Shearlet Transform,"Lecture Notes in Engineering and Computer Science: Proceedings of the World Congress on Engineering 2016 Vol I WCE 2016, June 29 - July 1, 2016, London, U.K, pp475-477. ISBN: 978-988-19253-0-5 ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)