Analysis of Noise Properties in Dental Images

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***Abstract*—Images used in medicine are often noisy. Noise might originate from different factors and it usually degrades image quality leading to less reliable diagnostics. There are stages and the corresponding methods of image processing for which it is extremely desired to know image characteristics to take them into account. In particular, this relates to dental images for which noise is clearly seen and its properties can differ from traditional assumptions if nonlinear operations are carried out to improve visual appearance of acquired images. In this paper, we apply several known (earlier designed) approaches to automatic (blind) estimation of noise statistical and spectral characteristics. It is shown that noise in dental images is spatially correlated and signal dependent with specific dependence. The obtained estimates of noise parameters demonstrate that signal-dependent component is prevailing and the term proportional to squared intensity is present. This can be a serious problem for many image processing techniques.**

Keywords—automatic analysis, dental images, noise properties

I. Introduction

Imaging and images are widely used in medical applications [1, 2]. Certain types of medical images are noisy as low doze radiological, magnetoresonance and ultrasound ones [3]. Noise degrades image quality and makes detection and identification of diagnostic features more problematic [4]. Noise also makes image segmentation, edge detection and other operations more complicated [5].

To carry out efficient processing (edge and object detection, lossy compression, filtering) of noisy medical images, one has to know noise characteristics a priori or to pre-estimate them with high accuracy. The latter is not an easy task since noise characteristics in medical images, both spatial spectral and statistical, are usually quite complex. In particular, speckle in ultrasound images is non-additive (commonly closer to pure multiplicative), non-Gaussian, non-white (spatially correlated) and, possibly, spatially non-stationary [6]. Different noise models are used for magnetic resonance images [7] and X-ray data [8, 9]. Having information on noise properties at disposal, it becomes possible to properly choose an image processing method and adjust its parameters [10].

Recently we have tried to solve a task of visually lossless compression of dental X-ray images [11]. Necessity of lossless compression arises from the facts that modern medical images have quite a large size, amount of images acquired in clinics each day can be large and they have to be stored or passed to other clinics via communications lines [11, 12]. Then, it is desired to carry out lossy compression with appropriately high compression ratios but without introducing visible distortions (losing diagnostically valuable information), i.e. with providing high quality [12]. Meanwhile, compression of noisy images has specific features [13] and this should be taken into account. Also note that images before recording in digital form can be subject to nonlinear transformations (e.g., contrasting to improve visual quality or to better detect and analyze objects under interest) and these transformations change noise statistics.

To make this properly, noise characteristics have to be estimated. In particular, one has to know the following:

- Is noise white or spatially correlated; in the latter case, what is the degree of spatial correlation?
- Is noise pure additive, Poisson, pure multiplicative, or signal dependent in some specific manner; in the latter case, what component is dominant, additive or signal-dependent?
- Is there impulsive noise?

Answers to these questions can be got in different ways. First, there are specialized image analysis/processing tools as, e.g., ENVI that allows carrying out a wide set of operations of image cropping, statistical and spectral analysis in interactive way. This way requires having a highly qualified expert to perform selection of homogeneous image regions, parameter setting, and decision undertaking. Another way is to apply blind (automatic) methods of image/noise analysis [14 – 17]. An advantage of blind methods is that noise characteristics can be quite quickly estimated for any analized image. This is important if parameters of afforementioned nonlinear transformations are different for each particular image.

So, we assume that noise present in dental images is signal-dependent and it can be spatially correlated. Then, some of known blind methods [14] intended for analyzing only the case of additive white noise cannot be applied. Another problem is that we do not know and have limited a priori assumptions concerning what exactly the characteristics of signal dependent noise in each particular dental image are.

Thus, the goal of our study is to analyze both spectral and statistical characteristics of the noise in dental X-ray images for a particular imaging system (Morita) and to discuss how such properties can influence further processing of the considered type of images.

II. PRELIMINARY ASSUMPTIONS ON NOISE TYPE AND CHARACTERISTICS

In our research, we used high resolution dental images acquired by the system Morita, panoramic X-ray (Veraviewepocs 3D R100 J) [18] with different radiation doses used. Note that, in this imaging system, images are usually viewed (presented at a screen to a specialist), then contrasted (subject to nonlinear transformation) and then recorded in digital form for saving, printing or passing via communication line.

As noise in such images might be spatially variant, we have divided images into fragments of size 512x512 pixels and studied noise characteristics in these fragments separately. In total, we have obtained 20 fragments, some of them are shown in Fig. 1.

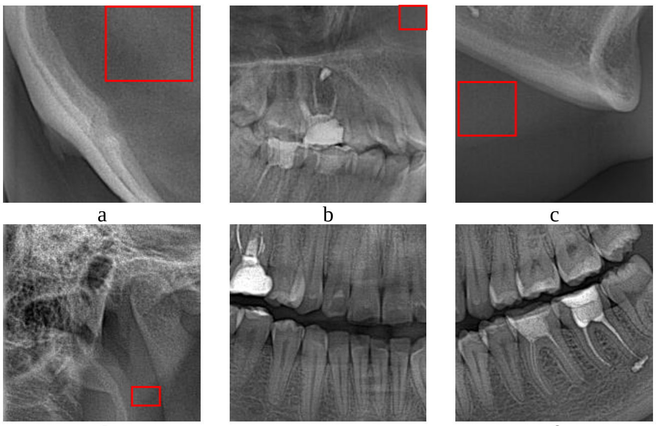

Fig. 1. Fragments of panoramic dental images with indices 2(a), 9(b), 12(c), 13(d), 19(e), 20(f)

The first characteristic feature of the presented images is that they contain quite many homogeneous (flat) or small gradient areas (some of them are marked with red rectangles), where a noise of rather high intensity can be seen. The noise is more noticeable in the light areas and less visible in the darker regions; this evidences in favor of its signal-dependent nature. Moreover, the noise has a specific grain structure that lets us assuming it to be spatially correlated in some extent.

The second observation is that visibility of grain structure essentially differs for different fragments. This gives us a reason to suspect the dependence of noise spatial correlation degree from some image acquisition (and, possibly, transformation) parameters.

The third aspect worth paying attention is the presence of several very light (close to white) flat regions in the places where metal or metal-like tooth elements are embedded. It indicates possible presence of clipping effect that appears due to the transformation of noisy images to bmp format (used by default in the Morita system). This effect might negatively influence further image processing stages; so, it should be taken into account.

Now let us apply some blind noise characteristics' evaluation methods to analysis of dental images in order to see if our assumptions on noise properties in these images get confirmed.

III. ANALYSIS OF NOISE CORRELATION LEVEL

Let us start our study from the analysis of noise spatial correlation. For this purpose, we have used the method [19] that allows quick and effective estimating the level of spatial correlation of noise present in an image. The advantage of this method is its independence on the noise type; so, it can be applied both to images corrupted with signal-independent, signal-dependent and mixed noise.

The method [19] is based on estimating the mode of local kurtosis estimates (M_h) obtained in discrete cosine transform (DCT) domain in non-overlapping image blocks of size 8x8 pixels. This block size is chosen because of several reasons. First, it is large enough to exceed the area of large correlation. Second, block size 8x8 pixels is often used in different image processing applications (like JPEG-based image lossy compression or video coding) and fast algorithms of 2D DCT exist.

According to [19], if M_h value is less than 3.75, the noise can be considered as spatially uncorrelated; if M_h is larger than 3.75 and less than 5.25, the noise has medium correlation level; and, finally, if M_h value exceeds 5.25, the noise in an analyzed image is characterized by a high spatial correlation level. Note that an advantage of tests based on M_h is that they can be applied to images corrupted by different types of signal dependent noise even if this dependence is a priori unknown.

The results of M_h estimation for all dental image fragments are presented in Fig. 2. The indices of fragments are shown along the horizontal axis. The red dashed lines correspond to the threshold values for medium and high correlation levels.

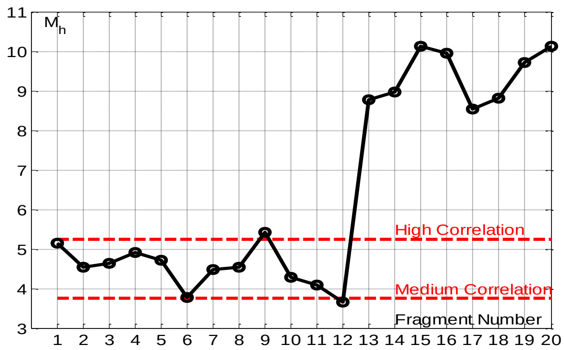

Fig. 2. Noise spatial correlation level estimation results for dental images

As it is seen, the noise is spatially correlated in all the images except the fragment #12 where the M_h value turned out to be slightly less than the lower boundary and noise was considered as spatially uncorrelated.

Obviously, there are two groups of image fragments that have significantly different noise correlation levels, medium for fragments ## 1 – 12 and high for fragments ## 13 – 20. These fragments belong to images obtained with different equipment settings (different fields of view and radiation doses). This totally confirms our assumption about the dependence of noise correlation level on image acquisition parameters and the equipment settings in particular.

IV. ANALYSIS OF NOISE TYPE AND CHARACTERISTICS

Most of modern blind methods of noise statistical parameters estimation either operate in spectral domain [14, 16, 17] or are based on the usage of neural networks [20]. The common drawback of both groups of methods is their sensitivity to noise correlation level. Methods operating in spectral domain tend to underestimate the statistical parameters of spatially correlated noise, while methods using neural networks may estimate them in an unpredictable way, because spatial correlation is very difficult to consider at the neural network training stage and, thus, it is usually not taken into account. To be able to apply such methods for images corrupted with spatially correlated noise, it is needed to eliminate the spatial correlation. This can be done by image downsampling. According to [19], downsampling by 2 times is required to turn noise with medium correlation into uncorrelated noise, while for highly correlated noise downsampling by 3 times or, sometimes, more is needed.

Since we suspect the existence of a signal-dependent component, but do not know the exact character of this dependence, let us consider the following models:

$$\hat{\sigma}^2 = \hat{\sigma}_\mu^2 \cdot I_{ij}^2 + \hat{\sigma}_a^2, \qquad (1)$$

$$\hat{\sigma}^2 = \hat{k} \cdot I_{ij} + \hat{\sigma}_a^2, \qquad (2)$$

$$\hat{\sigma}^2 = \hat{\sigma}_\mu^2 \cdot I_{ij}^2 + \hat{k} \cdot I_{ij} + \hat{\sigma}_a^2, \qquad (3)$$

where I_{ij} is an intensity value of ij-th image pixel ($i = \overline{1,N}$, $j = \overline{1,M}$, where N and M are vertical and horizontal image sizes, respectively); $\hat{\sigma}_\mu^2$ is an estimate of multiplicative noise relative variance; $\hat{\sigma}_a^2$ is an additive noise variance estimate; $\hat{k}$ is a quasi-Poisson noise parameter.

To evaluate the parameters of these models, it is logical to apply a method based on the scatter-plot approach. One of such methods is the technique [17]. The main idea of the method is to get a scatter-plot of local variance and local mean estimates obtained for quasi-homogeneous image blocks, then to estimate the centers of scatter-plot clusters and use these reference points to fit a polynomial curve into them and to take its parameters as the noise characteristics' estimates. The peculiarities of the method [17] are the usage of a detector based on the analysis of the fourth central moment [16] for selection of blocks belonging to quasi-homogeneous image regions and applying the method [16] for estimation of noise variance in clusters (image regions with similar intensity levels). Polynomial curve fitting is provided using double-weighted least mean squares algorithm with constraints (DWLMSC) [17].

The examples of quasi-homogeneous regions maps obtained using the method [17] for some fragments of dental images presented in Fig. 1 are shown in Fig. 3. The blocks belonging to detected quasi-homogeneous regions are marked with grey color.

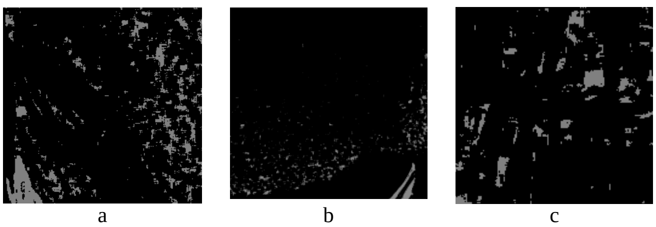

Fig. 3. Examples of quasi-homogeneous regions maps obtained using method [17] for fragments # 2(a), 12(b), and 19(c)

Despite the fact that during the visual analysis it seemed that some images contained quite many flat areas with almost constant intensities, most of those areas turned out to be gradients or low intensity texture and they were dropped by the detector. The percentage of blocks classified as quasi-homogeneous varied depending upon the fragment content and it was (on the average) about 10% from the total number of overlapping image blocks.

Fig. 4 shows the scatter-plots of local mean and variance estimates for dental images fragments presented in Fig. 1 with the marked cluster centers (red squares) and the fitted regression curves for the models (1), (2), and (3).

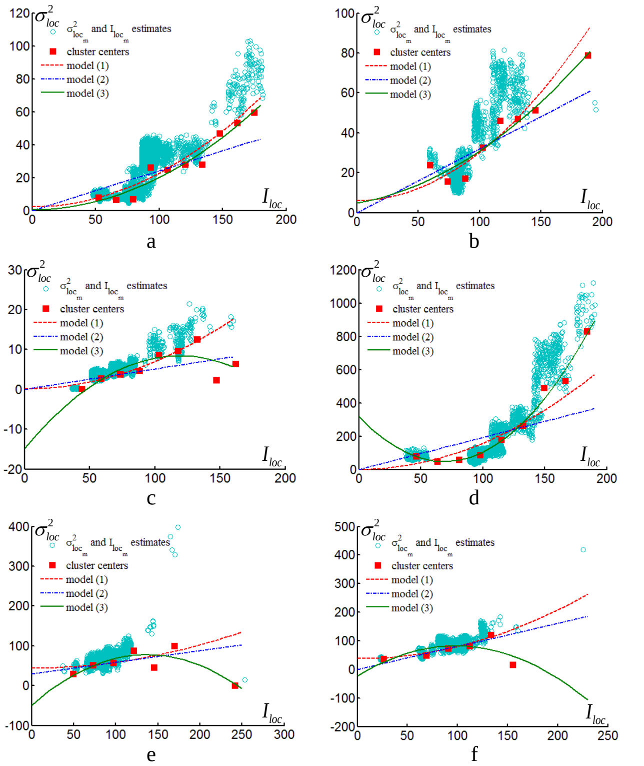

Fig. 4. Scatter-plots of local estimates with the marked cluster centers (red squares) and curves fitted under assumptions of different noise models for the fragments #2(a), 9(b), 12(c), 13(d), 19(e), 20(f)

As it is seen, noise variance changes depending on mean level; therefore, the noise is obviously signal-dependent. Another observation from the presented scatter-plots is that for some fragments clusters with noise variances close to zero are present and such clusters mostly appear at mean levels close to 255. This confirms our preliminary assumption about the presence of clipping effects.

Concerning the fitted regression curves, the situation essentially changes for different fragments. Obviously, in most situations, the model (2), corresponding to a mixture of quasi-Poisson and additive noise, is not in good agreement with the obtained experimental data, although according to the X-ray imaging theory the quasi-Poisson component should prevail. The situation with other two models is quite ambiguous as well. For some fragments (e.g. #13), the model (3) seems to be a perfect match, while in other cases (fragments #12, 19, 20) it is absolutely inadequate. For a number of situations, the model (1) approximates the dependence of variance on the mean value quite well. It is interesting that for some fragments (e.g. #2 and 9), the models (1) and (2) give very similar fitting results; this indicates that the noise-depending component is prevailing.

In [18], it is mentioned that some image optimization (contrasting) is provided within the Morita system; so, possibly, this internal (in-built) processing leads to some additional signal-dependent noise components appearing and complicating the noise model.

Fig. 5 shows the noise parameters estimation results obtained using the method [17] under the assumption of additive-multiplicative noise model (1). The additive noise variance estimates are shown in Fig. 5,a and multiplicative noise variances are shown in Fig. 5,b, the fragment indices are denoted along the horizontal axis.

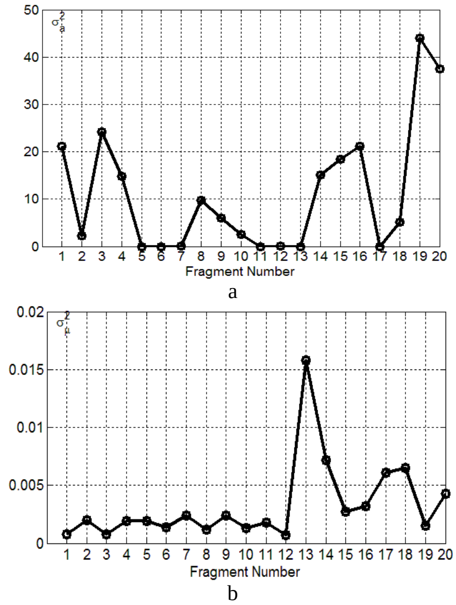

Fig. 5. Additive (a) and multiplicative (b) noise variance estimates for fragments of dental images

As it is seen, the estimates of additive noise variance $\hat{\sigma}_a^2$ significantly differ for different fragments; for some fragments the estimates of additive noise variance are equal to zero, while in other situations the influence of this component is essential.

Concerning the signal-dependent component, several observations can be done according to the data presented. Firstly, for all the fragments multiplicative noise variance $\hat{\sigma}_\mu^2$ is non-zero. Secondly, for fragments ## 1 – 12, the multiplicative noise variances are at almost the same level about 0.0015 while for the rest of fragments the variances are generally higher and vary in quite a wide range.

Figures 6,a and 6,b show two high-resolution dental images acquired in different conditions. In Fig. 6,c and 6,d the quasi-homogeneous regions maps for images presented in Fig. 6,a and Fig. 6,b are given. Finally, Fig. 6,e and Fig. 6,f show the scatter-plots of local variance and mean estimates with marked cluster centers and regression curves fitted according to the models (1 – 3).

The scatter-plots for the presented images demonstrate almost the same effects that were observed for the fragments. The noise is signal-dependent and this dependence is quite complex and it can significantly differ from quasi-Poisson noise. In low mean level fragments, noise may be considered as Poisson, but for higher means the noise model slightly differs from it. Sometimes clipping effect can be observed, that also should be taken into account.

To provide a better comparison of the considered noise models, we calculated several quantitative criteria traditionally used for evaluation of curve fitting. Their values are presented in Table I.

As it is seen, the first image model (1) shows the best consistency with experimental data according to all the three criteria for the image in Fig. 6,a, while for the second image the model (3) turns out to be the best according to R-squares and adjusted R-squares, but loses to models (1) and (2) according to the RMSE value.

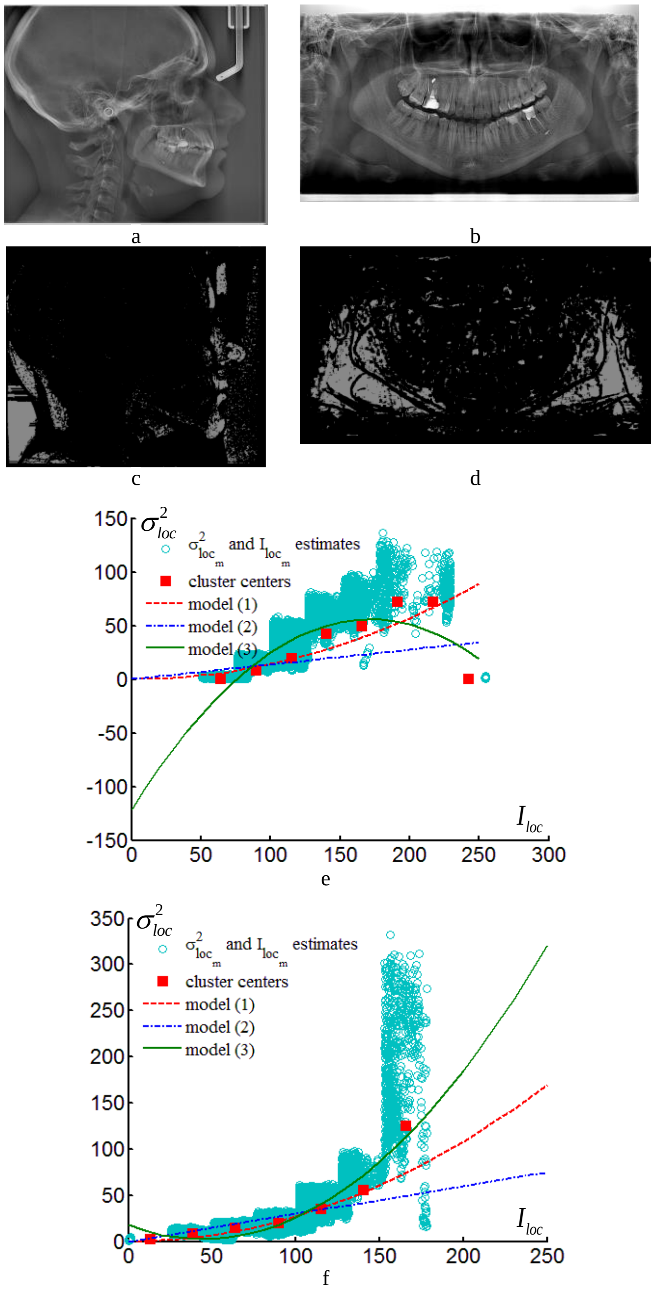

Fig. 6. High resolution dental images acquired by the Morita system (a, b), the corresponding quasi-homogeneous regions maps (c, d), and local mean and variance estimates with the marked cluster centers and the regression lines fitted according to models (1 – 3) (e, f)

We have estimated equivalent noise variance as $\hat{\sigma}_{eq}^2 = \left(\sum_{i=1}^{N} \sum_{j=1}^{M} \hat{\sigma}^2 \left(I_{ij} \right) \right) \Big/ \left(NM \right)$. Its values are equal to 14.5 for the image in Fig. 6,a and to 37.76 for the image in Fig. 6,b.

This corresponds to equivalent PSNR about 36.52 and 32.36 dB, respectively. These values of PSNR show one more time that noise is visible and, if possible, it has to been taken into account. Concerning visually lossless compression, distortions are practically invisible if introduced losses are by about 10 times smaller than equivalent noise variance. This opens opportunities for automatic visually lossless compression based on noise parameter estimation for a given image.

TABLE I. EVALUATION OF APPROXIMATION CURVES FITTING QUALITY

Image	**Noise Model**	**Fitting quality criteria**		
		R-square	***Adjusted R-square***	***RMSE***
Fig. 6a	Model (1)	0.93	0.92	2.28
	Model (2)	0.84	0.82	3.46
	Model (3)	0.62	0.46	17.59
Fig. 6b	Model (1)	0.82	0.78	3.47
	Model (2)	0.54	0.45	5.44
	Model (3)	0.94	0.92	9.34

The character of noise dependence of signal seems to be different for images acquired with different equipment settings, but this issue, as well as other questions on noise parameters in dental images require holding a more detailed research with a larger number of analyzed images.

V. CONCLUSIONS

Noise properties in dental images obtained by the modern digital X-ray system Morita have been considered. It has been shown that noise in such images is spatially correlated with medium or high level of correlation. The level of noise spatial correlation depends on the equipment settings used during image acquisition. It has been also shown that noise in dental images is signal-dependent, but the model of signal dependency is quite complex, non-linear and, sometimes, not monotonous due to the presence of clipping effect and image optimization (contrasting) techniques applied internally in the equipment. Moreover, noise model seems to depend on image acquisition conditions and equipment settings in particular.

Although the analysis has been done for dental images obtained by a particular system, we believe that our conclusions and methodology can be valid for dental images acquired by other systems as well. However, certainly, to better understand the nature of noise in such images, a more detailed analysis with a larger number of images is needed and this is a direction of our future research.

REFERENCES

[1] Stuart C. White, Michael J. Pharoah, Oral Radiology: Principles and Interpretation. Edition 7. Elsevier, 2014.

[2] Rognin N. G., Arditi M., Mercier L., Frinking P. J. A., Schneider M., Perrenoud G., Anaye A., Meuwly J., Tranquart F., “Parametric imaging for characterizing focal liver lesions in contrast-enhanced ultrasound,” IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control, 2019, 57 (11), pp. 2503–2511.

[3] Hiremath P.S., Akkasaligar P.T., Badiger S., “Speckle Noise Reduction in Medical Ultrasound Images,” in Advancements and Breakthroughs in Ultrasound Imaging, Gunti Gunarathne, IntechOpen, 2013.

[4] Goyal B., Dogra A., Agrawal S., Sohi B. S., “Noise Issues Prevailing in Various Types of Medical Images,” Biomed Pharmacol Journal, 2018, 11(3).

[5] Sreedhar Kollem, Katta Rama Linga Reddy, Duggirala Srinivasa Rao, “A Review of Image Denoising and Segmentation Methods Based on Medical Images,” International Journal of Machine Learning and Computing, 2019, 9(3), pp. 288 – 295.

[6] Ragesh. N. K, Anil A.R, Rajesh R., “Digital image denoising in medical ultrasound images: a survey,” ICGST AIML-11 Conference, Dubai, UAE, 2011, pp 12-14.

[7] S. Aja-Fern´andez, A. Trist´an-Vega, “A review on statistical noise models for Magnetic Resonance Imaging,” Tech Report of the LPI, TECH-LPI2013-01, Universidad de Valladolid, Spain, June 2013.

[8] M. J. Flynn, S. M. Hames, S. J. Wilderman and J. J. Ciarelli, "Quantum noise in digital X-ray image detectors with optically coupled scintillators," in *IEEE Transactions on Nuclear Science*, vol. 43, no. 4, pp. 2320-2325, Aug. 1996.

[9] Huda W., Abrahams R.B., “Radiographic Techniques, Contrast, and Noise in X-Ray Imaging,” American Journal of Roentgenology. 2015;204 (2): W126-W131. 10.2214/AJR.14.13116

[10] Thanh D. N., Prasath S., Minh H. L., “A Review on CT and X-Ray Images Denoising Methods,” June 2019, Informatica 43(2), pp. 151-159

[11] Krivenko S., Lukin V., Krylova O., “Visually Lossless Compression of Dental Images,” IEEE 39th International Conference on Electronics and Nanotechnology (ELNANO), Kiev, Ukraine, April 2019, 6 p.

[12] Alexander C. Flint, “Determining optimal medical image compression: psychometric and image distortion analysis,” BMC Medical Imaging, 2012, pp. 12 – 24.

[13] Krivenko S., Krylova O., Bataeva E., Lukin V., “Smart Lossy Compression of Images Based on Distortion Prodection,” Telecommunications and Radio Engineering, 2018, 77 (17), pp. 1535-1554.

[14] Pyatykh S., Hesser J., Zheng L., “Image Noise Level Estimation by Principal Component Analysis,” IEEE Transactions on Image Processing, 2013, 22(2).

[15] M. Colom, M. Lebrun, A. Buades, J.M. Morel, “A Non-Parametric Approach For The Estimation Of Intensity-Frequency Dependent Noise,” 2014 IEEE International Conference on Image Processing (ICIP).

[16] Abramova V., “A Blind Method for Additive Noise Variance Evaluation Based on Homogeneous Region Detection Using the Fourth Central Moment Analysis,” Telecommunications and Radioengineering, 2015, 74(18), pp. 1651 – 1669.

[17] Abramova V., Abramov S., Lukin V., “Iterative Method for Blind Evaluation of Mixed Noise Characteristics on Images,” Information and Telecommunication Sciences, 2015, 6(1), pp. 8 – 14.

[18] https://www.jmoritaeurope.de/en/products/diagnostic-and-imaging-equipment-overview/

[19] Abramova V., Abramov S., Lukin V., Roenko A., Vozel B., “Automatic estimation of spatially correlated noise variance in spectral domain for images,” Telecommunications and Radioengineering, 2014, 73(6), pp. 511 – 527.

[20] Tsekhmystro R., Rubel O., Abramova V., Zriakhov M., Uss M., “Mobile Deployment of NoiseNet: Noise Characteristics Assessment in Real-World Images,” 2019 IEEE 2nd Ukraine Conference on Electrical and Computer Engineering (UKRCON), 6 p.