INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE
ISSN: 2057-5688

EFFECTIVE DENOISING TECHNIQUE REGARDING IMAGE RESTORATION WHILE USING A HYBRID OPTIMIZATION FRAMEWORK

Rajamandrapu Srinivas, Research Scholar, Department of Computer Science and Engineering, Monad University, Hapur, U.P.

Dr.Amit Singhal, Professor, Supervisor, Department of Computer Science and Engineering, Monad University, Hapur, U.P.

Abstract

Denoising a photograph is a well-studied subject and a key technique utilized in the medical, environmental, educational, and communication domains. Many common and novel approaches to image denoising have lately been investigated. Although these strategies provide high-quality results, there is always opportunity for improvement. Using this concept as a guide, an upgraded framework consisted of four models was developed in order to generate high-quality and accurate photos for the purposes of its application. A learning framework is a supporting structure that may be established around a method or process that allows for the achievement of a certain objective. This research proposes a development framework that may be used to effectively denoise an image by overcoming the bottlenecks of existing approaches. The models selected and described in this study have been verified in prior research work and are compared to the results of the offered models to reach a conclusion. Despite the development of several conventional and novel approaches for image denoising, they have not yielded adequate, qualitative results in terms of enhanced performance. In order to create clear, noise-free images, the improvised model utilizes multiple strategies depending on the kind of noise to be removed. Four strategies are used to build models that may be used for denoising an image depending on the sort of noise to be removed: Dictionary Based, Non Local Means Decision Based Unsymmetric Trimmed Median, Patch Based, and Fourth Order Kernel Regression. Each model is assessed using typical database images available for denoising research work, which are well supported by efficient techniques. When the results are

compared to the existing methodologies, it is clear that the recommended method of Dictionary-based denoising offers effective results for removing Gaussian noise from an image. Furthermore, in the removal of Gaussian and impulse noise from pictures, the NLM-DBTUM-based denoising strategy surpasses previous models. The third strategy described, the Patch Based approach, assists in the elimination of Gaussian, Speckle, and Impulse noises, and the results have been shown to be effective utilizing the supplied algorithm. Fourth Order Kernel Regression is provided as a novel strategy for lowering Rician and Gaussian noises during image denoising for 3D medical images. The models solve the shortcomings of the earlier strategies by developing algorithms that create qualitative images while retaining their edges.

These suggested techniques are fully addressed in combination with the conventional database of images available for denoising and the extensive study of the execution of produced algorithms. These algorithms' results are used to provide a learning framework for image denoising and restoration. The models indicated in this framework may be used together or separately, depending on the requirement, application, nature of the image under examination, and types of noise present.

1. Introduction

In the modern day, digitalized visual information has become one of the most common forms of communication. Every time digital information (data and pictures) is conveyed across a medium, noise causes it to get damaged. Denoising an image is a problem for society as a whole and is prevalent in the medical, environmental, educational, and other sectors. We must provide photographs with improved quality and minimal noise to aid these groups in continuing their study. The'mantra' that has drawn researchers and academics to find the best algorithm, architecture, and model to get a better aesthetically qualitative picture is an image without noise. The past ten years have seen a rise in the use of digital photographs as a consequence of research into internet and intranet applications. Eminent experts and scholars have discovered a number of techniques and technologies to produce noise-free, clear, and high-quality photographs for assessment. The introduction of radiography has increased the need for high-quality pictures in the realm of medical diagnosis and research. The amount of noise in a picture, the pixel resolution, and the size all affect its quality. Moderate help for noise removal is provided by conventional techniques like noise filters and picture denoising algorithms.

Certain information pertaining to the picture might become invisible due to factors including contrast, sensitivity, blur, and noise. The majority of the time, altering one aspect of a picture may improve its quality while negatively impacting its other aspects. As a result, the choice of a denoising technique depends on the particular demands of the applications for which the picture is being utilized. An effective picture denoising and restoration approach is needed in the current era of digital image application requirements since these photographs are often captured in subpar lighting. Even when top-of-the-line current technology is used to take pictures, the requirement for image enhancement cannot be ignored. The best way to encrypt images is via a gray level matrix or color values. The main factors affecting a picture's accuracy are its blur and noise levels, with blur being an inherent concern since image capture systems only have a limited number of samples. For instance, the picture may be described as "x" and the denoising operator as "Dh" with "h" being the filtering parameter. The noise approach and image difference may be used to define this as x-Dh x.

When an image is being acquired or transmitted, noise is unavoidable; it is caused by a number of different processes and variables. The amount of damaged pixels in a picture determines how much noise there is. The following elements are thought to be the main contributors to noise in a picture.

(i) Environmental circumstances present at the time of picture collection that have an impact on the imaging sensor

(ii) Inadequate light and sensor temperature may cause noise to be injected into a picture.

(iii) Transmission interference may also cause noise to taint a picture.

(iv) Another factor that might contribute to noise in a picture is the presence of dust particles in the screen scanner.

ISSN: 2057-5688

An image's noise may be roughly categorized as either additive or multiplicative in nature. These sounds are inevitable and were created during the picture capture procedure. It is created from the optimal photon-length grainy noise of a picture. When the original signals of an image are combined with additive noise signals to form an additive noise model, corrupted noisy signals are generated. Multiplicative noise models refer to noise signals that multiply while the original signal is being used to capture a picture. Following is a quick explanation of several noise forms based on these factors:

2 Litreature Survey

Reading relevant books in the particular field of study is an essential element of any good research. It helps help to place research activities in the wider research area. Literature Survey is the process that involves analyzing, resummarizing research, organizing, and making new conclusions based on the findings of a technical analysis of a large quantity of research article. The findings of the literature study could be a contribution to the existing knowledge when they are peer reviewed and published as research articles. Literature surveys allow researchers the chance to make use of the of the work to evaluate qualitatively and contrast them with similar publications. Researchers can conduct a quantitative and qualitative analysis. It also implies that every research project or research study needs to be compared against certain standards which can serve as a reference point for review and comparison.

Many domains are available within the realm of image demoising to carry out research, such as Spatial Domain, Transform Domain and Dictionary based Domain. Each domain has various models and strategies which justify their use as well as the complexities of denoising images. In light of the significance and practicality of the field of research The following four strategies have been analyzed and tested to help develop an effective learning framework to restore and denoize images.

A) Dictionary based Model. 2.) Non-Local Means - DBUTM Model C) Patch-based model) Kernel Regression Learning Model In addition, models for domains such as Spatial as well as Transform models are purely primitive in nature, and therefore are not used in the previous four models. Therefore, these models aren't included in the studies of literature.

Ajit Rajwade et al. have proposed a simple and thoroughly designed path-based machine-learning method that uses Higher Order Singular Value Decomposition (HOSVD) to reduce image noise. This model is based on the idea that identical patches are put together with noise. The images have the sameness, as defined by the the criteria for the statistically driven 3D stack. Then, we calculate HOSVD coefficients to the similar. In turn, these coefficients can be modified using the hard thresholding technique as well as transforming the inverse of HosvD in order to produce the ultimate refined image. The technique can be employed on color images as well as grayscale images. It takes out Gaussian noise by itself and chooses the best patch size which isn't the same throughout the images. Boaz Ophir et al. developed an image denoising algorithm built on signals that are represented as unreliable and sparse, using multi-scalar dictionary learning models i.e K-Singular Value decomposition (K-SVD) as well as Wavelets.

The power of learned dictionaries paired with Generic Multi-scale Representations allows for the capture of signals that have intrinsic properties. This helps in representing data in a sparse way that makes it more efficient and also analyzes signals in a global manner. K-SVD can't be placed directly in large areas to create efficient image denoising. Hancheng Yu et al. have proposed the application to the Wavelet Based Trivariate Shrinkage filter that uses spatial-based mutual bilateral filter that removes Gaussian noise in images that are corrupted. The coefficient of the wavelet domains is modelled as the trivariate Gaussian distribution. A trivariate reduction filter is feasible making use of "Maximum A Posteriori" Estimator taking into account statistical dependences between waveslet coefficients at the intra-scale. This method provides insignificant results with real-time photos. The method is a powerful method of denoising to eliminate unnecessary noise and preserving edges. The algorithm receives two user-supplied parameters. Users must choose the appropriate

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE
ISSN: 2057-5688

parameter value in order to get the best outcome. Ling Shao et al. suggested a new method of image denoising that is based on looking over and completing a thorough evaluation of different algorithms ranging of The Heuristic Optimization in Dictionary learning. By learning a vast number of patches of an image database the method can perform the denoising process of images.

3 Methodology

Content Based Image Retrieval utilizes images' visual elements image to locate the desired image in an extensive database. CBIR has been used extensively in the retrieval of images from large digital image databases, with minimal humans involved Lopez-inesta et al Researchers are striving to improve CBIR-based systems since CBIR is extensively utilized in a variety of fields, including medical, security and libraries that are digital. Papushoy and a Figure 3.1 depicts the only feature-based image retrieval method. CBIR allows for the automatic indexing and retrieval by using the content of the image, which is known as features. Converting the image input into a series of characteristics is known as feature extraction. The process of feature extraction is an important step in the CBIR process, which involves removing the features of an image to a distinct level for efficient retrieval. The many kinds of attributes that can be taken from an image include the texture, color and form. In order for a learner algorithm to analyse the visual data, every image needs to be converted to a set of features that is able to reflect the visual information to the greatest extent possible. They can be classified as general or specific to a particular domain.

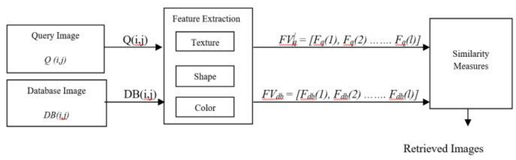

Figure 3.1 Single Feature based Image Retrieval System

Texture, color and form are among the most frequently used characteristics within CBIR. They can be both global and local. If the chosen region is considered as the entirety of an image, the features can be global and describe the entire image. If the chosen region is to be a part, salient or segmented region and features are local detailing specific elements in the photo. In this part, the various techniques for removing features from images used to auto-annotate images are reviewed in detail, as are the

ISSN: 2057-5688

characteristics of the features. Methods for estimating statistical features are thought to be useful in the classification and retrieval of images that are similar to each other. There are a variety of method of feature extraction, including 1D-GLCM and 4D-GLCM, LBP, LTrP, Dominant Color Descriptor (DCD), BSIF as well as MTSD.

One of these is GLCM statistical technique analyzes the spatial relation of pixels in order to study the appearance of the image and provides superior outcomes. The current 4D-GLCM computes the spatial relationship only in four directions, either Vertical and Horizontal directions, or Diagonal directions. 1D-GLCM calculates the spatial relationships in only single direction Min Huang & Manisha Verma. This means that the spatial relation of pixels to the other neighborhood pixels are not captured, and could be a source of details needed for obtaining exact outcomes. Thus, an 8D-GLCM algorithm that shows details about the mutual appearance of pixel patterns across every neighbourhood direction with an pixel separation of just one being proposed. This method is able to collect the spatial relation of the gray value with the entire neighbourhood pixel. Hence, there is no loss of information which increases the accuracy of retrieval as when compared with the current techniques. Color is by far the most commonly employed feature because of its ease of use. CCM is one of them, along with Weighted Dominant Colour Descriptor (WDCD), HSV Color Histograms, as well as RGBCM. Color Moments determine the color-related features of an image. They are unique in describing a probability-based distribution. The color moment represents the details of the whole image. It is derived using the color spaces of any. In a detailed literature study of techniques previously used based on color moment data, those derived from RGB colors were discovered to be comparatively more precise (Min Huang and . However, RGB, Cyan Magenta Yellow Black (CMYK) and comparable color models aren't good enough to describe color in terms that are suitable for the human eye to interpret. HSV color models are more preferred to alternative color models like RGB or CMYK due to it's similarities with the way people perceive the color. Thus, the

ISSN: 2057-5688

new HSVCM improves the accuracy in comparison to the previous RGBCM.

Proposed METHODOLOGY A streamlined image retrieval system based on 8D-GLCM as well as HSVCM is suggested. Image retrieval systems process the image input through enhancement of the image taking the basic features of the image and then using the subsequent analysis of similarity to identify those images that are most alike. Figure 3.2 illustrates the method proposed. Features Extraction is an important phase of the CBIR process that involves the extraction of image features to ensure precise retrieval. Geometric Shape Features (GSF) and 8D-GLCM texture features, as well as HSVCM characteristics are extracted by the input image, and from every image in the database.

4 Experiment & Results

The construction steps of 8D-GLCM follow these steps:

Step 1: Look at the possibility of a 4X4 image I that has 4 gray levels

Step 2. Measurement of GLCM is carried out using 8 angles and 8 pixels.

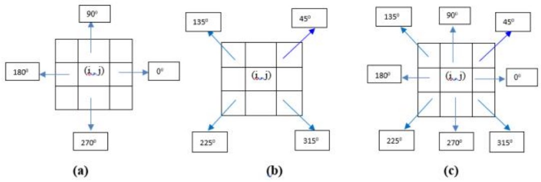

Figure 3.3 (a) GLCM formation with 4 angles (horizontal and vertical); (b) GLCM formation with 4 angles (diagonal); (c) GLCM formation with 8 angles (horizontal, vertical and diagonal)

Step 3: Computation of 8D-GLCM (,)

The size of the matrix is determined by the formulae

$$G[i,j] = (Max_{Inten} - Min_{Inten}) + 1$$

In this case, MaxIntern is the highest intensity value of the image. MinIntern represents the value of minimum intensity in the image.

G[i,j] matrix derived from eight directions (000 1, the 450 and 900, 800, 900 , 1350 , 1800 2250, 2700, 3150) is illustrated in the figure 3.4.

Step 4: Extraction of Feature from 8D-GLCM

The 8D-GLCM creates an a 32-Dimensional feature matrix (4 elements taken from every one of eight GLCM results in 4x8=32 feature). In the 8D-

GLCM feature matrix that is constructed The following features of texture are extracted.

Energy determines the amount of pixel pairs that are repeated. If the number of repeating Pixel Pairs is higher, the number is predicted to be very high.

$$\text{Ene} = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} G[i,j]^2$$

Color feature is commonly employed for representation of images because due to their efficiency and simplicity. Color feature is among the most popular and widely utilized features due to its unchanging nature to transformation, rotation as well as scale . It is a strong resist to noise and variation in the size of an image, its resolution and direction . Color moment is a measure of the properties of color distribution within an image. They define a probability distribution. CM is a benefit of being drawn from various colors. This work HSV model provides information on the color using ways that are than humanly recognizable. HSV model is a perfect instrument for the development of algorithms to process images based upon descriptions of color that are familiar and easy for human beings to understand .

Hue is the color that's pure and is defined in terms of an angle of 0 to 360 ° of rotation. The term "saturation" refers to the extent to which the original color gets diluted through white light. The range of values is from between 0 and 254. The less saturation means that more gray will be evident in the color which causes it to appear dull. It is the measure of brightness the color. The range is from 0 to the number 255. 0 is totally dark, and 255 being completely bright. Color feature extraction involves two stages:

(1) The transformation of an input RGB image to HSV hue space.

(2) Computation of Mean (average color information) Standard deviation (total amount of pixels which is different from the average) and Skewness for each one of three HSV components. The Color Moment generates the 9-dimensional feature vector.

$$\text{Mean} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} P_{cc}(i,j), \; cc = \{H,S,V\} \tag{3.8}$$

$$\text{Standard Deviation} = \left[\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (P_{cc}(i,j) - \text{Mean})^2\right]^{\frac{1}{2}}, \; cc=\{H,S,V\} \tag{3.9}$$

$$\text{Skewness} = \left[\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (P_{cc}(i,j) - \text{Mean})^3\right]^{1/3}, \; cc=\{H,S,V\} \tag{3.10}$$

In this case, N and M represent the column and row dimensions of the

ISSN: 2057-5688

image. Pcc(i,j) defines the pixel intensities of the ith row as well as the Jth column of the fastidious color channel.

Pre-processing can be described as an enhancement of the image that reduces distortions and enhances the aspects that are essential to image processing. The histogram of a photograph represents the an approximate frequency of the occurrence of different gray levels. For a smooth histogram, the process of histogram equalization. It displays the image of the query and the image converted to grayscale as well as its histogram, and the histogram-equalized image as well as its histogram. When comparing the histogram of the transformed grayscale image to that of the processed images, you can see that the histogram for the image that has been processed is distributed across the grayscale values, and consequently the brightness of the image increases. The figure shows the images obtained without processing and the accuracy achieved is 60 percent. The other image shows the collection of images that are retrieved using preprocessing, and the accuracy achieved is 90%. Therefore, when you include the pre-processing process in an imaging retrieval systems this precision is improved by 30 percent. Therefore, it can be observed that the process of histogram equalization can improve the efficiency of CBIR systems with respect to accuracy.

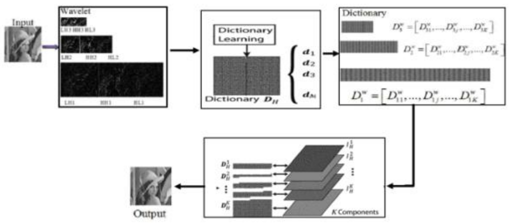

Figure 3.3 SLAD model

Clean image is considered as ‘x’ and noisy image as ‘y’ which is contaminated by additive noise with zero-mean. Initially, image “y” that is transformed into the wavelet domain contains a number of decomposition levels ; at each level, the wavelet coefficients are apportioned as overlapping patches of a fixed size. By applying Fuzzy C-Means clustering to the vectors, the individual patch is formed as a vector variable. Thereafter, a sub-dictionary is trained through reweighted aggregating moments in each cluster, wavelet coefficients are thereupon denoised by sparse coding process. A combination of the trained sub dictionaries over the complete dictionary of the scale and finally

ISSN: 2057-5688

transformation back to the spatial domain makes it possible to arrive at the estimated denoised image "^x". This process is explained in detail as follows:

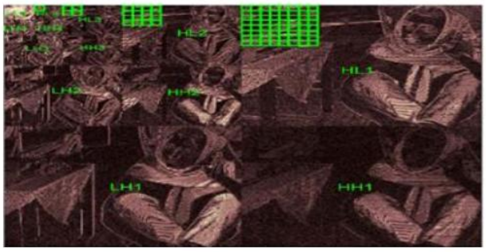

Figure 3.4 Wavelet decomposed image

Converting the signal to a waves that are mutually orthogonal can be done using this decomposition (LL LH, HL, and HH) of which the high-frequency part (LH, both HL and) is used to aid in studying the dictionary. Principle Component Analyse (PCA) is a search for an ideal dictionary in the signals. The signals are represented in a sparse manner by every signal. When considering the signals "N" as dimension of "n", the number of components in the dictionary as well as the iterations that are done to select the most suitable dictionary. The ideal dictionary is selected to be one that is an Adaptive Dictionary, where denoising the image is achieved by resembling each block in a sparse manner that are fully trained with a dictionary.

5 Conclusion

The technique proposed uses one feature to achieve efficient CBIR, based on color shape and texture. GLCM Based Texture Features and Color Moments that are derived from HSV color space, and Geometric Shape features are employed for this research. The tools that are used in the model provide useful outcomes. Results show that the low precision results could be obtained using GSF and 8D-GLCM textures, while the 8D-GLCM features led to higher accuracy and HSVCM produced high average precision of 76% for Corel 1K as well as 72% for Corel 10K, compared to the single features of shape and texture. To improve quality, these elements can be used together as hybrid functions. There isn't a single, perfect representation of a picture that is applicable to all perceptions as an image could be taken under different circumstances. Systems that were previously designed are dependent on the image's characteristics, specifically the shape, color and. Previous research has led to an improvement in results in retrieval through the integration of color, texture and shape details instead of relying on just one feature. Therefore, in the following chapter, hybrid feature-based retrieval of images is suggested to create an efficient CBIR model.

6 Reference

1. Aja-Fernández, S, Ciak, TP & Vegas-Sánchez-Ferrero, G 2015, 'Spatially variant noise estimation in εRI: A homomorphic approach',Medical Image Analysis, vol. 20, no. 1, pp. 184-197.
2. Algarin, JM, Breuer, F, Behr, VC & Freire, εJ 201η, 'Analysis of the noise correlation in MRI coil arrays loaded with metamaterial magneto-inductive lenses', IEEE Transactions on εedical Imaging, vol. 34, no. 5, pp. 1148-1154.
3. Bouhrara, M, Bonny, J, Ashinsky, BG, Maring, MC & Spencer, RG 2017, 'σoise estimation and reduction in magnetic resonance imaging using a new multispectral nonlocal maximum-likelihood filter', IEEE Transactions on Medical Imaging, vol. 36, no. 1, pp. 181-193.
4. Cao, Y, Mao, J, Yu, H, Zhang, Q, Wang, H, Zhang, Q & Guo, L 2020, 'A novel hybrid active contour model for intracranial tuberculosis εRI segmentation applications', IEEE Access, vol. 8,pp. 149569-149585.
5. Cao, Z, Wei, Z & Zhang, G 2014, 'A no-reference sharpness metric based on the notion of relative blur for Gaussian blurred image', urnal of Visual Communication and Image Representation, vol. 25, no. 7, pp. 1763-1773.
6. Caviedes, J & τberti, F 2004, 'A new sharpness metric based on local kurtosis, edge and energy information', Signal Processing: Image Communication, vol. 19, no. 2, pp. 147-161.
7. Chang, HH, Li, CY & Gallogly, AH 2018, 'Brain εR image restoration using an automatic trilateral filter with GPU-based acceleration', IEEE Transactions on Biomedical Engineering, vol. θη, no. 2, pp. 400-413.
8. Chen, G, Dong, B, Zhang, Y, Lin, W, Shen D & Yap, P 2019, 'Denoising of diffusion MRI data via graph framelet matching in x-q Space', IEEE Transactions on Medical Imaging, vol. 38, no. 12, pp. 2838-2848.
9. Chow, LS & Rajagopal, H 2017, 'εodified-BRISQUE as noreference image quality assessment for structural εR images', Magnetic Resonance Imaging, vol. 43, pp. 74-87.
10. Chow, LS, Rajagopal, H & Paramesran, R 201θ, 'Correlation between subjective and objective assessment of magnetic resonance (MR)

ISSN: 2057-5688

images', εagnetic Resonance Imaging, vol. 34, no. θ, pp. 820-831.

11. Cocosco, CA, Kollokian, V, Kwan, RKS, Pike, GB & Evans, AC 1997, 'Brainweb,τnlineinterfacetoa3DεRIsimulatedbraindatabase', NeuroImage, vol. 5, no. 4, pp. 425.

12. Coupe, P, Manjon, JV, Gedamu, E, Arnold, D, Robles, M & Collins, Dδ 2010, 'Robust Rician noise estimation for εR images', εedical Image Analysis, vol. 14, no. 4, pp. 483-493.

13. Damera-Venkata, N, Kite, TD, Geisler, WS, Evans, BL & Bovik, AC 2000, 'Image quality assessment based on a degradation model', IEEE Transactions on Image Processing, vol. 9, no. 4, pp. 636-650.

14. Decker, CM, Zöllner, FG, Konstandin, S & Schad, LR 2012, 'Comparing anisotropic diffusion filters for the enhancement of sodium magnetic resonance images', εagnetic Resonance Imaging,vol. 30, no. 8, pp. 1192-1200.

15. Fisher, RA 19η8, 'Statistical εethods for Research Workers', 13th Ed. Hafner.

16. Fuderer, ε 1988, 'The information content of εR images', IEEE Transactions on Medical Imaging, vol. 7, no. 4, pp. 368-380.

17. Gabarda, S & Cristóbal, G 2007, 'Blind image quality assessment through anisotropy', Journal of the τptical Society of America A, vol. 24, no. 12, pp. 42-51.

18. Gabarda, S, Cristóbal, G & Goel, N 2018, Anisotropic blind image quality assessment: Survey and analysis with current methods', Journal of Visual Communication and Image Representation, vol. 52,pp. 101-105.

19. Gerig, G, Kubler, O, Kikinis, R & Jolesz, FA 1992, 'σonlinear anisotropic filtering of εRI data', IEEE Transactions on εedical Imaging, vol. 11, no. 2, pp. 221-232.

20. Gvozden, G, Grgic, S & Grgic, ε 2018, 'Blind image sharpness assessment based on local contrast map statistics', Journal of Visual Communication and Image Representation, vol. 50, pp. 145-158.

21. Hamarneh, G & Hradsky, J 2007, 'Bilateral filtering of diffusion tensor magnetic resonance images', IEEE Transactions on Image Processing, vol. 16, no. 10, pp. 2463-2475.

22. Ho, KC, Speier, W, Zhang, H, Scalzo, F, El-Saden, S & Arnold, CW 2019, 'A machine learning approach for classifying ischemic stroke onset time

ISSN: 2057-5688

from imaging', IEEE Transactions on Medical Imaging, vol.38, no. 7, pp. 1666-1676.

23. Hong, Y, Ren, G & δiu, E 201θ, 'A no-reference image blurriness metric in the spatial domain', τptik, vol. 127, no. 14, pp. ηηθ8-5575.