EDGE DETECTION FOR BRAIN TISSUE SEGMENTATION IN MR IMAGE

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Title:

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Abstract:

Edges are a crucial aspect of object and image representation and analysis. They separate an object from its background, highlighting the object's surface characteristics and defining its inter-object boundaries and internal textures. In semi-automatic or fully automatic image analysis and understanding, edges play a significant role in the detection and representation process. They serve as a prominent characteristic feature for representing the shape of an object.

Magnetic resonance imaging (MRI) or nuclear magnetic resonance imaging (NMRI) is primarily a medical imaging technique used in radiology to visualize the internal structure of the body. MRI provides a much greater contrast between different soft tissues of the body. This ability makes it useful for neurological, musculoskeletal, cardiovascular, and oncological imaging. Human brain matter tissues can be categorized as White matter (WM), Gray matter (GM), and Cerebrospinal fluid (CSF). Most of the brain structures are anatomically defined by the edges of these tissues. Detection of these edges is an important step for quantitative analysis of the brain and its anatomical structures. It is also an important step for the detection of various pathological conditions affecting brain parenchyma. It is also used for surgical planning, simulation, and three-dimensional visualization to diagnose and detect abnormalities. It is also useful in the study of brain development and human aging. As a result of low contrast, various sources of noise, partial volume effects, structural variations, and various types of artifacts the edge detection process of MRI images of the brain is non-trivial.

Starting from the basic definition of the edge, the phenomenon of the appearance of edges in the image, different models used to model the edge like step, ramp, line, and roof edge models are presented. The well-known traditional edge detectors like Roberts Edge Detector, Prewitt Edge Detector, Sobel - Feldman

Edge Detector as well state of art and cutting-edge edge detectors like Holistically-Nested Edge Detector, Richer Convolutional Features Edge Detector, Bi-Directional Cascade Network for Perceptual Edge Detector and Dense Extreme Inception Network Edge Detector are implemented and analyzed.

MRI images always contain a significant amount of noise caused by operator performance, equipment, and the environment. This noise can lead to major inaccuracies in the edge detection process and hence in segmentation results. We conduct research in measuring the performance of Edge Detectors for edge detection in different noise levels for MRI images. To validate the accuracy and robustness of these Edge Detectors we carried out experiments on MRI brain scans. The performance of the edge detectors is analyzed by different quantitative measures. These quantitative measures like accuracy and F measure.

As a result of the increasing amount of noise in the MRI image, the performance of the edge detector degrades. The noise in the image causes spurious edges and results in a decrease in the accuracy of the edge detector. We proposed an edge detector with the ability to withstand the increasing amount of noise in the MRI image. We also proposed one variation of the proposed method with a spatial variation edge detector to improve the accuracy of the edge detector in the presence of noise.

State of the Art:

Edge is one of the key features of the characteristic representation and analysis of objects and images. As the object's surface characteristics make a difference from the background, the edges separate the object from its background. Also, the edges characterize the inter-object boundaries as well the textures within the object itself. In the semiautomatic or fully automatic analysis and understanding of the image, edges play a significant role in the representation and detection process. In the representation of the shape of the object, the edges are used as the prominent characteristic feature[1], [2].

Image is defined as the two (or three) dimensional function of intensity with respect to the spatial coordinates. These intensities are distributed over the spatial coordinates to represent any three-dimensional object or scene. hence the physics of the object or the objects in the scene and the background causes discontinuity in the intensity distribution function. This discontinuity in the intensity level of the image is called Edge[3]. Edge is any change of the intensity value with respect to the neighboring pixel's intensities. Higher change results in significant edges. And, lower the change results in spurious edges. The significant edges are considered to be one of the important features for image characteristics representation and spurious edges may represent very low-intensity variation, low-level texture, or noise in the image. The spurious edges increase as the noise level in the image increases. Hence, the significant edges increase in the image after low-pass filtering of the image[3], [4].

Edges in the image appear due to one of the three phenomena namely physical, geometrical, and non-geometrical events. The image of the physical object with the background causes the edges between the object and the background. Here, the resulting edges are due to the phenomenon of physical events. The object boundary, discontinuity in the object surface and textures also appear as edges in the image. Here, the resulting edges are due to the phenomenon of geometrical events. The shadows, internal reflections, and specularity also result in edges in the image. Here, the resulting edges are due to the phenomenon of non-geometrical events[1], [3], [5].

Edges represent one of the key characteristics of the image representing the object or scene. It is significant to identify and detect the edges in the image. As the mathematical representation of these edges involves the complexity of representation increasing with an increasing number of pixels, makes the representation computationally complex in terms of representation and calculation as well practical implementation and detection[6]. To simplify the complexities involved in the representation of these edges, edges are modeled with the simplified and minimal representational and computational expenses involved. Based on the intensity profile these edges are modeled. These simplified models are step, ramp, line, and roof edge model[7].

A step edge model is the catheterization of the intensity profile of the neighboring pixels with step change in the intensities. The step edge occurs in the image as a result of sharp and significant discontinuity. This edge model represents a clean and ideal edge, which results after significant preprocessing on the obtained raw image[3], [8].

A ramp edge model is the characterization of the intensity profile of the neighboring pixels with ramp-like monotonically increasing or decreasing change in the intensities. The ramp edge occurs in the image as the result of blur or defocused object. This edge model represents the degree to which the discontinuity is blurred in the image[1], [8].

A line edge model is the characterization of the intensity profile of the pixels with bumped line intensity profile with respect to their neighboring pixels. The line edge occurs in the image as the result of strip, road, or ridge-like objects or structures[8].

A roof edge model is the catheterization of intensity profile of the neighboring pixels with two conjugate ramps like monotonically increasing or decreasing with decreasing or increasing changes in the intensities. The roof edge occurs in the image as a result of pipes, digitization of line drawings, and satellite images with road-like structures[8].

In real life, the edges will be the mixture of the above-mentioned model with added different noises and biases. The addition of noises and bias in the image causes the task of edge detection to be non-trivial[9]. Noise in MRI images can stem from multiple sources, such as human error, technical limitations of equipment, and environmental factors, resulting in a noticeable level of noise in the images[10]–[12].

The operator or algorithm used to detect the edge in the image is known as the edge detector. In simple terms, the process to detect the edge in the image is known as an edge detector. It could be as simple as a differential operation or the difference operation. Also, it could be a highly complex algorithm with machine learning and deep learning techniques. Here, we describe some of the well-known traditional edge detectors as well as state-of-the-art and cutting-edge edge detectors.

The Roberts cross-gradient operator was proposed by Lawrence Roberts in 1965. It is a discrete two-dimensional differential operator used to emphasize and detect the gradient of the intensity function of the image. The operator computes the gradient of an image through discrete differentiation, achieved by calculating the sum of the squares of the differences between diagonally adjacent pixels. The result of this operator corresponds either to the intensity gradient or the norm of the intensity gradient in the image. This is based on the convolution of the image with two separable and integer-valued horizontal and vertical operators, frequently known as masks[13].

Due to the separable, integer-valued, and small-size nature of this edge detection approximation, it is relatively inexpensive in computations. Also, it produces significant behavior in the high frequency and sharp discontinuity intensity variation in the image. Although the formulation of Roberts edge detector approximation is generally used form two-dimensional images, this edge detector approximation can be further extended to other higher dimensions in case we have the higher dimensional image for the purpose of multi-dimensional edge detection[8], [13].

Prewitt edge detector approximation was proposed by J Prewitt presented the idea of a 3x3 Image Gradient Operator in 1970. It is a discrete two-dimensional differential operator used to emphasize and detect the gradient of the intensity function of the image. The result of this operator corresponds either to the intensity gradient or the norm of the intensity gradient in the image. This is based on the convolution of the image with two separable and integer-valued horizontal and vertical operators, frequently known as masks[14].

Sobel-Feldman edge detector approximation was proposed by Irwin Sobel and Gary Feldman, colleagues at the Stanford Artificial Intelligence Laboratory (SAIL). Sobel and Feldman presented the idea of an "Isotropic 3x3 Image Gradient Operator" at a talk at SAIL in 1968. It is a discrete two-dimensional differential operator used to emphasize and detect the gradient of the intensity function of the image[15]. The result of this operator corresponds either to the intensity gradient or the norm of the intensity gradient in the image. This is based on the convolution of the image with two separable and integer-valued horizontal and vertical operators. The gradient magnitude and directions are calculated at every single point in the image. The magnitude of the gradient will reflect the edge of the image. The higher value of gradient magnitude will refer to the strong edge value in the image. And the direction of the gradient will refer to the orientation of the edge in the image[15], [16].

Holistically-nested Edge Detector (HED) performs image-to-image prediction by means of a deep learning model. Deep learning model leverages fully convolutional neural networks and deeply-supervised nets. HED automatically learns rich hierarchical representations. Hierarchical representations (guided by deep supervision on side responses) are important in order to approach the human ability to resolve the challenging ambiguity in edge and object boundary detection [17].

Liu, Yun, Ming-Ming Cheng, Xiaowei Hu, Kai Wang, and Xiang Bai proposed edge detector based on Richer Convolutional Features. Richer Convolutional Features Edge Detector (RCF) Edge detector using richer convolutional features (RCF)[18]. Objects in nature images have various scales and aspect ratios, the automatically learned rich hierarchical representations by CNNs are very critical and effective to detect edges. The convolutional features gradually become coarser with receptive fields increasing. Use of multiscale and multi-level information to perform the image-to-image edge prediction by combining all of the useful convolutional features into a holistic framework [18]–[20].

In 2019, He, Jianzhong, Shiliang Zhang, Ming Yang, Yanhu Shan, and Tiejun Huang proposed an edge detector based on Bi-Directional Cascade Network. Exploiting multi-scale representations is critical to improving edge detection for objects at different scales [21]. To extract edges at different scales, authors proposed a Bi-Directional Cascade Network (BDCN) structure. Here an individual layer is supervised by labeled edges at its specific scale, rather than directly applying the same supervision to all CNN outputs. The authors introduced a Scale Enhancement Module (SEM) which utilizes dilated convolution to generate multi-scale features. These encourage the learning of multi-scale representations in different layers and detect edges that are well delineated by their scales [21], [22].

In 2020, Poma, Xavier Soria, Edgar Riba, and Angel Sappa proposed an edge detector based on Dense Extreme Inception Network. The authors proposed a Deep Learning based edge detector. Which is inspired by both HED (Holistically-Nested Edge Detection) and Xception networks. Xception by Google, stands for the Extreme version of Inception, a modified depth-wise separable convolution. This edge detector generates thin edge maps that are plausible for human eyes. Thin edge maps can be used in any edge detection task without previous training or fine-tuning process [23].

Definition of Problem:

Edge detection methods for brain tissue segmentation applications are having following problems:

- MRI images of the brain often have low contrast, which can make it difficult to distinguish between different tissues and structures.
- MRI images can be affected by various sources of noise, such as motion artifacts, thermal noise, and radiofrequency interference. Noise can result

in spurious edges or false positives, which can degrade the accuracy of edge detection algorithms.

- In MRI images, voxels may contain a mixture of different tissues, which can result in partial volume effects. This can make it challenging to accurately locate edges at tissue boundaries.
- The structure of the brain can vary widely across individuals, which can make it challenging to develop edge detection algorithms that are generalizable across different subjects.
- MRI images can be affected by various types of image artifacts, such as shading artifacts, ghosting, and ringing. These artifacts can result in false edges or edge gaps, which can affect the accuracy of edge detection algorithms.
- The spatial resolution of MRI images can affect the accuracy of edge detection algorithms, particularly for small or subtle edges.
- Edges can occur at different scales and orientations in an image. Detecting edges at all scales and orientations requires sophisticated algorithms and a careful selection of parameters.
- Edges can be characterized by changes in intensity, but intensity variations can occur for reasons other than edges, such as shadows, reflections, or texture. This makes it difficult to distinguish between true edges and false edges.
- Edge detection algorithms can be computationally intensive, particularly for large or high-resolution images. This can limit their usefulness in real-time applications or on devices with limited processing power.
- Edge detection can be subjective and depend on the specific algorithm and parameters used. Different algorithms can produce different results, and the choice of the best algorithm often depends on the specific application

Objective and Scope of Work:

Objectives:

- To analyze the effect on the performance of edge detectors as a result of the increasing amount of noise in MRI image of the human brain.
- To develop an edge detector for the detection of edges in the MRI image of the human brain.
- To develop an edge detector with the ability to withstand the increasing amount of noise in the MRI image of the human brain.
- To determine the performance of the developed edged detector with respect to the increasing amount of noise in the MRI image of the human brain.

Scope:

- We have focused on the MRI image of the human brain.
- We have focused on determining the effect on the performance of edge detectors as a result of the increasing amount of noise in the MRI image.
- We have focused on proposing an edge detector with the ability to withstand the increasing amount of noise in the MRI image.

Original Contribution by thesis:

We have analyzed the performance of edge detectors in MRI image of the human brain with respect to increasing amount of noise. We have proposed an edge detector to detect the edges in the MRI image of the human brain. The performance of the edge detector is analyzed for the MRI image of the human brain with an increasing amount of noise. The edge detector shows the ability to withstand the increasing amount of noise in the MRI image of the human brain.

The Methodology of Research:

As the interest in computer-aided, quantitative analysis of medical image data is growing, the need for validation of such techniques is also increasing. For the solution of the validation problem, Simulated Brain Database (SDB) is available [24]. The Simulated Brain Database contains a set of realistic MRI data volumes produced by MRI simulator [25], [26]. This data set is used in our work to evaluate the performance of the edge detector algorithms.

Roberts Edge Detector on the MRI image of the Human brain has been implemented. Prewitt Edge Detector on the MRI image of the Human brain has been implemented. Sobel - Feldman Edge Detector on the MRI image of the Human brain has been implemented. Holistically-Nested Edge Detector on the MRI image of the Human brain has been implemented. Richer Convolutional Features Edge Detector on the MRI image of the Human brain has implemented. Bi-Directional Cascade Network For Perceptual Edge Detector on the MRI image of the Human brain has been implemented. Dense Extreme Inception Network Edge Detector on the MRI image of the Human brain has been implemented.

For the above-implemented edge detectors, the performance measures like Accuracy and F Measure are computed. For increasing amount of noise the same edge detectors are implemented and performance measures are computed. The same procedure is followed for the Proposed Bitonic edge detector and its structural variation implementation SV Bitonic edge detector.

Results\Comparison:

After obtaining the confusion matrix for any classification experiment result, we have the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which are the number of counts in the respective class. The confusion matrix for the classification Problem is shown below

		Ground Truth	
		Condition Positive	Condition Negative
Predicted/ Observed Condition	Predicted Positive	True Positive (TP)	False Positive (FP)
	Predicated Negative	False Negative (FN)	True Negative (TN)

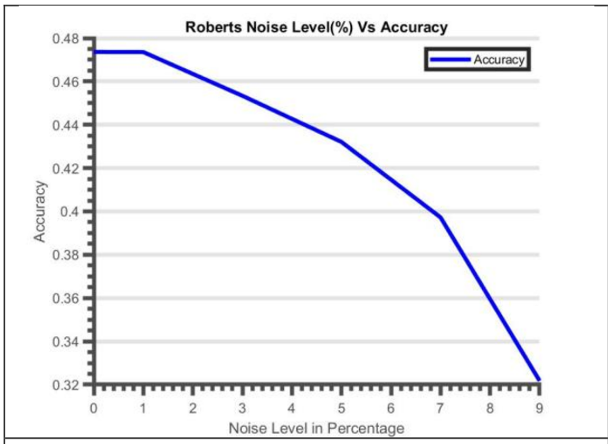
Confusion Matrix for the Classification

The Accuracy and F Measure are computed as

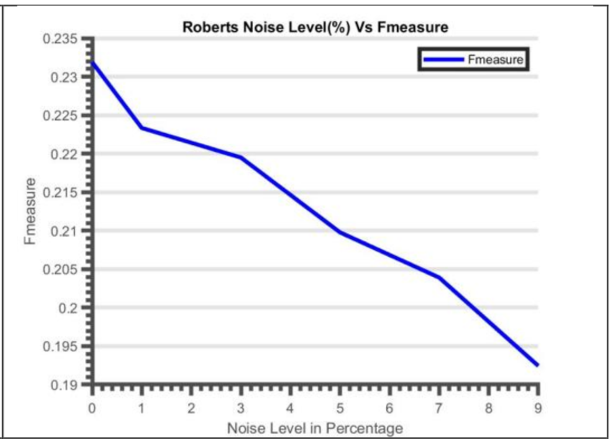
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{F Measure} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}}$$

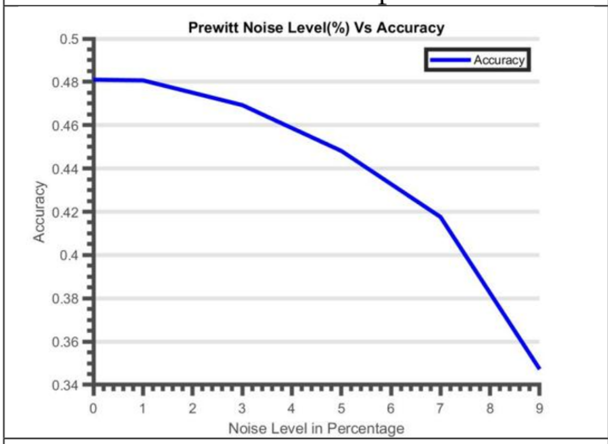
The Accuracy and F measure for various edge detectors with respect to the noise are graphically plotted in Figure 1. Here, in A) represents the Accuracy of the Roberts Edge detector with respect to noise level from 0% to 9%. In B) F measure of Roberts Edge detector with respect to noise level from 0% to 9%. In C) represents the Accuracy of the Prewitt Edge detector with respect to noise level from 0% to 9%. In D) F measure of Prewitt Edge detector with respect to noise level from 0% to 9%. In E) represents the Accuracy of the Sobel Edge detector with respect to noise level from 0% to 9%. In F) F measure of Sobel Edge detector with respect to noise level from 0% to 9%. In G) represents the Accuracy of HED Edge detector with respect to noise level from 0% to 9%. In H) F measure of HED Edge detector with respect to noise level from 0% to 9%. In I) represents the Accuracy of the RCF Edge detector with respect to noise level from 0% to 9%. In J) F measure of RCF Edge detector with respect to noise level from 0% to 9%. In K) represents the Accuracy of the BDCN Edge detector with respect to noise level from 0% to 9%. In L) F measure of the BDCN Edge detector with respect to noise level from 0% to 9%. In M) represents the Accuracy of the DexiNed Edge detector with respect to noise level from 0% to 9%. In N) F measure of the DexiNed Edge detector with respect to noise level from 0% to 9%. In O) represents the Accuracy of the Bitonic Edge detector with respect to noise level from 0% to 9%. In P) F measure of the Bitonic Edge detector with respect to noise level from 0% to 9%. In R) represents the Accuracy of the SVBitonic Edge detector with respect to noise level from 0% to 9%. In S) F measure of SVBitonic Edge detector with respect to noise level from 0% to 9%.



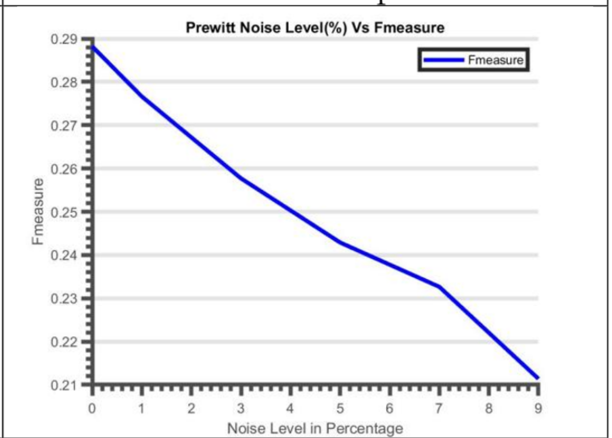
A) Accuracy of Roberts Edge detector with respect to Noise



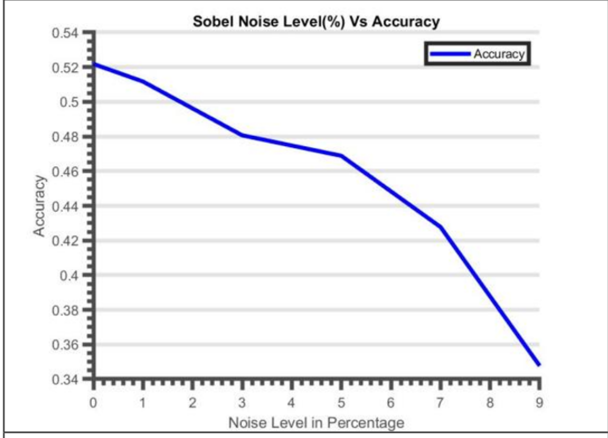
B) F measure of Roberts Edge detector with respect to Noise



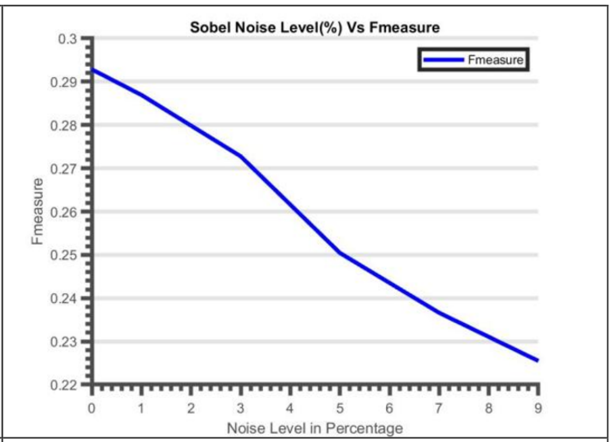
C) Accuracy of Prewitt Edge detector with respect to Noise



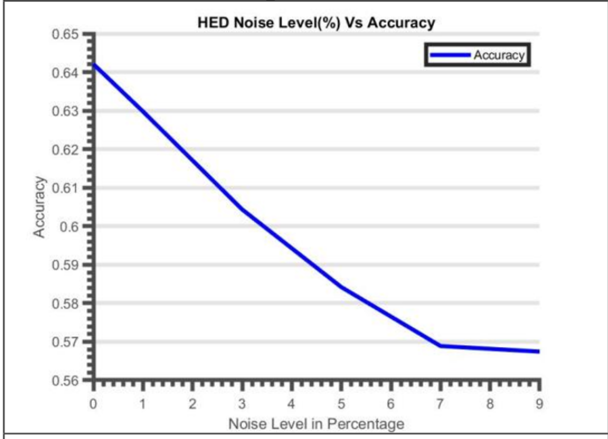
D) F measure of Prewitt Edge detector with respect to Noise



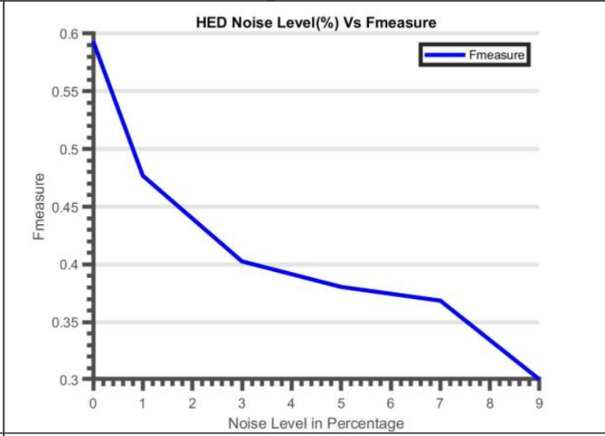
E) Accuracy of Sobel Edge detector with respect to Noise



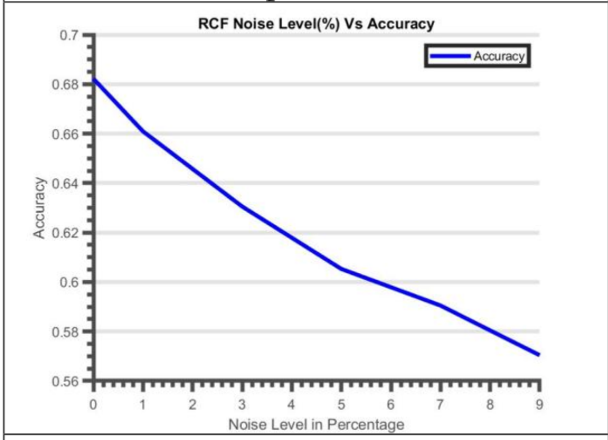
F) F measure of Sobel Edge detector with respect to Noise



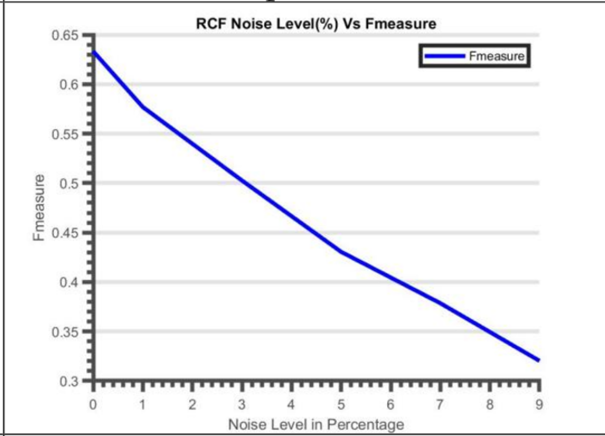
G) Accuracy of HED Edge detector with respect to Noise



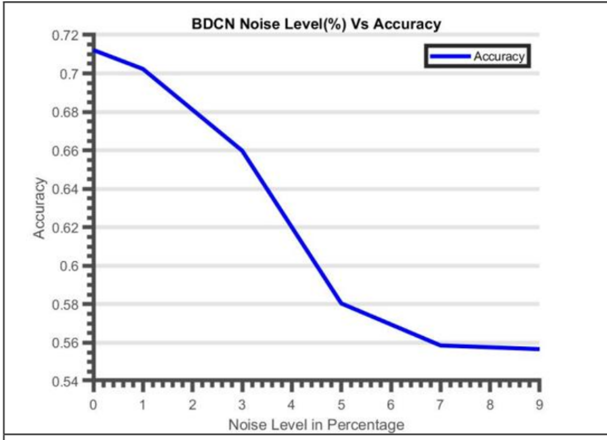
H) F measure of HED Edge detector with respect to Noise



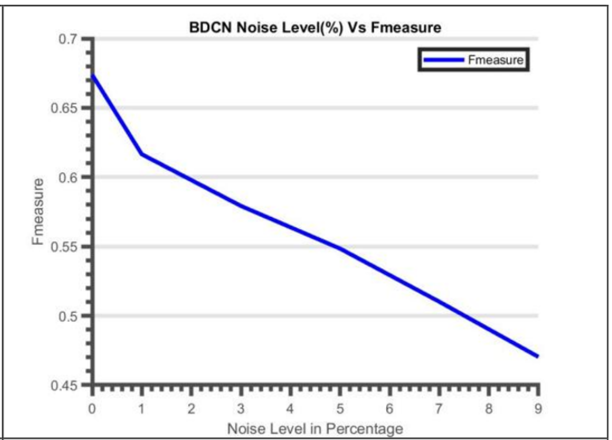
I) Accuracy of RCF Edge detector with respect to Noise



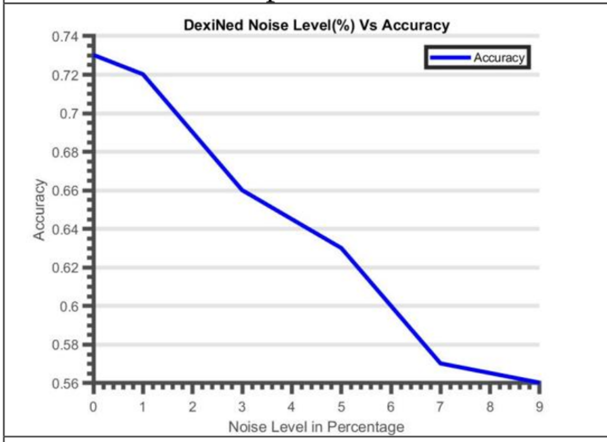
J) F measure of RCF Edge detector with respect to Noise



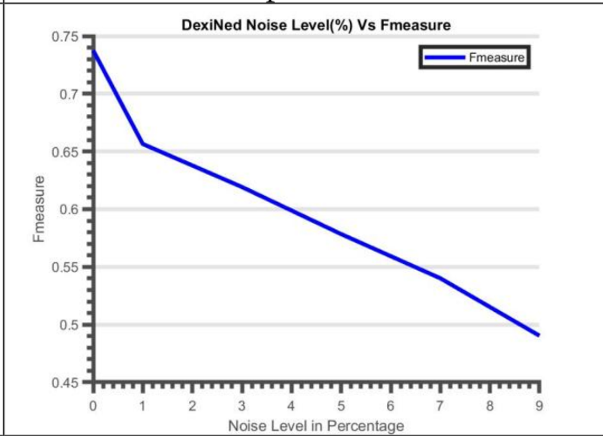
K) Accuracy of BDCN Edge detector with respect to Noise



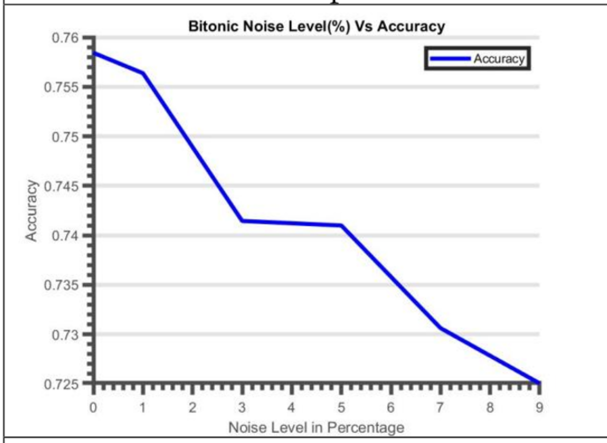
L) F measure of BDCN Edge detector with respect to Noise



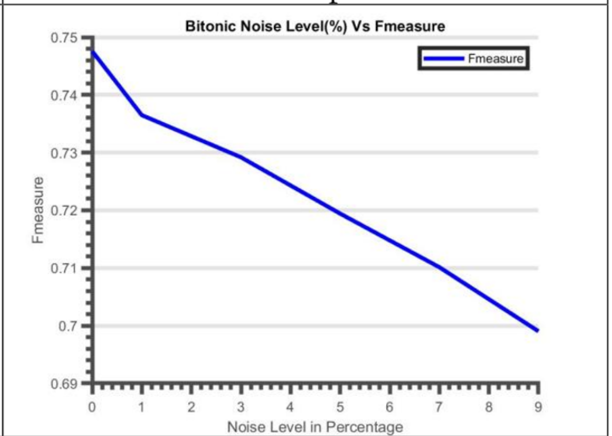
M) Accuracy of DexiNed Edge detector with respect to Noise



N) F measure of DexiNed Edge detector with respect to Noise



O) Accuracy of Bitonic Edge detector with respect to Noise



P) F measure of Bitonic Edge detector with respect to Noise

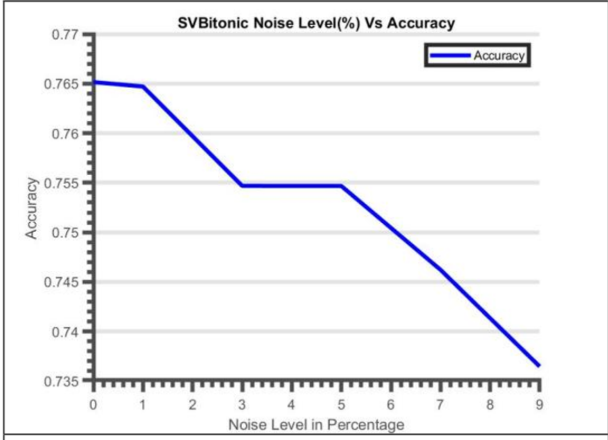
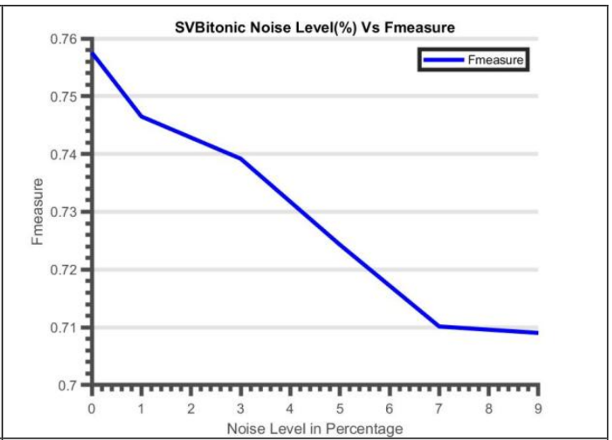
	
Q) Accuracy of SVBitonic Edge detector with respect to Noise	R) F measure of SVBitonic Edge detector with respect to Noise

Fig. 1 Accuracy and F measure for various edge detectors with respect to the noise.

From the above results we can prove that the noise in the MRI image of the human brain results in a reduction in the accuracy of the edge detector. As the amount of noise in the MRI image of the human brain increases the performance of the edge detector decreases. The results of the Bitonic edge detector show the ability to provide accurate results with respect to the increasing amount of noise in the MRI image of the human brain. Also, SVBitonic- the structural variation of the Bitonic edge detector show improved performance in the presence of noise.

Achievements with respect to objectives:

- We have analyzed the effect on the performance of edge detectors as a result of the increasing amount of noise in MRI image of the human brain.
- We have developed an edge detector for the detection of edges in the MRI image of the human brain.
- The developed edge detector has the ability to withstand the increasing amount of noise in the MRI image of the human brain.
- We have also determined the performance of the developed edged detector with respect to the increasing amount of noise in the MRI image of the human brain.

Conclusion:

From the above result, we can confirm that the presence of noise in the MRI image of the human brain affects the performance of the edge detector. As a result of the increasing amount of noise in the MRI image of the human brain, the performance measure like accuracy and F measure decrease. The traditional edge detectors as well as the state-of-the-art edge detector’s performance also get affected by the presence of noise in the MRI image of the human brain. From the above discussion we can conclude using the Bitnoinc and SVBitonic edge detectors we can reduce the effect of noise on the performance of the edge detector and also make a robust noise edge detector which is the main contribution of this research.

Paper Published:

1. Parmar, G. D. and Shah, T. V. “Traditional and state-of-the-art edge detectors” Stochastic Modeling & Applications Journal Vol. 25 No. 3 Page. 2048-2054, 2021.
2. Parmar, G. D. and Shah, T. V. “Effectiveness Analysis of Holistically-Nested Edge Detector for Brain Tissue Segmentation in Single-Channel MR Image” Stochastic Modeling & Applications Journal Vol. 26 No. 3 Page. 441-449, 2022.
3. Parmar, G. D. and Shah, T. V. “Effectiveness Analysis of Richer Convolutional Features Edge Detector for Brain Tissue Segmentation in Single Channel MR Image” NeuroQuantology Journal Volume 21, Issue 1 Page. 150-157, 2023.

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