Performance Analysis of Graph theory-based Contrast Limited Adaptive Histogram Equalization for Image Enhancement

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Abstract: - Nowadays, image enhancement has become a major area of research because of the development of applications that are based on vision.Several digital image processing systems employ such image enhancement strategies with the help of graph theory. As the visibility level in low contrast image features is very less,several image enhancement strategies have been introduced with spatial transformations to enhance image qualityfor improved visualization. Nowadays, image processing plays an important role in the analysis of a patient's health status and has become extremely popular in medical areas for a wide range of clinical assessments. Generally, medical images contain several complex areas and thereby,few pre-processing approaches are applied to reduce the challenges that occur during different phases of the CAD system. Furthermore, because of external noise interferences, poor illuminating settings as well as other imaging device limitations, the clinical diagnosis becomes a challenging process and medical images do not provide important information for precise categorization. Medical images are available in a variety of applications such as computed tomography, Magnetic Resonance Imaging (MRI), mammography, chest X-ray (CXR), and many more. Only the pixel intensity variations between different areas as well as object boundary information are essential for categorization and must be enhanced simultaneously. As a result, the rate of classification in medical images and intensity are increased so that every object during the analysis can be easily identified. The main goal of any image enhancement process is to enhance the quality of the image by reducing noise and on other hand by using three different algorithms such as Luminance Modulation (LM), Gradient Modulation (GM), and Dynamic Histogram Equalization (DHE). These three algorithms are designed with the help of graph theory for effective preservation of edges, losses, and efficient smoothing and to preserve the basic information without any modifications. Image restoration is also referred to as image enhancement and it is concerned with the precise assessment of real images. Generally, the degradation process is not included in many of the image-enhancement approaches that are already existing. Furthermore, with the application of enhancement techniques, the degradation process for medical images results in some significant performance loss. Several techniques have been proposed and the technique which is examined in this research is image enhancement that is based on histogram which mainly concentrates on equalizing the histogram of values. Histogram Equalization (HE) possesses a few basic properties such as altering spatial patterns as well as intensity which in turn results in significant challenges in medical imaging. As a result,Contrast Limited Adaptive Histogram Equalization (CLAHE) is proposed in this work as a feasible approach for medical image analysis to address the problem. The suggested research work demonstrates that the intensity limiting image enhancement with histogram equalization detects the irregularities in dense mammograms with enhanced quality.

Key-words: Dynamic Histogram Equalization and Gradient model, Luminance Modulation (GM), Contrast Limited Adaptive Histogram Equalization, Graph Theory.

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1 Introduction

In applications of image processing, graph theory plays a significant role. The techniques that are already existing for image processing applications have become unsuccessful because of their poor sensitivity at zero level pixels in an image and also due to their inability to identify the edges [23]. As a result, conventional methods have become a big challenge for many image processing applications such as Biomedical image processing, image enhancement, and image segmentationin edge preservation for low-quality images. Generally, to obtain suitable volumetric details as well as structural information, biomedical images do not contain sufficient information. Therefore, it requires the application of enhancement techniques for medical assessments. Furthermore, the techniques of biological imaging such as X-ray, MRI, and computed tomography result in low contrast, intricate noise and minimal illuminance [13]. The application of graph theory minimizes the above-mentionedissues. Medical images play a vital part in several clinical diagnostic assessments [14]. However, they frequently result in several types of noise as well as low luminance and thus produce significant variations in the performance of the entire system along with error rate. Image enhancement strategies are utilized as potential pre-processing approaches to enhance the quality of images in medical images. Histogram equalization is frequently used in various applications because of its simple structure as well as its ease of implementation. However, during the enhancement phase, the biological patterns that are important for diagnosing are influenced by its image transformation based on the mapping function [15]. A novel approach based on luminance-channel color space as well as gradient calculations is developed to reduce such problems in medical images while equalization that is based on a sub histogram is required to enhance the visual perception. Furthermore, a spatial texture pattern is employed to ensure texture retention. The suggested technique provides enhanced quality with maximum retention of biomedical patterns for all kinds of medical images when compared to the experimental observations obtained on MRI and CT images. Quantitative evaluations such as PSNR, SNR, information entropy (IE) as well as structural similarity index measurement (SSIM) are considered to measure the performance explained in [12]. Furthermore, there are numerous applications of graph theory such as image processing and computer vision that are exclusively meant for these areas. To set a framework for the image processing applications using graph theory, elaborate details are discussed on the existing concepts to explain the need for fundamentals of graph theory that have been adapted for image processing as well as computer vision [11].

To recognize cancerous tissue regions and to monitor patient's health, the slide images are extensively used by pathologists and the digitalization of histology slides are explained in [24]. Machine learning and deep learning algorithms are some of the advanced strategies that exhibit enhanced results and are used in the classification of automatic slide images. This study shows how graph convolutional networks could be utilized to examine the entire slide images uniquely. One of the forms of deep neural networks that can be used to construct node connections in a graph is graph convolutional networks. Graph convolutional networks are utilized to extract spatial information and, in this approach, the pixel is defined as a node as well as some features in a graph. The suggested method outperforms the conventional strategies in terms of efficiency [1]. The block-coded images encounter unwanted distortions at low data rates because DCT coefficients are independently quantized. The initial image concepts are extremely significant in compressed image reconstruction. Genuine image patches in a negligible area of the high-dimensional image space have a basic sub-manifold structure which is observed in this work. To set up signal distribution, the sub-manifold structure is used as prior knowledge [16]. The graph Laplacian regularization is employed to describe the structure of the sub-manifold at the patch level. In a similar way, virtually identical patches are often employed as samples to estimate the patch's distribution. Instead of utilizing Euclidean distance in this work, graph-domain distance is used to determine the patch's similarity. Furthermore, a similar-patch group is exposed to low-rank regularization using a non-convex l p penalty to replace a matrix rank. Finally, the issue of nonconvex is addressed by employing a unique approach. The suggested technique outperforms the existing strategies in terms of perceptual features as well as objectives [2].

The filter coefficients are exclusively determined based on data-driven methods and are not easy to interpret. Therefore, convolutional neural networks (CNNs) are employed and have shown exceptional performance in a variety of inverse imaging applications. The Graph Bio is used as a graph filter in this study to develop a unique layered graph neural network (GNN) [17].

Convolutional filters are used in traditional graph neural nets, whereas the suggested Graph Bio is theoretically described and does not involve any training, thereby enabling the improvement of the overall performance of the system by learning appropriate graph topology at every layer. It typically means that at every layer the linear graph filter can always be described using signal filtering and therefore it is low-pass under specified biorthogonal contexts. Meanwhile, the graph spectrum can be constructed using data training. The efficiency of the analytical graph neural net is better when compared to that of conventional techniques [3].

To assess variation in applications like the image as well as video coding, the mean square error (MSE) has been widely used. The primary goal of is to optimize a weighted MSE measure and hence assign distinct weights to each pixel to describe their perceptual value concerning the quality of the image. A unique transform coding strategy that is orthogonal as well as based on the irregularity-aware graph Fourier transform (IAGFT) is proposed in this work [19]. To validate the image quality after processing an image through an algorithm, MSE, PSNR, SSIM, and edge preservation index are important parameters, an inner product that is associated with the weighted MSE. The weights are generated from the local variations of the input image after processing through graph theory algorithms then the Structural Similarity is measured by the weighted Mean Square Error.the resulting irregularity-aware graph Fourier transform can increase the effectiveness of SSIM coding [4]. The functional relationship of the subcallosal cingulate gyrus (SCG), Nucleus Accumbens(NAc) are examined, as well as ventral caudate (VCC) using deep brain stimulation (DBS) which is further regarded as one of the key strategic domains for the assessment of major depression disorder (MDD). Major depression disorder is the most commonly known disorder and approximately 30% of patients with the major depressive disorder do not adhere to traditional therapies like psychotherapy or antidepressant medicines. As a result, nowadays deep brain stimulation is widely used to cure this major depression disorder. For seven major depressive disorder individuals and seventeen healthy individuals, the resting-state MRI is taken [18]. The functional connectivity network of the brain was constructed for all the individuals, also the 'degree' value of each SCG, NAC, and VCA region was examined via graph theory methodology. When contrasted to the healthy individuals, the major depression disorder group exhibits relatively large ventral caudate as well as relatively high left subcallosal cingulate gyrus degree values. For major depressive disorder patients, the degree values of patterns were different in both the right and left hemispheres. The outcomes of this methodology demonstrate that the degree values and the patterns produced can be used as a diagnostic tool to determine the brain areas with abnormal functional connectivity [5].

Extensively recognizing the image is regarded as one of the well-known subject areas because it is used in several applications such as picture compression, pattern recognition, image retrieval, and many other domains. With the use of recent breakthroughs in the area of graph signal processing, this exploratory study presents a strategy of salient object recognition [20]. Due to the picture boundary regions, a boundary comparison map that is based on distribution is produced which is regarded as a portion of the baseline image. The representation of an image as a graph is used to determine the area connectivity of the image to the boundary of an image as well as to determine the background of the connection picture to their immediate neighbors. By integrating the network maps as well as the boundary contrast map, the picture saliency map is being designed. To evaluate the efficiency of the suggested salient object identification approach, a large number of research studies are being carried out. The suggested technique outperforms the existing conventional approaches in terms of mean absolute error values, memory, and accuracy [6].

The approach of object-pose estimation acceleration was devised with the application of hierarchical-graph-reusing K nearest-neighbor search (KNN) to choose appropriate robot applications. A large number of estimations are used in the examination of object-pose which further enables the determination of various nearby points for every data point in the KNN search, and thus typical selecting robots have low selection efficiency. A hierarchical graph is used in this research study rather than a typical K-D tree to approximate object pose to enable a faster assessment process of KNN. The earlier work enables parallel accumulation of various adjacent points whereas the latter does not. In this paper [22] a generated graph reuse is recommended as a means of accelerating the production of a hierarchical graph. Experimental results illustrate that object-pose approximation takes 1.1 seconds with a factor of 2.6, whereas the overall selection procedure consists of image recognition, object-pose approximation, and motion planning which takes 2.5 seconds [7] using Amazon Selection Contest data sets and an Arm Cortex-A53 CPU. A light field is a set of information about light in space and due to this feature, the light field is popular in immersive media. As a consequence of increasing light field observations, the technique of light field compression has received lots of attention. This paper presents a light field compression strategy that is based on a graph convolutional network. This system outlines the link between the light field views. On the decompression side, the construction of a complete light field is carried out using the proposed methodology and using the acquired reference perspectives. According to the results, the proposed approach improves the performance of reconstructed images. The suggested framework produces a 4dB PSNR gain and is generalizable when compared to other standard approaches [8]. This research work introduces the development of unique research approaches as well as a software tool for obtaining and categorizing the data from a picture of a craquelure pattern. The proposed method addresses the craquelure network which is analogous to a graph. The network structure is derived from the graph representation which further includes the mutual structuring of connections and gaps [21]. The structure is not influenced by geometrical changes. Additionally, the technique utilized in this study independently analyses the properties of each node and edge thereby allowing to categorize the pattern statistically. The performance of graph representation and statistical characteristics shows enhanced performance with a large margin when compared to that of the existing strategies [9]. One of the important research areas is the analysis of human activity depending on sensor data. To represent the information regarding human motion distinctly, a graph structure is presented that is based on the skeleton as well as graph signal processing algorithms.The methodologies for designing a graph as well as the basis functions are discussed in this work [10]. The proposed models can accomplish excellent classification results in pattern analysis whereas it is more sensitive to interference and inadequate information.

2 Problem Statement based on Literature Survey on Graph Theory for Image Processing Applications

The tools that are used for representing pairwise relationships between data components are referred to as Graphs and are extensively employed in science as well as engineering applications. The models of a graph have a major impact on the development of computer vision and have become extremely prevalent in the latest works. But still there are challenges in terms of minute information extraction in biomedical images and this minute data is very important for detection of abnormalities and further analysis for precise accuracy. To represent spatial relationships between pixels in medical images that are close, far apart, between image regions, between characteristics, or to represent objects as well as components, graphs are widely utilized. For processing as well as analysis of the image, various representations and algorithms that are based on the graph are used with limitations.Therefore,the application of these techniques is an active vision system for an autonomous mobile robot for biomedical imagesis developed as part of the project "Active Vision System with Automatic Learning Capacity for extraction and identification of different abnormalities". In particular, the applications of representations as well as approaches that are based on graphs for image perceptual grouping, image segmentation and identifying the object has been discussed.

For color picture segmentation, we initially propose a generalization of a graph partitioning greedy technique. Furthermore, we explain a new combination of color-based segmentation as well as depth from the stereo that results in a graph that represents every object in the image.

In conclusion,Function Described Graphs (FDGs) representation of Attributed Graphs sets (AGs), a similarity measure for comparing attributed graphs sets and Function Described Graphs, as well as various robot vision applications [25].

3 Graph-Based Image Enhancement using HISTO AM Equalization GR

The techniques of biological imaging such as X-ray, MRI, and computed tomography always result in low contrast, intricate noise and minimal illuminance. With the application of graph theory, the above-said issues can be minimized by settingthe following strategies as a part of the primary research work.

1. To develop a technique that is based on graph theory to identify the edges of an image as well as for retaining their indexes to enhance the quality of the edge.
2. To develop texture-driven similarity match constraints for histogram equalization approaches by employing graph theory. To minimize noise and to improve texture features, by using contrast limited adaptive histogram equalization.
3. To implement Luminance-level modulation (LM) to enhance the dynamic range of luminance levels by using Graph theory. Luminous levels that are based on graph theory are compressed with the help of the Luminance level modulation (LM) technique which is based on their divergence from dynamic ranges.
4. To enhance the classification in biomedical applications, gradient modulation is presented utilizing Graph theory by suppressing the impact of distortions and thus retaining the precise texture information regarding the biomedical problems.
5. To extract texture features in terms of appropriate spatial coordinates by using Graph theory-based Adaptive histogram equalization (DHE).

Graph theory is used to restore texture features from enhanced output pictures and thereby reduce distortions.Using HE, the enhancement of the image changes the dynamic range and contrast levels into a required shape by utilizing a mapping function as the cumulative distribution function to form the histogram. By extending the peak values of the histogram, the intensity variations are directly related, and correspondingly brightness is changed as per flow chart is shown in Fig.1.

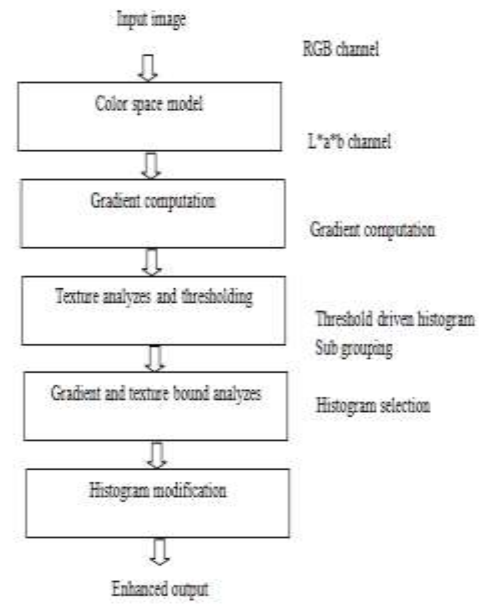


Fig. 1: Proposed flowchart of biomedical image enhancement based on Graph theory.

Algorithm 1:

```
//Input – image sequence
//Output – Enhanced image
Step 1:     Set sigma as TL1 //variance value
        Apply color space conversion – L channel
Step 2:     for i ← 1 to height do
              for j ← 1 to width do
                for m=1:3
                P1(i,j)=CG(i,j,m)  // gradient space
                end
              end
            end
B =Macro block conversion (i,j)    // 3x3 matrix
TM=LBP (B);
P3 =CUT(TM);
```

3.1 Image Transformation using Graph Theory

The model of color space is a three-coordinate system that is employed to interpret color in the processing of an image. The three-dimensional color space can be represented in a variety of ways with every model having unique image qualities. Primary colors, as well as their complementsare represented by traditional Cartesian coordinate systems like RGB and CMY. Every channel in a cylindrical coordinate system that distinguishesconcerning luminance and color depth. Differentiating the intensity channel from the luminance areas is essential for the entire enhancement process because the variations in intensity generate maximal visual perceptions and result in problems such as object shape distortions and varied texture patterns among various biomedical patterns. The efficiency of the suggested picture enhancement approach is significantly improved by using the model of Luminance Channel. During subsequent analysis of the histogram, the color space conversion technique through an RGB channel results in various misperceptions. However, a cylindrical-coordinate system such as the CIE lap space model excludes luminance channels that are not determined by their primary color.

3.2 Color Gradient Approach using Graph Theory

The techniques employed for extraction of texture information are employed as first-level detectors in medical objects to determine the area that constitutes the region of interest. The co-occurrence of pixel variations in every region is then represented using color gradients of pixels from all three principal channels. The correlative nature of adjacent pixels can be found accurately due to the computation of co-occurrence description by the neighboring pixels in the same area. The magnitude transition between the complexes as well as the smooth region can be easily determined using the gradient measure for every data model. Object distinctions are indicated by a considerable change in a gradient. For representing the object of interest, this basic linear variation is most suitable.Fig.5 depicts a color gradient with the variance metric.

3.3 Spatial Invariant Texture Model using Graph Theory

For analyzing the texture in vision applications, the local binary pattern operator is being utilized as a common feature. Even minor variations in the pixel's intensity values that are caused because of brightness or large variations result in a distinct LBP code. Invariant as well as homogeneous textures are relatively insensitive to variations. The extensions of the LBP operator are uniform as well as rotational-invariant texture models. In the preceding equations (1) and (2), the basic mathematical interpretation of LBP operation is been provided:

Bm for 0 = m € [0, 7] (1)

Bm for 1 = m € [0, 7] (2)

As indicated in equation 3, the uniform LBP patterns are those with minimal variations or breaks in the binary LBP pattern.

ULBP =|Bm(Mp-1-C)-Bm(M0-C) | (3)

Here, the central pixel of the 3x3 macroblock is represented by C. The windowing length and neighboring pixels are represented by P and Mp respectively. In general, whenever the LBP binary pattern involves at least two bitwise transitions from one to zero or zero to one, then the binary pattern is circular and is referred to as uniform. Rotation-invariant characteristics of such type are self-reliant on the input image angle for static textures. Local features acquire the ability to represent motion and provides the most discriminative patterns for object modeling when dynamic textures (DT), and uniform textures are paired with rotational-invariant feature descriptions.

4 Results and Discussion

The suggested contrast bound histogram equalizations performance metric assessment is carried out on a wide range of biomedical datasets that comprise images such as eye, MRI, CT, as well as standard test images [13]. Every dataset consists of 100 images with varying levels of texture as well as pattern complexity. Every set is tested independently throughout the performance and the corresponding variations, and reliability metricsare assessed for complete test validation. The suggested histogram equalization provides peak PSNR of specified image sets which are illustrated in Table 1.It is also demonstrated that by including texture compression as well as gradient techniques, the PSNR is marginally improved and outperforms the SSIM with better spatial information. The suggested threshold bound that is based on texture classification results in an increased structural similarity index as well as a PSNR rate. As shown below, the peak X-ray-to-noise ratio is often employed to evaluate the reconstruction quality of the suggested image restoration by SNR:

$$PSNR = 10log_{10}\frac{(2^n-1)^2}{MSE}$$

Here the mean squared error is represented by MSE. To compare the structural similarity of input LR and HR images,parameters like, brightness (μ) and contrast (σ) are considered in the structural similarity index (SSIM) and is asdescribed below:

$$C_L(I.I_0) = \frac{2\mu I\mu I_0\, C_1}{\mu I^2+\mu I_0{}^2+C_1} \qquad (4)$$

$$C_C(I.I_0) = \frac{\sigma I\sigma I_0 + C_1}{\sigma I^2\sigma I_0{}^2+C_1} \qquad (5)$$

Here, the constants are C_1 and C_2. With the help of normalization, the structure of the image is then determined and illustrated in Eqn. (5)

$$S = \frac{I-\mu I}{\sigma I}$$

In Table.1, the enhancement in terms of quality is measured through 8 matrices and compared with state-of-art results, each parameter and its mathematical models are described in equation (6) through equation (8).

$$SNR = \frac{\sum_x\sum_y E_{x,y}{}^2}{\sum\sum\left(E_{x,y}-I_{x,y}\right)^2} \qquad (6)$$

$$MSE = \frac{1}{P}\sum\sum\left(E_{x,y}-I_{x,y}\right) \qquad (7)$$

$$PSNR = 10.\,log_{10}\left(\frac{max_I^2}{MSE}\right) \qquad (8)$$

Where P is the size of the image, $E_{x,y}$ is the edges of the image in the x and y coordinate, and $I_{x,y}$ is an original input image.

After processing an image through the algorithm, structures are lost so retaining those structures at all edges is another challenge in biomedical images, Structural Similarity (SSIM) is an important parameter to calculate structures' edges and it is given Equation (9).

$$SSIM = \frac{\left(2\mu_x\mu_y+A_1\right)\left(2\sigma_{xy}+A_2\right)}{\left(\mu_x^2+\mu_y^2+A_1\right)(\sigma_x^2+\sigma_y^2+A_2)} \qquad (9)$$

Where $\mu_x = \sum_{j=1}^{P} W_i I_{x,y}$

and $\sigma_x = \sqrt{\sum_j^P\left(x_j-y_j\right)}^2$

For all stages of image processing using graph theory, the first step is to generate the nodes based on pixel intensity and contrast and group them as shown in Fig.2. These nodes with circle and edge of each along with line connected between any two nodes is edge orientation of pixel. Each edge orientation is an undirected graph which is based on a reference line to find the sign of flow edge. The graph is represented by combining several different common matrices to store and also viewed as an operator that behaves as a function associated with edges of a graph.

Table.1 Parametric study of hybrid image enhancement strategies for typical MRI/CT images utilizing graph theory

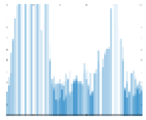
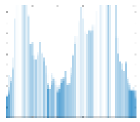
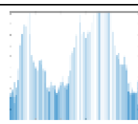
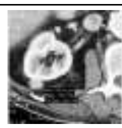
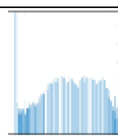
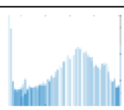
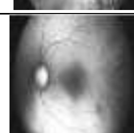
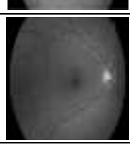
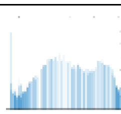
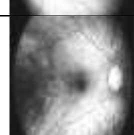
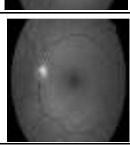
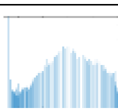
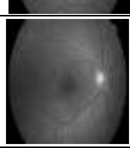
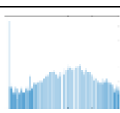
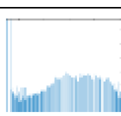
Database Image No	Input image	Enhanced Image	Histogram output	IE	REC	EME	EMME	MSE	SNR	SSIM	PSNR
1				2.4426	45.313	0.0012	0.0610	0.0083	63.072	0.9990	68.9475
2				2.6463	Inf	0.0012	0.0613	0.0379	54.699	0.9954	62.3487
3				2.6652	3.5098	0.0012	0.0613	0.0306	56.078	0.9964	63.2681
4				2.6775	4.9050	0.0012	0.0613	0.0101	62.396	0.998	68.0901
5				2.6857	2.6152	0.0012	0.0611	0.0082	63.289	0.9990	68.9992

Table.2. Parameter analysis of proposed hybrid image enhancement techniques for standard Eye images

Database Image No	Input image	Enhanced Image	Histogram output	IE	REC	EME	EMME	MSE	SNR	SSIM	PSNR
1				2.3040	1.58	0.0012	0.0607	0.0537	52.4	0.992	60.83
2				2.0150	1.32	0.0012	0.0604	0.0603	51.41	0.9917	60.33
3				2.0882	1.22	0.0012	0.0606	0.096	47.49	0.9863	58.30
4				2.1747	1.24	0.0012	0.0608	0.0837	48.72	0.9880	58.903
5				2.1208	1.061	0.0012	0.0607	0.0823	48.70	0.9882	58.976
6				2.1313	0.899	0.0012	0.0607	0.0834	48.52 2	0.9880	58.92

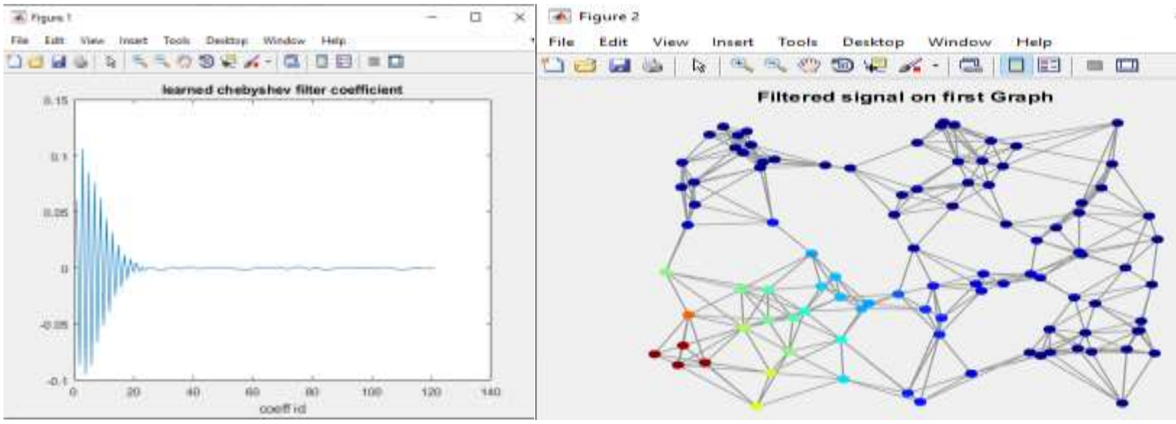


Fig. 2: Nodes creation and filtered signals using graph theory and its coefficients used for filter

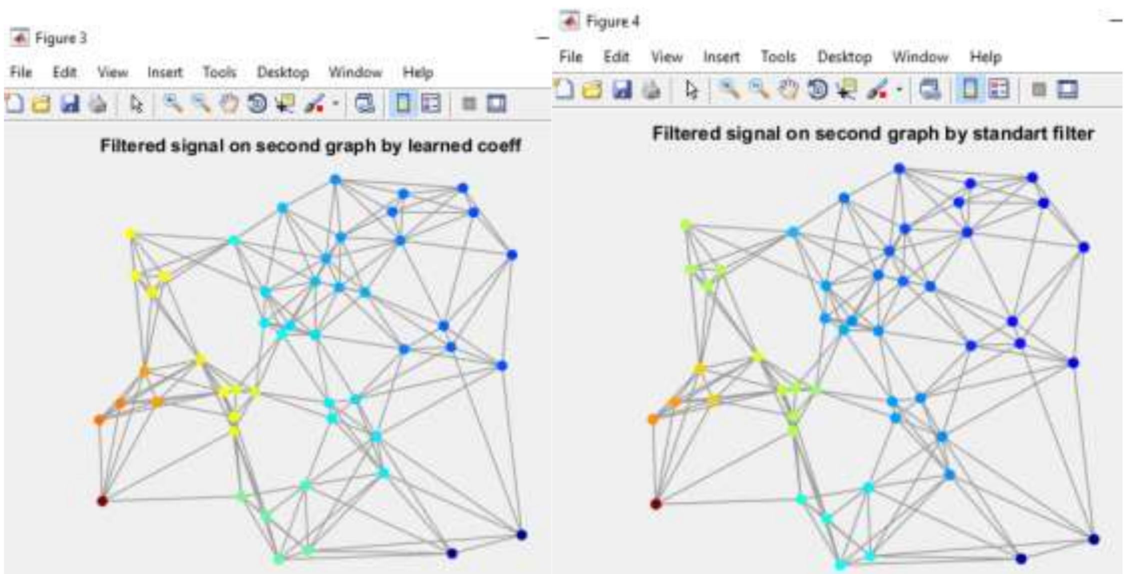


Fig. 3: Filtration of an image using learned coefficients and standard filter-based graph theory

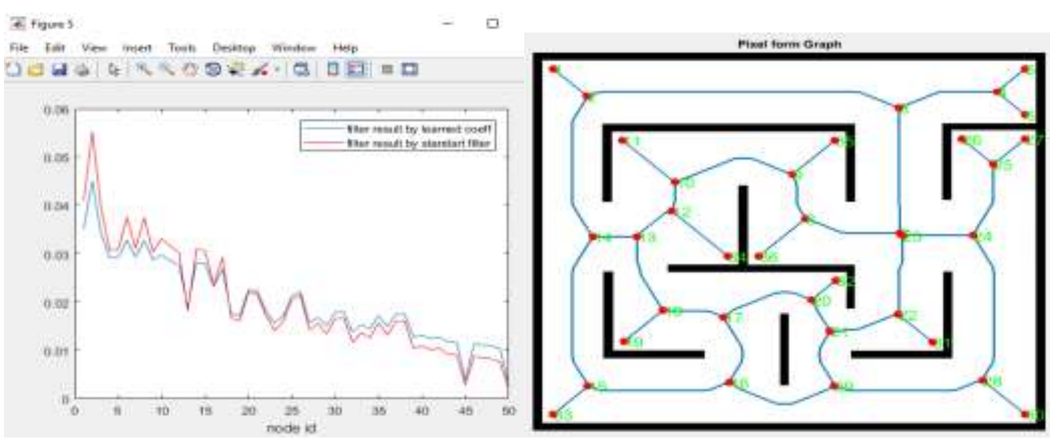


Fig. 4: Detection of pixels in Image and its connectivity and error between learned and standard filters

Fig. 5: Simulated results of Segmentation for different standard database images using Sparse algorithm

Fig.5 depicts the segmentation of different color images using proximity-based graph theory algorithms and these segmented images are mainly used for different analyses. The proposed methods used for performing various operations are scientific computing for performing triangular irregular grids to get finite elements for effective segmentation. Depending on correlation, the structural similarity is determined. The proposed graph theory-based algorithms are tested for the different standard images to perform segmentation for the images of capturing perceptual grouping cues using sparse global and local affinity graph-based superpixels to capture short and long-range cues. This algorithm is mainly concentrated on different parameters such as similarity, proximity, and continuity and these three features help to segment efficiently. The segmentation is mainly based on shape, color, and textures, the complete operation is based on gravitation law which is based on empirical interpretations and division of superpixels and all these are adapted into medium, small, and larger sized sets. The medium-sized is segmented and is separated using global grouping through a sparse algorithm by resolving 0-minimization issues to get the smoothness of small and larger sized superpixel images. At the last stage of segmentation, the bipartite graph enables grouping cues among superpixels of various scales. The simulated segmentation results are shown in Fig.5 and these results are the output of sparse algorithms and superpixels which are grouping cues.

5 Conclusion

In this proposed research work, we presented a sparse-based segmentation in globally and locally graph theory-based segmentation and parameters metrics are evaluated in terms of similarity, proximity, and continuity. Compared to existing segmentation techniques, the graph theory-based segmentation can encrypt adaptively in both global and local homogeneity of objects present in the image through two types of fusingsuch as adjacent graph point and sparse 0- minimization graph which has three distinct classes such as small, larger and medium-sizedsuperpixels.For unsupervised picture segmentation, the resulting GL-graph is fed into an efficient graph-cut technique. Extensive validations of the BSD data set reveal that our method outperforms state-of-the-art methods in terms of qualitative and quantitative segmentation. It could be interesting to find an ideal fusion scheme that integrates color, texture, and form cues using training data as a future expansion of our work. This would be a fascinating step forward in semi-supervised image segmentation. The quantitative impact of image enhancement that is based on histogram equalization for several types of medical images have been examined in this research work. The suggested image enhancement method which is based on color space conversion enhances the quality of the image and thereby minimizes pattern categorization issues as well as distortions produced during enhancement. To enhance the visual appearance of the improved output image, the spatial texture pattern, as well as gradient threshold constraints are widely used in this work to restore the basic information which is essential for the effective recognition of the medical pattern. Graph theory plays a major role in image quality enhancement, extraction of different category features, and segmentation and these techniques are used for analysis to identify different abnormalities in biomedical images. Graph theory also plays important role in engineering, computer vision, and image processing to distinguish between nearby or distant pixels.

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