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IMAGE QUALITY ENHANCEMENT AND CLASSIFICATION OF NATURAL IMAGE USING SPATIAL CONVOLUTED EDGE SMOOTHING WITH CONTINUOUS WAVELET TRANSFORMATION

Ms.M.Sakthivadivu Research Scholar, Bharathidasan College of Arts and Science, Erode, India
E-Mail: kaushalsakthi@gmail.com
Dr.P.Suresh Babu Associate Professor of Computer Science, Bharathidasan College of Arts and Science, Erode, India E-Mail: ptsuresh77@gmail.com

Abstract

Image quality enhancement aims to improve the rich details from degraded images. Image classification has become a vital task in many fields like object detection or recognition, visual concept learning, etc. Numerous techniques have been developed for image enhancement and classification. However, these techniques are only suitable for enhancing the images but it fails to remove the artifact-free quality improved results for various other types of images and in regarding classification some issues are existing in a time-efficient accurate classification. Therefore, to overcome this issues, an image enhancement technique called Damped Linear Filter Spatial Convoluted Edge Smoothing (DLF-SCES) is introduced for image preprocessing to enhance the image quality with the higher peak signal-to-noise ratio and minimum error along with Continuous Wavelet Transformation Classification (CWTC) method.The proposed DLF-SCES technique performs image preprocessing that includes two processes namely filtering and edge smoothing. In the DLF-SCES technique, number of natural images are collected from the dataset and considered as input. Then, every natural image gets pre-processed Bryson–Frazier Fixed Interval Filter. The designed filter employs the series of measurements observed over the different states including the statistical noise. The proposed filtering technique performs image pixels analysis at every observation state to determine the smoothed image and covariance with help of Damped Least-Squares method. After the noise removal, the DLF-SCES technique performs the edge smoothing by using spatial edge smoothing. This in turn helps to enhance the image quality.

After image enhancement, classification is done in two phase which includes feature extraction on various factors and Regularized canonical emphasis boost classification process. Experimental evaluation is carried out using natural images with different factors such as mean square error, peak signal-to-noise ratio with respect to a number of natural images and sizes for image enhancement. Factors such as classification accuracy and classification time with respect to a number of natural images are calculated to find the effectiveness of classification.

Keywords:Image quality enhancement, Bryson–Frazier Fixed Interval Filter, Edge Smoothing, Wavelet transforms, feature extraction, classification.

1. INTRODUCTION

Image enhancement and restoration are the fundamental processing steps of real vision systems. Therefore, the main purpose is to enhance the visual quality of images and offers reliable information for subsequent visual decision-making. Images collected in low-brightness environments often direct to poor visibility and reveal artifacts. These artifacts affect the visual observation of the human eye. The existing method-based image enhancements technique is faced many problems for accurate preprocessing.

A new adaptive weighted guided image filtering (AWGIF) technique was proposed in [1] to decompose an initial depth and to preserve the edges accurately. However, the performance of time consumption on image enhancement was not minimized. A Low Light Enhancement and Denoising (LLEAD) method was introduced in [2] for better-enhanced image contrast and minimizing the mean squared error. But it failed to develop a statistical model for the distortion of colors. An ensemble spatial method was developed in [3] for image enhancement. But, the designed method failed to improve the model with lesser mean squared error.

Image classification is an essential process in modern computer vision systems. It refers to a process that categorizes an image along with its visual content. It aims at categorizing an input image into multiple labels from a fixed set of classes. However, it reduces the computation requirements to a reasonable range and causes information loss, which affects the accuracy of image classification. Several methods have been developed for image classification.

A deep attention-based imbalanced image classification (DAIIC) method was developed in [4] by using a logistic regression function to perform the discriminative feature learning process and by assigning attention to different classes. However, the misclassification costs of the more discriminative feature learning were not minimized. In addition, it failed to improve the performance of multilabel imbalanced image classification through the correlation between different classes. A new regularization on augmented data (READ) method was developed in [5] using the generic augmentation techniques for improving the robust sparse representation-based image classification. But the performance of the time consumption was not minimized.

A new adaptive hybrid fusion network was developed in [6] for classifying the multiresolution remote sensing image based on data fusion and feature fusion. However, it failed to focus on designing a more reasonable and effective classification approach to improving multiresolution remote sensing image classification accuracy. A mirror transformation convolutional layer was introduced in [7] to perform the transformation of several feature maps to generate mirror-symmetrical features. But it consumed more training cost.

1.1 **Paper outline**

The remaining sub-sections of this paper are as follows. Section 2 presents the related work of conventional image quality enhancement models. The proposed CWTC and DLF-SCES techniques are described in section 3. Section 4 provides the results and discussion of different performance metrics. Finally, the conclusion is presented in section 5.

2. RELATED WORKS

A fast and lightweight deep learning-based algorithm was introduced in [8] for low-light image enhancement. However, the designed algorithm was not efficient in further improving the information in the enhanced image. The morphological operator-based image fusion algorithm was designed in [9] for improving the efficiency of enhancement using spatial filtering. But, the computational complexity was not minimized at optimum levels.

A regularized illumination optimization approach was developed in [10] to improve the quality of low-light images by eliminating the negative effect of unwanted noise. However, the performance of processing time and space consumption was not minimized. A new Retinex-based lowlight image enhancement approach was introduced in [11] using Retinex image decomposition. But, the efficient filtering technique was not applied to achieve better image enhancement.

An automatic image enhancement approach was introduced in [12] to provide better quality results for all types of images. But it failed to properly handle the image enhancement approach for particularly dark regions.

A deep network with Dimensionality Reduction Module (DRM) was developed in [13] for more accurate classification with minimum processing time and also a minimum number of parameters with regularization. A new robust regression method was developed in [14] by integrating convex regularization to perform image classification. However, it failed to improve the performance of the proposed model when dealing with large-scale data.

Deep Convolutional Neural Networks were developed in [15] for medical image classification to analyze the performance by applying ensemble learning techniques. But it failed to apply ensemble learning-based medical image classification. A novel unsupervised deep metric learning approach known as spatially augmented momentum contrast (SauMoCo) was developed in [16] to classify the unlabeled remote sensing scene images. However, the dimensionality reduction of hyperspectral imagery categorization was not performed.

A general multimodal deep learning (MDL) framework was developed in [17] for remote sensing image classification. But the higher accuracy of the image classification was a major challenging issue.

3. PROPOSAL METHODOLOGY

3.1 Image Enhancement

Image quality enhancement aims to increase the quality of images in terms of colors, brightness, and contrasts. Since the images captured in low-brightness situations often direct to poor visibility and illustrate the artifacts such as distortion. These artifacts not only change the visual observation of the human eye but also reduce the performance of computer vision. Various denoising methods have been proposed to enhance image contrast and noise also removed. Conversely, the conventional denoising methods did not provide satisfactory performance in the image quality enhancement. Therefore, a novel fast technique called DLF-SCES is introduced for enhancing the image enhancement and consequently, it is highly desired to improve the contrast enhancement by noise suppression as well as edge smoothing.

The collected images are first given to the Piecewise regressive damped Bryson–Frazier Fixed Interval Filtering technique for noise removal. The Modified Bryson–Frazier Fixed Interval Filtering technique analyzes the image pixels by using piecewise regression and identifies the normal and noisy pixels. The Piecewise regression is a machine learning technique for analyzing the pixels of input images and partitioning them into two segments (i.e. normal or noisy pixels). Then the Piecewise regression analyzes the relationship between the center pixels and other neighboring pixels. Then the regression function uses the Damped least-squares method to find the pixels with minimum deviation from the center pixels value. A damped least-square method is a mathematical model used to find the local minimum by reducing the non-linear least squares problems. As a result, the pixels with minimum deviation are called as normal. Otherwise, the pixels are said to be noisy. These noise pixels are removed from the image. Finally, the denoised image is obtained.

After the image noise removal, the edge smoothing process is performed for improving the image quality. The proposed DLF-SCES uses the spatial convolutive Marr–Hildreth technique for smoothing the edges of the image in the two-dimensional space through the convolution of Laplace and Gaussian function. Finally, the quality-enhanced image is obtained with minimum time as well as error. The preprocessing step also minimizes memory consumption.

After removing the noise in an image, edge smoothing is performed to enhance the quality of the image. Edge smoothing an image preprocessing step is used to smooth and retain the sharp edges. The purpose of detecting sharp edges in image brightness is to capture important objects with clear vision. Therefore, the proposed DLF-SCES technique uses the spatial convolutive Marr–Hildreth edge smoothing approach to obtain the quality improved image. The proposed edge smoothing method has functioned on the basis of convolution of the noise-free image with the Laplacian of the Gaussian functions. The edge smoothing is performed in the spatial domain method that refers to the partition of the image space into uniform pixels according to the spatial coordinates (i.e. x,y) with a particular resolution. Here, Marr–

Hildreth represents the author who derives the edge smoothing technique to obtain the quality improved image. Hence the proposed smoothing technique is called spatial convolutive Marr–Hildreth edge smoothing.

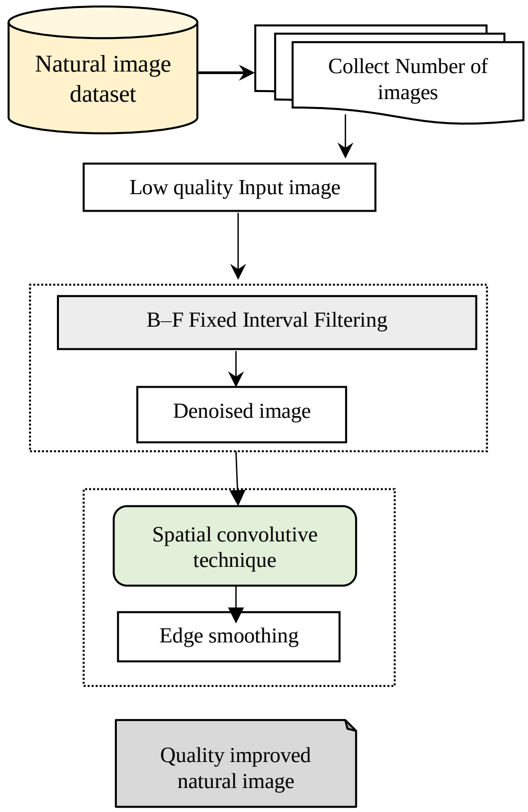

Figure 1 Architecture diagram of proposed DLF-SCES technique

Initially, the numbers of natural images are collected from the dataset. The image pixels are arranged in the form of a matrix. Apply the linear discrete-time system for analyzing the pixels to identify the noise pixels. Then the mean is taken for all the pixels in the matrix and the center value is replaced with the mean. After that, the covariance between the center and the neighboring state pixels is estimated. The damped least-squares method finds the minimum deviation pixels. These pixels are called normal and other peels are noisy. The noisy pixels are removed from the matrix. Finally, the denoised results are obtained. After the denoising, the spatial convolutive Marr–Hildreth method is applied for smoothing the edge of the images. Finally, the quality-enhanced image is obtained. In this way, efficient natural image preprocessing is performed by using the DLF-SCES technique to minimize the error rate and better PSNR value.

3.2 Image Classification

Image classification offers a significant basis for image depth processing and the application of computer vision technology. Timely and accurate classification of the image is a difficult task. To overcome these kinds of problems, many techniques have been presented based on Deep Learning and Machine Learning approaches. However, most of these systems have low classification accuracy. Therefore, proposes a novel CWTC technique introduced for accurate image classification with minimum time consumption as well as error rate. The architecture with different processes of CWTC technique is introduced for image classification.

Ricker wavelet is the continuous wavelet transforms that processes the input natural image at different ranges or resolutions. The designed wavelet transform partitions the input natural image into the different blocks at every scale.

First, the input natural images are decomposed into different levels by applying a Ricker wavelet transform. Then the correlation function is applied to extract texture features from the decomposed image. Followed by, quadruple chain code contour method is employed for shape feature extraction. Finally, the color features are extracted by transforming the RGB into the HSV. The feature extraction process reduces the time consumption of image classification. After that multiclass image classification using Regularized canonical emphasis boost ensemble technique is applied. The ensemble technique constructs a set of weak learner with the extracted features such as texture, shape and color.

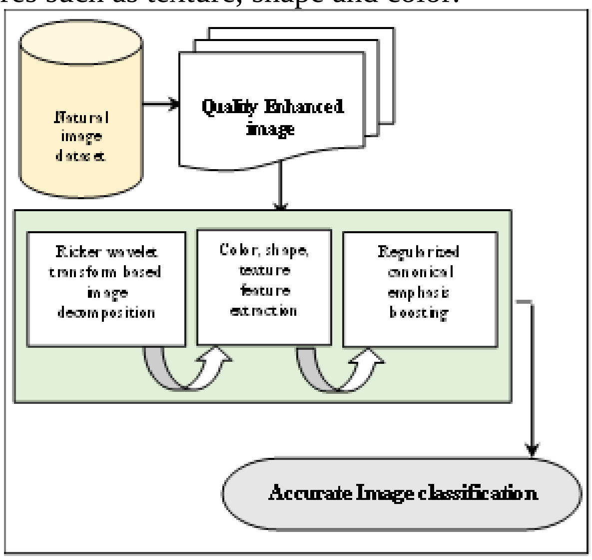

Figure2 Architecture Diagram of Proposed CWTC Technique

The weak learner initializes the different number of classes and their means value. Then the regularized canonical correlationis measured between the extracted features and mean of a particular class. Based on correlation analysis, the input image is classified into different classes. After that, obtained weak classification results are combined and initialize the weight value. The weighted emphasis function is applied to measure the quadratic error for each weak learner results. Finally, the weak learner with a lesser quadratic error is selected as final classification outcomes with higher accuracy.

4. RESULTS AND DISCUSSIONS

The performance analysis of the proposed DLF-SCES&CWTC technique with existing methods namely AWGIF [1], LLEAD [2],READ [3]and DAIIC [4]are discussed in this section with the various performance metrics. Performance analyses are explained with the help of tables and graphical representation.

Mean square error: It is measured based on the squared difference between the number of images and the number of natural images that are accurately preprocessed.

Table 1 Mean Square Error

Number of natural images	Mean square error		
	DLF-SCES	**AWGIF**	**LLEAD**
600	0.166	0.24	0.326
1200	0.243	0.3	0.385
1800	0.316	0.35	0.421

2400	0.326	0.375	0.444
3000	0.368	0.4	0.486

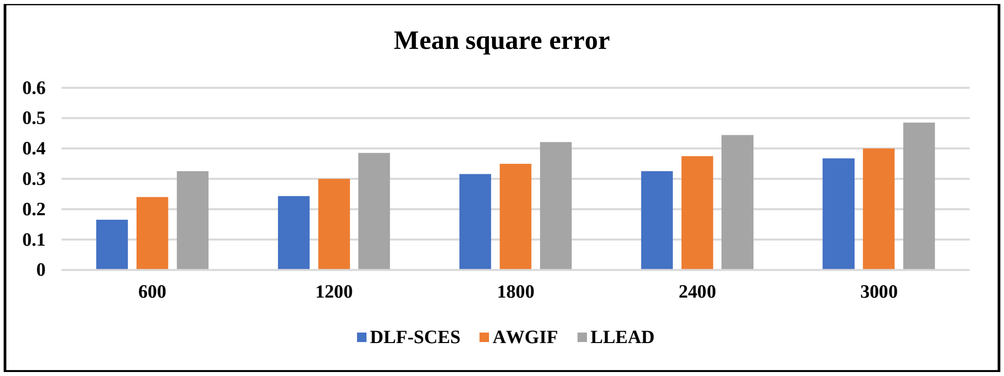

Figure 3 Performance results of Mean Square Error

Table 1 reports the performance results of the mean square error against the number of natural images for different enhancement methods namely SCES technique and existing methods namely AWGIF [1] and LLEAD [2]. The number of natural images collected from the dataset Figure 3 illustrates the performance results of the mean square error against a different number of natural images. The proposed technique accurately performs the preprocessing for all the images hence it minimizes the error rate.

Peak Signal to Noise Ratio: It is measured based on the mean squared difference between noisy image and quality enhanced natural image after pre-processing .Higher PSNR value provides high image quality for disease detection.

Table 2 Peak Signal-to-Noise Ratio

Number of natural images	Peak Signal-to-Noise Ratio (dB)		
	DLF-SCES	AWGIF	LLEAD
600	55.92	54.32	52.99
1200	55.40	54.32	52.90
1800	55.12	53.84	52.72
2400	54.32	53.64	52.39
3000	54.27	53.35	52.27

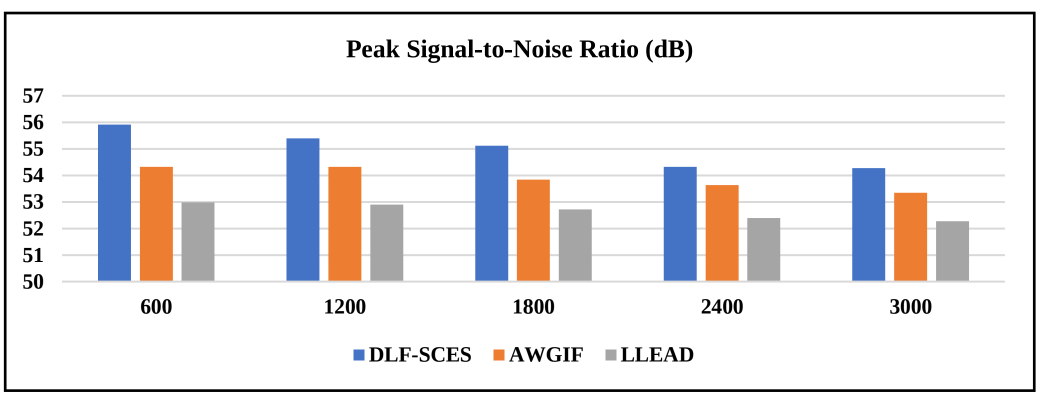

Figure 4 Performance results of Peak Signal to Noise Ratio

The observed results of the DLF-SCES technique are compared to the existing methods is shown in Table 2 and Figure 4. The average results of ten comparison outcomes indicate that the PSNR of the technique is increased by 2% and 4% when compared to the [1] and [2] respectively.

Classification accuracy: It is measured as the ratio of the number of images is correctly classified into different classes to the total number of images for the experimental evaluation.

Table 3 Comparison analysis of Classification Accuracy

Number of Natural images	Classification accuracy (%)		
	CWTC	DAIIC	READ
600	94.16	89.16	85.83
1200	95.16	86.83	83.75
1800	95.83	90.27	84.72
2400	94	89.37	83.83
3000	95.8	90.4	87.06

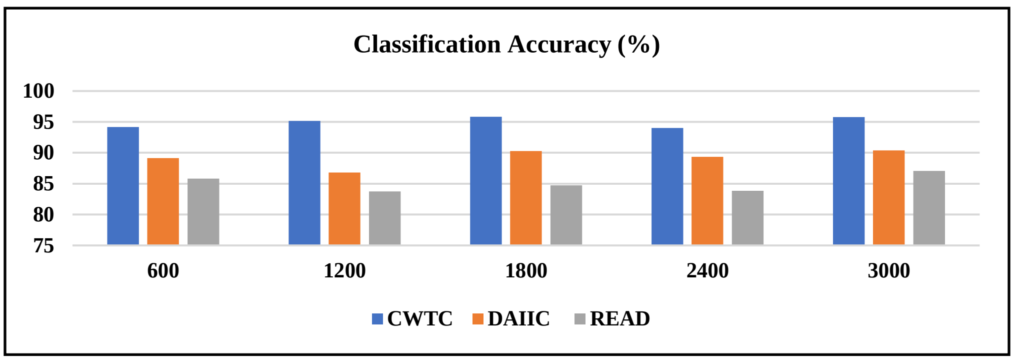

Figure 5 Graphical Analysis of Classification Accuracy

Table 3 and Figure 5 illustrates the comparison analysis of classification accuracy under a varying number of

natural images collected from the dataset. By applying the CWTC technique, 94.16% of the classification. Accuracy was observed. The classification accuracy of the existing DAIIC [1] and READ [2] were observed to be 89.16 % and 85.83 % respectively.

Classification time: It is defined as the amount of time taken by an algorithm for image classification.

Table 4 Comparison Analysis of Classification Time

Number of natural images	Classification time (ms)		
	CWTC	DAIIC	READ
600	18	24	30
1200	24	27.6	32.4
1800	27	30.6	34.2
2400	31.2	36	38.4
3000	36	40.5	42

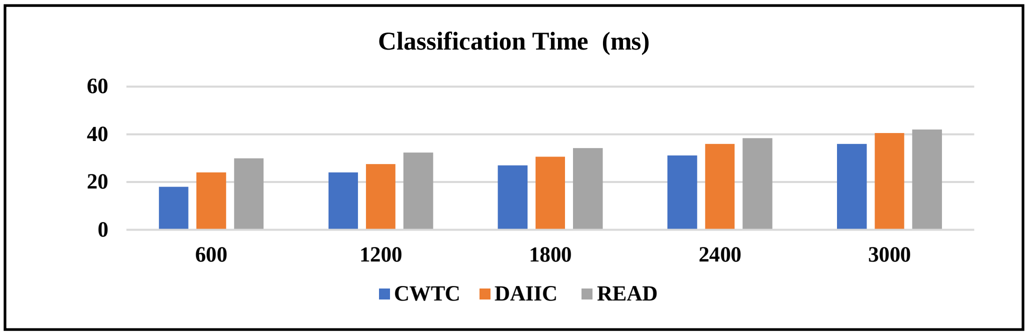

Figure 6 Graphical analysis of Classification Time

Figure 6 and Table 4 provides the impact of classification time for a different number of natural images collected from the dataset. Methods' [1], [2]. The classification times of proposed WT-RCEIC technique was observed by 18ms for data classification where as the DAIIC [1] and READ [2] takes 24ms and 30ms respectively.The observed results validate that the WT-RCEIC technique considerably outperforms well when compared to the existing

5. CONCLUSION

With the rapid development of image processing technology, image quality enhancement is the fundamental processing step of many real vision systems. In order to improve the quality of a given image, the DL-SCES technique is introduced in this paper for enhancing the image contrast by removing the noise as well as preserving the depth edges. First, Piecewise regressive damped Bryson–Frazier Fixed Interval Filtering is applied to a DL-SCES technique to denoise the input natural image by identifying the noisy pixels. Then, the edge smoothing is carried out for improving the image quality. Based on the denoising and edge smoothing, accurate image preprocessing is obtained with minimum time. The comprehensive experimental assessment is carried out with the natural image dataset.

CWTC technique is introduced to improve image classification accuracy. In order to minimize the time consumption of the image classification, the Ricker wavelet transform is employed for decomposing the input image into different levels. After that, texture, shape, and color features are extracted for accurate classification. Finally, regularized canonical emphasis boosting technique is applied to categorize the input images based on the extracted features with higher accuracy and minimum error.

The obtained quantitative result indicates that the proposed DL-SCES technique offers improved performance in terms of achieving higher PSNR, and lesser mean square error when compared to existing methods. At the same time the CWTC performance are measured in terms of classification accuracy and classification time. Results shows that increase of classification accuracy with minimize of classification time.

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