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Rice Leaf Image Contrast Enhancement through Joint Occurrence of Spatial Gray Levels

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Abstract: Rice leaf images are the main attributes in the diagnosis of several rice related diseases. As their acquirement in real time imposes several artifacts, they needs to be pre-processed before subjecting them for further processing. Towards such objective, this paper proposes a new method called as Spatial Relation Assisted Contrast Enhancement (SRCE). SRCE is a simple and effective method that considers the Joint Spatial Spread (JSS) to perform contrast enhancement. For every gray level, its JSS is measured through 2D Spatial Joint Histogram (2DSJH) and Mutual Information. Based on the mutual information, SRCE constructs a hyperlink matrix and assigns a rank which denotes the close occurrence of gray levels. Further, the rank is used for mapping input gray levels to output gray levels. Simulation Experiments on different types of rice leaf mages through qualitative and quantitative evaluation shows the effectiveness of SRCE in improving the quality. For performance assessment, different metrics including Contrast Improvement Index (CII) and Structural Similarity Index Measure (SSIM) are used and compared with different state-of-the art methods. On an average, the CII of proposed method is observed as 6.6733 while for conventional methods, it is observed as 2.2978, 3.1767, 3.7322, 3.9166 and 5.1385 for HE, CLAHE, CLAHE + HF, BPDFHE and SECE respectively. Further the average PSNR is observed as 16.9312 dB while for HE, CLAHE, CLAHE + HF, BPDFHE and SECE, it is observed as 9.4264 dB, 12.6688 dB, 13.4062 dB, 14.4186 dB and 15.5586 dB respectively.

Keywords: Rice leaf images, Contrast Enhancement, Histogram Equalization, Mutual Information, Spatial Window, CII and SSIM.

1. Introduction

Recently, the advanced and drastic growth in the information technology has led to a smart and easy farming in the agriculture filed [1]. The advanced techniques solve so many problems those impact the yielding of the crop. From past decades, the major problem in agriculture field is the plant diseases which have serious threats in the production as well as in the provision of food security. For example, in the year of 2004, it was reported that approximately 800 million people suffered from food scarcity and about 10% of food supply is lost due to the plant diseases [2, 3]. Approximately, it was noted that the 10% to 16% loss has been occurred at its appreciated cost in 220 billion dollars in global crop harvests [4]. These statistics explore the effect of plant diseases in the food scarcity problem that has become a global problem and it must be overlooked by plant pathologists [5]. Hence, to provide a sufficient food supply for the growing population, the productivity must be increased by approximately 70%.

Among the available several food items, Rice is the most widely consumed food in the world and it is approximated as 486.62 million metric ton in the year of 2018-2019 and 493.13 million metric tons in the year of 2019-2020 [6]. These statistics shows the proof of increment in the rice consumption from year to year. It is predicted that the growth rate will meet the consumption rate. However, the lack or absence of continuous surveillance of farmland results in the destruction of huge amount of rice due to several rice leaf diseases. Several diseases occur frequently in the rice and they consequences to a huge loss in the productivity followed by economy. Additionally, the excessive utilization of chemicals, for instance nematicides, fungicides and bactericides have resulted in an adverse situation in agricultural system to combat with the rice leaf diseases [7]. Hence, the detection and prevention of rice diseases has gained a huge research interest [8].

The success of diseases control and prevention is the correct and fast diagnosis of diseases so that the pesticide control measures can be applied in the correct time. Recently, most of the farmers are dependent on the manual judgment of disease statuses and they are accomplished with the help of smuts and scalds appearance of diseases on the rice leaf images [9]. However, the manual judgment based diseases diagnosis introduces a huge burden. Moreover, there is lack of human experts with sufficient knowledge over the diseases and their characteristics. Since the rice crop characteristics vary with environment, the human expert in one region can't support for the same crop in the other region. Hence, there is a necessity to develop an automatic rice leaf disease diagnosis system.

Recently, the computer vision has entered into the agricultural field for the estimation of crop yielding, detection of crop nutrition deficiencies, prediction of crop size geometry, and recognizing the diseases. In the case of diseases identification, the entire system is developed in three phases; they are pre-processing, feature extraction and classification. In the first phase, the input image is subjected to preprocessing means the external effect present in the input image are nullified. The external effects include noise, uneven contrast, abnormal illuminations etc. These effects are including in the image at the time of its acquirement and they shows significant effect on the detection performance. Hence the rice leaf image needs to be pro-processed such that its quality gets enhanced.

In earlier, several methods are focused on the pre-processing of rice leaf images [10, 11]. However, they have several limitations like over quality enhancement, original information loss etc. To overcome these problems, we propose a Spatial Relation based Contrast Enhancement (SRCE) in rice leaf images. Unlike the conventional methods those didn't concentrate on the pixel wise relationships, the SRCE consider Spatial Relation between image pixels for contrast enhancement. SRCE constructs a hyperlink matrix based on the mutual information of 2D Spatial Joint Histograms (2DSJH) and then assigns a weight based on their dependency. For the grey levels those have higher spatial relation, the SRCE ensures a larger gap such that the contrast of each pixel will get enhanced.

The remaining paper is structured as follows; the details of literate survey are explored in section II. The particulars of proposed SRCE method are explored in section III. Section IV explores the details of experimental investigations and the final section concludes the paper.

2. Literature Survey

The computer vision employs different image processing methods on rice leaf images for the assessment of diseases in rice crop. Due to the influence of uneven illumination, relative motion and weather changes, the visual quality of rice leaf images acquired through the electronic devices is drastically less. Such kind of images shows poor performance at the further tasks such as segmentation, feature extraction and recognition. Hence, the image enhancement is required to enhance the quality of images. In the past, so many methods are developed for quality enhancement like Histogram Equalization [12], Gamma Correction [13, 14], Guided Filtering [15, 16] and retinex theory [17-19] and some others [20].

Histogram equalization is one of the most popular and simple method that was developed in the earlier 90's and it is a non-linear mapping method that re-allocates the gray pixel intensities of input images thereby the same pixels in the output images have uniform distribution. However, it produces a problem of unrealistic effects in the output image. To solve this problem, contrast limited adaptive histogram equalization (CLAHE) [21] was introduced. However, an automatic parameter adjustment is not possible with CLAHE. Next, the Gamma Correction based methods employs specific contrast parameter and applies it over the image directly to enhance its contrast. This method is proven as simple method with fastest implementation. But, the main problem is the fixed parameter that won't contribute towards different types of images. Further, for the images like rice leaf those were captured under uneven illuminations, the gamma correction suffers from several over saturation and under saturation artifacts. These problems are addressed in the retinex theory, developed by D. J. Jobson et al. [22].This method is a complex algorithm that involves the paths of image to compute the relative brightness. So many interpretations and implementations of retinex theory are developed including single scale retinex (SSR), Multi Scale Retinex (MSR) and Multi Scale retinex with Color Restoration (MSRCR) [23]. The retinex theory involves a dynamic compression range, maintains color constancy and performs local contrast enhancement. However, the retinex theory introduces Halo artifacts in the output image. Halo artifacts induce confusion to the diagnosis system. Next, the guided filtering methods use an edge smoothening operators like Bilateral Filter for contrast enhancement. Compared to the retinex theory, the guide filtering methods are fast and linear algorithms and they are independent on the size of kernels [24]. However, the main problem with guided filters in the ignorance of structural inconsistency between the reference and target images in terms of color, depth and capturing environments etc.

S. O. Oppong et al. [25] used the combination of CLAHE and Homomorphic Filter (HF) for contrast enhancement in medicinal plant leaf images. They employed Otsu thresholding for the purpose of segmentation of background. The assessed the performance through Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Mean Absolute Error (MAE), and Jaccard Index. Even though HF boosts up the performance, the CLAHE needs an automatic parameter tuning which is a typical issue.

J. G. Thanikkal et al. [26] employed edge filtering methods for the purpose of contrast enhancement in plant leaf images. Further, for segmentation purpose, they employed contour based image segmentation through canny edge detector. However, the edge detection at quality enhancement has least effect on the segmentation process as they follow a uniform pixel distribution at noises and high frequency edges.

S. Kaur, and P. Kaur [27] performed a series of operations including RGB to gay scale conversion, gray scale to binary conversion followed by smoothing [28], filtering etc. at preprocessing stage. The pre-processing mechanism handles the noise removal along with resizing image and image enhancement. For contrast enhancement, they employed contrast stretching which expands the dynamic range of image pixels. Next, they applied contrast adjustment to saturate the top 1% and bottom 1% of entire pixel value. However, CS is restricted to linear mapping between input and output pixels. Even though the results appear dramatic, sometimes, it tends to artificial appearance on equalized images. Moreover, the outliers can reduce the effectiveness of operation.

I. Fatima Abbas et al. [29] proposed a Fuzzy- logic based Histogram Equalization (FHE) is to enhance the contrast of wheat leaf images. Initially, the applied Fuzzy logic on the image to divide its histograms into subparts, based on the mean value of image. Then they applied equalization freely and independently to preserve the image brightness. They employed PSNR, MSE for performance assessment. However, FHE introduces an indiscrimination between pixels and noises.

S. Sood et al. [30] employed the Histogram Equalization on three planes such as R, G and B. They also used Hue-Saturation-Value (HSV) as one more color space model and applied Histogram equalization for contrast enhancement. However, HE creates some unrealistic effects in the output image.

B. Kaur [31] developed proposed a Hybrid preprocessing method for leaf images quality enhancement. They used an Adaptive Mean Filtering for noise suppression and Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) for Contrast enhancement. BPDFHE cannot discriminate between small sized smuts and noises in rice leaf mages as the have similar pxel intensities.

M. A. H. Rony et al. [32] used an unsharp masking filter to enhance the blurred bottle guard leaf image. As an image enhancement, a green fire blue filter is employed to enhance the image's quality by improving contrast, color's removal and thresholding. For performance verification, they employed several metrics including PSNR, MSE, SNR and Structural Similarity Index Measure. This method enhances the contrast and edges effectively but it cannot discriminate the edges with disconnected contours.

Problem: even though different kind of methods is employed for contrast enhancement, they mapped the gray levels of input image to the gray levels of output image independently. No method has been focused on the spatial relationship between gray levels. Hence, most of the time, the output gray level is just a linear mapping of input gray level. This kind of enhancement results only a slight improvement tin the contrast of images and it is not sufficient for real time images those were acquired in diverse illumination conditions.

3. Proposed Approach

3.1 Overview

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In this section, we explain the details of proposed method for contrast enhancement in rice leaf images. The proposed method is a collaborative mechanism that considers the spatial relation between pixels in image. As the real time rice leaf images are acquired in real-time under uneven illumination conditions, their quality shows significant affect in the recognition accuracy at the detection or identification of several diseases. Hence we consider the contrast enhancement in rice leaf images as a main objective and develop a simple and robust method. This method defined the relation between the pixels of image in a novel way and considered as the overall dynamic range of image grey levels for enhancing the contrast. The spatial spread of Grey levels quantifies the dependency of each grade level on other grey levels. This kind of new definition of spatial collaboration measures the spatial statistics in an efficient manner. For a given low contrast rice leaf image, the proposed method maps its grey levels to the optimal values thereby the resultant contrast of output image is much better than original input image. A simple block schematic of proposed contrast enhancement method is shown in Figure 1.

3.2 SECE

SECE is the most significant method that was proposed in the year of 2014 for enhancing the contrast of natural images [33]. It had shown a significant effectiveness than the conventional methods like histogram equalization and CLAHE. SECE is a global contrast enhancement method and it considers the entire grey level range that is from 0 to 255 of the 8 bit rice leaf image. At first the SECE divides the input image into spatial grids (as shown in Figure.2) and then compute the histogram of each grade level in the spatial grid. The size selection of spatial grid must be nearly equal to the aspect ratio of the original input image. After the determination of spatial grid size, it slides over the entire image along both rows and columns. For each and every sliding, the proposed method computes the histograms of all grey levels. Further the obtained histograms are fed for the computation of Entropy followed by cumulative distribution function (CDF). Based on the obtained CDF values, the grey level of input image is mapped to an optimal value and the obtained mapped results are accumulated to form a contrast enhanced image. Consider rice leaf image X of size $M \times N$ where M denotes that size of rows and N denotes the size of columns. Hence the image can be represented as $X = \{x(m,n)|0 \leq m \leq M-1, 0 \leq n \leq N-1\}$.

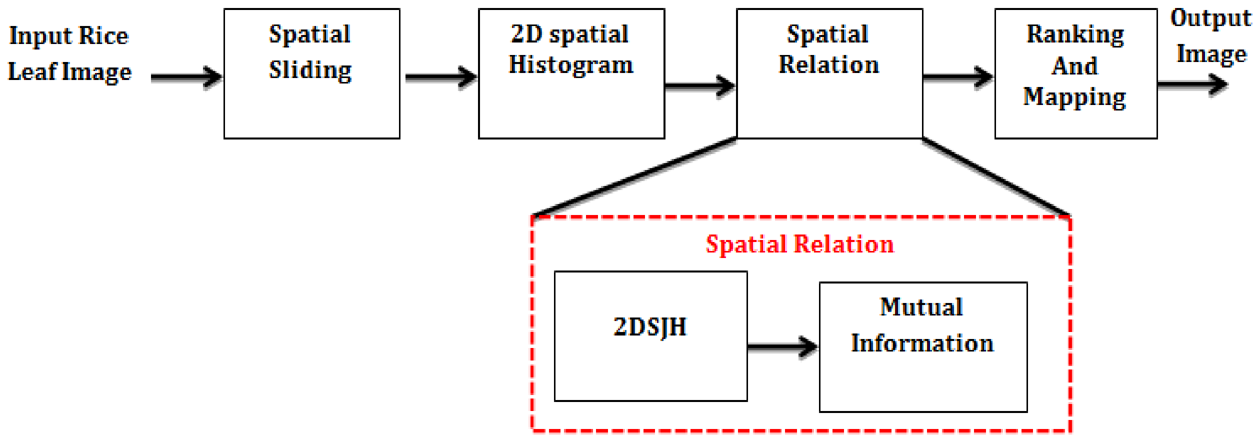

Figure.1 Block schematic of proposed method of CE

Next consider the dynamic range of image is $[x_i, x_u]$ where x_i denotes the the lower limit of the dynamic range and x_u denotes the upper limit of dynamic range such that $(m,n) \in [x_i, x_u]$. Assume Y be the contrast-enhanced image and it can also be represented as $Y = \{y(m,n)|0 \leq m \leq M-1, 0 \leq n \leq N-1\}$ and let y_i be the lower limit of dynamic range and y_u be the upper limit of dynamic range of the grey levels of the output image. Hence the output image Y's each pixel has an intensity within the range of y_l and y_u thereby $y(m,n) \in [y_i, y_u]$. To get optimal grey level intensities in the output image, we considered the entire dynamic range i.e., from 0 to 255 of an 8 bit image. Further SECE assigns the limits in such a way the y_l the must be always less than y_u, i.e., $y_l < y_u$ and $y_l = 0$ and $y_u = 255$ for an 8 bit input image.

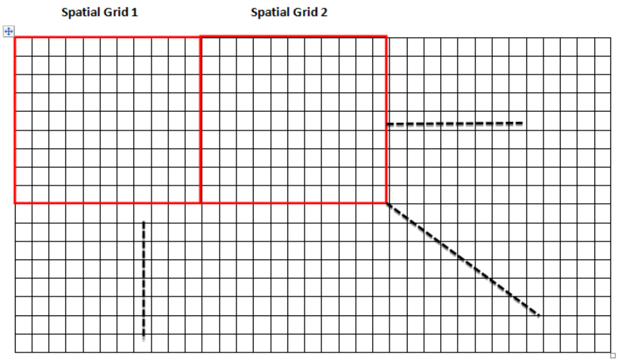

Figure.2 Spatial grid sliding over an image

3.2.1 Spatial Histogram

Generally histogram is defined with respect to the total number of occurrences of a pixel in the image. For an input image all grey levels are considered as one histogram bin and they are accumulated to get the entire histogram of image. Unlike the above, SECE considered only a partial portion of the image. To get the partial portion of an image it is subjected to spatial windowing and the histograms computed in each window is called as spatial histograms. At the time of spatial windowing the size of window has to be selected in such a way it must be less than the size of original image but the aspect ratio must be nearly equal to its aspect ratio. Let r be the aspect ratio, it is measured as

$$r = \frac{M}{N} \approx \frac{P}{Q} \qquad (1)$$

Where P and Q are the row and column size of spatial window. These two sizes are measured based on the row and column size of input image and the total number of Grey levels present in the input image.

$$P = \left\lfloor \sqrt{\left({}^{L}/_{r}\right)} \right\rfloor \text{ and } Q = \left\lfloor \sqrt{(L \times r)} \right\rfloor \qquad (2)$$

Where L denotes the total number of Grey levels and $\lfloor . \rfloor$ operator denotes the ceil operation that takes the round off of inner term. With the help of P and Q, the input image is divided into several spatial Windows and the total number of grids into which the image can be divided is $P \times Q$. Now define two variables p and q where $p \in P$ and $q \in Q$ and they are used to make the window to slide over the input image. The region into which the spatial window needs to be located is calculated as

$$\left[(p-1)\frac{M}{P}, p\frac{M}{P}\right] \times \left[(q-1)\frac{N}{Q}, q\frac{N}{Q}\right] \qquad (3)$$

Based on the above expression the total number of grids divided is $P \times Q$. For each region, the SECE computes the spatial 2D histograms. Consider there are L number of distinct grey levels in the input image denoted as $\{x_1, x_2, \dots, x_L\}$, where $\{x_1 < x_2 < \cdots < x_G\}$ after performing sorting operation. Further, in the similar manner the grey levels in the output image can also be represented as $\{y_1, y_2, \dots, y_L\}$, where $\{y_1 < y_2 < \cdots < y_G\}$ after performing sorting operation. For example the 2D spatial histogram of a grey level x_l on the spatial grid it is calculated as

$$h_l = \{h_l(p,q) | 1 \le p \le P \text{ and } 1 \le q \le \mathrm{Q}\} \qquad (4)$$

Here h_l denotes the total number of occurrences of a grey level x_l in the specified spatial grid.

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3.2.2 Entropy and Mapping

After the completion of histograms calculation of all grey levels in each and every spatial grid, then SECE computes the entropy of each level. Consider S_l be the entropy of a grey level x_l, it is calculated as

$$S_l = -\sum_{p=1}^{P}\sum_{q=1}^{Q} h_l(p,q)\ \log_2(h_l(p,q)) \qquad (5)$$

Next the relation between different entropies is calculated as

$$f_l = S_l/\sum_{l=1}^{L} S_l \qquad (6)$$

In the above expression, the f_l can also be called as weight that explores the relative significance of a grey level on the other grey levels. Here the value of l varies from 1 to L. The relative significance is said to be more if f_l is high and vice versa. For all the obtained f_l values the final cumulated distribution is assessed by the accumulation of all f_l values. The CDF is defined as

$$F_l = \sum_{l=1}^{L} f_l \qquad (7)$$

where F_l is the final CDF of a grey level x_l and it is mapped to $y_l$based on the upper and lower limits of Grey levels. The mapping is done as follows.

$$y_l = \lfloor F_l(y_u - y_i) + y_i \rfloor \qquad (8)$$

y_l is the finally mapped grey level and l varies from 1 to *L*. After completion of mapping the image is reconstructed to get the enhanced image.

3.3 Proposed SRCE

Even though the SECE performs the contrast enhancement effectively, it is a global contrast enhancement method with neglects the local variations in image. In SECE the grey level of output image is mapped to the grey level of input image through a weight factor that was computed based on spatial entropy of corresponding grey levels. For a specific grey level it's weight (calculated from Eq.6) is measured as a ratio of its entropy to the sum of entropies of all grey levels in the grid. This calculation of weight is also regarded as a normalization process and it explores the relative importance of corresponding grey level in the image. Due to this normalization process, SECE has gained a slight enhancement in the contrast of image. Moreover, the SECE formulates the output grey level as a linear combination of input gray-level because it performed a simple normalization but not mutual relation. Furthermore the SECE can't utilize the entire dynamic range that consequences to the loss of original contrast at some pixels.

To sort out this problem, we considered to include the spatial relation between histograms of image. For this inclusion, we calculate a weight between two grey levels based on their spatial spread and dependency. The spatial relation between two grey levels explores their mutual spatial spread in each grid and proximity in the entire image. After the computation of spatial relations, we assign One Rank based on the obtained values. This rank helps to ensure sufficient gap between consecutive grey levels. The larger value of spatial relation rank between two grey levels makes them to keep far away such that the corresponding pixels looks with appropriate contrast.

3.3.1 Spatial Relation

Let's assume x_l and x_k be the two grey levels of an input rice leaf image and h_l and h_k be the corresponding histograms. The spatial relation between these two grey levels is assessed based on their joint occurrence, called as 2D spatial joint histogram (2DSJH) and let it be denoted as $h_{l,k}$. Mathematically it is calculated as an average of individual histograms, as

$$h_{l,k} = mean(h_l, h_k) \qquad (9)$$

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For a spatial grid at p and q the above equation is modified as

$$h_{l,k}(p,q) = mean(h_l(p,q), h_k(p,q)) \quad (10)$$

The 2DSJH expose the joint occurrence of two grey levels in the spatial grid located at p and q. The 2DSJH helps in the assessment of joint spatial statistics and its computation is simple but effective. Based on the obtained 2DSJH, we compute the spatial relation through the mutual information calculation. For a given two grey levels x_l and x_k and its corresponding histograms h_l and h_k the mutual information is denoted as $I(l,k)$ and it is calculated as [34]

$$I(l,k) = \sum_{p=1}^{P} \sum_{q=1}^{Q} h_{l,k}(p,q) \log_2 \left(\frac{h_{l,k}(p,q)}{h_l(p,q) h_k(p,q)} \right) \quad (11)$$

For the above expression, $h_{l,k}(p,q)$ is obtained through Eq.(10) and $h_l(p,q)$ or $h_k(p,q)$ is obtained through Eq.(4). With the help of mutual information ($I(l,k)$) we can estimate the mutual dependency between grey levels x_l and x_k. If the mutual information is observed as high, it means that the corresponding grade levels x_l and x_k occurs mutually on the closest spatial regions. In such case, the output grey levels must keep far away by assigning a larger gap between them.

3.3.2 Ranking and Mapping

The spatial relation between two grey levels x_l and x_k helps in the evaluation of mutual relation between them. During the computation of spatial relation, each grey level is checked its mutual dependency with all the other grey levels. Hence the spatial relation Matrix can be regarded as a 2D symmetrical matrix and it is used here to compute the rank based on the obtained mutual information values. Let's assume an image have 255 distinct grey levels then the size of spatial relation matrix is 255×255. In that Matrix, the First row represents the spatial relation between first grey level with the remaining 254 grey levels. Similarly the second row denotes the spatial relation between second grey level and the remaining 254 grey levels and the last row denotes the corresponding spatial relation between last grey level and the remaining grey levels in the image. In this Matrix, the diagonal elements denote self-spatial relation which is one. The spatial relation matrix is also called as a hyperlink Matrix which has equal columns and rows.

Let's assume $T = \{t(l,k) | 0 \leq l \leq L-1, 0 \leq k \leq L-1\}$ is a hyperlink Matrix where L denotes the total number of Grey levels available in spatial grid, $t(l,k)$ represents the spatial relation between x_l and x_k. Simply it can be replaced with the corresponding mutual information ($I(l,k)$) between the same grey levels. Just to avoid the confusion between notations, here we have represented the mutual information with other term. If the grey levels have a uniform distribution in any spatial grid, then they will get a larger spatial relationship value. In an image there exists highly correlated pixels and hence their occurrence also has similar values which denote that they are uniformly spread over an image. For a specific row in hyperlink matrix, only few columns occupy the larger values which denote high correlation with the corresponding grey level. The remaining columns are almost occupies zero values with denote that they are not related to the corresponding grey level. Hence, for every gray-level x_l there exists at least one gray-level x_k for which $t(l,k) \neq 0$. Based on that assumption the rank is assigned as [35]

$$r(l,k) = \frac{t(l,k)}{\sum_{k=1, k \neq l}^{L} t(l,k)} \quad (12)$$

Based on the obtained rank value, a new mapping function is derived that provides a mapping relation between input and output grey levels. Here we derived a new mapping function and is mathematically represented as

$$y_l = \lfloor y_{l-1} + \Omega_{l-1,l}(y_u - y_i) \rfloor \quad (13)$$

Based on above expression we can understand that the current gray-level $y_l$is dependent on its earlier gray-level y_{l-1} as well as on the gap $\Omega_{l-1,l}$ between them. Here the grey levels are considered from $l = 2$ and ends at $l = 255$ for a grey level input image. As $x_i = 0$ and $x_u = 255$, we didn't consider them for processing. Next the gap form $\Omega_{l-1,l}$ is obtained as an average of ranks between *l-1* and l^{th} levels. Mathematically, it is represented as

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$$\Omega_{l-1,l} = \frac{(r(l-1)+r(1))}{2} \tag{14}$$

The above expression is the mean of successive ranks. Unfortunately if any output gray-level is not an integer then it was round it to the nearest integer. Furthermore, the proposed method utilizes the complete dynamic grey range from y_i to y_u. This kind of complete utilization along with spatial dependency ensures an increased contrast in the output rice leaf images.

The following Algorithm shows the step-by-step process of proposed methods contrast enhancement on rice leaf images.

Algorithm: SCCE

Input: Low Quality Rice lead image (I)
Output: Quality Enhanced Rice leaf image (O)

Start
1. Divide the input image I into several spatial grids by applying spatial windowing Through Eq.(3)
2. Compute Histograms for every gray level in each spatial grid through Eq.(4).
3. x_l and x_k be the two grey levels of an input rice leaf image and h_l and h_k be the corresponding histograms, then compute the 2DSJH through Eq.(9)
4. Evaluate the Spatial Relation between x_l and x_k through Eq.(11)
5. Compute the rank of spatial relations for every pixel through rank Eq.(12).
6. Map the Input gray level to output gray levels Through Mapping Eq.(13).

End

IV. SIMULATION RESULTS

In this section, we explore the details of simulation experiments conducted on the proposed method through different rice leaf images. The entire simulation is done in the MATLAB 2015 programming environment on the personal computer with 4 GB RAM, 1 TB hard Disk and Windows 8 operating system. In the MATLAB tool, we specifically used two toolboxes namely image processing and statistics toolboxes. To assess the performance in both qualitative and quantitative manner, we adopt both kinds of measures. In this section, initially, we discuss about the images used for testing and the obtained results. Then we discuss about the performance used for assessment and then the results followed by comparative analysis.

4.1. Testing Images and Results

For testing purpose, we used totally four types of rice leaf images; they are Bacterial Blight, Blast, Brown spot and Tungrow. All the images used for testing are obtained from public website [38]. The resolution of each image is observed as 300×300 and every image as three planes, they are R, G and B. There are totally 5932 image among which the 1584 are Bacterial Blight, 1440 are Blast, 1600 are Brown Spot and the reaming 1308 are Tungro images. Each image is in the compressed format and it is represented as .jpg. Some sample images are shown in the Following Figure.3. The obtained visual results are shown in Table.1.

(a) (b) (c) (d)

Figure.3 Different types of test images, (a) Bacterial Blight, (b) Blast, (c) Brown spot and (d) Tungrow

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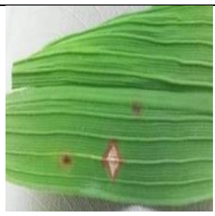
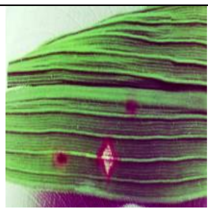
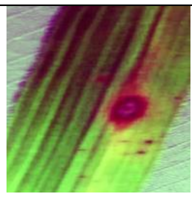
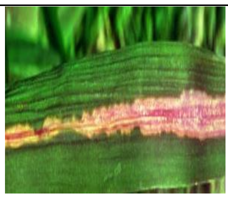
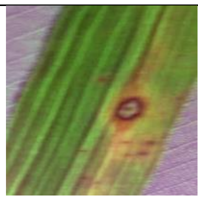
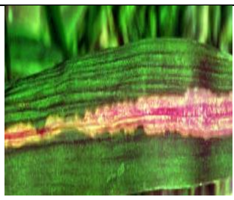
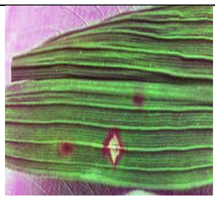
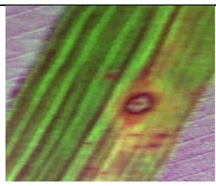
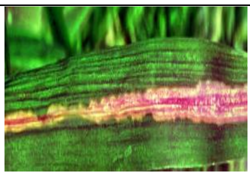
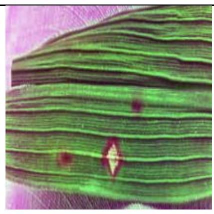
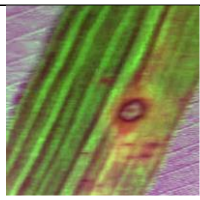
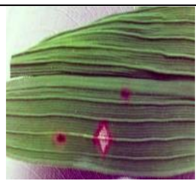
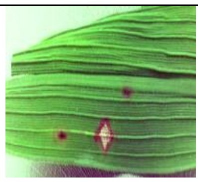
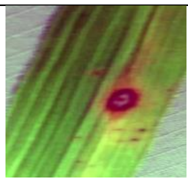
Table.1 Different Enhanced rice leaf images through different methods

Method/Image	Bacterial Blight	Blast	Brown spot	Tungrow
Original				
HE [30]				
CLAHE [21]				
CLAHE + HF [25]				
BPDFHE [31]				
SECE [33]				
SRCE				

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4.2. Performance Metrics

To further explore the performance effectivness of SRCE, the obatined visual results (output images) are subjected to quantitative evaluation and under this evaluation, several performance metrics are measured. Totally, we consider two metrics namely Structural Similarity Index Measure (SSIM), Contrast Improvement Index (CII) [36] and Linear Index of Fuzziness (LIF) [37]. CII measures the improvement in the contrast from original image to contrast enhanced image. CII is calculated with the help of two measures namely contrast of original image (C) and contrast of enhanced image (C_e). With the help of C and C_e, the CII is formulated as

$$CII = \frac{C_e}{C} \qquad (15)$$

Where C is initially measured with the help of the obejcts and background of original input image. In the input image, the objects are nothing but foreground pixels. Mathematically the C is computed as follows;

$$C = \left|\frac{Y-G}{Y+G}\right| \qquad (16)$$

Where Y and G are the gray values of foregorund and backgrounds respectively. Based on the above expression, we can understand that a larger value of C denotes a larger gap between background region and foreground regions. C_e is also measured in the same manner and a larger value of C_e indicates better perfromance. As the vlaue of C_e is high, the CII is also high and it denotes a better contrast enhancement in the resultant image.

The next meausre is LIF which is a one of quantitative meausre used for the analysis of quality improvement in images. Mathematcally the LIF is measuerd as

$$\gamma(I) = \frac{2}{M\times N}\sum_{m=1}^{M}\sum_{n=1}^{N}\min\{p(m,n),(1-p(m,n))\} \qquad (17)$$

Where

$$p(m,n) = \sin\left[\frac{\pi}{2}\times 1-\left(\frac{I(m,n)}{I_{max}}\right)\right] \qquad (18)$$

Where $I(m,n)$ denotes the gray value of the pixel at (m,n), I_{max} is the maximum gray level of image I of size $M\times N$. As the value of γ is small, the method is said to have better performance and the resultant images have better quality.

Next, SSIM explores the structural similarity between original and enhanced image. In this work, the original image is reflected by input low contrast image and output image is reflected by the contrast enhanced image. The SSIM is measured between them to find the deviations in the structure of image. Since the main objective of proposed method is to enhance only the contrast, the structural features must remain same. Hence, SSIM is considered here for the assessment of performance of proposed contrast enhancement method. The mathematical expression for SSIM is given as

$$SSIM = \frac{(2\times\bar{x}\times\bar{y}+C_1)(2\times\sigma_{xy}\times C_2)}{(\sigma_x^2+\sigma_y^2+C_1)(\bar{x}^2+\bar{y}^2+C_2)} \qquad (19)$$

Where $C_1 = (k_1L)^2$ and $C_2 = (k_2L)^2$ those avoids the fraction from infinity. L is the dynamic range of the pixel values (typically this is 2# bits per pixel -1). k_1 = 0.01 and k_2 = 0.03 by default. The default range of SSIM lies in between -1 and 1. Hence, the SSIM and CII value must be high and LIF value must be low to indicate the good performance.

Next, we employed Tenengrad criterion (TC) [38] for the assessment of performance effectiveness. TC is calculated as the summation of gradient magnitudes of all pixels of an image. Mathematically it is represented as

$$TC = \frac{\sum_{x,y}\sqrt{(g_x)^2+(g_y)^2}}{M\times N} \qquad (20)$$

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Where g_x an dg_y are the horizontal and vertical gradients of a pixel respectively. M and N are the row and column sizes of images respectively. The larger value of TC denotes the better quality of image and vice versa.

Further to check the performance, the obtained denoised image are processed for objective evalutaion through peak signal to noise ratio (PSNR). The mathematical formulae of PSNR is described as follows;

$$PSNR = 10 * \log 10 \left(\frac{Max^2}{MSE}\right) \qquad (21)$$

MAX is the maximum value of pixels (255 for grey scale images). MSE is the mean square error between the original and denoised images. It is given by equation (13).

$$MSE = \frac{1}{mn} \sum_{i=1}^{n} (O(i,j) - D(i,j))^2 \qquad (22)$$

O(I,j) is original image pixel and *D(I,j)* is denoised image pixel. Greater PSNR values indicate better quality. It is expressed in decibels (dB).

The following Table.2 shows the obtained CII, LIF, and SSIM values of after the accomplishment of proposed SRCE on different images.

Table.2 Performance of SRCE on different images

Image/Metric	**CII**	**LIF**	**SSIM**	**TC**	**PSNR**
Bacterial Blight	4.3214	0.4315	0.8447	14.0031	21.3356
Blast	4.8976	0.5555	0.9385	30.8163	20.4578
Brown Spot	3.9784	0.4110	0.8279	18.2115	23.8974
Tungrow	4.1028	0.4223	0.8333	29.9467	20.9967

Table.3 Comparison between proposed and existing methods

Image/Method		HE [30]	CLAHE [21]	CLAHE+HF [25]	BPDFHE [31]	SECE [33]	SRCE
Bacterial Blight	CII	1.5845	2.3346	2.8974	3.2478	3.6697	4.8564
	LIF	0.5193	0.6642	0.6401	0.6037	0.4721	0.3327
	SSIM	0.5148	0.7741	0.7964	0.8145	0.8694	0.9035
	TC	17.4589	20.1348	21.5589	23.4996	28.5679	35.3077
	PSNR	14.6345	16.5427	16.9968	17.2014	19.4578	21.3324
Blast	CII	1.6847	2.4214	2.9633	2.6872	3.4420	4.0784
	LIF	0.7888	0.8542	0.6342	0.6014	0.5638	0.5047
	SSIM	0.3923	0.4578	0.5924	0.6634	0.7045	0.8556
	TC	32.1457	35.6898	36.4578	38.5585	45.7986	56.7745
	PSNR	13.4578	15.8854	16.3335	17.0214	18.5525	20.4524
Brown Spot	CII	1.0012	1.9645	2.2145	2.3381	3.0074	4.5441
	LIF	0.6844	0.9691	0.6284	0.6241	0.6381	0.5853
	SSIM	0.3817	0.5234	0.5638	0.5966	0.6852	0.7555
	TC	21.5532	23.6894	22.8674	25.9678	30.2222	33.6784
	PSNR	15.7646	17.5585	17.9968	18.2047	20.3247	23.6635

Tungrow	CII	2.6784	2.9877	3.0245	3.2245	4.0017	4.2333
	LIF	0.5574	0.8421	0.5014	0.4971	0.5111	0.4586
	SSIM	0.4929	0.5231	0.5532	0.6417	0.7584	0.8774
	TC	32.1454	35.6685	32.1458	38.4471	42.6894	45.6653
	PSNR	12.4455	14.8637	15.6637	15.7845	16.8667	20.8679

4.3. Comparison

Under the comparison, we compare the proposed method with several existing methods through three performance metrics. The existing methods are namely Histogram Equalization [30], CLAHE [21], CLAHE with Homomorphic Filter [25], BPDFHE [31], and SECE [33]. As shown in the above Table.3, the performance of proposed approach is shown better than the existing methods. For every class, the proposed SRCE had shown an excellent performance. For instance, the SRCE has gained a maximum value of TC which denotes that the contrast enhanced image is preserved with sufficient gradients or edges and boundaries. At the time of contrast enhancement, the prime focus needs to be put on the quality enhancement along with edges preservation. As much as high TC value, the edges are said to be sufficiently preserved. From the above results, we can demonstrate that the proposed SRCE is effective in enhancing eh quality align with edge preservation. The results demonstrated in the Table.3 are the average values and they are obtained after performing an average of values obtained after simulation of 20 images in each class. For every class, we used totally 20 images and the obtained CII, LIF, SSIM and TC values are averaged to get the final average value. Among different classes of images, we observed that the Blast image class has gained an optimal performance in both quality and edge preserving perspectives.

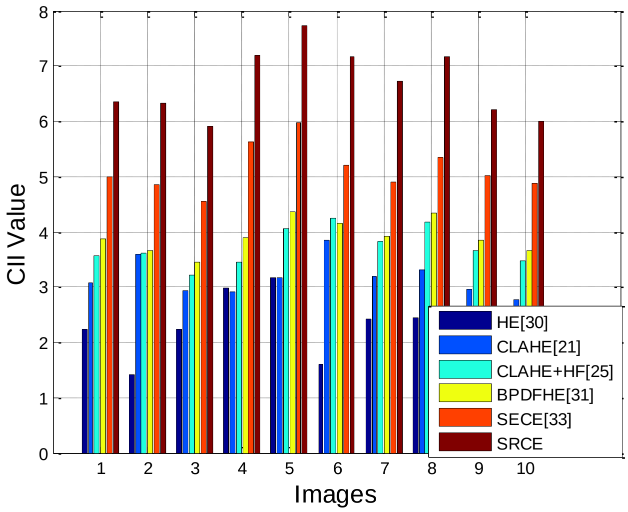

Figure.4 CII comparison between proposed and existing methods

Figure.4 shows the comparison between proposed and existing methods through the CII value obtained after the simulation. From this figure, the average CII of Histogram equalization method is observed as 2.2978, for CLAHE it is observed as 3.1767, for CLAHE+HF, BPDFHE and SECE, it is observed as 3.7322, 3.9166, and 4.5678 respectively. Finally, for SRCE, the average CII is noticed as 5.13865which is larger value than the existing methods.

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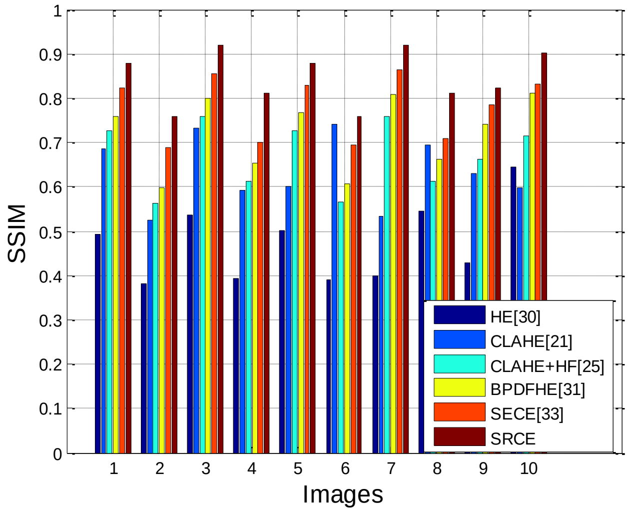

Figure.5 SSIM comparison between proposed and existing methods

Next, Figure.5 shows the comparison between proposed and existing methods through the SSIM value. From this figure, the average SSIM of Histogram equalization method is observed as 0.4713, for CLAHE it is observed as 0.6334, for CLAHE+HF, BPDFHE and SECE, it is observed as 0.6703, 0.7209, and 0.7779 respectively. Finally, for SRCE, the average CII is noticed as 0.8466 which is a very small value than the existing methods.

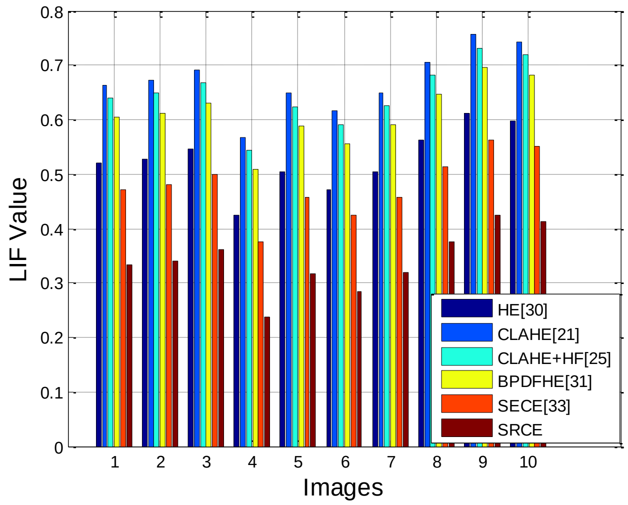

Figure.6 LIF comparison between proposed and existing methods

Figure.6 shows the comparison between proposed and existing methods through the LIF value. From this figure, the average LIF of Histogram equalization method is observed as 0.5269, for CLAHE it is observed as 0.6717, for CLAHE+HF, BPDFHE and SECE, it is observed as 0.6479, 0.6112, and 0.4796 respectively. Finally, for SRCE, the average CII is noticed as 0.3401 which is a very small value than the existing methods. Further, the edge preserving comparison is show in Figure.7. From the results we observed that the average TC of Histogram Equalization, CLAHE, CLAHE+HF, BPDFHE, SECE is 16.5525, 19.2504, 20.6686, 22.6152, and 27.6835 respectively.

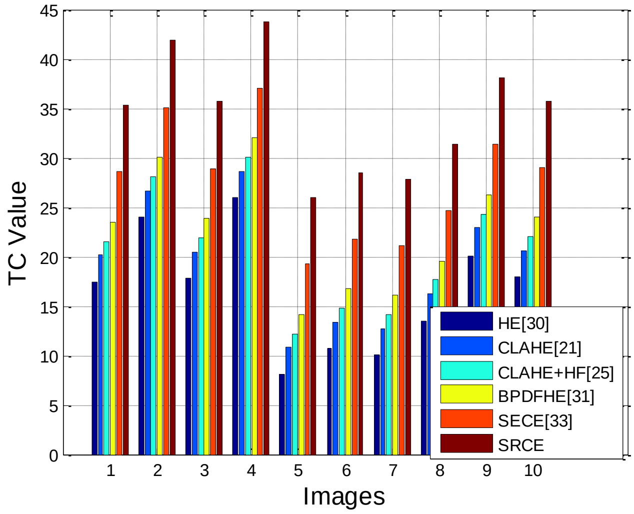

Figure.7 TC comparison between proposed and existing methods

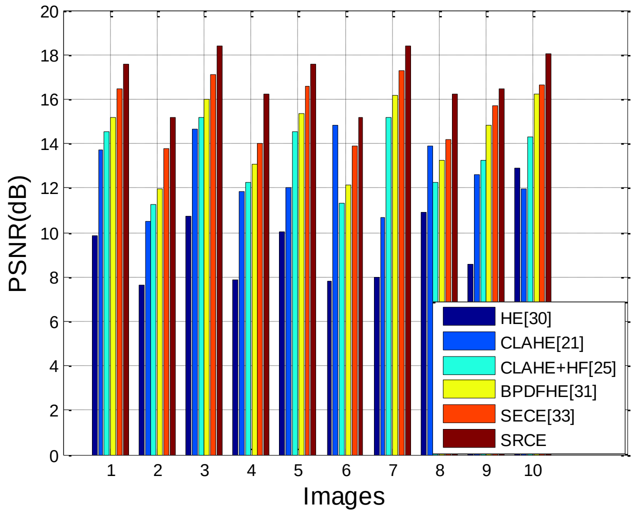

Figure.8 PSNR comparison between proposed and existing methods

The proposed method is observed have an approximate TC of 34.4233 which is a larger values compared to all the other existing methods. Further, the Quality improvisation comparison through PSNR is show in Figure.8. From the results we observed that the average PSNR of Histogram Equalization, CLAHE, CLAHE+HF, BPDFHE, SECE is 9.4264, 12.6688, 13.4062, 14.4186, and 15.5586 respectively. The proposed method is observed have an approximate PSNR of 16.9312 which is a larger values compared to all the other existing methods.

5. Conclusion

In this paper, we proposed a new contrast enhancement technique for rice leaf images as they composed of different types of artifacts. The quality of rice leaf image has significant role in the identification of several diseases. Hence we aimed to improve the quality and proposed a method based on the spatial relation between pixels in the mage. The spatial relation is derived based on 2D spatial joint Histograms followed by mutual information. Next, the proposed method constructs a hyperlink matrix and assigns one rank based on the dependency. Based on the rank, the adjacent gray levels are separated with sufficient gap such that the contrast of rice leaf image is enhanced. Simulation done on different types of images and the performance is measured through CII, LIF, SSIM and TC. Further, the comparative analysis between proposed and existing methods proves its outstanding performance. Based on the results the average improvement in PSNR is observed as 7.5048, 4.2644, 3.5250, 2.5126, 1.3726 from HE, CLAHE, CLAHE + HF, BPDFHE and SECE respectively. Similarly, the average LIF of proposed method is observed as 0.3401 while for conventional methods, it is observed as 0.5268, 0.6717, 0.6476, 0.6112, 0.4796 for HE, CLAHE, CLAHE + HF, BPDFHE and SECE respectively.

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