Improving Image Quality based on Feature Extraction and Gaussian Model

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ABSTRACT:
By expanding the use of digital images in various areas of everyday life, such as medicine, identification, satellite imagery, and even personal cameras and machine vision, it is felt more effective in applying quality improvements to the images used. The low-quality images in the machine's vision can expose the efficacy of later processing, such as feature extraction, classification, and pattern recognition. In this thesis, a new method for improving the quality of images based on the extraction of Godin’s combined feature and model has been proposed. Based on the fact that each homogeneous region in the image has a Gaussian distribution histogram, this distribution can be divided into smaller histograms. For the histogram division efficacy, the image is transmitted from the RGB space to the HSV space and the histogram division is applied to the severity region, and the histogram is applied to each sub Histogram based on the statistical characteristics, and the image. Improved results are returned to the RGB color space. Several qualitative and quantitative criteria have been used to evaluate the proposed method. Qualitative comparison results show improved image quality compared to histogram equivalence methods and linear contrast traction. Quantitative evaluation criteria, such as entropy and spatial frequency, as well as signal to noise ratio, peak signal and peak signal to noise ratio, are generally proposed for superiority of the method.

KEYWORDS: Improvement of Image Quality, Gaussian Combination Model, Feature Extraction, Qualitative and Quantitative Evaluation, Histogram

1. INTRODUCTION

By expanding the use of digital images in various areas of life, we need effective approaches to improve quality of image [1]. These malfunctions are because of dark environment, noise and hardware. A low-quality or low-contrast images has a low histogram representation and distribution changes or in the other words, it has low dynamical expansion (horizon). The lower dynamical expansion of image, the lower is the contrast and subsequently quality of image is low [2]. Images with low quality and contrast have narrow histogram distribution. To improve dynamical efficiency of image, various approaches are suggested known as approaches to improve contrast. Improving image quality is used in medical imagery, distant evaluation and machine vision [3-11].

Satellite imagery and even personal cameras and machine vision can influence efficiency of later processes like feature extraction, classification and pattern recognition. Improving image quality is one of the important aspects of image processes that can be used for each receiver. In cases where image details doesn’t have desirable apparent quality because of low brightness or other problems of inappropriate photography, we can improve them by various process approaches. In addition it is possible that because of image transmission, noise influences imagery. In this case we can reduce noise power. The goal of improving imagery algorithms is to signify and show details of the image with low contrast. In fact we are trying to find an approach to improve image details. These algorithms receive the image and output is an approach with better quality. This better quality is achieved by increasing contrast between objects in the image and background. There are various algorithms to improve image quality that can be divided into two groups.1. Spatial domain algorithm 2. Transformation algorithms [12-14,4]. Transformation algorithms can improve image quality locally and generally. In order to improve image in transformation domain, image is shown in different and suitable bands and different criteria. Usually transformation approaches have low calculation costs. On the other hand spatial domain algorithms can be divided into three groups. General, local and hybrid.

The main goal of this thesis is to present a new method to improve image based on Gaussian model and also feature extraction. In spite of variety in presented approaches to improve image quality and image contrast, these approaches are divided into two groups: spatial domain approach and transformation domain approach. From another perspective, these approaches are divided into two groups: histogram approaches [4], [6], [7], [9], [10], [14] and non-histogram approaches. One of the effective and useful approaches to improve quality and contrast is histogram equalization. In HE approach we try to expand mechanical domain of image and consequently improve the image. In other words image histogram is expanded and the quality improves. In spite of simplicity of this approach, there are weak points such as inability to maintain brightness of image when the image is dark or bright improving image more than enough so that image loses color. Strategies are suggested to overcome these weaknesses [15]. Although improving image quality is a new knowledge and it goes back to the processing of digital image, but this new science has improved theoretically and practically in the last decades. The speed of this improvement is not limited and nowadays after relatively a short time we can observe traces of process of improving image quality in many sciences and industries. Interest in approaches to improve image is derived from two main utilizations. Those domains include: improving imagery information for human's interpretation and processing of scene data for independent machinery understanding [16]. In spite of various attempts to improve image quality still some of the images don't have suitable quality for process. It is worth mentioning that image quality is very influential in subsequent steps of process like feature extraction, classification and pattern identification. Suggested approach in this thesis is histogram-based and uses feature extraction approach [17]. It is also related to transformation domain. The main idea in the suggested approach is using Gaussian combination GMM model and it is based on this idea that homogenous areas in the images usually have normal distribution and histogram of main picture can be transformed into sub histograms with normal distribution. In the other words, image histogram is composed of limited number of sub histograms with normal distribution. Distribution is normal. In suggested approach low quality image in RBB domain is transformed into HSV domain. Sub strand histograms are achieved, then parameters of each histogram is based on Gaussian combination model and are used for histogram equalization. This equalization and balance is performed on all sub histograms and mechanical domain of each sub histogram increases [18-21].

2. LITERATURE REVIEW

. Joe et.al [22] studied improved algorithms of images based on SVD to solve false identification problem. Suggested approach was tested against compact attacks of JPEG, Pepper, Salt and Resize. To evaluate experiment results, average square error parameters and signal peak ratio to noise and ratio of false positive identification were studied.

Results show that suggested approach is powerful and overcomes the problem of false positive identification.

Lee et.al [24] presented an algorithm to improve clarity of image in phasic method. Many researches have been conducted in computer machine vision that phasic image process is more significant than machine vision technique. Because in image process, clarity of image is important. We try to find strategies improve quality and increase clarity of images. This thesis offers a solution by a non-linear module. Kim et.al [20] studied interpretation of clarity of image by non-repeated edges. They simulated a virtual data base in which score of distorted images quality are estimated by general reference to IQA that is FISM. So a BIQA model from database is achieved by a single classification process.

Although this classification approach can be performed with four types of common distortion. Village et.al [11] studied extraordinary image with high clarity to learn multi-criteria similarities. Psychological evidence show that people prefer to conduct qualitative evaluation. Qualitative description usually has natural trend and the aim is to understand this behavior in natural context. Therefore, people don't like to show image quality by exact numbers. In return, qualitative attributes are used. Therefore, if people want to evaluate pictures qualitatively, it is a natural trend suitable for mental tests that can reduce scores and points significantly. Jo [22] studied a unified framework to learn an extraordinary image. For example above resolution and related issues causes problems in image. Therefore; noisy images are hard for people to use them and understand deficient performance of process algorithms on the other hand, this approach tries to solve puzzle of human's understanding. Results show the success of presented framework to increase high clarity of images. Tarsi et.al [12] tried to study image quality by deep understanding. Evaluation approaches for image quality (BIQA) are basically opinion-aware. They learn regression models from educational images used for estimation of conceptual quality of images by human mental ranking. These opinion-aware approaches need a lot of educational samples related to human mental scores and various types of distortions. BIQA models learned by opinion-aware approaches have weak generalizability power and it reduces their utilization in approaches.

3. SUGGESTED APPROACH

Various approaches have been offered to improve image quality by scientists. These approaches have high processing costs but have suitable results. But it is necessary to present a new method with low calculation cost and representing better images. In improving image quality two parameters of maintaining details and natural colors are very important.

In this chapter suggested approach to improve image quality and parameters are presented.

3.1. Block diagram of suggested approach

To improve image quality, which is assumed as pre-processing step and is influential in later steps of process including feature extraction and classification of image, therefore; a new method based on feature extraction and Gaussian combination model is suggested called GM-HSV-HE. Block diagram of figure 1 shows a general picture of suggested approach.

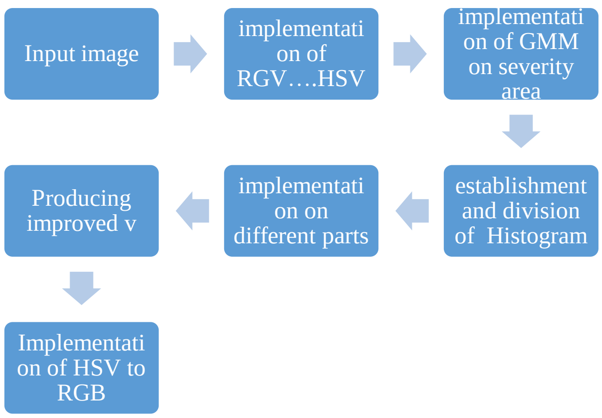

Fig. 1. General block diagram of suggested approach.

In suggested approach called GM-HSV-HE, input images are transformed from RGB to HSV. Main processes and implementation of Gaussian combination model are performed on severity part. This implementation is based on average variance parameters and possibility of sub histogram. Figure 2 shows block diagram with more details.

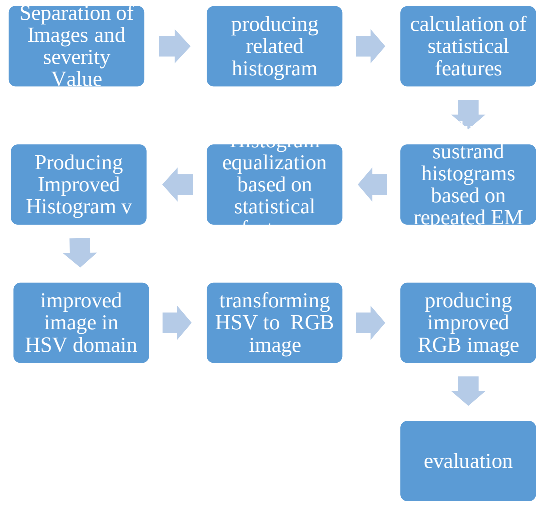

Fig. 2. Detailed suggested block diagram.

Every ideal image can be consist of significant domains. It may be homogenous. In significant domain of image Gaussian distribution is observed that mean average severity of color distribution and variation of each space is appropriate to contextual details of that space. These Gaussian are distributed based on average amount and their extension is based on variance of each domain.

In general histogram figure is like Gaussian distribution. Based on the fact that low-quality images with low contrast have limited and narrow domain, if each part is extended separately and based on its own parameters, each domain is improved and generally image quality is improved. In other words, image structure is directly influenced by its histogram and every significant peak in histogram. In fact average severity is proportional to homogenous domain extension in image of one domain or several domains. They form significant part of image. In one sample these levels are important for machine vision of image and they should be considered in improving process quality. Every significant area in general image is related to one local peak in histogram. Everything in the image has its own local histogram with one peak and normal distribution. Changes and frequencies around these peaks show Gaussian curve. It should be presented as Gaussian distribution and combination model. The number of Gaussians depends on complexities and image concepts.

4. SIMULATED RESULTS OF SUGGESTED APPROACH

To evaluate suggested approach different images with low-quality including images in open and closed domain are studied. In general evaluation criteria include two groups. Qualitative and quantitative evaluation criteria. Qualitative evaluation criteria are produced from human understanding of image quality. When contrast of image improves, image quality improves too. Qualitative evaluations have errors so quantitative criteria are used for evaluation. Quantitative criteria are divided into two groups: criteria that evaluated information of improved image and the second group criteria that compare improved information with the main image. These criteria are introduced in the second chapter.

4.1. Qualitative Evaluation

To evaluate images qualitatively by Cannon camera model CG 1725 and resolution of 4521 *3256 is used. To compare main image in models 18, 19, 20 C parameters that are parameters of extension in each area are shown. Figure 3 shows images in simulation approach. It is image of mountain.

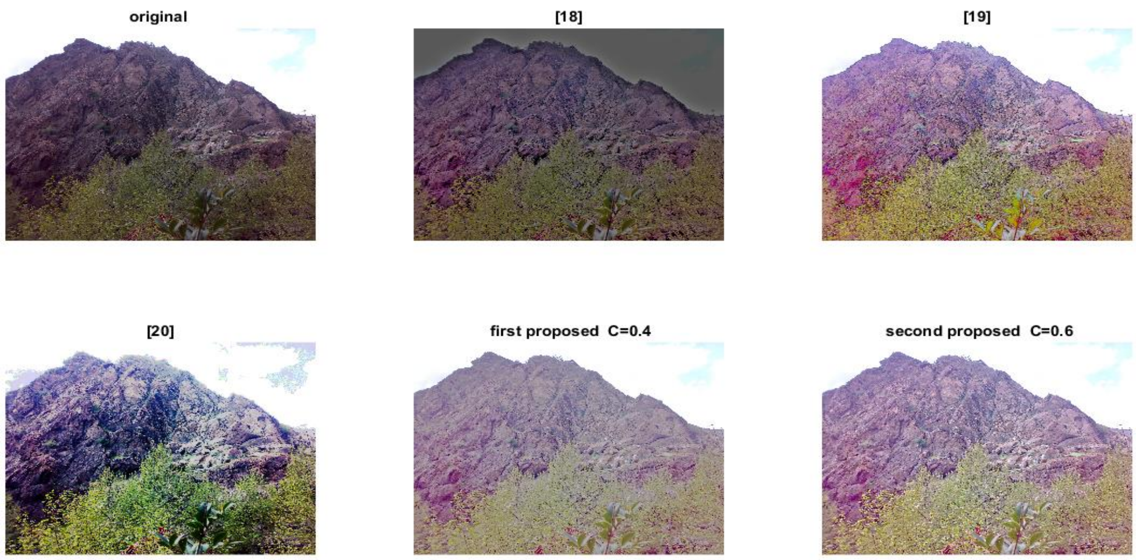

Fig. 3. Qualitative comparison of suggested approach in mountain image with [18], [19], [20] and also suggested approach for changing parameter C

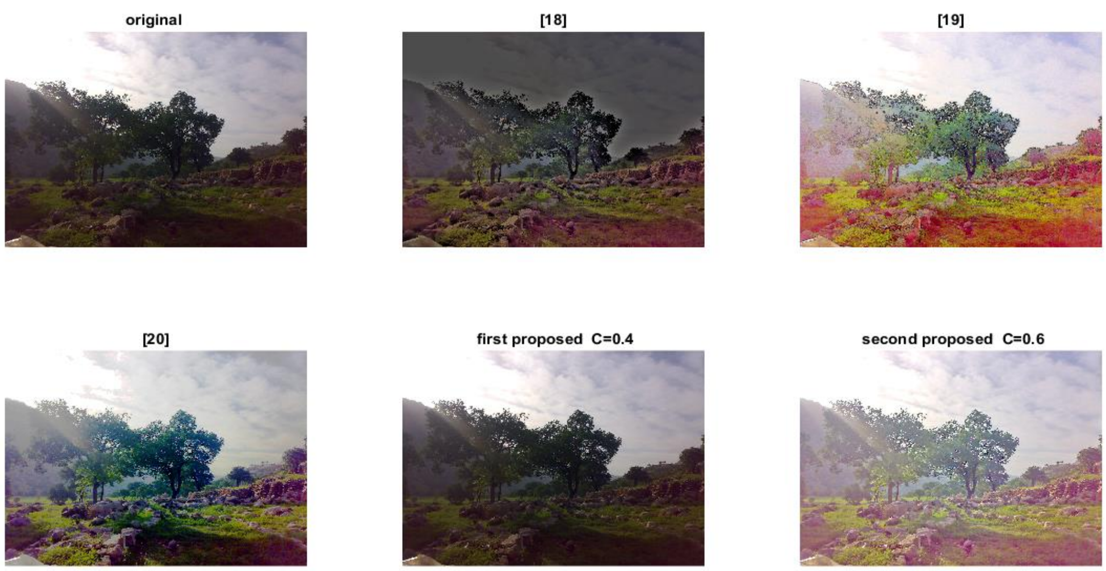

Fig. 4. Shows qualitative comparison of suggested approach in tree image with [18], [19] and [20] and also suggested approach for changing parameter C.

4.2. Experiments of Changing C

One of the significant parameters in suggested approach is parameter C. In the second group experiment ideal parameter is considered for improvement of image quality that is expanding effect and the numbers of histogram parts. The number of sub strand histograms is performed based on peaks and valleys in main histogram of picture parameter C [0 1] and controls possibility and expansion of each part. This parameter is determined manually as input. This experiment is repeated by four parameters C=%2 C=%4 C=%6 and C=%8 and C=1. Figure 5 shows image of a mountain with ideal amount.

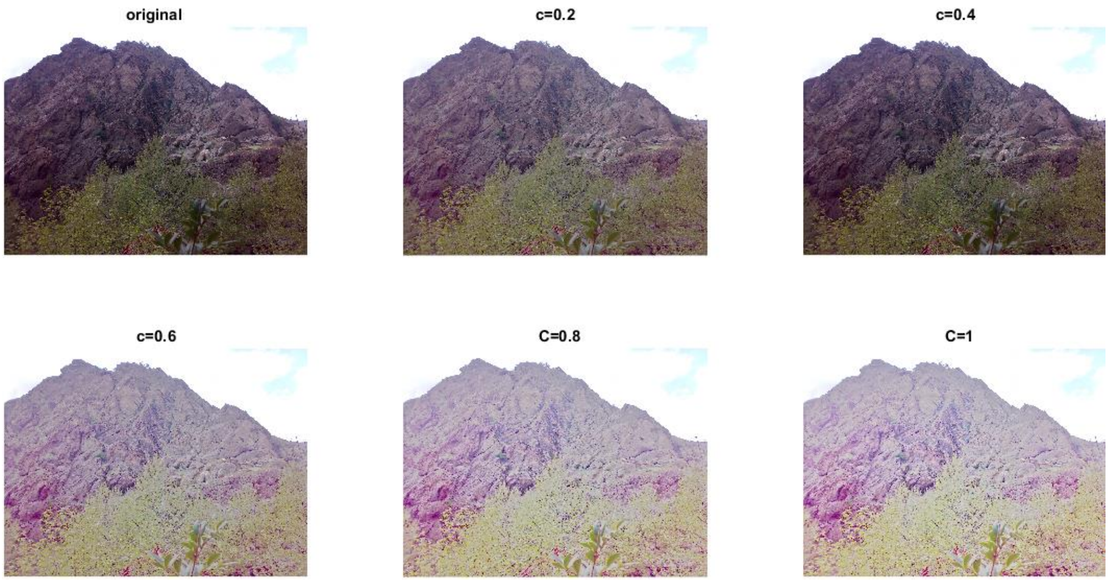

Fig. 5. Image of tree for different amounts of C.

4.3. Qualitative Evaluation

In order to compare approaches in [18],[19] and [20] and also suggested approach for C=%4, we used quantitative criteria to evaluate images in thesis. These criteria are divided into two groups:

1-some criteria evaluate each band of improved image with appropriate band like correlation coefficient ,signal to noise ratio (SNR), peak signal to noise ratio (PSNR), root mean square error (RMSE) and mean absolute error (MAE).

2- Criteria that measure internal information of each band of improved image like entropy (ENT), average gradient (AG), spatial frequency (SF), average (AG), standard deviation (SD),cross entropy (C, ENT).

4.4. First Type Criteria

In tables (1), (2) and (3) first type evaluation criteria are studied. These criteria are studied. These criteria compare improved images with main images in bands. As it is shown from tables and figures, suggested approaches in [18], [19] and [20] has its own special weaknesses and positive points.

Table 1. Results of first type evaluation criteria –Band 1 criteria and image.

Criteria / Method	C.C	MAE	SNR	PSNR	RMSE
[18]	1.3370	34.8870	23.9390	20.8410	38.5276
[19]	0.5248	63.3922	41.9174	20.6828	37.8341
[20]	0.9013	25.2398	31.7659	39.5621	26.5698
suggested approach	1.1267	38.5096	47.8954	29.4671	26.9422

Table 2. Results of first type evaluation criteria- comparison of band 2 improved image and image of band 2.

Criteria / Method	C.C	MAE	SNR	PSNR	RMSE
[18]	1.3370	26.5387	23.4353	21.4390	41.5087
[19]	0.5547	61.1105	39.8478	21.4459	34.4890
[20]	0.9127	24.5690	30.2707	34.9963	24.1097
suggested approach	1.1055	24.9289	47.0089	30.1275	26.1956

Table 3. Results of first type evaluation criteria- comparison of improved image band 3 and main image band 3.

Criteria / Method	C.C	MAE	SNR	PSNR	RMSE
[18]	1.3479	29.4410	23.9495	21.5423	41.5080
[19]	0.6083	54.6424	24.3367	23.1398	37.5685
[20]	0.9045	31.7651	31.7651	32.4900	23.1652
suggested approach	0.9810	22.2859	48.1131	32.0915	20.3662

To show results, they are presented in the form of diagrams in different bands. Correlation coefficient in three bands show superiority of suggested approach in improving image quality. As it shown in all 3 bands improved image by Gaussian combination approach and feature extraction have lower errors and this show superiority of approach. In the table of signal to noise, suggested approach has highest figures. In reference [18] weakest results are achieved. In comparison of peak ratio signal to noise, although in blue and red bands result is weaker than article [20] but it is better than two other sources. Red band can show its superiority.

In comparison of root square error, achieved figures are the lowest that shows less error in improved image quality. Source [18] has the highest error in improving quality.

4.5. Second Type Criteria

In table (4), (5), (6) second type evaluation criteria are studied. These criteria calculate information of improved image with original images in related bands. As it is shown in tables and figures presented approaches in [18], [19] and [20] each has its own positive and negative aspects. They are analyzed.

Table 4. Results of second type evaluation criteria in band 1- improved image.

Criteria / Method	AVG	ENT	SF	C.ENT	AG	SD
[18]	13.7081	5.1733	31.6063	0.0192	19.6872	3.6265
[19]	91.4072	0.9361	60.9643	0.0015	35.5027	3.6767
[20]	136.1690	0.9140	51.3634	0.0162	27.7684	3.4345
suggested approach	115.0929	0.8558	78.1002	0.0012	45.6802	3.9581

Table 5. Results of second type evaluation criteria- evaluation in band 2-improved image.

Criteria / Method	AVG	ENT	SF	C.ENT	AG	SD
[18]	149.4226	5.1516	37.4872	0.0089	19.1737	3.6818
[19]	89.3699	0.9545	54.5959	0.0227	45.3812	3.6767
[20]	130.8817	0.9101	51.8910	0.0101	17.9156	3.4150
suggested approach	112.6956	0.9416	71.7951	0.0013	51.9074	3.7110

Table 6. Results of second type evaluation- evaluation in band 3- improved image.

Criteria / Method	AVG	ENT	SF	C.ENT	AG	SD
[18]	109.4226	5.1516	37.4872	0.0089	19.1737	3.6818
[19]	78.3699	0.9545	54.5959	0.0227	45.3852	3.6767
[20]	119.8817	0.9101	51.8910	0.0101	17.9156	3.4150
suggested approach	108.6956	0.9416	71.7951	0.0013	51.9074	3.7110

In comparison of improved images in 3 different bands, higher average shows higher brightness. Average can't be a suitable criteria to evaluate brightness. The lower is the entropy, image information increases. Entropy of suggested approach is higher than other approaches. Suggested approach shows entropy less than %9 that is significant. Spatial frequency SF shows details of improved image. The bigger is the figure, the better are details of images. Results show averages higher than 75 shows superiority of suggested approach in maintaining details. Entropy close to zero shows the image has more information. Results of suggested approach are close to zero and this method is more efficient than other methods. Although values are near zero in other methods but this competition is very close. Suggested approach is superior than other approaches. Average gradient shows maintaining details in the process of image improvement. As it is shown from tables. If AG increases details are maintained more carefully. In suggested approach this point is considered. In [18] and [20] results are weaker than method [19]. Results in standard deviation in comparative approaches in [18] ,

[19] and [20] are similar to suggested approach. This criteria can't compare these methods appropriately. Therefore; with limited difference suggested approach is better than other approaches.

5. CONCLUSION

In this article results of suggested approach GM-HSV-HE are evaluated. Qualitative and quantitative criteria are demonstrated in the form of tables, figures and output images. New suggested approach is evaluated by different tests. In the first tests suggested approach GM-HS-HE was compared with methods [18], [19] and [20] and qualitative and quantitative results show superiority of suggested approach. In second group experiment parameter C that controls possibility and extension of each part has been changed and results are shown. Parameter C=%4 best result qualitatively or quantitatively. Results of quantitative comparison prove this claim. Quantitative comparison are evaluated from two perspectives. First type criteria that compare data of improved image with original image and second type criteria that measure data of improved image so that it can maintain natural color of output simultaneously. It also maintains details in the image.

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