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Image Quality Assessment of Color Doppler Images Using the BRISQUE Method

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Abstract
In a world heavily reliant on numerous medical diagnostic tests for treatments of patients, ultrasound sonography acquires a predominant position in the healthcare domain. Doppler ultrasound is an essential and effective medical test that is used to evaluate the flow of blood through blood vessels by rebounding high-frequency from circulating red blood cells. This test enables doctors to determine the chances of fertility in human females as well as the health of the patients affected by blood cancer. The Color Doppler ultrasound produces Color Doppler scans of organs which are further examined by doctors to make critical predictions. To increase the accuracy of these predictions with the aid of technological advancements, we proposed building a deep learning model which would be trained to tailor accurate predictions and avoid human miscalculations through manual analysis. This paper proposes a framework for image quality assessment of Color Doppler images using the Blind/referenceless image spatial quality evaluator (BRISQUE). This framework determines whether a Color Doppler scan of an organ is suitable for object detection. It is through object detection that the organ or a part of the organ is observed and then the further analysis is performed in order to predict results. We first exploited Python libraries and functions to preprocess the image and then calculated parameters such as local mean, local deviation, mean-subtracted contrast-normalized coefficients and pairwise product of these coefficients. Following this, we calculated the BRISQUE features based on the values obtained and implemented the method on the actual Color Doppler image. After evaluating the results of this approach, we then used deep learning to detect the intended organ part using one of the latest object detection algorithms, You Only Look Once (YOLO) and it was further used for predicting a score crucial for determining the state of the patient and suggesting the best course of action for the upcoming treatment of the patient. The proposed idea intends to benefit the healthcare sphere by predicting most accurate results.

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I. Introduction

Advancements in the medical field with the aid of computer technology have paved the way for the visual depiction of the visceral organs through copious diagnostic imaging procedures.

The availability of these images and the capabilities of computational techniques have created a wide scope in the field of diagnosis using deep learning algorithms. Analysis of images and their quality is very important in the domain of deep learning and its applications in the real world, especially the healthcare field. Most medical scans of the human body generated involve heavy post-processing of the images, which lead to the introduction of various distortions, sometimes visible even to the human eye. The proposed paper elaborates about the implementation of one of the image quality assessment methods on an existent medical scan received from actual medical professionals.

While the conventional full reference image quality assessment techniques take into consideration the undistorted version of the image in order to be compared with the distorted versions of the image, BRISQUE deals with only the distorted version of the image, thus named as Blind/Referenceless Image Spatial Quality Evaluator. With no original image present in this method, the quality metrics are developed based solely on the distorted image. This paper proposes the novel blind/referenceless image spatial quality evaluator which extracts the descriptive features i.e. the natural scene statistics are extracted. Following this, these extracted features are combined together to generate a quality-conscious feature vector. Finally, a model maps the combined data into a numerical value that constitutes the quality score of the image under test, known as the image quality score, the value of which ranges from 0 (very good quality) to 100 (very bad quality). The conversion to another coordinate form like wavelet and DCT is not required in this method. Apart from this, the discussed method is not involved in the computation of distortion-specific features such as ringing, blocking and blurring. The open source Computer Vision library of Python, OpenCV, facilitates the implementation of the BRISQUE algorithm.

The presented histograms and mathematical equations are helpful in the demonstrative capabilities of the proposed idea.

II. Previous Work

Image Quality Assessment plays a vital role in assessing any new hardware, software, image acquisition techniques, image reconstruction, or post-processing algorithms. The quality of doppler color images is a key information in medical-related applications. A Doppler ultrasound is a type of imaging test that employs sound waves to show the movement of blood through blood arteries.. Finding the image quality is an important preprocessing step. For color doppler images, we are using the BRISQUE method to assess the image quality. Because of its low computing complexity, it is particularly suited for real-time applications. BRISQUE characteristics can also be utilized to identify distortions.

No reference image quality assessment does not require a base image to evaluate the image quality. The first step involved in no reference image quality assessment is to describe the structure of the image and the next step finds patterns among the features. The BRISQUE model is shown to be highly efficient because it uses image pixels to calculate features. It relies on the spatial Natural Scene Statistics (NSS) model of locally normalized luminance coefficients in the spatial domain and the model for pairwise products of these coefficients.

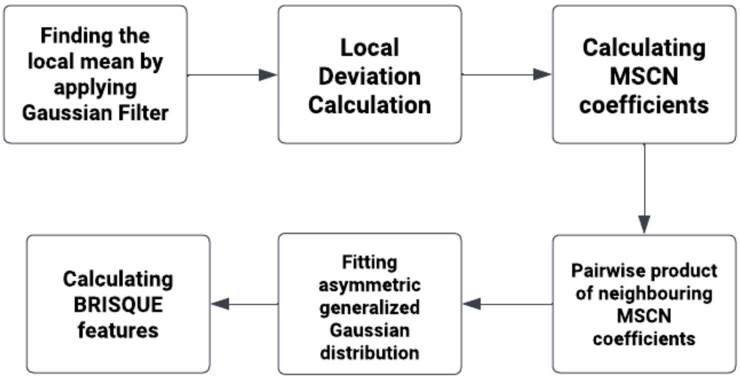


Figure 2.1 Block diagram

First, we find the locally normalized luminescence via local mean subtraction and divide it by the local deviation. A constant is added to avoid zero divisions. The local mean must be calculated before we can compute the mean subtracted contrast normalized (MSCN) coefficients.

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C} \qquad (1)$$

The local deviation is calculated by

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} I_{k,l}(i,j)$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} (I_{k,l}(i,j) - \mu(i,j))^2} \qquad (2)$$

where, $i \in 1, 2 \ldots M$, $j \in 1, 2 \ldots N$ are spatial indices, M, N are the image height and width respectively.

C = 1 is a constant that prevents instabilities from occurring when the denominator tends to zero. MSCN coefficients have distinct statistical properties that are affected by the presence of distortion.By measuring these changes, it will be feasible to forecast the type of distortion impacting an image as well as its perceptual quality. Figure (2.2) depicts a histogram of MSCN coefficients for a natural undistorted image and several distorted duplicates of it to demonstrate how MSCN coefficient distributions fluctuate as a function of distortion. For a broader spectrum of the deformed image, the MSCN coefficients are distributed as a Generalized Gaussian Distribution (GGD). The density function of the GGD is

$$f(x; \alpha, \sigma^2) = \frac{\alpha}{2\beta\Gamma(1/\alpha)} \exp\left(-\left(\frac{|x|}{\beta}\right)^{\alpha}\right) \qquad (3)$$

where,

$$\beta = \sigma\sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}} \quad (4)$$

and Γ is the gamma function. The parameter α controls the form and σ^2 the variance. The signs of adjacent coefficients also have a regular pattern that is disrupted by distortion. Pairwise products of neighboring MSCN coefficients along four directions (1) horizontal *H*, (2) vertical *V*, (3) main-diagonal *D1* and (4) secondary-diagonal *D2* are considered.

$$\begin{aligned} H(i,j) &= \hat{I}(i,j)\hat{I}(i,j+1) \\ V(i,j) &= \hat{I}(i,j)\hat{I}(i+1,j) \\ D1(i,j) &= \hat{I}(i,j)\hat{I}(i+1,j+1) \\ D2(i,j) &= \hat{I}(i,j)\hat{I}(i+1,j-1) \end{aligned}$$

GGD does not fit the empirical histograms of coefficient products well. Therefore rather than fitting it to GGD, the model is fitted to Asymmetric Generalized Gaussian Distribution. Its density function is given as,

$$f(x;\nu,\sigma_l^2,\sigma_r^2) = \begin{cases} \frac{\nu}{(\beta_l+\beta_r)\Gamma\left(\frac{1}{\nu}\right)} \exp\left(-\left(\frac{-x}{\beta_l}\right)^{\nu}\right) & x < 0 \\ \frac{\nu}{(\beta_l+\beta_r)\Gamma\left(\frac{1}{\nu}\right)} \exp\left(-\left(\frac{x}{\beta_r}\right)^{\nu}\right) & x \geq 0 \end{cases}$$

After fitting the Asymmetric Generalized Gaussian Distribution, we calculate the BRISQUE features. The summary of features extracted in order to quantify distortions is as follows:

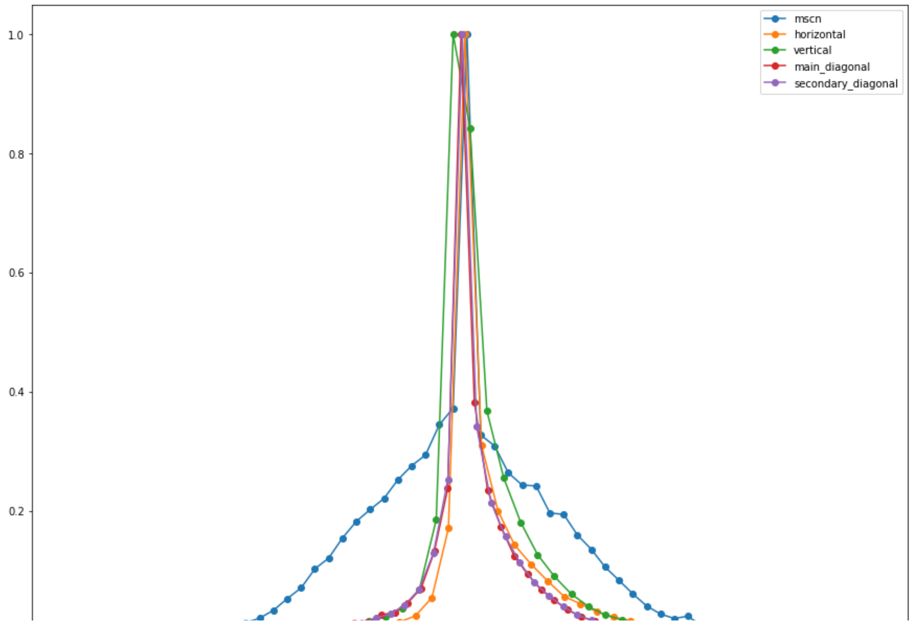
Feature ID	Feature Description	Computation Procedure
$f_1 - f_2$	Shape and variance	Fit GGD [32] to MSCN coefficients
$f_3 - f_6$	Shape, mean, left variance, right variance	Fit AGGD [35] to H pairwise products
$f_7 - f_{10}$	Shape, mean, left variance, right variance	Fit AGGD [35] to V pairwise products
$f_{11} - f_{14}$	Shape, mean, left variance, right variance	Fit AGGD [35] to $D1$ pairwise products
$f_{15} - f_{18}$	Shape, mean, left variance, right variance	Fit AGGD [35] to $D2$ pairwise products

III. Methodology

On the basis of the above mentioned mathematical concepts, we found the parameters required for the interpretation of the result. They served as a foundation for calculating the quality score of the distorted image having no reference image.

The local mean was extracted from the image. Based on our hypothesis, the local mean plays a vital role in calculating the locally normalized luminescence. This was enabled by using the Gaussian filter which incorporates a Gaussian kernel and applied it on the image. We created a function to calculate the local deviation from the mean. The extent of the deviation was useful in determining the perceptual quality of the image and confirming it against the same done subjectively by human observations. The MSCN features proved to be crucial as they have certain statistical parameters that have a tendency to fluctuate in the presence of distortion. As a result, quantifying these features facilitated in predicting the perceptual quality of the image. It was inferred that the distribution is normal for undistorted images whereas distortions in the image affect the distribution of the coefficients.

The signs of adjacent coefficients were observed to display a normal structure. But this structure was getting disturbed in the presence of distortion. We proposed the model of pairwise products of neighboring MSCN coefficients along four directions (a) horizontal, (b) vertical , (c) main_diagonal and (d) secondary_diagonal.Coefficients were fitted to Asymmetric Generalized Gaussian Distribution (AGGD) initially. The histogram for it generated was as follows:



By analyzing the graph, it was observed that the distribution for AGGD was different. Hence, we further fitted the MSCN features to Generalized Gaussian distribution (GGD). The features required to interpret the image quality are the result of fitting the MSCN coefficients and shifted products to the Generalized Gaussian Distributions. After this, implementation on the actual image was performed, by converting it from RGB to grayscale image. The image was downsized ensuring that the visual appearance of the image is preserved after it was resized. The BRISQUE features of the downsized image were calculated.

After scaling these features, they were feeded to a Support Vector Regression (SVR) model. We chose this model because it is a supervised learning algorithm which provides discrete values by finding the best fit line. In addition to this, SVR handles outliers in a much optimized way than the normal linear regression algorithm. This approach proved to be the most favorable one for the calculation of the image quality score. Finally, the image quality score was displayed, which was found to fall between the range 0 and 100, with 0 being excellent quality and 1 being very poor quality.

IV. Results

We created a function to calculate the image quality score. Here the scaled brisque features were taken into consideration. The scaling of data was performed in the range [-1,1] to obtain better results. The LIBSVM software was utilized for support vector regression. The kernel type employed here is ‘precomputed’, that applies the kernel function and includes the kernel distances between training and testing instances. The nr classifier is appointed the value 1.

The probability estimates is calculated and the prediction probability is then interpreted as a function of the probability estimates. Ultimately, the image quality score of the Color Doppler image was displayed. The score obtained was useful in interpreting the overall quality of the image in regards with noise, distortion and naturalness of the image.

```
calculate_image_quality_score(brisque_features)
```

```
CPU times: user 9.34 ms, sys: 0 ns, total: 9.34 ms
Wall time: 9.49 ms
33.93001220924472
```

The score predicted was around 34. As the image was a Color Doppler image, the predicted value represents moderate perceptual quality with respect to the original, unconsidered image. Few image processing steps following the image quality assessment were performed and the image proved to be suitable for further use in the application.

V. Conclusion

In the realm of deep learning and its implementations in the real world, particularly in the healthcare industry, the analysis of images and their quality is vital. This study helps to assess if a Color Doppler image can be used to detect objects. It is easier to perform object detection on high-quality images. It is thus important to perform an image quality assessment of Color Doppler images before implementing object detection. Color Doppler images having a high brisque score can be utilized for detection algorithms that reveal crucial clinical cues by demonstrating the presence or absence of blood flow, which can then be used to address a variety of industry-related problems. Since the Color Doppler images are used by professionals for diagnostic purposes, Brisque can be used to evaluate image quality which can increase the effectiveness of the application.

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