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Improving Image Quality Using Gradient Magnitude Similarity Deviation

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Abstract: **The project Assessment of Image Quality Using its Similarities and Deviation in Gradient Metrics is mainly done in order to increase the image quality and also to decrease the resulting time of the processed image for multiple images as input. To evaluate the perceptual quality of the single best output image in many applications such as image restoration, image compression and multimedia streaming. A image quality assessment (IQA) model with computationally efficient and also deliver high quality prediction accuracy. In case processing with images and in other fields the process of working on quality plays of image hits the major role. Likewise major project were based on improving image quality by comparing the spoof images and reference images. In case of existing system there were four techniques like GMSD, PNSR, SSIM and MSE that were used to increase the image quality and resulting time. Yet, the image that is obtained is still not clear due to the use of top-down framework. Hence in order to improvise the existing system, we have created a proposed design to find the best image among multiple images, includes another four techniques like MAMS, SME, SPE, RRED that are used to improve the image quality. The pixel wise similarity between gradient magnitude maps of reference and distorted image is computed .These methods are also helpful in improving the calculating time of the models. These methods are used with high performance IQA applications and with perfect GMSD model.**

Keywords: **GMSD, PNSR, SSIM and MSE, image quality assessment (IQA).**

I. INTRODUCTION

The image gradient metrics technique is implemented for FR-IQA methods in various simulation. Mostly, the gradient based FR-IQA methods undergoes the similarity function with dual images which is similar to that in SSIM technique to compute gradient similarity.

In SSIM technique, four types of similarity methods are computed: Luminance Similarity (LS), Contrast Similarity (CS), Structural Dissimilarity (SD) and Structural Similarity (SS). The Process in measuring of image quality hits a major role in different image processing tasks, such as restoration, transmission,ploting axis compression, enhancemet,etc.Therefore, it is in the place of highly importance with quantify the visual impact of the distortions in these processing in order to computate the performance of every algorithms. However, the process of image quality assessment is consider as an open problem and occupies a peak place in the area of research active.

In general, commercial services such as image compression/ transmission system, quality of images are measured by using simple quantitative metrics such as the peak signal-to-noise ratio (PSNR) and the mean squared error (MSE). Especially, subjective quality metric was used instead of the PSNR and MSE for rate-distortion control in video compression technique .PSNR and MSE are used as metrics of errors in images or distances between images. However, these two methods do not faithfully reflect the human visual perception. By using the PSNR method, performance improvement in video compression is obtained. Therefore, development of human visual perception reflecting quality metrics is of very much importance and has been researched. The structural similarity (SSIM), a modified version of the UQI, was also developed. The Universal Quality Index (UQI) was presented as an image quality metric (IQM) using the structural information of an image.

However, in case of badly blurred image, the SSIM gives poor performance of the image quality evaluation. To reduce the degradation of performance, new methods have been developed. Edge-based SSIM is mainly based on the edge information as the most important image structure information.

Currently, image quality metrics can be classified into three categories (full reference, reduced reference and no reference) depending on the amount of information about the original image required. The main focus is on full reference image quality assessment. IQA means the complete original image is to be known at the receiver side. The most common image quality assessment (IQA) is peak signal-to-noise ratio (PSNR).This method is widely used because of its simplicity in calculation, it also contains the clear physical meanings, and for optimization purpose it is easy to deal mathematically.

In practice, digital images are subjected to a wide variety of distortions during the process of acquisition, processing, compression, storage, transmission and reproduction. These distortions may result in a degradation of visual quality. The subjective evaluation is the only correct method for applications in which images are ultimately to be viewed by human beings. The main drawback is subjective evaluation is usually too inconvenient, time consuming and expensive. The development of quantitative measures that can automatically predict perceived image quality is the main goal of research in objective image quality assessment.

II. RELATED WORK

On considering the existing system, process of measuring the visual quality is of prime importance for numerous image and video processing applications. Whereas, automatic assess the quality of images or videos in agreement with human quality judgments is the important goal of quality assessment (QA). Over the years, many researchers have taken plenty of approaches to the problem in image processing and have done significant research in this area. They have also claimed to have made progress in their respective domains. It is important to evaluate these algorithms performance in a comparative setting and analyze the strengths and weaknesses of these methods.

The quality of video for off line video coding were also in consideration. The proposal to use video quality metric (VQM) with an evolution strategy algorithm, which is capable of selecting the best possible quantization parameters for each and every frame to encode the video sequence such that it would maximize the subjective quality of the entire video sequence subjected to the target bit rate. With the proposed technique, up to 35% bit rate reduction can be achieved at the same video quality. Simulation results suggest that the proposed technique can improve the RD performance of the H.264/AVC codec significantly.

On referring other existing systems, for the process of objective image quality assessment conventional mean squared error based methods are not well correlated with human evaluation. The design of better quality objective measures has earned a lot of attention and several image quality metrics based explicitly on the properties of the Human Visual System HVS have been proposed in recent years. In accounting for visual masking, all these metrics assume that the multiple visual perception mediating channels are independent of each other. However, only in a few cases the performance of such metrics been demonstrated on real images Recent neuroscience and psychophysical experiments have established that there is the presence of interaction across the channels and those interactions are important for visual masking.

III. SYSTEM DESCRIPTION

In our proposed system, we have overcome the drawbacks of existing with help of gradient magnitude similarity deviation method. In this GMSD, with the presence of new effective and efficient IQA model we aim to increase the proliferation of high-volume visual data in high-speed networks. This paper focuses on FR-IQA models, which are widely used for measuring the quality of the output images in order to evaluate image processing algorithms. A good FR-IQA model can shape many image processing algorithms along their implementations and optimization procedures. The FR-IQA was widely used to evaluate image processing algorithms by measuring their output quality. We devised a simple FR-IQA model called gradient magnitude similarity deviation (GMSD), where the pixel-wise gradient magnitude similarity (GMS) is used to capture image local quality. The standard deviation of the overall GMS map is computed as the final image quality index. As the result, the proposed GMSD model performs better in terms of both accuracy and efficiency with high performance IQA applications.

DMOS Image with Similarity Observes:

The DMOS of a given image clearly gives the explanation for the similarity or quality of that image as judged by a group of human observers. The DMOS measure will be better if the correlation between the DMOSs and the scores of a given similarity measures is higher. By taking the Mean Opinion Score (MOS) of a test image and subtracting it from the MOS of the original, undistorted image the DMOS is computed.

Gradient Magnitude Similarity Deviation:

In SSIM, average pooling is used in G-SSIM to yield the final quality score. The proposal of geometric structure distortion (GSD) metric to predict image quality, that computes the presence of similarity between the gradient magnitude maps, the gradient orientation maps and contrasts of **r** and **d**. Average pooling is also used in the method of GSD.

The prediction of the image quality using a weighted summation (i.e., a weighted pooling strategy is used) of the squared luminance difference and the gradient similarity combines the similarities of phase congruency maps and gradient magnitude maps between **r** and **d**. A phase congruency based weighted pooling method is used to produce the final quality score in result.

GMSD image:

The resulting Feature Similarity (FSIM) model is among the leading FR-IQA models in term of accuracy in prediction. However, sits very costlier in the process of the computation of phase congruency feature.

Pooling with Standard Deviation:

The LQM explains about the local quality of each small patch in the distorted image. The pooling stage via LQM gives the image overall quality score estimation. The most commonly used pooling strategy is average pooling, i.e., averaging the LQM values as the final IQA score. Reference of IQA model by applying average pooling to the GMS map as Gradient Magnitude Similarity Mean (GMSM):

(b)

This is a new pooling strategy with the GMS map. The natural image generally has a variety of local structures in its scene. Due to the image distortion the different local structures will suffer different degradations in gradient magnitude. This is an inherent property of natural images. For example, the distortions introduced by JPEG2000 compression include blocking, ringing, blurring, etc. Blurring will create less quality degradation in flat areas than in textured areas. Blocking will cause higher quality degradation in flat areas than in textured areas.

CSIQ database:

The reference images from the CSIQ database, their distorted images and the corresponding GMS maps are taken into consideration. The first image Fishingis corrupted by additive white noise, and the second image Floweris affected due to Gaussian noise. From the GMS map of distorted image *Flower*, we can understand that the local quality in the center area is much worse than at other areas. From the GMS map of distorted image Fishing we can find that its local quality is more homogenous.

Image Quality Compared With Similarity:

The human subjective DMOS scores of the two distorted images are 0.4403 and 0.7785, respectively, indicating that the quality of the first image is obviously better than the second one. (Note that like GMSD, DMOS also measures distortion; the lower it is, the better the image quality.) By using GMSM, however, the predicted quality scores of the two images are 0.8853 and 0.8745, respectively, indicating that the perceptual quality of the first image is similar to the second one, which is inconsistent with the subjective DMOS scores.

Quality Score with Images:

By using GMSD method, the predicted quality scores of the two images are 0.1421 and 0.1926, respectively, which is a consistent judgment relative to the subjective DMOS scores, i.e., the first distorted image has good quality than the second one.

Performance Comparison:

We have compared the competing IQA models performance under three IQA databases in terms of SRC,PCC and RMSE. The top three models for each evaluation criterion are given in boldface. We can also observe that the top models are mostly GMSD (9 times), FSIM (7 times), IW-SSIM (6 times) and VIF (5 times). On considering all the three criteria (SRC, PCC and RMSE), the proposed GMSD outperforms all the other models on the TID2008 and CSIQ databases. In case of the LIVE database, VIF, FSIM and GMSD perform almost the same.

On Comparing with the gradient based models such as GSD, G-SSIM and GS, GMSD performs well by a large margin. Comparing with GMSM, the superiority of GMSD is obvious, demonstrating that the proposed deviation pooling strategy outperforms than the average pooling strategy on the GMS induced LQM. The FSIM algorithm also employs gradient similarity method. It has similar results to GMSD on the LIVE and TID2008 databases. It also lags GMSD on the CSIQ database with a lower SRC/PCC and larger RMSE.

Six Types of Distortions in Gradient Image:

When the distortion is severe (i.e., large DMOS values), GS, GMSM and PSNR has the less accuracy in prediction process. The information fidelity based VIF performs very well on the LIVE database. But it doesn't works very well on the CSIQ and TID2008 databases.

This is mainly because VIF does not predict the image quality consistently across different distortion types on these two database. In-order to make statistically meaningful conclusions this can be observed from the scatter plots on the models performance. We further conducted a series of hypothesis tests based on the prediction residuals of each model after nonlinear regression.

The results of significance tests is by assuming that the model's prediction residuals follow the Gaussian distribution (the Jarque-Bera test shows that only 3 models on LIVE and 4 models on CSIQ violate this assumption).The first model has better IQA performance than the second model with a confidence greater than 96%. A value of H=0 means that the first model is not significantly better than the second one. We apply the left-tailed F-test to the residuals of every two models to be compared.

Performance Comparison on Individual Distortion Types:

We compare the performance of competing methods on each type of distortion to more comprehensively evaluate an IQA model's ability to predict image quality degradations caused by specific types of distortions. A good IQA model should also predict the image quality consistently across different types of distortions. On speaking generally , performing well on specific types of distortions does not guarantee that an IQA model will perform well on the whole database with a broad spectrum of distortion types.

For example, it points corresponding to JPEG2000 and PGN distortions are very close to each other. However, the points corresponding to JPEG2000 and PGN for VIF are relatively far from each other. This explains why some IQA models perform well for many individual types of distortions but they do not perform well on the entire databases .We can have similar observations for GS on the distortion types of PGN and CTD. That is, these IQA models behave rather differently on many types of distortions, which can be offered to the different ranges of quality scores for those distortion types.

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Standard Deviation Pooling on Other IQA models

The method of standard deviation (SD) pooling applied to the GMS map leads to significantly elevated performance of image quality prediction. To explore this, we modified six representative FR-IQA methods, in which all are able to generate an LQM of the test image: MSE (which is equivalent to PSNR but can produce an LQM), SSIM, MS-SSIM, FSIM G-SSIM and GSD. It is therefore considered as the natural to wonder whether the SD pooling strategy can deliver similar performance improvement on source codes of all the other models were obtained from the original authors except for G-SSIM and GSD, which are implemented by us.

To more clearly demonstrate the effectiveness of the proposed deviation pooling strategy, we also present the results of GMSM that uses average source codes of all the other models were obtained from the original authors except for G-SSIM and GSD, which are implemented by us. To more clearly demonstrate the effectiveness of the proposed deviation pooling strategy, we also present the results of GMSM that uses average other IQA models.

The original pooling strategies of these methods are either average pooling or weighted pooling. To yield the predicted score in their LQMs for MSE, SSIM, G-SSIM, GSD and FSIM, we directly applied the SD pooling. For MS-SSIM, we applied SD pooling to its LQM on each scale, and then computation process of the product of the predicted scores on all scales as the final score. The SRC results of these methods by using their nominal pooling strategies and the SD pooling strategy are listed finally.

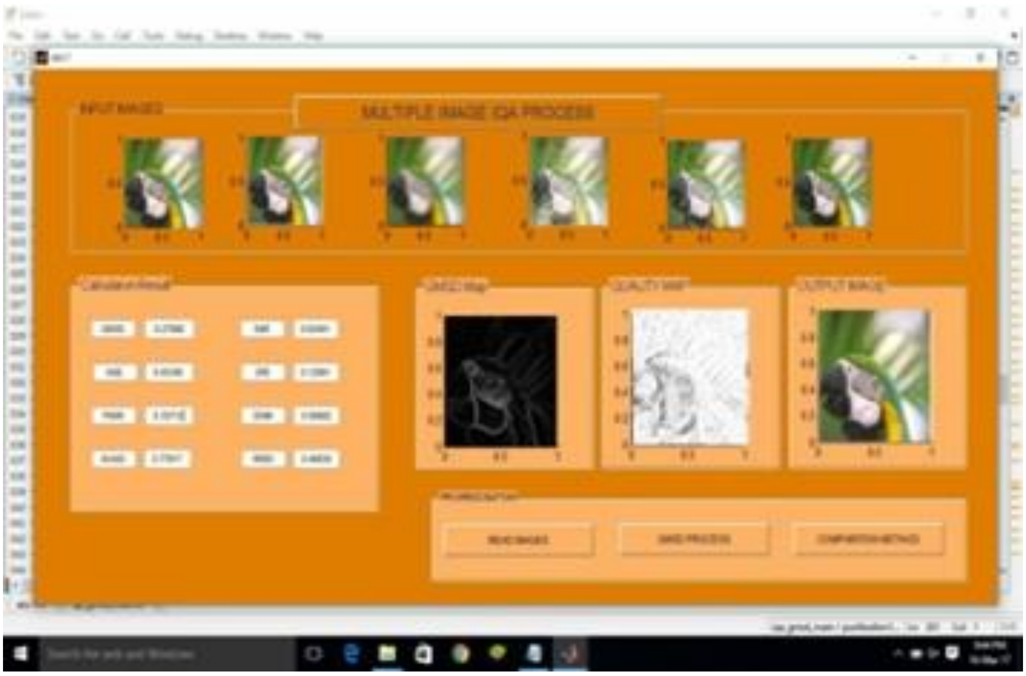
IV. RESULT AND ANALYSIS

The IQA models performance is typically evaluated from three aspects regarding its prediction power. They are prediction *accuracy*, prediction *monotonicity*, and prediction *consistency*. The regression procedure is required for the computation of these indices to reduce the nonlinearity of predicted scores. We denote by Q, $Q\ p$ and S the vectors of the original IQA scores. The logistic regression function is employed for the nonlinear regression

To demonstrate and explain the performance of GMSD, we compare it with 11 state-of-the-art and representative FR-IQA models, including PSNR, IFC, VIF, SSIM, MS-SSIM, MAD, FSIM, IW-SSIM, G-SSIM, GSD and GS. On considering all the FSIM, G-SSIM, GSD and GS explicitly exploit gradient information.The pooling. As in most of the previous literature, all of the competing type of algorithms are applied to the luminance channel of the test images.

Result Obtained in Proposed Work

Result Obtained in Proposed Work:



V. CONCLUSION

The usefulness and effectiveness of image gradient comparison between the reference and spoof image were studied in this paper. An important IQA model called gradient magnitude similarity deviation (GMSD) is used where the pixel-wise gradient magnitude similarity (GMS) is used to capture image local quality. The standard deviation of the overall GMS map is computed as the final image quality index. The different IQA techniques were used to compare the image gradients and the information in the spoof images are obtained by gathering the details from the reference image. Both in terms of accuracy and efficiency the proposed GMSD model performs well. GMSD method became an ideal choice for high performance IQA applications.

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