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Research Article

An Algorithmic Approach for Multispectral Image Quality Assessment

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Abstract

A multispectral image is one that captures image data at specific frequencies across the electromagnetic spectrum. The wavelengths may be separated by filters or by the use of instruments that are sensitive to particular wavelengths, including light from frequencies beyond the visible light range, such as infrared. Spectral imaging can allow extraction of additional information the human eye fails to capture with its receptors for red, green and blue. The terms image quality and image fidelity is used synonymously i.e. how close an image is to a given original or reference image. Image Quality Assessment (IQA) plays a fundamental role in the design and evaluation of imaging and image processing systems. Quality Assessment (QA) algorithms can be used to systematically evaluate the performance of different image compression algorithms that attempt to minimize the number of bits required to store an image, while maintaining sufficiently high image quality. An algorithmic approach to find the quality of images can be achieved through the techniques such as metrics calculations and models. The results predict how good the quality of the image is and hence can be used for imaging systems.

Keywords: *Multispectral image, MSE, PSNR, Luminance masking, Error pooling, SSIM, Quality, VDP, IFC*

1. Introduction

[1]Recent advances in digital imaging technology, computational speed, storage capacity, and networking have resulted in the proliferation of digital images, both still and video. As the digital images are captured, stored, transmitted, and displayed in different devices, there is a need to maintain image quality. The end user of these images, in an overwhelmingly large number of applications, is human observers. The terms image quality and image fidelity are used synonymously, i.e. how close an image is to a given original or reference image.

Image Quality Assessment (IQA) plays a fundamental role in the design and evaluation of imaging and image processing systems. Quality Assessment (QA) algorithms can be used to systematically evaluate the performance of different image compression algorithms that attempt to minimize the number of bits required to store an image, while maintaining sufficiently high image quality. Subjective evaluations are accepted to be the most effective and reliable, albeit quite cumbersome and expensive, way to assess image quality. Objective IQA measures aim to predict perceived image/video quality by human subjects, which are the ultimate receivers in most image processing applications. Usually one of the images is the reference which is considered to be original, perfect, or uncorrupted. The second image has been modified or distorted in some sense. The output of the QA algorithm is often a number that represents the probability that a human eye can detect a difference in the two images or a number that quantifies the perceptual dissimilarity between the two images.

2. Literature review

A new fusion image quality assessment method according with human vision system and quaternion was introduced in this paper. After encoded RGB channels into three imaginary parts of quaternion's, the matrix of pure quaternion, which with null real part for every element, can describe color image transactions as some kind of transformations, so that the entire color information of image was preserved. Treating multispectral image to be fused as reference image, fusion image as image to be assessed, both of two images were executed by singular value decomposition. Then fusion image quality assessment having referenced information was realized via distance and angle between the two singular vectors. The tests results show that the method mentioned in this paper have the consistency of objectivity and subjectivity, and can not only verity human visual system, and the definition and spectrum retain-ability capability of fusion image can be evaluate also.

This paper focuses on quality assessment of fusion of multispectral (MS) images with high-resolution panchromatic (Pan) images. Since most existing quality

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assessments take the entire image into account simultaneously and generate some uncertainties, a novel and rather objective quality index has been proposed for image fusion. The index is comprised of geometric and radiometric parts. Both geometric and radiometric measurements are calculated using morphological algorithm applied on an edge image to create a mask which is used to separate high frequency regions from low frequency ones.

In this paper, a method is proposed to assess the fusion quality at high resolution by making use of modulation transfer function filters in the frame works of Wald's spectral consistency protocol and Zhou's spatial quality protocol. The results are compared with the recently proposed QNR quality index which also does not require a reference high resolution multispectral image, Zhou's protocol, Q4, ERGAS and SAM.

The fusion of panchromatic and multispectral satellite images is an important issue in many remote sensing applications, especially in urban area . The popular image fusion methods in remote sensing community usually distort the spectral characteristics. To reduce the spectral distortion, some image fusion techniques have been developed. This paper addresses the issue in quality assessment of fused images from three recently developed methods. These are synthetic variable ratio (SVR), smoothing filter-based intensity modulation (SFIM) and Gram_Schimdt transform (GS).

This letter presents a novel image quality index which extends the Universal Image Quality Index for monochrome images to multispectral and hyperspectral images through hypercomplex numbers. The proposed index is based on the computation of the hypercomplex correlation coefficient between the reference and tested images, which jointly measures spectral and spatial distortions. Experimental results, both from true and simulated images, are presented on spaceborne and airborne visible/ infrared images. The results prove accurate measurements of inter and intraband distortions even when anomalous pixel values are concentrated on few bands.

A crucial step in image compression is the evaluation of its performance, and more precisely the available way to measure the final quality of the compressed image. Usually, to measure performance, some measure of the covariation between the subjective ratings and the degree of compression is performed between rated image quality and algorithm. Nevertheless, local variations are not well taken into account[7]. The author uses the recently introduced Maximum Likelihood Difference Scaling (MLDS) method to quantify suprathreshold perceptual differences between pairs of images and examine how perceived image quality estimated through MLDS changes the compression rate is increased. This approach circumvents the limitations inherent to subjective rating methods.

This chapter introduces the basic ideas and algorithms of structural approaches for image quality assessment. We describe the concepts, the structural similarity index algorithm, as well as the image synthesis-based performance evaluation algorithm in the image space. The paper demonstrates that image distortions along different directions in the image space have different perceptual meanings. The structural approaches attempt to separate the directions associated with structural distortions from those with non-structured distortions. This separation gives a new coordinate system in the image space, which is not fixed as in traditional image decomposition frameworks (e.g., Fourier and wavelet types of transforms), but adapted to the underlying image structures.

Objective methods for assessing perceptual image quality have traditionally attempted to quantify the visibility of errors between a distorted image and a reference image using a variety of known properties of the human visual system . Under the assumption that human visual perception is highly adapted for extracting structural information from a scene, an alternative framework for quality assessment based on the degradation of structural information is introduced. As a specific example of this concept, a Structural Similarity Index and demonstrate its promise through a set of intuitive examples is developed, as well as comparison to both subjective ratings and state-of-the-art objective methods on a database of images compressed with JPEG and JPEG2000.

Even with modern graphics hardware, it is still not possible to achieve high fidelity renderings of complex scenes in real time. However, as these images are produced for human observers we may exploit the fact that the human eye is good, but not that good. In particular, it may be possible to render parts of an image at high quality and the rest of the scene at lower quality without the user being aware of this difference. Image quality assessment algorithms, such as the Daly model, provide a measure of the perceptual quality difference between image pairs. This paper presents a psychophysical evaluation of an image quality metric and investigates how such models can be developed to rapidly determine the parts of the scene with the most noticeable perceptual difference.

In this paper, to target the fore mentioned problems in IQA, a novel framework for IQA to mimic the human visual system (HVS) by incorporating the merits from multiscale geometric analysis (MGA), contrast sensitivity function (CSF), and the Weber's law of just noticeable difference (JND) is developed. In the proposed framework, MGA is utilized to decompose images and then extract features to mimic the multichannel structure of HVS. Additionally, MGA offers a series of transforms including wavelet, curvelet, bandelet, contourlet, wavelet-based contourlet transform (WBCT), and hybrid wavelets and directional filter banks (HWD), and different transforms capture different types of image geometric information.

Perceptual image distortion measures can play a fundamental role in evaluating and optimizing imaging systems and image processing algorithms . Many existing measures are formulated to represent just noticeable differences (JNDs), as measured in psychophysical experiments on human subjects. But some image distortions, such as those arising from small changes in the intensity of the ambient illumination, are far more tolerable to human observers than those that disrupt the spatial structure of intensities and colors. Here, a framework in which the author quantify these perceptual distortions in terms of just intolerable differences (JIDs) is introduced.

There has been an increasing number of tone mapping algorithms developed in recent years that can convert high dynamic range (HDR) to low dynamic range (LDR) images, so that they can be visualized on standard displays. Nevertheless, good quality evaluation criteria of tone mapped images are still lacking, without which, different tone mapping algorithms cannot be compared and there is no meaningful direction for improvement. Although subjective assessment methods provide useful references, they are expensive and time-consuming, and are difficult to be embedded into optimization frameworks. In this paper, the author proposes a novel objective assessment method that combines a multiscale signal_delity measure inspired by the structural similarity (SSIM) index and a naturalness measure based on statistics on the brightness of natural images. Validations using available subjective data show good correlations between the proposed measure and subjective rankings of LDR images created by existing tone mapping operators.

Reduced-reference image quality assessment (RR-IQA) provides a practical solution for automatic image quality evaluations in various applications where only partial information about the original reference image is accessible. In this paper , the author proposes an RR-IQA method by estimating the structural similarity index (SSIM), which is a widely used full-reference (FR) image quality measure shown to be a good indicator of perceptual image quality. Specifically, the statistical features from a multiscale, multiorientation divisive normalization transform are extracted and develop a distortion measure by following the philosophy in the construction of SSIM. There is an interesting linear relationship between the FR SSIM measure and RR estimate when the image distortion type is fixed. A regression-by-discretization method is then applied to normalize our measure across image distortion types.

3. Techniques

Noises

The process of assessing the quality of the multispectral images requires the gathering of information regarding the metrics and also the noises affecting the quality.

- Additive White Gaussian Noise (AWGN)
- Salt And Pepper Noise
- Speckle Noise
- Poisson Noise

Metrics

- Peak Signal-To-Noise Ratio (PSNR)
- Mean Square Error (MSE)
- Root Mean Square Error (RMSE)
- Luminance Masking
- Entropy
- Error pooling

Models

- Visual Description Predictor (VDP) model
- Teo and Heeger model
- Watsons DC Tune model
- Safrenek Johnston Perceptual Image Decoder (PIC) model
- Visual Signal to Noise Ratio (VSNR)
- Sarnoff JND Vision model
- Structural Similarity (SSIM)
- Information Fidelity Criterion
- Visual Information Fidelity Criterion

4. Metrics

Mean squared error (MSE)

Let f (n) and g (n) represent the value (intensity) of an image pixel at location n. usually the image pixels are arranged in a Cartesian grid and n = (n1, n2).

MSE is the amount of error present in the image and which is calculated for each row with all elements. And later the mean is calculated and this MSE is accounted for PSNR as the inverse of it, applying log to make in terms of dB. The MSE is defined as:

$$MSE\,[f(n), g(n)] = 1/N \sum [f(n)-g(n)]^2$$

Where N is the total number of pixel locations in f (n) or g (n).

Peak Signal to Noise Ratio (PSNR)

The PSNR is defined as:

$$PSNR\,[f(n), g(n)] = 10 \log_{10} E^2 / MSE\,[f(n), g(n)]^2$$

Where E is the maximum value that a pixel can take. For ex: E=255 for an 8-bit grayscale images.

Root Mean Square Error (RMSE)

In mathematics, the root mean square (abbreviated RMS or rms), also known as the quadratic mean, is a statistical measure of the magnitude of a varying quantity. RMSE, is the root mean square error, which is also calculated based on MSE. It is especially useful when variates are positive and negative, e.g., sinusoids. RMS is used in various fields, including electrical engineering. The RMS of the differences is a meaningful measure of the error.

Entropy

Entropy is an extensive property, but it is often given as an intensive property of specific entropy as entropy per unit mass or entropy per mole. The notions of order and disorder were introduced into the concept of entropy. Entropy is the amount of information present in the data or image. It basically interprets the complexity of the image in terms of its quality.

Luminance masking

Lumi masking (derived from luminance) is a technique which reduces quality in very bright or very dark areas of the picture, as quality loss in these areas is less likely to be visible. LMSK, this is calculated for each element with comparison of input and output, and by normalizing it w.r.t the input. It is also known as psycho visual enhancements or adaptive quantization. The reduction in quality (and therefore bit rate) in certain areas of the picture caused by using lumi masking allows more bits to be allocated, thus improving overall quality. Lumi masking is not perfect, however, and in some cases the degradation in quality it causes is visible.

Error Pooling

Error pooling or pooled variance is a method for estimating variance given several different samples taken in different circumstances where the mean may vary between samples but the true variance (equivalently, precision) is assumed to remain the same. If the normalization is done w.r.t mean of the row elements, then accounts for the Error pooling.

5. Noises

Gaussian Noise

Additive White Gaussian Noise (AWGN) is a channel model in which the only impairment to communication is a linear addition of wideband or white noise with a constant spectral density and a Gaussian distribution of amplitude. The model does not account for fading, frequency, selectivity, interference, non linearity or dispersion. However, it produces simple and tractable mathematical models which are useful for gaining insight into the underlying behavior of a system. The AWGN channel is a good model for many satellite and deep space communication links. It is not a good model for most terrestrial links because of multipath, terrain blocking, interference, etc.

Salt and Pepper Noise

Salt and pepper noise is a form of noise typically seen on images. It represents itself as randomly occurring white and black pixels (ON and OFF pixels). An effective noise reduction method for this type of noise involves the usage of a median filter, morphological filter or a contra harmonic mean filter. Salt and pepper noise creeps into images in situations where quick transients, such as faulty switching, take place.

Speckle Noise

Speckle noise is a granular noise that inherently exists in and degrades the quality of the active radar and synthetic aperture radar (SAR) images. Speckle noise in conventional radar results from random fluctuations in the return signal from an object that is no bigger than a single image-processing element. It increases the mean grey level of a local area. Speckle noise in SAR is generally more serious, causing difficulties for image interpretation.

Poisson Noise (Shot Noise)

Shot noise is a type of electronic noise which originates from the discrete nature of electric charge. The term also applies to photon counting in optical devices, where shot noise is associated with the particle nature of light. In short, the fluctuations in signals are due to are Shot or Poisson noise.

6. Models

Human Visual System Based Models

1) Visual Description Predictor (VDP) model
2) Teo and Heeger model
3) Watsons DC Tune model
4) Safrenek Johnston Perceptual Image Decoder (PIC) model
5) Visual Signal to Noise Ratio (VSNR)
6) Sarnoff JND Vision model
7) Structural Similarity (SSIM)

Theoretic Approach Based Models

1) Information Fidelity Criterion
2) Visual Information Fidelity Criterion
3)

Visible Difference Predictor Model

The Visible Differences Predictors (VDP) is a model developed by Daly for the evaluation of high quality imaging systems. It is one of the most general and elaborates image quality metrics in the literature. It accounts for variations in sensitivity due to light level, spatial frequency (CSF), and signal content (contrast masking). Contrast sensitivity function (CSF, also called the modulation transfer function) provides a characterization of its frequency response. The contrast sensitivity function can be thought of as a band pass filter. Contrast masking refers to the reduction in visibility of one image component caused by the presence of another image component with similar spatial location and frequency content.

Teo And Heeger Model

Teo and Heeger propose a normalization model that explains baseline contrast sensitivity, contrast masking, as well as masking that occurs when the orientations of the target and the masker are different.

Watson's DC Tune Model

Watson presented a model known as DCTune that computes the visibility thresholds for the DCT coefficients, and thus provides a metric for image quality. Watson's model was developed as a means to compute the perceptually optimal image dependent quantization matrix for DCT-based image coders like JPEG. The original reference and degraded images are partitioned into 8 × 8 pixel blocks and transformed to the frequency domain using the forward DCT. The DCT decomposition is similar to the sub ban decomposition.

Safranek-Johnston Perceptual Image Coder (PIC) model

It uses a separable generalized quadrature mirror filter (GQMF) bank for sub band analysis/synthesis. The perceptual model specifies the amount of noise that can be added to each sub band of a given image so that the difference between the output image and the original is just noticeable.

Visual Signal to Noise Ratio Model

VSNR differs from other HVS based techniques in three main ways. Firstly, the computational models used in VSNR are derived based on psychophysical experiments conducted to quantify the visual detect ability of distortions in natural images. Second, VSNR attempts to quantify the perceived contrast of supra-threshold distortions and the model is not restricted to the regime of threshold of visibility (such as the Daly model). Third, VSNR attempts to capture a midlevel property of the HVS known as global precedence.

Sarnoff JND Vision Model

The Sarnoff JND vision model received a technical Emmy award in 2000 and is one of the best known QA systems based on human vision models. Pre-processing steps in this model include calibration for distance of the observer from the images. In addition, this model also accounts for fixation depth and eccentricity of the observer's visual field.

The Structural Similarity Index

The most fundamental principle underlying structural approaches to image QA is that the HVS is highly adapted to extract structural information from the visual scene, and therefore a measurement of structural similarity (or distortion) should provide a good approximation to perceptual image quality. The SSIM index measures the structural similarity between two images. If one of the images is regarded as of perfect quality, then the SSIM index can be viewed as an indication of the quality of the other image signal being compared.

The Information Fidelity Criterion

The IFC quantifies the information shared between a test and the reference image. The reference image is assumed to pass through a channel yielding the test image, and the mutual information between the reference and the test images is used for predicting visual quality.

The Visual Information Fidelity Criterion

VIF assumes that both the reference and distorted images pass through the HVS, which acts as a 'distortion channel' that imposes limits on how much information could flow through it. The purpose of HVS model in the information fidelity setup is to quantify the uncertainty that the HVS adds to the signal that flows through it. As a matter of analytical and computational simplicity, we lump all sources of HVS uncertainty into one additive noise component that serves as a distortion baseline in comparison to which the distortion added by the distortion channel could be evaluated.

7. Work in this direction

- The use of image quality assessment algorithms as objective functions for image optimization problems. For example, the SSIM index has been used to optimize several important image processing problems, including image restoration, image quantization, and image de-noising.
- Another interesting line of inquiry is the use of image quality algorithms - or variations of them - for other purposes than image quality assessment - such as speech quality assessment.
- Lastly, assessing the quality of digital videos. There are many sources of distortion that may occur owing to time-dependent processing of videos, and interesting aspects of spatial-temporal visual perception come into play when developing algorithms for video QA. Such algorithms are by necessity more involved in their construction and complex in their execution.

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