Determine the Structural and Gradient Similarity using Super Resolution Algorithm

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Abstract:
The central aim of Super-Resolution (SR) is to generate a higher resolution image from lower resolution images. High resolution images offer a high pixel density and thereby more details about the original scene. In this paper image super resolution based on gradient magnitude and direction. Finally, in order to allow quality assessment of the results, a comparison of a variety of image quality measures is also performed. Besides the visual quality measurement, image quality measurements including correlation coefficient, peak signal-to-noise ratios, and mean structural similarity, are also presented. Image quality assessment plays an important role in various image processing applications. A great deal of effort has been made in recent years to develop objective image quality metrics that correlate with perceived quality measurement. The main function of the human eyes is to extract structural information from the viewing field, and the human visual system is highly adapted for this purpose. Therefore, a measurement of structural distortion should be a good approximation of perceived image distortion.

Keywords: matlab software, image quality assessment, super resolution algorithm

I. INTRODUCTION

The image super-resolution technique aims to construct a high-resolution (HR) image with one or several given low-resolution (LR) images. It has been widely used in various applications, including medical image processing, infrared imaging, face/iris recognition, image editing, etc. According to the number of available LR images, the super-resolution algorithms can be classified into two categories: multi-frame super-resolution and single-frame super-resolution approaches. Traditional interpolation based methods try to reconstruct the HR image by a base function, including bilinear, bicubic and nearest neighbour algorithms. The full-reference IQA metrics such as PSNR, SSIM, etc. are used to evaluate the visual quality of HR images. Image quality assessment (IQA) is useful in many applications such as image acquisition, watermarking, compression, transmission, restoration, enhancement, and reproduction. The goal of IQA is to calculate the extent of quality degradation and is thus used to evaluate/compare the performance of processing systems and/or optimize the choice of parameters in processing. Image distortion is often present in almost all images. Different types of distortion are there. For example, noise, blur, contrast change, etc. These distortions can degrade the entire quality of the image. For example in image compression, if the captured image contains distortions then it would not match with the original image that is stored in the database. So finding the quality of the image in those areas is very necessary. For instance, reliable judgement of visual quality plays an important role in improving end users’ quality of experience in color image reproduction systems. In order to be adequately reproduced across various imaging systems, e.g., monitors, printers, and handheld devices, color images should be processed according to the color gamut of a target device. A mechanism called color gamut mapping converts each out-of-gamut color in image data into the closest reproducible color. This process often introduces visual artifacts, resulting in degradation of the reproduced image quality. Ideally, gamut mapping should be carried out in a way that visual distortion in the reproduction is minimized. Hence, visual quality prediction models can be embedded into gamut mapping systems to ensure faithful reproduction of color image data over different platforms. These systems typically involve tradeoffs between system resources and the visual quality of the output. In order to make these tradeoffs efficiently, we need a way of measuring the quality of images or videos that come from a system running under a given configuration. The obvious way of measuring quality is to solicit the opinion of human observers. However, such subjective evaluations are not only cumbersome and expensive, but they also cannot be incorporated into automatic systems that adjust themselves in real-time based on the feedback of output quality.

II. SUPER RESOLUTION ALGORITHM

The possibility of reconstructing a super-resolved image from a set of images was initially proposed by Huang and Tsay in [30], although the general sampling theorems previously formulated by Yen in [31] and Papoulis in [32] showed exactly the same concept (from a theoretical point of view). When Huang and Tsay originally proposed the idea of the SR reconstruction, they faced the problem, with respect to the frequency domain, of demonstrating the possibility of reconstructing an image with improved resolution from several low-resolution under sampled images without noise and from the same scene, based on the spatial aliasing effect. They assume a purely translational model and solve the dual problem of registration and restoration (the registration implies estimating the relative shifts among the observations and the restoration implies the estimation of samples on a uniform grid with a higher sampling rate). The restoration stage is actually an interpolation problem dealing with nonuniform sampling. From the Huang and Tsay proposal until the present days, several research groups have developed...
different algorithms for this task of reconstruction, obtained from different strategies or analyses of the problem. The great advances experimented by computer technology in the last years have led to a renewed and growing interest in the theory of image restoration. The main approaches are based on nontraditional treatment of the classical restoration problem, oriented towards new restoration problems of second generation, and the use of algorithms that are more complex and exhibit a higher computational cost. Based on the resulting image, these new second-generation algorithms can be classified into problems of an image restoration, restoration of an image sequence, and reconstruction of an image improved with SR. In the scientific literature, several algorithms have been proposed for this classical problem and for the problems related to it, contributing to the construction of a unified theory that comprises many of the existing restoration methods. In the image restoration theory, mainly three different approaches exist that are widely used in order to obtain reliable restoration algorithms: maximum likelihood estimators (MLE) maximum a posteriori (MAP) probability, and the projection onto convex sets (POCS). An alternative classification based on the processing approach can be made, where the work on SR can be divided into two main categories: reconstruction-based methods and learning-based methods. The theoretical foundations for reconstruction methods are no uniform sampling theorems, while learning-based methods employ generative models that are learned from samples. The goal of the former is to reconstruct the original (supersampled) signal while that of the latter is to create the signal based on learned generative models. These similarity maps are combined and pooled by a proposed deviation pooling strategy. In this paper, conversion to luminance is done through the following formula: \( L(x) = \frac{R(x)}{2} + \frac{G(x)}{2} + \frac{B(x)}{2} \). 

**A) Gradient similarity**

It is very common that gradient magnitude in the discrete domain is calculated on the basis of some operators that approximate derivatives of the image function using differences. These operators approximate vertical \( G_y(x) \) and horizontal \( G_x(x) \) gradients of an image \( f(x) \) using convolution:

\[
G_x(x) = h_x * f(x) \quad \text{and} \quad G_y(x) = h_y * f(x),
\]

where \( h_x \) and \( h_y \) are horizontal and vertical gradient operators and \( * \) denotes the convolution. The first derivative magnitude is defined as

\[
G(x) = \sqrt{G_x^2(x) + G_y^2(x)}.
\]

The Sobel operator the Scharroperator, and the Prewitt operator are common gradient operators that approximate first derivatives. Within the proposed IQA model, these operators perform almost the same. Through this paper, Prewitt operator is used to compute gradient magnitudes of luminance \( L \) channels of reference and distorted images, \( R \) and \( D \). From which, gradient similarity (GS) is computed by the following SSIM induced equation:

\[
\text{GS}(x) = 2G_R(x)G_D(x) + C_1 / G_R^2(x) + G_D^2(x) + C_1
\]

where, parameter \( C_1 \) is a constant to control numerical stability. The gradient similarity (GS) is widely used in the literature and its usefulness to measure image distortions was extensively investigated. In many scenarios, human visual system (HVS) disagrees with the judgments provided by the GS for structural distortions. In fact, in such a formulation, there is no difference between an added edge to or a removed edge from the distorted image with respect to the reference image. An extra edge in \( D \) bring less attention of HVS if its color is close to the relative pixels of that edge in \( R \). Likewise, HVS pays less attention to a removed edge from \( R \) that is replaced with pixels of the same or nearly the same color. In another scenario, suppose that edges are preserved in \( D \) but with different colors than in \( R \). In this case, GS is likely to fail at providing a good judgment “on the edges”. These shortcomings of the GS motivated us to propose a new GS measure. Here we define the quality of a super-resolved HR image as how similar it is to the true HR image. Therefore, similarity measures are used as indicators of quality. The SR reconstruction process introduces distortions, such as noise and artifacts like ringing. A good objective quality metric for SR should account for these artifacts. In this chapter, we introduce three different metrics to compare the results: peak signal-to-noise ratio, correlation coefficient, and structural similarity [62]. All of them are full-reference metrics, which means that a complete reference image is assumed to be known. This will be useful in comparing the various algorithms.

**B) Peak Signal-to-Noise Ratio**

The Peak Signal-to-Noise Ratio (PSNR) is a very common quality measure in image processing and is based on the Mean Squared Error (MSE), which is computed by averaging the squared intensity differences of distorted and reference image pixels. Given the super resolved HR image \( f \) and the original HR image true whose size is \( M \times N \), MSE is defined as:

\[
\text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \| f(i,j) - g(i,j) \|^2
\]

PSNR mentioned above is obtained from the MSE and the maximum signal value, \( \max \{ \star \} \), using the following definition:

\[
\text{PSNR} = 20 \log_{10} \left( \frac{\text{MAX}_f}{\sqrt{\text{MSE}}} \right)
\]

PSNR is expressed in decibels (dB) and higher values correspond to a lower error and thus a higher quality image. Even though there are some criticisms about using PSNR, see it is the most widely used full-reference quality metric. This is because, compared with other metrics, it is simple to calculate, has clear physical meanings, and is mathematically convenient in the context of optimization.

**C) Correlation Coefficient**

Correlation Coefficient (CC) is defined the same way as in the image registration step. As a natural extending, we can also use CC to show the similarity of super-resolved HR image and the original HR image. The CC is defined as: The maximum absolute value of CC is 1 and denotes perfect Correlation.

**D) Mean structural similarity**

Although PSNR and CC are easy implemented and efficient, they do not necessarily represent what is observed by the human visual system, Wang et al. introduce and test the Mean Structural SIMilarity (MSSIM) error measure. MSSIM is designed to improve on traditional methods like PSNR and MSE. Based on the assumption that the human visual system is highly adapted to extract structural information from the viewing field, Structural Similarity (SSIM) measures the structural information change to provide a good approximation to perceived image distortion.
III. RESULT AND DISCUSSION

Here the image is taken in the video the image converted into gray scale image applying super resolution algorithm and measure the similarities and calculate the psnr, correlation coefficient, mean squared error in the image.

![Input image](image1.png)

![Input(grayscale image)](image2.png)

![Compressed image](image3.png)

![Resolution image](image4.png)

![Structural similarity value is 0.0061](image5.png)

f) Gradient magnitude and direction
- No. of frames produced in the video = 1264
- Mean squared error produced in the image = 0.1936
- The value of peak signal to noise ratio = 55.2624
- The correlation factor produced in the image = 0.9926

IV. CONCLUSION

In this paper the selection of particular image from the extracting frames in video to improve quality by using super resolution algorithm and calculate the structural similarities, psnr value, correlation coefficient, mean squared error by using image quality assessment. Full reference IQA model based on the gradient similarities. The gradient similarity was used to measure structural distortions. Image quality assessment (IQA) is useful in many applications such as image acquisition, watermarking, compression, transmission, restoration, enhancement, and reproduction. The goal of IQA is to calculate the extent of quality degradation and is thus used to evaluate /compare the performance of processing systems and/or optimize the choice of parameters in processing.

V. REFERENCES


