BLUR DETECTION METHODS AND MEASUREMENT IN IMAGE COMPRESSION USING DWT

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ABSTRACT

This paper deals with using discrete wavelet transform derived features used for digital image texture analysis to detect the blur images. In terms of Blur the number of digital images increases rapidly, raising the demand for assessment of image quality. Blur is one of the conventional image quality degradation which is caused by various factors like limited contrast; inappropriate exposure time and improper device handling indeed. Wavelets appear to be a suitable tool for this task as they allow the analysis of images at various levels of resolution. There are several methods to detect blur from blurry images some of which requires transform like DWT, DCT or wavelet and some doesn't require transform.

Keywords: Blur, DWT, Compression, Measurement

I. INTRODUCTION

In this paper, we focus on detecting and analyzing the blur from the blurry images and propose a method to detect extract possible blurred. Advances in computational photography over the last decade have laid the foundations for the mass production of powerful low-cost digital cameras. This technology is indeed helpful to conventional users to generate high-quality content with inexpensive and bulky professional cameras. Now a days, cameras with having the property of auto focusing and motion compensation functions. The goal of such functions is to improve picture quality by automatically post-processing and enhancing the quality of images captured with low-quality, cheap sensors and lenses. High-quality lenses and sensors are not only expensive but bulky and thus inappropriate for integration in small cameras and other devices such as mobile equipments. Computational photography offers highly efficient tools that improves the quality of pictures captured with low-quality lenses and sensors at very low cost. This approach offers a very appealing alternative to image capturing with high-quality lenses.

Blur is an image is due to the attenuation of the high spatial frequencies, which generally occurs during filtering or visual data compression. In the spatial domain this causes ripples or oscillations around sharp edges or contours in the image. We classify the detected blur regions into two types: near isotropic blur (including out-of-focus blur) and directional motion blur. We also classify image blur into these two classes because they are most commonly studied in image restoration. The blur classified images also easily find applications in motion analysis and image restoration. For blur detection and recognition previous approaches aim at measuring blur extent of edges and are based on the analysis of edge sharpness [1]

In our system, blur detection and blur type classification are achieved in two steps. First, detection of blurred images is performed. In this step, we propose to use a combination of three features, namely, *Local Power SpectrumSlope*, *Gradient Histogram Span*, and *Maximum Saturation*, to model the blur characteristics in different ways. Second, directional motion blurred regions are distinguished from out-of-focus blurred regions by using another feature, i.e., *Local Autocorrelation Congruency*. We can also say that these are the feature of the blur in the system.

1.1 Local Power Spectrum Slope

Due to the low-pass-filtering characteristic of a blurred region, some high frequency components are lost. So the amplitude spectrum slope of a blurred region tends to be steeper than that of an unblurred region.

1.2 Gradient Histogram Span

The distribution of gradient magnitude serves as an important visual clue in blur detection. Blurred regions rarely contain sharp edges, which results in small gradient magnitude. Accordingly, the distributions of the log gradient magnitude for blurred regions should have shorter tails than that for other region.

1.3 Maximum Saturation

Unblurred regions are likely to have more vivid colors than blur regions. The maximum value of saturation in blurred regions is correspondingly expected to be smaller than that in unblurred regions.

1.4 Local Autocorrelation Congruency

If a region is blurred by relative motion between an object and the background in a certain direction, all edges of the object will be blurred, except those sharing the same direction with the motion. This is regarded as another important visual clue in our blur analysis.

II. EXISTING BLUR DETECTION METHODS

There are several method to detect the Blur from the Blurry images. These are HWT, DCT and DWT.

2.1. HWT

It is a direct method which is generally used to blur detection. With the help of edge type analysis it can not only judge whether or not a given image is blurred, but also determines to what extend the image is blurred, which is based on analysis of edge sharpness. In this method, different type of edges are generally classified into three types: these are, Dirac-structure, Step-structure and Roof-structure. In this paper, we further classify Step-structure into Astep-structure and Gstep-structure according to whether the change of intensity is gradual or not. Note that for Gstep-structure and Roof-Structure edge, there is a parameter a $(0 < a < n/2)$ indicating the sharpness of the edge: the larger a is, the sharper the edge is.The general idea of this scheme is to determine the most natural images includes different types of edges more or less and whatever the reason of Blur occurance it doesn't depend upon out of focus or linear motion. This figure explain the concept of blur *image and what extent of image is blur*.

Fig.1. Structure of The HWT Blur Detection Scheme

2.2. DCT

This is the second techniques by which we can detect blur from the blurry images. A discrete cosine transform (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are essential to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be removed), to spectral methods for the numerical solution of partial differential equations. In this approach, DCT is applied to each block to represent its features and then truncating it yields a reduced dimension representation of the features. This method has been proven to be robust to JPEG compression, blurring or AWGN distortions but have failed to consider the multiple copy-move forgery. Most recently, proposed an approach based on improved DCT that has the advantages to be robust to various attacks, such as multiple copy-move forgery, Gaussian blurring, and noise taint; and also to have a lower computational complexity.

2.3. DWT

Blur detection proposed a new solution to take advantage of existing DCT information in MPEG or JPEG images and condensed video whereas linking a minimal computational load, this technique established on histograms of non-zero DCT occurrences which are computed directly from MPEG or JPEG compressed images. the schemes is fit for all types of pictures I-frame, P-frames or B-frames. Discrete wavelets transform consequential features used for digital image texture analysis. Wavelets are best device for this job. It allows analysis of images at different levels of resolutions DWT is a linear transformation that works on a data vector whose length is an integer power of two, convert it into a numerically different vector of the same length. It split data into different frequency components. DWT [2] is computed with a cascade of filterings followed by a factor 2 sub-sampling (Fig.2).

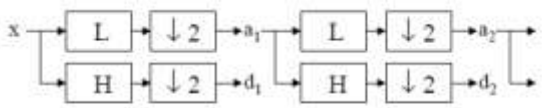

Fig.2.DWT Tree

H=high pass filters

L= low pass filters,

↓2 denotes sub-sampling. Output has been shown by these equations

$$a_{j+1}[p]=\sum_{n=-\infty}^{+\infty} l[n-2p]a_j[n]$$

$$d_{j+1}[p]=\sum_{n=-\infty}^{+\infty} h[n-2p]a_j[n]$$

a_j used for next step (scale) of transform & elements d_j, called wavelet coefficients, it determine output of the transform.

h[n] and L[n] are thecoefficients of low and high pas filters . One can assume that on scale $j+1$ there is only half from number of a and d elements on scale j causing DWT occurance until only two aj elements remain in the analyzed signal. These elements are called as scaling function coefficients.

DWT algorithm for two-dimensional pictures are similar. The DWT is performed foremost for all image rows and then for all columns (Fig.3)

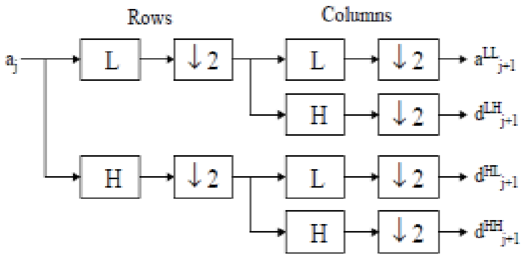

Fig 3 Wavelet Decomposition for Two-Dimensional Pictures

DWT main feature is multiscale representation of function. By using wavelets, we can analyze given function at various levels of resolution. DWT can be invertible and orthogonal.

On recording with different resolution Wavelets appears to be effective for analysis of textures. It is crucial problem in NMR imaging, because high-resolution images need long time of acquisition. This causes an enhancement of artifacts caused by patient movements, which should be avoided. It has been expected that the proposed approach will provide a tool for fast, low resolution NMR medical diagnose.

III. TEXTURE FEATURES

Here only one set of DWT derived features is considered. It is a vector, which include energies of wavelet coefficients calculated in sub-bands at successive scales.

A special module for Mazda program was developed which allows evaluating of those features.For computing the wavelet features in the first step Harr wavelet is calculated for whole image. As a result of this transform there are 4 sub-band images at eachscale in (fig.4)

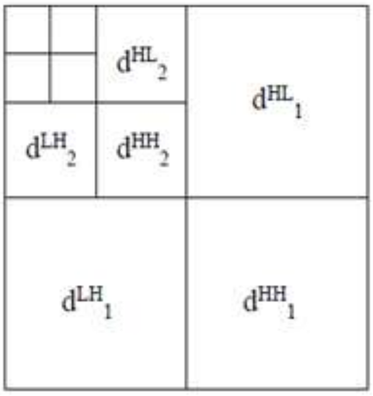

Fig.4. Sub-Band Images

Sub-band image a^{LL} is used only for DWT calculation at the next scale.

For given image, the maximum of 8 scales can be calculated. The Harr wavelet is calculated only if output sub-bands have dimensions at least 8 by 8 points.

In the next step, energy of d^{LH}, d^{HL} and d^{HH} is calculated at any considered sale in marked ROIs.

$$E_{subband,scale} = \frac{\sum_{x,y \in ROI} \left(d_{x,y}^{subband} \right)^2}{n}$$

here n is the number of pixels in ROI, both at given scale and sub-band. Of course, ROIs are reduced in successive scales in order to correspond to sub-band image dimensions. In a provided scale the energy is calculated only if ROI at this scale contains at least 4 points.

Outcome of this procedure is a vector of features containing energies of wavelet coefficients calculated in sub-bands at successive scales.

IV. METHODS

For all pictures, the wavelet-derived features were calculated by means of Mazda for 32 different ROIs with sizes of 64x64 pixels and normalization “□ 3σ”. This normalization was done by changing the original grayscale to the range $[\mu-3\sigma,\mu+3\sigma]$ where μ is the image mean and σ denotes its standard deviation (both □ and σ are computed for whole image containing homogenous grain). The image intensity within the new range was quantized using 256 discrete levels. In the following step, using Convert program, for each pair of textures, Fisher (4) coefficient was calculated and

$F=D/V$ (1)

Where, D– mean between-class separation

V – means within-class variance.

Ten features with highest F were used as an input to B11 program where the nearest neighbor classification test (1-NN) [3] was performed.

V. BLUR DETECTION MEASUREMENT

Measurement technique of the perceptual blur in an image or a video sequence has been investigated to an extent, related research topics include blur identification, blur estimation [4], image de-blurring [5]. Thegoal is to establish metrics, which correlate with the human visual experience by mapping the objective measurements onto subjective test results. For the assessment of overall quality of the image various objective parameters are given by [6][7][8].

These parameters do not consider any artifact in isolation but gives overall degradation result. When we want to assess effect of processing technique in terms of artifacts, these parameters are not desirable. Pina Marziliano1 [9] has given procedure to measure blur measurement. For every edge in reference imageand de-compressed image, edge width is measured here. Difference in width is blur indication.

Here using canny detector edges of reference image are found. By dilating these edges binary mask can be created. Edge profile of Processed image undergoes pixel wise ‘AND’ operation with this mask. Variance between covered edges in managed image and orientation edges uses area near the edge region to catch blur. These methods are difficult and computationally composite.We present simple process to extent blur and using Wavelet transform.

(5)

Fig.5. Original Image

(6)

Fig.6.Blurred Image

VI. BLUR CALCULATION

6.1 Flow Chart

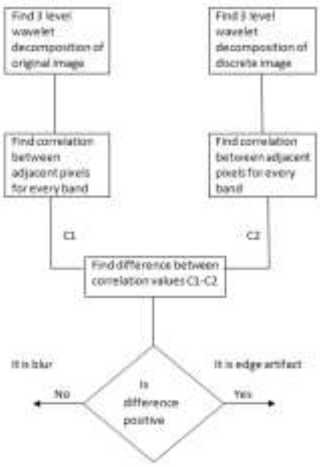

Fig. 7 Flow Chart For Blur Measurement

6.1.1 Wavelet Decomposition of the Image

Using analysis and synthesis bank image can be decomposed to get frequency spectrum at different resolution.

6.1.2 Correlation Between Coefficients

If we find Wavelet decomposition of the image, we know that LH, HL, and HH bands show edges in horizontal vertical and diagonal directions respectively. When the image is blurred it affects edges or variations in an image. Blurring gives thick edges.When image get blurred the edges become thicker or they are not sharp. Hence we expect that correlation between adjacent pixels in the same row (column) for LH (HL) orientation will increase.

6.2 Blur Measure

Reference image and decompressed image are transformed into wavelet domain, three level decomposition is used. Correlation between reference pixel and pixel in same row and previous column is calculated for every band of reference image (c1) and decompressed image (c2), using Pearson's correlation. Steps for calculation are

$$\bar{I} = \frac{1}{(N*M)} \sum_{i=0}^{n-x} \sum_{j=0}^{m-y} I(i,j) \quad (2)$$

Where I(i,j)- wavelet coefficient at ith row and jth column

N= number of rows

M= number of columns in the given Image

$$\bar{S} = \frac{1}{N*M} \sum_{i=0}^{n-x} \sum_{j=0}^{m-y} I(i+x, j+y) \quad 3)$$

$$SQI = \sqrt{\sum_{i=0}^{n-x} \sum_{j=0}^{m-y} (I(i,j) - \bar{I})^2} \quad (4)$$

$$SQS = \sqrt{\sum_{i=0}^{n-x} \sum_{j=0}^{m-y} (I(i+x, j+y) - \bar{S})^2} \quad (5)$$

$$R_{xx} = \frac{\sum_{i=0}^{n-x} \sum_{j=0}^{m-y} (I(i,j) - \bar{I}) * (I(i+x, j+y) - \bar{S})}{SQI * SQS} \quad (6)$$

If difference, c1-c2 is negative it is as blur. Difference c1-c2 is found for all bands negative values are added together which gives overall blur.

Total blur value = 2*(blur artifact at resolution level 3) + 1.414(blur artifact at resolution level2) + (blur artifact at resolution1)

To validate the result we compared it with subjective test taken. Subjective tests are mainly done used for overall quality. To carry out subjective assessment MOS test was conducted. 20 non-expert viewers were asked to give their opinion about quality. Bubble sort method explained in [6] was used for this purpose.Correlation coefficient among subjective and objective test was calculated.

VII. CONCLUSION AND FUTURE WORK

Detecting the blur in an image is very essential for improving the image quality. The proposed DWT method showing the favourable results for upgrading the image quality. DWT method have the feature of multiscaling of function & it is also invertable & orthogonal. Such features are the core of the proposed method. The identification of blur images are done by given formula. This method is very useful in Digital Image Processing field. There are many aspects in proposed method which may be used for future enhancement of this methods. Identification & removal of blurness from the images can be used for future enhancement. Digital Image Processing is an emerging area of research & there is many possibilities of improving the quality of the images by upgrading the current methods.

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