BISPECTRUM TECHNIQUE TO IMAGE RECOVERY FROM WATER IMAGING

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Abstract— A new method is proposed for removing geometric distortion in images of submerged objects observed from outside shallow water. The water waves will affect the appearance of the individual video frames such that no single frame is completely free of geometric distortion. This suggests that, in principle, it is possible to perform a selection of a set of low distortion sub-regions from each video frame and combine them to form a single undistorted image of the observed object. Under mild conditions where the wavy surface normal weakly satisfy a Gaussian distribution, it demonstrates that the geometric distortion can be removed and a corrected image can be recovered. The bispectrum concept is utilized to recover undistorted images from videos.

Index Terms— Water Imaging, Bispectrum, Bicoherence, Quadrature Phase Coupling (QPC), Gaussian Distribution.

I. INTRODUCTION

It is widely known that when the water is uneven by virtue of having waves, the images of submerged objects observed from outside shallow water gets distorted. This distortion is due to the effect of light refraction and motion blur.

Main focus is on the problem of how to recover the target image from the video stream of distorted images. More specifically, an object submerged in water is observed by a video camera from a static view-point above the water. Figure 1 shows the sample of distorted image.

Figure 1: A sample of distorted image.

An effective technique to recover an undistorted image; it is referred as the water image recovery problem. To solve the water image recovery problem, a new algorithm is proposed. This algorithm is based on the bispectral analysis technique, which is used in analyzing the data structures such as electroencephalogram (EEG) data.

The bispectrum analysis has great potential to water image recovery in the case of refraction i.e., looking through a wavy water surface. Some obvious applications include texture discrimination, reconstruction of shift and invariant objects, tomography and non-Gaussian image modeling.

II. RELATED WORK

Some of the existing methods have been reviewed for recovery of distorted images due to a wavy water surface. A simpler approach is described by Shefer et al. to reconstruct a submerged object by simply taking the time average of a large number of continuously distorted video frames [1]. It is based on the assumption that when the water surface is flat and still, each point in the object viewed through dynamic water surface moves around a point which is its true position. This means that the integral of the movement is zero or close to zero when time tends to infinity. Therefore, the average of the captured images is geometrically correct. However, this method is still a low pass version of the true image and results in loss of fine detail.

There are two methods proposed by Donate et al. [2] and Donate and Ribeiro [3] which is similar but more robust approach to form an estimate of the target that presents a true view of the region being analyzed by finding local regions. This method attempts to separate image blocks into high- and low-distortion groups (corresponding to the movements with high and low energy) using the Kmeans algorithm. Then normalized cross correlation (NCC) is used to select an image region that is closest to all other regions. These two methods produce much sharper and more detailed images of the target.

In order to recover the through-the-water image, a graph-embedding technique is proposed by Efros et al. [4]. Their method points out that, when observing for a long time and considering a particular point in an object, one can find that the point is exactly in its correct position whenever the water surface imaging that point happens to be locally flat. A shortest path algorithm is used to select the image having the shortest overall path to all the other images. The local distance is computed transitively by normalized cross correlation (NCC).

A new algorithm is presented to estimate the real image distorted by moving water waves. The reconstruction problem of water imaging is regarded as a "phase tracking" task, which employs a lucky region selection followed by bispectral analysis to recover an undistorted image. The lucky region technique is an extension to the lucky imaging technique, which finds superior quality images from a large set of detected astronomical images [5]. In this algorithm, smaller image patches are selected with good quality instead of the entire image. The good regions are then used for further processing to produce an estimate of the likely image.

III. PROPOSED ALGORITHM

This is a step-by-step algorithm is described in which the input is taken as a water-distorted video sequence and then it results a single geometrically correct image.

Consider a water surface which is uneven by virtue of having waves; a particular point is visualized through the water surface. As the waves pass through, almost the point is extended or deformed or moves away from its geometrically correct position. This results in an indiscriminately distorted and spread image at that spatial location. Nevertheless, at some instants, the consequence of the unstable flow of water i.e., water surface turbulence perhaps less or even negligible, and a snapshot of that area at that moment approaches its ground truth. By acknowledging that when this happen and pick out such regions from a sequence of video frames, these less distorted observations are used in succeeding post processing such that it can make better final image reconstruction. This preprocess step forms "lucky region" selection. This is a popular technique in astronomical photography commonly known as lucky imaging or lucky exposures. It focus is to take a series of thousands of short-exposure images and then select and fuse only top sharpest ones. Fried [6] mathematically showed that if the captured video is long enough, the high probability one will capture a sharp lucky exposure.

Globally, the proposed algorithm consists of three major steps:

A. Preprocessing: In this step, a water distorted video sequence is taken as input and then split up each of the input unprocessed images in to small image patches or plots or regions of equal size; each patch overlaps or collides partially or wholly with its adjacent patches.

B. Lucky region selection: The basis for observing and discarding any severely distorted image patches inside each frame and all over the entire video sequence is by image quality measurement.

C. Image recovery using bispectral analysis: In order to reconstruct and form an overlapping mosaic, the bispectrum-based speckle imaging technique is used. Then the Fourier amplitude and phase of each undistorted image region is computed.

Detailed explanation follows:

A. Preprocessing

In this step, each of the input image frames is split up into small patches of equal size having 50% overlap between each pair of adjacent patches.

There are two reasons for dividing each frame into patches and working on them. The first reason is, naturally to allow lucky region selection. An entire image with negligible distortion can be discovered but an objection is that the probability of obtaining such an image with negligible distortion is much lower than that of obtaining a good image patch. Because in a sustainable observing period, only a part of the scene may happen to have very less distortion while the remaining part is still severely affected by the moving water surface. In order to separate less distorted from severely distorted image regions, the division of frames into patches is done.

A second reason for subdividing the images in to patches is to reduce computational complexity in the next processing stages.

Here, Overlapping patches are used in order to reduce boundary effects. The boundary problems include edge effects, in which patterns of interaction or interdependency across the borders of the bounded region are ignored or distorted, and shape effects which affect the perceived interactions between patches. It is chosen to have 50% of overlap with neighboring patches. Then in order to reduce artifacts from the overlapping and adding of the regions, a two-dimensional Hanning window is applied to each patch. The Hanning window is weighted so that each of the four quadrants sum to unity, specified to be four-way overlap.

B. Lucky Region Selection

A more general problem of image quality measurement is the "lucky region" selection. The factors that are commonly linked up with image quality are sharpness, noise and loss of detail. The factor of geometric distortion is also included as a measure of image quality.

Two methods of lucky region selection exists: one is based on bicoherence, which refers to the degree of phase correlation between different frequencies in the Fourier domain in advance. And the other is a common image quality index.

a) Bicoherence Method

To determine lucky regions or good quality image patches from a captured video sequence, bicoherence is the approach which is a measure of quality. The image quality regions are selected according to the magnitude of the average value of the bicoherence of each region. Before mosaicing to an overall restoration, each image patch is restored using bispectral phase estimation from lucky regions.

An imaging process is said to be nonlinear if the effect of a moving water surface on an image varies over both time and spatial position. Bicoherence represents the normalization of the bispectrum, and therefore provides a measure of phase coupling which is used to search for nonlinear interactions. The bicoherence measures the proportion of the signal energy at any bifrequency that is quadratically phase coupled. Hence, an effective way of detecting quadratic phase coupling is the bicoherence. The presence of quadratic phase coupling (QPC) is a strong indicator of a nonlinear process. The degree of phase coupling between different spatial frequencies can be predicted from the bicoherence.

The bicoherence is obtained by averaging the bispectrum over statistically equivalent realizations, and normalizing the result.

The normalization is such that $0 \leq b \leq 1$. This means the value of bicoherence is bounded between zero and unity.

The bicoherence $b(u_1, u_2)$ is defined as

$$b(u_1,u_2) = \frac{\left|\sum_{i=0}^{N-1} I(u_1)\, I(u_2) I^{*}(u_1+u_2)\right|}{\sqrt{\sum_{i=0}^{N-1}|I(u_1)I(u_2)|^2 \sum_{i=0}^{N-1}|I^{*}(u_1+u_2)|^2}} \quad (1)$$

Note that the bicoherence is a real-valued quantity. Above equation shows the one-dimensional (1D) case, where I(·) is the Fourier transform of the real valued i(x), u_1 and u_2 denote the frequency coordinates, and * denotes the complex conjugation of I(·). If there is no phase coupling between two frequencies, the value of bicoherence will be very small or even zero. If the degree of phase coupling is high, then the value of the bicoherence will be close to unity. Hence, the degree of nonlinearity i.e., QPC is detected such that the smaller the value, the better the image quality.

While dealing with 2D data, the bicoherence of an image region will be four dimensional (4D). The phase correlations between spatial frequencies in the one-dimension scan lines or columns of an image region are similar to those calculated over a 2D image region[7,8].

The bicoherence of an image region is given by the average of the bicoherence values of the horizontal and the vertical scan lines in the region domain.

This is described by

$$\boldsymbol{b_{region}} = \sqrt{\left(\frac{1}{N_h}\sum_{k=1}^{N_h} \boldsymbol{b_k^h}\right)^2 + \left(\frac{1}{Nv}\sum_{k=1}^{N_v} \boldsymbol{b_k^v}\right)^2} \quad (2)$$

where the average bicoherence $b_k^{(\cdot)}$ is given by

$$\boldsymbol{b_k^{(.)}} = \frac{\sum_{u_1=0}^{N_{u_1}-1}\sum_{u_2=0}^{N_{u_2}-1} b_{line}(u_1,u_2)}{N_{u1}N_{u2}} \quad (3)$$

and N_h and N_v are the number of horizontal and vertical scan lines of an image region. b_k^h and b_k^v are the average bicoherence of the kth horizontal and vertical lines. $b_{\text{line}}(u_1, u_2)$ is calculated by Eq. (1), and N_{u1} and N_{u2} represent the number of sampled frequencies u_1 and u_2. Note that both b_{region} and $b_k^{(\cdot)}$ are scalar values, which represent the average of the bicoherence over the frequency domain.

One can obtain a sequence of lucky regions among the given distorted image set by selecting the regions that have lower average bicoherence as lucky regions and discarding the other regions.

b) Image Quality Index Method

Any image distortion is modeled as a combination of three factors: loss of correlation, luminance distortion, and contrast distortion. These three factors carry important information about the inter-dependencies especially when the two images are spatially close in the visual scene. Luminance distortion is a phenomenon whereby image distortions tend to be less visible in bright regions, while contrast distortion is a phenomenon whereby distortions become less visible where there is significant texture in the image. It exhibits surprising consistency with subjective quality measurement. The advantage of this method is its short computation time.

$$Q = \frac{4\sigma_{xy}\bar{x}\,\bar{y}}{(\sigma_x^2+\sigma_y^2)[\bar{x}^2+\bar{y}^2]} \quad (4)$$

where x is the clean image and y is the test image, $\overline{x}$ and $\bar{x}^2$, $\overline{y}$ and $\bar{y}^2$ are the expectation and the variance of x and y, respectively, σ_{xy} is the covariance of x and y. The value of M lies of [−1, 1], when $x = y$ or y is close to x, M gains the best value 1. M tends to −1 when y is very different from x. Among the sequence of raw images, the clean image is unknown and has to be found. In [9], Fraser et al. assumed that the temporal mean of a full set of affected images is geometrically correct, although it may be uniformly blurred. The mean image is substituted for x. Hence, the image quality index method detects the likelihood between the tested image and the true image, therefore the higher the value, the better the image quality.

C. Image Recovery in Fourier Domain

In general, a signal can be recovered given that the magnitude and phase in the Fourier domain are known. Here, the bispectrum technique is used to recover the phase of the signal. In order to reconstruct a clear image using lucky regions, the simple method is to compute the temporal average over the lucky region to obtain separate image patches of the entire image. Among these obtained clean regions, each of the region is moved to its true position in the mosaic and fused to form an estimate of the scene. But this simple method introduces information loss resulting in more blurring than necessary, and deficiency in

fine details. Therefore a better post processing technique is needed for image reconstruction. As the nature of moving water surface "turbulence", the image reconstruction method is required that is able to take away both blur and geometric distortion. Hence, bispectrum is the better selection because of its properties of zero value for Gaussian distributed noise while preserving the phase information.

Consider the standard problem of image formation. The model of one-dimensional image formation is expressed

$$i(x) = o(x) * h(x) \quad (5)$$

where $i(x)$ is a detected image, $o(x)$ is the true object and $h(x)$ is the point spread function. Here, x is a variable and the true object is convolved with $h(x)$, point spread function. By taking the Fourier transform on both sides of Eq.(5) , it becomes $I(u) = O(u) H(u)$, where $I(u)$, $O(u)$ and $H(u)$ denote the Fourier transform of $i(x)$,$o(x)$ and $h(x)$ respectively. Hence, the Fourier transform of a convolution is equivalent to the product of the two individual Fourier transforms.

The input is two-dimensional data, so assume that $I(u_1,u_2;v_1,v_2)$ is the Fourier transform of a 2-D signal. The bispectrum is the Fourier form of the triple correlation of a signal. The bispectrum of a 2-D signal is given by

$$\begin{aligned} B(u_1,u_2;v_1,v_2) &= I(u_1, u2)\, I(v_1, v2)\, I^*(u_1 + v_1, u_2 + v_2) \quad (6) \\ &= I(u_1, u2)\, I(v_1, v2)\, I(-(u_1 + v_1), -(u_2 + v_2)) \end{aligned}$$

where $B(u_1,u2; v1,v2)$ denotes the bispectrum, and * indicates the complex conjugate.

The bispectrum of model of image formation of 2-D signal is expressed as

$$\begin{aligned} I^{(3)}(u_1,u_2;v_1,v_2) &= O(u_1,u2)\, O(v_1,v2) O^*(u_1 + v_1, u_2 + v_2)\, H(u_1, u2)\, H(v_1, v2)\, H^*(u_1 + v_1, u_2 + v_2) \\ &= O^{(3)}(u_1,u_2;v_1,v_2)\; H^{(3)}(u_1,u_2;v_1,v_2) \quad (7) \end{aligned}$$

where $O^{(3)}(u_1,u_2;v_1,v_2)$ and $H^{(3)}(u_1,u_2;v_1,v_2)$ are the bispectra of $O(u, v)$ and $H(u, v)$ respectively. Since the normal of the water surface is a Gaussian distribution, the phase distortion of a submerged object is also considered as Gaussian distributed. The overcome of the phase corruption is by averaging the bispectrum of the ensemble of the raw images given as

$$\langle I^{(3)}(u_1,u_2;v_1,v_2)\rangle = \langle O^{(3)}(u_1,u_2;v_1,v_2)\rangle \langle H^{(3)}(u_1,u_2;v_1,v_2)\rangle \quad (8)$$

where $\langle H^{(3)}(u_1,u_2;v_1,v_2)\rangle$ is an average transfer function in the bispectrum domain, which is real and larger than zero. This means that the phase of the object in the bispectrum domain is identical to the phase of $\langle I^{(3)}(u_1,u_2;v_1,v_2)\rangle$:

$$\Phi_O^{(3)} = \Phi_{\langle I(3)\rangle} \quad (9)$$

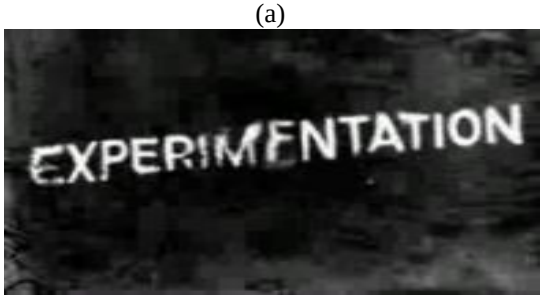
In order to calculate the true phase of the object, we have the equation as given by

$$\Phi_{\langle I(3)\rangle}(u_1,u_2;v_1,v_2) = \Phi_O(u_1,u_2) + \Phi_O(v_1,v_2) - \Phi_O(u_1 + v_1, u_2 + v_2) \quad (10)$$

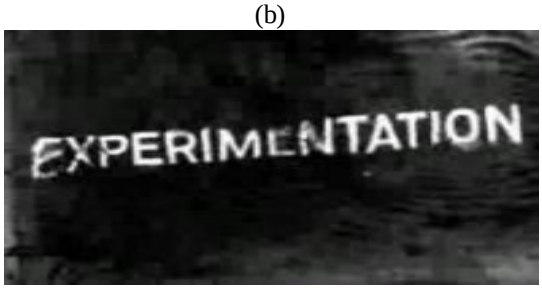
In order to calculate the phase of higher order frequency terms $\Phi_O(u_1+ v_1, u_2+v_2)$, $\Phi_O(u_1,v_1)$ and $\Phi_O(u_2,v_2)$ should be estimated first; therefore, the estimates must be calculated recursively. The phases at lower frequencies are computed first, and then the phase information of the higher frequencies is estimated based on the calculated phases. Moreover, there are many combinations of $\Phi_O(u_1,v_1)$, $\Phi_O(u_2,v_2)$ that contribute to the same $\Phi_O(u_1+ v_1, u_2+v_2)$; thus an average should be taken, over a number of combinations to increase the signal-to-noise ratio. In the recursive algorithm, it should be noted that the values of the phase at (±1, 0) and (0, ±1) are unknown but are required initially. One can randomly initiate these values that give a random shaping to the resulting image. To obtain a geometrically correct estimate of the object, the average of the image ensemble is used here: $\Phi_O(\pm1, 0) = \Phi_{mean}(\pm1, 0)$ and $\Phi_O(0, \pm1) = \Phi_{mean}(0, \pm1)$. It has been assumed that lower frequency phase is less affected by the distortion. However, it does introduce cumulative errors to the phases of the higher frequencies, because the errors in the lower frequencies affect those of the higher frequencies.

IV. RESULT ANALYSIS

(a)



(b)



(c)

Figure: 2 (a) – (c) A few frames of input video

Figure: 3 The output image of proposed algorithm

To test the proposed method, a real wavy water surface is taken. The natural data is captured by a video camera fixed above the water surface with the object laid on the planar ground under the water. Due to the wavy water waves and the effects of refraction, the text will appear as distorted and blurred frames as shown in Fig. 2 and it shows the various instants of image frames in a distorted video sequence. The size of each image frame is 132x180. Totally, 50 images are used. The size of image tiles is 64x64. After the processing of image frames using bispectrum technique, place each restored image patch in its true position in the mosaic of the result. This forms a geometrically correct image as shown in Fig. 3. It is observed that the proposed method in recovery of wanted object from water images outperform in comparison with the existing methods.

CONCLUSION

The water imaging has been studied, involving a disturbed, time varying wavy water surface. Here, imaging occurs through the air-water surface, involving refraction effects at the surface.

An effective method has been proposed to reconstruct a submerged object distorted by moving water surface. The bispectrum technique is employed to recover the phase of the true object, which was originally introduced in astronomical imaging. Although experiments show that this approach is promising, there exist some limits. One limit is that our algorithm has high computational complexity because the bispectrum of an image is four dimensional. Another limit is the recursive phase recovery method with only a subset of the phase information of the averaged bispectrum being used. This may reduce the resolution of the output.

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