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Haze-Free Underwater Image Enhancement

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Abstract:
Image enhancement is a process of improving the quality of image by improving its feature. The underwater image suffers from low contrast and resolution, due to Light Scattering and color change. hence object identification become typical task. In this project a fish tank is designed the camera and light source is inserted in the tank for taking the still photograph of the object. This image is taken as the source image. That is equalized using Histogram equalization. To reduce the noise in the image noise reduction filter is used and a new up scaling method, Iterative Curvature Based Interpolation (ICBI) based on a two-step grid filling and an iterative correction of the interpolated pixels obtained by minimizing an objective function depending on the second order directional derivatives of the image intensity. The constraints used to derive the function are related with a well-known New edge-directed interpolation (i.e., NEDI) method that providing good results but computationally heavy. The high quality of the images enlarged with the new method is demonstrated with objective and subjective tests, while the computation time is reduced of 1-2 orders of magnitude with respect to NEDI.

Key words*: Image enhancement, color change, light scattering, Equalization, Noise Reduction, image interpolation*

1.Introduction

An important issue in ocean engineering is to obtain a clear image. In scientific mission such has taking census, monitoring sea life and assessing geological and biological environment. In underwater image get blurred due to the haze caused .Haze is caused due to the particles such as stones, sand and plankton etc.That is present in the lake, ocean and rivers. The light reflected from the particle propagates towards the camera a portion of the light meets the particle which absorbs and scatters the light beam, as shown in the Fig.1.Due to the scattering and absorption of light the captured image has to be enhanced which is done using up scaling methods

Depth based methods can estimate scene depth and haze thickness effectively but it does not provide additional information about the image. Single dehazing algorithm has been used overcome the drawbacks of the multiple image[1]. In contrast maximization technique, assuming that a dehazing

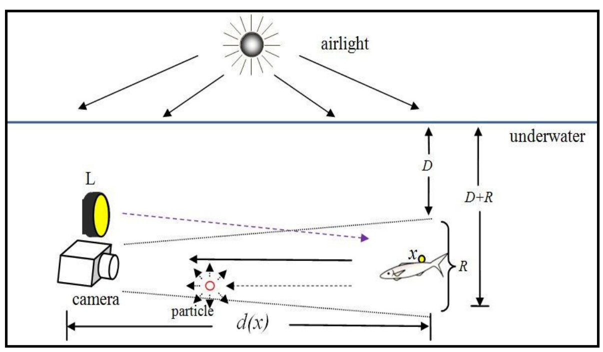

Figure 1: Natural Light Illuminates an Underwater Scene Point x and the Reflected Light Travels to the Camera by Direct Transmission and Scattering

image should have high contrast. This algorithm often generates halo artifacts and overstretched contrast of the restored image. It is physically not valid but visually compelling [2].In medium transmission, the transmitted image and surface sharing are locally uncorrelated. This approach is physically sound and can produce impressive result but this algorithm was not able to handle heavy haze image and may be failed in the cases if the assumption is broken [3] .In dark channel prior to remove haze from a single input image. It is a kind of statistics of the haze-free outdoor images. It is based on a key observation - most local patches in haze-free outdoor images contain some pixels which have very low intensities in at least one color channel. Using this prior with the haze imaging model, we can directly estimate the thickness of the haze and recover a high quality haze-free image. Results on a variety of outdoor haze images demonstrate the power of the proposed prior. Moreover, a high quality depth map can also be obtained as a by-product of haze removal[4].

In up scaling methods when an image needs to be scaled up, each pixel of the original image needs to be moved in a certain direction based on the scale constant. However, when scaling up an image by a non-integral scale factor, there are pixels that are not assigned appropriate pixel values. In this case, those holes should be assigned appropriate RGB or gray scale values so that the output image does not have non-valued pixels.

Bilinear interpolation can be used where perfect image transformation with pixel matching is impossible, so that one can calculate and assign appropriate intensity values to pixels. Unlike other interpolation techniques such as nearest neighbor interpolation and bicubic interpolation, bilinear interpolation uses only the 4 nearest pixel values which are located in diagonal directions from a given pixel in order to find the appropriate color intensity values of that pixel. Bilinear interpolation considers the closest 2x2 neighborhood of known pixel values surrounding the unknown pixel's computed location. It then takes a weighted average of these 4 pixels to arrive at its final, interpolated value. The weight on each of the 4 pixel values is based on the computed pixel's distance from each of the known points.

This algorithm reduces some of the visual distortion caused by resizing an image to a non-integral zoom factor, as opposed to nearest neighbor interpolation, which will make some pixels appear larger than others in the resized image. Bilinear interpolation tends, however, to produce a greater number of interpolation artifacts than more computationally demanding techniques such as bicubic interpolation. In bicubic data points on a two dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear or nearest-neighbor interpolation. Bicubic interpolation can be accomplished using either La grange polynomials, cubic splines, or cubic convolution algorithm., bicubic interpolation is often chosen over bilinear interpolation or nearest neighbor in image resampling, when speed is not an issue. In contrast to bilinear interpolation, which only takes 4 pixels into account, bicubic interpolation considers 16 pixels. Images resample with bicubic interpolation are smoother and have fewer interpolation artifacts. In order to overcome this artifact we go for a method called new edge-dected interpolation.

In the NEDI method, the weights are computed by assuming the local image covariance constant in a large window and at different scales. With this constraint, an over constrained system of equations can be obtained and solved for the coefficients. Images upscale with this method are visually better than those obtained with the previously described methods, especially if some tricks are used to adapt window size and handle matrix conditioning, as done in . However, even applying the rule only in non uniform regions and using instead a simple linear interpolation elsewhere, the computational cost of the procedure is quite high. . the brightness changes only perpendicular to the edge and it means that the over constrained system solved to obtain the parameters is badly conditioned due to the rank deficiency of the problem . The simple solution we applied in to avoid computational problems by using a modified well-conditioned NEDI where for a better constraint we assuming that co- efficient in multiplying opposite neighbours are equal. The solution is clearly faster and most important, the quality of the interpolation is the same obtained with the NEDI method [8].

2.Underwater Image Formulation Methodology

An underwater image is captured then the captured image is equalized using histogram equalization and the noise present in the image is reduced using wiener filter and for the performance calculation (i.e., PSNR) we compare three interpolation methods such has new edge-directed interpolation, bilinear or bicubic interpolation, iterative curvature based interpolation. Hence the resultant image has less computation time and good image quality, as illustrated in Fig.2.

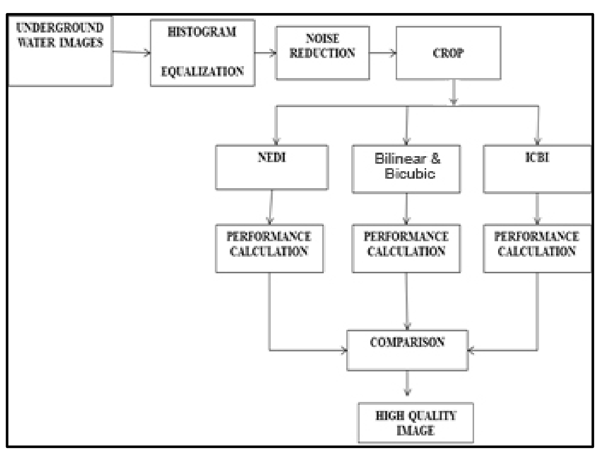

Figure 2: Block diagram of Haze-Free image

2.1.Gobal Contrast Equalization

This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. For an color image first converted to another color space, Lab color space, or HSL/HSV color space in particular, then the histogram can be applied to the luminance or value channel without resulting in changes to the hue and saturation of the image A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal. So in order to reduce the noise we use noise reduction filter.

2.2.Noise Reduction Filters

The noise present in the image after Global Contrast Equalization is reduced by Wiener filter. Wiener filter has two separate parts, an inverse filtering part and a noise smoothing part. To implement the Wiener filter we have to estimate the power spectra of the original image and the additive noise. For white additive noise the power spectrum is equal to the variance of the noise. To estimate the power spectrum of the original image many methods can be used. A direct estimate is the period gram estimate of the power spectrum. The advantage of the estimate is that it can be implemented very easily without worrying about the singularity of the inverse filtering. Another estimate which leads to a cascade implementation of the inverse filtering and the noise smoothing which is a straightforward result. The power spectrum can be estimated directly from the observation using the period gram estimation. Wiener filter reduces addsive Gaussian noise and increase brightness of the image.

2.3.Bilinear And Bicubic Interpolation

Bilinear interpolation can be used where perfect image transformation with pixel matching is impossible, so that one can calculate and assign appropriate intensity values to pixels. Unlike other interpolation techniques such as nearest neighbor interpolation and bicubic interpolation, bilinear interpolation uses only the 4 nearest pixel values which are located in diagonal directions from a given pixel in order to find the appropriate color intensity values of that pixel. Bilinear interpolation considers the closest 2x2 neighborhood of known pixel values surrounding the unknown pixel's computed location. It then takes a weighted average of these 4 pixels to arrive at its final, interpolated value. The weight on each of the 4 pixel values is based on the computed pixel's distance (in 2D space) from each of the known points. This algorithm reduces some of the visual distortion caused by resizing an image to a non-integral zoom factor, as opposed to nearest neighbor interpolation, which will make some pixels appear larger than others in the resized image. Bilinear interpolation tends, however, to produce a greater number of interpolation artifacts (such as aliasing, blurring, and edge halos) than more computationally demanding techniques such as bicubic interpolation.

Bicubic interpolation is an extension of cubic interpolation for interpolating data points on a two dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear interpolation or nearest-neighbor interpolation. Bicubic interpolation can be accomplished using either Lagrange polynomials, cubic splines, or cubic convolution algorithm., bicubic interpolation is often chosen over bilinear interpolation or nearest neighbor in image resampling, when speed is not an issue. In contrast to bilinear interpolation, which only takes 4 pixels (2x2) into account, bicubic interpolation considers 16 pixels (4x4). Images resample with bicubic interpolation are smoother and have fewer interpolation artifacts. In order to overcome this artifact we go for a method caller new edge-ducted interpolation.

2.4.Interpolation From Four Neighbors: Fast Methods And The Nedi Algrothim

In the NEDI method, the weights are computed by assuming the local image covariance (i.e., the vector) constant in a large window and at different scales. With this constraint, an over constrained system of equations can be obtained and solved for the coefficients. Images upscale with this method are visually better than those obtained with the previously described methods, especially if some tricks are used to adapt window size and handle matrix conditioning, as done in. However, even applying the rule only in non-uniform regions and using instead a simple linear interpolation elsewhere, the computational cost of the procedure is quite high. . The brightness changes only perpendicular to the edge and it means that the over constrained system solved to obtain the parameters is badly conditioned due to the rank deficiency of the problem. The simple solutions we applied in to avoid computational problems by using a modified well-conditioned NEDI where for a better constraint we assuming that co- efficient in multiplying opposite neighbors are equal. The solution is clearly faster and most important, the quality of the interpolation is the same obtained with the NEDI method.

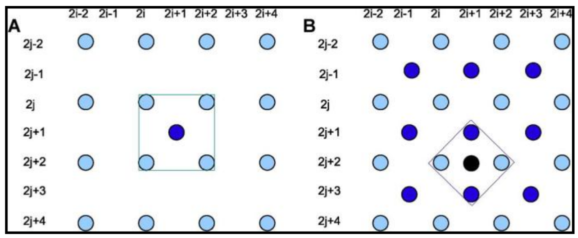

Figure 3: Two-step interpolation based on a weighted average of four neighbors

In this method the higher resolution grid is usually filled in two steps: in the first one, pixels indexed by two odd values [e.g., darker pixel in Fig. 3(a)] are computed as a weighted average of the four diagonal neighbors (corresponding to pixels of the original image); and in the second, the remaining holes [e.g., black pixel in Fig. 3(b)] are filled with the same rule, as a weighted average of the four nearest neighbors (in horizontal and vertical directions).

2.5.Iterative Curvature Based Interpolation

The idea of Iterative curvature based interpolation is : compute the new pixel values with the simple rule (i.e., NEDI) then initializing the new values with the FCBI algorithm (Fast curvature based iteration). The first step, computing local approximations of the second-order derivatives and along the two diagonal directionsI11 (2i+1, 2j+1) andI22 (2i+1, 2j+1) using eight-valued neighbouring pixels (see Fig. 4)

$$I_{11}(2i+1,2j+1)=I(2i-2,2J+2)+I(2i,2j)+I(2i+2,2j-2)-3I(2i,2j+2)-3I(2i+2,2j)+I(2i,2j+4)+I(2i,2j+2)+I(2i+4,2j)$$

$$I_{22}(2i+1,2j+1)=I(2i-2,2J+2)+I(2i,2j)+I(2i+2,2j-2)-3I(2i,2j+2)-3I(2i+2,2j)+I(2i,2j+4)+I(2i,2j+2)+I(2i+4,2j) \qquad \textbf{(1)}$$

And then, assigning to the point (2i+1, 2j+1), the average of the two neighbors in the direction where the derivative is lower

$$\begin{cases} \frac{I(2i,2j)+I(2i+2,2j+2)}{2}, if I_{11}(2i+1,2j+1) \prec I_{22}(2i+1,2j+1) \\ \frac{I(2i+2,2j)+I(2i,2j+2)}{2}, otherwise \end{cases} \quad (2)$$

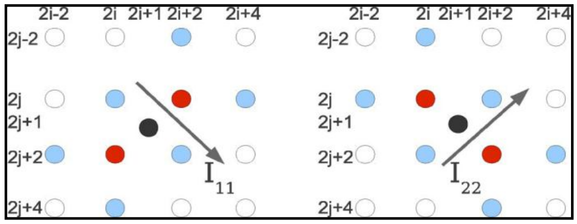

Figure 4:At each step (here, it is shown the first), the FCBI algorithm fills the central pixel (black) with the average of the two neighbors in the direction of the lowest second-order derivative (or). And are estimated using for each one the eight-valued neighboring pixels (evidentiated with different colors).

Interpolated values are then modified in an iterative procedure trying to minimize an "energy" function. The main energy term defined for each interpolated pixel should be minimized by small changes in second- order derivatives. This energy term sums local directional changes of second-order derivatives. Weights are set to 1 when the first-order derivative in the corresponding direction is not larger than a threshold and to 0 otherwise. In this way, smoothing is avoided when there is a strong discontinuity in the image intensity. The complete for each pixel location (2i+1, 2j+!), sum of the "curvature continuity," "curvature enhancement," and "isophote smoothing "term becomes, there from,

$$U(2i+1,2j+1)=\alpha u_c(2i+1,2j+1)+bu_e(2i+1,2j+1)+cu_i(2i+1,2j+1). \quad (3)$$

Finally we modify the interpolated pixel value in an iterative greedy procedure trying to minimize the global energy. The same procedure is repeated after the second interpolation step. The image obtained by this method has good image quality and less computation time.

3.Experimental Result

For our experimental needs, we use an image captured from the fish tank using a camera. That provide a wide range of color and natural textures which has RGB color image with depth of 8 bit per channel .The captured image is hazed, so in order to get a haze-free image we use a wiener filter which reduces the addsive noise present in the image. Then in order to find the quality of the image we use a three up scaling methods such as

Bicubic, NEDI, and ICBI for which a portion of the image is cropped and they are enlarged then three up scaling methods are applied for fifty iterations.

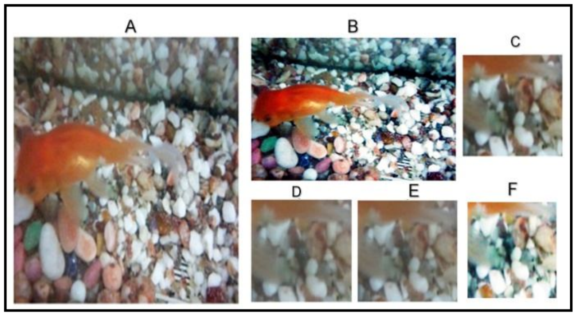

Figure 5 : (a) Captured Image (b)image obtain using wiener filter (c) Enlargement of a natural image using pixel replication creates obviously a pixelized result. (d) Bicubic interpolation removes this effect, but creates evident-jagged artifacts. (e) Techniques like NEDI provide better results (even if at the cost of a high computational complexity), but still create evident artifacts due to the effect of edge discontinuities in the window used to estimate the covariance. Images in (d) and (e), which appear identical, are obtained with the original NEDI constraint and the modified constraint. (f) Result obtained with the ICBI technique does not present relevant artifacts.

From Fig.5. The high quality of the image obtained with the new method (i.e.) ICBI can be seen clearly when comparing with the other up scaling methods such as bicubic andNEDI.The high quality of the different upscale image are measured using the PSNR value

$$PSNR = 20\log_{10}\frac{MAXPIX}{\sum_{i=1}^{W}\sum_{j=1}^{H}\left(I_{up}(i,j)-I_{orig}(i,j)\right)^2/(WxH)}--(4)$$

$I_{up}(i,j)$ is the upscale sub sampled image, I_{orig} the original one W & H, the image dimensions, and MAXPIX the end scale value of the pixel intensity.

	ICBI	NEDI	BIC
time(s)	52.78	528.50	600.25
PSNR	87.676	79.996	70.36

Table 1: Peak Snr & Computation Time Obtained By Comparing Different Upscaling Methods

From Table I we absorbed The Computation Time of ICBI is comparatively less than the NEDI and BIC interpolation algorithm. The image Quality (PSNR) of ICBI is better than NEDI and BCI.

4.conclution

In this paper, several issues related to the problem of creating high-quality upscale images from low-resolution original data. First, we showed that the well-known NEDI method can be slightly modified by removing the necessity of solving ill-conditioned over constrained systems of equations and obtaining the same image quality. Then, we showed how the modified NEDI constraint is related to the constraint used in our new ICBI technique. This technique uses mainly the assumption that the second-order derivatives of the image brightness are continuous along the interpolation directions and is able to obtain very good results, especially for its ability of removing artifacts without creating “artificial” detail, as proved by our objective and subjective tests. The new technique, based on a greedy minimization of an energy function defined at the interpolated pixel locations, is not computationally expensive like example-based methods or the NEDI procedure and is easily parallelizable.

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