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Image Restoration Based on Combined Dark Channel and Image Registration

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Abstract - **Due to the influence of water surface fluctuation and water turbulence, underwater target imaging detection technology faces great difficulties. This paper proposes an image restoration method combining dark channel prior theory and image registration technology, mainly using B-spline based non-rigid registration framework to correct image distortion. Since the conventional image registration algorithm often uses the average image of the sequence as a reference image, the average image tends to have severe blurring, which reduces the accuracy of registration. Therefore, this paper proposes to use the dark channel prior theory for the deblurring of the average image, and then use the deblurred average image as a reference for image registration. The test results show that the method can effectively improve the imaging distortion caused by surface turbulence.**

Index Terms – Image restoration, Water turbulence, Dark channel prior, Image registration.

I. INTRODUCTION

Image restoration in water turbulence is a meaningful study that can be applied to underwater detection. When the image is turbulent through the water, the captured image will be severely degraded, including noise and geometric distortion.

In a real underwater environment, since the refractive index difference between air and water is large, the imaging light will be significantly reflected on the water surface when light passes through the water from the air, the angle of refraction is related to the undulating appearance of the water surface. Due to the influence of water surface ripple and water turbulence, different imaging rays are incident on the imaging system at different refraction angles, the obtained image has severe distortion and local blur compared to the real image. A strong absorption effect on visible light because of the water body, suspended organisms, soluble organic matter. In addition, the water body has a strong scattering effect on the light energy, especially in the turbid water with suspended particles, the scattering phenomenon is more serious. The more serious the scattering phenomenon, the greater decrease in image contrast. The decline in image quality will greatly hinder subsequent image recognition and automated processing.

Most of conventional image restoration processing methods are used for image distortion caused by atmospheric turbulence, there are few studies on underwater images.[1] The restoration of the water-reducing image and the restoration of the original image before degradation can obtain a lot of valuable information for practical applications in the economic and military fields.

Compared with atmospheric turbulence, the effect of water on the image is more severe and the distortion is more serious, the restoration of underwater images is more difficult. At present, methods for recovering image degradation caused by turbulence in water bodies mainly include restoration methods based on water surface waveform estimation, restoration methods based on lucky block selection, restoration methods based on image degradation models, restoration methods based on image registration.

The image registration-based restoration algorithm obtains a transformation model between the distorted image and the reference image through image registration technology, then uses the transformation model to recover the distorted image.

This paper proposes a turbulence image restoration method combining dark channel theory and B-spline based non-rigid image registration algorithm. The method mainly uses image registration algorithm to correct the geometric distortion in the image. In order to improve the accuracy of registration, the dark channel theory is applied to the average image of the sequence, and the sharpened average image is used as the reference image. The experimental results show that the restoration algorithm of this paper can effectively alleviate the image distortion caused by turbulence.

II. RELATED WORK

Restoration methods based on water surface waveform estimation mainly estimates the waveform of the water surface through the image sequence, after that restores the distorted image by the shape of the waveform. Tian et al. [1] present an algorithm based on model tracking. Although image registration and prior knowledge are not required for this algorithm compared to other algorithms, motion blur is not considered. Since the state cycle wave generated by one-way blur can be regarded as a space-invariant condition, Seemakurthy et al. [2] establish a mathematical model of blur formation to remove the motion blur caused by the one-way cyclic wave. It also reveals the mechanism by which circular corrugations cause blurring and models them in the polar domain, which in turn proposes a method of correction in the case of circular corrugations. Restoration methods based on water surface waveform estimation does not require prior knowledge, it can be applied to the restoration of image degradation caused by most water ripples, which also can eliminate distortion and blur to some extent.

The lucky block selection method was originally used to process atmospheric turbulence images. Efros et al. [3] first introduced the idea of lucky block selection to the processing of underwater images. In [4], Wen et al. present a lucky block fusion method based on bispectrum analysis technology. Kanaev generalizes the general steps of the lucky block restoration method based on the optical flow method, who compares the processing effects based on the Sun optical flow method and the Brox optical flow method. In [5], he proposed the image quality evaluation based on the structure tensor, and compared the processing effects of a variety of restored water turbulence image algorithms.

The restoration method based on the underwater imaging model is an inverse transformation of the degraded image to obtain a restoration method of the original image. It comprehensively considers the light source, transmission medium, sensor and other aspects to establish a functional relationship between the degraded image and the original image.

Model proposed by Jaff-McGlamery[6,7] is a well-known underwater imaging model. It summarizes the relationship between degraded images and related factors, including light sources, transmission media, receiving systems. However, the formula is complex, due to the large parameters and high selective freedom, it is difficult to use in practice.

Image registration is often used for image distortion correction. Image registration operations on warped images can effectively reduce distortion in the image.

Oreifej et al. [8] solved the problem of wavy surface clear imaging through a two-stage approach, where the first stage uses the average image of the image sequence apply to each frame to overcome the structural turbulence of waves and the second stage eliminate sparse noise from sequences by rank minimization.

Halder et al. proposed an iterative recovery method for structural distortion image sequences. This method is similar to Oreifej's two-stage image restoration method for water surface imaging. The difference is that in the second stage, the image sequence is subjected to non-local mean filtering to compensate for unstructured random noise.

Hu et al. [9] used a method based on motion field kernel regression. The first step, the registration frame and the corresponding motion field are generated by image registration, then a set of constant blocks in the registration frame is found by calculating the local motion amount, finally use a time kernel regression to reconstruct a block and to obtain a restored image.

Halder et al. [10] selected the prototype frame from the video sequence based on the sharpness evaluation, non-rigid image registration techniques are employed to accurately align warped frames with respect to prototype frames and estimate deformation parameters and to remove image distortion using deformation parameters. Recently in [11], Halder et al. improved on the basis of the previous, using k-means clustering technology to discard too fuzzy frames, which can remove the inaccuracy of the displacement map estimation caused by fuzzy frames.

Restoration methods based on image registration typically perform iterative operations, which results in a large amount of computation. In the case of known prior knowledge, it is possible to reduce the number of iterations and improve the registration accuracy, but this may introduce motion blur.

In many imaging scenarios, the camera and the scene of interest are immersed in different media with an interface in-between. As a common example where the camera observes the floor of a pool through the water surface. The task is to recover the image of the floor that is severely distorted by water fluctuation. Since the air is the medium during the imaging process of the camera, we use the dehazing method in the atmosphere for the pre-treatment of the underwater turbulence to observe the effect.

The dark fog-based image dehazing algorithm proposed by He et al.[12] is a milestone in the research of defogging algorithm. Due to the similarity between the haze-containing image and the blurred image, Pan et al. [13] applied the dark channel prior theory to the blind image deblurring method, and achieved good results in motion blurred images, low-illumination blurred images, and non-uniform blurred images. Zhang et al. [14] proposed an underwater image restoration method based on blind deconvolution and image registration, which first blindly deconvolves the average image to achieve the definition that can registration, and then uses the image registration method to get image restoration.

III. PROPOSED METHOD

A. Algorithm overview

Related researches show that due to the turbulent motion is randomly, the image distortion of each frame in the image sequence also varies randomly with time, but the offset of each pixel approximates a zero-mean Gaussian distribution centered on its true position. Therefore, the local deformation field of the turbulent distortion image can be calculated by the image registration algorithm, and then the original position of the offset pixel is obtained by compensation. The algorithm flow is as follows:

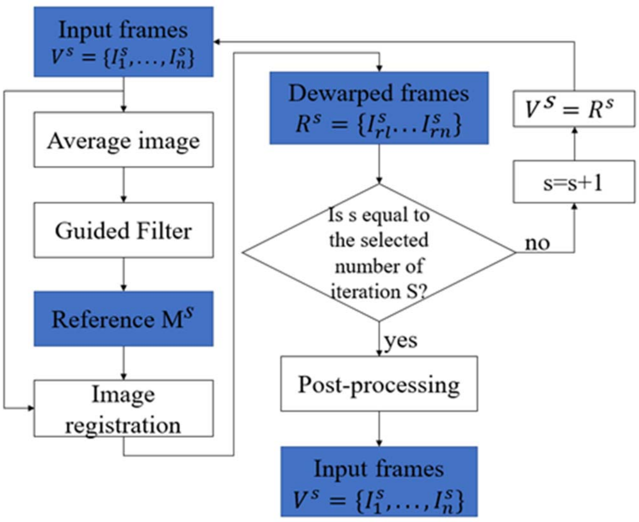

Fig. 1Algorithm flow chart based on image registration.

*1)*Input image sequence $V = \{I_1,...,I_n\}, I_k \in \mathbb{R}^{h\times w}(k = 1,...,n)$, calculate its average image M;

2) Use dark channel based deblurring algorithm get the deblurred image R.

3) Image R as a reference image, elimination of distortion caused by turbulence in images using a non-rigid registration algorithm based on B-spline, and get corrected new image sequence $V_f = \{I_{f1}, \ldots, I_{fn}\}$.

By taking a new sequence of images as input and repeating the above three steps multiple times, a stable restored image sequence can be obtained.

B. Deblurring algorithm based on dark channel prior

In computer vision and computer graphics, the model widely used to image haze removal technology research is as follows:

$$I(\mathbf{x}) = J(\mathbf{x})t(\mathbf{x}) + A(1-t(\mathbf{x})) \quad (1)$$

where **I** is the observed intensity, **J** is the scene radiance, **A** is the global atmospheric light, and *t* is the medium transmission describing the portion of the light that is not scattered and reaches the camera. The goal of haze removal is to recover **J**, **A**, and *t* from **I**.

The first term J(x)t(x) on the right hand side of Equation (1) is called direct attenuation, and the second term A(1−t(x)) is called airlight. Direct attenuation shows the scene radiance and its damping in the medium, while airlight generates from previously scattered light and results in the motion of the scene color. When the atmosphere is homogenous, the transmission t can be showed as:

$$t(\mathbf{x}) = e^{-\beta(\eta)d} \quad (2)$$

where the scattering coefficient of the atmosphere expressed as β. It displays that the scene radiance is attenuated exponentially with the scene depth *d*. The transmission *t* in a local patch is considered by maximizing the visibility of the patch and satisfying a constraint that the intensity of **J**(x) is less than the intensity of **A**.

This approach is physics-based and can manufacture a natural haze-free image together with a not bad depth map. Since this way is on account of a statistically independent assumption in a local patch, it needs the independent components varying distinctly. It may statistics unreliable due to any lack of variation or low signal-to-noise ratio. In addition, as color information is the basis of statistics, it is invalid for gray scale images and difficult to deal with dense haze which is often colorless and prone to noise.

The dark channel prior is the law that He et al. statistic on the large number of outdoor fog-free images are obtained: in most of the non-sky patches, at least one color channel has very low intensity at some pixels. In other words, the minimum intensity in such a patch should has a very low value. Formally, for an image ***J***, we define

$$J^{dark}(\mathbf{x}) = \min_{y\in\Omega(\mathbf{x})}\left(\min_{c\in\{r,g,b\}} J^c(\mathbf{y})\right) \quad (3)$$

where y is the position of the pixel, $\boldsymbol{J}^c$ is a color channel of ***J*** and $\Omega(\mathbf{x})$is a local patch centered at **x**. The equation(3) indicates that the dark channel value represents the minimum pixel value of an image block.

Because of the additive airlight, a haze image is brighter than its haze-free version in where the transmission t is low. Hence the dark channel of the haze image will have greater intensity in regions with denser haze. Visually, the intensity of the dark channel is a rough approximation of the thickness of the haze.

Assuming that the atmospheric light value A is known, according to the dark channel prior, the estimation formula of the transmittance t is:

$$\tilde{t}(\mathbf{x}) = 1 - \eta \min_{\mathbf{y}\in\Omega(\mathbf{x})}\left(\min_{c} \frac{I^c(\mathbf{y})}{A^c}\right) \quad (4)$$

Where η is a constant parameter which can keep a small amount of fog in the far away from the foggy image, making the image look more realistic.

Since the minimum filtering is used in the dark channel prior theory, the transmittance obtained by Eq. (4) contains the halo effect and the block effect.

In order to solve this problem, He et al. have proposed soft-matting [12] and guided filter[15] optimization algorithm, because the complexity of the soft-matting optimization algorithm is too high, so this paper uses a less complex steering filter algorithm to optimize the transmittance.

The final recovery formula is obtained from the atmospheric light value *A* and transmittance t:

$$J(\mathbf{x}) = \frac{I(\mathbf{x}) - A}{\max(t(\mathbf{x}), t_0)} + A \quad (5)$$

where the lower bound of the transmittance is 0.1.

When recovering directly, if transmittance $t(\mathbf{x})$ close to zero, $J(\mathbf{x})t(\mathbf{x})$ will be zero because of equation (1). And it will cause the loss of the original image information and introduce noise.

Therefore, it is necessary to set a lower boundary to retain a certain amount of fog in a place where the fog density is large.

C. Non-rigid registration algorithm based on B-spline

The registration method based on B-spline is to cover the control point grid with uniform distribution on the two-dimensional image, adjust the position of the control point, and use the B-spline interpolation of the control point in the neighborhood to obtain the pixel position of the non-control point, thereby fitting the image. The displacement of each point in the middle. The process of registration is essentially to find the optimal deformation field of the distorted image and the reference image.

For an image domain $\Omega = (\mathrm{x}, \mathrm{y}) | 0 \le x \le h, 0 \le y \le w$,if we denote Φ as a $n_x \times n_y$mesh of control points $\Phi_{i,j}$ with uniform spacing, the free-form deformation can be formulated as

$$T(x,y) = \sum_{m=0}^{3}\sum_{l=0}^{3} B_m(v)B_l(u)\varphi_{i+l,j+m} \quad (6)$$

where $i = \lfloor x/n_x \rfloor - 1$, $j = \lfloor y/n_y \rfloor - 1$, $u = x/n_x - \lfloor x/n_x \rfloor$, $v = y/n_y - \lfloor y/n_y \rfloor$, B_m and B_l are the standard cubic B-spine base function. The cubic B-spline base function are defined as: $B_0(t) = (1-t)^3/6$, $\mathrm{B}_1(\mathrm{t}) = (3\mathrm{t}^3 - 6\mathrm{t}^2 + 4)/6$, $B_2(t) = (-3t^3 + 3t^2 + 3t + 1)/6$, and $B_3(t) = t^3/6$, where $0 \le t \le 1$。

The degree of density of the B-spline control point grid determines the degree of freedom of deformation and also determines the computational complexity. The smaller the grid spacing, the higher the registration accuracy, but the greater the computational complexity. Therefore, in order to improve the registration accuracy while improving the registration speed, this paper adopts a multi-level B-spline registration method from coarse to fine.

For the convenience of calculation, the Mean Square Difference (MSD) is used as a measurement method.

Where R denotes the reference image, I represent the floats image, the area of the frame expressed in Ω. The mean square difference is defined as

$$\mathrm{MSD} = \frac{\sum_{(x,y)\in\Omega}\left(M(x,y)-I(x,y)\right)^2}{w\times h} \tag{7}$$

IV. EXPERIMENT

This paper used data sets come from [8] which include data "checkboard" and data "small fonts" to verify the performance of the proposed method. The proposed method experiments were run on MATLAB 2018.

To verify the performance of the proposed method, we compared it with Oreifej method. The data set comes from Tian[1], and we test both methods using the same data set.

In experiments, we find that the algorithm based on the dark channel prior theory is imperfect. Therefore, this paper attempt to deblur frames only use the guided filter which is the part of the dark channel prior theory. In the deblurring process, this step enhancement the image edge which makes to obtained sharper reference images.

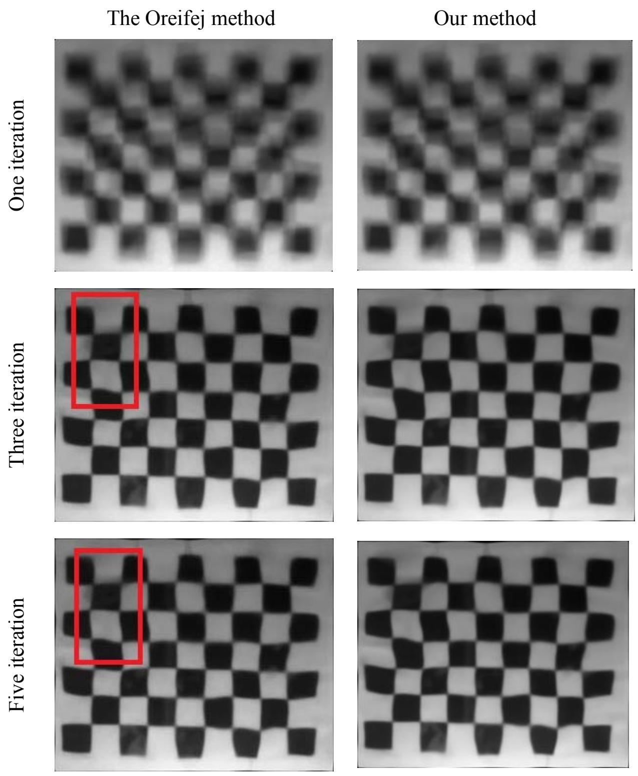

Fig. 2 The mean results of "checkboard" sequence of the two methods after different iterations of the registration process. The regions with larger distortions are marked with red rectangles.

Fig. 3 The mean results of "small fonts" sequence of the two methods after different iterations of the registration process. The regions with larger distortions are marked with red rectangles.

As we can see from Fig. 2 and Fig. 3, as the number of registration iterations increases, the two results are becoming less distorted and getting cleaner.

The severely blurry mean will impede the standard mean of frame registration. In order to solve this problem, we decide to use different way for that. We found that reconstruct a sharper and correct frame as a reference of the course will be better. The images are shifted nearer toward the reference image at every iteration. After that, the registered frames will create a preferable reference for the next step. However, the Orefej method determine to bring the images keep the same level of the mean by estimating a blur kernel, in order to guided the registration process to concentrate on the sharper regions of the mean.

The frame blurring process may introduce unexpected partial misalignments is the deficiency of the means. Since blurring the frames, some edges of the images are moved, meanwhile the edges of the mean are also indistinct. In this case, the course of registration will cannot adjust the distortions and even result in unexpected misalignments.

The sample frame and mean of each data set are shown in Fig. 4. Each data set contains 61 frames. The frame size of each sequence is 238 × 285 for "checkboard" and 255×284 for "small fonts".

Using the PSNR and SSIM can quantitatively make comparison between our method and Oreifej method in processing. A frame without distortion used as the ground-truth image required in calculating these two metrics. Since the ground-truth frames of the "checkboard" data is unusable, this paper only implemented image quality evaluation of "small fonts" sequence. The greater value of the metric means that the image clearer. The consequences of the comparison are performed in Table I. It is apparently show that our method performs come near to the Oreifej method.

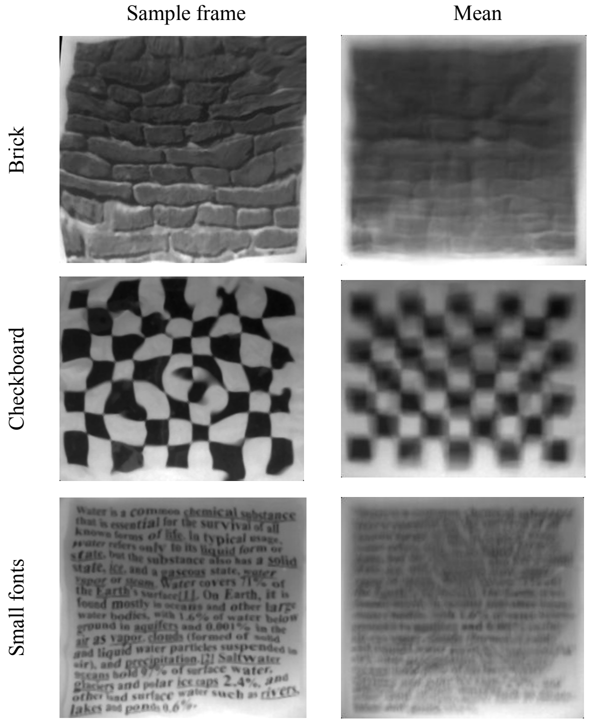

Fig. 4 Sample frame and mean of each data set.

TABLE I
COMPARISON OF IMAGE QUALITY METRICS OF "SMALL FONTS" SEQUENCE BETWEEN THE PROPOSED METHOD AND THE OREIFEJ METHOD

	Our method	Oreifej method
SSIM	0.6722	0.6572
PSNR	18.97	24.47

V. CONCLUSION

This paper mainly uses a B-spline based non-rigid registration framework to remove geometric distortions in the sequence, including overall image offset and local distortion. Some image registration-based algorithms use the average image of the sequence as the reference image. However, the average image often has very serious blur, and the outline of the image is not clear, which will reduce the accuracy of registration. To solve this problem, this paper applies the dark channel prior theory to the deblurring of the average image, we found that use guided filter, the part of the dark channel prior theory, can get the good deblurred image and then uses the deblurred image as the reference image. The experimental results show that the proposed algorithm can effectively correct the image distortion caused by turbulence.

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