An Approach of Image Decomposition for Underwater Target Detection by Inhomogeneous Illumination Based on G-Space and PDE

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***Abstract*— This paper presents a new approach of image decomposition for underwater target detection by inhomogeneous illumination based on G-Space and Partial Differential Equation(PDE). Underwater target images with high contrast visibility (less back-scattering) can be obtained within the inhomogeneous illumination field which power density is allocated inversely propotional to the rule of the light attenuation in water medium. Then the image f is decomposed into a sum of two functions $u+v$, where u component is modeled by a function of bounded variation (a cartoon or sketchy approximation of f), while v component representing the texture or noise is modeled by an oscillatory function. In this paper, the Vese-Osher(VO) model and Mumford-Shah-G(MS-G) model based on G-Space and PDE are introduced for texture image extraction. And the experimental results show that it's effective to obtain the cartoon and texture components as well as edge component of the underwater targets by MS-G model, which can be applied to further procedures such as image reconstruction and object recognition for underwater target detection.**

I. Introduction

Because of the absorption and scattering which are generated by the suspended particles during light transmission for underwater target detection, illumination is attenuated rapidly and the back-scattering induces background noise in the image while the forward-scattering yields to blurring of the image. In fact, for underwater homogeneous illumination or laser, the strong back-scattering is mainly generated at the range close to the detector, yielding low visibility. Therefore, we proposed a new approach for underwater target detection by inhomogeneous illumination, which intensity distribution relates to the attenuation pattern of light transmission with an inverse form as illustrated in Fig. 1. And it is proved effective to decrease the back-scattering within a wide field-of-view(FOV) which improves image contrast as the energy visibility is hold the same time by our pool and sea experiments. [1] [2]

Based on the theory of inhomogeneous illumination field, we build the underwater target detection system including underwater image acquisition by inhomogeneous illumination, image transmission and image processing as shown in Fig. 2. For underwater target detection, the image processing task is to extract the most meaningful information from underwater images. Therefore, we aim to decompose the underwater image into cartoon(structure) and texture, which is an important issue for further procedures such as image reconstruction as well as object recognition.

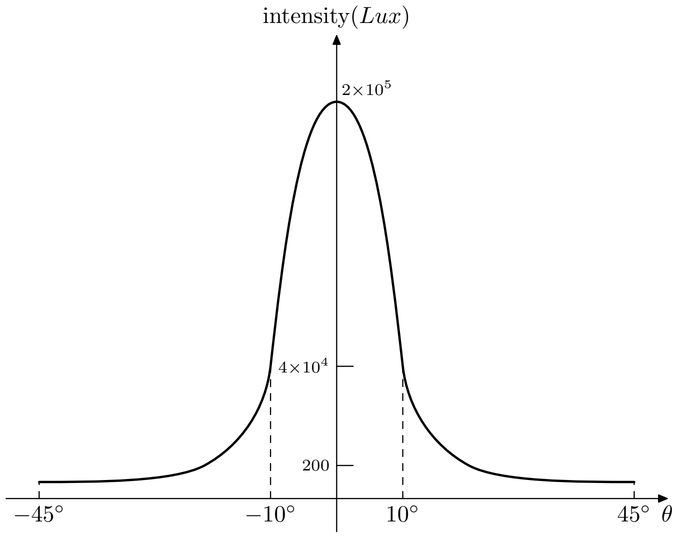

Fig. 1. The intensity distribution of light source

PDE-based decomposition is employing the total variation energy to split an original image into the structural part and textural part. [3] [4] [5] [6] [7] Given a real image f, and it is decomposed as $f=u+v$, where u component is modeled by a function of bounded variation (a cartoon or sketchy approximation of f) carrying geometric information, while v component is modeled by an oscillatory function representing the texture or noise which are characterized as repeated and meaningful structure of small patterns.

In this paper, the Vese-Osher(VO) model and Mumford-Shah-G(MS-G) model based on G-Space and PDE are introduced for texture image extraction. And the experimental results show that it's effective to obtain the cartoon and texture components as well as edge component of the underwater targets by MS-G model, which can be applied to further pro-

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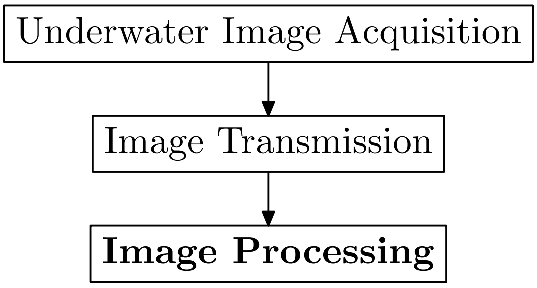


Fig. 2. Underwater target detection system

cedures such as image reconstruction and object recognition for underwater target detection.

II. Underwater Target Detection by Inhomogeneous llumination

The image quality obtained by underwater imaging system mainly depends on contrast visibility. Increasing the illumination power will result in the enlargement of the back-scattering power. Therefore increasing the energy visibility alone has little contribution to improve the image quality. Because general underwater imaging system use uniform illumination source, strong background of back scattering at short range is inevitable. We proposed a new theory of inhomogeneous illumination field which power density is allocated inversely proportional to the rule of the light attenuation in water medium and the corresponding imaging system was designed.

As illustrated in Fig. 3, a concentrated light beam illuminates the space in underwater by a reflector. A CCD detector is located at a distance S_0 to the rotating axis of the reflector, whose receiving axis is vertical to the concentrated light beam axis OO', toward the inhomogeneous illumination field with target C. We set a coordinate system (X, Y, Z) originated at C, and let Z be coincident with the detection axis MN. Y is vertical to the plane XCZ. YCX forms a detection plane whose center is coincident with light center. Because the angle brightness is in accordance with exponential decaying distribution, the intensity of illumination (illumination field E) on YCX is also in accordance with exponential decaying distribution along X and Y. There will be a small-angle high density illumination power at large distance. Detection axis MN intersects with beam at short distance D where the density power is low at a large angle of the concentrated light beam. Therefore the illumination field E varies along Z axis according to exponential decaying distribution. Within such inhomogeneous illumination field, the back-scattering light is weak at short range because of the low power density of illumination, while the high power density occurs at large range, but the scattering light will be attenuated during the transmission and become too weak to be detected by the receiver. The sensing scheme is indenpendent to view angle and depth of field.

Within such an inhomogeneous illumination pattern, the contrast visibility is improved so that a normal receiver can work in a broad dynamic scale and the energy visibility is

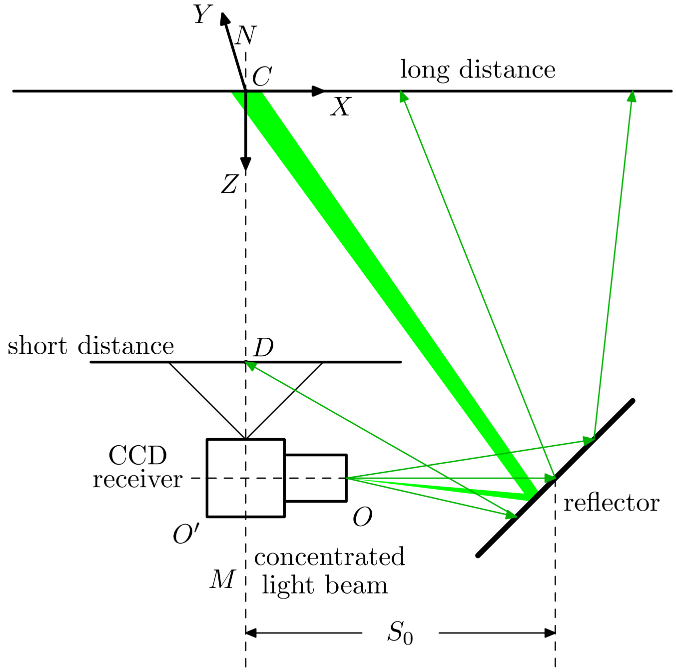


Fig. 3. Underwater target detection by inhomogeneous illumination

improved so that good image quality is got at near distance. The working range of the system can be up to the level of watts-scale laser scanning imaging system.

III. G-Space and PDE Theory

A. The spaces BV and G

The Banach space BV, also known as the space of functions with bounded variation in mathematical analysis, plays an important role in image processing because such functions are allowed to have discontinuities and hence keep edges. It can be defined as: [8]

Definition 1: Assumed $u \in L^1$, and the total variation of u is

$$TV(u) := \sup \left\{ \int u \ \mathrm{div}(\vec{g}) : \begin{array}{l} \vec{g} \in C_0^1(\mathbb{R}^n; \mathbb{R}^n), \\ |\vec{g}(x)| \leqslant 1 \text{ for all } x \in \mathbb{R}^n \end{array} \right\} \tag{1}$$

where $|\cdot|$ denotes the Euclidean norm. Also, $u \in BV$ if $\|u\|_{BV} := \|u\|_{L^1} + TV(u) < \infty$. In equation (1), $\vec{g} \in C_0^1(\mathbb{R}^n; \mathbb{R}^n)$, the set of continuously differentiable vector-valued functions, serves as a test set for u. If u is in the Sobolev spaces $W^{1,1}$ or H^1, it follows from integration by parts that $TV(u)$ is equal to $\int |\nabla u|$, where ∇u is the weak derivative of u. However, the use of test functions to define $TV(u)$ allows u to have discontinuities. Therefore, BV is larger than $W^{1,1}$ and H^1. Equipped with the $\|\cdot\|_{BV}$-norm, BV is a Banach space.

$BV(\Omega)$ with Ω being a bounded open domain is defined analogously to BV with L^1 and $C_0^1(\mathbb{R}^n; \mathbb{R}^n)$ replaced by $L^1(\Omega)$ and $C_0^1(\Omega; \mathbb{R}^n)$, respectively.

Definition 2: Let G denote the Banach space consisting of all generalized functions $v(x, y)$ defined on $\mathbb{R}^n$, which can be written as

$$v(x,y) = \partial_x g_1(x,y) + \partial_y g_2(x,y) \quad g_1, g_2 \in L^\infty(\mathbb{R}^n; \mathbb{R}^n) \tag{2}$$

Its norm $\|v\|_G$ is defined as the infimum of all L^∞ norms of the function $|\vec{g}|$ over all decompositions (2) of f, where $|\vec{g}(x,y)| = \sqrt{g_1^2(x,y) + g_2^2(x,y)}$. [9] G is the dual of the closed subspace $\mathcal{BV}$ of BV, where $\mathcal{BV} := (|\nabla f| \in L^1)$.

An immediate result of the above definitions is that

$$\int uv = \int u\nabla \cdot \vec{g} = -\int \nabla u \cdot \vec{g} \leqslant TV(u)\|v\|_G \tag{3}$$

holds for any $u \in \mathcal{BV}$ with compact support and $v \in G$. And it shows that (u,v) is an extremal pair if (3) holds with equality.

The use of the space BV and the total variation seminorm in image processing goes back to ROF model [4] for removing noise from images. Among the TV(Total Variation)-based cartoon-texture decomposition models, the VO model based on G-Space is typical and classic.

B. Veso-Osher model

Motivated by the definition of spaces BV and G, Vese and Osher proposed the following texture model: [5]

$$\inf_{u,g_1,g_2} \left\{ G_p(u,g_1,g_2) = \int |\nabla u| + \lambda \int |f - u - \partial_x g_1 - \partial_y g_2|^2 \, dxdy + \mu \left[\int \left(\sqrt{g_1^2 + g_2^2} \right)^p dxdy \right]^{\frac{1}{p}} \right\} \tag{4}$$

where $\lambda, \mu > 0$ are weight parameters, and $p \to \infty$. The first term of (4) is a regularizing term to remove noise or small details; the second term in the energy is a fidelity term which can keep important features and sharp edges. Moreover, here $\vec{g} = (g_1, g_2)$, $|\vec{g}(x,y)| = \sqrt{g_1^2(x,y) + g_2^2(x,y)}$, and g contains the texture component of the real image (including noises).

In $\mathbb{R}^2$ minimizing Veso-Osher ($p = 1$) with respect to u, $\vec{g} = (g_1, g_2)$ yields the associated Euler-Lagrange equations:

$$u = f - \partial g_1 - \partial g_2 + \frac{1}{2\lambda} \text{div} \left(\frac{\nabla u}{|\nabla u|} \right) \tag{5}$$

$$\mu \left(\left\| \sqrt{g_1^2 + g_2^2} \right\|_p \right)^{1-p} \left(\sqrt{g_1^2 + g_2^2} \right)^{p-2} g_1 = 2\lambda \left[\frac{\partial}{\partial x}(u - f) + \partial_{xx}^2 g_1 + \partial_{xy}^2 g_2 \right] \tag{6}$$

$$\mu \left(\left\| \sqrt{g_1^2 + g_2^2} \right\|_p \right)^{1-p} \left(\sqrt{g_1^2 + g_2^2} \right)^{p-2} g_2 = 2\lambda \left[\frac{\partial}{\partial y}(u - f) + \partial_{xy}^2 g_1 + \partial_{yy}^2 g_2 \right] \tag{7}$$

And it is proved that different values of positive parameter p have little effect on the result. [5] Therefore, considering the computing complexity, we let $p = 1$.

C. Mumford-Shah-G model

Mumford-Shah-G(MS-G) model is presented [3] [7] for eliminating the staircase effect induced by VO model which makes non-edge not smooth in the image. The MS-G model combines the Mumford-Shah model describing the cartoon component by piecewise smooth functions and G space describing the texture component by oscillating functions. The minimizing energy formation of MS-G model is:

$$\begin{aligned} G_p(u,w,g_1,g_2) = &\alpha \int_\Omega (1-w)^2 |\nabla u|^2 \, dxdy \\ &+ \lambda \int_\Omega |f - u - \partial_x g_1 - \partial_y g_2|^2 \, dxdy \\ &+ \mu \left[\int_\Omega \left(\sqrt{g_1^2 + g_2^2} \right)^p dxdy \right]^{\frac{1}{p}} \\ &+ \int_\Omega \left[\frac{\rho}{2} |\nabla w|^2 + \frac{w^2}{2\rho} \right] dxdy \end{aligned} \tag{8}$$

where u and g is described the same as that in VO model, and w is described as the edge function of the image. $w(x,y) \approx 0$ denotes that (x,y) is not the edge point while $w(x,y) \approx 1$ denotes that (x,y) is the edge point. The first term of (8) is the smoothing constraint for cartoon(structure) components of non-edge points; the second term is the data dependence which needs the decomposition error small enough; the third term is the oscillating constraint of texture components which needs the norm of obtained texture parts small enough in the G space; and the last term needs the edge simple enough and the edge function closes to 0 or 1 as far as possible.

It is solved by variational method to get the Euler-Lagrange equations as follows:

$$f - u = \partial_x g_1 + \partial_y g_2 - \frac{\alpha \nabla \left[(1-\omega)^2 \nabla u \right]}{\lambda} \tag{9}$$

$$\mu \frac{g_1}{\sqrt{g_1^2 + g_2^2}} = 2\lambda \left[\frac{\partial(u-f)}{\partial x} + \partial_{xx}^2 g_1 + \partial_{xy}^2 g_2 \right] \tag{10}$$

$$\mu \frac{g_2}{\sqrt{g_1^2 + g_2^2}} = 2\lambda \left[\frac{\partial(u-f)}{\partial y} + \partial_{xy}^2 g_1 + \partial_{yy}^2 g_2 \right] \tag{11}$$

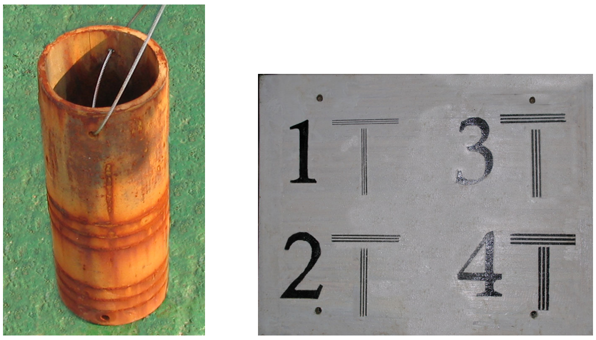
$$\alpha |\nabla u|^2 = \left(\alpha \left| \nabla u^2 + \frac{1}{2\rho} \right| \right) \omega - \frac{\rho}{2} \nabla^2 \omega \tag{12}$$

Since M-S model explicitly describes the cartoon component as piecewise smooth functions and applies L^2 norm to constraint the gradients of non-edge pixels, it can avoid the staircase effect. Furthermore, the oscillating characteristics of texture functions defined by G space ensure that the resultant cartoon component contains less texture information.

IV. Experimental Results

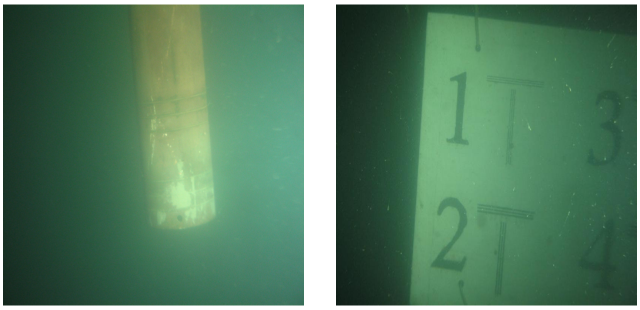
For underwater target detection by inhomogeneous illumination, we use iron pipe and scale board as targets in the sea, which are shown in Fig. 4.

We put them into the sea and detect them by our imaging system based on the theory of inhomogeneous illumination



(a) Iron pipe (b) Scale board

Fig. 4. Underwater targets



(a) Iron pipe (b) Scale board

Fig. 5. Underwater target images

field. After the underwater image acquisition and image transmission illustrated in Fig. 2, we got the target images as Fig. 5.

Then we use VO model and MS-G model to decompose Fig. 5(a) and Fig. 5(b) respectively, and the results are shown in Fig. 6 and Fig. 7.

For iron pipe in the sea shown in Fig. 5(a), we can see the corrosion and $1mm$ wide-scale ring more clearly from MS-G texture image Fig. 6(f). And about the scale board in the sea shown in Fig. 5(b), we can get more detailed scale information from MS-G texture image Fig. 7(f). Besides, we also obtain the contour of the targets by Fig. 6(d) and Fig. 7(d).

V. Conclusion

In this paper we propose a novel method of image decomposition for underwater target detection by inhomogeneous illumination based on G-Space and Partial Differential Equation(PDE). We use M-S model to describe the cartoon component as piecewise smooth functions and applies L^2 norm to constraint the gradients of non-edge pixels, and the oscillating characteristics of texture functions defined by G space to ensure that the resultant cartoon component contains less texture information. The experimental results also show that it's effective to obtain the cartoon and texture components as well as edge component of the underwater targets by MS-G model, which can be applied to further procedures such as image reconstruction and object recognition for underwater target detection.

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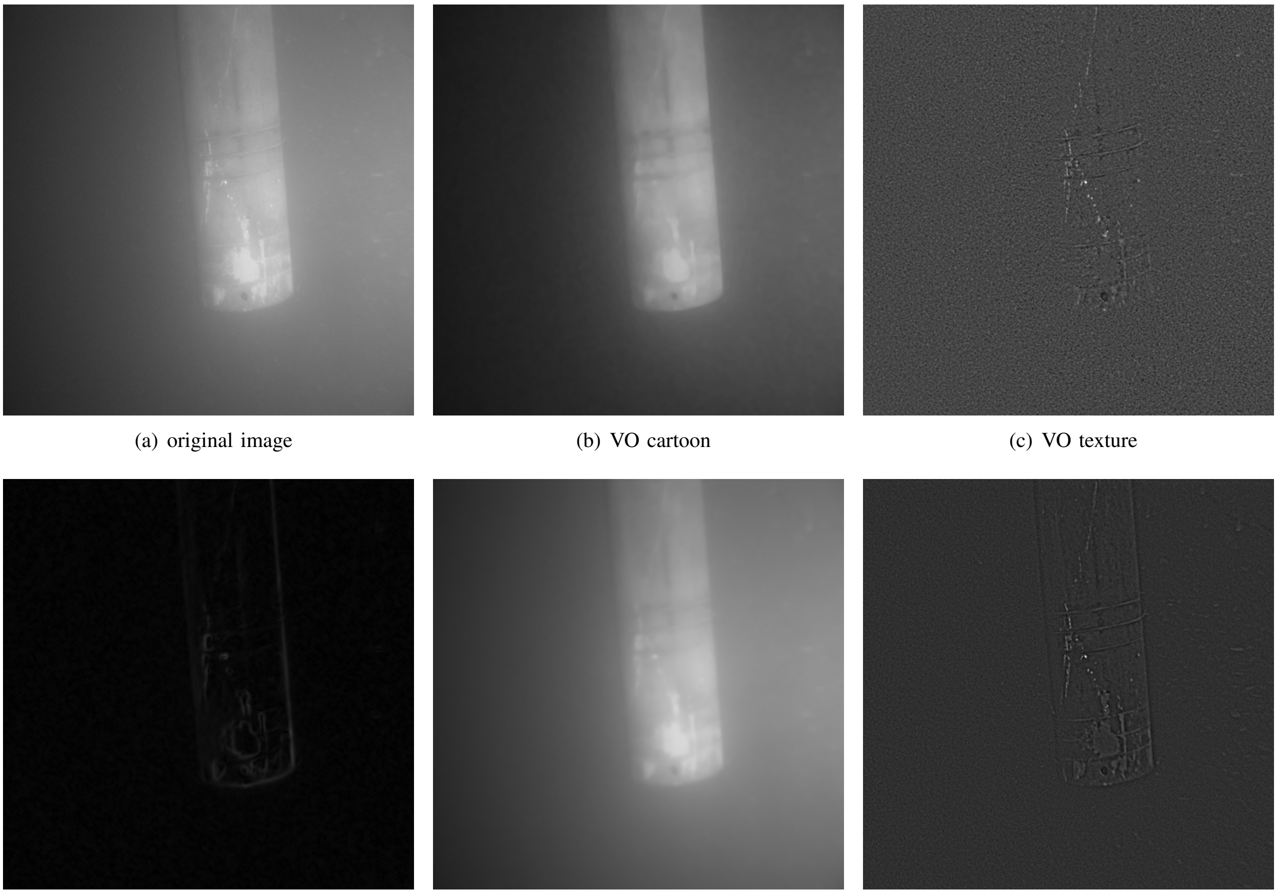
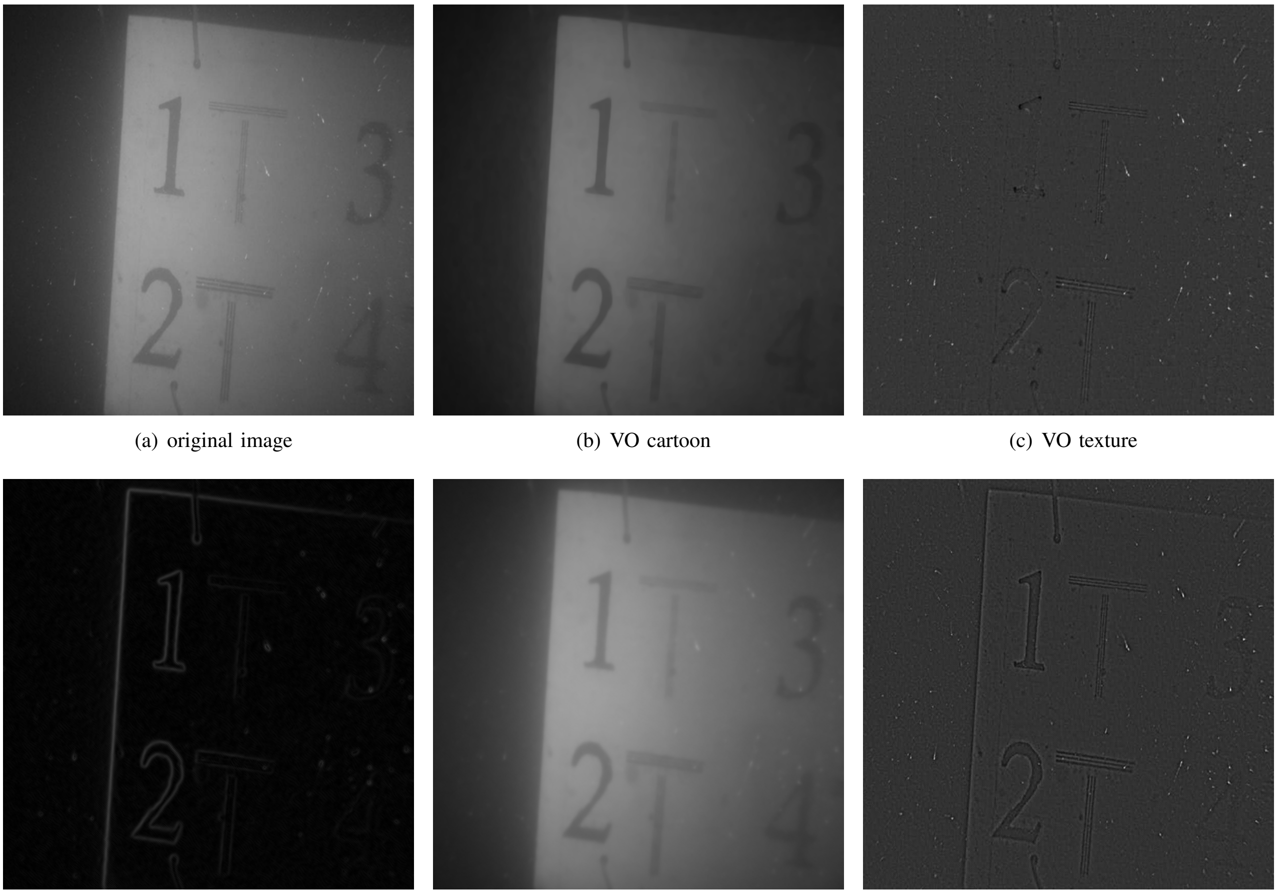


(a) original image (b) VO cartoon (c) VO texture

(d) MS-G edge (e) MS-G cartoon (f) MS-G texture

Fig. 6. Iron pipe



(a) original image (b) VO cartoon (c) VO texture

(d) MS-G edge (e) MS-G cartoon (f) MS-G texture

Fig. 7. Scale board