Three-Dimensional Lidar Total Variation Denoising

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ABSTRACT
New imaging capabilities have given rise to higher dimensional image processing. This paper presents a generalization of total variation (TV) based denoising with specific application to three-dimensional flash lidar imagery. The generalization uses a weighted norm, rather than the standard Euclidian measure, that accounts for sampling differences that may exist along different axes. We compare this new method against successive two-dimensional denoising and standard three-dimensional TV denoising.

1. INTRODUCTION

Flash lidar 3-D cameras are cameras that produce range delimited imagery using a single illuminating laser pulse\(^1\). The light reflected from a certain distance is captured in a plane. High speed timing collects the planes in fast succession. Together, the planes form a three-dimensional image.

These cameras represent one of the latest advances in imaging technology. They offer advantages of small size, low weight, high speed, and near perfect plane-to-plane registration. These advantages arise primarily because each laser pulse generates an entire three-dimensional frame of data, rather than one range image for each laser pulse. This avoids the problems usually associated with other systems\(^2\).

Flash lidar cameras operate and appear very much like these conventional 2-D digital cameras only with smart pixels substituted for simple signal integrators; each pixel can accurately and independently count time to the target. A broad area, short laser pulse replaces the flash of the 2-D camera.

The outgoing laser pulse is reflected from an object and its return focused on the focal plane. The time between the laser pulse and the return is proportional to the range via the velocity of light. The range sample distance (RSD) refers to the depth covered by each plane, expressed in ground units. Similarly, the GSD refers to the horizontal area covered by a pixel in the image.

The RSD is a function of the speed of the camera. The GSD is a function of pitch (pixel spacing), among other factors. It is easier to obtain high GSD through close pixel spacing than speeding up the camera electronics. As a consequence, the voxels are anisotropic. A similar situation applies to CT and some MRI images\(^3\).

The imagery presented in this paper was collected to demonstrate through-water target detection. The camera and laser illuminator were suspended several meters above a test tank. The camera delay was adjusted so that each image contained the water surface and the depth levels extended to the bottom of the tank. The aim of this test setup is to provide for investigation of airborne lidar processing in a controlled environment. The eventual application of this system will be for near surface and underwater object detection similar to other oceanic applications\(^4,5\).

Several objects were placed in the tank. They included a staircase, and medium height elevated sphere, a short elevation sphere, and objects with various shapes placed on the bottom. Figure 1 shows the three-dimensional image cube and the same cube with the water set to black.
The data can also be viewed as a sequence of two dimensional \( xy \)-planes. Figure 2 shows several intermittent planes of an image sequence. The plane “a” depicts objects closer to the camera and “b”, “c”, and “d” are successively farther. Plane “a” is the first visible depiction of an elevated sphere. In the prior plane, shown in Figure 6, the sphere is not visible, but is numerically detectable. The remaining figures depict a staircase on the left and then several objects on the bottom.
While the technologies for acquiring these three-dimensional images continue to improve, resulting in images of higher and higher resolution and quality, noise remains an issue. Removing noise remains one of the major challenges in the study of new imaging technologies. Figure 3 shows a close up of a depth plane in the water column, well away from the surface, the bottom and any targets.

![Figure 3: Close-up showing intra-plane variation.](image)

Noise presents a problem because it could mask and blur important, but subtle features. Many denoising techniques reduce feature boundary definition. This reduces the ability of algorithms to determine important identification features, such as curvature. The goal of Total Variation based denoising is to obtain a smooth image which remains close the observed image. One of the first applications of Total Variation to noise removal was given in. Among all the PDE based techniques, the TV minimization scheme is a candidate that offers the best combination of noise removal and feature preservation.

Total Variation denoising is reviewed in the following section. Section 3 presents three extensions of TV denoising to three-dimensions. The last model in that section is a generalization which can account for differences in x, y, and z dimensions. The discussion of the generalization demonstrates which parameter selection is most appropriate for this system. Section 4 shows the results for all of the extensions.

2. DENOISING

Two standard techniques for finding edges and denoising incorporate first and second order partial differential equations. These PDEs are sensitive to both edges and noise variations. The denoising problem can be approached by solving these PDEs as a constrained minimization problem. The constraints balance feature preservation and noise removal.

Consider the equation model $u_0 = u + \eta$, where $u_0$ is the observed image, $u$ is an uncorrupted image and $\eta$ is additive noise. The objective is to find a reasonable approximation to $u$, which hopefully will offer better object recognition. Underlying the following PDE approach is the assumption that $u$ is a smooth image.

A first order PDE that can be used for denoising is the norm of the gradient. The magnitude of the gradient is given by $|\nabla u|$, where $|\cdot|$ is the standard Euclidian norm. This is often called the total variation of the function $u$. The minimization is written

$$\min \int |\nabla u|$$

The integral is taken over the domain of definition and the minimization is subject to some constraints. Constraints are discussed in the next subsection.

The second derivative is implemented using the Laplacian, $\Delta u$. Constrained least squares restoration uses the Laplacian. The minimization can be written using the Laplace equation with
\[
\min \int |\Delta u|
\]

Again, the integral is taken over the domain of definition and the minimization is subject to some constraints.

As a second derivative operator, the Laplacian is more sensitive to intensity changes than the gradient. It also produces double edges at boundaries as can be seen in Figure 4. The figure was produced using simple numerical implementation of the second derivative which is

\[
\frac{\partial^2}{\partial x^2} u = u(x+1) - 2u(x) + u(x-1)
\]

Figure 4: Laplacian of an edge.

If the norm of the gradient and the Laplacian are subject to identical constraints, then minimizing the Laplacian suppresses both noise and edges more than the gradient. Constraints are discussed in the next section.

2.1. Constraints

In least squares restoration, the constraints can be on the mean and standard deviation of the noise. For example, if the noise has zero mean then \( \int u = \int u_0 \) and if the standard deviation, \( \sigma^2 \), is known then \( \int (u - u_0)^2 = \sigma^2 \). In the present case, the characteristics of the noise are unknown. Therefore, a different constraint is selected. We chose a fitting tolerance parameter, \( \gamma \), to limit the deviation of the solution from the observed image. Our constraints have the form \( \| u - u_0 \| \leq \gamma \), where \( \| \cdot \| \) is the standard \( L^2 \) norm.

3. EXTENTION TO 3 DIMENSIONS

Three dimensional imaging methods lend themselves to a variety of processing techniques. We investigate three models for extension to three dimensions.
• The first model is the application of two-dimensional denoising to each plane using a global threshold.
• The second is the natural extension, using the three dimensional definition of gradient.
• The third model uses a weighted norm to place the proper emphasis on the z connections.

Based on the equation $u_0 = u + \eta$, we further denote the image $u$ and $u_0$ are sequences of planes, $u = \{z_k\}_{k=1}^K$ and $u_0 = \{z_{0,k}\}_{k=1}^K$. $K$ is the total number of planes.

### 3.1. Individual Plane Model

The initial model is to operate on each plane completely separately.

$$\min \int_{\mathbb{R}^3} |\nabla z_k| \ dx \ dy \ , \ \text{subject to} \ \|z_k - z_{0,k}\| \leq \gamma_k, k = 1,2,\ldots, K . \quad (2)$$

where $\gamma_k$ is a fitting tolerance parameter to limit the deviation of $z_k$ from $z_{0,k}$. Since there is no a priori information on plane differences and for general simplicity we set all $\gamma_k, k = 1,2,\ldots, K$ to be identical. The corresponding unconstrained minimization equation is

$$\min z_k F(z_k, z_{0,k}) = \int_{\mathbb{R}^3} |\nabla z_k| \ dx \ dy + \frac{1}{2} \lambda \|z_k - z_{0,k}\|^2 \quad (3)$$

Where $\lambda$ is the Lagrange multiplier.

### 3.2. Standard 3-D Model

The natural extension of two dimensional techniques to $\mathbb{R}^3$ uses a gradient magnitude of

$$|\nabla u| = \sqrt{\left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 + \left(\frac{\partial u}{\partial z}\right)^2} \quad (4)$$

The minimization equation is

$$\min \int_{\mathbb{R}^3} |\nabla u| \ dx \ dy \ dz , \ \text{subject to} \ \|u - u_0\| \leq \gamma . \quad (5)$$

This model can be translated into an unconstrained minimization problem stated as:

$$\min_u F(u, u_0) = \int_{\mathbb{R}^3} |\nabla u| \ dx \ dy \ dz + \frac{1}{2} \lambda \|u - u_0\|^2 . \quad (6)$$
3.3. Weighted 3-D Model

We now discuss a generalization of Standard 3-D Model. In this imagery, there can be a significant difference between the ground sample distance (GSD) and range sample distance (RSD). The GSD changes depending on the distance between an object and the camera, the RSD does not. The RSD is technologically determined by the sample speed of the system. The geometry of this test provided a GSD that is much finer than the RSD. In other words, $\Delta z$ is larger than $\Delta x$ and $\Delta y$. This would naturally suggest that $\frac{\partial u}{\partial x}$ and $\frac{\partial u}{\partial y}$ are more reliable than $\frac{\partial u}{\partial z}$.

However, the camera’s electronic structure implies the different consideration. Since each pixel independently counts time to the target, peaks in $\frac{\partial u}{\partial x}$ and $\frac{\partial u}{\partial y}$ could be based on the bias of independent pixels or on scene differences. However, peaks in $\frac{\partial u}{\partial z}$ may be more of a measure of noise. In the imagery, all the values $(x, y, z)$, $i = 1, 2, \ldots$, are obtained by a single pixel. Therefore, the bias should remain constant. This is similar to the theory behind using multiple images of a static scene to improve SNR \([7]\).

Both considerations can be addressed by using a weighting function. Let the weight function be given by $g(x, y, z) = [A^{\frac{1}{2}} x, B^{\frac{1}{2}} y, C^{\frac{1}{2}} z]$. So that

\[
g(\nabla u) = \left[ A^{\frac{1}{2}} \left( \frac{\partial u}{\partial x} \right), B^{\frac{1}{2}} \left( \frac{\partial u}{\partial y} \right), C^{\frac{1}{2}} \left( \frac{\partial u}{\partial z} \right) \right] \tag{7}
\]

and

\[
\left| g(\nabla u) \right| = \sqrt{A \left( \frac{\partial u}{\partial x} \right)^2 + B \left( \frac{\partial u}{\partial y} \right)^2 + C \left( \frac{\partial u}{\partial z} \right)^2} \tag{8}
\]

The minimization equation is

\[
\min \int_{\mathbb{R}^3} |g(\nabla u)| \, dx \, dy \, dz, \text{ subject to } \|u - u_0\| \leq \gamma, \tag{9}
\]

Equation (9) translates to

\[
\min_u F(u, u_0) = \int_{\mathbb{R}^3} |g(\nabla u)| \, dx \, dy \, dz + \frac{1}{2} \lambda \|u - u_0\|^2 \tag{10}
\]

Since $\Delta z$ is larger than $\Delta x$ and $\Delta y$ perhaps the smoothness assumption may be more safely enforced on $\frac{\partial u}{\partial x}$ and $\frac{\partial u}{\partial y}$ by weighting them more than $\frac{\partial u}{\partial z}$. However, if there is less noise in the $z$ direction, then it is safer to enforce smoothness on $\frac{\partial u}{\partial z}$ and it should have a higher weight.
The question can be answered by comparing column, row, and depth vector correlation matrices. If there is a high correlation among the column or row vectors, then they are dominated by true information (recall that they are electronically independent) and so smoothness can safely be more strongly enforced on $\frac{\partial u}{\partial x}$ and $\frac{\partial u}{\partial y}$. On the other hand, if the correlation is higher for depth vectors, then $\frac{\partial u}{\partial z}$ should have the most weight.

We selected rows, columns and depth vectors with no targets so that the imagery should be been fairly locally consistent. The following tables show a few column, row and depth vector correlations. The results presented are consistent across all the local areas in the data. Table 1 and 2 show the correlation coefficients for several columns and rows from a plane without targets.

Table 1: Column Correlation Coefficients

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<th>COL68</th>
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Table 2: Row Correlation Coefficients

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Table 3 shows the correlation for several depth vectors.

Table 3: Depth Correlation Coefficients

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<th>PIXEL17</th>
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<td>.99</td>
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</tr>
</tbody>
</table>
These tables clearly show that the correlation is much stronger for depths, with near perfect correlation between neighboring pixels. So, the weighted norm will enforce more smoothness on \( \frac{\partial u}{\partial z} \). The exact choice is subjective, however the data justify \( C > A, B \).

### 3.4. Numerical schemes

To solve the models, we will derive their Euler-Lagrange equations and use the gradient descent strategy to find the minimizers. The Euler-Lagrange equations are the PDE’s satisfied by the minimizers of the variational models.

For the Individual Plane Model the minimizer \( \hat{z}_k \) must satisfy

\[
\frac{\partial F(z_k, z_{0,k})}{\partial z_k} \bigg|_{z_k = \hat{z}_k} = 0
\]

(11)

For the Standard 3-D Model and the Weighted 3-D Model, the minimizer \( \hat{u} \) must satisfy

\[
\frac{\partial F(u, u_0)}{\partial u} \bigg|_{u = \hat{u}} = 0
\]

(12)

By calculus of variations, we have for the Individual Plane Model:

\[
\frac{\partial F(z_k, z_{0,k})}{\partial z_k} = -\nabla \cdot \left( \frac{\nabla z_k}{|\nabla z_k|} \right) + \lambda (z_k - z_{0,k}),
\]

(13)

The Standard 3-D Model results in:

\[
\frac{\partial F(u, u_0)}{\partial u} = -\nabla \cdot \left( \frac{\nabla u}{|\nabla u|} \right) + \lambda (u - u_0)
\]

(14)

and for the Weighted 3-D Model:
\[
\frac{\partial F(u, u_0)}{\partial u} = -\nabla \left( \frac{g(\nabla u)}{|g(\nabla u)|} \right) + \lambda (u - u_0).
\] (15)

There are many different ways to solve for the minimizers, such as prime-dual method, fixed-point method and so forth. Among them, the following described time marching scheme is the simplest strategy based on gradient descent. To realize it for equation on (13), we introduce an artificial time for the plane \( z_k(t, x, y) \) with initial condition \( z_k(0, x, y) = z_k(x, y) \). The plane \( z_k(t, x, y) \) satisfies the following time evolution equation,

\[
\frac{dz_k(t, x, y)}{dt} = -\frac{\partial F(z_k, z_{k,0})}{\partial z_k}
= \nabla \left( \frac{\nabla z_k}{|\nabla z_k|} \right) - \lambda (z_k - z_{k,0}).
\]

It is obvious that \( z_k(t, x, y) \) converges to \( \hat{z}_k(x, y) \) as \( t \to \infty \). In other words, when \( z_k(t, x, y) \) tends to its steady state, which corresponds \( \frac{dz_k(t, x, y)}{dt} = 0 \), the plane \( z_k(t, x, y) \) satisfies the Euler-Lagrange equation defined in (13).

The schemes based on (14), and (15) are

\[
\frac{du(t, x, y, z)}{dt} = -\frac{\partial F(u, u_0)}{\partial u}
= \nabla \left( \frac{\nabla u}{|\nabla u|} \right) - \lambda (u - u_0)
\]

And

\[
\frac{du(t, x, y, z)}{dt} = -\frac{\partial F(u, u_0)}{\partial u}
= \nabla \left( \frac{g(\nabla u)}{|g(\nabla u)|} \right) - \lambda (u - u_0)
\]

respectively.

The first part of each of these equations resembles the basic isotropic (linear) diffusion, \( \nabla \cdot (k \nabla u) \), where \( k \) is a constant known as the diffusion coefficient. When \( k \) is a function that depends on location, the equation becomes anisotropic. In equation (14), \( k = 1/|\nabla u| \) and in equation (15), \( k = 1/|g(\nabla u)| \).

The numerical schemes will be based on (13), (14), and (15). To simplify the formulation for the numerical schemes, we use the standard forward and backward divided finite difference operators. To fin-
ish the computation, we also need to specify the boundary conditions. Here we can simply use the Neumann boundary conditions, which just set the derivative at the boundary to be zero.

4. RESULTS

In this through-water target detection application, water obscures the targets. Several different images are shown to demonstrate the effectiveness of the denoising algorithms. The demonstration uses three views. First, there is a look through the water. To do this a threshold is selected for water transparency. All pixels below the threshold will be set to transparent. The better the denoising, the more uniform the water. Therefore, a global threshold should work better. Being able to better select these types of thresholds is often the subject of current research [10] [11].

The second view is of the suspended sphere. The suspended sphere gives an indication of how object can be seen across different depths. The third view is of a bottom object. This object has a low contrast with the bottom and can only be seen in one plane. This view tests single plane effects.

4.1. Original

With the water pixels set to be transparent, Figure 5 shows the view from the top of the original image. One of noticeable noise artifact is horizontal (to this view) stripping.

![Figure 5: Original Image viewed from the top with water pixels transparent.](image)

There is a slight numerical indication of the sphere in the original plane 26, but it is not visually recognizable. It is shown in Figure 6. This plane best demonstrates the primary difference between the models.
Figure 6: Original plane above the suspended sphere.

Figure 7 shows bottom objects. The low contrast object is in the middle on the right side. Multi-plane denoising may adversely affect this object since it is only visible in one plane.

Figure 7: Original plane near the bottom.

4.2. Individual Plane Model
Denoising the plane individually produces very little difference when looking through the water at the bottom. Figure 8 is nearly identical to the original shown in Figure 5.

Figure 8: Individual denoising model through the water image.

The slight numerical indication of the sphere that was in the original plane 26 has been completely eliminated. Figure 9 shows an almost area where the sphere used to be.
Figure 9: Individual denoising model plane above the suspended sphere

Figure 10 shows a slight blurring of the low contrast bottom object. This is expected from any denoising algorithm and the object remains fairly well defined.

Figure 10: Individual denoising model frame near the bottom.

Compared to the original cube shown in Figure 1, the individual approach improves the plane sharpness. The layers are more slightly more distinguished in Figure 11 than in Figure 1.

Figure 11: Individual denoising model image cube.
4.3. Standard 3-D Model

The striping that remained in the individual method has been reduced in the through water view in Figure 12.

![Figure 12: Three-dimensional denoising model through the water image.](image)

In Figure 13 we see that in this model the sphere starts to become visually detectable in plane 26.

![Figure 13: Three-dimensional denoising model plane above the suspended sphere.](image)

The low contrast bottom object is slightly more blurred than in the individual approach. However, it is still easily visible.

![Figure 14: Three-dimensional denoising model plane near the bottom.](image)
The cube view in Figure 15 shows that the planes have a smoother transition that both than the individual method or the original image.

![Figure 15: Three-dimensional denoising model image cube](image)

4.4. Weighted 3-D Model

The weights used for this imagery were $A = 1$, $B = 1$, and $C = 2$. The weighted approach produced Figure 16. It is nearly identical to the original shown in Figure 12.

![Figure 16: Weighted three-dimensional denoising model through water image.](image)

In Figure 17 the sphere that was not visible in the original is now clearly discernable. In addition, the staircase on the left is becoming visible.
Figure 17: Weighted three-dimensional denoising model plane above the suspended sphere.

Figure 18 shows a slight blurring of the low contrast bottom object. This is expected from any denoising algorithm and the object remains fairly well defined.

Figure 18: Weighted three-dimensional denoising model plane near the bottom.

Again, as in Figure 15, Figure 19 demonstrates that the weighting produces a smoother transition between the planes.
5. CONCLUSION

New three-dimensional imaging technology provided by flash lidar cameras presents an opportunity to design algorithms that exploit their unique imagery features. The total variation generalization that has been presented can be used to account for non-cubic voxels in a variety of systems. The experimental results of this flash lidar camera led to placing a larger weight on the depths than on the horizontal axes. The final images show that denoising with these weights presents much better object recognition for multi-plane objects and it does not blur single plane object beyond that of the individual plane method.

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