GRAY-SCALE RESOLUTION ENHANCEMENT

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Abstract - The number of bits assigned to represent the color intensity at image pixels is usually referred as the bit depth. When the bit depth is not sufficient, images suffer from ridge-like structures known as *false contours*. Bit-depth limitations become important when low-contrast details are required, as in medical imaging, aerial/satellite photography, and high-quality scanning applications. In this paper, we investigate a method for increasing bit depth. Specifically, we show that when a sequence of video frames is available, then it is possible to achieve a higher bit depth through a projections onto convex sets (POCS) based reconstruction method.

INTRODUCTION

When images are digitized, a certain number of bits is assigned to each pixel to represent its intensity. The number of bits, the *bit depth*, determines the number of gray levels between the minimum and maximum intensities that the imaging device can capture. There will be a loss of gray-scale resolution if the bit depth is not sufficient. When a set of low bit-depth images is available that are slightly different from each other because of motion or illumination, their non-redundant information can be combined to enhance the gray-scale resolution. We refer to this process of multi-frame gray-scale resolution enhancement as *superprecision.*

Superprecision can be used in several application areas. One of the most important of these is medical imaging. In medical imaging low-contrast details are often extremely critical for diagnosis, but when the bit depth is insufficient, these details may be lost. Superprecision reconstruction has the potential to regain these details by combining the non-redundant information that is present in a set of images. Military automatic target detection, aerial and satellite remote sensing, and high-quality scanning applications can also make effective use of superprecision reconstruction to enhance gray-scale resolution. The conversion of images from a low bit-depth format to a higher one (e.g., conversion from 8-bit GIF to 24-bit JPEG) is also a potential application of this technology.

The superprecision problem is similar to the superresolution problem where higher spatial resolution is sought from a set of low spatial resolution images [1]. Although the superresolution has received a significant amount of attention, the superprecision has not been researched sufficiently. In an early paper, Cheeseman *et al.* [2] proposed to increase the spatial and gray-scale resolution at the same time by using a Maximum *A Posteriori* probability approach. They assumed a Gaussian model for all

This work was supported by the Office of Naval Research (ONR) under the award N000140110619.

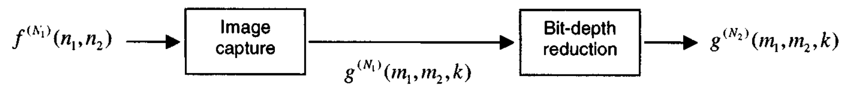

Figure 1: The model

distributions, and used Jacobi's method to solve the problem iteratively. In this paper, we propose a deterministic method based on Projections Onto Convex Sets (POCS) technique. In this method, an initial high-resolution image estimate is projected onto constraint sets that are obtained from low gray-scale image observations.

The next section presents the imaging model to be used in the reconstruction. POCS-based superprecision algorithm, experimental results, and conclusions are given in the following sections.

IMAGING MODEL

As seen in Figure 1, the model has two sub-blocks. The first sub-block models image capture process. A high-resolution image, $f^{(N_1)}(n_1, n_2)$, is captured by an imaging device to result in the low-spatial-resolution images, $g^{(N_1)}(m_1, m_2, k)$. The superscript N_1 represents the number of bits used in each pixel. (n_1, n_2) and (m_1, m_2, k) are the spatial pixel coordinates of the high-resolution image and the k^{th} low-resolution image, respectively. Image capture process is a linear shift varying (LSV) process that includes motion (of the camera or the objects in the scene), blur (because of nonzero sensor aperture time, nonzero physical dimensions of the individual sensor elements, out-of-focus, etc.), and sampling with a low-resolution grid [3]. In this paper, we model all these effects except for the sensor aperture time, which is taken to be zero. According to this model, the mapping from high-resolution image to low-spatial-resolution image is computed as a weighted sum of the high-resolution image pixels, where the weights are the values of a space-invariant Point Spread Function (PSF) at the corresponding pixel locations. The center of the PSF is determined by the motion between the high-resolution image and the low-spatial-resolution images. This is depicted in Figure 2. Motion vectors from each low-spatial-resolution image to the high-resolution image determine where each pixel comes from. The normalized PSF that characterizes the camera is centered at that location, and the weights at the high-resolution image grid are found. This will give the mapping from the high-resolution image to the low-spatial-resolution images. Defining $h(m_1, m_2, k; n_1, n_2)$ as this mapping, we can write the image capture process as:

$$g^{(N_1)}(m_1, m_2, k) = \sum_{n_1, n_2} h(m_1, m_2, k; n_1, n_2) f^{(N_1)}(n_1, n_2). \tag{1}$$

Equation 1 gives the relation between a single high-resolution image and a set of low-spatial-resolution images. Details of this modeling can be found in [4].

The second sub-block models gray-scale resolution reduction. Gray-scale resolution reduction is nothing but reduction in the number of bits used to represent each

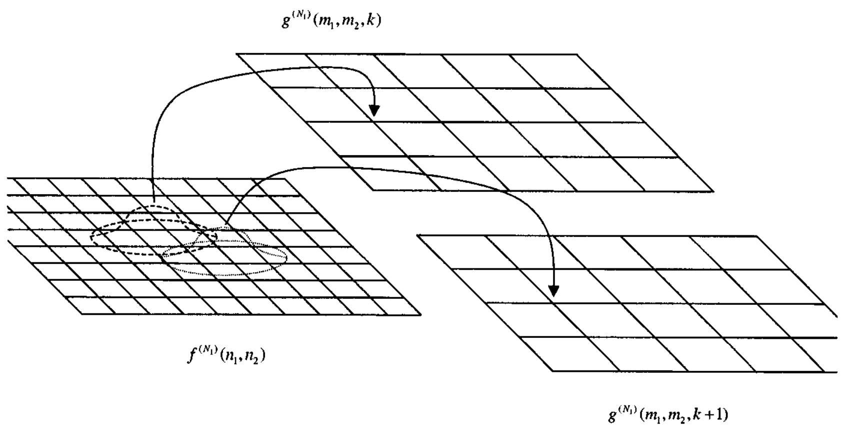

Figure 2: Illustration of the image capture process

pixel. Bit depth reduction from N_1 bits to N_2 bits is given by:

$$g^{(N_2)}(m_1, m_2, k) = round\left\{2^{N_2-N_1} g^{(N_1)}(m_1, m_2, k)\right\}, \tag{2}$$

where $g^{(N_2)}(m_1, m_2, k)$ is the low-resolution (both in gray-scale and spatial dimensions) image observations. The factor $2^{N_2-N_1}$ gives the reduction in gray levels, and $round\{\cdot\}$ rounds the argument to the nearest integer.

Equations 1 and 2 together establish the relationship between the low-bit-depth images $g^{(N_2)}(m_1, m_2, k)$ and the high-resolution image $f^{(N_1)}(n_1, n_2)$. This relationship will be the basis of POCS-based gray-scale resolution enhancement method.

POCS SOLUTION

The proposed method is based on the Projections Onto Convex Sets (POCS) technique [1]. The convex sets used in the reconstruction come from the rounding operation given in Equation 2. The value of $2^{N_2-N_1} g^{(N_1)}(m_1, m_2, k)$ is rounded to the nearest integer, which means, although its exact value is lost, it is known that it is within the 0.5 proximity of the observed pixel intensity. This information can be used to define convex constraint sets. The method works as follows:

The image capture process shown in Figure 1 is applied on an initial high-resolution image estimate $x^{(N_1)}(n_1, n_2)$, and then scaling by the factor $2^{N_2-N_1}$ is done. The result is compared with the observations $g^{(N_2)}(m_1, m_2, k)$. It is known that the residual, the difference between the computed and the observed images, must be less than 0.5 in magnitude if the estimate $x^{(N_1)}(n_1, n_2)$ is correct. If the residual is greater than 0.5, then the error is back-projected onto the initial estimate so that the next time capture process and scaling are applied, it will be within the 0.5 proximity of the observations.

Defining the residual as:

$$r_x(m_1, m_2, k) \equiv g^{(N_2)}(m_1, m_2, k) - 2^{N_2 - N_1} \sum_{n_1, n_2} h(m_1, m_2, k; n_1, n_2) x^{(N_1)}(n_1, n_2) \quad (3)$$

we can write the convex constraint sets for an arbitrary image $x^{(N_1)}(n_1, n_2)$ as follows:

$$C_{(m_1, m_2, k)} = \left\{ x^{(N_1)}(n_1, n_2) : |r_x(m_1, m_2, k)| < 0.5 \right\}. \quad (4)$$

The projection operation onto these convex sets is given by:

$$P_{(m_1, m_2, k)}\left[x^{(N_1)}(n_1, n_2)\right] = \begin{cases} x^{(N_1)}(n_1, n_2) + \frac{2^{N_1 - N_2}(r_x(m_1, m_2, k) - 0.5) h(m_1, m_2, k; n_1, n_2)}{\sum_{n_1, n_2} |h(m_1, m_2, k; n_1, n_2)|^2}, & r_x(m_1, m_2, k) > 0.5 \\ x^{(N_1)}(n_1, n_2), \quad -0.5 \le r_x(m_1, m_2, k) \le 0.5 & \\ x^{(N_1)}(n_1, n_2) + \frac{2^{N_1 - N_2}(r_x(m_1, m_2, k) + 0.5) h(m_1, m_2, k; n_1, n_2)}{\sum_{n_1, n_2} |h(m_1, m_2, k; n_1, n_2)|^2}, & r_x(m_1, m_2, k) < -0.5 \end{cases} \quad (5)$$

As a result, the final algorithm is as follows.

1. Choose a reference frame, and bilinearly interpolate it to get an initial estimate.
2. Compute the motion between the high-resolution image estimate $x^{(N_1)}(n_1, n_2)$ and one of the low-bit-depth images, $g^{(N_2)}(m_1, m_2, k)$.
3. Compute the mapping $h(m_1, m_2, k; n_1, n_2)$ for each pixel in the current image $g^{(N_2)}(m_1, m_2, k)$.
4. For each pixel in the current image $g^{(N_2)}(m_1, m_2, k)$,
   (a) Compute the pixel intensity from the estimate $x^{(N_1)}(n_1, n_2)$ by applying image capture process and scaling,
   (b) Compute the residual and back-project the error to the estimate $x^{(N_1)}(n_1, n_2)$ using Equation 5.
5. Stop if a stopping criterion is reached, otherwise, choose another low-bit-depth image, and go to step 2.

It should be noted that, by construction, this algorithm has the potential to achieve both spatial and gray-scale resolution enhancement at the same time. If the high-resolution image estimate has a finer grid than the observations, both spatial and gray-scale resolution enhancement is achieved. If they have the same sampling grid, only gray-scale resolution enhancement is achieved.

EXPERIMENTAL RESULTS

A high-resolution image (in both spatial and gray-scale dimensions) is jittered, blurred by a Gaussian kernel (support of 5×5, variance of 2.5), and downsampled to produce spatially low-resolution images. The gray-scale resolution is then reduced from eight bits to three bits. One of the three-bit images is given in Figure 3.

The proposed superprecision algorithm is applied to the three-bit images. The reconstructed (eight-bit) image, given in Figure 4, shows significant improvement in both gray-scale and spatial resolution. The original image, and more results can be obtained from the following URL: *http://users.ece.gatech.edu/ gte714q/gs.html*

In the experiments, motion is computed by Hierarchical Block Matching (HBM) method of Bierling [5]. Three hierarchical levels are used with Mean Absolute Difference (MAD) as the matching criterion. In the final level, motion estimates are obtained with one-quarter-pixel accuracy.

CONCLUSION

In this paper, we presented a superprecision method that increases the gray-scale resolution by combining the non-redundant information from a set of low-gray-scale resolution images. It is based on the projections onto convex sets (POCS) technique where the convex sets are defined using the bit-depth-reduction information. The method also increases the spatial resolution if a finer sampling grid is used for the initial high-resolution image estimate. Therefore, the proposed method can be considered as a generalization to superresolution reconstruction.

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Figure 3: One of the 3-bit images

Figure 4: Reconstructed from 3-bit images