Deblurring and Restoration in Barcode Signal Processing

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Introduction

A barcode is a series of alternating black and white vertical bars that encodes a data string in the relative widths of the bars. Ideally, the barcode is given as a one-dimensional 0-1 signal when scanned by a laser, where 0 represents white space and 1 indicates a black bar. However, the signal is blurred and distorted by various factors, including speckle noise and ambient light. We introduce a deblurring technique based on the minimization of the Total Variation (TV) norm by Newton's method. For testing purposes, we use the 10-digit UPC barcode familiar to grocery shopping.

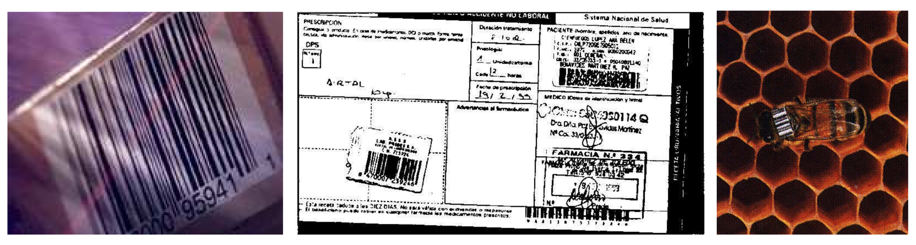

Figure 1: Examples of Noisy Barcode Images

Data Model

The observed signal u_0 is a noisy version of the clean 0-1 signal u. We model the noise process by convolving u with a Gaussian kernel of unknown size.

$$u_0 = G_{a,w} * u + n \tag{1}$$

where G is the Gaussian kernel, or point-spread function, with width w and amplitude a

$$G_{a,w} = ae^{-(x/w)^2} \tag{2}$$

The signal reconstruction reduces to a partially blind deconvolution problem. The width w of the Gaussian depends on the speckle noise created by the finite spot size of the laser. In particular, w will increase as the scanner is moved farther away from the barcode. The amplitude a will depend on the intensity settings of the scanner, as well as outside factors such as the ambient light. The additive noise, n, is due to electrical noise in the scanner and source defects such as stray marks or smudges on the barcode paper. Recovering the ideal signal u from the observed signal u_0 requires proper estimation of the blurring parameters a and w.

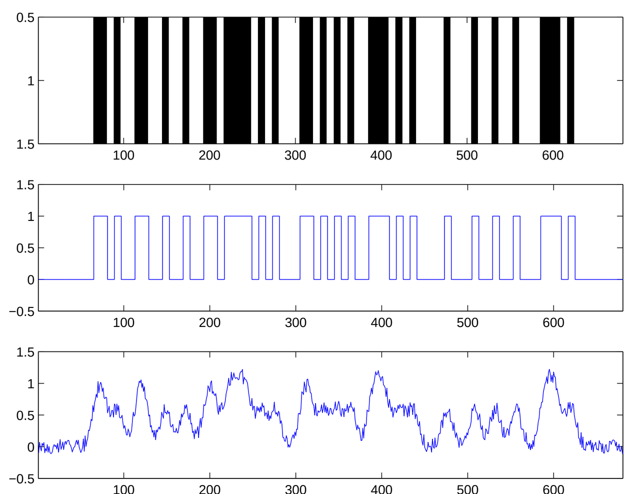

Figure 2: (Top to bottom) Barcode 0123456789, ideal 0-1 signal u, convolved noisy signal u_0.

Standard Denoising Techniques

Currently, the standard approaches to barcode signal reconstruction are based on classical edge detection filters. One approach is to look for the zero-crossings of the second derivative, an idea attributed to David Marr. Since the ideal signal is a 0-1 step function, the first derivative should consist of Dirac delta functions and the second derivative will cross zero at the edges of the bars. A second approach, Otsu's Algorithm, creates a histogram of the peaks of the first derivative. The peaks are then thresholded to remove noise from the histogram. The threshold is set by minimizing the sum of the variances between the two groups, ideally clustering the histogram into two distinct sets [1].

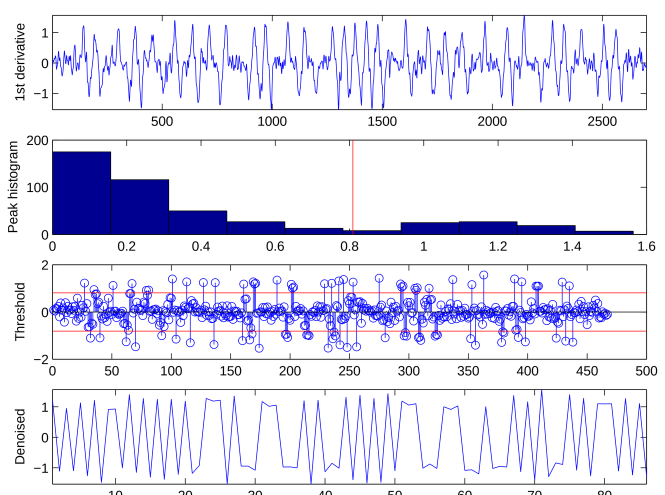

Figure 3: Otsu's Algorithm

Both approaches have two major drawbacks. First, they do not make any use of the knowledge of the data model (1). Second, they only look at local edge information. That is, they do not look at the overall signal to try to determine the type and extent of noise applied to the signal. These two methods give us a baseline to judge the performance of our TV-based deconvolution technique.

The TV Norm

To perform the blind deconvolution, we propose minimizing the Total Variation (TV) norm of the reconstructed signal u given the observed signal u_0 [2].

$$\min_{u,a,w} E[u|u_0] := \int_{\Re} |u_0 - G_{a,w} * u|^2 dx + \alpha \int_{\Re} |u'| dx \tag{3}$$

Here α is a constant that needs to be set experimentally. The first term measures the fidelity of the reconstructed signal u to the original signal u_0, essentially measuring the additive noise n. The second term controls the total variation of our reconstructed signal u.

Note that the energy functional is convex in u, but not necessarily in a and w. So this minimization is not guaranteed to be a well-posed problem. Esedoglu [3] proved that we are guaranteed the existence of a solution under certain conditions. If we assume $w \geq 0$, a lies in a compact set K, and $u = 0$ a.e. outside the barcode region, then

$$\inf_{u,a \in K, w \geq 0} E[u|u_0] \tag{4}$$

is attained. For actual computation, the conditions on a and w are reasonable and we generally assume that the signal u will be surrounded by sufficient white space on both ends.

Numerical Computation

Our first attempt at minimizing equation (3) was a steepest descent approach for known paramters a and w . Since the second term of (3) is not differentiable at the origin, we use the standard approximation

$$|u'| \approx \sqrt{u'^2 + \epsilon} \tag{5}$$

for some small constant ϵ . The update of the steepest descent is

$$u^{(n+1)} = u^{(n)} - \lambda \nabla_u E[u|u_0] \tag{6}$$

where $\nabla_u E[u|u_0]$ denotes the gradient of the energy (3) with respect to u

$$\nabla_u E[u|u_0] = -2G * (u_0 - G * u) - \alpha \left(\frac{u'}{\sqrt{u'^2 + \epsilon}} \right)' \tag{7}$$

The steepest descent approach would introduce artifacts in the signal u, creating jagged bumps in undesirable locations. Esedoglu's implementation of a steepest descent method achieved cleaner results, but it had the minor drawback of being unable to grow interfaces. To overcome this, he used an initialization $u^{(0)}$ that alternated 0 to 1.

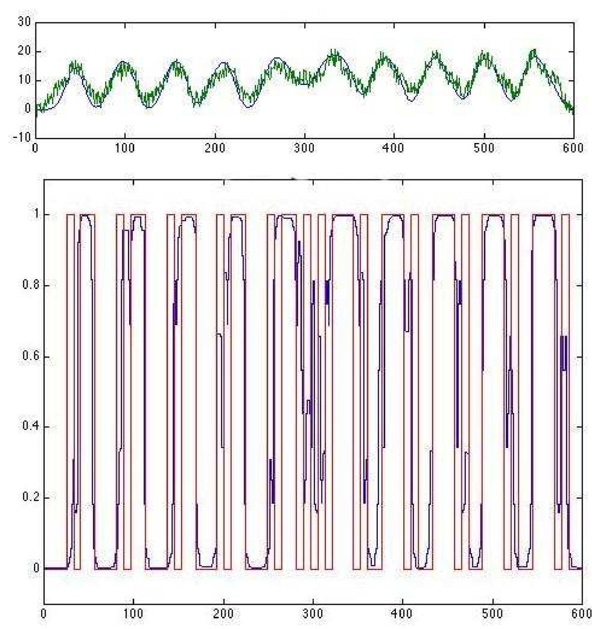

Figure 4: Artifacts in Steepest Descent: (Top) Original signal u_0 vs. $G * u$ in blue. (Bottom) Clean barcode vs. recovered signal u.

To try to remove artifacts and also to improve the convergence rate of the minimization, we implemented a damped Newton's Method minimization of (3). The update step is

$$u^{(n+1)} = u^{(n)} - \lambda H^{-1} \left(\nabla_u E[u|u_0] \right) \tag{8}$$

where H is the Hessian matrix of the TV energy with respect to u [4]. If we treat the kernel G as a matrix with rows of shifted Gaussians, then we can calculate H as

$$H = 2G^T G - \nabla_u \left(\frac{u'}{\sqrt{u'^2 + \epsilon}} \right)' \tag{9}$$

We found that this approach resulted in cleaner signals u and could handle higher noise levels than the steepest descent minimization. Also, the minimization was independent of the initialization $u^{(0)}$. When a and w were known, our Newton's Method implementation could successfully reconstruct signals roughly up to $w = 0.013$.

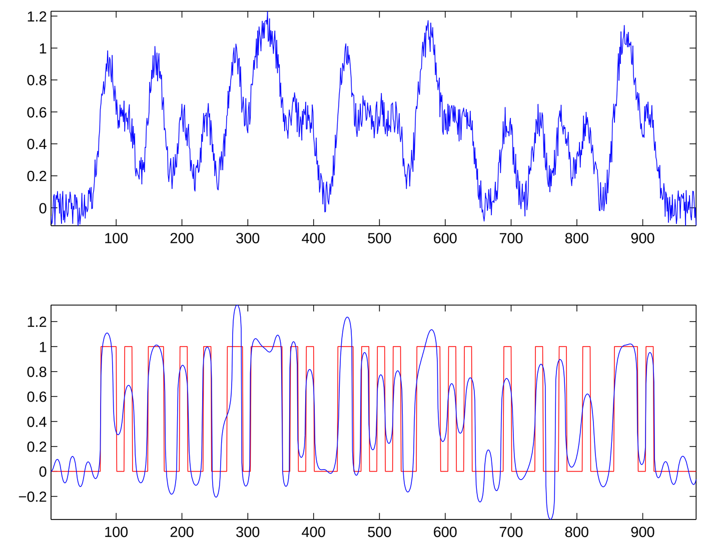

Figure 5: Newton's Method: (Top) Noisy signal u_0 with $a = .05$, $w = .013$. (Bottom) Recovered signal u vs. clean barcode. Run time = 21.6 m.

When a and w are unknown, we perform a steepest descent calculation similar to (6). When the initializations $a^{(0)}$ and $w^{(0)}$ are close to the actual values, we are able to recover the parameters a and w while also reconstructing the signal u. However, the algorithm fails when the initializations are too far off. Proper initialization of these parameters requires some prior knowledge of the point-spread function.

Conclusions

The Newton's Method minimization of the TV norm is an effective means for recovering the barcode signal u when the point-spread function is known or when there is decent estimation of the blurring parameters. The algorithm fails when the initial guesses for the blurring parameters are too far off or when the blurring kernel width w is too large. This method is not specific to barcode signals, rather it could be adapted to any 1D signal that has undergone Gaussian blurring. Santosa and Li showed that this method can be extended to general 2D image denoising [5]. Further research could involve optimizing this method specifically for barcode signals or extending it to 2D for denoising barcode images. This algorithm may be too slow and computationally sophisticated to be implemented in barcode scanners, so some thought should be given as how to streamline and simplify the denoising procedure.

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References

[1] Eugene Joseph and Theo Pavlidis. Bar code waveform recognition using peak locations. *IEEE Trans. on Pattern Anal. and Machine Intel.* Vol. 16, 1994, p. 630-40.

[2] Tony Chan, Stanley Osher, and Jianhong Shen. The digital TV filter and nonlinear denoising. *IEEE Trans. on Image Proc.* Vol. 10, 2001, p. 231-41.

[3] Selim Esedoglu. Blind deconvolution of bar code signals. *Inverse Problems.* Vol. 20, 2004, p. 121-35.

[4] Curtis Vogel. *Computational Methods for Inverse Problems.* SIAM Press: 2002.

[5] Fadil Santosa and Yi Li. A computational algorithm for minimizing total variation in image restoration. *IEEE Trans. on Image Proc.* Vol. 5, 1996, p. 987-95.