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Timothy R. Tuinstra
University of Dayton

Russell C. Hardie
University of Dayton, rhardie1@udayton.edu

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High-resolution image reconstruction from digital video by exploitation of nonglobal motion

Timothy R. Tuinstra  
Russell C. Hardie  
University of Dayton  
Department of Electrical and Computer Engineering/Electro-Optics Program  
300 College Park Ave  
Dayton, Ohio 45469-0226  
E-mail: rhardie@engr.udayton.edu

Abstract. Many imaging systems utilize detector arrays that do not sample the scene according to the Nyquist criterion. As a result, the higher spatial frequencies admitted by the optics are aliased. This creates undesirable artifacts in the imagery. Furthermore, the blurring effects of the optics and the finite detector size also degrade the image quality. Several approaches for increasing the sampling rate of imaging systems have been suggested in the literature. We propose an algorithm for resolution enhancement that exploits object motion in digital video sequences. Unlike previously defined techniques, we use an automated segmentation method to isolate rigid moving objects. These are accurately registered and the multiple observations of the object are used to produce an effectively high sampling rate over the object. The experimental results presented illustrate the breakdown of resolution enhancement algorithms that assume global scene motion when the actual scene motion is nonglobal. The performance of the proposed algorithm is illustrated using images from a forward looking IR imager and a visible range camera. © 1999 Society of Photo-Optical Instrumentation Engineers. [S0091-3286(99)01205-2]

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1 Introduction

A problem of considerable importance in image acquisition is achieving the proper sampling rate. The factor that often limits the sampling rate of imaging systems is the spacing of the detectors that are used in the array. Current semiconductor technology limits the size and therefore the spacing of the individual detectors in the array, which therefore limits the spatial sampling rate of the system.1 This limitation is especially problematic in the arena of IR staring arrays where the data are very often severely undersampled and aliased. The aliasing in these data due to inadequate sample spacing along with the blur from the finite detector size can cause serious artifacts in the data, which decreases the utility of the images and makes fine details and structures difficult to interpret. This is especially true in military and surveillance applications where image understanding for the user is of great importance.

The optical system including the apertures and lenses provides spatial low-pass filtering of the image, which bandlimits the signal in the spatial frequency domain.2 However, the highest spatial frequencies admitted by the optics are often much greater than one half the sampling rate of the system, leading to aliasing in the acquired image. One method that has been proposed in the literature for increasing the sampling rate of images obtained from an imager is to use multiple globally translated and rotated frames to form one higher resolution image. Tsai and Huang were the first investigators to make use of additional information present within a shifted version of the same scene to produce higher resolution images.3 Several variations of the multiframe approach have been proposed in the literature.1,4–6 The translations and rotations of the detector array relative to scene provide more unique samples than exist with just one frame. Most of the algorithms proposed exploit global frame shifts and/or rotations. The key to success for the multiframe algorithms is having highly accurate registration of the observed frames.

One case that has received only limited attention is the case where objects move with more than one trajectory within the scene. This is the focus of this paper. Examples of such motions include the movement of vehicles or other objects within the scene. The problem is that if global motion is assumed, when processing images with nonglobal motion, serious errors in the reconstructed image are introduced. The scene-based motion registration algorithms tend to find the average of the motions within the scene. This is practical for global scene motion, but for scenes with nonglobally shifting objects, this is undesirable.

A technique proposed by Schultz and Stevenson7,8 to address the problem of nonglobal motion is based on optical flow as calculated using a hierarchical block-matching scheme. Another of the methods proposed by Schultz and Stevenson employs manual segmentation of moving objects.9 Once these regions of motion are determined, the average of the dense optical flow values for each region is used in the image algorithm. Other researchers have also investigated this problem.10–12

In this paper, we propose a method for treating nonglobal motion that uses automated motion segmentation and registration. A general block diagram of the algorithm is...
given in Fig. 1. The first step in the algorithm is to determine the approximate optical flow field between the first two images in the sequence. Many techniques have been proposed for optical flow computation. We have observed, however, that scene-based optical flow techniques generally do not provide the desired level of accuracy for use in resolution enhancement algorithms. The approximate optical flow, however, can be used to perform segmentation of moving objects in the scene. In our object-oriented approach, we now estimate the registration parameters associated with each moving object. By making certain assumptions about the object motion (e.g., rigid body moving in the image plane only), object registration can be done far more accurately than the general dense optical flow. From the object registration results, a more precise optical flow field is generated. Finally, the refined optical flow along with the observed frames and known system parameters are used to form a Bayesian maximum a posteriori (MAP) estimate of the high resolution scene.

In this paper, we assume that the motion in the scene is due to rigid bodies moving parallel to the image plane (shift only). However, the basic methodology summarized in Fig. 1 can be applied in the future to more complex motion.

The organization of the remainder of this paper is as follows. The image observation model is described in Sec. 2. In Sec. 3, the problem of finding the approximate optical flow is addressed. Object segmentation and registration is described in Sec. 4. The MAP image reconstruction portion of the algorithm is developed in Sec. 5. In Sec. 6, experimental results using image data from a forward looking IR (FLIR) imaging system and from a charge coupled device (CCD) camera are presented. Finally, some conclusions are presented in Sec. 7.

## 2 Observation Model

The task of reconstructing a high-resolution image from a sequence of undersampled low-resolution frames requires an intimate understanding of the degradation processes that operate on the scene information during image acquisition. We use a discrete model to emulate the actual degradation processes and transform an ideal properly sampled image into the sequence of low-resolution frames observed. This model is applicable only to staring arrays. Such a model is key to the Bayesian estimation framework. This observation model will include the object motion within the scene, the point spread function (PSF) from the finite-size detector array, and undersampling of the detector array.

A block diagram of the discrete observation model is provided in Fig. 2. The ideal or desired high-resolution image is denoted $z(n_1, n_2)$. This image is of dimensions $N = LN_1 \times LN_2$, is assumed to be sampled at the Nyquist rate, and is not blurred by the imaging system in any way. Here $N_1 \times N_2$ are the dimensions of the observed frames, and $L$ is the downsampling factor in the model. In a lexicographical format, the ideal image is written as

$$
z = [z_1, z_2, \ldots, z_N]^T.
$$

(1)

To account for motion in scene, the optical flow parameters, $h_k(n_1, n_2)$ and $v_k(n_1, n_2)$ are required and represent the horizontal and vertical movements, respectively, of the intensity associated with each pixel from the fixed ideal image to the $k$'th frame. The $k$'th image after the motion is written as $z_k(n_1, n_2)$. In practice, these images are created using interpolation guided by the estimated optical flow.

The PSF of the system is accounted for by a discrete equivalent, denoted $h_k(n_1, n_2)$. The operation of the PSF on the ideal image can be modeled by a 2-D, discrete convolution operation

$$
\tilde{z}_k(n_1, n_2) = h_k(n_1, n_2) * z_k(n_1, n_2).
$$

(2)

Finally, to account for the undersampling of the imaging system, downsampling by a factor of $L$ in the horizontal and vertical dimensions is performed and additive noise is assumed. Thus, the $k$'th observed frame is given by

$$
y_k(n_1, n_2) = \tilde{z}_k(n_1L, n_2L) + \eta_k(n_1, n_2).
$$

(3)

Let the size of each low-resolution frame be $N_1 \times N_2$ and in lexicographical notation each frame is written as $y_k$
or more succinctly as

\[ y = \begin{bmatrix} y_1^T, y_2^T, \ldots, y_p^T \end{bmatrix}^T = \begin{bmatrix} y_1, y_2, \ldots, y_p \end{bmatrix}. \] (4)

The operation of the entire observation model on the desired discrete high-resolution image may be expressed succinctly in one equation. To do so, recognize that each low-resolution pixel is simply a weighted sum of the high-resolution pixels that contribute to it plus a noise term. However, the weighting of the high-resolution pixels is a function of the true optical flow field and the system PSF.

Therefore, the observation model can be written as

\[ y_{k,m} = \sum_{r=1}^{N} w_{k,m,r} (h_k(n_1,n_2), v_k(n_1,n_2)) z_r + \eta_{k,m}, \] (5)

or more succinctly as

\[ y_m = \sum_{r=1}^{N} w_{m,r} z_r + \eta_m, \] (6)

where \( w_{m,r} \) is the contribution of the \( r \)th high-resolution pixel to the \( m \)th low-resolution pixel. Here \( y_m \) represents the blurred pixel.

To make the observation model clear for the nonglobal motion case, a diagram illustrating the model is shown in Fig. 3. In the diagram, the desired high-resolution image (a tank) is visible superimposed on the low-resolution array. One of the low-resolution pixels is highlighted. This pixel value will be the sum of the shaded pixels that are contained within the span of that detector. Those pixels that are on the edge contribute less and are more lightly shaded. It is important to notice that in the successive frames, the same low-resolution detector has different high-resolution pixels contributing to its value. Thus, a possibly independent linear equation of the form in Eq. (6) is formed with each observed pixel. The goal of the high-resolution image reconstruction is to effectively solve this set of linear equations (i.e., find \( z \) from \( y \)). For more details on the calculation of the exact system PSF, the reader is urged to consult earlier work by the authors.

3 Problem of Optical Flow

Before moving on to the description of optical flow computation, let us first consider a description of how translational shifts between images can be calculated using a least squares technique. This will then be adapted to optical flow calculations. To begin, assume that two continuous images \( A(x,y) \) and \( B(x,y) \) are shifted versions of one another. That is,

\[ A(x,y) = B(x + \Delta x, y + \Delta y). \] (7)

Writing this using a Taylor series expansion yields

\[ A(x,y) = B(x) + \Delta x g_x(x,y) + \Delta y g_y(x,y), \] (8)

where \( g_x(x,y) \) and \( g_y(x,y) \) are the horizontal and vertical gradients, respectively, at point \((x,y)\). Terms higher than second order are omitted from the Taylor series for simplicity. Note that the equation has two unknowns, so that it is impossible to solve if only one data point is available. However, assuming that many measurements are made all with the same shift, the system of equation becomes overdetermined and can be solved using a least squares technique. Specifically,

\[ \Delta x, \Delta y = \arg \min_{\Delta x, \Delta y} E(\Delta x, \Delta y), \] (9)

where \( \Delta x \) and \( \Delta y \) are the shift estimates and

\[ E(\Delta x, \Delta y) = \sum_{(x,y) \in S} \left[ A(x,y) - B(x,y) - \Delta x g_x(x,y) - \Delta y g_y(x,y) \right]^2, \] (10)

where \( S \) represents a grid of points where discrete samples exist. The ‘‘arg min’’ notation used in Eq. (9) simply means that the desired values are the values of \( \Delta x \) and \( \Delta y \) that minimize the cost function \( E(\Delta x, \Delta y) \). Assuming that the discrete versions of \( A \) and \( B \) are denoted \( A_s \) and \( B_s \), this can be written as

\[ E(\Delta x, \Delta y) = \sum_{n \in N} \left[ A_s(n) - B_s(n) - \Delta x \tilde{g}_x(n) - \Delta y \tilde{g}_y(n) \right]^2, \] (11)

where \( n = [n_1, n_2] \) is the vector containing the coordinates of 2-D pixel sites, \( N \) is the set of all possible pixel locations in the image, and \( \tilde{g}_x(\bullet) \) and \( \tilde{g}_y(\bullet) \) are the discrete versions of the gradients. Equations (10) and (11) are used to find the solutions to Eq. (8) using a linear least squares technique.

The strategy for minimizing the cost function is to differentiate Eq. (11) with respect to the independent variables \( \Delta x \) and \( \Delta y \) and to simultaneously set the derivatives to zero and solve for the shifts. This yields

fig:3 Diagram of the operation of the observation model.
\[
\sum_{n \in N} [\Delta x \hat{g}_x(n) + \Delta y \hat{g}_y(n) \hat{g}_z(n)] \\
= \sum_{n \in N} \hat{g}_z(n) [A_1(n) - B_1(n)],
\]

(12)

and

\[
\sum_{n \in N} [\Delta x \hat{g}_x(n) \hat{g}_y(n) + \Delta y \hat{g}_y^2(n)] \\
= \sum_{n \in N} \hat{g}_z(n) [A_1(n) - B_1(n)].
\]

(13)

Equations (12) and (13) can be solved simultaneously. It is most useful to place these equations into a linear algebraic formulation. To do this, one matrix and two vectors are set up such that

\[
\mathbf{M} = \begin{bmatrix}
\sum_{n \in N} \hat{g}_z^2(n) & \sum_{n \in N} \hat{g}_z(n) \hat{g}_y(n) \\
\sum_{n \in N} \hat{g}_z(n) \hat{g}_y(n) & \sum_{n \in N} \hat{g}_y^2(n)
\end{bmatrix},
\]

(14)

\[
\mathbf{R} = \begin{bmatrix}
\Delta x \\
\Delta y
\end{bmatrix},
\]

(15)

and

\[
\mathbf{V} = \begin{bmatrix}
\sum_{n \in N} \hat{g}_z(n) [A_1(n) - B_1(n)] \\
\sum_{n \in N} \hat{g}_y(n) [A_1(n) - B_1(n)]
\end{bmatrix}.
\]

(16)

The relationships between these matrix expressions is given by

\[
\mathbf{MR} = \mathbf{V}.
\]

(17)

To solve for the registration parameters \( \mathbf{R} \) simply involves a matrix inverse and a left multiply operation, as in

\[
\mathbf{R} = \mathbf{M}^{-1} \mathbf{V}.
\]

(18)

We now turn our attention to the optical flow problem. Since the calculation of the dense optical flow field from any two frames is inherently an underconstrained problem, it is absolutely necessary to introduce additional constraints if there is to be any hope of finding a meaningful solution. Typically this is done by assuming that the solution will generally be smooth. Alternatively, it is often assumed that for any pixel, the pixels in the neighborhood immediately surrounding the pixel under consideration will have the same motion parameters. Of course, this is true for pixels in the interior of moving objects within the scene. However, this assumption is usually violated at the borders of objects, causing errors.

The latter assumption is made in the technique used here. The least squares shift parameters are found for every pixel in the observed frame based on a neighborhood surrounding the pixel under consideration. Figure 4 illustrates this approach to optical flow computation. Assuming the block size is small enough, this technique will accurately determine optical flow for both translational motion and for rotating bodies.

4 Problem of Object Segmentation and Registration

The estimated optical flow between the first two frames is used to segment the image into independently moving objects. Once the scene has been segmented, the objects are then registered again to find a more exact motion estimate for each object. The fundamental assumption in this algorithm is that all of the pixels within a given object will move with the same trajectory. This is valid if the object is rigid and is moving parallel to the image plane.

One of the algorithms that has been typically used for image and data segmentation of all kinds is the so called \( k \)-means clustering algorithm. This algorithm requires \textit{a priori} knowledge of the number of classes of data or the number of objects in the scene.

Assuming that the image has been properly segmented, all of the moving objects will have the correct pixels assigned to them. It is important also to note that some post-processing of the segmentation field is usually required to reduce the presence of outlier pixels and disconnected regions that might be present. Usually some kind of an erosion technique will work quite well in cleaning up the segmentation field.

Once the segmentation of all objects within the scene is complete, the least squares registration within each of the object boundaries is performed. The difference between this step and the optical flow step is that during the optical flow computation, the location of boundaries was unknown. Thus, motion estimates were based on small square neighborhoods. Now, because the boundaries are known, the estimates are based on all of the interior object pixels. This should lead to a more accurate motion estimate.
A consideration that further complicates this problem is the fact that the motion of the objects may be either small or large scale over the course of the frames that are considered in the computation. If the motions are very small, the standard least squares technique works well given the object boundaries. For larger shifts, however, it is necessary to obtain the large scale motion prior to performing the least squares estimate. In particular, we use a block-matching algorithm to track the objects through the sequence and obtain the whole pixel shifts of the segmented objects in each frame. A minimum absolute difference (MAD) criterion is used. This, together with the least squares technique, provides accurate object shift for small and large object trajectories. With these motion estimates all the parameters of the observation model in Fig. 2 can be specified. We now turn our attention to the high-resolution image reconstruction.

5 Bayesian Image Reconstruction

The high-resolution image reconstruction is performed by the minimization of a cost function. The cost function is derived from the observation model [Eq. (6)]. First, the minimization of the cost function can be written as

$$\hat{z} = \arg \min_z C(z), \quad (19)$$

where the cost function is written as

$$C(z) = \frac{1}{2} \sum_{m=1}^{p} \left( y_m - \sum_{r=1}^{N} w_m, r_z r \right)^2 + \frac{\lambda}{2} \sum_{i=1}^{N} \left( \sum_{j=1}^{N} \alpha_{i,j} z_j \right)^2, \quad (20)$$

and where $\hat{z}$ is the high-resolution image estimate. It can be shown that this represents a MAP estimate in the case of Gaussian noise.\(^1\)

Equation (20) is composed of two different terms. The first term in Eq. (20) is the sum of squared differences between the actual observed low-resolution pixel values $y_m$ and the low-resolution pixel values that are predicted by the observation model (see Fig. 2). The problem with seeking to minimize just the first term in Eq. (20), is that it is under-constrained or ill-posed. Multiple solution sets $\hat{z}$ will serve to minimize the first term.

The second term is a smoothness constraint that regularizes the problem. To put it in Bayesian terminology, this term represents the prior information that can be exploited in finding the solution. The parameter $\alpha_{i,j}$ is defined as

$$\alpha_{i,j} = \begin{cases} 1 & \text{for } i = j \\ -\frac{1}{4} & \text{for } j: z_j \text{ is a four-connected neighbor of } z_i \end{cases} \quad (21)$$

This term will tend to be minimum when the image estimate is smooth. In particular, note that when all of the four-connected pixels in the neighborhood of a given pixel have the same value, then the second term will go to 0. The parameter $\lambda$ in the regularization term indicates the "strength" of the smoothness constraint. A large value for $\lambda$ will tend to yield a smooth solution, while a low value for $\lambda$ will tend to produce a noisier image. The practical values of $\lambda$ can be determined by qualitatively evaluating images using different values for $\lambda$. Our research used a value for $\lambda$ of 0.05 because previous research has shown that this number produces very good results.\(^1\)

One of the most practical ways to minimize the function in Eq. (20) is to use gradient descent minimization. The gradient descent method finds the global minimum by following the greatest downward slope of the function. This requires knowledge of the partial derivative of the cost function with respect to each of the unknown high-resolution pixels $z_k$. The partial derivatives are given by

$$g_k(z) = \frac{\partial C(z)}{\partial z_k} = \sum_{m=1}^{p} w_m,k \left( \sum_{r=1}^{N} w_m,r z_r - y_m \right) + \lambda \sum_{i=1}^{N} \alpha_{i,k} \left( \sum_{j=1}^{N} \alpha_{i,j} z_j \right). \quad (22)$$

The gradient descent algorithm is an iterative procedure that is initialized using the bilinear interpolation of the first frame. The pixel value after the next iteration can then be written as

$$z_k^{n+1} = z_k^n - \varepsilon^n g_k(\hat{z}^n), \quad (23)$$

where $\varepsilon^n$ represents the step size that will be used at the $n$'th iteration. Each iteration updates the estimate of the image by moving all of the high-resolution pixels toward the global minimum of the cost function by the step size prescribed. This optimum step size is calculated in a previous paper.\(^1\)

In computing the gradient it is useful to recognize that the second term can be computed for all high-resolution pixels via a convolution operation. The first term gradient component for each high-resolution pixel is the error between all the model predicted low-resolution pixel values and the actual low-resolution pixel values, weighted by its contribution to those low-resolution pixels.

6 Experimental Results

Here we illustrate the performance of the proposed algorithm using a FLIR image sequence and a sequence obtained with a digital CCD camera.

6.1 FLIR Image Data

The FLIR sequence consists of 16 frames recorded using an Amber AE-4128 IR imager. This imager has an array of 128×128 pixels whose individual detector width is 0.04 mm. The detector spacing for this particular camera is 0.05 mm. This spacing introduces sufficient aliasing into the imagery that room exists for considerable improvement in the imagery. The first frame of the collected imagery is shown...
in Fig. 5. The image sequence contains a car that moves from left to right while the background remains fixed.

A previous algorithm designed only to treat global motion has been applied to the image sequence for comparison. The results are illustrated in Fig. 6. Clearly, this reconstruction would not be acceptable in most applications. We now turn our attention to the results for the proposed algorithm.

The initial optical flow for the first two frame of the FLIR sequence is shown Fig. 7. Here the neighborhood block size that was used is $9 \times 9$.

The object segmentation result is shown in Fig. 8. The segmentation masks have been eroded several times to remove most of the small isolated regions. The segmentation map is far from perfect as it carries with it some of the background region immediately surrounding the car. This is probably due to the large block size used in the original optical flow computation.

The next process in the algorithm is to reregister the blocks on an individual basis based on the algorithm described in Sec. 4. This reregistration process can best be understood as the finding of two motion parameters for every object as opposed to the optical flow computation, which was concerned with finding two parameters for every
pixel. The trajectories of both the vehicle and the background are shown in Fig. 9. Using the trajectories as given in Fig. 9, a high-resolution estimate of the scene can be calculated. The reconstruction results for this algorithm are shown in Fig. 10.

6.2 Visible CCD Data

The visible sequence consists of 20 frames recorded using a Dalsa visible imager. This imager has an array of 256 × 256 pixels, although the images have deliberately been blurred and subsampled by a factor of 4 to introduce aliasing into the imagery. The sequence contains a soda can that is moving from right to left during the course of the sequence. For this sequence, we show a set of four images in Fig. 11 to illustrate the results.

Since the high-resolution frame is known in this case, it is possible to use certain metrics to describe the improvement in the images. In this case, the average pixel error was calculated on a per pixel basis over the entire image based on 256 gray levels. In the bilinearly interpolated case, the average gray level pixel error is 22.1 levels per pixel. In the case of the reconstructed image, the average gray level pixel error is 18.04 levels per pixel. This represents some significant improvement in the image and remember that all of this improvement comes from the region over the area of

Fig. 9 Motion trajectory parameters for the background and the vehicle.

Fig. 10 Comparison of a bilinearly interpolated frame (left) and a reconstructed frame (right).
the can since the background is not improved. Clearly, there are visual improvements in the data as well as the word “always” is now fully readable along with a generally sharper appearance in the can.

The experimental evidence, then, seems to indicate that it is possible to perform high-resolution reconstruction on digital video that contains the movement of individual objects in the scene.

7 Conclusions

It was shown that imagery captured using IR detector arrays tends to be aliased because of the sample spacing of the detectors. This kind of aliasing can introduce artifacts into the imagery that make it difficult to interpret.

Various multiframe techniques have been proposed to combat this problem by exploiting various kinds of motion. The contribution of this paper is that it extends the previous works to include the possibility of nonglobal motions within the scene. This motion is exploited by moving object detection, segmentation, tracking, registration, and reconstruction.

Applications of this work include possible real time reconstruction of digital video with high-resolution video output. Previous algorithms have seen success in doing so and it is expected that in years to come, algorithms like this one may be implemented in real time systems.

A second application is in the field of postprocessing of digital data acquired in surveillance, security or other infrared imaging systems. Object motion in these sequences could be exploited to produce a higher resolution output frame. Such an application could possibly be used in military or commercial systems.

This research is still in its infancy and therefore getting a good handle on the quantitative metrics of improvement is complicated. Future work could focus on applicable metrics. Future work in this area could also focus on improved motion segmentation techniques or improved object registration techniques. Perhaps edge detection algorithms could be implemented to enhance motion segmentation of the scene. These are all issues to be pursued by future researchers. It is our hope that this paper will encourage further

Fig. 11 (a) First frame in low-resolution sequence, (b) bilinear interpolation of the frame in (a), (c) original high-resolution image, and (d) high-resolution reconstruction using 20 frames.
effort in this area and that ultimately new digital video processing algorithms will be the result.

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References


Timothy R. Tuinstra received his BS degree in electrical engineering in 1996 from Cedarville College and his MS degree in electrical engineering from the University of Dayton in 1998 while serving as a research assistant at Wright Patterson Air Force Base. His research and engineering interests include digital signal, image, and video processing along with the application of linear system theory to problems in a variety of disciplines. Mr. Tuinstra is an electrical engineer for General Dynamics Information Systems in Beavercreek, Ohio, where he works in the areas of signal and image processing, and is a member of the IEEE.

Russell C. Hardie graduated magna cum laude and received his BS degree from Loyola College, Baltimore, in 1988. He received his MS and PhD degrees in electrical engineering from the University of Delaware in 1990 and 1992, respectively. Dr. Hardie is currently an assistant professor in the Department of Electrical and Computer Engineering at the University of Dayton. In 1997 he received the Engineering Professor of the year award from students. Prior to teaching at the University of Dayton, he was a senior scientist with Earth Satellite Corporation EarthSat in Rockville, Maryland. His research interests include signal and image processing, IR and multispectral imaging systems, nonlinear filters, adaptive filter theory, pattern recognition, and remote sensing.