Multisensor Data Fusion Algorithm Development

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Prepared by
Sandia National Laboratories
Albuquerque, New Mexico 87185 and Livermore, California 94550
for the United States Department of Energy
under Contract DE-AC04-94AL85000

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Abstract
This report presents a two-year LDRD research effort into multisensor data fusion. We approached the problem by addressing the available types of data, preprocessing that data, and developing fusion algorithms using that data. The report reflects these three distinct areas. First, the possible data sets for fusion are identified. Second, automated registration techniques for imagery data are analyzed. Third, two fusion techniques are presented. The first fusion algorithm is based on the two-dimensional discrete wavelet transform. Using test images, the wavelet algorithm is compared against intensity modulation and intensity-hue-saturation image fusion algorithms that are available in commercial software. The wavelet approach outperforms the other two fusion techniques by preserving spectral/spatial information more precisely. The wavelet fusion algorithm was also applied to Landsat Thematic Mapper and SPOT panchromatic imagery data. The second algorithm is based on a linear-regression technique. We analyzed the technique using the same Landsat and SPOT data.
Acknowledgments

The authors thank Bob Cover, formerly of the Advanced Transportation Programs Department, Walt Caldwell of the Technical Assessments Department, David Borns of the Geophysics Department, Mike Gray of the Starlos Program Department, Doug Bickel of the Radar Analysis Department, Dick Thomas of the Environmental Information Management Department, and Paul Eichel of the Optical Systems and Image Processing Department for their help by providing data and information. A special thanks to Kathie Hiebert-Dodd, manager of the Analysis Department III, for her guidance and suggestions. This research was supported by Sandia’s Laboratory Directed Research and Development.
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Nomenclature

Abbreviations

2DWT  two-dimensional wavelet transform
Dcr   Daubechies wavelet with c coefficients taken to resolution level r
GIS   geographical information systems
IHS   intensity-hue-saturation
IM    intensity modulation
IR    infrared
MS    multispectral
MWD   multiresolution wavelet decomposition
NMSE  normalized mean square error
SAR   synthetic aperture radar
SPOT  Systeme Pour l’Observation de la Terre
RGB   red-green-blue
TM    Thematic Mapper

Mathematical Notations

\( \phi(x) \)  scaling function
\( \psi(x) \)  wavelet function
\( g(x) \)  impulse-response of equivalent wavelet high-pass filter
\( h(x) \)  impulse-response of equivalent scaling low-pass filter
\( R \)  real numbers
\( Z \)  integer numbers
\( f(x) \)  one-dimensional functions
\( L^2(R) \)  measurable, square-integrable, one-dimensional vector space
\( \hat{j}_{2^j}(x) \)  wavelet function approximation at scale \( 2^j \)
\( d_{j_{2^j}}(x) \)  detail difference between scale \( 2^{j+1} \) and scale \( 2^j \)
Multisensor Data Fusion Algorithm Development

Introduction

Information is used in many forms to solve problems and monitor conditions. When multiple source information is combined, it is essentially used to derive or infer more reliable information. However, there is usually a point of diminishing returns after which more information provides little improvement in the final result. Which information and how to combine it is an area of research called data fusion.

In many cases, the problem is ill-defined when data is collected. More information/data is gathered in hopes of better understanding the problem, ultimately arriving at a solution. Large amounts of information are hard to organize, evaluate, and utilize. Less information/data giving the same or a better answer is desirable. Data fusion attempts to combine data such that more information can be derived from the combined sources than from the separate sources.

Significant effort has been devoted to defining and accomplishing “data fusion”. Whether the task is displaying multiple bands of a multispectral image, overlaying and vectoring data as performed in geographic information systems (GIS) software, or using Dempster-Shafer evidence reasoning for multi-sensor decision making,1 the task has been called “data fusion.” It is no wonder that confusion can arise about the concept of data fusion. To eliminate confusion, we present a structured approach that separates data fusion into three categories:

- **Pixel Fusion**
- **Display (Image) Fusion**
- **Decision Fusion**

These three categories provide a hierarchical methodology for fusing data and addressing the algorithms. In the following discussion, imagery data may be implied, but cartographic (geological, elevation, etc.), meteorological, symbolic, and other ancillary data can be exploited using this approach.

Pixel fusion is the lowest abstraction level of data fusion. Since dissimilar sensors may detect different physical characteristics of a target (i.e., reflectance, emissivity, radar cross section, etc.), the data represents intrinsic target properties. Combination of these basic characteristics with other sensor responses using physical relationships or analytical equations can produce a fused characteristic not detectable by a single sensor. In this manner, intrinsic detected properties (spatial, spectral, geometrical) are combined to produce a new quantity or to reduce the original feature space. Single sensor data can also be fused with itself by acquiring data at separate times.

Display or image fusion takes higher order features, such as statistical, structural, syntactical, groups of pixels, or the whole image, and again attempts to reduce or provide a new characteristic not acquired when using one sensor’s data. Examples of this procedure are uses of Fourier manipulations, Boolean operations, band ratioing, overlaying vectors, and global manipulations.
At this level of abstraction, the target and background are known. Target certainties can be inferred from image or data contextual information.

Decision fusion is the highest level in the fusion hierarchy. It uses target probabilities, “decisions” from sensors, and ancillary data to make an overall recommendation. For example, multisensor target data may be used to place the target into a category of “friend” or “foe.” If the target’s radar cross section signature denotes a friendly target with a confidence of 55% and the target’s infrared (IR) signature denotes a “foe” with a confidence of 75%, what recommendation or final decision should be given to the analyst? Decision fusion addresses, but is not limited to, this type of application. Different techniques for combining these separate decisions or probabilities have been used, such as Bayesian probability, weighted voting, evidence reasoning, and fuzzy logic.

The research presented herein is a two-year Laboratory Directed Research and Development (LDRD) effort into data fusion. The data fusion level at the onset of research was directed at pixel and image fusion. We approached the problem by addressing the available types of data, preprocessing of that data, and developing fusion algorithms. The report reflects these three distinct areas. First, the possible data sets for fusion are identified. Second, automated registration techniques for imagery data are analyzed. Third, fusion techniques are presented.
Data Availability and Acquisition

Before pursuing multisensor fusion algorithm development, we familiarized ourselves with different sensors available today. Without this preliminary investigation, the fusion of different data is limited to sensors familiar to the authors. We searched for a diverse sensor data set. This data set gives the foundation from which we can develop fusion algorithms.

To limit the search and so that synergistic fusion could be performed, a target was determined. In the wide-area coverage, Kirtland Air Force Base (AFB)/Sandia National Laboratories (SNL) was chosen as the target. At this time, a smaller target has not been officially identified. Optimal sensor coverage is the primary driver of this decision. One likely candidate, however, is the Sandia North Atlantic Treaty Organization (NATO) site.

Collection Site

Kirtland AFB is located directly adjacent to southeast Albuquerque, New Mexico. The climate has low precipitation, wide temperature extremes, frequent drying winds, heavy rain showers (usually of short duration and often with erosive effects), and erratic seasonal distribution of precipitation. Air temperatures are characteristic of high-altitude, dry, continental climates. Daytime temperatures during the winter average about 10 °C, and the summer daytime temperatures average less than 32 °C, with maximum reaching 34 °C in July. The average precipitation is 21 cm, half of which occurs from July through September in the form of brief thunderstorms. Winter months are typically dry with less than 5 cm of precipitation. Strong winds often accompanied by blowing dust, occur mostly in late winter and early spring. Wind speeds may reach 13 m/s. The soil in Albuquerque is sandy loam that supports grassland vegetation consisting of grasses, sages, and salt brush.

Possible Sensors for Data Fusion

Sensors for data fusion include imaging and non-imaging sensors. Imaging sensors are not limited to imaging visible radiation similar to the human eye. Instead, they can detect different radiation types spanning the electromagnetic spectrum from ultraviolet to microwaves. These imaging systems gather radiation from a given target and background producing a spatially correct context without processing, except for corrections for the platform’s motion. Non-imaging sensors also detect a wide range of the electromagnetic spectrum in addition to different properties like magnetic and gravimetric field strengths. Non-imaging systems provide point information about a target and background. This may be in an integrated form where target and background are not spatially distinguishable. To identify the target and background, the non-imaging data is usually gathered in a grid for later reconstruction. In a reverse or back-propagation process, the grid-wise data can be used to estimate the target and background.

Imaging and non-imaging sensors can be sub-divided further into active and passive systems. The active sensors generate and transmit a signal toward the target and receive and record the return signal after its interaction with the target. Passive sensors do not generate or transmit a
signal. Instead, they detect and record the natural electromagnetic energy reflected and/or emitted from the target.

There are two major types of passive imaging systems. One type provides a film image. The other provides a digital image. The digital image integrates the reflected/emitted radiation and quantizes the signal into gray levels over a resolution cell which is the instantaneous field of view (IFOV) on the ground. This digitized resolution cell is also called a pixel. An image of the ground is formed by scanning the IFOV. One dimension of the image is scanned by the motion of the satellite or airplane. The other cross-dimension needs a mechanized or digital method of scanning. There are two general methods of cross scanning. One is the whiskbroom or scanning spot method which scans cross-track by using a rotating mirror projecting the collected signal onto one or a group of detectors. The other cross-scanning method is the pushbroom method. The pushbroom method uses a linear array of detectors. The detectors, when projected back through the optics to the ground, compose the cross-track dimension. There are no moving parts except for the aircraft or satellite.

Active systems generally have a source and a receiver. The source can be a microwave antenna or a laser for example. The receiver can be a single sensor, a sensor array, or a receiving antenna. Creating an image depends on the type of system being used. The advantage of the active system is the source is known and controlled.

Passive and active systems may have sensor or antenna steering capabilities. This is usually referred to as a pointing capability. On the other hand, stationary sensors are usually configured in a down-looking (nadir) or side-looking position.

As alluded to in the preceding sensor discussion, sensors can be categorized by platform into ground-based, airborne, and spaceborne classes. For nonproliferation activities in general, the focus is on information collected primarily by satellite or aircraft systems like the Department of Energy (DOE) sponsored Airborne Multisensor Pod System (AMPS) and Multispectral Thermal Imager (MTI).

In many cases, these collections may be the only alternative when ground measurements are not feasible. They can provide repeat coverage of wide areas.

Given the variety of sensor types, we did a survey of current sensors and their platforms that are available for use in data fusion algorithm development. There are also graphical data types that usually are digitized attributes like roads, utility poles, sewers, boundaries, etc. These are another source of information that are usually generated in conjunction with GIS exploitation. Details of available sensor and graphical data types are given in the Appendix. This survey is not a total representation of all the fusion-feasible sensors.
Automatic Registration Algorithm Study

Given a data set of the same area, the data needs to be spatially registered. Registration ensures that the fused information combines information about the same area or the same object. In presenting the registration problem, we use image registration as an example.

Traditionally, the registration of two or more images requires one image to be designated as the reference image. The reference image may be rectified to a global projection or map. This is usually referred to as path or map projections respectively. The process of registration then requires the user to view the reference image and the unregistered image and pick features that appear in both images. These features are called control or tie points. The tie points are used to calculate a polynomial fit between the two images. The highest possible order of the polynomial fit depends on the number of tie points. The polynomial fit is usually calculated using a least-squares type of error minimization. The polynomial will fit well at the tie points, providing interpolated points for registering the whole image. This is known as warping. An accurate interpolation can be achieved if the tie points are distributed evenly throughout the image. Areas with sparse tie point population will tend to be the worst fit. Also, higher order polynomials cause rapid deviation from a “good” fit in areas of minimum tie points and at the image edges.

Because of the vast amount of image and non-image data that is available, and the requirement for fusion algorithms to have co-registered data, automated registration is a way to stream-line the fusion algorithm development process. Issues concerning automated registration that were addressed are: different spatial resolutions, different wavelengths, down-looking (nadir) versus pointing capabilities, different times of acquisition, etc.

Algorithm Considerations

Many sensor data have different spatial resolutions. The possible impact on a registration algorithm corresponds to uniqueness of an object at different spatial resolution levels. If the algorithm uses features as a way of establishing tie points, then some features may change or be absent at different spatial resolutions. The resolution-dependent nature of identifying objects may be of concern.

Sensors don't necessarily capture optical/visual imagery. For instance, the Landsat Thematic Mapper (TM) has seven wavelength bands gathering reflected and emitted radiation and forming seven separate images. Features and structures can be dissimilar in different wavelength bands; i.e., vigorous vegetation is usually dark in the red wavelength region, but light in the near infrared. An automated algorithm would have to address feature differences at diverse wavelengths.

As discussed in the Data Availability and Acquisition section, some sensors are fixed, nadir-looking sensors, and others have the ability to point. The sensor’s pointing angle is the elevation angle (nadir being 90° or 0° depending on reference frame; target or sensor). For a pointing sensor, if an object has some relief (height), the height of the object causes it to “lay over” in the image. Lay over is caused by the three-dimensional real world being imaged into a two-
dimensional plane. In lay over, the height of the object is projected onto the surrounding area, possibly covering up other features or objects. The lay over magnitude is dependent on the true height of the object and the sensor's elevation angle. The shallower the elevation angle, the more lay over. Another difference between images may occur because of the sensor's viewing direction. The viewing direction can be specified by the azimuth angle. The azimuthal differences are analogous to viewing an object from different sides (i.e., north versus west).

Different times of acquisition could change the characteristics of the object or the scene. For instance, the length and direction of shadows depends on time and season. Seasons also bring about physical changes in plants (foliage) and the surface of some objects (i.e., snow and ice). An automated registration algorithm should handle the seasonal and shadow differences.

Caution must be exercised to distinguish between automated and semi-automated algorithms. As an example, a technique proposed by Schowengerdt and implemented by Bonrud and Henrikson is called automatic registration. Schowengerdt's approach is to calculate the correlation between images. To calculate the correlation, an N-by-N window area is selected in one image and a M-by-M search area is selected in the reference image where M is greater than N. This is really semi-automatic then if the areas are selected by the user.

With these types of considerations in mind, automatic registration algorithms were evaluated. We looked for algorithms that were fully developed and readily available.

**Automated Algorithm Descriptions**

The following sections present short descriptions of the algorithms we were able to learn about. These sections will attempt to convey the technique used by the algorithm and point out positive and negative aspects of the algorithm with consideration given to the major points in preceding discussion.

**Sandia National Laboratories Registration Algorithm**

An algorithm developed at Sandia was the first algorithm that came to our attention. It was originally developed to register two synthetic aperture radar (SAR) images that were offset (azimuthal direction) by a few degrees. After registration, the SAR images could be used for generating elevation maps and coherent change detection images. These subjects are beyond the scope of this paper.

The Sandia program implements automatic tie point generation on pairs of images using two-dimensional cross-correlation between image samples. This algorithm assumes the sample areas are similar. If they are similar, the cross-correlation will be high. If they are dissimilar, the cross-correlation will be low. The amount of shift and rotation between the two images will also be apparent through the position of the correlation peak.

To register two images, image samples are evenly distributed on a square grid in both images. These samples are usually processed in square patches of 64 x 64 pixels. The patches must be a power of two because the cross-correlation is performed as a Fourier-space multiplication. The patches can overlap in the image. The middle of each reference image patch is considered one set
The first file contains the tie point data - one record being written for each image patch. Each record contains the coordinates for the reference patch center, the tie point offsets for the non-reference image patch, and a measure of the correlation signal-to-noise ratio. A second file contains the image plane correlation surfaces for each patch processed. This is just an image displaying the cross-correlation function of each patch simultaneously for all the correlation patch pairs.

In practice, the automated part makes a down-sized image that is user-specified (usually 2:1) to perform a coarse registration. The registration is based on the cross-correlation as defined above. The signal-to-noise ratio determines the compactness and support around the correlation and is a metric to decide which tie point should be kept or discarded. The edited tie points are stored and the coarse image is warped via a polynomial fit. The process then continues using the warped image and reference image in full resolution, repeating the cross-correlation and tie point selection process described above. The polynomial fit is a global transform for the image. It provides good warping ability for images where there is little height relief. For images with undulating terrain, tall trees, buildings, tanks, etc. there is a poly-spline option that was developed to correct areas having lay over.

This technique is similar to Schowengerdt’s semi-automatic registration algorithm described in the Algorithm Considerations section. Yet, there is no need to select search areas because the correlation patches are evenly spread on a grid. Note that if the corresponding areas in the two images are not within the correlation patches calculation area, the algorithm will not work. This limitation can be quite detrimental with many sets of data and sensor orientations. Although the code allows the user to input initial tie points so that the images will fit the above criteria, this also moves the algorithm from the realm of being purely automated to being semi-automated.

Loral Automated Registration

This automated registration algorithm was developed on an IBM RISC System/6000. The approach adopts two main assumptions about the imagery:

1. The viewing orientations differ by no more than two or three degrees.
2. The imaging geometry is parallel projection.

The first assumption may be violated by pointing sensors that create perspective and occlusion distortions. The second assumption is valid when the imaging sensor is far away, as is a satellite or a sensor with a narrow field of view.

This algorithm also uses two-dimensional cross-correlation to identify pairs of corresponding points in the images. Since this technique does not attempt to identify features, it applies to many satellite images such as Landsat, SPOT, and ERS-1.

The Loral algorithm was developed after consultation with Sandia. Its approach in downsizing and correlation is similar to Sandia’s. What makes this algorithm different is that it uses the epipolar constraint. The epipolar constraint is used in stereo imagery registration, where the
orientation of the sensors is known \textit{a priori} or can be derived from knowledge of the three-dimensional coordinates of a few scene points.\textsuperscript{6-8} When the sensor orientations are unknown and no three-dimensional information is available, in general, the principle cannot be used. However, for the special case in which the imaging geometry is a parallel projection, the epipolar constraint can be derived from the image data without knowledge of the viewing orientations or scene coordinates.\textsuperscript{9}

Because of the two assumptions made (parallel projections and similar acquisition angle), the displacement between sensors is purely horizontal (because of the angle difference) as well as corresponding points in the images. This is analogous to stereo pairs. The search for matching points is reduced to one-dimension along the epipolar lines. In fact, the registration can be described as a global polynomial transform (affine) and a correction for the relief or height distortions depending on the epipolar vector (the direction of the epipolar lines).

As pointed out in discussing the Sandia algorithm, globally defined polynomial fits for warping one image to a reference image cannot accurately represent the local distortions because of lay over. The Loral algorithm uses the stereoscopic approach by implementing the epipolar correction outlined above to correct for lay over. The Sandia algorithm used a poly-spline fit for local distortions.

\textbf{ERDAS AutoWarp}

ERDAS Imagine is a multispectral image exploitation software package produced by ERDAS, Incorporated, of Atlanta, Georgia. AutoWarp is a separate module that can be added to the core ERDAS package. It embodies the Harris Corporation’s (Melbourne, Florida) Reggie algorithm. The concept behind Reggie is to support completely automatic registration of cross-sensor data. Although developed under DEC VMS, it was recently ported to the UNIX operating system and has a reported two-minute Landsat-to-SPOT image registration with accuracy to within two pixels on a SPARCstation 2.

The Harris algorithm remains robust because it relies on a fundamental, model-based approach and employs an iterative search and evaluation of scene matches. The final registration is done by perturbing variables in the sensor’s reference model and “projecting” the image through this model as opposed to the warping as performed in other registration algorithms. Thus there is no requirement for tie points. Yet, it too has a semi-automatic option in which the tie points are given for the first iteration. The model-based approach makes the algorithm’s speed independent of image size. It is dependent on the image complexity along with resolution and geometry adjustments. Another feature in the semi-automatic mode is to do a correlation-assisted method similar to Schowengerdt’s approach.\textsuperscript{3}

The diverse types of data registration have been documented by Harris. They include Landsat TM, SPOT, Almaz, JERS-1, and ARC/INFO vector GIS data.\textsuperscript{10}

Unfortunately, although marketed as part of ERDAS Imagine, AutoWarp is still in the beta stage. Its documentation is sketchy. Performance is limited to certain geocorrected projects.
**Pacific Northwest Laboratories AVS Algorithm**

In the late stages of our algorithm search, we found that Pacific Northwest Laboratories (PNL) has an automatic registration algorithm that runs under Advanced Visual Systems (AVS) environment. AVS is a visual programming environment that lets the programmer select functions and tie them together to make a program in either C, C++, or FORTRAN without the programmer having to write the code. It also makes objects out of C structures and functions, FORTRAN subroutines, or C++ classes. This allows proven applications integration into the AVS environment. AVS runs on a Sun UNIX system at Sandia.

The PNL algorithm is based on progressive generation of control frameworks. This approach attempts to generate uniformly distributed tie points and provide sub-pixel registration accuracy. The algorithm uses subsampled layers, thus performing coarse to fine registration. Tie points are automatically generated by employing a target-defined ground operator (TDGO) on feature points. Feature points are described by their high variance or steep gradients with their surroundings and are inherent in the scene. The TDGO refines the selection of feature points using a metric called the bit value. The bit values are found in the reference image.

The similarities of the reference and conjugate image are assessed by the adjacent pixel difference (APD) method. A least-squares affine transformation predicts the location of the conjugate points in the non-reference image down through the hierarchy of coarse to fine resolution. The correlation coefficient calculated by APD algorithm provides the figure of merit for the “goodness” of the tie points. A framework is then constructed from the remaining tie points using the Voronoi-Delaunay diagram. The Voronoi-Delaunay diagram is used to predict new points. The process begins again if more registration points are needed.

In reference 11, the target window sizes varied from 64 x 64 (coarse) to 16 x 16 (fine). The correlation coefficient was thresholded at 0.80 for a successful match. The maximum iterations for the least squares matching was 30 iterations. The registration accuracy was about 0.2 pixels.

How PNL implements the algorithm has yet to be seen. Although we requested the software in October 1994, as of this report’s printing, we have not received it.

**Jet Propulsion Laboratory Algorithms**

Researchers at the National Aeronautics and Space Agency’s Jet Propulsion Laboratory (JPL) have investigated automated registration algorithms in conjunction with the Earth Observing System (EOS). One approach they developed uses ancillary data in the form of digital elevation maps (DEM). The DEM is used to simulate solar-illuminated scenes matching the conditions under which the sensor data was acquired. This synthesized, illumination image is registered with other images using a simple cross-correlation method. This approach uses the DEM as reference image. Errors reported are in the two- to three-pixel range.

Other registration algorithms from JPL utilize features in the scene. These features may be edges, regions, lines, vertices of line intersections, shapes, etc. Such features must be robust to change in sensor geometry, wavelength, signal-to noise ratio, and noise statistics. For example, the JPL researchers used region boundaries provided through unsupervised segmentation. The
registration is performed through cross-correlation of the segmented regions. This region boundary technique results in registration errors of about three pixels. Edges can also be derived from the images through various edge filters and thresholding. The registration results using edges were similar to the region boundary method results.

We were unable to receive DEM data that coincided with our other data areas until the last few weeks of this research period. Lack of DEM data delayed us in trying to code the DEM registration algorithm described above.

Other Algorithms

Other algorithms that have been coded or that are under development have been identified. The University of Maryland has developed codes for automated registration. We are still waiting for copies of them. Hughes Aircraft is also working on code for automated registration. They are in the developmental stages at this time.

Algorithm Testing

Since other algorithms were not available, proprietary, or needed ancillary data, we only tested the Sandia method. The Sandia auto-registration algorithm was tested using Landsat and SPOT satellite data of KAFB/SNL. Four images from each satellite made the entire data set of eight images. These images were subimages of the original data; 2048 x 2048 pixels for the Landsat images and 4000 x 4000 pixels for the SPOT images. The Landsat satellite data is multispectral, containing seven separate bands spanning the visible to far infrared wavelengths. The SPOT satellite produces a higher resolution, single band, panchromatic image. The panchromatic image encompasses the visible spectrum.

The initial testing of the Sandia auto-registration algorithm involved only similar satellite image registration; i.e., Landsat-to-Landsat, SPOT-to-SPOT registration. The size of the images made the processing time longer, so to understand the code initially, the sub-images described above had regions selected from them, usually 512 x 512 pixels.

As described in the Sandia Algorithm section, the registration proceeded to completion if the images were already within the cross-correlation patch size with subpixel accuracy. This of course is not always the case, especially when dealing with cross sensor registrations (i.e., Landsat to SPOT). This limitation in itself caused us to believe this registration algorithm is, in general, a semi-automated algorithm.
Image Fusion Algorithm

Although we defined three distinctions in data fusion, pixel, display/image, and decision fusion, the following sections are dedicated to presenting a novel image fusion technique. It is referred to as a merger technique because of terminology from previous work in this area.\textsuperscript{18-28} It is compared to mature image merger techniques that can be found in commercial software.

The \textit{ad hoc} merging techniques we studied provide enhanced spatial information in the final multispectral image by approximating the spatial response in each wavelength band with high resolution panchromatic information. We chose two simple and commonly used techniques along with a new technique. We compared the intensity modulation (IM) merger, the intensity-hue-saturation (IHS) merger,\textsuperscript{18} and the multiresolution wavelet decomposition (MWD) merger.\textsuperscript{29,30} In this section, we present some background motivation for the wavelet image merger based on wavelet data compression. From these underlying concepts, we then explore the use of the MWD as a means of merging a low-spatial resolution, multispectral image with a high-spatial resolution panchromatic image although the merging technique is not limited to this merger scenario. The concept is applied to test images and to a practical application using Landsat TM and SPOT panchromatic data. Although we concentrated on the application of this process to images, the concepts apply to the simpler one-dimensional signal problem.

Merging Techniques

In the following, we present the merging techniques. The techniques assume there are two images, one three-channel “multispectral” and one single-channel “panchromatic” image. The multispectral image channels are assigned the color gun designations Red, Green, and Blue (RGB).

\textbf{Intensity Modulation Merger}

The intensity modulation method uses the intensity (gray level) of each panchromatic pixel to change the gray level of each individual color band the same amount or:

\[
(R', G', B')_{i,j} = (P)(R; G; B)_{i,j}
\]

where \(R\), \(G\), and \(B\) are the normalized channel intensities at the pixel coordinates \((i, j)\) of red, green, and blue respectively. \(P\) is the panchromatic gray level values. The left side of the equation is the modified RGB signal.

This merger approach preserves shadowing and relief as captured by the panchromatic sensor. It is useful for adding shading information to bands outside of the visible region such as the thermal infrared as well as enhancing visible imagery. Cliche \textit{et al.}\textsuperscript{31} used an IM method in combining simulated multispectral and panchromatic data. Others have used IM for combining SAR and multispectral imagery.\textsuperscript{32,33}
**Intensity-Hue-Saturation Merger**

Intensity, hue, and saturation refer to parameters of human color perception.\textsuperscript{34,35} Intensity is the total brightness of a color. Hue refers to the dominant wavelength contributing to a color. Saturation specifies the vividness of the color with respect to gray.

The IHS merger transforms the RGB multispectral channels into IHS components. To create the merger, the resulting intensity component is replaced by the high spatial resolution panchromatic data. The transform is reversed giving an RGB image with merged panchromatic information. RGB to IHS algorithms can be found in Smith,\textsuperscript{36} Haydn et al.,\textsuperscript{37} as well as in commercial software.

**The Wavelet Transform**

A major initiative in our research was using the discrete two-dimensional wavelet transform as a novel approach to image merging. In presenting the image merger concept, we first briefly review multiresolution wavelet decomposition.

**Review of Multiresolution Wavelet Decomposition**

Multiresolution decomposition\textsuperscript{38-40} provides a simple hierarchical framework for integrating image information. In a pyramidal fashion, image manipulation and analysis can be performed at coarse resolutions proceeding to fine resolutions or visa versa. Mallat showed how the wavelet transform provides this type of decomposition.\textsuperscript{41} The wavelet transform is an intermediate representation between Fourier and spatial representations, and it can provide good localization in both Fourier and space domains.\textsuperscript{41-44} MWD is computed with a pyramidal algorithm and decomposes a given signal or image into a set of frequency channels of constant bandwidth on a logarithmic scale. To understand the MWD better, we briefly review the wavelet transform.

**One-Dimensional Wavelet Transform**

We start with the one-dimensional wavelet transform. In the following, \( \mathbb{Z} \) and \( \mathbb{R} \) denote the set of integers and real numbers respectively. \( L^2(\mathbb{R}) \) denotes the vector space of measurable, square-integrable one-dimensional functions \( f(x) \). The multiresolution wavelet decomposition is an increasing sequence of closed subspaces \( \{V_j\} \) which approximate \( L^2(\mathbb{R}) \).

There exists a unique function \( \phi(x) \), called a scaling function, such that

\[
\phi_{2^j}(x) = 2^j \phi(2^j x)
\]

then

\[
\sqrt{2^{-j}} \phi_{2^j}(x - 2^{-j} n)_{(n, j) \in \mathbb{Z}^2}
\]
is an orthonormal basis built by dilating a function with a coefficient $2^j$ and translating the resulting function on a grid whose interval is proportional to $2^j$. For any $n \in \mathbb{Z}$, the scaling function is a member of $V_{2j}$ which is included in $V_{2j+i}$ ($V_{2j} \subset V_{2j+i}$).

The wavelet orthonormal basis is a family of functions that is built by dilating and translating the function $\psi(x)$, sometimes called the "mother" wavelet. The wavelet representation is the orthogonal complement of the original signal space, $V_{2j}$. Denote this complement space as $O_{2j}$.

Let

$$\psi_{2^j}(x) = 2^j \psi(2^j x)$$

(4)

denote the dilation of $\psi(x)$ by $2^j$. Then

$$\sqrt{2^{-j}} \psi_{2^j}(x - 2^{-j} n) (n, j) \in \mathbb{Z}^2$$

(5)

is an orthonormal basis that can be computed by scaling the wavelet with a coefficient $2^j$ and translating it on a grid whose interval is proportional to $2^j$.

In decomposing the signal, the resolutions are reduced by a factor of two for each level by using the scaling function and decimating the result by two. The difference in signal at resolutions $2^{j+1}$ and $2^j$ can be extracted on a wavelet orthonormal basis of $L^2(\mathbb{R})$. The decomposition is a new signal approximation and a detail signal. The signal approximation is given by

$$\hat{\phi}_{2^j}(x) = \sum_k \langle \phi_{2^{-j}}(x), \phi(x - (k - 2n)) \rangle \langle f(x), \phi_{2^j+1}(x - 2^{-j-1} k) \rangle$$

(6)

where $k \in \mathbb{Z}$ and $\langle a, b \rangle$ is the inner product of $a$ and $b$. The resolution change is obtained by the first inner product that acts as a low-pass filter

$$h(n) = \langle \phi_{2^{-j}}(x), \phi(x - n) \rangle$$

(7)

and by subsampling by two. Using equation 7, equation 6 becomes

$$\hat{\phi}_{2^j}(x) = \sum_k \tilde{h}(2x - k) \hat{\phi}_{2^j+1}(k)$$

(8)

where $\tilde{h}(n) = h(-n)$.
Similarly, the detail signal from the orthogonal projection of \( f(x) \) onto \( O_{2^j} \) is given by:

\[
d_{f_{2^j}}(x) = \sum_k (\langle \psi_{2^{-1}}(x), \phi(x - (k - 2n)) \rangle \langle f(x), \phi_{2^{-1}}(x - 2^{-j-1}k) \rangle)
\]

The detail difference between resolutions is obtained by the first inner product that acts as a high-pass filter:

\[
g(n) = \langle \psi_{2^{-1}}(x), \phi(x - n) \rangle
\]

Using equation 10, equation 9 becomes

\[
d_{f_{2^j}}(x) = \sum_k \tilde{g}(2x - k) \hat{f}_{2^{j+1}}(k)
\]

Thus, the signal approximation at the next lower resolution \((j + 1 \rightarrow j)\) is decomposed into a low-pass approximation and a high-pass detail signal (actually wavelet coefficients).

Perfect reconstruction of the original signal \( \hat{f}_{2^j+1}(x) \), requires that the filters \( h(n) \) and \( g(n) \) have regularity constraints. The reconstruction is the inverse wavelet transform that takes the form of

\[
\hat{f}_{2^{j+1}}(x) = \sum_k \tilde{h}(2k - x) \hat{f}_{2^j}(k) + \tilde{g}(2k - x) d_{f_{2^j}}(k)
\]

**Two-Dimensional Wavelet Transform**

The discrete two-dimensional wavelet transform (2DWT) is just an extension of the one-dimensional case. The 2DWT can be interpreted as a one-dimensional wavelet transform along the x- and y-axes. As in the one-dimensional case, the original image is reduced in resolution by a low-pass filter and subsampling to form an approximation image, but this time for both rows and columns of the image. This is a separable multiresolution approximation of \( L^2(R^2) \) in which the scaling function is

\[
\Phi(x, y) = \phi(x)\phi(y)
\]

The resulting two-dimensional decomposition at a given resolution level also results in detail images that are three-fold. The three detail images are a set of independent, spatially-oriented
frequency channels that detail vertical high frequencies, horizontal high frequencies, and cross-directional high frequencies. The three "wavelets" that give these detail images are:

\[
\begin{align*}
\Psi^1(x, y) &= \phi(x)\psi(y) \\
\Psi^2(x, y) &= \psi(x)\phi(y) \\
\Psi^3(x, y) &= \psi(x)\psi(y)
\end{align*}
\]  

(14)

Figure 1 shows the MWD of the mandrill image found in many image libraries. In this case, the resolution has been reduced by eight. Each resolution level is represented by the three detail images for that level. The image in the top left corner is the image approximation for the final resolution level being one-eighth the resolution of the original image.

**MWD Image Merger**

The concept of image merger via MWD arose from wavelet transform usage in data compression applications. For 2DWT data compression, the lowest resolution image approximation is usually kept. The other parts of the image decomposition are evaluated for their information content. This information content can be thresholded, quantized, or eliminated based on criteria such as total energy or entropy content. The remaining wavelet coefficients can be encoded to further the compression of information. Although this is lossy compression, the above references and others have shown that the loss of information can be negligible to the human eye for compression ratios of 30:1 or more. Since wavelets are used in lossy data compression and reconstruction schemes, it follows that they may be useful in sensor-compressed information problems. What is meant by "sensor-compressed" information and how this problem is addressed by image merging will be discussed below.

A real scenario in data collection is one sensor provides high spatial resolution at the expense of a wide spectral bandwidth while the other sensor has high spectral fidelity at the expense of spatial resolution. This describes the Landsat TM and SPOT satellite pair. The information from both sensors is compressed information since the real world covers all resolutions and most of the energy spectrum. The information is compressed at the sensor, because of the sensor's imaging characteristics. The information gathered by SPOT has retained spatial information, but the color information has been compressed, a lossy compression. The information gathered by Landsat TM has retained color information, but the spatial information has been compressed; again a lossy compression. Note the information compression for the sensor pair is in different information bands; spatial and spectral. Because of the lossy compression of these information bands, the individual decompression of each sensor's information to a higher resolution level is not possible. However, using the differing high-resolution information bands (i.e., spatial, spectral), a mutual (merged) decompression may be possible, because information compressed in one sensor is preserved at a higher resolution in another sensor.

MWD provides image approximations for multiresolutions and extracts detail differences between resolution levels. Either the approximation of the image or detail difference can be provided by different sources before the inverse transform or reconstruction. The insertion of an approximation image from a different data source at the completion of the forward MWD can
provide the “seed” to reconstruct a merged image. The “seed” will provide the initial approximation image. The insertion of the detail differences from another source or a combination of detail differences from both sources in the form of the wavelet coefficients can provide another means to reconstruct an image with combined information via the inverse transform. In the one-dimensional case this can be represented for one inversion step as

\[ \hat{f}_{2^{i+1}}(x) = \sum_k \tilde{h}(2k-x)\hat{\alpha}_{2^i}(k) + \tilde{g}(2k-x)d_{2^i}(k) \]  

(15)

and

\[ \hat{f}_{2^{i+1}}(x) = \sum_k \tilde{h}(2k-x)\hat{\alpha}_{2^i}(k) + \tilde{g}(2k-x)\Delta_{2^i}(k) \]  

(16)

where \( \alpha \) and \( \Delta \) are the approximation image and detail from a source other than \( f \) respectively. \( \alpha \) must be inserted at only one resolution level since the next approximation is calculated by the inverse transform. On the other hand, \( \Delta \) is provided at every resolution level until the inverse transformation is completed.

Both of these approaches are accomplished by the following steps:

1. The two original images must encompass the same area. They may not originally be the same array size, so make them the same size by interpolation or replication of pixel values.
2. Choose the wavelet basis for the transform and final resolution for the MWD. The final resolution should be the same for each MWD pyramid.
3. Perform the MWD on both images.
4. Extract the desired sensor image approximation from its decomposition pyramid and totally replace the approximation image in the other sensor’s decomposition pyramid.
5. Perform the inverse MWD on the image combination.

Although two spatially different images can be transformed to two separate resolution levels in their respective pyramids (step 3, i.e., 1/2 for one and 1/8 for the other), to merge them (step 4), the image approximation must be the correct size to insert into the other sensor’s decomposition pyramid. This will not be the case in general, thus the reason for step 1. Another approach is to decompose the two images to equivalent spatial resolution levels and then resize the image approximation to fit correctly into the other decomposition pyramid.
Figure 1. Wavelet decomposition of a black and white mandrill image. The wavelet transform used Daubechies wavelets with four coefficients. The final image approximation (top left corner) is 1/8 the original resolution.
Concept Discussion

One could argue that MWD merger is just high-pass filtering. Yet, using the MWD’s pyramidal approach, at each level of the resolution pyramid, we can evaluate the images and manipulate how they are being reconstructed. Techniques like conservation of energy, contrast stretching, maximum-likelihood ratioing, and edge enhancement can be implemented or monitored at each stage of the reconstruction. Also, arithmetic manipulation of wavelet coefficient such as adding, subtracting, normalization, min/max selection, weighted averaging, and logical (AND, OR, XOR, etc.) manipulations as opposed to simple wavelet substitution and reconstruction are possible.

In presenting the MWD merger, we apply no modifications to the wavelet coefficients or intermediate images. Thus, we call this procedure the “standard” ad hoc MWD image merger implying that future algorithms may make use of some of the above manipulations.

Generation of Test Images

In the past, image merging has been mainly applied to remote sensing. Because of the nature of remote sensing, one shortfall is the lack of an image standard at the merged resolution that can be compared to the final merged image. To eliminate this problem as well as to validate and study mergers presented above, we developed test images. The first test image was a color ramp. The other image used is the mandrill that is common to many image processing libraries.

Ramp Test Images

To better understand the functioning of each technique, a 256 x 256, 22 color horizontal ramp centered on a 512 x 512 magenta background (R=127, G=0, B=255) “multispectral” image and a 256 x 256 continuous gray level vertical ramp (0-255) centered on a 512 x 512 zero gray level background “high resolution” panchromatic image were constructed. These images are shown in Figure 2a and 2b.

Mandrill Test Images

The original mandrill image (Figure 3a) was processed to simulate images sensed by two different sensors. One sensor creates a multispectral image at one-fourth the original’s spatial resolution. The original RGB image was subsampled and blurred using a low-pass filter giving the final image as

\[ I(i, j, \lambda_k) = \sum_{\lambda} \sum_{x} \sum_{y} I(x, y, \lambda) R_k(\lambda) \Gamma(x, y;i, j) \]  

where \( R_k(\lambda) \) is the kth spectral band response and \( \Gamma(x, y;i, j) \) is the blurring and subsampling optical transfer function. Then we replicated pixels so that the beginning image arrays were identical in size, 512 x 512. This test image is shown in Figure 3b.

The other simulated sensor was a high-resolution panchromatic image generated by

\[ I(x, y) = al(x, y, \lambda_1) + Bl(x, y, \lambda_2) + cl(x, y, \lambda_3) \]
as an approximation to a hypothetical sensor with imaging characteristics of

\[ I(x, y) = \sum_{\lambda} I(x, y, \lambda) R(\lambda) \]

where \( R(\lambda) \) is the sensor's spectral response quantized by the variables \( a, b, \) and \( c, \) and \( I \) is the pixel intensities at \( x \) and \( y. \) An example of this sensor's test image is shown in Figure 3c where \( a, b, \) and \( c \) were all one-third.

To explore the sensitivities of the merger techniques to registration, we translate the panchromatic image of the mandrill with respect to the original mandrill image before merging. We then performed the merger. Translation was in the \( x \)-direction by 0.125, 0.25, and 0.50 pixels.

**Landsat-SPOT Images**

For our data set, we used a Landsat TM image of Albuquerque, New Mexico, acquired on August 15, 1992. The SPOT panchromatic data was acquired over the same area on November 7, 1993. The two data sets were registered to within 0.25 pixels RMS using control points and a first-order polynomial fit, the Landsat data being resampled. The satellite data was roughly corrected for the earth's atmosphere by using known low reflecting materials or large shadows in the scene. A linear stretch was then applied to each channel separately to fill the full data range. 1024 x 1024 sections of the data were used in the merging procedures described below.

**Merger Procedures**

The image mergers were conducted according to the IM, IHS and MWD techniques. The MWD merger used simple, orthonormal bases called Daubechies wavelets. The basis selection was not determined by any type of optimization. Rather, their mathematical properties are used to present the MWD concept. The Daubechies decomposition will be denoted using the following convention: \( Dc_r \) where \( D \) is for Daubechies, \( c \) is the number of coefficients and \( r \) is the resolution level (i.e., for a 512 x 512 original image, \( r = 1 \) gives a 256 x 256 signal approximation and \( r = 4 \) gives a 32 x 32 signal approximation). The test and satellite images are different sizes so the meaning of \( r \) will be different for these cases.

**Test Image Merger**

Although the Daubechies wavelet set contains wavelets with 4 to 20 coefficients, we did not seek the optimal wavelet for each merger. For each case, the wavelets were arbitrarily chosen. The MWD merger with the ramp image used the D63 wavelet. The mandrill merger used two sets of Daubechies wavelets, D6r and D14r.
Figure 2. Test images for merging. a) Pseudocolored horizontal ramp, b) Panchromatic (black and white) vertical ramp.
Figure 3. Test images for mandrill merge. a) Original mandrill image, b) Simulated low spatial resolution multispectral image, c) Simulated high spatial resolution panchromatic image.
**Standard MWD Landsat-SPOT Image Merger**

TM bands 3, 2, and 1, and the registered SPOT image were merged using the D4r wavelet basis. The panchromatic and multispectral images were decomposed to five different resolution levels ending with the image approximations of 32 x 32 pixels (r=5). The multispectral MWD was performed for each TM spectral band. At the end of the forward transform, each 1/32 resolution TM spectral approximation was inserted into the 1/32 resolution SPOT panchromatic MWD pyramid and the inverse transform performed giving three separate merged bands, red, green, and blue. A linear stretch was then applied to the images. The MWD merger was compared with the IHS merger.

**Additive MWD Landsat-SPOT Image Merger**

In the standard MWD image merging technique, the wavelet coefficients from the multispectral are discarded and only the original low resolution energy distribution (approximation image) is used. This procedure limits the amount of information that can be combined. Another approach is to add the wavelet coefficients (detail images) for each resolution level and then perform the reconstruction. Thus, the detail information from both sensors are used. We did this using D45 wavelets.

**Selective Resolution MWD Landsat-SPOT Image Merger**

Since the MWD merger takes place in the context of a pyramidal structure, we are able to apply techniques at different resolutions. One application of this selective resolution ability is to allow the user to select the acceptable level of SPOT correlation trade-off with the TM correlation in the final product. Using *a priori* knowledge of spectral and spatial characteristics, the merged product can be "tuned" to selectively provide the user with the best MWD merger for the task. This maybe useful in developing merged data automatic target recognition (ATR) algorithms.

A variation on the additive method was performed by adding in TM wavelet coefficients only up to selected pyramid levels (resolutions). Four separate selective resolution images were created using D45. Starting with the 32 x 32 TM wavelet approximation image placed in the SPOT wavelet pyramid, TM and SPOT wavelet coefficients were added ending at pyramid levels 64 x 64, 128 x 128, 256 x 256, and 512 x 512. In each case, the remaining resolution levels used just the remaining SPOT coefficients to reconstruct the final 1024 x 1024 image.

**Evaluation Metrics**

**Error Metric**

The spectral and spatial quality as compared to the original image was performed employing the normalized mean square error (NMSE) band by band. NMSE is given by

\[
NMSE = \frac{1}{MN} \sum_{m} \sum_{n} (x - \hat{x})^2
\]

\[
NMSE = \frac{1}{MN} \sum_{m} \sum_{n} x^2
\]

(20)
$x$ is the original value, $\hat{x}$ is the estimated merger value, and $m$ and $n$ are the pixel indices of a $M \times N$ pixel array. Since it is a band-integrated metric, it gives the normalized average pixel deviation from the ideal object for a given spectral band.

**Correlation Metric**

As suggested by Carper et al., another method of quantifying the spectral changes resulting from the data merger is to determine the change in correlation between the pre- and post-merger multispectral and panchromatic. A good merger technique should alter the correlation less when preserving spectral data. Still another method examines the correlation between original multispectral data and the merged products. This correlation should be high so that objects that were bright in the original multispectral bands are also bright on the merged image. This metric was used only in the Landsat-SPOT mergers because of the lack of ground-truth images.

**Merger Results**

**Ramp Merger**

The ramp mergers are shown in Figure 4. Figure 4a is the resulting IM merger. The figure shows that the shadowing provided by the vertical ramp is retained, and the merger intensity increases from left to right.

Figure 4b shows the IHS version of the merger. The merged image's spectral content varies at both the high and low intensity parts of the vertical ramp which implies intensity dependence on the final color.

Figure 4c is the MWD merger of the ramp images. The vertical ramp function has little influence on the final image. The lack of details by the MWD merger is because of the vertical ramp’s gray level continuity and Daubechies 6 being insensitive to first moments. On the other hand, the edge between the ramp and the background is a strong discontinuity at many resolution levels. This edge is enhanced. There are very subtle changes in the RGB channels because of contrast discontinuities between the color channels and the vertical ramp intensities. Since these discontinuities between images are higher order, the wavelet will be sensitive to their existence. Higher order Daubechies wavelets will be insensitive to higher moments making them candidates for reducing these intensity variance effects. On the other hand, the Haar-Walsh wavelet (two coefficients) would provide good building functions for creating box-like features similar to those in the ramp.

**Mandrill Merger**

Reconstructions of the original mandrill image via merger of the mandrill multispectral and mandrill panchromatic test images are shown in Figure 5. Figure 5a shows the IM merger. Figure 5b shows the IHS merger. Figure 5c shows the D63 MWD merger. Each merged image was compared to the original mandrill image band by band using the NMSE. The low-resolution (LR) multispectral test image was also compared. The results are shown in Table 1.
Figure 4. Merged ramp images using Figures 2a and 2b. a) Intensity modulation merger, b) Intensity-hue-saturation merger, c) Multiresolution wavelet decomposition merger.
As seen in Table 1, the IM merger errors are the greatest. They are larger than the LR’s errors. This may be expected since the pixel intensities follow the panchromatic data. Shadows and low intensities will cause large errors if they are not highly correlate in the color bands.

The IHS merger reduces the LR test image error by a factor of two as is desirable with merging. One downfall of this technique is it expects equal intensity contributions from each channel. In many remote sensing cases, this assumption may not be radiometrically correct.

D144 is the MWD merger’s best case for the wavelet sets. The error compared to the LR’s error is reduced by a factor of four, outperforming the IHS by a factor of one and one-half and the IM merger by a factor of six.

It is interesting to see the error decrease with the MWD merger as the resolution factor r increases. We pursued this a little farther to see if an increase in the resolution level would reduce the error further for D6 and D14 and the mandrill image. The combined results are shown in Table 2. Note that while the red and blue channel minimum error is achieved at \( r = 4 \), the green channel has its minimum error at \( r = 6 \). Since we are not restricted to applying the same wavelet or ending resolution level for all bands, we can select the best performing wavelet and resolution band by band. For the mandrill image, the combination would be Red: D144, Green: D146, and Blue: D144 with a total image NMSE of 0.0160.

Misregistration simulation results are shown in Table 3. Although we stated that the test images were exactly registered, the effects of low-pass filtering, subsampling the original image and resizing the image to the 512 x 512 size via pixel replication may have induced a shift in the integrated pixel intensities. The translation findings show a minimum in the RMS error at 0.125 pixel translation. The misregistration affects both the IHS and MWD mergers. Note that the MWD merger continually outperforms the IHS merger even with the misregistration. From these results, we can conclude that there are no large statistical instabilities in the wavelet reconstruction within these bounds.

**Standard MWD Landsat-SPOT Merger**

In previous research, we have used the IM merger with pseudocolored Landsat TM band 6 temperature maps and SPOT data. However, because of the IM merger’s ill-performance above, we used only the IHS and MWD mergers for the Landsat-SPOT mergers in this comparison. The lack of ground-truth images made us rely on the correlation metric. Figure 6 shows the outcome of both the IHS merger and the MWD merger of SE Albuquerque and Kirtland/SNL’s Manzano base. Figure 6a is the original TM image, 6b is the SPOT image, 6c is the IHS merger, and 6d is the MWD merger. In this case, the IHS merged image has spectral distributions that make the final image look more green and purple than the original. The MWD merger, on the other hand, visually provides a better spectral representation compared to the IHS. To show this quantitatively, we selected nine portions of the scene to compare color to the original TM. These areas are 9 x 9 pixels centered at every 256 pixel interval both in rows and columns. The results are shown in Table 4. Although there are no high resolution real color image for ground-truthing, Table 4 supports the results found in our previous research with laboratory-generated test images.
Figure 5. Merced mamlakta: unguis, Ruffus, 4b and 4c. a) Intensity modulation merced.
Table 5 shows the correlation results between the original TM, SPOT, MWD merger, and IHS merger (PAN is the SPOT panchromatic). Note that the IHS correlation with the SPOT is very high compared to its correlation with the original TM. Although the IHS has the spatial details of the SPOT, it also has many of the intensity characteristics of the SPOT at the expense of intensity (color) characteristics of the TM. On the other hand, the MWD has the spatial details of the SPOT and yet has higher correlation with the original TM, meaning the merged intensities retain more of the TM spectral information.

The IHS merger also changes the intensities of merged colors. This is shown in Figure 7, an image of the Rio Grande valley south of Albuquerque. Figure 7a is the original TM, 7b is the SPOT, 7c is the IHS merger. In Figure 7c, the colors of fields by the river change because of the difference in the reflectivity between the TM and SPOT. If the spectral information from the TM is important it will be lost.
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<tr>
<td>D67</td>
<td>0.0619</td>
<td>0.0072</td>
<td>0.0480</td>
<td>0.0390</td>
</tr>
<tr>
<td>D142</td>
<td>0.0313</td>
<td>0.0378</td>
<td>0.0524</td>
<td>0.0405</td>
</tr>
<tr>
<td>D143</td>
<td>0.0219</td>
<td>0.0180</td>
<td>0.0328</td>
<td>0.0242</td>
</tr>
<tr>
<td>D144</td>
<td>0.0188</td>
<td>0.0095</td>
<td>0.0236</td>
<td>0.0173</td>
</tr>
<tr>
<td>D145</td>
<td>0.0248</td>
<td>0.0068</td>
<td>0.0250</td>
<td>0.0189</td>
</tr>
<tr>
<td>D146</td>
<td>0.0303</td>
<td>0.0057</td>
<td>0.0294</td>
<td>0.0218</td>
</tr>
<tr>
<td>D147</td>
<td>0.0626</td>
<td>0.0074</td>
<td>0.0477</td>
<td>0.0392</td>
</tr>
</tbody>
</table>

Table 2: NMSE as a function of resolution level for two Daubechies wavelet bases.

<table>
<thead>
<tr>
<th>Translation</th>
<th>Image</th>
<th>NMSE</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Red</td>
<td>Green</td>
<td>Blue</td>
<td>Average</td>
</tr>
<tr>
<td>0.125 pixels</td>
<td>IHS</td>
<td>0.0189</td>
<td>0.0240</td>
<td>0.0270</td>
<td>0.0233</td>
</tr>
<tr>
<td></td>
<td>D63</td>
<td>0.0102</td>
<td>0.0163</td>
<td>0.0136</td>
<td>0.0134</td>
</tr>
<tr>
<td>0.25 pixels</td>
<td>IHS</td>
<td>0.0212</td>
<td>0.0268</td>
<td>0.0301</td>
<td>0.0260</td>
</tr>
<tr>
<td></td>
<td>D63</td>
<td>0.0113</td>
<td>0.0215</td>
<td>0.0157</td>
<td>0.0162</td>
</tr>
<tr>
<td>0.50 pixels</td>
<td>IHS</td>
<td>0.0285</td>
<td>0.0355</td>
<td>0.0396</td>
<td>0.0345</td>
</tr>
<tr>
<td></td>
<td>D63</td>
<td>0.0163</td>
<td>0.0346</td>
<td>0.0237</td>
<td>0.0249</td>
</tr>
</tbody>
</table>

Table 3: Misregistration effects on NMSE
Figure 6. Data set of Sandia National Laboratories, Kirtland AFB, and SE Albuquerque, New Mexico. a) Landsat TM, b) SPOT panchromatic, c) Intensity-hue-saturation merged image, d) Multiresolution wavelet decomposition merged image.
Table 4: MWD and IHS merger comparison using the average absolute gray level error in nine separate areas.

<table>
<thead>
<tr>
<th>Image</th>
<th>Absolute Gray Level Error</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Red</td>
<td>Green</td>
<td>Blue</td>
<td>Average</td>
</tr>
<tr>
<td>MWD</td>
<td>7.24</td>
<td>5.25</td>
<td>5.291</td>
<td>5.93</td>
</tr>
<tr>
<td>IHS</td>
<td>8.46</td>
<td>7.75</td>
<td>9.22</td>
<td>8.48</td>
</tr>
</tbody>
</table>

Table 5: Correlation comparison between the original TM, SPOT, MWD merged, and IHS merged images.

<table>
<thead>
<tr>
<th>Image</th>
<th>Correlation</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Red</td>
<td>Green</td>
<td>Blue</td>
<td></td>
</tr>
<tr>
<td>TM/PAN</td>
<td>0.806</td>
<td>0.805</td>
<td>0.778</td>
<td></td>
</tr>
<tr>
<td>MWD/PAN</td>
<td>0.951</td>
<td>0.949</td>
<td>0.939</td>
<td></td>
</tr>
<tr>
<td>IHS/PAN</td>
<td>0.981</td>
<td>0.988</td>
<td>0.974</td>
<td></td>
</tr>
<tr>
<td>MWD/TM</td>
<td>0.864</td>
<td>0.869</td>
<td>0.848</td>
<td></td>
</tr>
<tr>
<td>IHS/TM</td>
<td>0.809</td>
<td>0.827</td>
<td>0.797</td>
<td></td>
</tr>
</tbody>
</table>
The MWD standard merger also has problems. The spectral content of one- or two-pixel objects is lost with the multispectral image approximation substitution into the panchromatic pyramid. Also, since the MWD acts as high- and low-pass filters, the final reconstructed image may suffer from ringing. However, the MWD merger pyramidal structure allows possible artifact-eliminating algorithms to be applied at all resolution levels during the reconstruction. The standard MWD may also have problems distributing pixel intensities in large, featureless areas like the fields in Figure 7d. Although the original TM colors (Figure 7a) are low reflectance and fairly uniform, the high reflectance SPOT (Figure 7b) and its wavelet coefficients cause a phenomena we call “clumping”.

**Additive MWD Landsat-SPOT Merger**

For the additive MWD (AMWD), the apparent spatial resolution of the final merge was less than the standard MWD merger because of the blockiness of the larger TM pixels preserved as “detail” in the TM’s wavelet coefficients. At the same time, the spectral fidelity of the AMWD merger increased (as measured by the correlation with the original TM).

An example of the AMWD technique is shown in Figure 8. In addressing MWD clumping because of ringing and the IHS color change presented above, the AMWD merger preserves the spectral information to a greater extent while increasing the spatial resolution. In fact, when there is little detail in a large area, the reconstruction of the merged TM spectrum is very close, if not identical, to the original TM because of the exact reconstruction ability of the two-dimensional wavelet transform and the minute values of the SPOT wavelet coefficients in those areas. The correlation of the AMWD with the original TM and SPOT are shown in Table 6.

**Selective Resolution MWD Landsat-SPOT Merger**

The selective resolution merged images are called MWD64, MWD128, MWD256, and MWD512 are shown in Figure 9a, b, c, and d respectively. Their correlation with the original TM and SPOT images are also given in Table 6. From Table 6, the additional correlation with the TM data and decorrelation with the SPOT data is evident as more TM wavelet levels are used. The decorrelation with the SPOT data can be seen as the spatial resolution seems to slightly degrade in Figure 9.

The results in Table 6 suggest that arithmetic addition of TM and SPOT wavelet coefficients is channel-dependent as can be expected. For example, the highest TM/merged correlation in the red channel for the Albuquerque south valley data occurs with the AMWD technique. The AMWD performs addition at all resolutions. On the other hand, the green channel does not gain appreciable correlation after the 128 x 128 resolution (MWD128). Similarly, the blue channel reaches maximum correlation using MWD512. In addition, we are not constrained in how we combine the final RGB channels. We can choose AMWD for red, MWD128 for green, and MWD512 for blue. This type of selection is not possible with the IHS merger.
Figure 7. Data set of Albuquerque's South Rio Grande valley region. (a) Landsat TM; (b) SPOT; (c) Enhanced image; (d) Multi-resolution wavelet decomposition.
Figure 8. Additive multiresolution wavelet decomposition (AMWD) of Figures 7a and 7b.
<table>
<thead>
<tr>
<th>Image 1</th>
<th>Image 2</th>
<th>Red</th>
<th>Green</th>
<th>Blue</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAN</td>
<td>TM</td>
<td>0.642</td>
<td>0.676</td>
<td>0.666</td>
</tr>
<tr>
<td></td>
<td>MWD</td>
<td>0.855</td>
<td>0.881</td>
<td>0.855</td>
</tr>
<tr>
<td></td>
<td>IHS</td>
<td>0.985</td>
<td>0.950</td>
<td>0.975</td>
</tr>
<tr>
<td></td>
<td>AMWD</td>
<td>0.814</td>
<td>0.838</td>
<td>0.844</td>
</tr>
<tr>
<td></td>
<td>MWD64</td>
<td>0.831</td>
<td>0.853</td>
<td>0.867</td>
</tr>
<tr>
<td></td>
<td>MWD128</td>
<td>0.821</td>
<td>0.840</td>
<td>0.855</td>
</tr>
<tr>
<td></td>
<td>MWD256</td>
<td>0.815</td>
<td>0.833</td>
<td>0.847</td>
</tr>
<tr>
<td></td>
<td>MWD512</td>
<td>0.813</td>
<td>0.831</td>
<td>0.844</td>
</tr>
<tr>
<td>TM</td>
<td>MWD</td>
<td>0.838</td>
<td>0.841</td>
<td>0.819</td>
</tr>
<tr>
<td></td>
<td>IHS</td>
<td>0.701</td>
<td>0.685</td>
<td>0.629</td>
</tr>
<tr>
<td></td>
<td>AMWD</td>
<td>0.900</td>
<td>0.869</td>
<td>0.850</td>
</tr>
<tr>
<td></td>
<td>MWD64</td>
<td>0.864</td>
<td>0.859</td>
<td>0.837</td>
</tr>
<tr>
<td></td>
<td>MWD128</td>
<td>0.875</td>
<td>0.867</td>
<td>0.846</td>
</tr>
<tr>
<td></td>
<td>MWD256</td>
<td>0.876</td>
<td>0.868</td>
<td>0.829</td>
</tr>
<tr>
<td></td>
<td>MWD512</td>
<td>0.877</td>
<td>0.868</td>
<td>0.850</td>
</tr>
</tbody>
</table>

Table 6: Correlation comparison between original TM, SPOT, MWD merged, IHS merged, AMWD merged, and selective resolution MWD mergers.
Figure 9. Selective resolution merger of Figures 7a and 7b. a) MWD64, b) MWD128, c) MWD256, d) MWD512.
Discussion

The IM merger did not perform well in preserving spectral information. However, the addition of shadowing via the merger creates patterns that the human eye is accustomed to seeing in visible imagery. This technique may be useful in making infrared imagery more informative for image analysts with limited infrared exploitation experience.

The IHS merger performs well in merging the panchromatic’s spatial information. At times, this is at the expense of the spectral information. From the NMSE results, the IHS merger can create a good estimate in some cases. In other cases, it can actually creates more error than the nonmerged spectral data. Another drawback is the IHS merger requires three initial components (RGB). It cannot combine information between two sensors that are both single band unless one data set is transformed into RGB via a lookup table.

The MWD merger performs well in merging both the spatial and spectral information. In both NMSE and correlation, it outperformed the IHS and IM merging techniques. Most of the measured errors originate from the smoothing and sub-sampling of the original RGB images. Sharp spectral edges are not reconstructed well because of spatial quantization from pixel replication in the spectral image.

The MWD merger has been compared to a RGB-type merger because the IHS is a three-space transform. On the other hand, the MWD merger was performed on independent channels, merging the information separately and then combining them via display. This capability demonstrates the larger flexibility of the MWD merger. It can be used on two independent (black and white) channels or sets of data. This is something the IHS merger cannot do.

The MWD merger techniques show that the pyramidal structure of the wavelet decomposition approach to image merger opens many possibilities of future algorithms. Yocky also found that some Daubechies wavelets gave better results than others in the merging results, which suggests an optimal wavelet for each merger. Optimization utilizing orthonormal, biorthogonal, or another wavelet bases as well as how to combine the sensor approximation images for the initial “seed” are subjects for future research.

The MWD merger’s link to compression-type algorithms can be exploited in other ways. If sensors are coexistent on a platform, collection, compression, and merging of the data before transmission is a distinct and desirable possibility. Such on-board merging will reduce the transmission from two sensors to that of one and since the data will be in a wavelet pyramid format, the merged data can be readily encoded with standard wavelet encoding algorithms. This could be extended to a multisensor data fusion approach which is not limited to images such as a signal compression and fusion process.
Pixel Fusion Algorithm

As in the MWD merger approach, we looked at combining images from similar sensors to create a multiband image in which the high spatial resolution image is used to resolve features into finer detail. Yet for the algorithm we present in this section, we examined the characteristics of each pixel in each band to develop our algorithm. This approach is a pixel fusion technique. Again, the motivation was to assist an image analyst in the task of scene classification so we needed to maintain spectral integrity as much as possible so that classification would be enhanced by the introduction of spatial information.

For the method described here, we utilized the same satellite images as in the MWD merger, the Albuquerque SPOT panchromatic (PAN) and Landsat Thematic Mapper (TM) images.

Initially we proposed a general solution method for this task along the following lines. Consider the panchromatic image to be a weighted sum of the bands of the multispectral image. Determine the weight for each band, either from comparison of sensor characteristics or by estimation of the weights using linear regression. Derive the proportion of energy in the PAN image from each band of the TM image. Transform the PAN image into a high-resolution, multispectral image using the weighted sum and the proportional energy values.

We encountered some difficulty with this approach. The information we had about the SPOT panchromatic sensor was expressed in terms of absolute spectral response. We had only the relative spectral response for the Landsat TM sensor. This situation caused us to consider linear regression techniques as a first line of investigation, and we were unable to return to our first approach during the time allotted for this research.

Data Fitting Method

We chose a least-squares estimation technique to fit the data from the high-resolution PAN image to each of the low-resolution TM bands. The parameters obtained from the data fitting process are used to transform the PAN image into a high resolution banded image. A correction factor that preserves the pixel intensity of the original TM bands is then applied. The result is a fitted and corrected, spatially enhanced multiband image. The technique is described fully by Price. Since our actual PAN and TM data were well correlated, we did not need to use the method which he outlines for poorly correlated images.

In the description of the algorithm that we implemented, we use these conventions. Pixel values in an image with the larger ground sampling distance (gsd) are denoted by uppercase X; and x represents pixel values in an image with the smaller gsd. Uppercase indices I, J represent a range of indices. Since the Landsat TM gsd is three times larger than the SPOT panchromatic gsd, I and J denote $3i:3i + 3$ and $3j:3j + 3$, respectively. Superscript p means the pixel value is associated with a panchromatic image, and superscript m is used to refer to the Landsat TM band number. Thus we can say that a pixel value $Xm(i, j)$ in TM band m corresponds to a $3 \times 3$ chip $xp(I, J)$ in the high resolution PAN image.
We now present the steps of the algorithm.

1. **Average the panchromatic image to get a large gsd image.** On each $3 \times 3$ chip,
   \[
   X_p(i, j) = \frac{1}{9} \sum_{I,J} x_p(I, J) \quad (21)
   \]

2. **Use least squares estimation to fit data from each TM band to the panchromatic average.** Fit the data to a line, and so determine parameters $a_m$ and $b_m$ for the curve
   \[
   X_m = a_m \cdot X_p + b_m \quad (22)
   \]

3. **From the PAN pixel values, estimate a small gsd image for each TM band $m$**
   \[
   x_m(i, j) = a_m \cdot x_p(i, j) + b_m + e_m \quad (23)
   \]
   where $i, j$ range over the pixels in the original PAN image and $e_m$ is the error in the estimation.

4. **Derive a correction factor from the criterion of TM pixel intensity preservation;** that is, the average of the estimated (small gsd) pixel values must equal the measured (large gsd) pixel values.
   \[
   f(I, J) = \frac{X_m(i, j)}{\frac{1}{9} \sum_{i,j} x_m(I, J)} \quad (24)
   \]

5. **Apply the correction factor to the estimated pixel values in each TM band.**
   \[
   x_m(i, j) = f(i, j) \cdot x_m(i, j) \quad (25)
   \]

The correction factor is blocky in the sense that the same correction factor was applied over a $3 \times 3$ chip in an estimated image. The blockiness of the correction factor appears to introduce unpleasant side effects which will be discussed later in this part of the report.

**Algorithm Development**

The system environment for this research was a Sun Sparc 10 running the SunOS 4.1.3 operating system. Software development tools included a C compiler, X Windows, and the Khoros image processing system. Algorithm development proceeded in two phases: creation of a small C function library for data fitting, and incorporation of the Price method into Khoros as a toolkit.

In the initial phase, we required functions for reading and writing an image file, averaging an image, and fitting the data from two images to a straight line. We modified a function from the Numerical Recipes\textsuperscript{52} to fit the data using least squares estimation. In order to test the C function library which implemented the Price method, we synthesized PAN and multiband TM images using Khoros. We wrote a C program to process the synthetic data and write out raw image data.
Khoros routines were used to view output images and to collect statistics about the input and output images.

After we were satisfied with the behavior of the algorithm on the test input, we used Khoros software development utilities to implement the C function library as Khoros routines. These routines were combined into a Khoros toolkit. Evaluation of the Price method was simplified by use of Khoros image manipulation. Within the Khoros system we had greater flexibility with respect to image size and number of spectral bands with no additional programming.

Test Data

For the initial development phase we wanted input data which had characteristics which we controlled. To simulate high spatial resolution PAN data we chose a 256-level, or 8-bit, grayscale image of an airport. We used the same image to synthesize a multiband TM image. By mapping the grayscale values into the Scientific American pseudocolor map, we obtained a color image which was separated into red, green, and blue image bands. Each of these images was degraded by a blurring filter and subsampled to simulate a low spatial resolution image. The resulting multiband image had two bands which were reasonably well correlated with the grayscale image. The third band was very poorly correlated with the simulated PAN image.

For the next phase of development and testing, we used actual satellite data from SPOT and Landsat images. We chose three areas near Albuquerque to obtain a variety of scenes for analysis: (1) a populated area with regions of dense vegetation, (2) a small airport surrounded by desert, (3) a mountainous area with clusters of man-made structures. These scenes with the exception of (2) have been described above. (1) is south Albuquerque, Rio Grande Valley. (2) is Double Eagle Airport west of Albuquerque. (3) is Sandia National Laboratories, Kirtland AFB, and SE Albuquerque.

The PAN images had a ground sampling distance of 10 meters. The TM images were composed of three spectral bands, each having a ground sampling distance of 30 meters. The TM images were expanded so that each pixel was represented as a 3 x 3 image chip. This expansion made the TM band and PAN images nearly the same size, thus simplifying further processing. The TM bands of a particular image were assumed to be perfectly coregistered, and these images had been semi-automatically registered with the corresponding PAN image.

Observations and Conclusions

Results from the initial algorithm test phase, using our synthetic data, were very good visually. We were thus encouraged to extend the implementation into the Khoros environment, where it would be easier to manipulate actual data images. At this stage in the development, we discovered an error in the implementation of the correction factor described in the section on data fitting methods. Unfortunately, the improved implementation of the correction factor did not improve the fitted and corrected image. However, our results on synthetic data were still comparable to results on simulated data described by other authors.23,25
Application of the data fitting method to actual PAN and TM data produced disappointing results. On the positive side, the method preserved radiometric integrity; that is, the false color representation of the low resolution TM image did not change significantly in the fitted and corrected image. This effect was due largely to the correction factor, which ensured that the measured value of each pixel in the low resolution TM image equalled the average intensity of the corresponding pixels in the fitted image. A less positive characteristic of the method was that spatial resolution enhancements occurred effectively only in areas where both the PAN image and the TM image have medium to high intensity.

Two problems with the method were visually apparent in the fitted and corrected image. Linear features, such as streets or runways, which align in a particular way with the coarse pixel grid of the TM image, appear banded as though frequency aliasing has occurred in the transformation to higher spatial resolution. In some areas where the TM image pixels have higher intensity than the corresponding PAN pixels, the blocky edges of the TM pixels override the features that the PAN image resolved into finer detail.

The data fitting method described here does not significantly enhance the ability of an analyst in classification of a scene. Although the method does not destroy information in the low-resolution image, the introduction of artifacts such as aliasing along linear features and spurious edge enhancement are serious flaws. The application of a color-preserving correction factor to the fitted image together with the blocky nature of the correction does not seem to be a good combination.
Summary

We have presented a two-year effort into data fusion. We investigated the possible data sets and registration algorithms to automatically register diverse data sets. These were precursors to developing algorithms. Given a satellite imagery set over Albuquerque, and test images, we explored two image-enhancing fusion techniques, one based on the wavelet transform (MWD), the other based on linear regression. We found that the MWD merger is a viable new technique for merging. The linear regression technique was not developed to its desired state because of lack of satellite specifications. However, we found that it preserved spectral integrity well, but suffers from other artifacts because of intensity differences and misregistration.

We recommend further studies into the fusion techniques developed for this research. The MWD merger itself has applications to neural network, automatic target recognition, and data compression. Further research should be applied to variations on the MWD technique, like model-based wavelet coefficient interpolation, or hybridized techniques using MWD and applicable remote sensing merger techniques at each resolution level. Applicable techniques include our pixel fusion technique and those in references 23 and 28. Extensions to the pixel fusion technique can be investigated with a small investment if satellite sensor specifications are available.
References


2The viewpoint of the authors is from a remote-sensing perspective of the terms multispectral and panchromatic. In signal processing, multispectral can be confused with Fourier information, also referred to as spectral information. In this paper, multispectral and spectral deal only with the wavelength, electromagnetic spectrum sense of the words.


Appendix: Sensor and Data Survey

The following is a review of the possible sensors and types of data.

Imaging Sensors

In the following section some general imaging sensors will be presented. These are not all of the imaging sensors available, but this provides a flavor of the diverse nature of these sensors.

Photographic

One of the oldest methods of passive remote imaging is to use photographs of an object. There are many camera assemblies that can be used in airborne or even satellite applications. Ones relevant to the location at hand will be presented.

In June of 1990, airborne collections were made over Kirtland/SNL for the DOE Argus project. The flight-lines included collections over Coyote Canyon, the Solar Power Tower, and TOSI. The optical camera used was an Aviophot Wild RC10 with a 15 cm focal length, Universal-Aviogon (f/4) lens. The film size was 24 cm.

In April of 1993, contractors took aerial photographs of the entire Kirtland/SNL reservation. These photographs were at two scales, 1:6000, 1:30,000.

Panchromatic

Panchromatic sensors have one band that covers a broadband of wavelengths, from the visible to the short wavelength infrared (SWIR). A notable commercial satellite that provides this type of coverage is the French Systeme Pour l'Observation de la Terre (SPOT) satellite. It has a silicon charge coupled device (CCD) as the detector with a bandwidth of 0.50 - 0.73 μm. The spatial resolution is 10 m. The SPOT 2 is currently commissioned. It uses a pushbroom scan and is pointable to 27° off nadir.

The United States Landsat 3 had a return beam vidicon (television camera) on board. The bandwidth was 0.505 - 0.750 μm. with 30 m resolution. The Landsat 6 satellite was to have a 15 m resolution panchromatic band going from 0.50 - 0.90 μm. Unfortunately, Landsat 6 never achieved orbit. The U.S. also has the Geostationary Operational Environmental Satellite (GOES) 7 which uses eight photomultiplier tubes (PMTs) as detectors. It has a bandwidth of 0.55 - 0.75 μm and a resolution of 890 x 790 m.

The DOE Argus project flew a high performance low, light level COHU television camera during the June 1990 aerial collections. This camera had an intensified silicon target which was read using a separate mesh, magnetic deflection and focussed, readout beam. The camera was sidelaying.
The Russians have the MIR/Soyuz system which is panchromatic with a spatial resolution of 60 m and a bandwidth of 0.50 - 0.70 μm. The Russian Resurs-F also has a panchromatic band with a spatial resolution of 5.0 - 8.0 m and a bandwidth of 0.4 - 0.70 μm.

Japan’s MOS-1 visible and thermal infrared radiometer (VTIR) has a panchromatic band. The spatial resolution is 1 km and the sensor bandwidth is 0.50 - 0.70 μm. The MOS-1 uses silicon diodes as visible detectors.

Infrared

Infrared imagers can range over the broad spectrum of infrared: SWIR: 0.9 - 3.0 μm, mid-wavelength IR (MWIR: 3.0 - 8.0 μm), long-wavelength IR (LWIR: 8.0 - 30.0 μm), and very long-wavelength IR (30.0 - 100.0 μm).

The Argus project flew a Barr and Stroud IR18 that produces a video output. The spectral bandwidth of this instrument is 8.0 - 13.0 μm and the IFOV is 1.73 mR. This was an airborne platform flown with other sensors.

SNL division 2756 operates two Inframetrics Model 600 imaging IR radiometers. One camera has a bandwidth of 3.0 - 5.0 μm, and the other 8.0 -12.0 μm. Both radiometers use cryogenically cooled mercury-cadmium-telluride (HgCdTe) detectors with 200 active lines and 400 lines per frame. The image is sampled at a 30 Hz frame rate in a 2:1 interlaced mode. Each line provides 256 digital samples at 7 bits. The recording medium is standard VHS format video tape.

GOES is geostationary weather satellite. Since it does not move with respect to the earth, it needs a scanning mechanisms. The GOES satellite spins to scan a path. It also has a whiskbroom scan to get cross-track information. GOES has two bands, one from 0.55 - 0.75 μm which was discussed in the panchromatic section, and the other 10.3 - 12.1 μm. The LWIR ground pixel size is 6.9 km.

The European Radar Satellite (ERS-1) has an infrared radiometer (IRR) with four bands. At this time, the bands are unknown. The radiometer employs a scanning technique that will enable the Earth’s surface to be viewed at two different angles (0 and 52°). Data from the two paths can be combined in an attempt to eliminate atmospheric influences in temperature calculations. The instrument is designed for sea temperature measurements with an accuracy of better than 0.5 K. One pixel is 1 x 1 km.

Forward-Looking Infrared Detector

Forward-looking infrared (FLIR) systems are scanning systems. A scanning pattern is scanned over the field of view. The scan pattern can be created by moving the whole sensor or by fixing the sensor and moving an internal part, like the whiskbroom scan. This configuration allows simpler focal planes and a reduced number of detector elements.

The FLIR scanning method is usually a serial scan of a horizontal line that is repeated for adjoining vertical lines. This type of scan is compatible with TV scans. The FLIR usually employs two scanning components. One is a high speed, azimuthal scanning mirror. The other is a
slow speed, elevation scanner (usually 60 Hz for video formatting). In this manner, the entire two-dimensional scene is scanned. The detectors are usually linear arrays, but others employ CCD array technology to increase the thermal signal.

**Synthetic Aperture Radar**

Synthetic aperture radar (SAR) is an active system that emits and collects microwave radiation. It was developed in the early 1950's. It is a coherent system because it retains both phase and magnitude of the backscattered echo signal. Because it is a coherent system, polarization can be specified when transmitting and receiving. High resolution is achieved by synthesizing, in the signal processor, an extremely long antenna aperture, hence the name synthetic aperture. Because it senses in the microwave region, it is also an all-weather sensor. Most SARs operate in the 1 - 10 GHz region.

ERS-1 was first presented in the infrared section. The main sensor is a 5.25 GHz (C-band) frequency, 4-look capable SAR. The look angle is fixed at 20° with a 10.0 x 1.0 m antenna. It is vertical/vertical (VV) polarized. The ERS-1 can achieve a 26 m ground range resolution cell or higher depending on the mode of operation.

RADARSAT is a satellite-based SAR that is being developed by Canada. It will be a 5.3 GHz (C-band) SAR with a 15.0 x 1.5 m antenna. It will provide eight imaging modes with range-azimuth sampling in the range of 9 x 9 m to 100 x 100 m depending on the mode and number of looks. The scene width will vary from 45 km to 510 km. The incidence angle will be variable from 10 to 60°. Scheduled time of operation is 1996.

The Russians have a SAR satellite called the ALMAZ II. It has a range of look angles from 30 - 60° and operates at 3.0 GHz. The antenna size is 15.0 x 1.5 m. The ground resolution with up to two looks is from 15 - 30 m.

The Japanese Earth Resources Satellite (JERS-1) has a SAR on its platform. It has a fixed look angle of 35° and operates at 1.275 GHz (L-band). The antenna size is 11.9 x 2.4 m. The ground range resolution is 18 m with up to 3-looks.

The Seasat SAR was a satellite-based sensor that flew for four months in 1978. It was a 1.275 GHz frequency (L-band) SAR with horizontal/horizontal (HH) polarization. The look angle was fixed at 20° and the incident angle was 23°. The ground-plane resolution was 25 m.

The SIR-A and SIR-B were Space Shuttle SARs that flew on one mission each. The SIR-A had a fixed look angle of 45°, L-band 1.28 GHz frequency, and HH polarization. The azimuthal resolution was 4.7 m with a range resolution of 33 m. It used an optical recorder. SIR-B had a range of look angles from 15° to 60°. It was an L-band, 1.28 GHz, polarized system. The resolution was 5.4 m in azimuth and 14.4 m in range.

The National Aeronautics and Space Agency’s (NASA) Jet Propulsion Laboratory (JPL) has been fielding airborne SARs for a while. Another notable developer and user of SARs is the
Environmental Research Institute of Michigan (ERIM). Other countries like Canada, Denmark, France, Germany and China operate their own airborne SAR systems.

SNL has several SARs. One operates at 15 GHz, the other at 35 GHz. These are airborne instruments that have been flown over many target sites. Most of SNL Technical Area I as well as the NATO and Electromagnetic Pulse (EMP) sites have been imaged.

**Ground-Penetrating Radar**

One possible limitation with microwave SAR is foliage reflection obscuring the target. To penetrate through foliage, the SAR can be operated at lower frequencies. The lower frequencies have the additional possibility of penetrating into the ground and reflecting back to the antenna. This ground penetration opens the possibility of searching for buried objects.

Many companies in the United States have been working on ground penetrating radars. Some companies are SRI, Hughes, General Dynamics, and Lockheed Martin. The radars don’t have to be in a SAR format. Some are being deployed on the ground. Others are airborne systems. We have no specific details on their efforts.

Sweden's National Defence Research Establishment has developed a prototype airborne radar for foliage and ground penetration surveillance. The Coherent All Radio Band Sensing (Carabas) radar is an ultra-wide-band SAR that operates at low frequencies, 20 - 90 MHz. The resolution of the current system is 2 m. The radar transmits in a series of narrow bands of about 1 MHz that step up in frequency at about 100 microsecond intervals. Needless to say, Carabas requires very extensive signal processing. A single scene requires about 1 gigabyte of data. Ground penetration is expected to be 5 - 10 m depending on soil conditions.

The High-Powered Electromagnetics Department at SNL has developed extremely powerful impulse transmitters. The transmitters have power outputs ranging from 0.01 to 10 Gigawatts, pulse risetimes of 50 - 200 picoseconds, and pulse repetition rates exceeding 1 kHz. Use of such transmitters may increase the performance of ground-penetrating radar systems by providing several orders of magnitude increase in power levels.

**Laser Radar**

Laser radar (LADAR) is an active system that uses collimated laser light at a known power to reflect off the targets of interest. The laser light diverges and attenuates as it travels through the atmosphere, so this technique is limited in the range from the target based on the laser power and spot size. This system is usually an airborne platform operated in a low flight pattern above the site. The laser is coaxial with the collection optics, allowing diffuse and specular reflections to be collected and detected. A detector like a PMT or CCD can be used. The range is calculated through signal processing based on the inverse range squared law of intensity. The types of lasers used vary from helium neon (HeNe) to trivalent neodymium-doped glass (Nd³⁺:YAG).
Multispectral

Multispectral (MS) sensors make up the majority of sensors that are used in remote sensing today. They provide tens of spectral bands which in turn can be used in classification of materials and inferring conditions on the ground. The interpretation of the multispectral data is an ongoing research area.

The most notable multispectral sensor in research is the United States’ satellite-based Landsat series. The Landsat satellites have two multispectral sensors on them. The Landsat 4 and 5 have a Multispectral Scanner (MSS), which uses the whiskbroom scanning technique. The MSS has four channels spanning the visible to SWIR with a 83 x 68 m resolution. The Landsat satellites also have the Thematic Mapper (TM) sensors which have seven different channels that coarsely span the visible to the LWIR. The six visible to SWIR channels have 30 m resolution. The LWIR channel has a 120 m pixel size. For Landsat 4 and 5, the MSS is just bands 1-4 of the TM.

The DOE Argus project also flew with a 12 channel Daedalus MS sensor. The Daedalus separates the incoming radiation into eleven spectral bands ranging from the visible blue to the thermal IR. The twelfth band is a redundant band in the thermal IR. The Daedalus uses the whiskbroom or flying spot scanning technique. Being an airborne platform, the spatial resolution depends on the aircraft’s flight altitude. The IFOV is 2.5 mR.

The Multispectral Thermal Imager (MTI) is a satellite proposed by SNL for the DOE. It is a next generation Landsat satellite. It will have up to 18 bands spanning the blue-green to the LWIR. The ground resolution will vary with the wavelength bands from 6.25 to 50 m. It will use a pushbroom scan with pointing capabilities of 45°.

The Advanced Very High Resolution Radiometer (AVHRR) is a nadir-viewing satellite operated by the National Oceanographic and Atmospheric Administration (NOAA). It has five bands, one in the visible, one in the SWIR, one in the MWIR, and two in the LWIR. The ground resolution is 1082 m. So why is it called “very high resolution?” The radiometric resolution (gray levels) is what is high resolution, not the spatial resolution.

The Calibrated Airborne Multispectral Scanner (CAMS) is an airborne sensor which has 9 spectral bands, seven of which are identical to the Landsat TM. It has two extra visible bands. The scanning mechanism is whiskbroom. The IFOV is 2.09 mR.

The Thermal Infrared Multispectral Scanner (TIMS) is a six band, airborne sensor that only senses in the LWIR. It uses a whiskbroom scan and has an IFOV of 2.09 mR.

The SPOT satellite has three MS channels. These span from 0.50 - 0.89 μm and are 20 m on a side. This instrument has off-nadir capabilities identical to the SPOT panchromatic band.

On the Russian Resurs-F satellite platform, exist 6 spectral bands that span the blue visible to the far red. The resolution is between 5 and 8 m.

The Russian Resurs-01, 02 have two sensor configurations. The High Resolution Multiband Scanner (HRMS) has 3 bands that span the visible with a pixel size of 45 m. The Medium
Resolution Multiband Scanner (MRMS), has 3 bands spanning the visible and one band in the LWIR with a resolution of 170 m.

Along with the SAR presented above, JERS-1 is also multispectral. Its MS sensor is nadir-looking with eight bands that start in the blue-green and end in the SWIR. The pixel resolution is 24 m. Another sensor configuration on the JERS-1 is the Visible, Near Infrared Radiometer (VNIR) which has 4 bands that begin in the blue-green and end in the SWIR. It uses a whiskbroom scan and has a 50 m pixel resolution.

Japan’s MOS-1 has two sensor configurations on it. The VTIR has a panchromatic and 3 MS bands. The MS bands are in the MWIR and LWIR having pixel sizes of 1 x 3 km. The STIR uses a whiskbroom scanning mirror. The other configuration is the Multispectrum Electronic Self-scanning Radiometer (MESSR). This uses a pushbroom scanning with silicon CCD detectors split into 4 bands that span the visible and SWIR. It has 50 m pixels.

India has a pushbroom MS sensor called the Indian Earth-resources Satellite (IRS). It uses a linear silicon CCD to capture four bands in the visible. The best pixel size is 36.25 m.

Hyperspectral

Hyperspectral sensors seek higher spectral resolution than MSS sensors. They have 100s of bands instead of tens of bands. This type of sensor configuration is gaining popularity because it is able to give high spectral signatures of targets, and of constituents in the atmosphere. One drawback is the enormous amount of data that is generated using hundreds of spectral bands.

The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) is operated by NASA JPL. It flies on the NASA U2 and ER2 aircraft. AVIRIS is a pushbroom scanner of four spectrometers. It has 224 bands from 0.40 - 2.45 μm in 10 μm bandwidth increments. At an altitude of 20 km, the ground resolution is 20 m. The digital image size is 614 pixels wide by a variable flight length. The visible spectrometer detector is silicon and the other three are indium antimonide (InSb).

Ultraspectral

Ultraspectral sensors strive for even higher spectral resolution than hyperspectral sensors. Instead of hundreds of spectral bands, the ultraspectral sensor will have thousands of bands. At this point in time, we have not found an ultraspectral sensor.

Non-Imaging Sensors

In the following section some general non-imaging sensors will be presented. Again, these are not all non-imaging sensors. This section does provide a flavor of the diverse nature of these sensors.

Seismic Sensors

Seismic sensors can be active or passive. The active sensors use sources that vibrate the ground. Geophones are usually placed in a grid to receive the seismic waves after they propagate through the local geology. The delays and refractions of the seismic waves are used to infer the
underlying geological structures. Passive seismic detectors include laser systems that detect earth
movements, seismographs, and geophones. The geophones can be passively waiting for a natural
seismic occurrence.

**Electromagnetic (EM) Sensors**

Electromagnetic geophysical exploration is an active system used in determining the
conductance of materials. This is useful in geological structures, bathymetry, and ice thickness
measures. In most cases, the airborne system can use coaxial or coplanar coils that emit and
collect over the frequency range of 45 - 100,000 Hz. If sampling is done in a grid, a spatial
representation can be generated of the collected signal.

**Magnetic Sensors**

Magnetic remote sensing measures the variations in the magnetic field of the earth. It is a
passive system. The sensor’s are usually nuclear precession or optically pumped sensors (cesium,
rubidium, sodium, or helium) in which a signal is generated because of atomic magnetic
interaction. Some configurations only measure the total magnetic field. Using two sensors, a
gradient or vector field measurement can be made. The sensitivities are on the order of 0.01 nT.
These kind of sensors can be placed on an airborne platform, which if flown in a grid-like pattern,
can be used to synthesize spatially relevant data.

**Gravimetric Sensors**

Gravimetric sensors, or gravimeters, passively measure the variations in the earth’s
gravitational field. Two main types are the Worden and the Gulf sensors. These are used usually in
conjunction with magnetic sensors in geophysical searches for precious metal and oil deposits.
They may also be instrumental in finding buried structures including clandestine buildings, power
lines, or armaments.

**Weather Sensors**

For many of the imaging sensors, those that are satellite or airplane-based, the atmosphere
absorbs, scatters, and reradiates the radiative energy in their spectral bands, thus degrading the
signal. Weather sensors would monitor the atmospheric conditions and may be used in inverse
modeling to back-out the atmospheric effects.

The SNL’s Analysis Department III has worked with the Environmental Characterization and
Monitoring Systems Department in collecting atmospheric data at SNL for September 1993 and
February 1994. They have used the grid of weather stations now in place on SNL for
environmental monitoring. These included collections for the National Weather Service (NWS). 
These collections consist of ambient air temperature, humidity, and wind speed and direction.
NWS collections also used upper air soundings which use weather balloons instrumented to
measure temperature and humidity. SNL made other independent upper air soundings. A
radiotheodolite measured azimuth, elevation, wind speed and direction. A three-wavelength
integrating nephelometer, which measures the atmospheric particle scattering coefficient, and an
aerodynamic particle sizer, which measures the atmospheric particle size distribution, were also deployed.

Contact Sensors

There are a wide variety of contact sensors. For brevity, we present only thermal contact sensors. Thermal contact sensors are important for monitoring and ground-truthing temperature measurements. Temperature signatures are possible tip-offs for proliferation activities, or environmental dumping. Two major types of contact sensors are used. One is thermocouples, which monitor temperature by generating electrical current because of the temperature of dissimilar metals joined together at the contact point. The other is thermistors, whose resistance changes due the temperature.

Thermistors were used in the ground-truth experiment described in section 4.2.5 at SNL during September 1993 and February 1994. Their accuracy was within 0.4 °C.

Graphical Data

Geographical Information Systems (GIS) Data

GIS is designed to digitize features and attributes into vectors or lines that can be displayed in a layered manner. For example, a Landsat image can be displayed as the base image. Overlaying the image, roads, sewer lines, power lines, residential areas, and county boundaries can be displayed as different colored vectors, each color representing one of the above attributes. These overlays can be quite involved and may use multisystem imagery as portions of the overlay. Also, Boolean logic can be applied to find areas of interest (e.g. all areas that are inside the county line but have no sewer services).

Sandia has tremendous amounts of data in digital format. In fact, they have approximately 500 layers of data that can be used. At this time, there is not a formal catalog of all the data available, but we have received a partial listing.

The United States Geological Survey (USGS) Earth Science Information Center produces Digital Line Graph (DLG) data which has borders, highways, transportation etc. Sandia has a variety of this type of data in house.

Digital Terrain Elevation Data

The Defense Mapping Agency (DMA) for the whole world on CDROM with an average 130 m grid or posts (3 arc seconds) and 30 m horizontal detail. Elevation data is useful in rendering other types of data by draping the data over the elevation data. Higher resolution elevation data may be desirable. The USGS puts out a product called Digital Elevation Models (DEM) which covers the United States. Specifics on this product are not known at this time.
TIGER

The Census Bureau TIGER data is census data that is gathered every decade. This data includes ethnic, religious, financial, and family size over the area of interest. We have had little experience with this data.

Cartographic Data

We already pointed out that DTED data give topographic information. We can also use maps to provide landmarks, cities, and road infrastructure. To be useful to our research, they need to be in a format accessible via computer.

DMA has three types of maps. One type is on analog video laser disks. These cover the whole world with scales of 1:10,000 up to 1:60,000,000.

Another type of map are digital maps on CDROMs distributed by DMA. These maps are of the whole world and come in scales of 1:250,000, 1:500,000, 1:1,000,000, and 1:5,000,000.

Lastly is the Digital Chart of the World, also distributed by DMA. This map is really a GIS representation, including major transportation lines, boundaries, etc. for the whole world. While the other types of maps really need an interface to allow the user to peruse through the maps, the Digital Chart of the World is easily used as a stand-alone program. The scale is 1:1,000,000.

National Technical Means (NTM)

The United States has means by which it can provide surveillance in denied access territories. Some of these assets have come to light over the years, such as the U2, and the SR-71 reconnaissance airplanes. National Technical Means may provide other data sources that can be used in our fusion algorithms. Discussion of such assets is beyond the scope of this report.

Data Available over Kirtland AFB/SNL

We summarize the data available to our group as of March 1994 for the Kirtland AFB/SNL target area.

Photographic:

Aviaphot Wild RC10 of Coyote Canyon, the Solar Power Tower, and TOSI from June of 1990, airborne collections. On April 26, 1993, contractors took aerial photographs of the entire Kirtland/SNL reservation. These photographs were at two scales, 1:6000, 1:30,000.

Panchromatic:

SPOT satellite coverage.

Infrared:

Barr and Stroud IR18 video, airborne collection from June of 1990.
SAR:
Most of SNL Tech Area I, TOSI, NATO, EMP sites, Albuquerque Airport, Solar Power Tower, and Coyote Canyon have been covered by SNL SAR. There are probably many more.
ERS-1 data.
AMPS SAR data.

Laser Radar:
A piece of Kirtland AFB, not including SNL, has been collected.

Multispectral:
Landsat TM, 1991-92 and others
AVHRR data
AMPS MS data from June 1994 and May 1995.

Magnetic Data:
Magnetic data was gathered over 20 acres of SNL by a cesium vapor magnetometer, using a towed array behind a vehicle or by walking. Data was gathered in SNL Tech. Area II and parts of Tech. Area III. The data is total field data.

Gravimetric Data:
Gravimetric data was collected largely by the USGS.

Weather Data:
The Systems Research Center has worked with the Environmental Programs Center in collecting atmospheric data at SNL for September 1993 and February 1994. These included collections for the National Weather Service (NWS).

Contact Sensor Data:
Thermistor temperature data for September 1993 and February 1994 on the Exterior Intrusion Detection Facility’s asphalt pad and adjacent bare ground near Area III.

GIS Data:
GIS data of SNL includes boundaries, environmental remediation sites, transportation grid, hydrology, soils, vegetation, precipitation, geology, utilities, fences, sewer trenches, etc.

Digital Elevation Data:
DEM of Albuquerque

Cartographic Data:
Elevation maps of the Albuquerque area.
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