SEGMENT BASED IMAGE ANALYSIS AND IMAGE FUSION

Manfred Ehlers, Director
Institute for Geoinformatics and Remote Sensing IGF
University of Osnabrueck, Seminarstr. 19 a/b
D-49074 Osnabrueck, Germany
mehlers@igf.uni-osnabrueck.de

ABSTRACT

Over the last years, image fusion techniques have gained a renewed interest within the remote sensing community. The reason for this is that in most cases the new generation of remote sensors with very high spatial resolution records image datasets in two separate modes: the highest spatial resolution is obtained for panchromatic images whereas multispectral information is associated with lower spatial resolution. The ratios between panchromatic and multispectral imaging modes of one sensor vary between 1:2 and 1:5. For multisensor fusion, ratios can exceed 1:20 (e.g. Ikonos and SPOT merge).

   An emerging technique for the analysis of high-resolution images, on the other hand, is the use of segmentation algorithms as a pre-processing step. In this paper, we investigate techniques for the combination of image fusion and segment based image analysis. We will present a color preserving iconic fusion with subsequent segmentation and classification, a 'cookie cutter' approach for the integration of high resolution RGB and low resolution hyperspectral image data and a GIS based fusion technique for rapid image enhancement.

INTRODUCTION

   The availability of remote sensing data that are needed for global, regional and local monitoring has greatly increased over the recent years. While the increase in spatial resolution for digital images has been hailed as a significant progress, methods for their automated analyses (i.e. land cover mapping, change analysis, GIS integration) are still in the process of being developed. Object (or segment) based preprocessing techniques seem to be an adequate methodology because inter-class variances can be minimized and the image interpretation techniques of the human eye be mimicked. However, the question of appropriate data fusion techniques within this context has hardly been addressed.

   Over the last years, image fusion techniques have gained a renewed interest within the remote sensing community. The reason for this is that in most cases the new generation of remote sensors with very high spatial resolution acquires image datasets in two separate modes: the highest spatial resolution is obtained for panchromatic images whereas multispectral information is associated with lower spatial resolution. The ratios between panchromatic and multispectral imaging modes of one sensor vary between 1:2 and 1:8. For multisensor fusion, ratios can exceed 1:20 (e.g. Ikonos and SPOT merge). Consequently, for analyses that require both, high spatial <u>and</u> high spectral resolution, fusion techniques have to be developed to extract 'the best of both worlds'.

   Usually, the term 'fusion' is used by the imaging community it to address the problem of sensor fusion, where images from different sensors (or different modes of one sensor) are combined. They can be classified into three levels: pixel level (iconic), feature level (symbolic) and knowledge or decision level (Pohl and van Genderen 1998). Until now, of highest relevance for remote sensing data processing and analysis have been techniques for iconic image fusion for which many different methods have been developed and a rich theory exists. Unfortunately, for many fusion techniques we experience more or less significant color shifts which, in most cases, impede a subsequent automated analysis (Ehlers & Klonus 2004). Even with a fusion technique that preserves the original spectral characteristics, automated techniques often do not produce the desired results because of the high resolution of the fused datasets.

   For this purpose, feature based or decision based fusion techniques are employed that are usually based on empirical or heuristic rules. Because a general theory is lacking, these fusion algorithms are usually developed for certain applications and datasets. To discuss the advantages and disadvantages of segment based image fusion techniques, we introduce three fusion methods ('Ehlers fusion', 'cookie cutter' approach and a GIS based data fusion) in this paper.

SPECTRAL CHARACTERISTICS PRESERVING IMAGE FUSION

Iconic Image Fusion

Iconic image fusion techniques can be grouped into three classes: color related techniques, statistical methods and numerical methods (Ehlers 2004b). The first class includes the color composition of three image bands in the RGB color space as well as the more sophisticated color transformations such as intensity hue saturation (IHS) or the hue saturation value (HSV) transforms. On the basis of band statistics including correlation and filters, statistical approaches were developed, such as the principal component (PC) transform. The numerical methods employ arithmetic operations such as image multiplication, summation and image rationing. More sophisticated numerical approaches use wavelets in a multi-resolution environment.

Many publications have focused on how to fuse high resolution panchromatic images with lower resolution multispectral data to obtain high resolution multispectral imagery while retaining the spectral characteristics of the multispectral data. It has been proven that these methods seem to work well for many applications, especially for single-sensor single-date fusion. Most methods, however, exhibit significant color distortions for multitemporal and multisensoral case studies (Zhang 1999, Ehlers 2004b, Klonus & Ehlers 2007). Over the last few years, a number of improved algorithms have been developed with the promise to minimize color distortion while maintaining the spatial improvement of the standard data fusion algorithms. One of these is the so called Ehlers fusion which was designed to overcome these problems and has already proven its superiority over the standard pansharpening techniques such as IHS, PC, Brovey and multiplicative fusion methods (Ehlers 2004b, Ehlers and Klonus 2004, Ling et al. 2007).

Ehlers Fusion

The Ehlers fusion was developed specifically for a spectral characteristics preserving image merge (Ehlers 2004b). It is based on an IHS transform coupled with a Fourier domain filtering. The principal idea behind a spectral characteristics preserving image fusion is that the high resolution image has to sharpen the multispectral image without adding new gray level information to its spectral components. An ideal fusion algorithm would enhance high frequency changes such as edges and high frequency gray level changes in an image without altering the multispectral components in homogeneous regions. To facilitate these demands, two prerequisites have to be addressed. First, color and spatial information have to be separated. Second, the spatial information content has to be manipulated in a way that allows adaptive enhancement of the images. This is achieved by a combination of color and Fourier transforms.

For optimal color separation, use is made of an IHS transform. This technique is extended to include more than 3 bands by using multiple IHS transforms until the number of bands is exhausted. If the assumption of spectral characteristics preservation holds true, there is no dependency on the selection or order of bands for the IHS transform. A subsequent Fourier transform of the intensity component and the panchromatic image allows an adaptive filter design in the frequency domain. Using fast Fourier transform (FFT) techniques, the spatial components to be enhanced or suppressed can be directly accessed. The intensity spectrum is filtered with a low pass filter (LP) whereas the panchromatic spectrum is filtered with an opposite high pass filter (HP). After filtering, the images are transformed back into the spatial domain with an inverse FFT and added together to form a fused intensity component with the low-frequency information from the low resolution multispectral image and the high-frequency information from the high resolution panchromatic image. This new intensity component and the original hue and saturation components of the multispectral image form a new IHS image. As the last step, an inverse IHS transformation produces a fused RGB image that contains the spatial resolution of the panchromatic image and the spectral characteristics of the multispectral image. These steps can be repeated with successive 3-band selections until all bands are fused with the panchromatic image. The order of bands and the inclusion of spectral bands for more than one IHS transform are not critical because of the color preservation of the procedure (for a complete description of the method see Klonus & Ehlers 2007).

Fusion Results

The effects of the Ehlers fusion are demonstrated in Figure 1. We selected a multispectral SPOT 5 image (10 m ground sampling distance – GSD) of July 2004 and a panchromatic Ikonos image from 30 May 2005 (1 m GSD) out of a series of multitemporal satellite images (Ehlers et al. 2007). Figure 1 shows the original multispectral SPOT 5 (bands 1 – green, 2 – red, and 3 – near infrared) as a standard false color infrared display and the panchromatic Ikonos image data as well as the results of the Ehlers fusion and a standard iconic fusion technique (here: Brovey transform). The superiority of the Ehlers fusion is clearly visible. Especially the green field in the lower left corner appears darker in the Brovey transform than in the original image. A comparison with the panchromatic Ikonos image confirms that the

darker color is due to the panchromatic information in this region. In a comprehensive test with eight different fusion algorithms only the Ehlers fusion maintained the spectral characteristics of the original data and produced at the same time a significant spatial enhancement (Ehlers et al. 2007).

Figure 1a). Original multispectral Spot 5 image recorded on 24 July 2004 in the band combination 3 (near infrared), 2 (red), 1 (green)

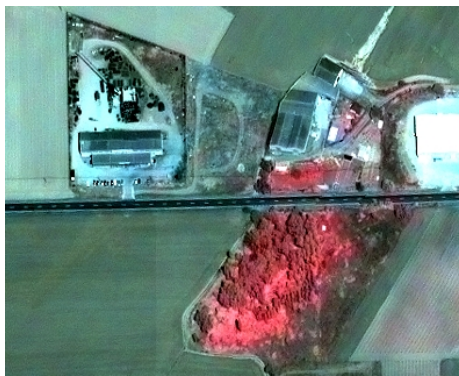**Figure 1b)**. Original panchromatic Ikonos image recorded on 3 May 2005

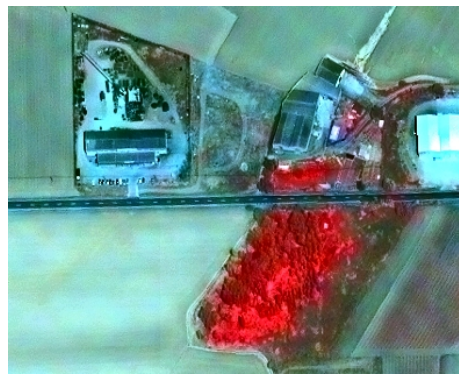**Figure 1c)**. Brovey fusion: the brightness of the two fields on the left is reversed

Figure 1d).Ehlers fusion: colors are well preserved.

While iconic fusion techniques work well for the production of spatially enhanced multispectral images they show deficiencies when it comes to subsequent automated processing. It is a well-known fact that higher spatial resolution might actually be detrimental to standard per-pixel based analysis techniques such as maximum likelihood (ML) classification. However, in a series of initial tests with several algorithms for the fusion of Landsat multispectral with SPOT 10-m panchromatic image data we achieved a classification accuracy improvement with the Ehlers method. We performed a maximum-likelihood classification for nine selected classes in the original and fused datasets. The study site was in an agricultural area for which the original classification accuracy was about 87% - a sufficient result for such type of landscape (see Figure 2). Using exactly the same training and test areas for the fused images, the only fusion technique that improved the classification accuracy was the Ehlers fusion (Figure 3, Table 1).
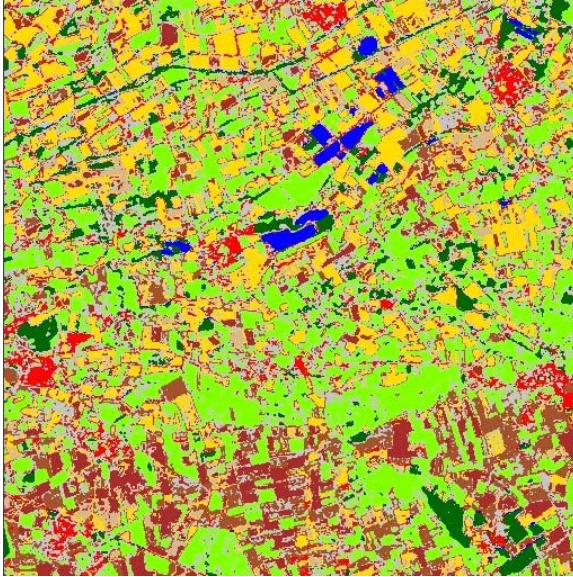
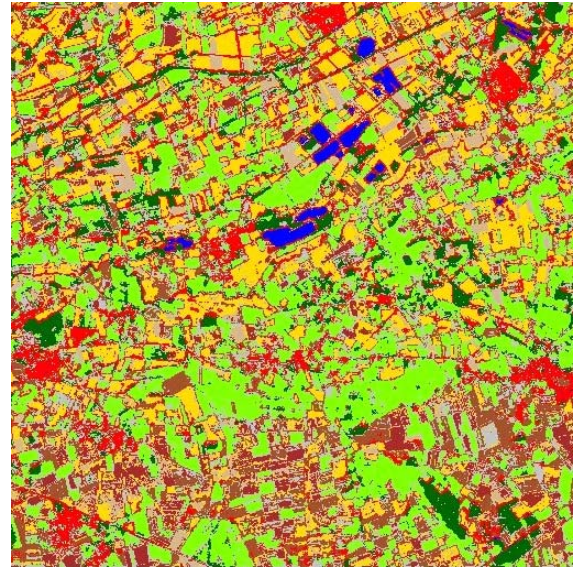**Figure 2.** Landsat TM maximum likelihood (ML) classification (9 classes).

Figure 3. Landsat/SPOT fusion: ML classification with the same classes as in Fig. 2 (results for Ehlers fusion).

Table 1. Maximum likelihood classification accuracies for the original and fused datasets.

Image Data	Class Based Classification Accuracy (min-max)	Overall Classification Accuracy	Kappa Coefficient
Original Landsat Data	40% - 100%	87%	0.86
Landsat/SPOT IHS Fusion	20% - 95%	74%	0.71
Landsat/SPOT Brovey Fusion	40% - 100%	77%	0.74
Landsat/SPOT PC Fusion	25% - 100%	73%	0.70
Landsat/SPOT Multiplicative Fusion	25% - 100%	79%	0.76
Landsat/SPOT Ehlers Fusion	70% -100%	90%	0.89

While these results are sufficient for rural and natural areas, for more challenging tasks such as automated settlement detection and mapping of urban areas we combined fusion with subsequent segmentation for an object based classification (Ehlers et al. 2006). Preliminary assessments of the results of the segment based classification of the fused image data showed that the class "settlement" (red) contains agriculture areas (border regions of fields) as well as streets (elongated segments with a similar spectral signature as the class "settlement") outside the settlement regions (Figure 4). Based on manually digitized ground-truth data, we calculated users' and producers' accuracy (Congalton and Green 1993).

As result, we achieved a users' accuracy of about 50 % and a producers' accuracy of about 88% for the class "settlement". One has to consider that urban classes are usually mixed classes and often show poor results compared to natural classes or water. Also, these are just the preliminary results of some initial tests which will have to be investigated further. However, even at this stage we can conclude that fusion and subsequent segmentation do not seem to work well for urban settlement detection. For tasks such as these, we make use of feature based or decision based fusion techniques. The disadvantage of these procedures is that they have to be developed for specific applications whereas iconic image fusion is based on general theories. In the following chapter we will discuss an example for feature based image fusion.

Figure 4. Result of fusion and subsequent segment based classification for the class 'settlement' (red overlay).

FEATURE BASED FUSION ('COOKIIE CUTTER' APPROACH)

Remote Sensing Datasets

To derive material classes for an urban study site, low spatial resolution hyperspectral information was fused with high resolution RGB and digital surface (DSM) data. For our analysis we developed a 'cookie cutter' approach (i.e. segmentation of the high resolution images and subsequent analysis of these segments in the low resolution images). The geometrically co-registered data consisted of:

- Digital orthophoto mosaic (Digital Camera Kodak DC14n)
- Digital elevation model (DEM) derived from cadastral data
- Digital surface model (DSM) derived from HRSC-A image data
- Hyperspectral image data (HYMAP)

More information about the sensors can be found in Greiwe (2006). The digital airphotos were resampled to a spatial ground resolution of 0.25 m. An orthoimage was generated using softcopy photogrammetry software with a resulting horizontal accuracy of $\sigma_{x,y} = 0.2$ m. Information about the surface elevation in the study area exists in two datasets:

- Digital elevation model (DEM, derived from cadastral data, grid size 12.5 m, vertical accuracy 0.5 m)
- Digital surface model (DSM, derived from the triplet stereo camera HRSC-A, grid size 0.5 m, vertical accuracy 0.2 m)

The DSM was normalized (nDSM) by subtracting the DEM data. The HyMap Sensor records 128 reflective bands covering the visible and near infrared range (VNIR) and the short wave infrared domain (SWIR) between 0.4 µm and 2.5 µm. With an operating altitude of 1,500 m and a scan frequency of 16 Hz data could be recorded with a ground sampling distance (GSD) of 3 m across and 4 m along flight track.

Methodology

Our methodological approach for data fusion is characterized by a segmentation of the high spatial resolution orthophotos and a spectral angle mapper (SAM) score generation of hyperspectral data. The method is based on a mutual support of both data types and a segment based endmember selection. The geometric location of the pixel in the hyperspectral dataset which represents an endmember of an urban surface type is determined by a segmentation of the high resolution image data. Hyperspectral pixels that are fully contained in a segment are candidates for the definition of reference spectra and are considered for the creation of a spectral library (Ehlers at al. 2006).

With the user-specific knowledge contained in spectral libraries, the hyperspectral data are classified by a SAM

full pixel classification approach. The classification results are transformed to an 8-bit SAM score by a user-independent automated algorithm (see Greiwe et al. 2004 for more details). Due to the exact geometric registration of both images the SAM scores provide additional feature values for the image segments of the high resolution orthophoto. The end product of this approach is a map produced by the classified segments. The workflow of our approach is shown in Figure 5.

For the classification process a score for each pixel of the hyperspectral data has to be determined (SAM score). SAM values are calculated by the cosine of a spectral angle for each given reference spectrum. This procedure produces a class image and an additional layer of SAM values, i.e. a "rule image" which contains n spectral angles for each image pixel at n given endmembers. A value near zero in a rule image represents a good fit to a given endmember (see Greiwe 2006 for more details).
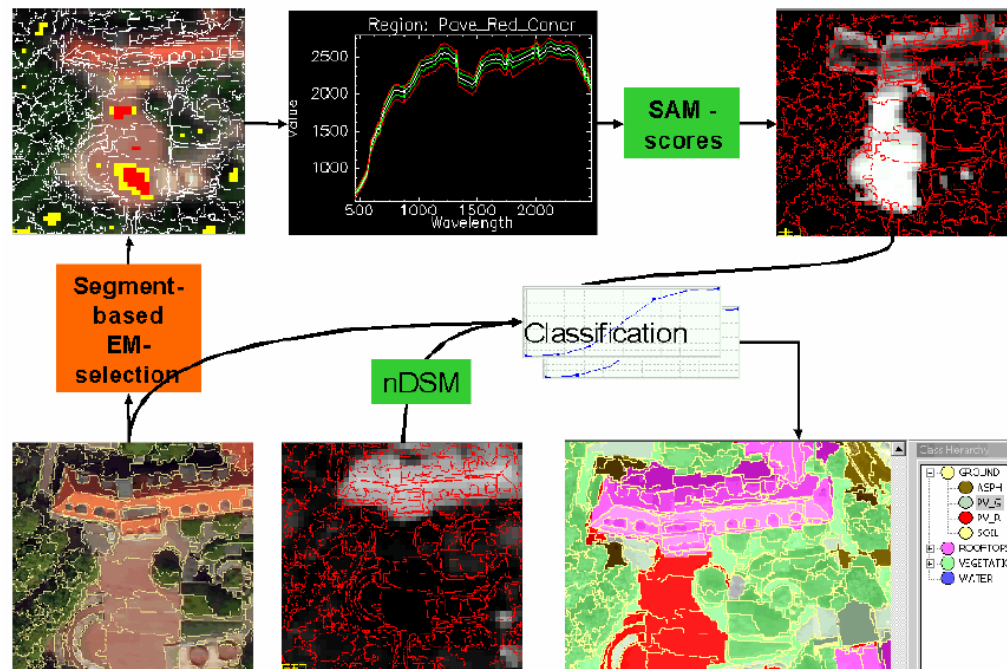

Figure 5. Segments of high resolution data (top left) are used for endmember selection in hyperspectral data (top right). Minimum distance classification and SAM score image are fused using a linear membership function. Results are produced by a neural network classifier.

Information about the average height of a segment and the RGB values from the orthophotos can be used as additional feature information. Like a DSM, the 8-bit SAM score layer is also stored in a gray scale image and averaged by overlay operation in a GIS. As a result, for each given class, an average SAM score is available (see Figure 6). The creation of image objects (segments) and the final classification is performed within the software eCognition. This software provides a neural network classifier which allows the user to create feature specific membership functions considering the SAM scores.

Results

Nineteen different classes were defined with a differentiation in material classes in order to test the methodology. It has to be noted that many classes were undistinguishable in the RGB image. For example, red roof tops were divided into "red roof concrete" and "red roof clay". Three different classification scenarios were defined to investigate the performance of the presented approach: A minimum distance classification applied on the RGB feature space of the orthoimage, an additional combination with the segment's elevation and at last the implementation of SAM scores into the classification process (Figure 6). For each of the classification scenarios the overall accuracy was estimated (see Figure 7). The relative low overall accuracy of the RGB scenario could be explained by the strong similarities of the defined classes in the visible domain.
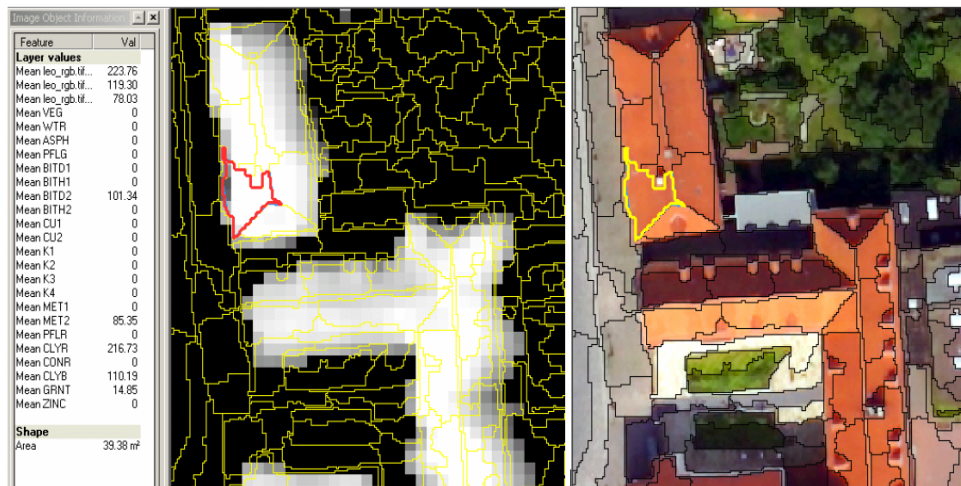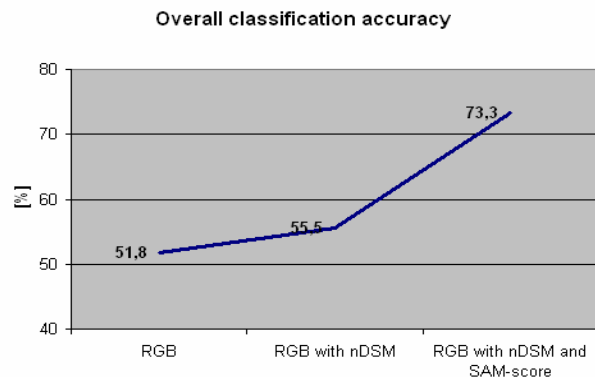
Figure 6. SAM scores for a segment

Figure 7. Increasing overall classification accuracy

The cookie cutter approach improved the classification accuracy by nearly 20%. Using this technique, the benefits of an integration of hyperspectral image data into the classification process (e.g. the differentiation of surfaces with similar features but different materials) is feasible.

GIS BASED FUSION FOR RAPID IMAGE ENHANCEMENT

Study Site and Datasets

Image enhancement techniques are usually applied to remote sensing data to improve the appearance of an image for human visual analysis. Enhancement methods range from simple contrast stretch techniques to filtering and image transforms. Image enhancement techniques, although normally not required for automated analysis techniques, have regained a significant interest in recent years. Applications such as virtual environments or battlefield simulations require specific enhancement techniques to create 'real life' environments and/or to process images in near real time.

Problems with standard fast enhancement techniques such as contrast stretch or histogram equalization are that they are usually optimized for whole images and might not prove appropriate for selected features. This affects especially coastal areas that may contain land, water and beach classes. Using global image enhancement techniques, the image will be transformed in a way that would produce a compromise for the different classes. Water is usually dark (especially in CIR display), beach will be very bright with little discernible structures (similar for urban classes),

and other land classes (e.g. vegetation) will not make use of the full possible range of spectral values. Also, different features might require different band combinations for optimal display. This cannot be done using conventional enhancement and display strategies. Water, for example, may reveal more information in a true color display whereas vegetation requires a false color infrared approach. The indicated problems will only get worse with the availability of hyperspectral data where possible combinations of narrow bandwidth spectral bands can differ for land and water features.

The proposed methods make use of existing GIS information, if available, and/or image preprocessing such as NDVI calculations. Using this approach, it is possible to design a procedure for completely automated image enhancement that works in an optimized way for the selected features.

The study site is located southeast of Jacksonville, North Carolina, USA. It presents one of the largest US Marines sites for which an extensive amount of ground truth, GIS, and remote sensing data is available. The datasets consisted of Landsat, SPOT, IKONOS and Qickbird images as well as GIS landuse/landcover data in shape format (Ehlers et al. 2004, Figure 8).

Figure 8. IKONOS multispectral image (2048 x 2048 subset) of the Camp Lejeune study site
overlaid with vector GIS information.

Methodology

Selected stretching especially for regions of low contrast is nothing new in the analysis of remotely sensed data. Usually, this is done interactively by the analyst either by selecting a box or digitizing a certain area of interest in the image. This area is then enhanced using standard image processing techniques (e.g., histogram equalization or linear contrast stretch). The subset is then displayed separately to highlight certain features that would have been impossible to discern in a global enhancement mode.

The goal of this study was to develop automated procedures for feature based image enhancement techniques for rapid display purposes, especially of high resolution remote sensing images (Ehlers 2004a). Feature based enhancement means that different feature classes in the image require different procedures for optimal display. The procedures do not only encompass locally varying enhancement techniques such as histogram equalization or contrast stretch but also the selection of different spectral bands. The image class water, for example, may be best displayed in a true color mode whereas for the feature class vegetation a false color infrared display is more appropriate. It is envisioned that this technique could be implemented in a near–realtime environment making use of a priori information.

There are two main sources for this kind of information: (a) storage of a priori knowledge in a GIS, and (b) context based image information that can be extracted through a segmentation process. Both techniques can also be applied for optimum feature class selection. For many areas in the world, there exists a wealth of a priori information in existing spatial databases, digital maps or previous analyses of remotely sensed data. Usually, this type of information is stored in a raster or vector based GIS. With the progress in the integration of remote sensing and GIS software, many commercial systems allow the simultaneous display and use of GIS and image layers. For a joint analysis, however,

usually GIS vector layers have to be converted to raster data.

The case study for our research was conducted in an integrated ArcGIS/ERDAS environment. The developed procedure, however, is system independent and can work in any integrated GIS/remote sensing environment. The procedure consists of five steps involving either GIS based or image context based masking (Figure 9).
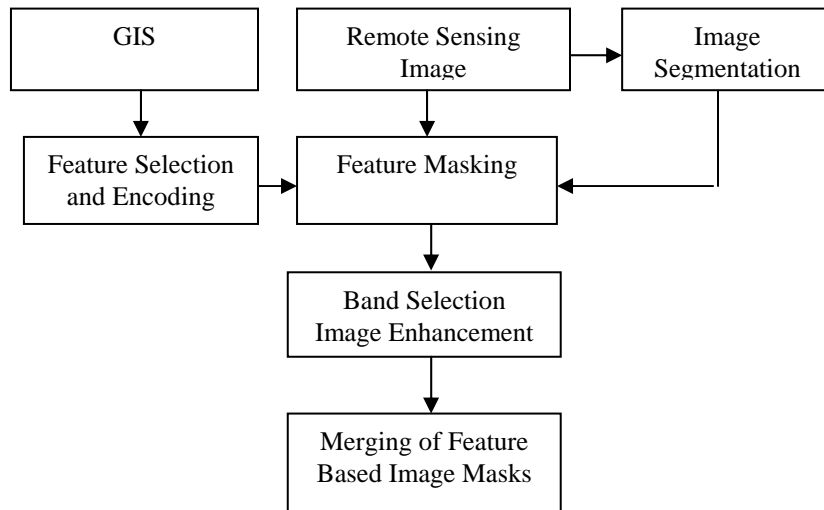
```
┌─────────────┐   ┌─────────────────┐        ┌──────────────┐
│     GIS     │   │  Remote Sensing │ ─────▶ │    Image     │
│             │   │      Image      │        │ Segmentation │
└─────────────┘   └─────────────────┘        └──────────────┘
       │                   │                          │
       ▼                   ▼                          │
┌──────────────────┐ ┌──────────────────┐            │
│ Feature Selection│ │                  │            │
│   and Encoding   │▶│ Feature Masking  │◀───────────┘
└──────────────────┘ └──────────────────┘
                           │
                           ▼
                  ┌──────────────────┐
                  │  Band Selection  │
                  │ Image Enhancement│
                  └──────────────────┘
                           │
                           ▼
                  ┌──────────────────┐
                  │ Merging of Feature│
                  │ Based Image Masks │
                  └──────────────────┘
```

Figure 9. Concept for GIS and context based image enhancement.

Results

First, all image and GIS layers have to be registered to a common coordinate system, e.g., UTM. GIS layers should be displayed as polygons or raster boundaries overlaid on the remotely sensed image to check for inaccuracies or geometrical and semantical inconsistencies of the data sources. In a second step, GIS information to be used as feature masks for local enhancement is analyzed and merged into meaningful classes. If, for example, vegetation classes are to be evaluated, all non-vegetation classes can be recoded into one mask. Other GIS masks that can be used for local image enhancement may separate water from land or built-up areas from open fields. The GIS layers can be overlaid on the image data for visual inspection. With this, editing can be performed if required (Figure 10).

The third step is the creation of separate image layers that are based on the selected feature classes. After recoding, the GIS layers form 0/1 input masks (0 = area outside the feature class, 1 = area inside the feature class) to segment the image into independent layers (Figure 11). Each spectral band of the image is multiplied with the individual GIS masks to form separate multispectral image layers with have the original nonzero pixel values only inside the selected GIS masks. The last image to be created contains the complement mask to all selected feature classes. Using this procedure, it is assured that for each pixel location only one of the image layers contains the original image value. All the others will have a zero value at this location. Using the 'union' operator, a simple overlay of all separate image layers recreates the original image.

In a fourth step, each layer is processed separately. This step does include the selection of an appropriate enhancement algorithm and the choice of suitable bands for display or printing purposes. In our study, we worked with 4-band remote sensing data. This step, however, will become more important if it involves hyperspectral images. For example, water information is usually displayed with a higher lever of detail if the blue band is included. Narrow band widths will make it possible to select spectral bands that depict physical phenomena such as turbidity or sediment content. Vegetation, on the other hand, is displayed best in standard false color infrared band combination due to the high reflectance in the near infrared domain.

Figure 10. Selected and recoded GIS classes for 'Water/Ocean', 'Water/River', 'Beach', and 'Open Field/Roads/Built-Up' overlaid on multispectral Ikonos data.
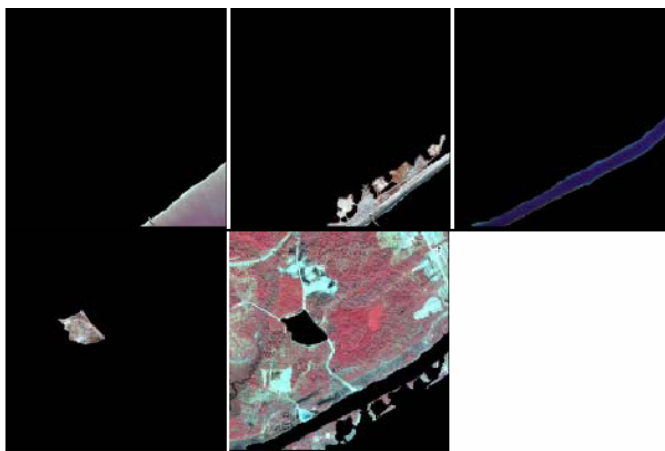

Figure 11. Separate image layers for the selected GIS classes 'Water/Ocean' (top left), 'Beach' (top center), 'Water/River' (top right), 'Open Field' (bottom left) and the complementary class (mostly vegetation) (bottom center).

The user can be interactively involved in this process or can leave the display and contrast enhancement to the default options. The default display options are established based on user experience and standard image processing literature. For water classes, the standard bands to be displayed are near infrared, green and blue (or for Ikonos and Quickbird bands 4, 2, 1). For all other areas, the standard display is near infrared, red, green (or bands 4, 3, 2, respectively). For image enhancement, we selected a contrast stretch based on $\pm 2.5\sigma$. This means that the digital numbers (DNs) for each band are stretched so that the values $[\mu - 2.5\sigma, \mu + 2.5\sigma]$ are mapped to $[0,255]$ (μ being the mean value of the input image band). Values outside the selected range are mapped to 0 and 255, respectively. This contrast stretch usually produces better visual results than the histogram equalization process with often too saturated areas of less discernible level of detail.

The last step involves merging of the separate image layers into a single image file using standard GIS overlay procedures. As the image masks do not overlap, the procedure is based on a simple union process. Figure 12 shows the result of the GIS based local image enhancement process compared to the standard full image enhancement option. The GIS layers selected from the database were 'Water/Ocean', 'Water/River', 'Beach', 'Open Field/Roads/Built-Up', and 'Vegetation'. The GIS based enhanced image shows more detail in all parts of the study area. There are almost no areas that are too bright or too dark to convey any information as is the case in the globally enhanced image which represents a compromise over the different spectral reflectance distribution for the image.

Figure 12. GIS based enhancement of the Ikonos image.

The process can be modeled in a flow chart or scripting language environment and thus be applied to other images and geographic regions. It has to be noted that the choice of suitable feature classes is still an interactive process and has to be performed by the user.

Often, there is not enough a priori information for a GIS based feature selection process or the information is not accurate and/or outdated. In this case, the information contained in the image itself is the most reliable source for feature based enhancement. The image has to be segmented into meaningful features classes which are again mutually exclusive and can be used as masks to create independent image layers. A promising approach is the segmentation based on NDVI classes. Using thresholds to select disjoint NDVI classes, Ehlers et al. (2004) created an enhanced image of very similar features as the GIS based approach.

CONCLUSIONS

Several aspects of image fusion and GIS/remote sensing integration were investigated in this paper. All presented fusion techniques use the benefits of a combination of high spatial and high spectral resolution remote sensing. For iconic image fusion in remote sensing (pansharpening) we showed the superiority of the Ehlers fusion algorithm for spectral characteristics preservation even for multitemporal and multisensoral fusion. The Ehlers fusion integrates color and spatial features from multispectral and panchromatic images, respectively, with minimal color distortion. This means that the fused image provides almost identical spectral characteristics as the original image and can be subjected to multispectral analyses just like the original image. This could be demonstrated in first tests with standard maximum likelihood classification of agricultural areas. Only the Ehlers fusion produced classified images with a higher accuracy than the classification of the original data.

For high spatial resolution remote sensing images of urban areas with mixed classes, however, maximum likelihood techniques are nor sufficient to extract information with high classification accuracy. This is due to the high in-class variances in the images and the mixed pixels in urban environments. For urban material detection in hyperspectral images we developed a feature based 'cookie cutter' fusion technique that uses a combination of very high spatial resolution RGB orthoimages and hyperspectral data of lower spatial resolution. It could be proved that a segment based endmember selection results in a suitable spectral library. With the automated SAM score generation, additional feature values for the image segments could be generated. As result, the additional inclusion of hyperspectral image data into a classification process of high spatial resolution images shows significant improvements and allows material differentiation of urban surfaces.

In comparison to pixel based classification procedures (like the maximum likelihood method) it is evident that the introduced feature ('cookie cutter') based fusion technique is a significant improvement for the design of future

automated processing modules. Through the adoption of object based image processing methods and data fusion techniques it is possible to avoid the salt-and-pepper effect of pixel based analyses and to enhance the classification accuracies. In our opinion, a feature and/or decision based fusion seems to be the most promising technique for the improvement of classification accuracy.

Information stored in GIS databases can be used for rapid image enhancement with realtime potential. GIS selected image classes were separately enhanced and fused at the final steps. If no GIS information is available, use can be made of segments that are produced by NDVI values. Both procedures work well for the display of multispectral images. As individual band selection can be incorporated in this enhancement process, the extension to rapid hyperspectral image display is possible. Known optimum band selections can be combined with spectral enhancement in this procedure. The method can also be automated to a large degree using a flow chart environment or scripting language. With more investigations in the future, some of the interactive steps can be replaced by default values.

REFERENCES

Congalton, R. and K. Green (1993). A practical look at the sources of confusion in error matrix generation, *Photogrammetric Engineering and Remote Sensing*, 59(5): 641-644.

Ehlers, M. (2004a). Remote Ssensing for GIS applications: New sensors and analysis methods, in: Ehlers, M., Kaufmann, H.J., Michel, U. (Eds.) Remote Sensing for Environmental Monitoring, GIS Applications, and Geology III, *Proceedings of SPIE Vol. 5239*, Bellingham, WA: 1-13.

Ehlers, M. (2004b). Spectral characteristics preserving image fusion based on Fourier domain filtering, in: Ehlers, M., Posa, F., Kaufmann, H.J., Michel, U., de Carolis, G. (Eds.) Remote Sensing for Environmental Monitoring, GIS Applications, and Geology IV, *Proceedings of SPIE Vol. 5574*, Bellingham, WA: 1-13.

Ehlers, M. and S. Klonus (2004). Erhalt der spektralen Charakteristika bei der Bildfusion durch FFT basierte Filterung. *Photogrammetrie-Fernerkundung-Geoinformation*, 6: 495-506.

Ehlers, M., R. Welch and Y. Ling (2004). GIS and context based image enhancement, *Proceedings of the XXth International Congress of ISPRS, Istanbul, Turkey*, IAPRS XXXV/B4: 397-402.

Ehlers, M., A. Greiwe and D. Tomowski (2006). On Segment Based Image Fusion, Proceedings of the First International Conference on Object-Based Image Analysis (OBIA 2006), Salzburg, (CD Publication), 7 pp.

Ehlers, M., S. Klonus and P.J. Astrand (2007). Spectral change analysis for multi-date multi-sensor image fusion, *Photogrammetric Engineering and Remote Sensing* (under review).

Greiwe A. (2006): Detektion von Referenzspektren in multisensoralen Bilddaten. Ph.D. Thesis, University of Osnabrück (http://elib.ub.uni-osnabrueck.de/publications/diss/E-Diss556_thesis.pdf)

Greiwe, A., M. Bochow and M. Ehlers (2004). Segmentbasierte Fusion geometrisch hochaufgelöster und hyperspektraler Daten zur Verbesserung der Klassifikationsgüte am Beispiel einer urbanen Szene, *Photogrammetrie-Fernerkundung-Geoinformation* (PFG) 6/2004: 485-494.

Klonus, S. and M. Ehlers (2007). Image fusion using the Ehlers spectral characteristics preserving algorithm, *GIScience and Remote Sensing* (accepted for publication).

Ling, Y., M. Ehlers, E.L. Usery and M. Madden (2007). FFT-enhanced IHS transform for fusing high-resolution satellite images, *ISPRS Journal of Photogrammetry and Remote Sensing* (in print).

Pohl, C. and J. van Genderen (1998). Multisensor image fusion in remote sensing: concepts, methods and applications. *International Journal of Remote Sensing*, 19: 823–854.

Zhang, Y. (1999). A new merging method and its spectral and spatial effects, *International Journal of Remote Sensing*, 20(10): 2003 – 2014.