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Computer Automated Image Classification

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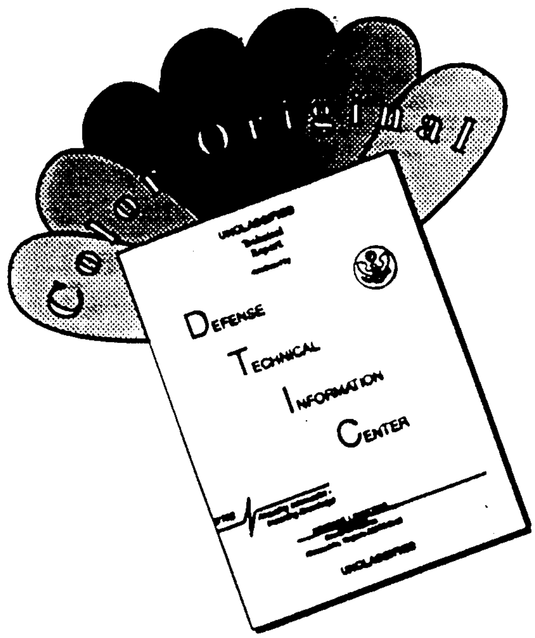

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13. ABSTRACT *(Maximum 200 words)*
The primary objective of the research and development was to achieve classification and feature extraction from high resolution digital terrain elevation (DTE) data and corresponding fine resolution SAR imagery generated from interferometric synthetic aperture radar (IFSAR) data. The report contains six sections. Section 1 contains a project summary that describes the objectives, approach, results, and conclusions of the Phase I project. Section 2 presents a discussion of future research and development recommended for a Phase II SBIR program. Section 3 presents details on the image data used for developing the image classification algorithms. Section 4 describes details of neural network (NN) algorithms investigated for image classification. Section 5 describes an image processing technique for extracting a specific feature type (water drainage systems) from high resolution digital terrain elevation (DTE) data. Section 6 presents the technical results obtained during the Phase I project.

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PREFACE

This report documents work performed and findings obtained on a Phase I Small Business Innovation Research (SBIR) Program (Contract DACA76-95-C-0012), conducted for the U.S. Army Topographic Engineering Center (TEC), Alexandria, VA. The Contracting Officer's Technical Representative was Elisa Gonzalez.

INTRODUCTION

Recent advances in interferometric synthetic aperture radar (IFSAR) and high throughput computing offer the potential for generating fine resolution SAR imagery and highly accurate digital terrain elevation (DTE) data. The availability of this data presents the opportunity for the rapid generation of maps for the support of military operations as well as civilian applications. The significance in providing a solution for rapid map production lies in the cost savings for the entire mapping community, the benefits to resolving environmental problems on a local and global scale, and to assist in resolving problems of a military nature for the purpose of securing peace worldwide.

This SBIR Phase I final report documents work that establishes the basis for developing a ***rapid map production*** system. The primary objective of the research and development was to achieve classification and feature extraction from high resolution DTE data and corresponding fine resolution SAR imagery generated from Environmental Research Institute of Michigan's (ERIM) IFSARE data. A majority of the Phase I work concentrated on developing, validating, and integrating algorithms for SAR and DTE feature classification and extraction. The classification algorithms were evaluated for their accuracy and ability to be integrated in an ***automated*** image classification system. The algorithm research and development focused on innovative neural network (NN) approaches. The researched and developed neural network algorithms demonstrate the ability to accurately classifying features from IFSARE imagery. They also can be integrated into an automated classification system.

The development of a ***rapid map production*** system based on IFSAR imagery will benefit the commercial world in areas such as geological exploration, urban planning, roadway construction/optimization, and environmental research. The availability of an automated rapid map production system will also assist tremendously in reducing the cost of generating and distributing highly accurate and information rich map products.

1.0 PROJECT SUMMARY

This section presents a comprehensive summary of the Phase I project, and is separated into several sub-sections. First, the Phase I *objectives* are reviewed and put into context with the completed Phase I work. Next, the *approach* taken to meet the project objectives is presented in summary form. The IFSARE image classification *results* are then presented, followed by *conclusions* on the feasibility of utilizing the developed neural network classification algorithms in a **rapid mapping** system using IFSARE data. Finally, future research and development for a *Phase II program* is introduced (refer to Section 2.0 for a concise description of the proposed Phase II program).

1.1 PHASE I OBJECTIVES

The research and development conducted on the Phase I project possessed the proper balance of work demonstrating the feasibility of IFSARE image classification using innovative neural network techniques (NN), and maintaining a focus on the goal of developing a computer automated rapid mapping capability. The primary objectives of the Phase I project were:

1) Demonstrate computer automated feature classification/extraction from IFSARE imagery using neural network (NN) techniques.

2) Determine classification categories for features in SAR, DTE, and Correlation imagery that would prove useful in a rapid map production system.

3) Determine the feasibility of developing a computer automated feature classification/extraction system utilizing the developed algorithms.

<u>**All Phase I objectives were met**</u> resulting in the conclusion that a NN approach can classify features from IFSARE imagery in an automated manner. The combination of a NN approach and conventional pattern recognition techniques will provide the complete algorithmic solution for a rapid map production system.

1.2 APPROACH

The approach taken on this Phase I project was straight forward and well defined, resulting in an optimized effort to reach the desired objectives. In order not to repeat or spend wasted time on any particular aspect of the project, an extensive search for *related work* was conducted early in the program which proved to be very insightful. Another activity that was conducted early in (and throughout) the program was the *analysis of the IFSARE data*. A large part of the Phase I work concentrated on the *development and accuracy assessment of neural network* (NN) algorithms for classifying features from IFSARE data. Techniques for feature extraction from the high resolution DTE data was also examined. Finally, an *evaluation* was completed of the developed NN and DTE feature extraction algorithms for their utility in an automated rapid map production system.

1.2.1 "Related Work" Research

A number of sources were searched for work conducted on the "classification of remote sensing data" (automated and non-automated). These sources include; IEEE Geoscience and Remote Sensing, DTIC, image processing literature, and various INTERNET sites related to remote sensing activities (e.g., EROS, USGS, JPL, etc.). The following lists the most relevant information obtained:

1) "*Application of Neural Nets to Radar Image Classification*", Y. Hara, R. Atkins, S. Yueh, R. Shin, and J. Kong. IEEE Geoscience and Remote Sensing, vol 32 #1.
2) "*A Neural Net Approach to Land Cover Mapping*", T. Yshida and S. Omatu. IEEE Geoscience and Remote Sensing, vol 32 #5.
3) "*A Dynamic Learning Neural Net for Remote Sensing Applications*", Y. Tzeng, K. Chen, W. Kao, and A. Fung. IEEE Geoscience and Remote Sensing, vol 32 #1.
4) "*Automatic Terrain Cover Classification using IFSAR Imagery*", Technology Service Corporation". Funded by ARPA. DTIC search.

5) *"The Application of Neural and Statistical Classifiers to the Probleem of Seafloor Characterization"*. Zoi-Heleni Michalopoulou (et al). IEEE Journal of Oceanic Engineering, vol 20 #3.

1.2.2 IFSARE Data Analysis

The data used for developing the classification algorithms was Interferometric Synthetic Aperture Radar (IFSAR) data. The data covers a 10 Km x 16 Km area of Dexter/Chelsea Michigan. The data consists of three components; radar magnitude data, height data, and a correlogram. The data is at 2.5 meter post spacings and was derived from 3 meter resolution, 3.5 look imagery. The received IFSAR data was corrected for any determined data anomalies, and a statistical analysis was performed to obtain a better understanding of the informational content. Details of the IFSAR imagery and the statistical analysis is presented in Section 3.0 of this report.

1.2.3 Image Classification using Neural Networks (NN)

Recent work using neural networks for feature classification of remotely sensed data has shown great promise. In a truly "automated" image classification system using IFSARE data and NN algorithms, the system should take in the data and directly classify the imagery without any system operator intervention (see Figure 1).

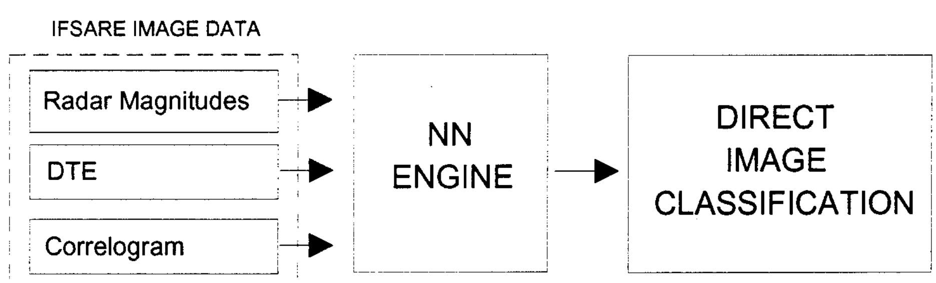

Figure 1. Automated NN Image Classification

In the Phase I proposal, submitted to the US Army Topographic Engineering Center (TEC), PSR proposed to research a supervised (requiring apriori information about the features to be classified) NN algorithm, the feed forward backpropagation (FFBP) NN. Since the main goal of Phase I project was to demonstrate the feasibility of developing a rapid map production system that is automated, PSR has investigated four NN algorithms, two of which are unsupervised techniques (not requiring any apriori information about the data before classification). The four NN algorithms identified for research and development were; feed forward backpropagation (FFBP), learning vector quantization (LVQ), self-organizing maps (SOM), and adaptive resonance theory (ART). Details of the four NN algorithms used for classification are presented in Section 4.0 of this report.

Six image feature types have been selected for classification; *roads*, *urban areas*, *water*, and *three classes of vegetation* (mainly distinguishable by their average height). All selected NNs require the input of feature descriptors for identifying the desired image feature types. These inputs form the basis for all the researched NN algorithms (see Section 4.0). The following design steps were followed for all NN algorithm development:

1) Define suitable inputs (and outputs for supervised NNs) and NN structure (i.e., how many layers, nodes, connectivity, etc.).

2) Choose training method and train NN until converged (or some acceptable error is reached).

3) Assess performance of network (i.e., speed, convergence, classification accuracy).

4) Change NN structure and/or NN inputs and re-evaluate.

Details on the NN inputs and structures are presented in Section 4.0. A discussion of the classification results obtained from the four researched NNs is presented in Section 6.0.

1.2.4 Feature Extraction from Digital Terrain Elevation (DTE) Data

The primary feature identified for extraction directly from the high resolution IFSARE DTE data was *drainage systems*. A standard pattern recognition algorithm was implemented to extract this feature, and is described in Section 5.0. Other features have been identified, and algorithms to extract these features are recommended to be developed early in a Phase II program.

1.2.5 Classification Accuracy Assessment

PSR received ground truth data for the Dexter/Chelsea area from TEC (produced by Horizons Inc.). The ground truth data was used for a "partial" evaluation of the NN classification accuracy. The data consisted of two primary sources of information; a *tree mask image* compiled from an orthophoto mosaic of the ERIM-IFSARE Dexter/Chelsea calibration site, and a *triangulated irregular network* (TIN) mask image collected from aerial photography (also of the ERIM-IFSARE Dexter/Chelsea calibration site). The ground truth data was not co-registered with the received IFSARE imagery, and the accuracy of the ground truth data is unknown. Section 3.5 describes the ground truth data in greater detail.

Visual inspection of gray-scaled images of the IFSARE magnitude and DTE data was also used to subjectively determine the accuracy of the NN classification algorithms. For example, there are several lakes that are prominent in the Dexter/Chelsea imagery. The NNs, however, classified parts of the lakes as belonging to the *roadway* class. This is thought to be because the lakes are partially frozen and possess widely varying radar backscattering properties (indicating the need for a new class, *ice*). Results of the NN algorithm(s) accuracy evaluation are given in Section 6.5.

1.3 RESULTS

The results and accomplishments of the work conducted on this Phase I project essentially fall into three categories; **1)** the accomplished IFSARE classification, **2)** the developed prototype software (NN algorithms and inter-active image analysis tools), and **3)** the preliminary design and evaluation of a prototype rapid map production system based on **1)** and **2)**.

1.3.1 IFSARE Classification

FFBP and LVQ were used as supervised NNs, thus they were trained with apriori information about features in the IFSARE imagery. SOM and ART2 were trained with arbitrary data selected from the IFSARE imagery, thus training was unsupervised. The final classification of the IFSARE imagery using the SOM and ART2 NNs required selecting and combining feature classes determined by the NNs that represented the six desired feature classes (roadways, urban areas, water, and three vegetation types). Only one of the four NN algorithms, ART2, performed poorly in classifying the IFSARE imagery.

Figures 2 through 4 present classifications of a 5.9 square Km patch (#19) from the Dexter/Chelsea IFSARE imagery for the FFBP, LVQ, and SOM NNs respectively (all three NNs used feature descriptor type 3). Figure 5 presents a gray-scaled image generated from the IFSARE magnitude data for patch #19. Figures 6 through 8 also present classifications of a 5.9 Km patch (#24) from the Dexter/Chelsea IFSARE imagery for the respective NNs. Figure 9 presents the gray-scaled image generated from the IFSARE magnitude data for patch #24.

Figure 2. FFBP NN Classification of Dexter/Chelsea (patch #19)

Figure 3. LVQ NN Classification of Dexter/Chelsea (patch #19)

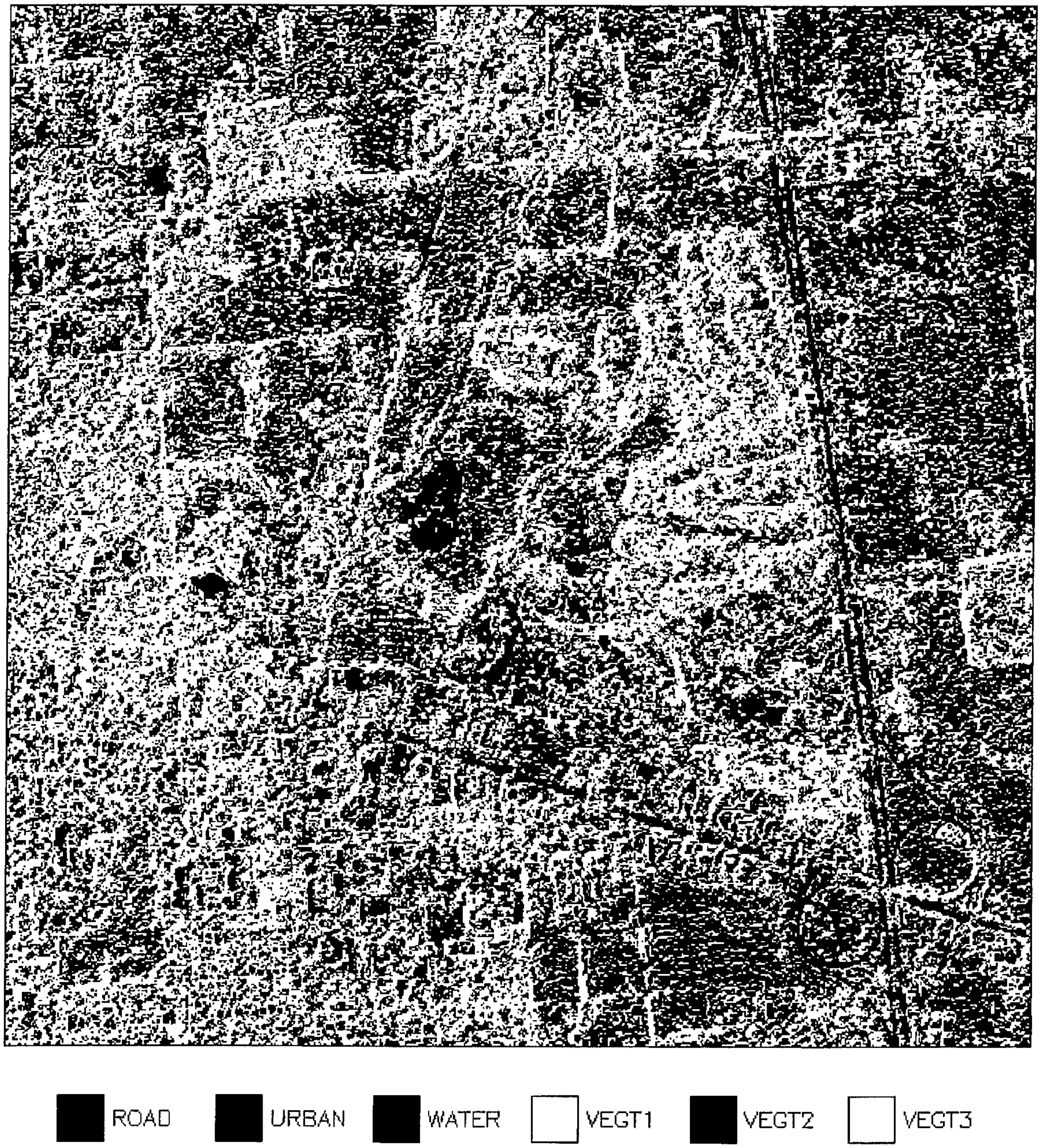

Figure 4. SOM NN Classification of Dexter/Chelsea (patch #19)

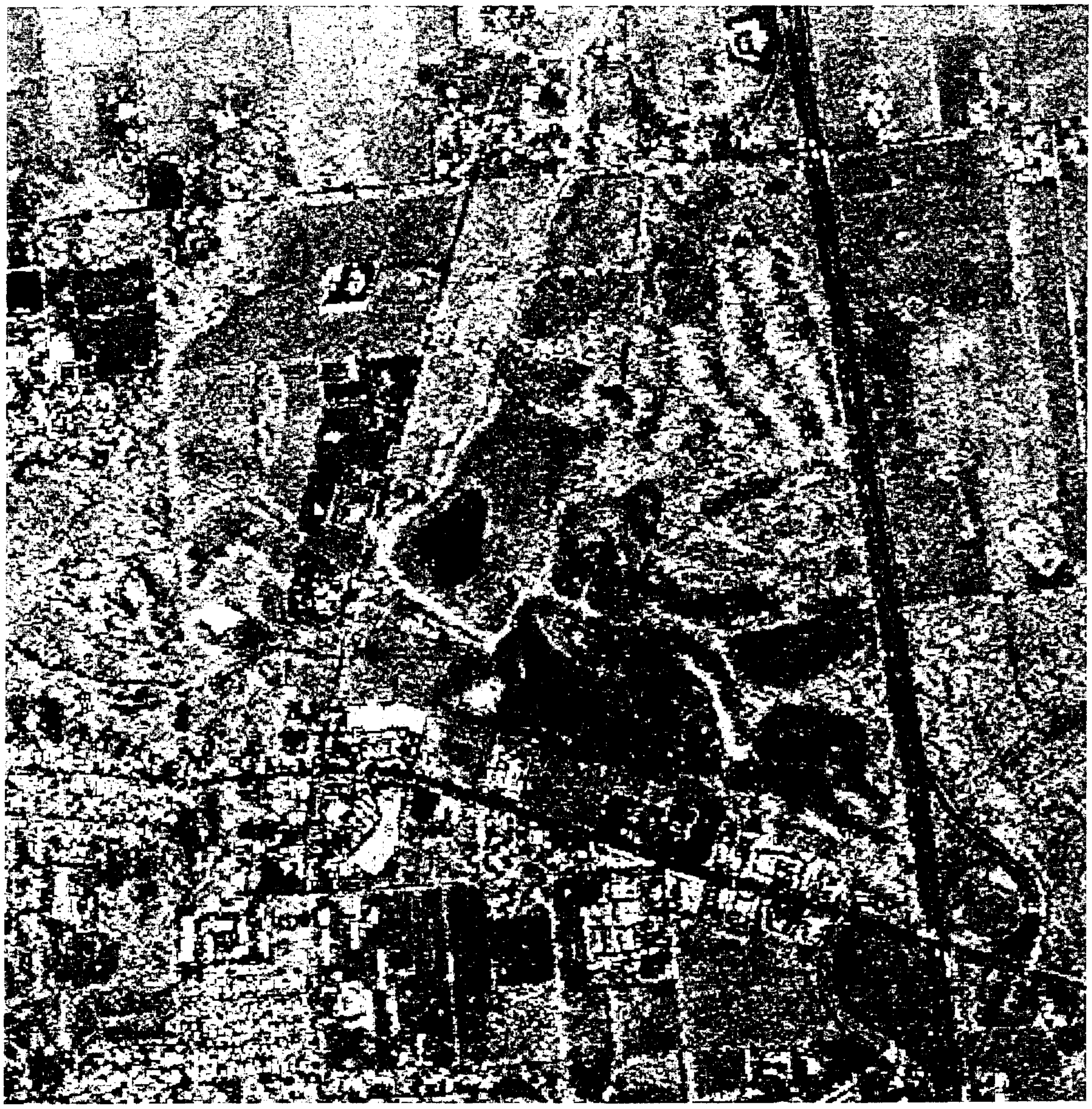

Figure 5. Gray-scaled Image - Patch #19 IFSARE Radar Magnitude Data

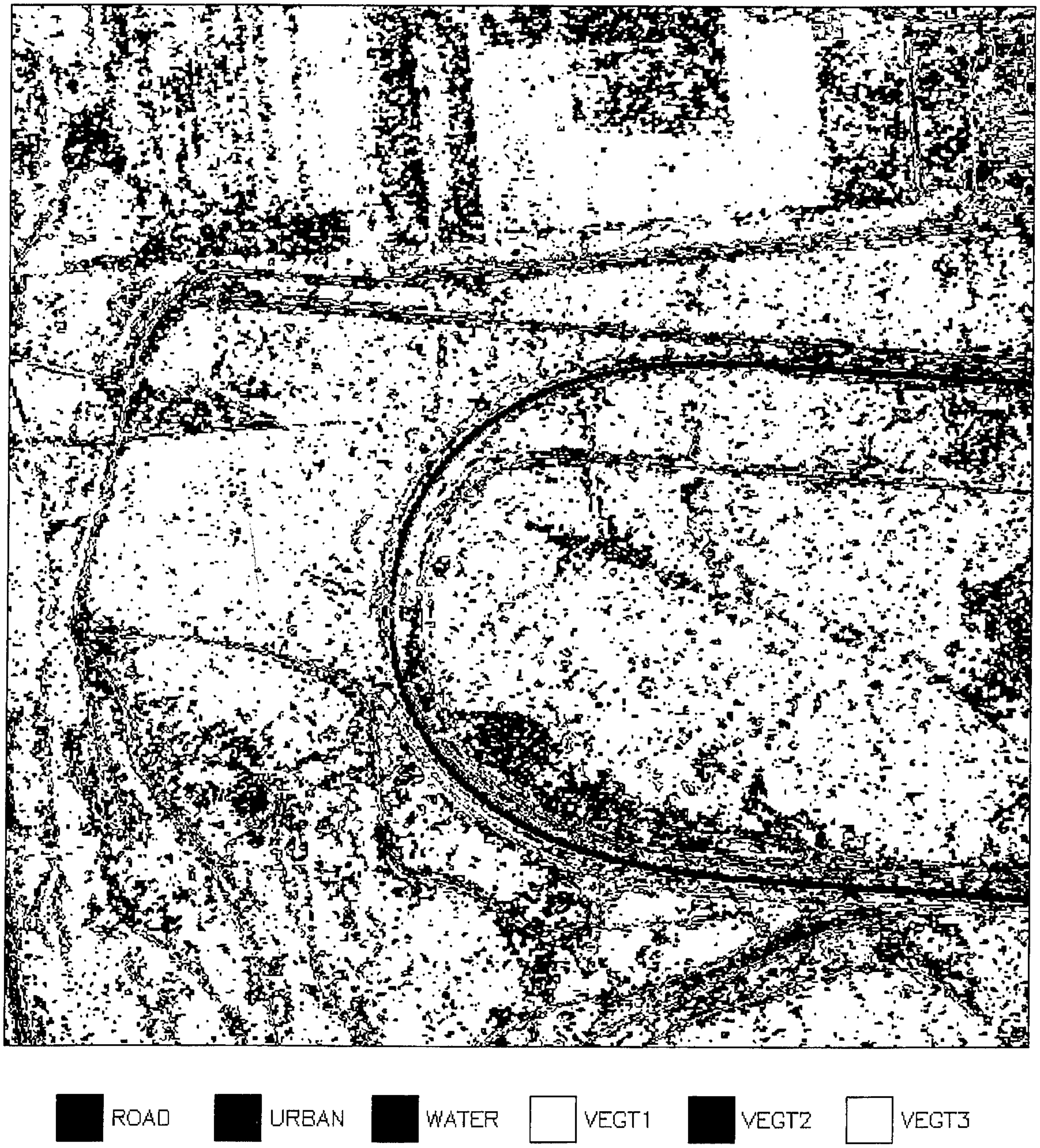

Figure 6. FFBP NN Classification of Dexter/Chelsea (patch #24)

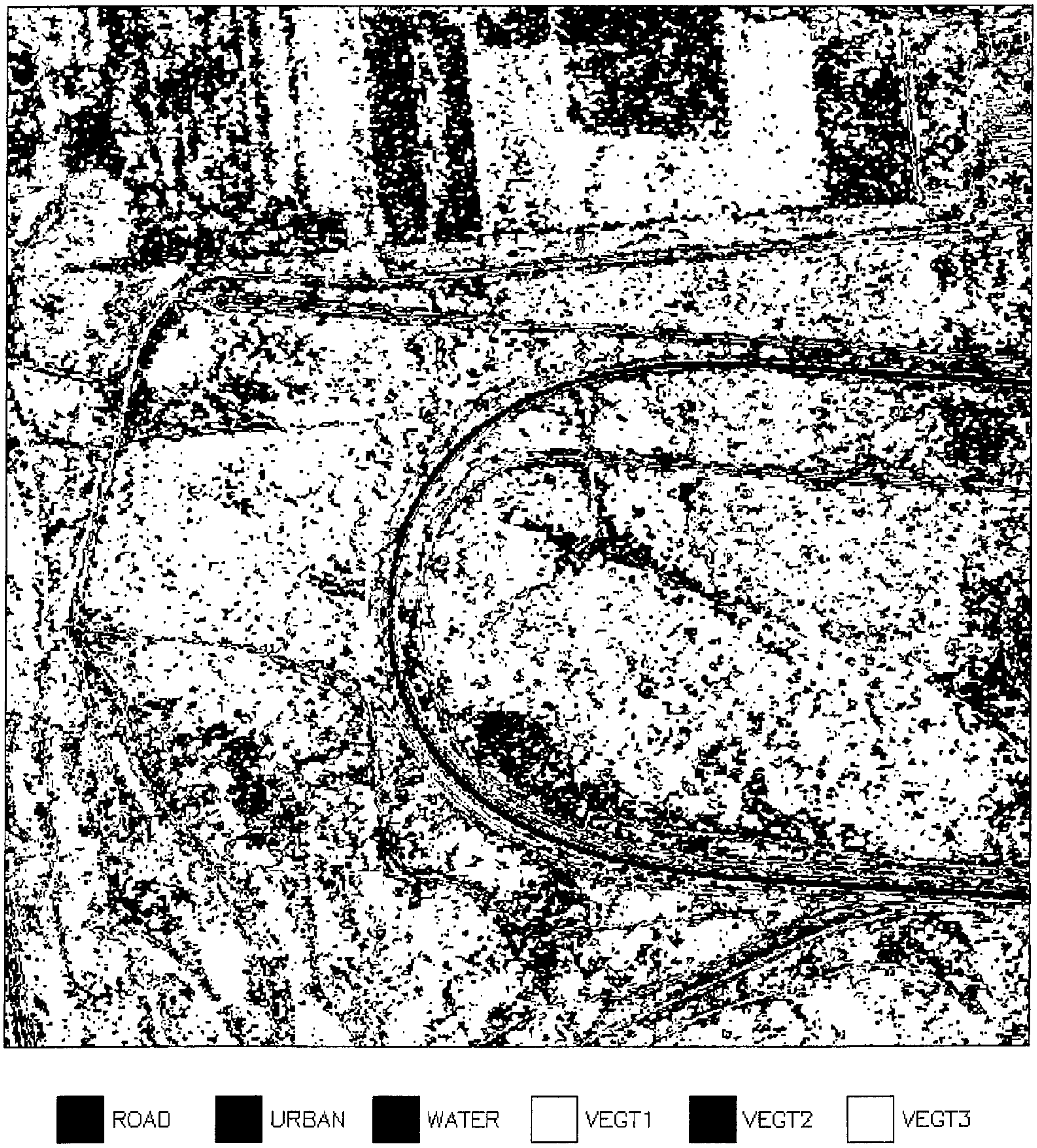

Figure 7. LVQ NN Classification of Dexter/Chelsea (patch #24)

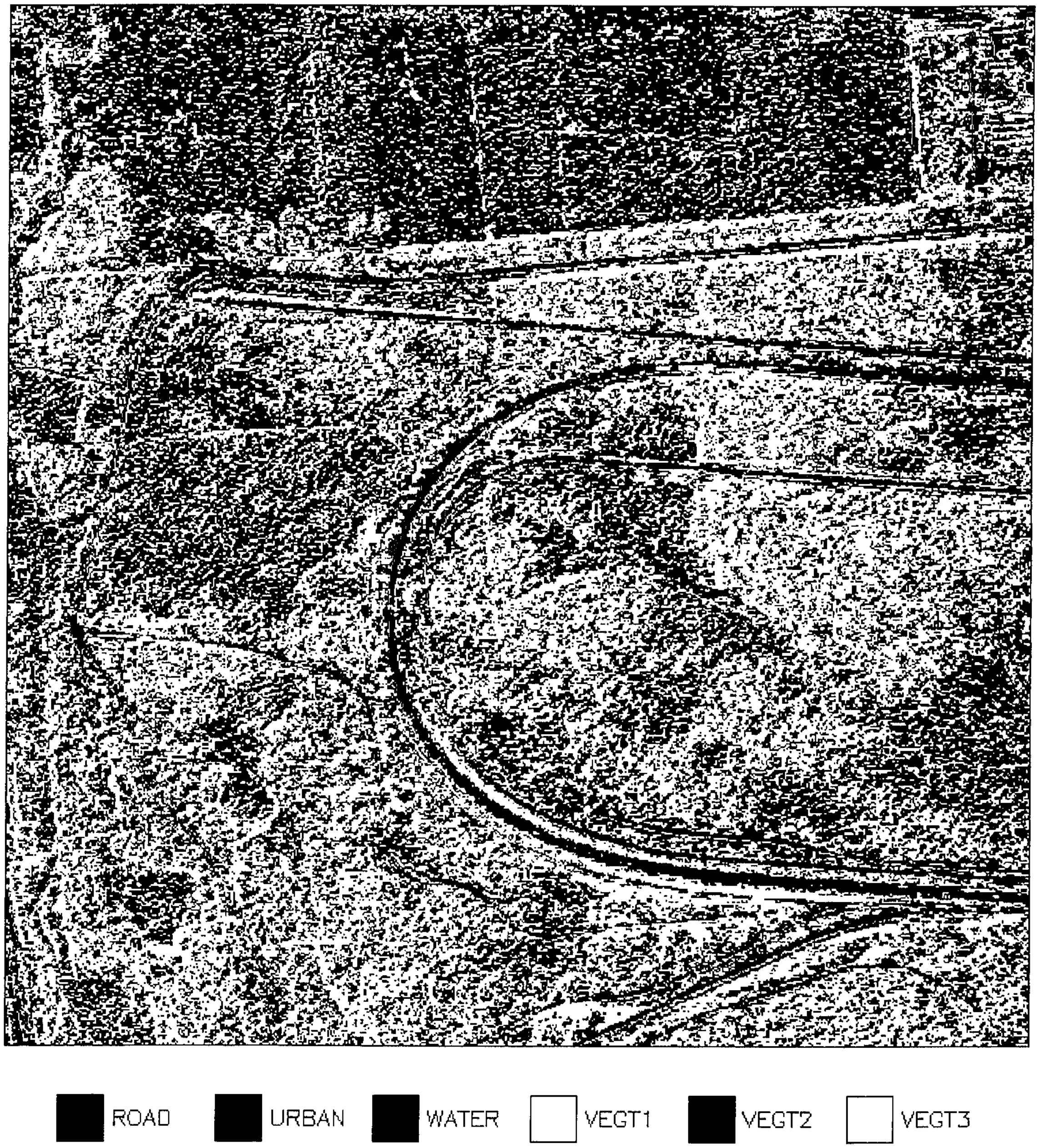

Figure 8. SOM NN Classification of Dexter/Chelsea (patch #24)

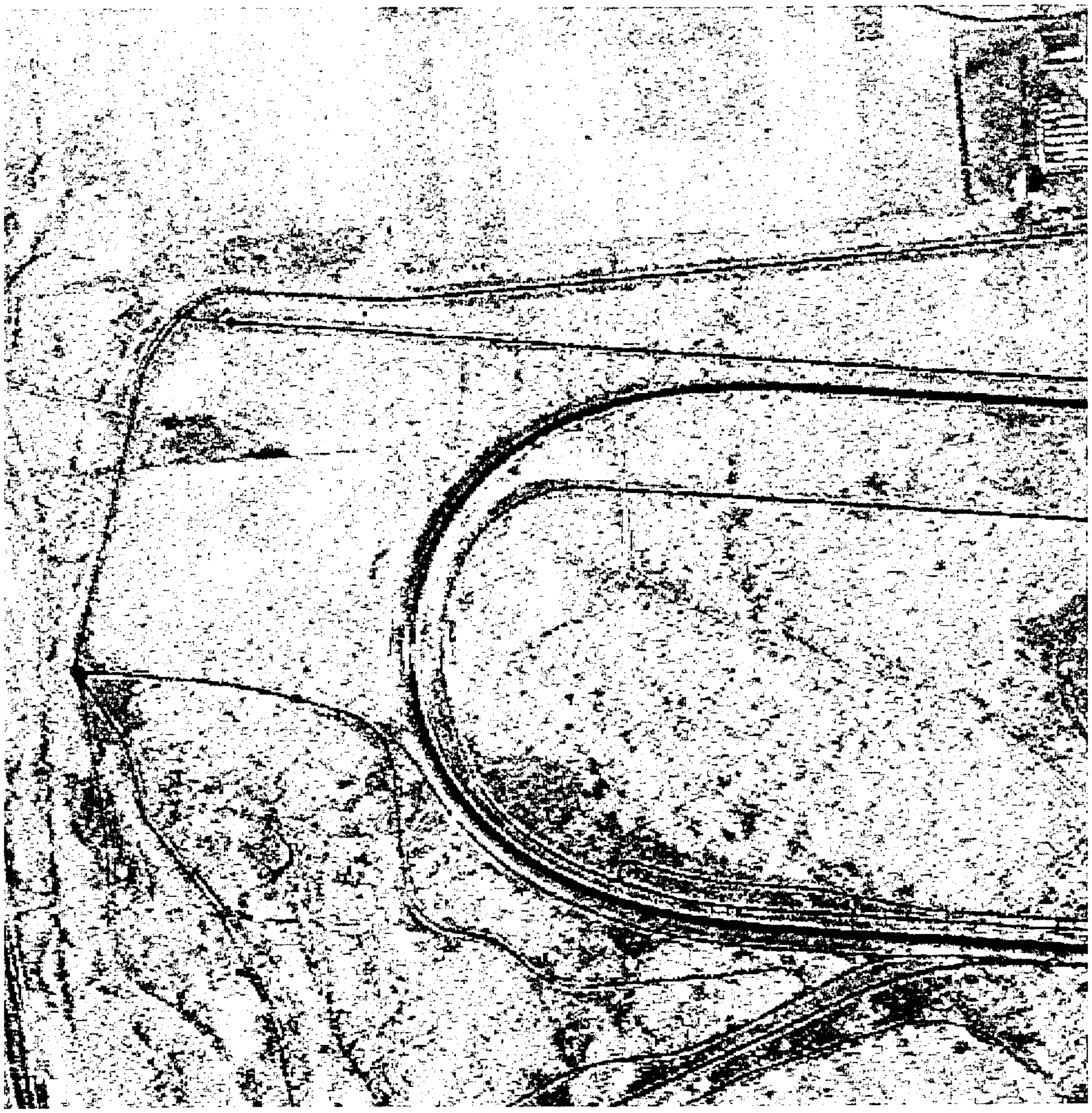

Figure 9. Gray-scaled Image - Patch #24 IFSARE Radar Magnitude Data

1.3.2 Developed Prototype Computer Software

Two prototype computer software tools were developed during the Phase I project to perform image processing/analysis of the IFSARE data, semi-automate NN training, and to perform final IFSARE image classification. The first software tool allows for detailed viewing and analysis of the three IFSARE data types (magnitudes, DTE, and correlogram). It also provides functionality for the generation of neural network training datasets for the supervised and unsupervised NNs. See Figure 10 for an illustration of the NN training and IFSARE data analysis tool.

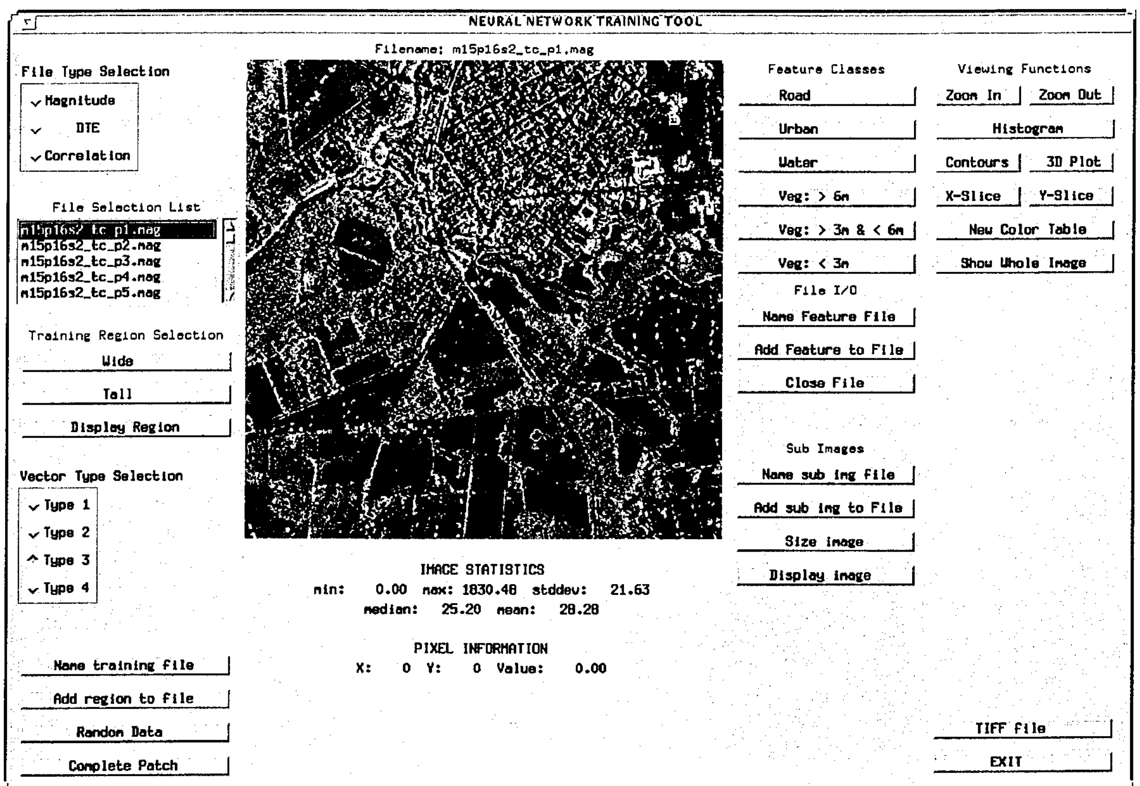

Figure 10. NN Training and IFSARE Data Analysis Tool

The second software tool displays a set of SOM (or ART2) reference vectors (representing the SOM NN clusters), and allows the user to color code the selected reference vectors. This process dynamically builds a classified image which is displayed directly below an original gray-scaled IFSARE SAR image. This tool allows for quick analysis of which SOM reference vector represent a particular feature class (or part of a feature class) in the IFSARE imagery. The software tool saves the classification information which is used in conjunction with the SOM NN to automate the classification procedure. Refer to Figure 11 for an illustration of the unsupervised NN IFSARE classification tool. Section 6.3 presents numerous examples of using this software tool to optimize the SOM NN for IFSARE image classification.

Figure 11. Unsupervised NN IFSARE Classification Tool

1.4 CONCLUSIONS

The **primary objective** of achieving classification and feature extraction from high resolution DTE and corresponding fine resolution SAR imagery **was accomplished** by three of the four NN algorithms (FFBP, LVQ, and SOM) researched and developed during the Phase I project. One unsupervised NN, ART2, did not perform well in classifying the IFSARE imagery. Although the NN algorithms achieved reasonable classification results, fine-tuning the algorithms (NN inputs and structures) will improve the classification results and increase the classification accuracy. Also, the NN inputs (feature descriptor vectors) are probably not optimal feature descriptor types for all desired IFSARE feature classes to be determined. The work required for fine-tuning and optimizing the best candidate NN for IFSARE classification will be outlined in the Phase II proposal.

The NN algorithms do show great promise for inclusion into an "automated" classification system. Once NN classification algorithms are trained, they run automatically and can process large quantities of data (inherent in image processing) very efficiently. The key to obtaining a NN classification algorithm that is robust (not requiring additional "learning") is to train the algorithm with data that represents a majority of the input that the algorithm will ever see. SOM, the unsupervised NN, obtained reasonable classification results, and did not require any apriori information about the feature classes prior to training and classification. The SOM NN determined classes for the IFSARE imagery automatically. It should be possible to take the SOM feature classes, and automatically determine which specific feature types they represent. This process will be outlined in the Phase II proposal.

There are some other conclusions that can be made about the results obtained during this Phase I project, and are summarized next

1) There are particular feature classes that are very similar in terms of the feature reference vectors. One group of features that are closely matched are; urban areas and some particular trees. Another grouping includes; highways and waterways. A third group includes what appears to be bare ground (plowed fields, dirt roads, etc.) and shadows. And a fourth includes all the various field types.

2) The SOM and LVQ NNs should have enough nodes (reference vectors) in the network to allow for differentiating the features in the grouping mentioned in **1)** above.

3) A more detailed textural analysis of the IFSARE imagery might suggest that additional feature descriptor components (e.g., greater spatial information to be included in the feature descriptor vectors) are required to further refine the neural networks capability to accurately classify the particular features in the IFSARE imagery.

4) It is possible that a particular feature descriptor (reference vector type) would work better for one feature class than another. This would involve multiple neural networks to determine different features in the IFSARE imagery.

Refer to Section 2.0 for details on recommended future research and development to be conducted in a Phase II program.

2.0 FUTURE RESEARCH AND DEVELOPMENT (PHASE II)

This section provides recommendations for future research and development to be conducted in a Phase II program. The sub-sections discuss important aspects of the recommended Phase II work. Recommended Phase II work areas include:

1) Obtain additional IFSARE data.
2) Extend algorithm development to address problems known to be inherent in the IFSARE data (such as shadows that cause the absence of data and the breakup of identifiable features).
3) Extend algorithm development to address variations in IFSARE data due to the collection of the data from different geographical regions (i.e., regions having terrain categories ranging from heavily forested to desert) and under different environmental conditions.
4) Determine the "real" utility of the IFSARE correlation data.
5) Finalize SAR and DTE feature descriptors for NN classification algorithms.
6) Finalize feature extraction from high resolution DTE data.
7) Define the "Rapid Map Production (RMP)" system functional requirements.
8) RMP system design.
9) RMP system development, implementation, and testing.

2.1 OBTAIN ADDITIONAL IFSARE DATA

The research and development conducted during the Phase I program utilized a single IFSARE image for classification algorithm development. This was satisfactory for demonstrating the feasibility of the researched neural network (NN) algorithms to accurately and automatically classify the IFSARE data. The NN algorithms have been biased, however, to the informational content in the Dexter/Chelsey IFSARE data. It is anticipated that data collected on different ERIM IFSARE missions (specifically over different geographical regions with varying environmental conditions) will contain slightly (or more than slightly) differing radar magnitude data for similar features in the IFSARE imagery. It will be important to rigorously test the developed NN classification algorithms using data unseen by the algorithms during development to determine the robustness of the algorithms.

2.2 EXTENDED ALGORITHM DEVELOPMENT

The analysis of the Dexter/Chelsea IFSARE imagery showed several problem areas that are present.

1) Radar shadowing effects are easily seen in the SAR image. This causes the absence of data (low radar magnitude returns for given pixels), and the break up of other identifiable features in the SAR imagery. The NN algorithms were tested to see if they could classify the shadows in the SAR imagery, and some success was made. However, the shadow identification process needs to be reviewed and refined.
2) Even though the NN algorithms have reasonable success classifying roadways in the SAR imagery, there are obvious discontinuities seen in the final classified images (most probably due to automobiles, bridges, trees, etc.). An image processing technique (computer vision) will be utilized for post-processing of roadways.
3) Lakes in the SAR imagery were not completely classified as water. The radar magnitudes were highly variable across the lakes. This is thought to be due to the lakes being frozen in parts (causing a higher radar return for the frozen parts of the lakes). The NN algorithms will be tested for the classification of ice.

An image classification system could easily be developed for a specific geographical region with static environmental conditions (assuming data collection systems were also consistent). Probably the most difficult problem in developing a "truly" automated image classification system is to get the system to classify data that it has never seen before. The Phase II program **must** extend the algorithm development to address variations in IFSARE data due to the collection of the data from different geographical regions (i.e., regions having terrain categories ranging from heavily forested to desert) and under different environmental conditions. An interesting test for the NN algorithms developed during this Phase I project would be to present new SAR and DTE data collected from the Dexter/Chelsea area, however, have the actual radar swath oriented from East to West (or vice versa) instead of from South to North. Also, data collected from a different geographic region (say the Rockies) classified by the current algorithms would immediately demonstrate the limitation of the developed algorithms. The following questions should be answered early in the Phase II program (during the Extended Algorithm Development phase):

1) Are there extreme variations in IFSARE imagery as a function of geographics and environmental conditions (or do the features simply shift in radar magnitude)?
2) Do the developed NN classification algorithms need to completely re-learn the new IFSARE imagery?
3) Are there simple adjustments in the current algorithms (NN weights, structure, etc.) that could be determined by preprocessing the IFSARE imagery, thus maintaining the "automated" quality of the classification system?
4) When does the classification algorithms need to re-learn the new IFSARE imagery?

Answering these questions and developing solutions for them will bring the IFSARE image classification system closer to being a "truly" automated system. Details on promising approaches will be outlined in the Phase II proposal.

2.3 RAPID MAPPING SYSTEM (RPM)

To successfully develop a rapid map production system, an accurate functional requirements document and a detailed system design must be completed early in the development cycle. The system design must address such issues as software functionality, portability, usability, and applicability. Next, hardware and software development requirements must be specified, including a review of current hardware and software technologies. This is then followed by the generation of a preliminary software design that integrates all image classification algorithms with a graphical user interface (GUI). PSR's Phase II proposal will present detailed descriptions of all tasks involved in the development of a prototype Rapid Mapping system.

3.0 IFSARE DATA DESCRIPTION

The data used for developing the classification algorithms under this Phase I SBIR program was produced by the Environmental Research Institute of Michigan (ERIM). PSR received the Interferometric Synthetic Aperture Radar (IFSAR) data from the US Army Topographic Engineering Center (TEC). The data originated from ERIM's IFSARE mission 15, pass 16, segment 2 which covered a 10 Km x 16 Km area of Dexter/Chelsea Michigan. The received data consists of three components; radar magnitude data, height data, and a correlogram. The data is at 2.5 meter post spacings derived from 3 meter resolution, 3.5 look imagery.

Some pre-processing of the three IFSARE data types was performed prior to using the imagery for classification algorithm development. First, all images were cropped so that the Northern and Eastern areas void of data were removed. Next, data anomalies (such as missing data) were removed from the images. Further evaluation of the magnitude and correlation data revealed that both images contained a bias. The bias found in both images was removed using the following steps:

Step 1 - The average pixel value from East to West was computed for each row in the image.

Step 2 - The resulting data was curve fitted using a polynomial of degree 4.

Step 3 - The resulting curve was then normalized with respect to the pixel farthest to the North (1st pixel in North-South column).

Step 4 - The cropped magnitude and correlation images were corrected using their respective curves.

The following sections (2.1-2.3) present the corrected images used for developing the classification algorithms. The radar magnitude image presented in section **2.1** also illustrates how all three image types were further broken down into patches for easier data access and processing. Section **2.4** presents information on ground truth data for the Dexter/Chelsea area that PSR received from TEC (via Horizons Inc.). The ground truth data was used for classification comparisons.

3.1 SAR MAGNITUDE DATA

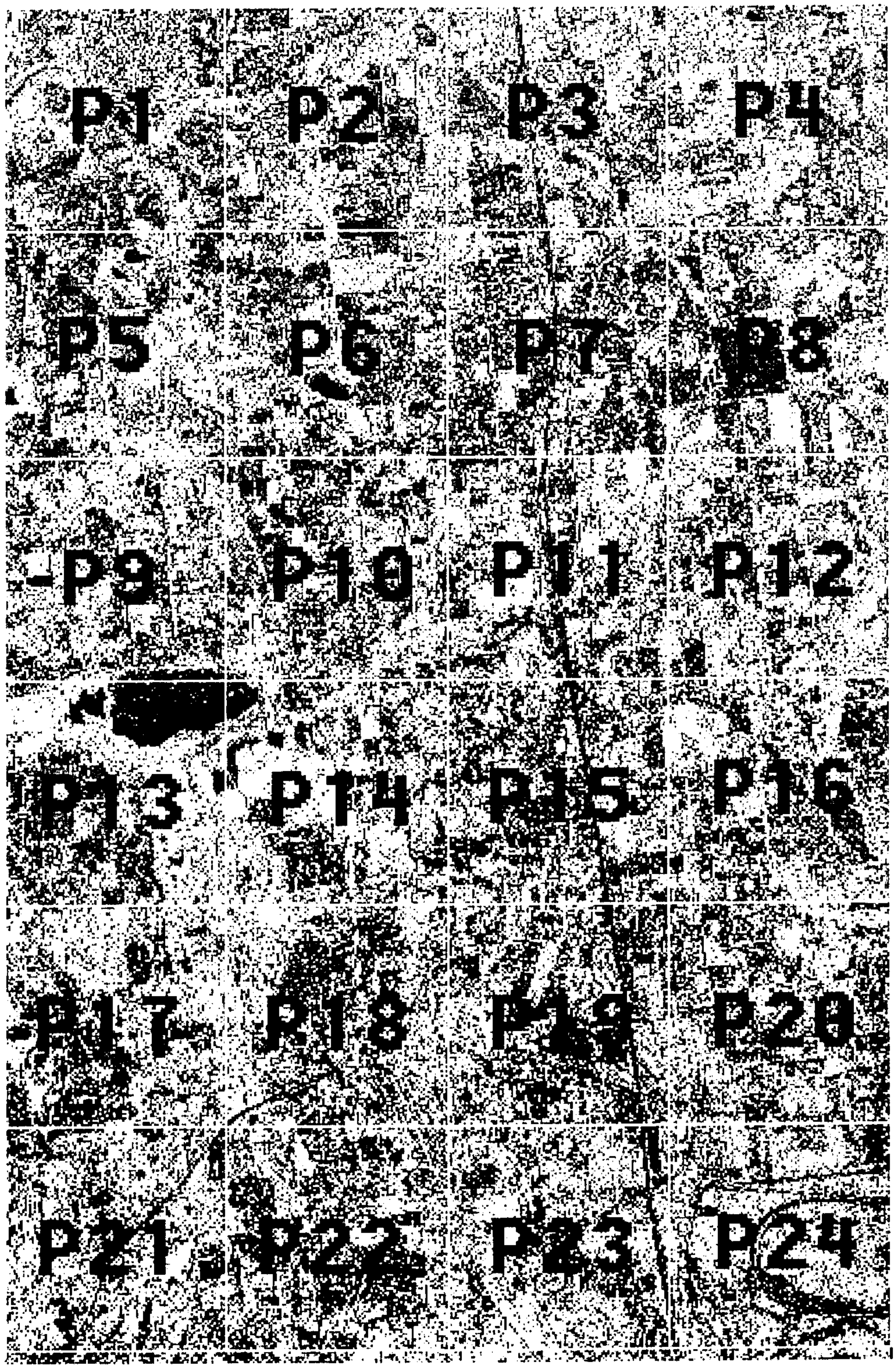

Figure 12. SAR Image for the Dexter/Chelsea Area

3.2 DIGITAL TERRAIN ELEVATION (DTE) DATA

Figure 13. DTE Image for the Dexter/Chelsea Area

3.3 CORRELATION DATA

Figure 14. Correlogram for the Dexter/Chelsea Area

3.4 IFSARE DATA ANALYSIS

To obtain a better understanding of the informational content of feature vectors being used to train the various neural networks (SOM, LVQ, FFBP, and ART2), a simple statistical analysis has been performed on six (6) selected sub-images that have been visually identified as belonging to a specific feature type. The analysis was performed on all three IFSARE data types, and is presented in Tables 1 and 2.

Table 1. Statistics for sub-images 1-3

Statistic	Sub-image # 1	Sub-image # 2	Sub-image # 3
Feature Type	Veg 2 to 5 m	Veg > 5 m	Water (lake)
Source	patch 19	patch 19	patch 19
Center X position	859	614	400
Center Y position	767	664	504
Sub-image size (pixels)	21 x 21	21 x 21	21 x 21
Magnitude min	15.96	21.66	5.67
Magnitude max	36.22	55.11	20.14
Magnitude average	24.88	39.18	12.06
Magnitude std dev	3.58	6.05	2.72
Magnitude median	24.62	38.36	11.55
DTE min	256.36	248.13	242.06
DTE max	260.76	260.23	252.05
DTE average	258.22	254.35	244.54
DTE std dev	.956	2.33	1.52
DTE median	257.99	254.23	244.35
Correlation min	.9919	.9522	.6800
Correlation max	.9978	.9948	.9840
Correlation ave	.9951	.9748	.9320
Correlation std dev	.0011	.0079	.0617
Correlation median	.9949	.9745	.9530

Table 2. Statistics for sub-images 4-6

Statistic	Sub-image # 4	Sub-image #5	Sub-image # 6
Feature Type	Highway	Urban Area	Veg < 2m
Source	patch 19	patch 19	patch 19
Center X position	814	209	424
Center Y position	348	83	152
Sub-image size (pixels)	5 x 5	21 x 21	21 x 21
Magnitude min	8.78	12.64	10.93
Magnitude max	19.54	114.52	24.76
Magnitude average	12.72	39.97	16.29
Magnitude std dev	2.34	15.76	2.50
Magnitude median	12.39	37.06	16.15
DTE min	247.30	245.35	249.14
DTE max	248.93	255.83	254.56
DTE average	248.13	250.26	251.86
DTE std dev	0.53	2.21	1.03
DTE median	248.19	249.85	251.79
Correlation min	.9127	.9600	.9662
Correlation max	.9373	.9976	.9873
Correlation ave	.9221	.9856	.9782
Correlation std dev	.0066	.0086	.0034
Correlation median	.9203	.9883	.9784

3.5 GROUND TRUTH DATA

PSR received ground truth data for the Dexter/Chelsea area from TEC (produced by Horizons Inc.) . The data is contained in four files and consists of the following.

1) TREEMASK.RAW. This file contains a tree mask image 5021 x 6621 in size (2.5 pixel resolution). The tree mask image was compiled from an orthophoto mosaic of the ERIM-IFSARE Dexter/Chelsea calibration site. Although the binary image (0's and 255's) has the same resolution as the obtained SAR and DTE data for Dexter/Chelsea, the image is not co-registered with the previously obtained data. The tree mask image is presented in Figure 15. The dark areas in the image represent areas where trees may obscure the ground. The white areas represent areas where the ground may be visible. The coordinates for the image are => LL: -6100 E, -7250 N; LR: 10450 E, -7250 N; UR: 10450 E, 5300 N; UL: -6100 E, 5300 N.

Figure 15. Tree mask image of the Dexter/Chelsea area

2) TINMASK.RAW. This file contains a triangulated irregular network (TIN) mask image 5209 x 6760 in size (2.5 meters pixel resolution). The TIN points were collected from aerial photography of the ERIM-IFSARE Dexter/Chelsea calibration site. As with the tree mask image, the TIN mask binary image (0's and 255's) is the same resolution as the obtained IFSARE magnitude and DTE data for Dexter/Chelsea. However, the TIN mask image is also not co-registered with previously obtained magnitude and DTE data or the tree mask image. The TIN mask image is presented in Figure 16. The dark areas in the image represent points with no corresponding TIN point. The white pixels represent points with corresponding TIN points. The coordinates for the TIN mask image are => LL: -6277.5 E, -7505 N; LR: 10620 E, -7505 N; UR: 10620 E, 5515 N; UL: -6277.5 E, 5515 N.

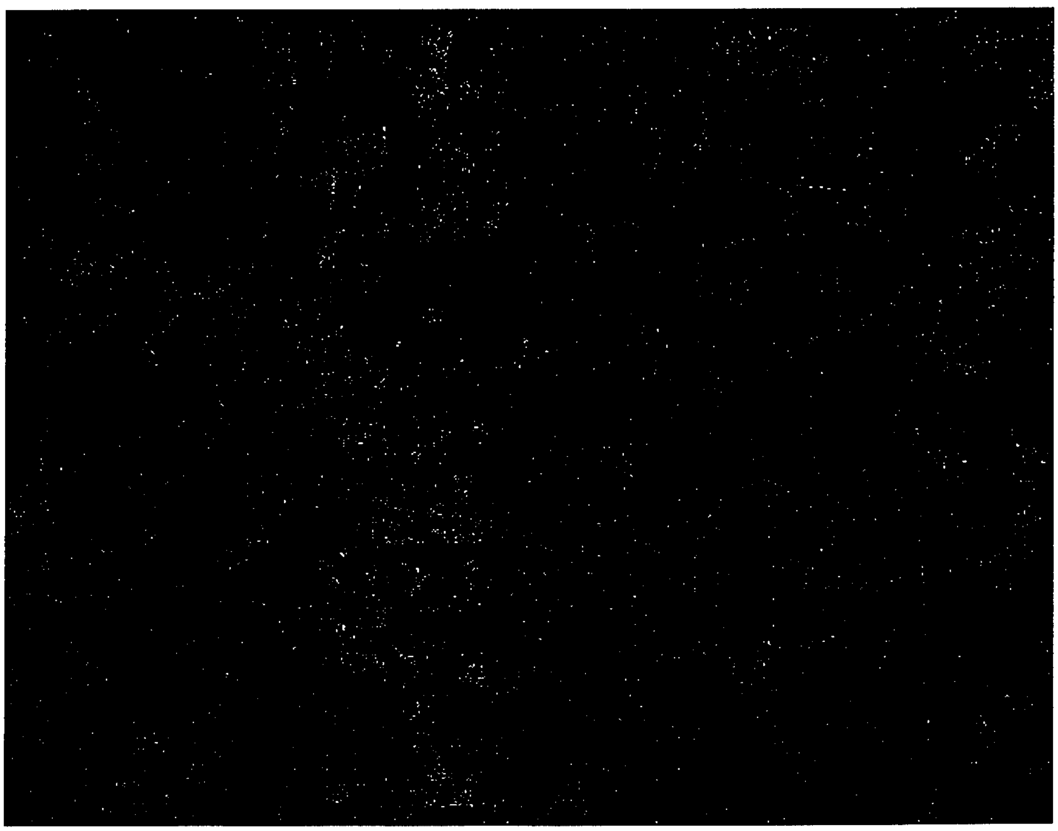

Figure 16. TIN mask image of the Dexter/Chelsea area

3. TINPTS.ASC. This is an ASCII file containing one TIN point represented by four values per line in the file. The first three elements are floating point values expressing the local East/North/Up coordinate of a point. The fourth value is an integer flag (0 or 1) indicating whether the point falls within an area that may be obscured by trees or within an unobscured area.

4. GRDPTS.ASC. This is an ASCII file containing a digital terrain model (DTM) of the Dexter/Chelsea area. The DTM was generated using the TINPTS.ASC data and interpolating it to a 5 meter grid matrix. The coordinates for the DTM are => LL: -6200 E, -7450 N; LR: 10600 E, -7450 N; UR: 10600 E, 5400 N; UL: -6200 E, 5400 N

PSR contacted Horizons Inc. and learned that the rms error between the TIN data and the IFSARE DTE data was around 1.5 meters. The provided ground truth data was used for classification accuracy analysis. The tree mask image was used to evaluate the accuracy of the neural network (NN) techniques in classifying trees. The TIN data was used to evaluate the accuracy of the NN techniques to classify forested areas as well as ground areas.

4.0 NEURAL NETWORK ALGORITHM DESCRIPTIONS

PSR researched and developed four NN algorithms for classifying IFSARE imagery, two of which are supervised (requiring apriori information about the features to be classified) algorithms, and the other two are unsupervised (not requiring any apriori information about the data before classification) algorithms. The two supervised NN algorithms are the Feed Forward Back-Propagation (FFBP) NN and the Learning Vector Quantization (LVQ) NN. The two unsupervised NN algorithms are Self-Organizing Maps (SOM) and the Adaptive Resonance Theory (ART2) NN.

All four NNs require the input of feature descriptor vectors for training. The NN training data sets possess the following four characteristics:

1) Size (number of input vectors)
2) Input vector sampling method
3) Input vector definition
4) Input vector normalization

The "basic" input vector contains localized pixel information (i.e., a particular pixel's attributes, and local pixel attributes). The Dexter/Chelsea IFSARE data contains approximately 24 million pixels (after image cropping). The final training vector set sizes were 500+ for the supervised NN algorithms, and 100,000+ for the unsupervised NN algorithms. The input vector sampling methods were specific pixel identification for the supervised algorithms, and random sampling from a specified Dexter/Chelsea patch for the unsupervised algorithms. The input vector definitions analyzed were (common to both supervised and unsupervised algorithms):

1) A pixels magnitude value and its immediate neighbors' magnitude values (size=9).
2) Type 1 plus a slope and standard deviation derived from IFSARE DTE (size=11)
3) Type 1 plus height differences between the pixel and its neighbors (size=17)
4) A pixels neighborhood average value, standard deviation, and slope for magnitude, DTE (average value not include for DTE), and correlation (size=8)

All input vectors were normalized with respect to some appropriate threshold. For example, magnitude data was threshold at the average value plus three standard deviations (determined from the complete Dexter/Chelsea IFSAR magnitude image). Height differences were threshold a 7.5 meters.

The input vectors form the basis and are common to all the researched NN algorithms. The following design steps were followed for all NN algorithm development:

1) Define suitable inputs (and outputs for supervised NNs) and NN structure (i.e., how many layers, nodes, connectivity, etc.).
2) Choose training method and train NN until converged (or some acceptable error is reached).
3) Assess performance of network (i.e., speed, convergence, classification accuracy).
4) Change NN structure and/or NN inputs and re-evaluate.

The following sub-sections provide detailed information on the supervised and unsupervised NN algorithms.

4.1 SUPERVISED NN ALGORITHMS

Learning Vector Quantization (LVQ)

The LVQ algorithm uses reference vectors in the hyperspace of the input feature vectors to represent the classes to be learned. Classification is accomplished by adjusting the reference vectors during training, such that boundaries determined by the minimum Euclidean distance (or some other appropriate measure) from reference vectors separate the feature space into clustered regions. Training proceeds by first calculating the Euclidean distance between a given input feature vector and the LVQ reference vectors using,

$$\mathbf{d_j = \Sigma(x_i(t)\text{-}w_{ij}(t))^2\,,\ i=1,...,N}$$

where $\mathbf{d_j}$ is the distance between reference vector $\mathbf{w_{ij}(t))=\{w1j,w2j,...,wjN\}}$ and the input $\mathbf{x_i(t)=\{x1,x2,...,xN\}}$, and **N** is the number of training samples. The reference vector with the minimum distance is chosen. If the selected reference vector matches the desired output, this vector is rewarded by,

$$\mathbf{w_{ij}(t+1) = w_{ij}(t) + \alpha(t)(\ x_i(t)\text{-}w_{ij}(t)),\ \ i=1,...,N}$$

If it does not match, the vector is punished by,

$$\mathbf{w_{ij}(t+1) = w_{ij}(t) - \alpha(t)(\ x_i(t)\text{-}w_{ij}(t)),\ \ i=1,...,N}$$

In these equations, $\boldsymbol{\alpha}$**(t)** is a gain term that may start at any value on the interval (0,1), which decreases monotonically with time, but its initial value is usually set to a small quantity. The other vectors are left unmodified by this procedure which is repeated until convergence is obtained.

Feed Forward Back-Propagation (FFBP)

The FFBP neural network consists of objects called nodes and weighted paths connecting the nodes. Each node has an activity represented by a real number. This activity value is computed as a nonlinear-bounded monotone-increasing function of a weighted sum of the activities of other nodes that are directly connected to it. Figure 17 illustrates an example three layer FFBP network.

The determination of the appropriate weights for the nodes in the network is referred to a network learning. Back propagation refers to the process of iteratively determining the weights that locally minimize the global error of the network.

The basic concept in FFBP network design is to select the number of feature descriptors possible for identifying the desired image feature types and define that as the input layer to the network. The output layer will consist of the number of nodes that represent the features classes to be determined. The number of hidden layers (and nodes per hidden layer) is not obvious, and is determined through an interative process.

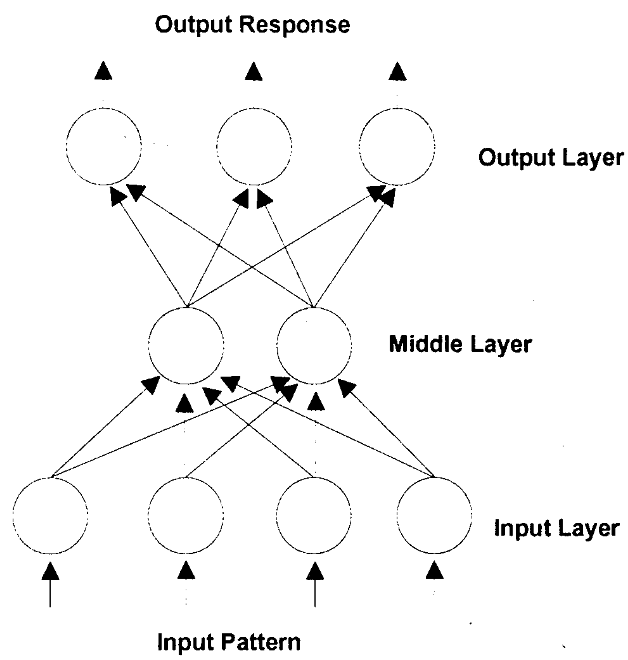

Figure 17. Example 3 Layer FFBP Network

4.2 UNSUPERVISED NN ALGORITHMS

Self Organizing Maps (SOM)

The SOM NN creates a vector quantization by adjusting reference vectors during training. These reference vectors are represented as the weights connecting common input nodes to output nodes arranged in a two-dimensional grid. Analog valued inputs are presented sequentially during training, and network weights are adapted in such a manner that the reference vectors tend to approach the cluster centers. In addition, the vectors are organized such that topologically close output nodes are sensitive to inputs that are similar.

This localized sensitivity is accomplished during training by defining a neighborhood around each node, which is slowly decreased in size as training progresses (see Figure 18). For each input, the distances, $\mathbf{d_j}$, between the input and each output node $\mathbf{j}$ are determined using,

$$\mathbf{d_j = \Sigma(x_i(t)\text{-}w_{ij}(t))^2 \, , \, i=1,...,N}$$

where $\mathbf{x_i(t)}$ is the input to node $\mathbf{i}$ at time $\mathbf{t}$, and $\mathbf{w_{ij}(t)}$ is the weight from input node $\mathbf{i}$ to output j at time $\mathbf{t}$. The output node $\mathbf{j_{max}}$, whose distance to the input nodes is minimum, is selected and weights are updated for $\mathbf{j_{max}}$ (and all nodes in the neighborhood about jmax) using,

$$\mathbf{w_{ij}(t+1) = w_{ij}(t) + \alpha(t)(\, x_i(t)\text{-}w_{ij}(t)), \;\; i=1,...,N}$$

for all j belonging to Neighborhood(t)

To utilize the trained SOM as a pure classifier, an additional process is required after training to associate each output node with a class.

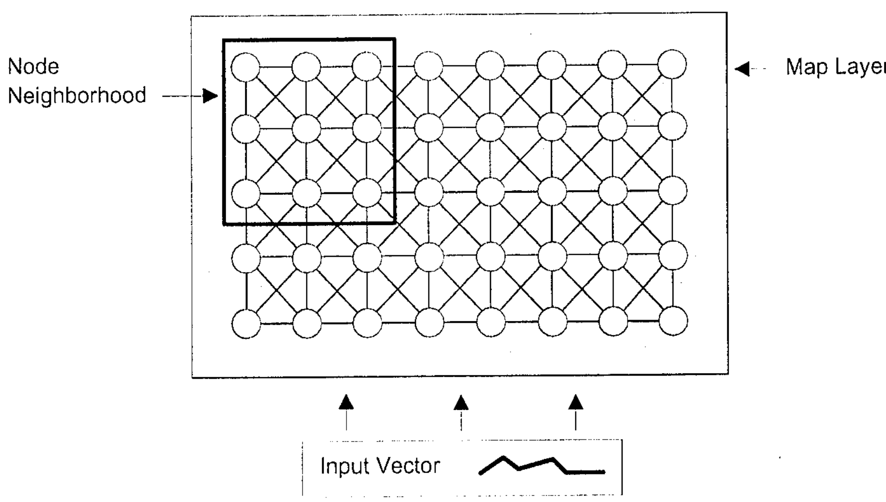

Figure 18. SOM Map

Adaptive Resonance Theory (ART2)

In this technique, input data are clustered into classes without outside supervision. A vigilance factor, which represents how similar the input must be to the exemplar (reference vector) of a class in order to be classified as an existing class, must be specified. Larger vigilance factors require greater similarity, and lead to the generation of a larger set of classes. This algorithm is distinct from other clustering neural networks (like SOM) in its use of two sets of weights (or two layers, see Figure 19), referred to as bottom-up and top-down weights. Bottom-up weights are used to calculate matching scores, and are used to determine which class an input vector might possibly belong. Top-down weights are used to check that the input is close enough to a chosen exemplar so that a new class need not be formed.

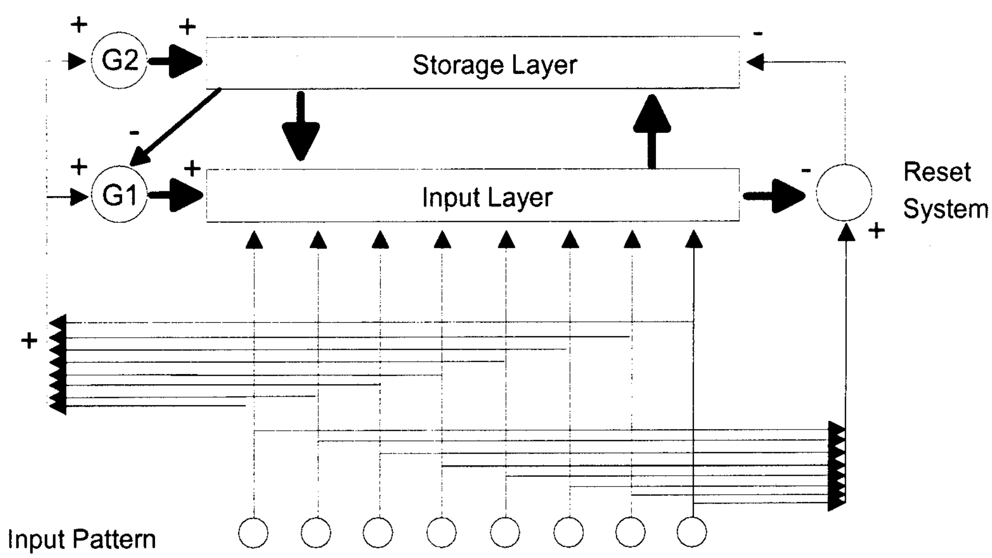

Figure 19. ART - Two Layers of Nodes, Fully Interconnected

The clustering algorithm is similar to the "leader clustering algorithm". The first input is selected as the exemplar for the first cluster, and the next input is then compared to this exemplar. If the distance between the input and the exemplar is small enough, the data are clustered into the first class and the weights for this class are modified.

Otherwise, a new class is formed by selecting the data as the exemplar for the new class. Subsequently, every input is compared to all stored exemplars in parallel using bottom-up weights, and the exemplar with the highest matching score is selected as the candidate for the class..

4.3 NNs for IFSARE Image Classification

Supervised NNs

Figures 20 depicts the IFSARE classification process using the FFBP and LVQ supervised NNs.

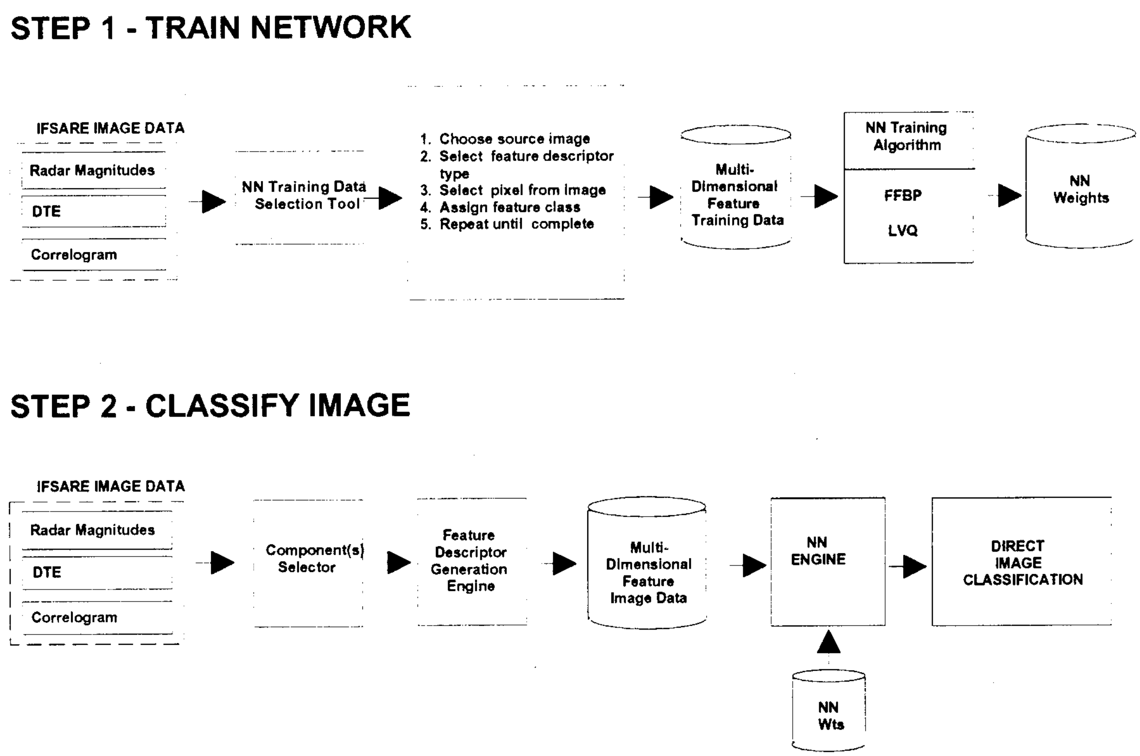

Figure 20. Supervised NN IFSARE Classification Process

Unsupervised NNs

Figures 21 depicts the IFSARE classification process using the SOM and ART2 unsupervised NNs.

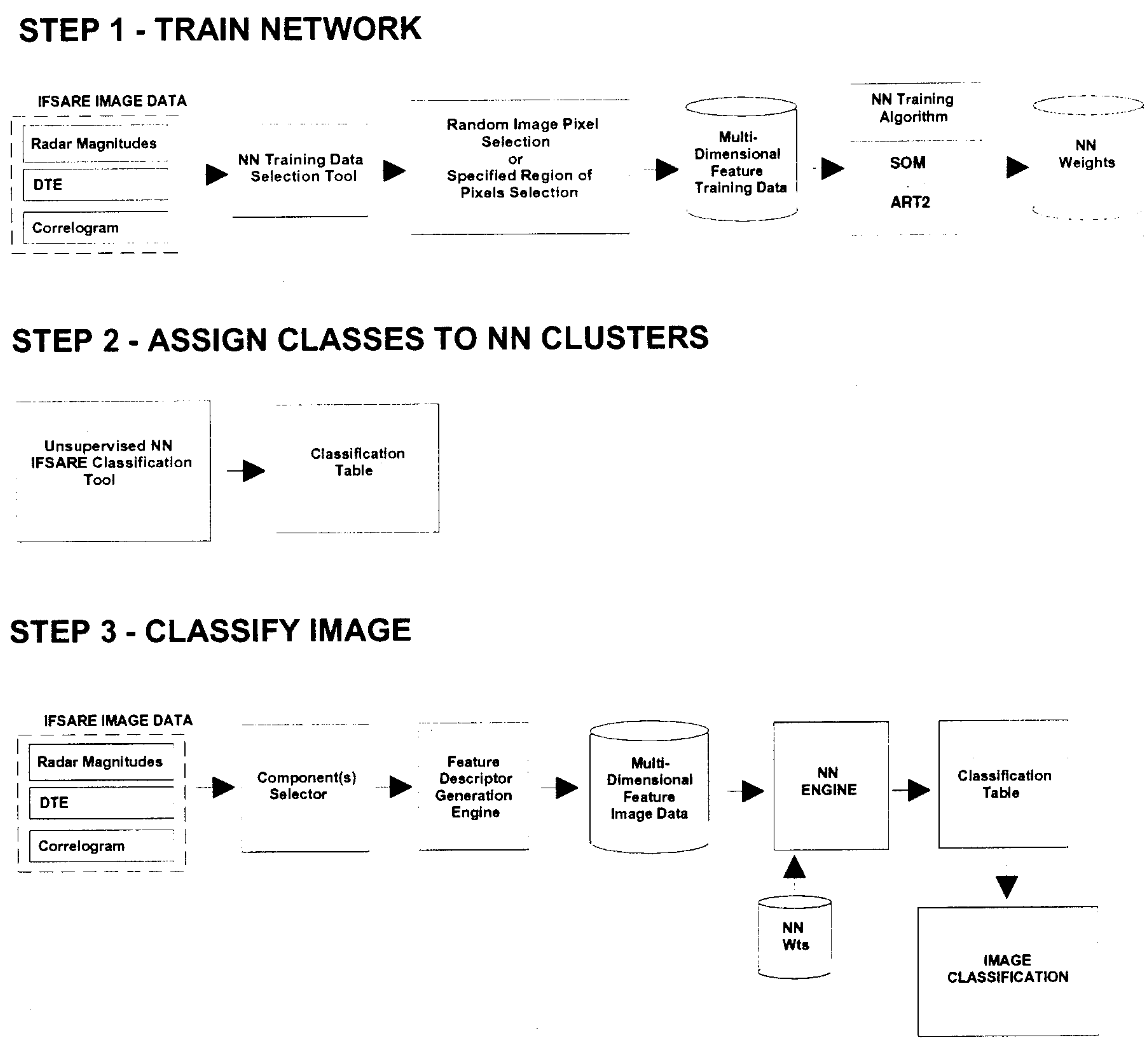

Figure 21. Unsupervised NN IFSARE Classification Process

5.0 DTE FEATURE CLASSIFICATION

The primary feature identified for extraction directly from high resolution IFSARE DTE data was *drainage systems* (the inverse of ridge systems). A standard pattern recognition algorithm was implemented to extract this feature. For each data point in the DTE grid, the heights of the points adjacent to it are compared. The highest point in each group is eliminated from being a drainage point (the lowest is eliminated from consideration as a ridge point). Grid points which have not been eliminated after this operation are drainage (or ridge candidates), depending on whether they were never marked as highest or never marked as lowest. The drainage candidates are then connected into lines that represent the topographic drainages in the area, and a similar process connects the ridge candidates into ridges in the area (see Figure 22).

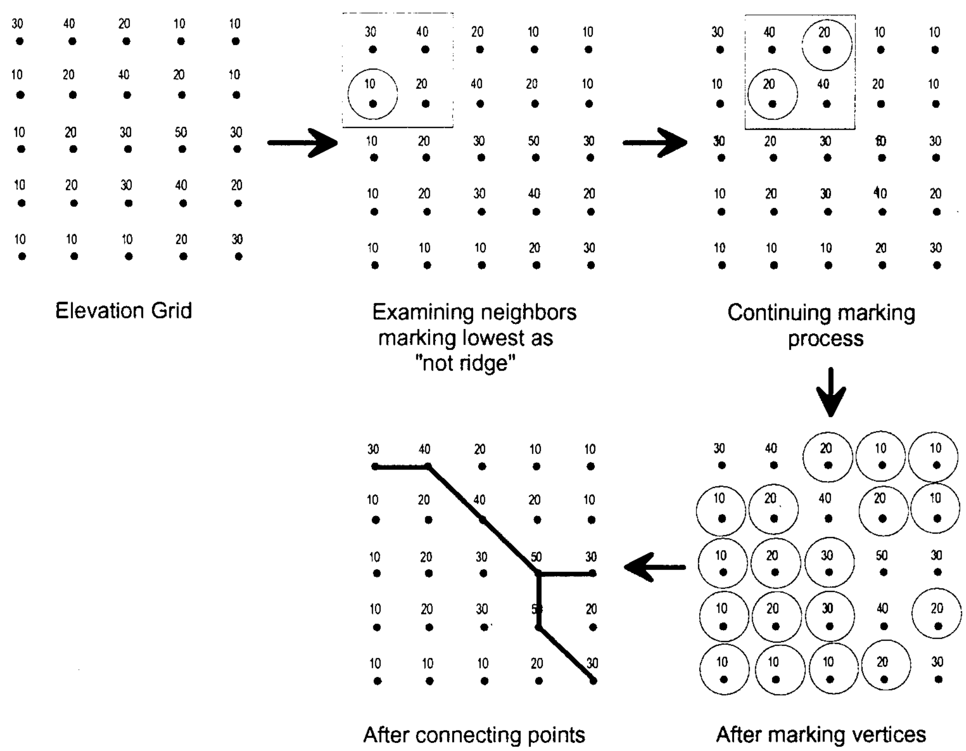

Figure 22. Example Ridge Feature Extraction Technique

6.0 TECHNICAL RESULTS

This sections presents details of the technical results obtained during the Phase I project. First, information on the feature descriptor input vectors generated from the IFSARE data is presented. Second, the technical details of implementing the supervised and unsupervised NNs as image classifiers is described. Next, additional classification results of Dexter/Chelsea patches #19 and #24 utilizing feature descriptor type 1 are given (**NOTE**: The classification results presented in Section 1.0 were obtained using feature descriptor type 3).

6.1 IFSARE FEATURE DESCRIPTORS

The NN Training Tool was used to extract reference vectors from visually identified features in the Dexter/Chelsea scene. Over 500 reference vectors were extracted from patch 19 for the following visually identified features; *highways*, *urban areas*, *water*, and *three vegetation types*. Figures 23 through 28 present examples of the reference vectors for the six feature classes (feature descriptor type 1 - 9 magnitude values).

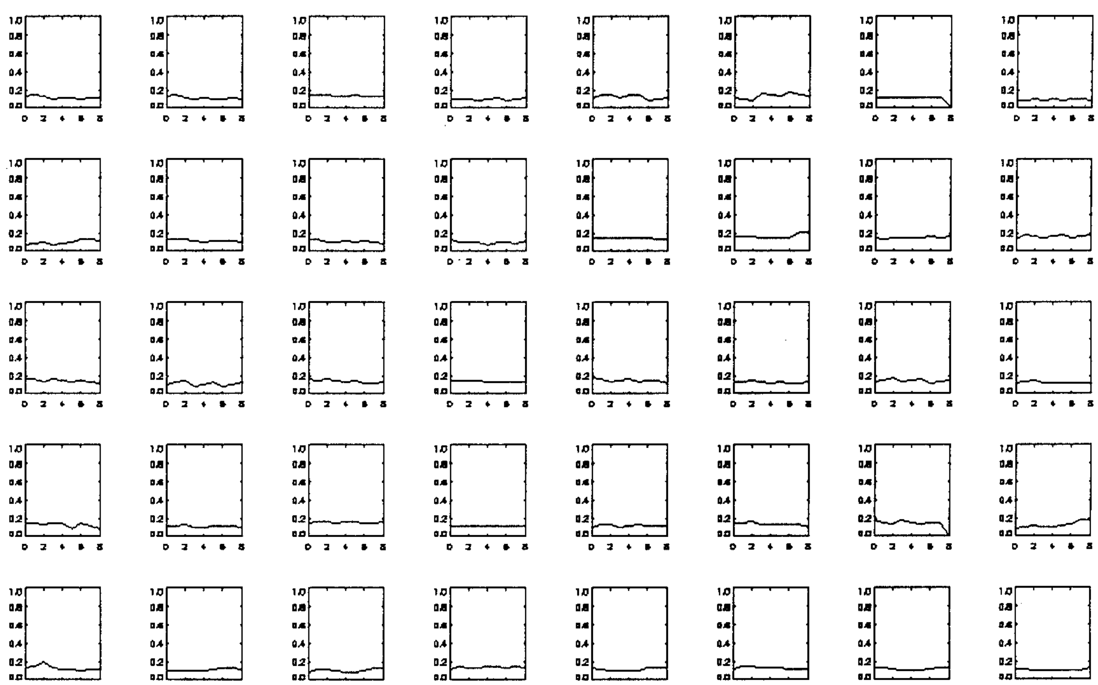

Figure 23. Reference Vectors for Roadways - Feature Descriptor Type 1

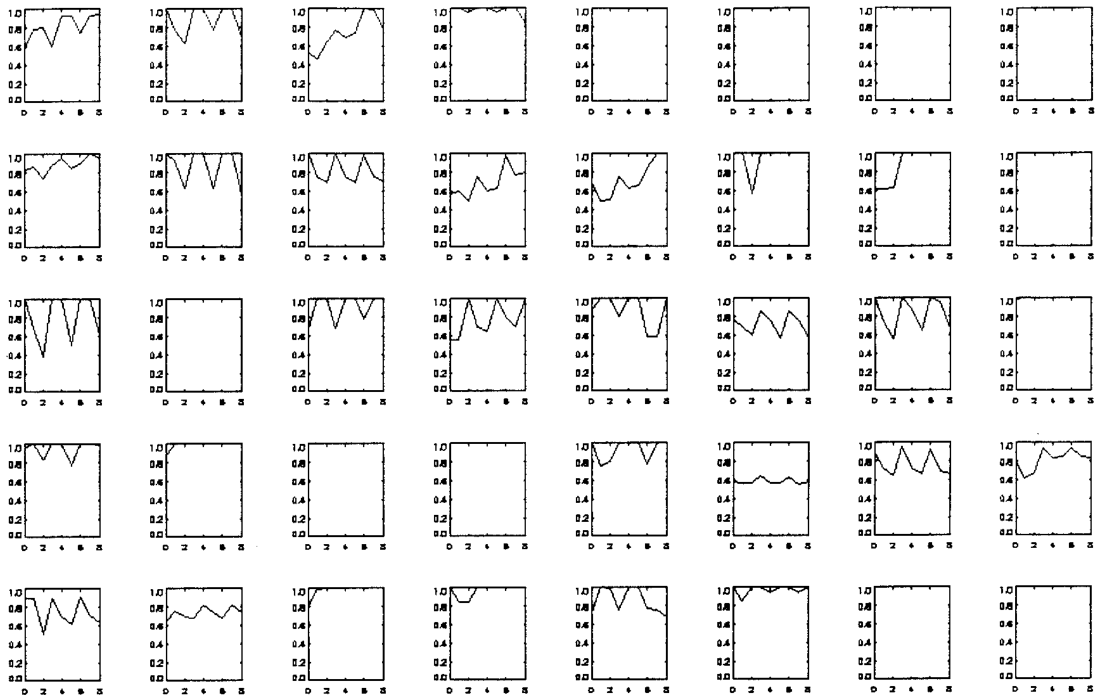

Figure 24. Reference Vectors for Urban Areas - Feature Descriptor Type 1

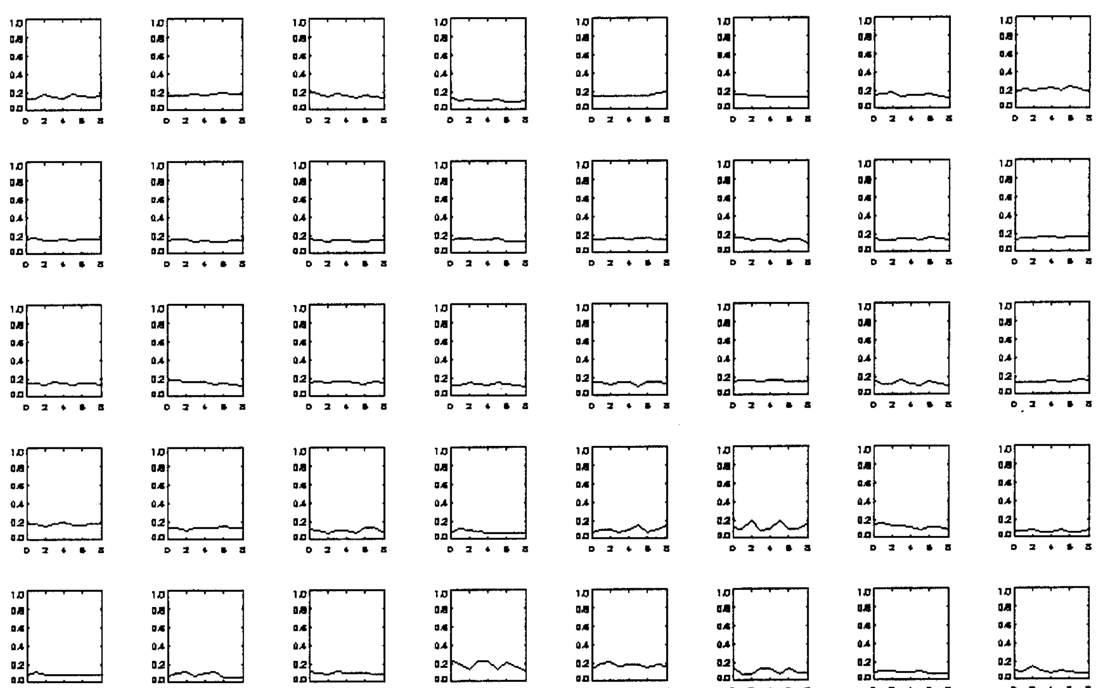

Figure 25. Reference Vectors for Water - Feature Descriptor Type 1

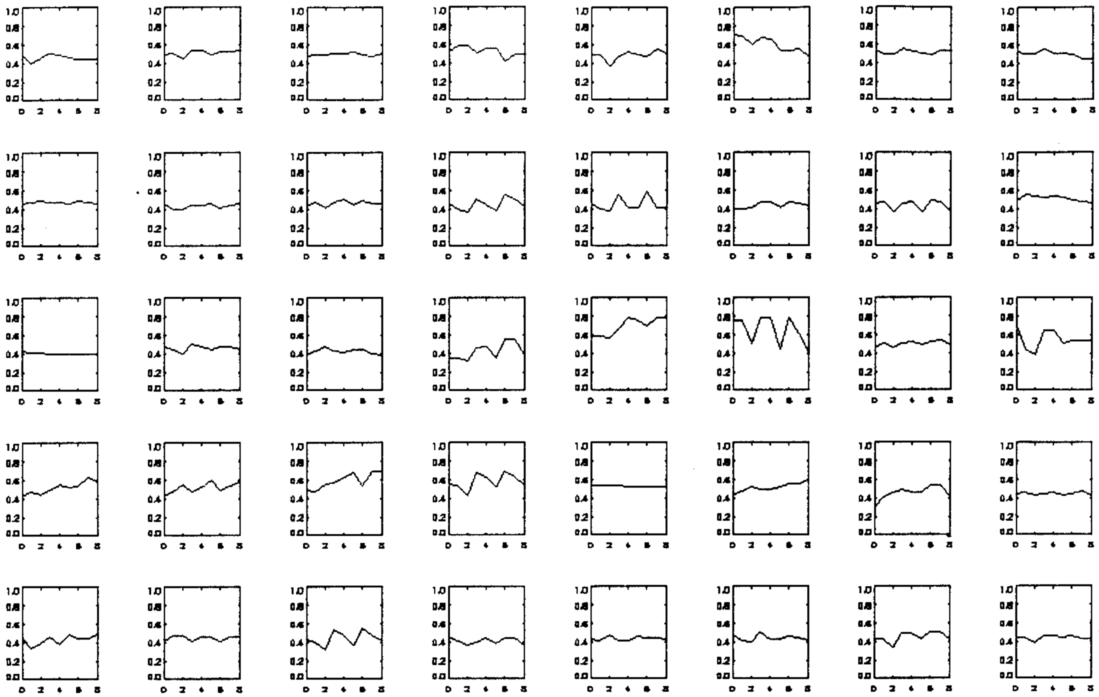

Figure 26. Reference Vectors for Vegetation (type 1) - Feature Descriptor Type 1

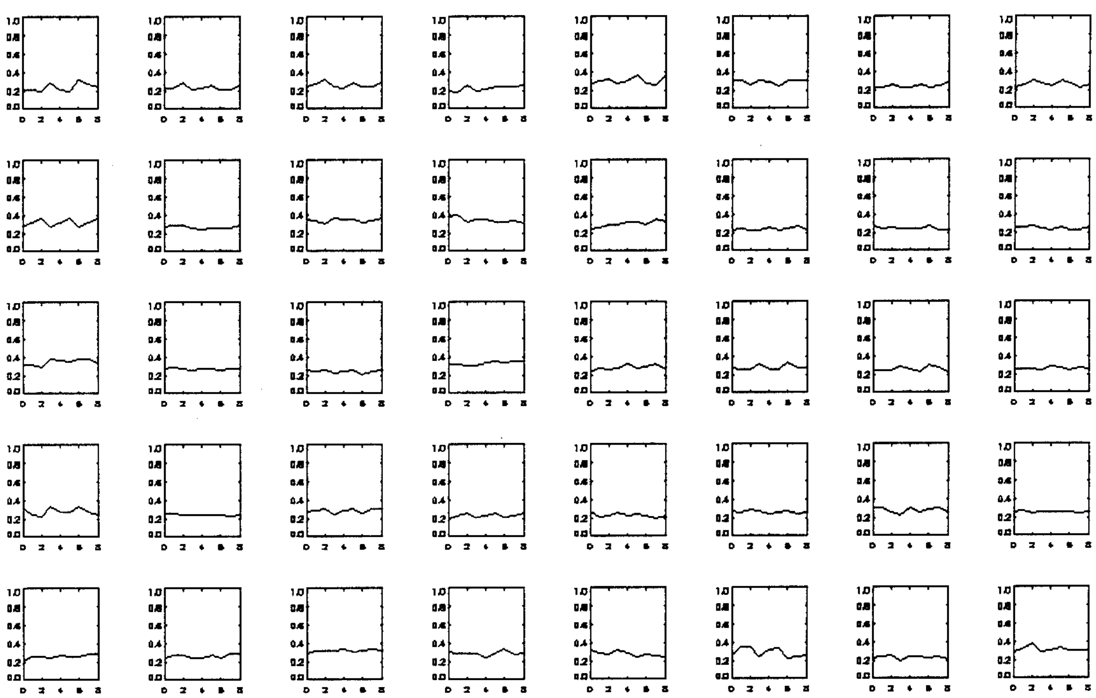

Figure 27. Reference Vectors for Vegetation (type 2) - Feature Descriptor Type 1

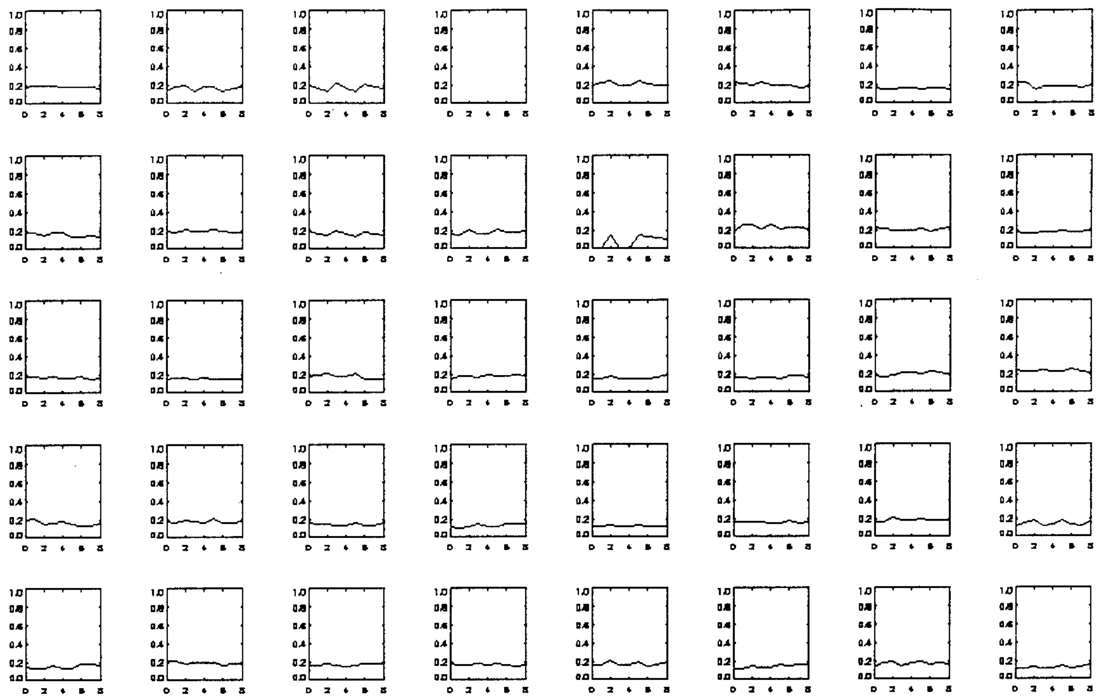

Figure 28. Reference Vectors for Vegetation (type 3) - Feature Descriptor Type 1

6.2 SUPERVISED NN CLASSIFICATION APPROACH

This section presents details of implementing LVQ and FFBP to classify the Dexter/Chelsea IFARE data. Input feature descriptor vectors (described in Section 4.0) were used as input to both the LVQ and FFBP NN algorithms.

Learning Vector Quantization (LVQ)

"In the LVQ algorithms, vector quantization is not used to approximate to density functions of the class samples, but to directly define the class borders according to the nearest-neighbor rule. The accuracy achievable in any classification task to which the LVQ algorithms are applied and the time needed for learning depend on the following factors :

- an approximately optimal number of codebook vectors assigned to each class and their initial values,

- the detailed algorithm, a proper learning rate applied during the steps, and a proper criterion for the stopping of learning." [1]

The above excerpt was taken out of the documentation for LVQ_PAK version 3.0 (March, 1995), a LVQ program package written by Teuvo Kohonen (et al) at the Helsinki University of Technology. The documentation describes various LVQ implementations and documents the use of the LVQ program package. LVQ_PAK has been used to classify the IFSARE Dexter/Chelsea image. The steps taken for utilizing the LVQ method (as a supervised approach) is described next.

LVQ Classification Approach

Classification of the IFSARE imagery from patches #19 and #24 using LVQ was accomplished in four steps :

STEP 1 - Initialization of the LVQ reference vectors

First, the program **"eveninit"** selects the initial reference vectors from a specified training data file. All the entries used for initialization must fall within the borders of the corresponding classes, which is automatically checked by knn-classification (the initialization program takes care of this). The number of reference vectors is also specified in this step. A total of 120 reference vectors have been chosen to represent all classes (each class having approximately the same number of representative reference vectors).

Next, the program **"balance"** computes the medians of the shortest distances for each class and corrects the distribution so that into those classes in which the distance is greater than the average, entries are added, and from those classes in which the distance is smaller than the average, some entries are deleted. Thereafter one learning cycle of the optimized-learning-rate LVQ (the **"olvq1"** program), is automatically run within the program **"balance"**. After this, the medians of the shortest distances are computed again and displayed. This program may be iterated.

STEP 2 - LVQ Training

The program "**olvq1**" is used to train the codebook of reference vectors (120 in this example). This LVQ algorithm utilizes an optimized-learning-rate for each codebook reference vector. The program accepts four command-line arguments; input filename containing a training vector data, input filename for the initialized reference vectors obtained from step 1, output filename for converged reference vectors, and program run-time length (iteration count).

STEP 3 - Classification of Unknown Image Data

The program "**classify**", is used for classification of unknown data vectors. This program accepts three command-line arguments; input filename containing unknown vector data, input filename containing the trained codebook reference vectors obtained in step 2, and an output filename that classification results are saved to. The unknown vectors are always classified by determining its nearest neighbor in the trained codebook of reference vectors.

STEP 4 - Visualization of Classification Results

This last step has been accomplished by using IDL (on a SPARC 20) to color code the classified data from step 3, and to present the resulting color image on the computer display. The results are printed in hardcopy form, and saved to harddisk for later retrieval.

Feed Forward Back-Propagation (FFBP)

The FFBP NN was a four layer network with one input layer, two middle (or hidden) layers, and one output layer. The input layer was the size of the input reference vectors (9 nodes for input vector type 1, and 17 for input vector type 3). The two middle layers had thirty (30) nodes each. The output layer consisted of 6 nodes (one node per feature class). The FFBP used the "generalized delta rule" with adaptive learning and momentum in the backpropagation of network errors during training. Classification of the IFSARE imagery from patches #19 and #24 using FFBP was accomplished in four steps :

STEP 1 - Initialization of the FFBP weights

All network weights were initialized with random numbers between the values of +0.5 and -0.5. The total number of weights for the FFBP network were (9 inputs)x(30 nodes for middle layer #1) + (30 nodes for middle layer #1)x(30 nodes for middle layer #2) + (30 nodes for middle layer #2)x(6 output nodes) = 1350 weights.

STEP 2 - FFBP Training

There were 500+ input reference vectors (representing the six desired classes) used for training the FFBP NN. All 500+ input vectors were fed forward through the NN layers (in random order), then backpropagated. The overall network error was then checked, resulting in learning and momentum constant adjustments. This process was repeated until the total network error reached an absolute error value of 8%. The weights of the network were subsequently saved.

STEP 3 - Classification of Unknown Image Data

As depicted in Figure 20 (Section 4.0), feature vectors for each pixel in an image are generated and are fed forward through a FFBP NN engine (useing the weights from Step 2), resulting in an image that has been classified into the six classes.

STEP 4 - Visualization of Classification Results

This last step has been accomplished by using IDL (on a SPARC 20) to color code the classified data from step 3, and to present the resulting color image on the computer display. The results are printed in hardcopy form, and saved to harddisk for later retrieval.

6.3 UNSUPERVISED NN CLASSIFICATION APPROACH

This section presents details of implementing SOM and ART2 to classify the Dexter/Chelsea IFARE data. Input feature descriptor vectors (described in Section 4.0) were used as input to both the SOM and ART2 NN algorithms.

Self Organizing Maps (SOM)

Determining the optimal self-organizing map (SOM) for SAR classification could be a laborious effort since there are almost limitless SOM configurations possible. An unlimited number of SOM reference vectors could be determined to represent a vector database that is large in size (> 10,000). Since the number of features desirable for classification is approximately 10, SOM configurations with reference vectors numbering an order of magnitude or less (<100) have been analyzed. Five SOM configurations were examined; 12x8, 10x6, 8x5, 6x4, and 5x3. Even with these limited number of configurations, examining each SOM reference vector and applying it to an image for classification could take a while.

The unsupervised NN IFSARE Classification Tool was used to classify a portion of patch #19 from Dexter/Chelsea imagery. This computer tool displays a set of SOM reference vectors (representing the SOM NN clusters), and allows the user to color code the selected reference vectors. This process dynamically builds an image which is displayed directly below an original gray-scaled SAR image. This interactive tool allows for quick analysis of which SOM reference vector represents a particular feature (or part of a feature) in the SAR scene.

Figures 29 through 33 demonstrate the generation of classified images for SOM sizes of 5x3, 6x4, 8x5, 10x6, and 12x8 respectively. Four dominant features were color coded; black for *roadways*, red for *urban*, green for *trees*, and yellow for *fields* (and everything else). The number of pixels belonging to the 4 feature types for the five SOM configurations are summarized in Table 3.

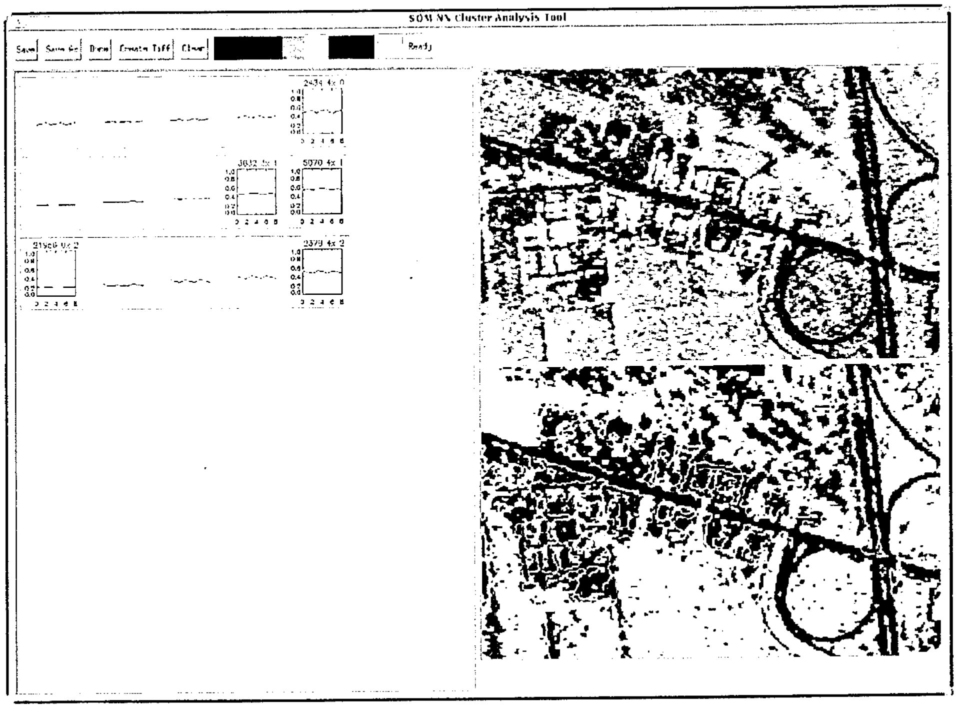

Figure 29. SOM Cluster Analysis (5x3 SOM)

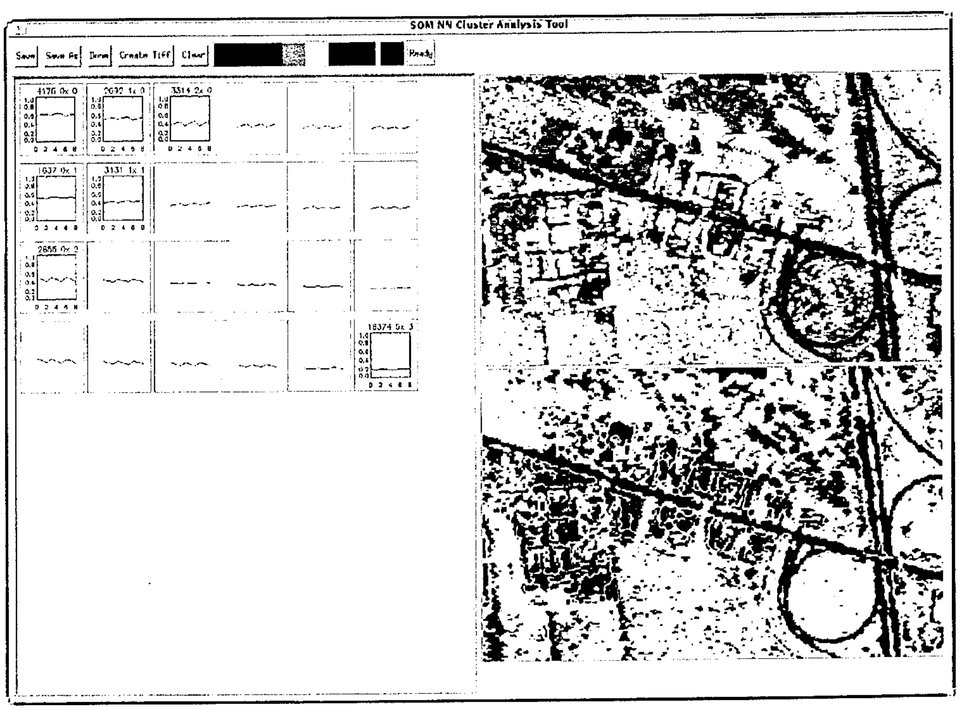

Figure 30. SOM Cluster Analysis (6x4 SOM)

Figure 31. SOM Cluster Analysis (8x5 SOM)

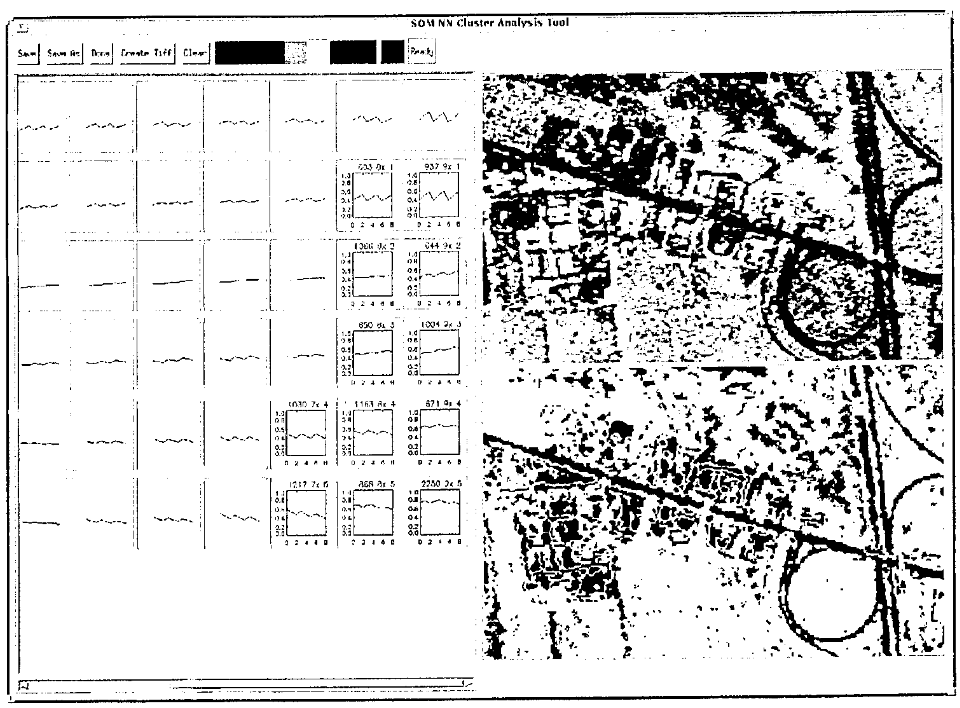

Figure 32. SOM Cluster Analysis (10x6 SOM)

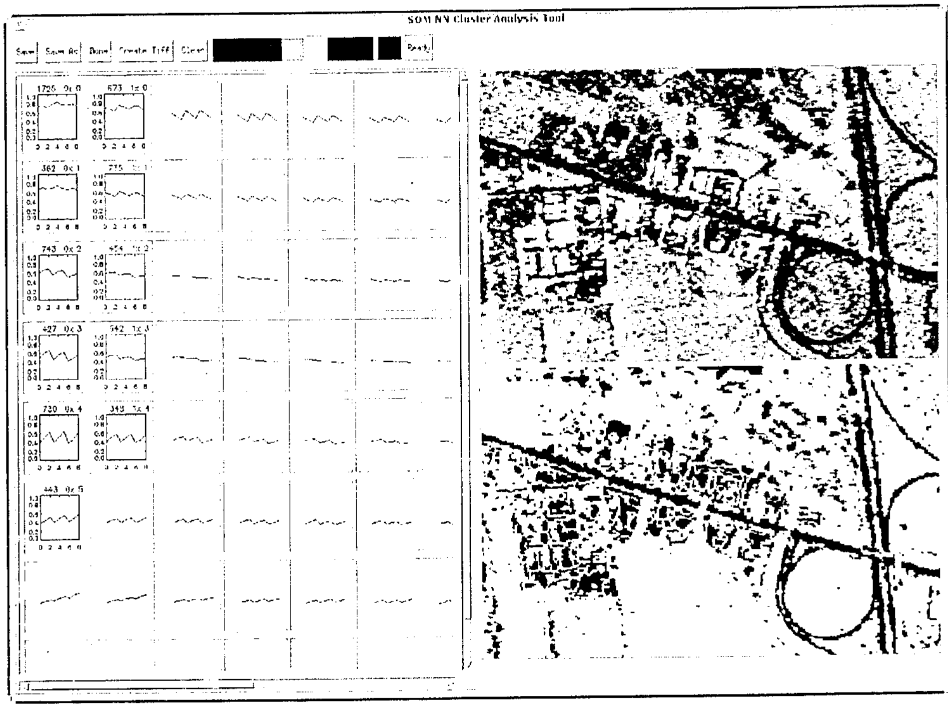

Figure 33. SOM Cluster Analysis (12x8 SOM)

Table 3. Pixel Allocation to SOM Clusters

Feature Class	# of pixels 5x3 SOM	# of pixels 6x4 SOM	# of pixels 8x5 SOM	# of pixels 10x6 SOM	# of pixels 12x8 SOM
Highway	21,956	16,374	10,088	13,475	12,327
Urban	7,448	4,175	2,822	2,921	4,660
Field	64,530	66,622	77,519	74,427	80,491
Trees	6,066	12,829	9,571	9,177	2,522

Adaptive Resonance Theory (ART2)

The same sub-region of patch #19 from the Dexter/Chelsea IFSARE data was classified using the unsupervised NN ART2. The ART2 algorithm proved computationally slow and resulted in a dramatically less accurate classification as compared to SOM, LVQ, and FFBP (see Figure 34).

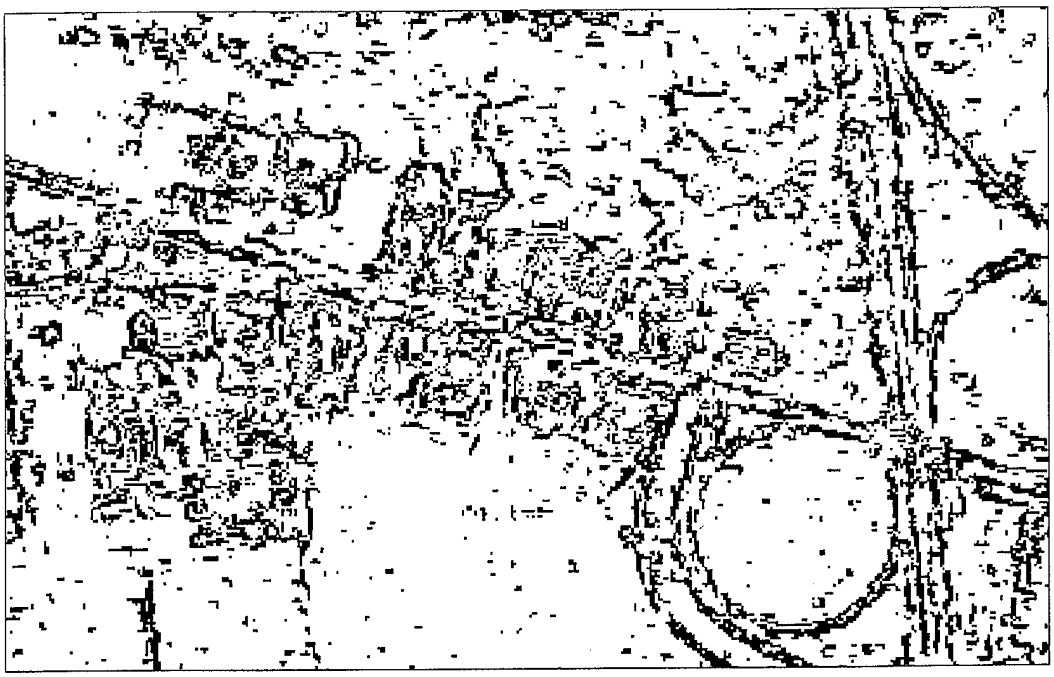

Figure 34. ART2 Classification of a sub-region from patch # 19

6.4 ADDITIONAL DEXTER/CHELSEA IMAGE CLASSIFICATIONS

Figures 35 through 37 present classifications of a 5.9 square Km patch (#19) from the Dexter/Chelsea IFSARE imagery for the FFBP, LVQ, and SOM NNs respectively (all three NNs used feature descriptor type 1). Figures 38 through 40 also present classifications of a 5.9 Km patch (#24) from the Dexter/Chelsea IFSARE imagery for the respective NNs.

Figure 35. FFBP NN Classification of Dexter/Chelsea (patch #19)

Figure 36. LVQ NN Classification of Dexter/Chelsea (patch #19)

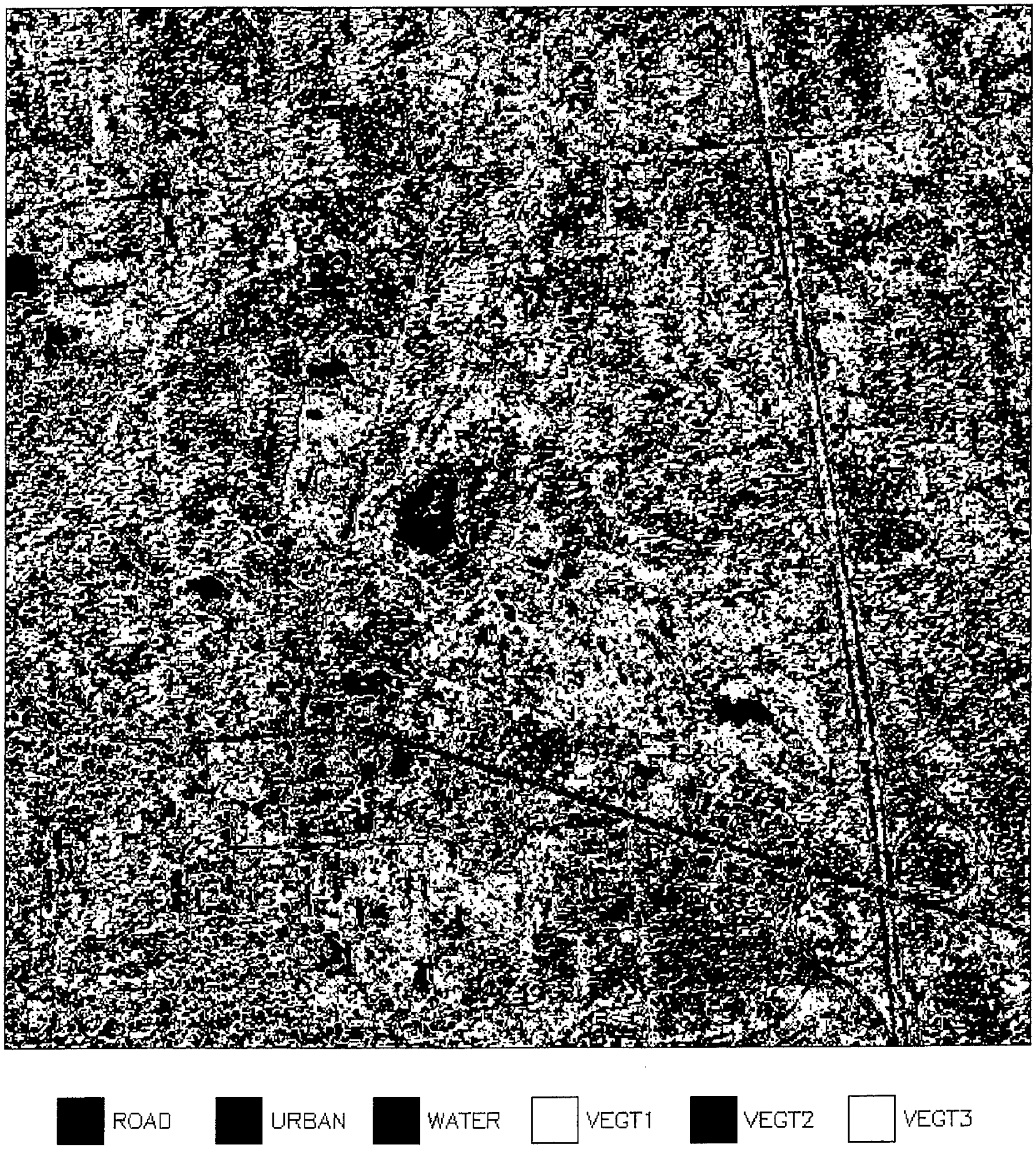

Figure 37. SOM NN Classification of Dexter/Chelsea (patch #19)

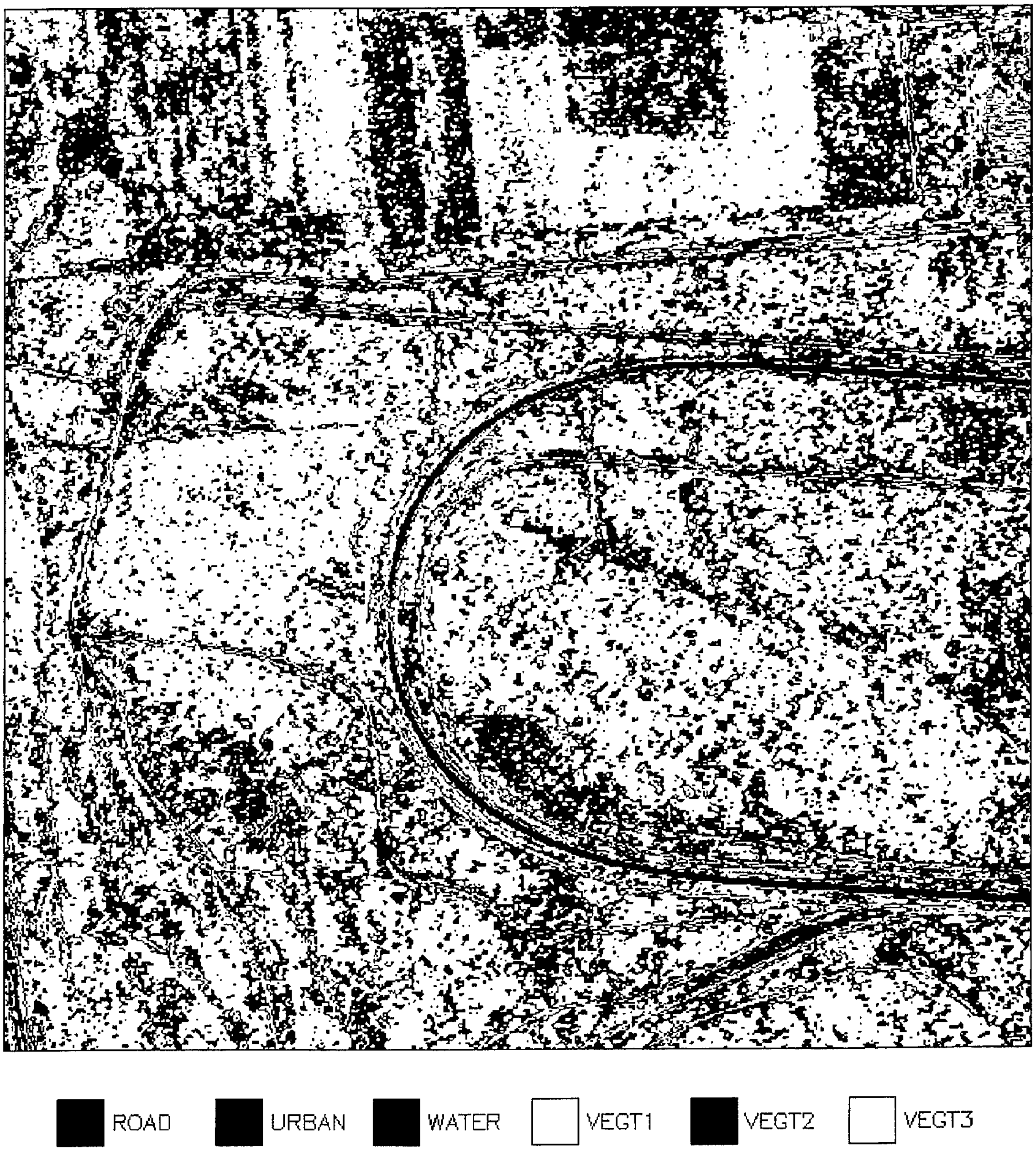

Figure 38. FFBP NN Classification of Dexter/Chelsea (patch #24)

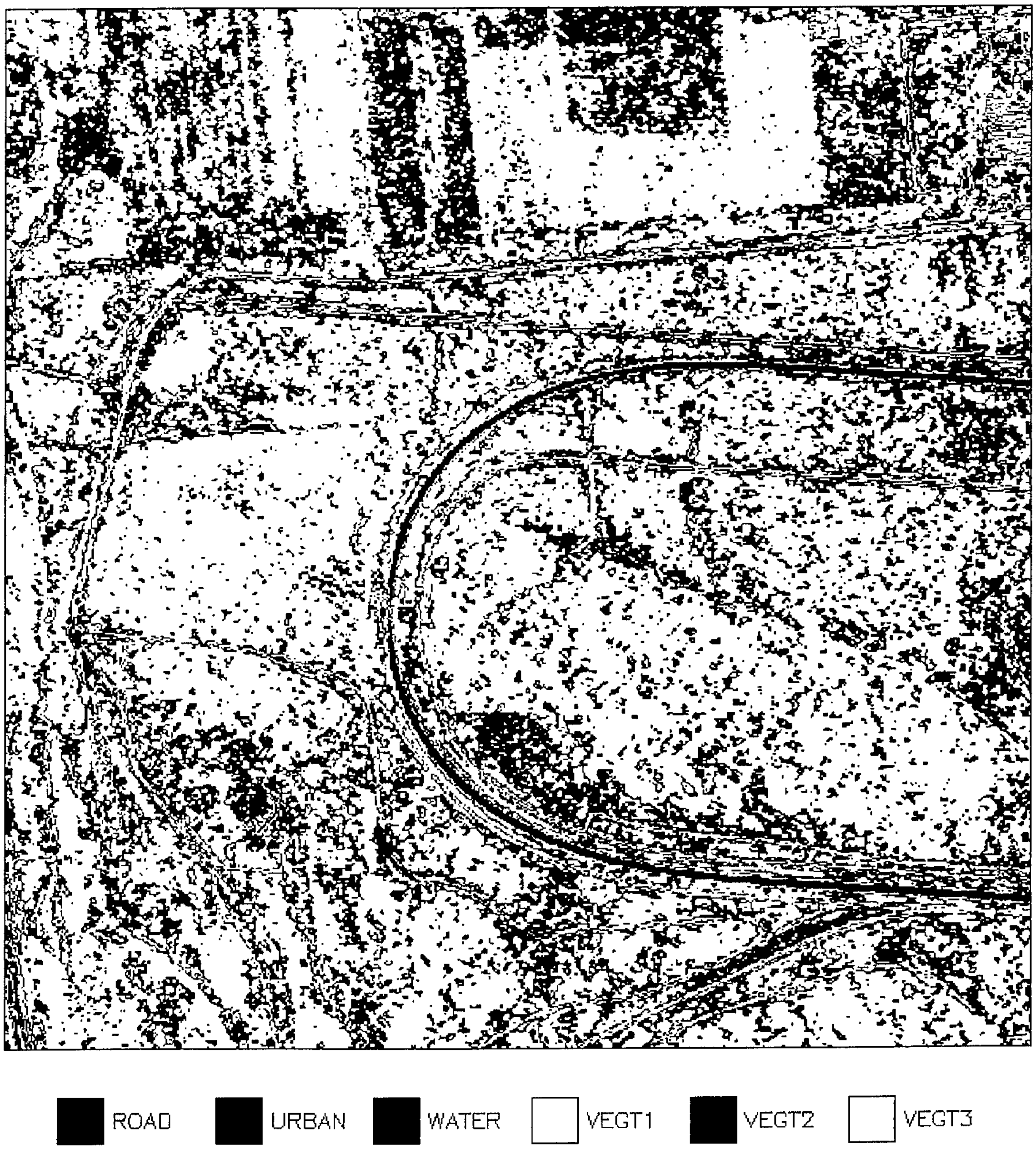

Figure 39. LVQ NN Classification of Dexter/Chelsea (patch #24)

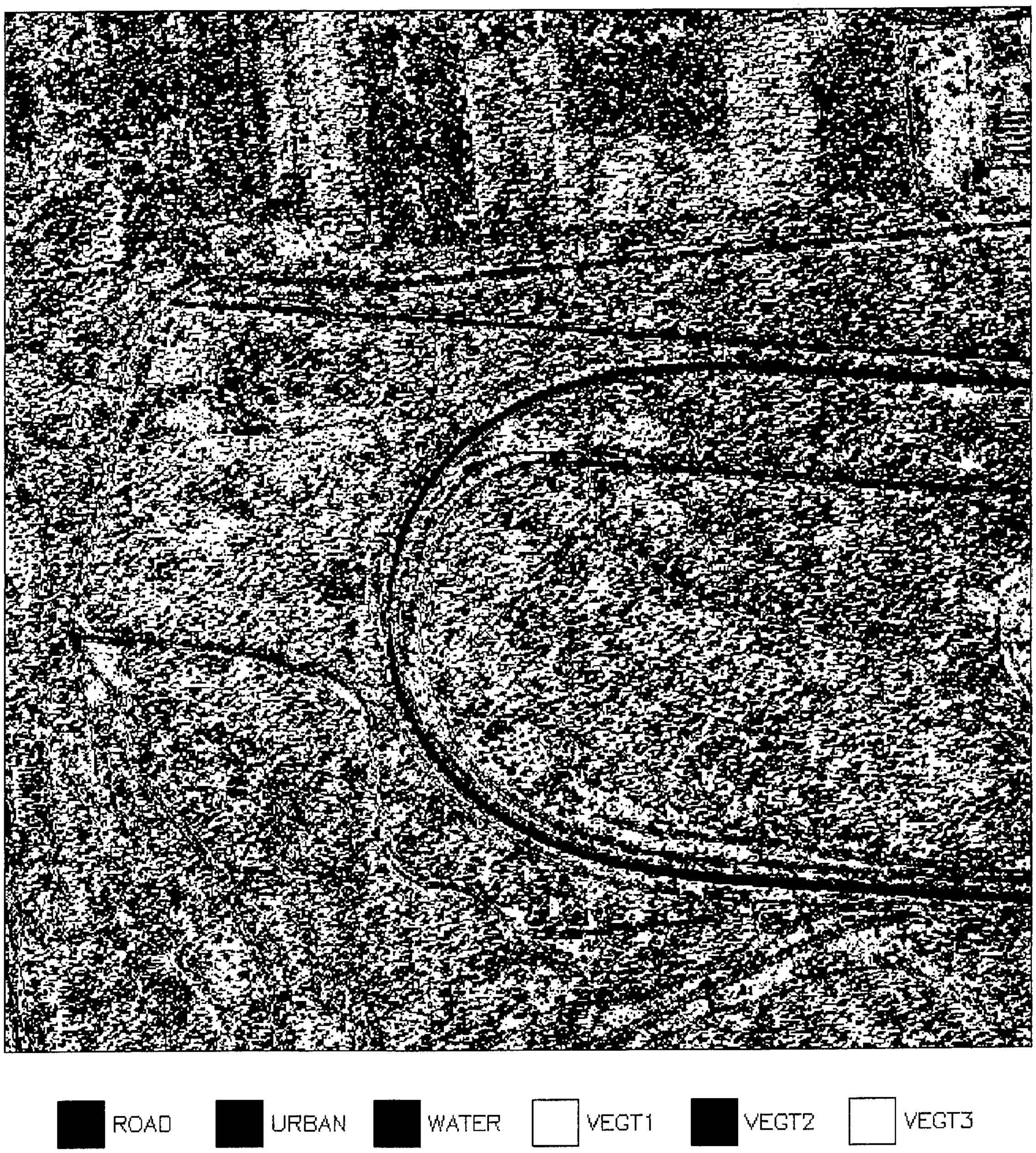

Figure 40. SOM NN Classification of Dexter/Chelsea (patch #24)

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