RAPID–RESPONSE IMAGING SENSOR SIMULATION

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ABSTRACT

Simulation of infrared, radar, and other imaging sensors plays an important role in the planning and rehearsal of military missions and in the training of mission personnel. The challenge is to develop technology that can use recently acquired intelligence information to quickly simulate cockpit sensor displays that accurately represent the real world while insuring correlation with the out–the–window displays and among the sensors.

This paper describes a novel, neural–network–based technique for infrared and radar image simulation directly from multi–spectral imagery. Source imagery, its processing using neural networks, and infrared and radar image simulation results are presented.

INTRODUCTION

The importance of imaging sensors, including infrared and radar, to the successful execution of navigation and air–to–ground targeting functions has been clearly demonstrated in practice. Such sensors could be applied even more effectively by mission personnel who have planned, previewed, and rehearsed the use of these imaging sensors prior to actual mission execution. To support this training process it is important that sensor imagery be simulated rapidly using the most recently acquired intelligence data.

Currently available image generators employed for sensor simulation use databases that describe mission gaming areas in terms of discrete features, three–dimensional models, and digital terrain elevations. Such information is derived from terrain photography, digital imagery, and a variety of cartographic products. Unfortunately, the process of reducing the original source imagery into a compressed set of attributed features and terrain models "filters out" most of the detailed spectral information available in the source imagery and also discards the desirable real–world appearance of the imagery. Because such databases are coarse representations of the real world, sensor images simulated from these databases also represent a coarse approximation to the real world.

Furthermore, although a semi–automatic process of extracting feature models and attributes from source imagery can produce highly detailed representations of selected areas of interest, this can be a very time–intensive and subjective process. Consequently, in situations requiring rapid database generation or updating, only the most critical areas can be modelled adequately to support high–fidelity sensor simulations. The remainder of the mission gaming area is still simulated at low fidelity using sparse and/or old data.

This paper addresses image–based techniques intended to overcome the limitations of traditional feature–driven sensor simulation approaches by directly transforming multi–spectral imagery into a sensor image. Such techniques have the potential to provide rapidly simulated, high–fidelity, sensor imagery correlated with other sensor imagery and the real world over large gaming areas.

After a brief introduction to image–to–image transformations and artificial neural networks, initial results in infrared and radar image intensity simulations are presented, followed by conclusions regarding future investigations.

IMAGE–TO–IMAGE TRANSFORMATIONS AND ARTIFICIAL NEURAL NETWORKS

Figure 1 compares traditional and image–to–image sensor image generation approaches. The image–to–image approach directly and in real time transforms multi–spectral imagery (MSI) from a run–time database into the desired sensor image. The run–time database is a mosaic of multiple resolution images reformatted and pre–processed off–line from real–world MSI. Both infrared and radar images, for example, are to be generated directly, at run–time, from the same multi–spectral database, ensuring correlated infrared and radar displays and an accurate representation of the real world.

In contrast, the traditional approach to sensor image generation requires an intensive analysis of MSI to develop models of real world features which are then inserted into a common database. The database is converted into either a mosaic of gridded data or polygons which are in turn used to simulate the sensor imagery. A major limitation of this approach is the substantial time and resources required to perform the necessary feature extraction and modelling needed to generate or modify the common and run–time databases.

The ability to perform successful image–to–image transformations for sensor simulation requires the selection of a set of multi–spectral input image channels that, in combination, contain sufficient information to predict the desired image waveband. Also needed is a way to deduce the inter–band relationships to be used for the image prediction/transformation function, and to apply that transform to the stored database images to produce the desired sensor image in real time. The technique presented here attempts to achieve this by applying the learning and recall capabilities of artificial neural networks to multi–spectral imagery.

Figure 1 illustrates infrared (IR), radar, and night–vision goggle (NVG) processors implemented using artificial neural networks (ANNs). Figure 2 shows a typical multi–layer, feed–forward neural network having three inputs, eight outputs, and three trainable

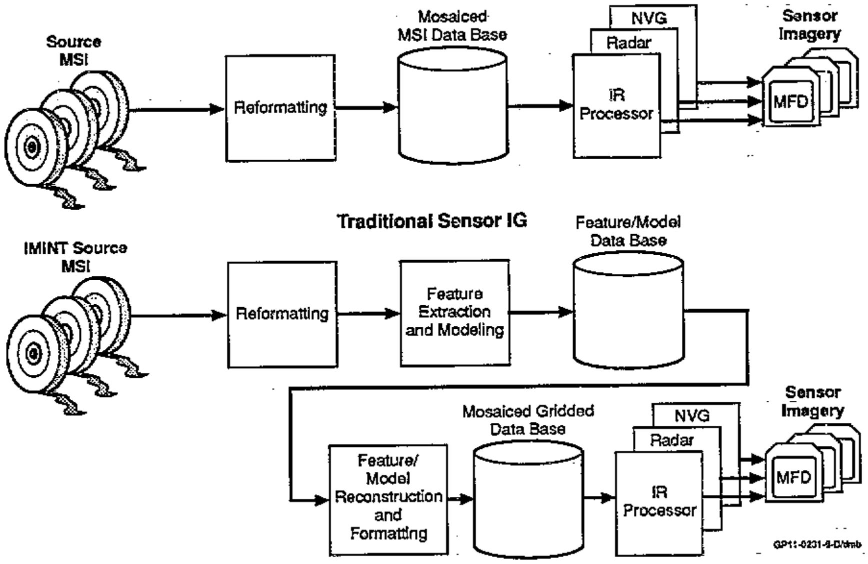


Figure 1. A Comparison of Image–to–Image and Traditional Sensor Simulation Approaches

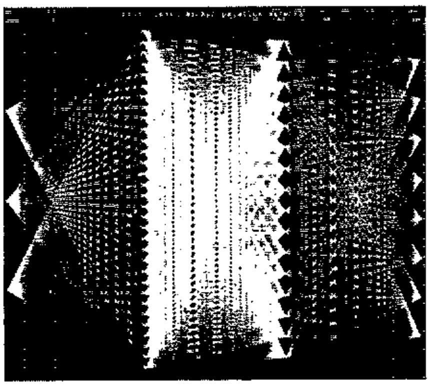


Figure 2. A 3–32–16–8 Multi–Layer Feed–Forward Artificial Neural Network

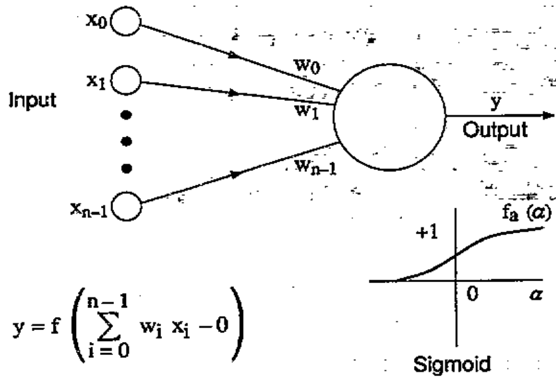


Figure 3. Neuron – The Basic Processing Element of Artificial Neural Networks

layers. Each layer contains many identical processing elements referred to as "neurons". A typical neuron, as shown in Figure 3, consists of a summation operator followed by a non–linear transfer, or "activation", function. Using a backpropagation–of–errors algorithm[1], the network is trained by iteratively presenting examples of input values paired with corresponding desired output data and adjusting the neuron input weights until optimal agreement between the predicted and desired output values is achieved.

Figure 4 illustrates the concept of training and applying neural networks for radar image prediction using MSI. During training, synthetic aperture radar (SAR) imagery is presented to the network's output while MSI of the same geographic area is simultaneously presented to the three network inputs. During production, MSI produced by the same or similar sensors is passed through the neural network to predict SAR image intensities.

INFRARED AND RADAR IMAGE SIMULATION RESULTS

We have performed two experiments to investigate the potential for direct transformation of MSI into IR and SAR imagery.

The first experiment involved training a back–propagation neural network (BPN) on Landsat Thematic Mapper (TM) MSI to predict a near–IR band from other TM MSI bands as an initial step toward predicting Forward–Looking IR (FLIR) sensor imagery. Multi–spectral pixels for network training were randomly selected from the region surrounding Washington, Missouri. Their values in TM bands 2 (0.52–0.60 um), 4 (0.76–0.90 um), and 5 (1.55– 1.75) were used to train a multi–layer feed–forward neural network to predict the near–IR band 7 (2.08–2.35 um). The network had three–inputs, two hidden layers consisting of thirty–two and sixteen nodes, and an eight–node output layer (256 intensity levels). It was trained using the back–propagation–of–errors technique by repetitively "showing" the network a training database containing 16,384 pixels randomly sampled from the Washington, Missouri, MSI database.

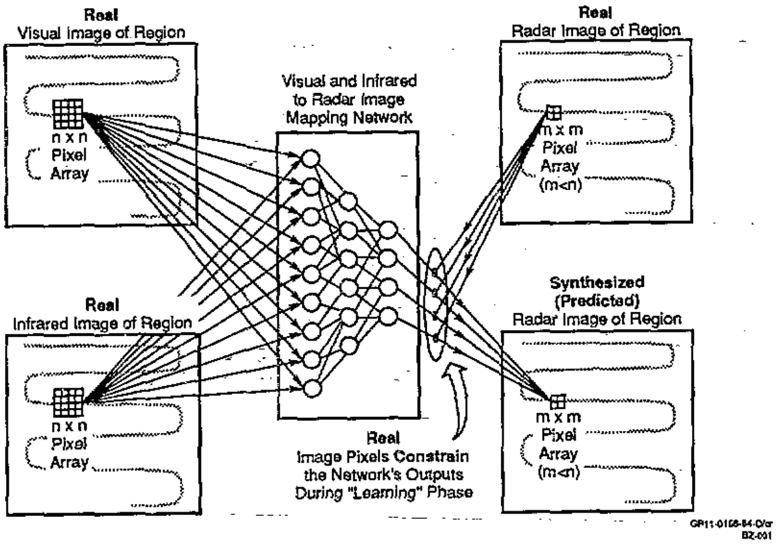


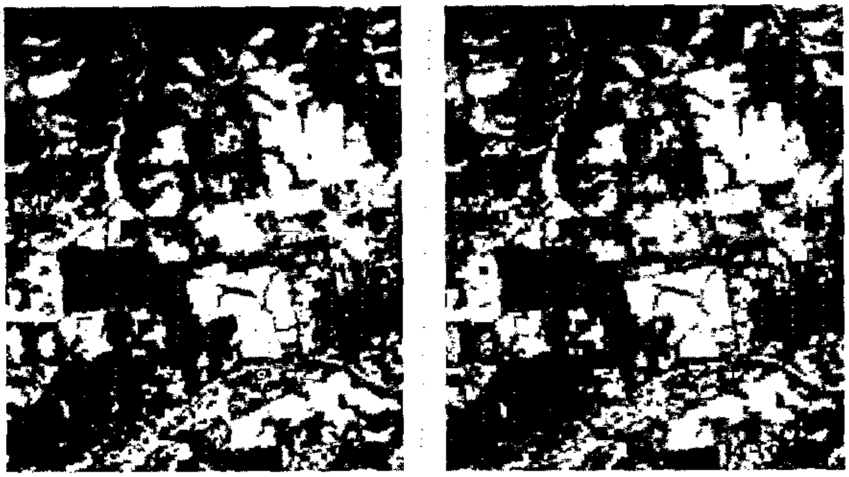
Figure 4. Training an Artificial Neural Network for Image Prediction

After ten passes through the training data, the network error had stabilized and the connection weights were stored. The trained network was then used to predict the near–IR TM band 7 for an area near Wentzville, Missouri, again using TM bands 2, 4, and 5 as input. The predicted pixel intensities were formed by converting the eight BPN outputs into an 8–bit, 256–grey–level pixel intensity. The results are shown in Figure 5 where the actual band 7 image is on the left and the predicted band 7 image is on the right. The differences in grey levels between the predicted and actual TM band 7 images were minor, indicating the network learned the multi–band intensity transformation quite well.

The long–wave IR TM band 6 (10.4–12.5 um) was also used for FLIR simulation experiments. However, the low spatial resolution (120 m/pixel) and coarse grey–level quantization (9 grey levels in the training pixels and 22 levels in the testing images) of TM band 6 contributed to the production of highly segmented images that were not good reproductions of the actual band 6 image.

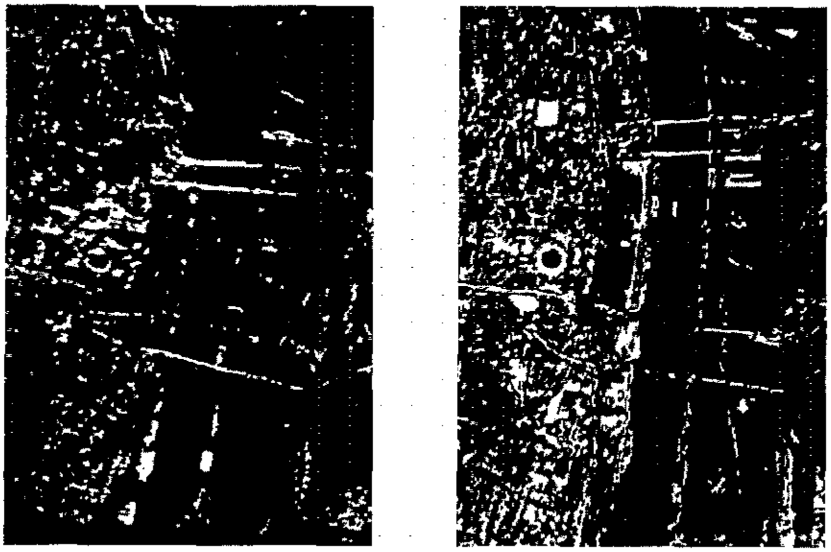
In the second experiment a similar BPN network was trained to predict a SAR image of downtown St. Louis, MO. This time, a training database was created by manually selecting 400 pixels of SPOT satellite MSI data registered with a flight–test SAR image. The SPOT MSI bands 1 (0.50– 0.59 um), 2 (0.61–0.68 um), and 3 (0.79–0.89 um) and an X–band (10–GHz) radar were used. The training data included pixels taken from the river, a bridge, streets, highways, bare ground, grass, and several structures including a stadium, parking garage, and power plant.

After 1,400 iterations through the database, the network was used to predict the SAR image shown in Figure 6. Over fifty percent of a random set of pixels taken from the actual SAR image were found to be identical to those predicted by the neural network.



Actual | Predicted

Figure 5. A Comparison of Actual and Predicted Landsat TM Near–IR Band 7 Images of Wentzville, Missouri



Actual Predicted

Figure 6. A Comparison of Actual and Predicted X–Band SAR Images

One result of particular interest is that the two northern bridges showed up clearly in the predicted image, but only the supporting piers of the southernmost bridge were highlighted. This was due to the fact that the northern bridge, from which training pixels were taken, is primarily a stone and concrete structure, while the southernmost bridge is constructed almost entirely of dark metal. No pixels from the southern bridge were included in the original training database. As a result, only the concrete piers were "recognized" by the neural network and shown in the predicted radar image. This omission was resolved by adding six pixels from the upper portion of the "missing" bridge to the training database and retraining the network. The newly sampled bridge (and other spectrally similar objects) then appeared in subsequent predicted radar images.

Another interesting feature of the predicted SAR image is the presence of a bright, square structure in the upper left that is not present in the actual SAR image used to train the network. This is not a "stealth building", but instead is not visible in the actual radar image simply because the structure did not exist when the radar image was made but was present several years later when the SPOT satellite imagery was acquired.

CONCLUSION

The infrared and radar image prediction results achieved so far are promising but indicate the need for additional research. For example, although the neural–network predictions of near–IR images were very good, the far–IR imagery produced so far has been much less accurate. To what degree the low fidelity is due to the inherent difficulty of the prediction and how much it is caused by other factors remains unclear and requires further investigation.

The unexpected appearance of a recently completed building in the predicted SAR image of St. Louis (not present in the SAR imagery used to train the network) demonstrates one of the advantages of simulating sensor displays directly from the latest reconnaissance imagery. The predicted sensor imagery, even if not perfect in every respect, will be as up–to–date as the latest reconnaissance imagery, and will be automatically correlated with other sensor and visual displays also generated directly from the same MSI.

The results described here represent the initial phase of our investigation into the capabilities and limitations of this approach to imaging sensor simulation. Further research is required in many areas including limitations due to the effects of weather, Sun angle, clouds, and other atmospheric conditions on neural–network training and image prediction over a variety of geographic areas.

Experimentation is also needed to determine how to best generate and blend terrain–dependent 3–D effects into the predicted radar imagery. For example, no attempt was made to predict the "speckle noise" evident in real SAR images or 3–D effects such as shadowing and far–shore brightening.

Although our research has only begun to investigate the potential, and limitations, of a direct–from–MSI, image–to–image approach to sensor simulation, we believe that our neural network based techniques for learning multi–spectral image transformations will provide a powerful tool to support the rapid simulation of sensor imagery over large gaming areas.

REFERENCES AND SUGGESTED READING

[1] Rumelhart, D., and McClelland, J., "Parallel Distributed Processing, Explorations in the Microstructure of Cognition, Volume 1: Foundations", MIT Press, Cambridge, MA, 1986

[2] Aleksander, I., "Neural Computing Architectures", MIT Press, Cambridge, MA, 1989

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Budimir Zvolanek is a Technical Specialist in Product Development at McDonnell Douglas Training Systems (MDTS) in St. Louis. Mr. Zvolanek has concentrated his career on the application and development of electronic imaging systems, image processing, digital signal processing, and computer–based data acquisition. Having conceived the image–to–image sensor simulation approach, he is currently responsible for research and development activities in sensor simulation and correlated databases. Previously, he lead the development and design of the F–14A radar simulator under the Navy 2E6 Tactical Scenario Improvement program at MDTS and the Video Image Dynamics System for the Standoff Land Attack Missile at McDonnell Aircraft Company Flight Simulation Laboratory. While at the McDonnell Douglas Missile Systems Company, he led the Advanced Anti–Ship Targeting Development effort to automatically recognize ship targets from infrared imagery and supported algorithm development for laser radar imaging. Mr. Zvolanek received his M.S.E.E. degree from Washington University in St. Louis, Missouri.

Erv Baumann has specialized in the application of artificial intelligence methods to sensor simulation, machine vision, and automated planning. As Technical Specialist at MDTS, he has conceived and developed innovative applications of neural networks to multi–spectral image analysis and sensor simulation. While working in MCAIR's Advanced CAD/CAM Technology group, he was responsible for the enhancement and application of an internally developed expert–system–shell used to implement a generative process planning system and several stand–alone expert systems. Prior to this, he assisted in the design and implementation of two model–based machine vision systems and developed sensor simulation software for an industrial robot simulation and programming workstation. Mr. Baumann received his B.S.E.E. degree from the University of Minnesota.