STATISTICAL PREDICTION OF AN INFRARED IMAGE FROM MULTI-SPECTRAL IMAGERY FOR COMMON VISUAL DATA BASE GENERATION

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ABSTRACT

A major problem in the present flight simulators is that simulated displays such as visual, infra red, synthetic aperture radar etc., do not correlate well with each other. A common data base to drive these displays would facilitate such correlation. A subset of this problem of creating a common data base is the following question: given a mix of input spectra of imagery, is it possible to predict using statistical prediction techniques an infrared image that is not part of the original spectra.This research work is directed towards predicting an infrared image from the best and the smallest subset of the input spectra. Simulations were performed on seven bands of LANDSAT Thematic Mapper images. Three types of predictions were developed and implemented and the results analyzed. The results proved that such predictions were indeed possible and that the statistical prediction may give as good results as those obtained from more complicated neural networks based predictions.

ABOUT THE AUTHORS

Dr. Venkat Devarajan has been an associate professor of Electrical Engineering at the University of Texas at Arlington since March 1990. Earlier he was an Engineering Project Manager at LTV Missiles and Electronics where he was involved in the development of the first photo-based mission rehearsal system for the US Navy. He has over 19 years of experience in several aspects of visual systems development. Besides performing research in this field at UTA, Dr. Devarajan has also been a consultant to several companies.

Dr. McArthur is a Research Associate in the Electrical Engineering department of the University of Texas at Arlington specializing in real time simulation and image processing algorithm development. He has also worked in these areas at Texas Instruments specializing in target tracking algorithms and at LTV Missiles and Electronics specializing in real time image generation for pilot training systems. Previously, he worked in digital hardware design at Singer-Link. He received his education at the University of Nebraska and spent nine years in teaching and nuclear physics research.

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 led the development and design of the F-14A radar simulator under 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.

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INTRODUCTION

One of the major problems with the present flight simulators is that the simulated displays do not correlate well with one another when each of the displays is generated by different image generators made by different manufacturers and there is no built-in correlation among the data bases used by these image generators. The logical question is whether it possible to build such a common correlated data base that could drive all of these displays? A subset of this question is addressed in this paper. Given a mix of input spectra of imagery (a common database), is it possible to economically predict a spectrum, say an infrared image, that is not part of the original database?

INFRARED PREDICTION

The possibility of developing a system for simulating an infrared image by using other spectral bands as input, and finding a grey level mapping depends on the properties of the function

$$I_{IR}(x,y) = F\left[I_1(x,y), I_2(x,y), I_3(x,y)\right]$$

where $I_1(x,y)$, $I_2(x,y)$ and $I_3(x,y)$ are the intensity levels at each pixel of the input image, and $I_{IR}(x,y)$ is the desired infrared image. This function, although nonlinear, must be reasonably smooth and well defined by the training data. Our problem in effect is finding F with the minimum number of I's.

The work described in this report was performed to determine the feasibility of predicting an image in an IR band by using images in other bands as inputs. Such a prediction would be useful for flight simulation applications and might be implemented using a neural network. A linear prediction of specific selected areas in the regions of Washington and Wentzville, Mo. has been achieved which supports the contention that in general this prediction is possible. Furthermore, a method has been developed to select a subset of the input images to be used for a linear prediction, and a measure of the accuracy of this method has been calculated. Also the linear method, which is based on the entire intensity range, has been extended to a multidimensional, piecewise linear approximation, and a measure of the improvement in the prediction has been calculated

STATISTICAL PREDICTION TECHNIQUES

This section outlines the algorithm for prediction of IR image from the multi spectral image (MSI) bands. It is based on standard multivariate regression analysis and assumes that there is a piecewise linear relation between the IR image intensities and the MSI intensities. Subimages are defined by selecting the set of pixel coordinates (x,y) for which the IR intensity is in a definite range, thus

$$\text{subimage} = \left\{(x,y) \mid a \le I_{IR}(x,y) \le b\right\}$$

where a and b are the lower and upper limits of intensity for each subimage. These values are chosen such that the collection of subimages covers the entire IR image. For each band, and for each subimage the intensities will be renormalized to obtain a set of values with zero mean.

$$Y_j(x,y)=I_j(x,y)-(\text{subimage mean})_j$$

The assumed linear relation for *estimating* the IR subimage from the other MSI bands can be written as (letting band 7 represent the IR band)

$$Y_7^{est}(x,y)=\sum_{j=1}^{6} C_j\, Y_j(x,y)$$

The values for C_j may be determined by *minimizing the sum of the squares of the* difference between the estimated values and true values of the IR subimage.The covariance matrix

$$A_{ij}=\sum_{subimage} Y_i(x,y)\, Y_j(x,y)$$

and the vector

$$B_j=\sum_{subimage} Y_7(x,y)\, Y_j(x,y)$$

are related to C by the matrix equation

$$C=A^{-1}B$$

The predicted image is then

$$Y(x,y)=\sum\left\{\begin{matrix} \textit{Mean of Original}+ \\ \sum C_j(Y_j(x,y)-\textit{subimage mean})\end{matrix}\right\}$$

where the first summation indicates a selection of the pixel intensity as predicted within the subimage and the second summation indicates a sum over input bands. The selection is based on the definition of subimages of the original image.

SIMULATION METHODOLOGY

A Landsat TM quarter-scene image of Southwest St. Louis area was used for this work. Two regions, each of size 512 x 512 pixels, were selected for detailed analysis, one near Washington, Mo. and one near Wentzville, Mo. The means and standard deviations of selected bands of these regions are tabulated below.

All calculations and analysis described in this work were performed on an International Imaging Systems M75 hosted by a Sun 4/380 workstation running the S-600 software package.

DISCUSSION OF RESULTS

Linear prediction -- full intensity range

For the regions of interest, a linear prediction of band 5 with bands 1,2,3,4, and 7 as inputs and a linear prediction of band 7 with bands 1,2,3,4, and 5 as inputs were investigated with the subimage defined as the full intensity range. The 5x5 covariance matrix equation was solved to obtain the weights in the prediction formula The numerical values of the weights are tabulated in tables 4, 5, 6, and 7.

The accuracy of these predictions are measured by the standard deviation (SD) of the difference between the original image and the predicted image as shown in the Table 3 below. As can be seen in the third line of table, in each case the SD of the difference is approximately 30% of the SD of the corresponding original image, indicating a good prediction. There was no visible difference between the original images and the predicted images and therefore they are not reproduced here.

Dominant Bands

Predictions were made for bands 5 and 7 of Washington and Wentzville regions by choosing the three dominant bands.The solutions of the covariance matrix gives the weights.The three bands with the greatest weights represent the dominant bands. The statistics of the difference between the original image and the predicted images are shown in the Table 3. The standard deviations of the dominant band case (original - predicted) as can

Table 1 Image Means and Standard Deviations

IMAGE	MEAN	STD. DEV.
Washington band 1	63.918	5.735
Washington band 2	25.394	3.951
Washington band 3	30.950	6.646
Washington band 4	37.682	12.961
Washington band 5	61.916	18.770
Washington band 7	28.922	10.034

Table 2 Image Means and Standard Deviations

IMAGE	MEAN	STD DEV
Wentzville band 1	64.690	6.097
Wentzville band 2	25.751	4.166
Wentzville band 3	32.288	7.015
Wentzville band 4	38.862	10.218
Wentzville band 5	66.368	15.398
Wentzville band 7	29.738	8.598

be seen from the table are less than the SD of the original image. However, as might have been expected, the SD for the full-range, 5-band prediction is less than the SD for the dominant band prediction in all of the four cases examined. Visual examination of the images revealed that the predicted images are very similar to the original images.

It can be seen from tables 4 and 6 that in the case of band 5, the dominant bands are 2,3, and 7 for both geographical areas. In the case of band 7 (tables 5 and 7), the dominant bands are 3, 4, and 5 for Washington and 2, 3, and 5 for Wentzville. Band 1 never dominates, and band 3 and either 5 or 7 dominate all the time .

Piecewise Linear Prediction

The selected images were also predicted by using a piecewise linear prediction method. The end points for the definition of the subimages are obtained by examination of the histogram of the band to be predicted. The images were divided into three subimages having nearly the same number of pixels in each. A prediction was done for each of the subimages, and then a combined prediction was obtained. The numerical values of the weights are tabulated in tables 4, 5, 6, and 7.

The standard deviation of the difference between the original and the piecewise predicted image was calculated. As can be seen from Table 3, this value is lower than the SD for the corresponding linear prediction by about 13 to 20% indicating an improved prediction for each of the selected images. Visual examination of the images reveals that the predicted images are very similar to the original images.

Table 3 Standard Deviation of Original image and difference between Original and predicted images.

	Wentzville 5	Wentzville 7	Washington 5	Washington 7
Original image	15.398	8.598	18.770	10.034
Original - Dominant 3	7.332	3.454	10.399	3.546
Original - predicted	4.538	2.583	5.097	3.191
Original - piecewise	3.712	2.160	4.102	2.778

Table 4 Weights used in predicting Washington band 5

Band No	Linear Prediction	Subimage 1	Subimage 2	Subimage 3
1	-0.235	-0.357	-0.283	0.078
2	-1.688	-0.888	-1.039	-1.178
3	0.931	0.474	0.813	0.476
4	0.740	0.527	0.480	0.489
7	1.234	1.429	0.764	0.713

Table 5 Weights used in predicting Washington band 7

Band No	Linear Prediction	Subimage 1	Subimage 2	Subimage 3
1	0.133	0.158	-0.024	-0.130
2	0.230	-0.292	0.680	0.581
3	0.311	0.156	0.295	0.236
4	-0.297	-0.122	-0.358	-0.420
5	0.482	0.435	0.362	0.413

Table 6 Weights used in the prediction of Wentzville 5

Band Number	Linear Prediction	Subimage 1	Subimage 2	Subimage 3
1	-0.127	-0.269	-0.234	0.073
2	-1.224	-0.750	-0.497	-0.972
3	0.636	0.449	0.330	0.537
4	0.604	0.438	0.340	0.402
7	1.338	1.572	1.030	0.822

Table 7 Weights used in the prediction of Wentzville 7

Band No	Linear Prediction	Subimage 1	Subimage 2	Subimage 3
1	0.062	0.082	0.084	-0.091
2	0.294	-0.214	0.145	0.503
3	0.289	0.193	0.109	0.242
4	-0.245	-0.098	-0.118	-0.316
5	0.433	0.370	0.254	0.362

CONCLUSIONS AND FUTURE WORK

The following is a summary of the major results of this work:

1) Prediction of an infrared image from other multi spectral images is possible with several different techniques and, the predicted images are very similar to the original images.

2) Prediction is improved when a nonlinear method is used resulting in about 13 to 20% reduction in SD compared to the 5-band linear prediction.

3) A subset consisting of three dominant bands out of the five may be used to obtain a prediction . This results in a slightly larger SD compared with the linear prediction. Some definite trends were clear in the identification of the dominant bands.*For the purposes of flight simulation this simple approach to creating correlated data bases might well work. Reducing the number of input bands required has obvious implications for the data base turnaround time and required computing resources.*

The work reported here forms the basis for extensions in several possible directions:

1) A piecewise linear prediction which uses a subset of the input bands could be developed and tested. An optimal choice of weights within the subspace of the input bands may produce an improved prediction. The testing could be performed over a larger selection of the input images.

2) The prediction algorithms could be tested on spatially filtered versions of the images. An investigation of the spatial properties of the residual images and the correlations with the spatially filtered input images may lead to an improvement in the prediction.