AN INDEPENDENT COMPONENT ANALYSIS BASED IMAGE CLASSIFICATION SCHEME

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Abstract-In this paper, an image classification scheme based on Independent Component Analysis (ICA) is proposed. The scheme used independent components as image templates for which an image was projected. The output of the image projection was fed to a classifier. Three classifiers were presented using this approach. The experiment results were presented with extensive simulations documenting how well this method classified images.

I. INTRODUCTION

Independent Component Analysis (ICA) is emerging as a new standard area of signal processing and data analysis [1]. ICA attempts to solve the blind source separation problem in which sensor signals are unknown mixtures of unknown source signals [2]. While there are no general analytical solutions, in the last decade researchers have proposed good approximate methods based on simple assumptions about the source statistics and using maximum likelihood, information maximization and minimization of higher-order moments.

ICA theory has received attention from several research communities including machine learning, neural networks, statistical signal processing and Bayesian modeling. More recently numerous applications of ICA have appeared including applications to adaptive speech filtering, speech signal coding, biomedical signal processing, image compression, text modeling and financial data analysis [4], [5], [6].

II. INDEPENDENT COMPONENT ANALYSIS BACKGROUND

This section will provide a brief overview of ICA. ICA is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals [3].

ICA defines a model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear or nonlinear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed non-Gaussian and mutually independent and they are called the independent components of the observed data. These independent components, also called sources or factors, can be found by ICA.

ICA can be seen as an extension to principal component analysis and factor analysis. ICA is a much more powerful technique, however, capable of finding the underlying factors or sources when these classic methods fail completely.

Using vector-matrix notations, the ICA mixing model is written as

$$x = As \qquad (1)$$

where x is the observation, A is the mixing matrix, and s are the independent components, respectively. Or, if using the columns of matrix A, denoting then by a_j, the model can also be written as

$$x = \sum_{i=1}^{n} a_i s_i . \qquad (2)$$

The ICA model is a generative model, which means that it describes how the observed data are generated by a process of mixing the components s_i. The independent components are latent variables, meaning that they cannot be directly observed. Also the mixing matrix is assumed to be unknown. The only observation is the random vector x, and we must estimate both A and s using it.

This proceeding section provides an overview of the classification algorithm. There are two broad areas of classification: supervised and unsupervised. For this paper, the supervised approach was examined for the classification scheme shown is Figure 1. Supervised classification, often called discriminant analysis in statistics, requires the knowledge of the classes, and seeks to find the rule for best separating the groups based on the measured variables.

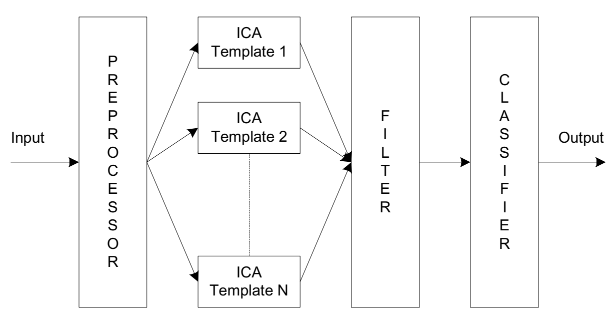

Figure 1. Classification Block Diagram.

III. METHODOLOGY

The architecture for the classification scheme can be decomposed into five parts.

A. Preprocessor

Prior to classification, scaling the raw image to a normalized form preprocesses the image. First, the center of mass of a threshold version of the image is computed, and the image is centered on its centroid. The determination of the correct presentation orientation may improve classification performance.

B. ICA Templates

Once the input image has been preprocessed, it's projected onto a series of ICA templates. The templates, consists of a set of independent components derived from a set of clustered training data. Performing the projection between the template and input image provides a set of coefficients, which are in turn fed to a filter.

C. Filter

The filter is a hard limiting function, which selects the maximum coefficient set generated from the projection. This coefficient set is fed to the classifier for classification.

D. Classification

Based on the coefficients generated from the filter, the following classifiers were trained and tested:

- Vector Quantization [10]
- Neural Network [7], [8], [9]
- Fisher Classifier

Training and testing were preformed using the public release of the MSTAR target chips from the Air Force Research Laboratory. The results and extensive simulations of the classifiers are presented in the following section.

IV. EXPERIMENTAL CONDITIONS

The data sets used for this experiment were from the public MSTAR release. Training images consisted of BMP2 SN 9563 tanks at a 17-degree depression angle. A total of 233 images were used distributed over four classes:

- Class 1 – 61 images
- Class 2 – 60 images
- Class 3 – 51 images
- Class 4 – 61 images

The tank targets at a particular range of azimuths represent each class (shown in Figures 2-9).

For purposes of the classification experiment, two sets of independent component templates were constructed, i.e., 2 independent components per class and 4 independent components per class. The independent components were obtained from each of training data classes, i.e., 2 or 4 independent components were obtained by using the class member images as the mixed signal.

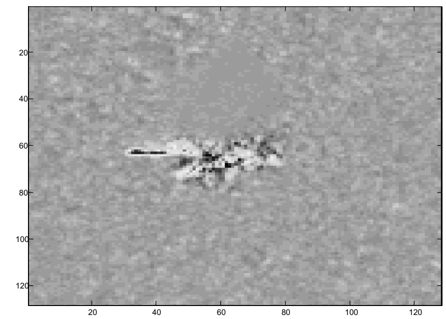

Figure 2. Class 1 – Independent Component 1.

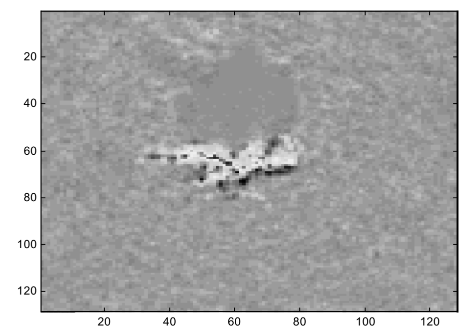

Figure 3. Class 1 – Independent Component 2.

Figure 4. Class 2 – Independent Component 3.

Figure 5. Class 2 – Independent Component 4.

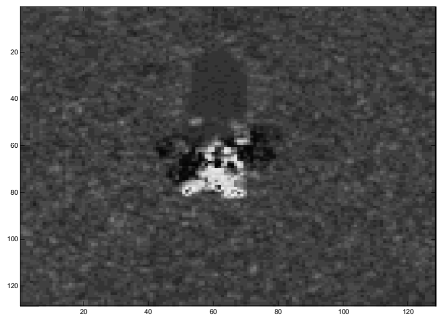

Figure 6. Class 3 – Independent Component 5.

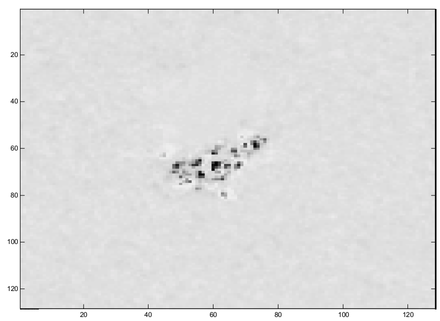

Figure 7. Class 3 – Independent Component 6.

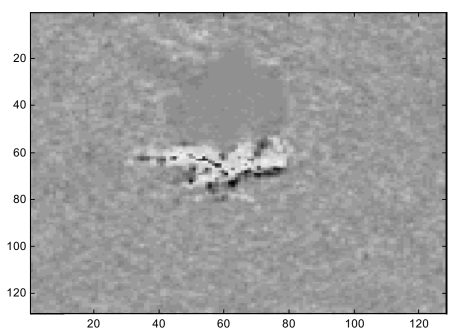

Figure 8. Class 4 – Independent Component 7.

Figure 9. Class 4 – Independent Component 8.

Testing was completed using 64 BMP2 SN 9563 tank images, also from the public MSTAR release, at a 15 degree depression angle (16 test images per class), as shown in Figures 10 and 11.

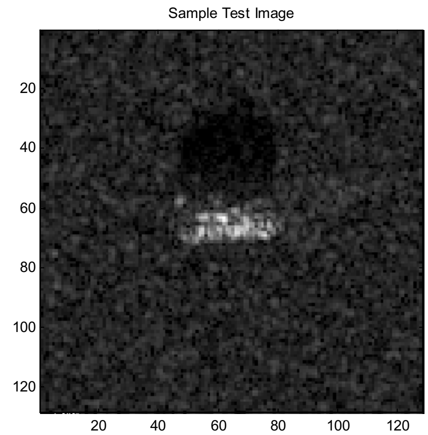

Figure 10. Sample Test Image.

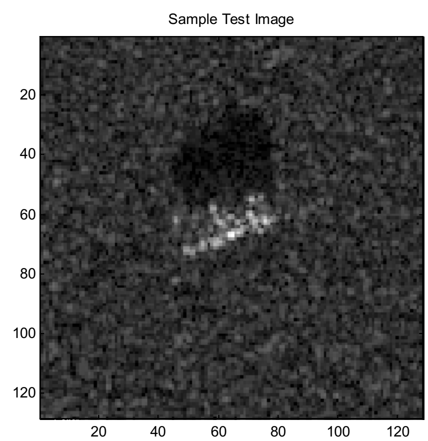

Figure 11. Sample Test Image.

V. CLASSIFICATION RESULTS

The classification results for two experiments are shown in Figures 12 and 13 for three different classifiers: Vector Quantization (VQ), Fisher Classifier, and a Neural Network (NN). Using two independent components, the classification accuracy achieved during training was approximately 76% for VQ, 83% for the Fisher Classifier, and 82% for the NN, and testing yielded accuracies of 73% for VQ, 75% for the Fisher Classifier, and 75% with the NN.

Using four independent components, the classification accuracy improved for training accordingly: 84% for VQ, 88% for Fisher, and 86% for NN. The testing accuracy achieved was 80% for VQ, 81% for the Fisher Classifier, and 83% for NN.

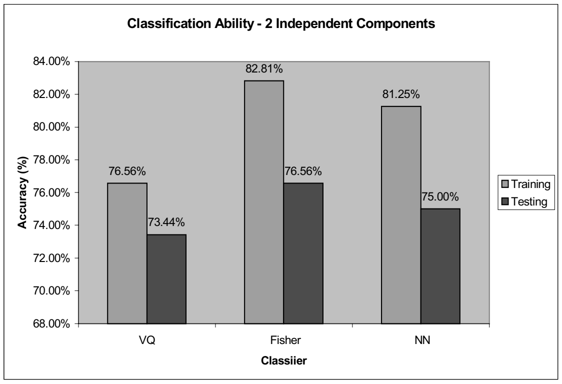

Figure 12: Classification Accuracy with 2 Individual Components.

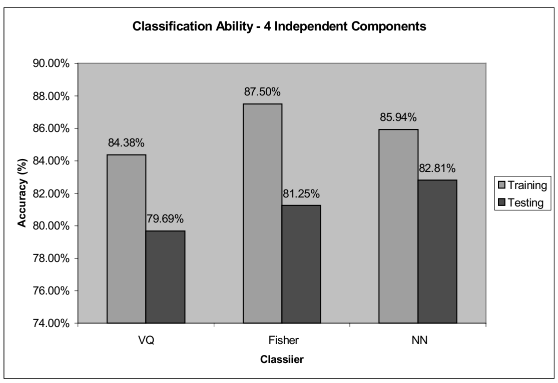

Figure 13: Classification Accuracy with 4 Individual Components.

VI. CONCLUSIONS

The algorithm for classification presented here is based on an approach using ICA to model the structure of the image filters or templates. Results of classification using VQ, the Fisher Classifier, and a multi-layer NN have been presented showing better performance for the Fisher Classifier. It is seen that the use of additional ICA templates improved classification. Future work involves investigating additional classifiers, i.e. the Support Vector Machine [11] and Learning Vector Quantization (LVQ) for comparison to the classifiers presented here. The eventual goal of the classification scheme presented here is an alternative approach to Automatic Target Recognition (ATR) applications.

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