Flexible Histograms: A Multiresolution Texture Discrimination Model

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The Problem: We describe a technique for using the joint occurrence of local features at multiple resolutions to build a model to measure the likelihood that images contain the same textures. Preliminary experiments indicate that this approach may have sufficient discrimination power to perform target detection is synthetic aperture radar (SAR).

Motivation: The notion of texture is difficult to capture formally. Textures are usually the output of some random physical process wherein local structure is repeated seemingly at random and there is a lack of global structure. So, while the fur of a leopard is considered to be a texture, the entire leopard is not. This distinction is unavoidably arbitrary. We present an approach to texture recognition that is successful at modeling random repeating textures such as fur or bark and which naturally and automatically extends to structural patterns of many scales.

Previous Work: Previous approaches to texture have focused on models of local structure. Beginning with the work of Julesz, these texture discrimination models typically analyze a patch of texture by computing the outputs of local oriented filters such as the Gabor filters (e.g. [4, 1].) In related computational approaches, a single feature vector which contains the outputs Gabor-like filters at multiple scales is used to describe a patch of "texture." Two textures are said to be different if their Gabor features vectors are different. While these Gabor-like models are simple and somewhat effective, they make serious limiting assumptions regarding the definition of texture; and though they may be true for very fine textures like sand or fur, they do not hold for those with significant internal structure like a brick wall or a striped shirt.

Recently, the notion that a texture can be described as a Gabor feature vector has been applied in the problem of *synthesizing* texture images [3]. There approach to generated very pleasing results in simple textures, but failed on those with more complex structures. In [2] we presented a related texture generation procedure which models the statistical dependence between different filters at multiple resolutions. In this work we invert this generation procedure and use it as the basis for a texture discrimination model.

Approach: Flexible Histograms Given an example image, which contains the texture of interest, features are extracted at each image location at multiple resolutions. For each location in the image, we collect the responses of a set of local oriented filters at each resolution. This collection forms the *parent vector* of each location, and is used as a center of a bin in the *flexible histogram.*

Because the bin labels used to generate these histograms are dependent on the model image, we term them "flexible." In this way, when searching for different types of textures (i.e. when using different model images) the bins used in the histogramming process are specialized.

A flexible histogram for a test image is computed by accumulating the number of parent vectors in the test image which are within threshold distance of each model image parent vector. Similarly a flexible histogram is computed for the model image with respect to *itself.* A similarity likelihood is acquired from the inverse of χ^2 difference measure.

Difficulty: Vehicle detection and classification are the key problems in Automatic Target Recognition (ATR) tasks. Using a model constructed from four SAR images of a particular vehicles, we detect target containing chips and classify them. Data was acquired from the Model Based Vision Lab MSTAR project MBVLabURL. In on the left of Figure 1 two images of a T72 tank (a) BMP2 personnel carrier (b), and clutter images (c) are shown.

The ROC plot on the right of Figure 1 shows the performance of the current technique at discriminating between clutter images and images containing *either* vehicle type, given two model images of *only* the T72. Perfect performance, over this preliminary data set, is achieved. However, this measure is only preliminary; in real applications the the maximum acceptable probability of false-alarm, (Neyman-Pearson criterion) is below the $\pm \sim 1\%$ precision of these experiments. They are however, suggestive of the potential of this technique.

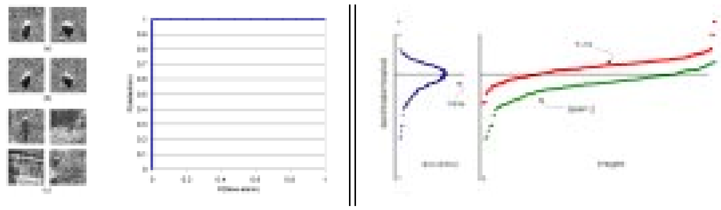

Figure 1: Left: 128×128 SAR images of (a) T72 tanks, (b) BMP2 personnel carriers, and (c) clutter images which contain no vehicles. Middle: ROC curve for discriminating full resolution (128×128) T72, or BMP2 vehicles from clutter images. Right: Classification of BMP2 vs. T72 vehicles

We now turn to the question of discriminating between the T72 and BMP2 vehicles. Using just examples of one vehicle type, only 67% are correctly classified. By combining the information provided by both pairs of model images performance can be improved.

The left plot of Figure 1 is the accuracy achieved by the system as a function of the threshold. In the right, the output of the classification system is shown for the two types of images. The top curve are the sorted responses to the T72, and the bottom to the BMP2 (Of course, when performing classification, of course, the system does not have access to these labels, as finding them is the objective!) From the peak on the left plot, we see that the maximum accuracy obtained is 78%.

Impact: The flexible histogram multiresolution texture discrimination approach described here makes explicit the requirement that to be considered similar, textures must contain similar distributions of *joint* feature responses over multiple resolutions.

Future work: The SAR detection and classification rates shown here are only preliminary, and further analysis, including experiments on larger data sets, and on data which includes images with targets and clutter in close proximity, are required to further refine the system and obtain a better estimate of its overall potential.

Research Support: Research supported in part by AFOSR under contract No. F49620-93-1-0604, DARPA under contracts No. 95009-5381, and J-08011-S95042 and by ONR under contract No. N00014-96-1-0311.

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