LOCATING SMALL VOLCANOES ON VENUS USING A SCIENTIST-TRAINABLE ANALYSIS SYSTEM; **J.C. Aubele** and **L.S. Crumpler,** Dept. of Geological Sciences, Brown University, Providence, RI 02912. **U.M. Fayyad** and **P. Smyth**, Jet Propulsion Laboratory M/S 525-3660, California Institute of Technology, Pasadena, CA 91109. **M.C. Burl** and **Pietro Perona**, Electrical Engineering Department, M/S 116-81; California Institute of Technology, Pasadena, CA 91125.

INTRODUCTION. Data collected by modern instruments are ever growing in sizes and rates, reaching gigabytes and terabytes. Complete and comprehensive scientific analysis of large volumes of image data necessitates the use of automated computational aids. Combining techniques from image processing/pattern recognition, machine learning, and a graphical user interface, we have developed a system called JARtool (JPL Adaptive Recognition Tool) for the detection of the "small-shield" volcanoes (less than 15km in diameter) that constitute the most abundant visible geologic feature in the more than 30,000 synthetic aperture radar (SAR) images of the surface of Venus [1,2]. Our long-term goal is to develop a general, trainable tool for locating small-scale features where scientists specify what to look for simply by providing examples of patterns of interest and possibly quantities of interest (attributes) to measure. This avoids the need to develop problem-specific programs for detecting given patterns. We report on our approach and initial results in the specific context of locating small volcanoes. The results reported are based on four training images labeled by geologists into four different categories of volcanoes, and include 163 small shield volcanoes.

It is estimated, based on extrapolating from previous studies and knowledge of the underlying geologic processes, that there should be on the order of 10^5 to 10^6 of these volcanoes visible in the Magellan data [3,4]. Identifying and studying these volcanoes is fundamental to a proper understanding of the geologic evolution of Venus. However, locating and parameterizing them in a manual manner is forbiddingly time-consuming. Hence, we have undertaken the development of techniques to partially automate this task.

THE APPROACH. Most pattern recognition algorithms in SAR remote-sensing imagery are geared towards detecting straight edges or large changes in texture/reflectivity. While this works well for detecting man-made objects, edge detection and Hough transform approaches deal poorly with the variability and speckle noise present in SAR imagery [5,6]. This, along with the desirability of developing a general tool rather than manually programming each detection problem, led us to develop an approach based on a learning from example approach [7]. The system is based on three components: 1. Focus of attention (FOA) is designed to efficiently and quickly scan an input image and roughly determine regions of interest (regions potentially containing objects similar to those specified by the scientist). It is designed to be an aggressive filter and is thus expected to generate a large number of false detections (*false alarms*); 2. Feature extraction : on each of the regions of interest selected by the FOA component the FE component transforms the data from the high-dimensional pixel space to a lower dimensional feature space where recognition can be performed more effectively; and 3. Classification learning: discriminates between false alarms and true volcanoes using a classification learning algorithm. See [8,9] for more details.

The system functions in two modes: the *training* and the *detection* modes. In the training mode, a scientist brings up some images and labels regions in the image containing objects of interest. The system then constructs the FOA method, defines the features to map FOA detected objects from pixel space to a low-dimensional feature space, and finally learns a classifier whose goal is to separate false alarms from true detections in the feature space. In detection mode the system simply applies the learned components to extract volcanoes out of new image pixels. Note that learning happens off-line. The FOA algorithm used constructs a matched filter by taking a normalized average of kxk pixel widows centered on the training data (k=15, after spoiling the local 30x30 region by 2). For extracting features, we use a general method inspired from data compression. The training data pixel vectors are aligned in a matrix, and using singular value decomposition the eigenvectors (principal components) and eigenvalues of the data are derived. Typically we project the FOA regions down to a 6 or 10 dimensional feature space representing the projection along the most dominant eigenvectors. The classification component uses a multi-dimensional Gaussian fit to each of the two classes of examples (volcanoes and false alarms) to be used in the future to predict the probability that a given future feature vector belongs to each of the two classes.

CURRENT STATUS AND RESULTS. In order to evaluate the performance of JARtool in detecting volcanoes, we compare its performance to individual scientists. The reference (or ground truth) will be a consensus labeling where two geologists (authors JCA and LSC) argue the merits of each volcano label. Training sets using F1-MIDR images (at the 75m/pixel resolution) were constructed. Figure 1 shows a sample labeled image: circle diameters indicate extent while numbers indicate categories. Category 1 represents objects that are estimated to be volcanoes with better than 95% confidence, higher number categories represent decreasing levels of confidence: 85% or better for category 2, 75% for category 3. Category 4 objects only have pits visible hence are estimated at 50% confidence. An individual scientist labeling the image will have a percentage false alarm rate and a percentage detection rate relative to total number of true volcanoes in the test set. JARtool's FOA component, typically detects more than 80% of all the volcanoes (all category 1 and 2 volcanoes are detected), while generating 5-6 times

as many false alarms. Based on the eigenvector derived features, the Gaussian classifier gives a locus in the ROC (receiver operating characteristics) curve where each point represents JARtool's performance at a given probability threshold. At one extreme, the threshold requires a detection to have probability 1.0 before it is called a volcano, as this threshold is lowered we generate the locus up to the point where all detections are classified as volcanoes (probab. threshold = 0.0). Figure 2 shows an ROC curve of JARtool's performance vs. consensus labeling. This figure shows that we are relatively close to the performance of a trained analyst, although we fall short of it at the operating point (when all categories of volcanoes are considered, i.e. in the least conservative mode). Similar accuracy results are reported in [10]. The results are reported on an initial set of 4 images, with three used to train and the fourth used to test. The results represent an average over all 3-1 train-test pairs. Note that these results are preliminary and do not accurately reflect performance on the entire planet. There are many issues of invariances, normalization, great variation in the training and test patterns that need to be properly addressed before a feasible system for volcano location exists. However, it is also noteworthy that the entire approach reported here is general and is not dependent on special knowledge of the problem. This effort is part of our long-term goal of developing trainable tools for automated science data analysis [11].

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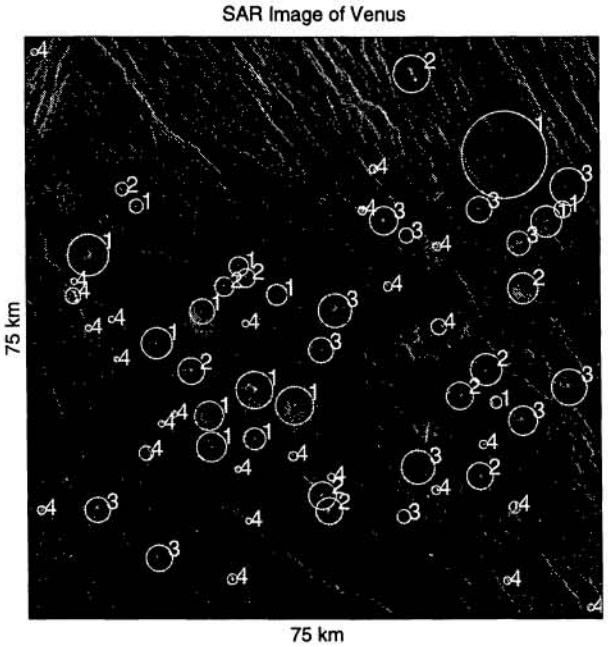

Figure 1: Magellan image with consensus labeling showing location, size, and category od volcanoes.

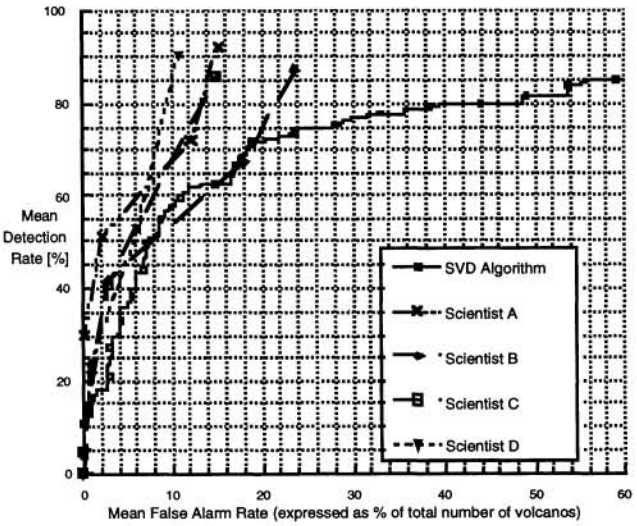

Figure 2: Performance of JARtool compared to individual scientists (relative to consensus).