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MULTIRESOLUTION PATTERN RECOGNITION OF SMALL VOLCANOS IN MAGELLAN DATA. P. Smyth[1], C. H. Anderson[1], J. C. Aubele[2], and L. S. Crumpler[2], [1]Jet Propulsion Laboratory 238-420, California Institute of Technology, 4800 Oak Grove Drive, Pasadena CA 91109, USA, [2]Department of Geological Sciences, Brown University, Providence RI 02912, USA.

Introduction: The Magellan data is a treasure-trove for scientific analysis of venusian geology, providing far more detail than was previously available from Pioneer Venus, Venera 15/16, or ground-based radar observations [1]. However, at this point, planetary scientists are being overwhelmed by the sheer quantities of data collected—data analysis technology has not kept pace with our ability to collect and store it. In particular, "small-shield" volcanos (less than 20 km in diameter) are the most abundant visible geologic feature on the planet [2].

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 volcanos visible in the Magellan data [3,4]. Identifying and studying these volcanos is fundamental to a proper understanding of the geologic evolution of Venus. However, locating and parameterizing them in a manual manner is very time-consuming. Hence, we have undertaken the development of techniques to partially automate this task. The goal is not the unrealistic one of total automation, but rather the development of a useful tool to aid the project scientists. The primary constraints for this particular problem are (1) the method must be reasonably robust and (2) the method must be reasonably fast. Unlike most geological features, the small volcanos of Venus can be ascribed to a basic process that produces features with a short list of readily defined characteristics differing significantly from other surface features on Venus [2]. For pattern recognition purposes the relevant criteria include (1) a circular planimetric outline, (2) known diameter frequency distribution from preliminary studies, (3) a limited number of basic morphological shapes, and (4) the common occurrence of a single, circular summit pit at the center of the edifice.

Pattern Recognition of Natural Objects: There has been little prior work on detecting naturally occurring objects in remotely sensed SAR images. Methods such as direct edge detection and Hough transform approaches deal poorly with the variability and speckle noise present in typical SAR imagery [5,6,7]. One approach toward detecting small volcanos is to use a template-matching method whereby a template of the object of interest is compared with the original target image by scanning the template over the entire scene. For an $N \times N$ square image and a $k \times k$ size template this operation takes the order of N^2k^2 operations. If scale-invariance is sought then typically the procedure is repeated using a range of template sizes. Wiles and Forshaw [8] have obtained promising results using this method despite the fact that the Magellan data contains significant speckle noise and ambiguity in terms of the appearance of volcanos in the imagery.

We have pursued an alternative approach motivated by the desire to develop real-time search methods that could be used as an interactive software tool by a planetary scientist. The key concept behind our approach is to carry out the detailed pattern matching at the lowest image resolution possible and to focus attention only on relevant parts of the image. Although our work is focused on developing useful image analysis tools rather than biologically plausible visual models, it is interesting to note that this general approach is consistent with high-level models of primate visual systems [9].

Multiresolution Pattern Recognition: The multiresolution paradigm emphasizes the decomposition of an image into a sequence of spatial band-pass components [10]. In this manner, image analysis can occur across various spatial frequencies while still retaining local spatial structure. The basic process is a series of recursive low-pass Gaussian decompositions of the original image, which in turn produces a bandpass Laplacian pyramid (the difference of Gaussians). From a pattern recognition standpoint the key feature of the method is the ability to analyze the image only at the coarsest scale necessary. For pattern matching the computational savings are significant, order of 4^k by working at the kth level of decomposition [11]. Furthermore, provided sufficient detail is retained for discrimination; by reducing the effective resolution of the image the input dimensionality to the detector also decreases by a factor of 4^k. The lower dimensionality makes it much easier to train an accurate detector. Focus of attention is implemented by simply "binning" the pixel values of the Laplacian components and then thresholding. Figure 1 contains an example of this process (note that a significant number of linear features are automatically omitted by focusing attention at the appropriate scale).

Volcano Discrimination: The focus of attention mechanism typically produces about 100 regions of interest (ROIs) per Laplacian image, roughly half of which contain volcanos and the other half primarily ridge or graben segments. Each ROI is labeled and a standard pattern recognition method (a neural network feed-forward classifier using backpropagation) is trained on samples of 5×5 windows of pixel values surrounding the detected bright spots. In our experiments with Magellan data the multiresolution filtering and focusing typically reduces the number of pixels that must be examined to order of 0.5% of those in the original image with a resultant speed-up in computation at the pattern-matching level. Using separate test and training images, roughly 70% mean ROI classification accuracy was attained (up from 50% by simply guessing).

The concept of having "ground truth" classification labels is actually incorrect since there are a significant proportion of ROIs whose labelings are not certain. Hence, by using subjectively estimated probability vectors of class labels (rather than deterministic class-label vectors of 0s and 1s) the mean ROI classification rate improved to about 82%. This probabilistic training method is consistent in terms of modeling posterior probabilities and, furthermore, will produce better posterior estimates than using "hard-decision" class labels given a finite amount of training data [12]. The mean missed detection and false alarm rates were about equal (roughly 20%)—almost all the incorrect decisions were made on windows where local context was not sufficient for accurate discrimination.

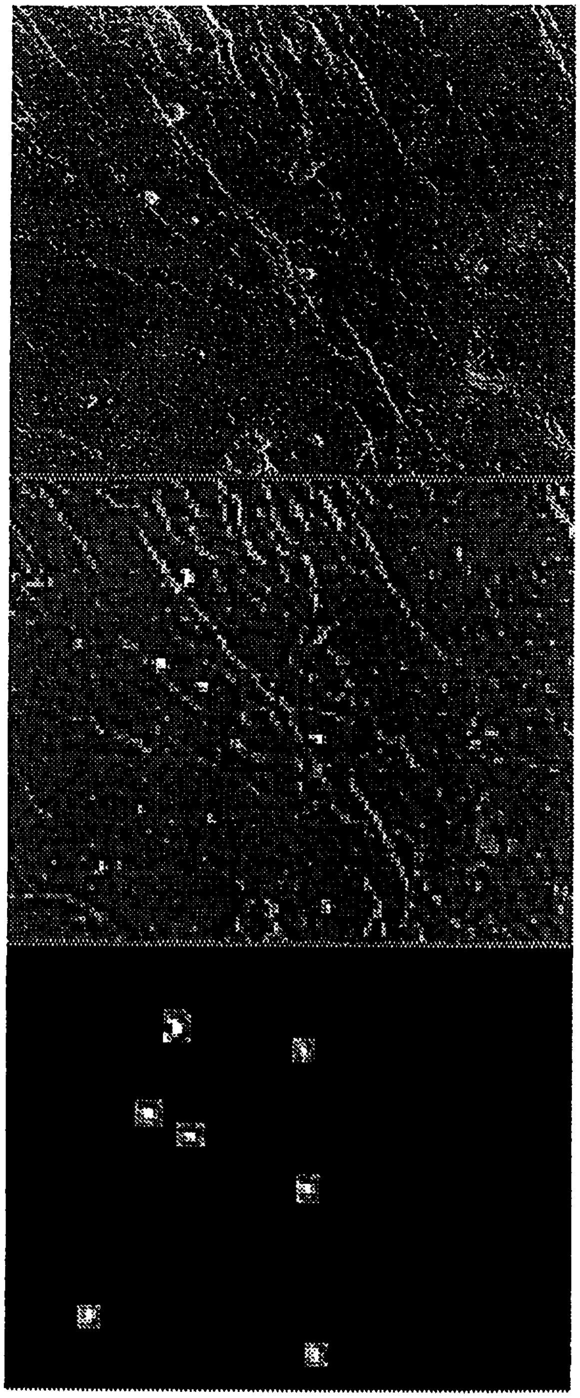

Fig. 1. Original Magellan SAR data (top), bandpass filtered version of same (center), and detected regions of interest (at 1/4 resolution) (bottom).

Ongoing Work: We anticipate that a much higher classification accuracy can be achieved by incorporating prior knowledge about the imaging and geologic processes, i.e., noise properties, surface radar reflectivity, expected volcano diameters, and so forth. By treating the output activations of the network as estimates of posterior class probabilities, both data-driven evidence and prior knowledge can be integrated directly in terms of a coherent probability model such as a Bayesian network, which incorporates appropriate conditional independence assumptions. Note that if the posterior probabilities at a given level are not confident enough (not close to 0 or 1), the Laplacian hierarchy can be descended for a higher-resolution analysis. Another significant issue is the incorporation of global context models (spatial correlation of geologic features) with local evidence. In the context of currently available image analysis algorithms and tools, these issues somewhat push the state-of-the-art.

Conclusions: In terms of pattern recognition, even though 100% accuracy will not be achievable due to the inherent ambiguity in the image data, the general method has significant practical benefit as a basic tool for aiding rapid scientific exploration of the large Magellan database. A short-term scientific benefit will be to answer the basic question regarding the approximate number and distribution of these volcanos on the surface of Venus. Long-term scientific benefits would include subsequent spatial cluster analysis of the volcano locations and the association of the volcanos with local structural patterns. It is reasonable to suggest that the application of pattern recognition techniques will enable basic scientific research that otherwise would not be possible by manual methods.

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MELTING AND DIFFERENTIATION IN VENUS WITH A "COLD" START: A MECHANISM OF THE THIN CRUST FORMATION. Viatcheslav S. Solomatov and David J. Stevenson, Division of Geological and Planetary Sciences, 170–25, California Institute of Technology, Pasadena CA 91125, USA.

Recent works [1–3] argue that the venusian crust is thin: less than 10–30 km. However, any convective model of Venus unavoidably predicts melting and a fast growth of the basaltic crust up to its maximum thickness about 70 km limited by the gabbro-eclogite phase transition [4]. The crust is highly buoyant due to both its composition and temperature and it is problematic to find a mechanism providing its effective recycling and thinning in the absence of plate tectonics. There are different ways to solve this contradiction [5,6]. This study suggests that a thin crust can be produced during the entire evolution of Venus if Venus avoided giant impacts [7].

The absence of giant impacts means that Venus' interiors were more cold and more water-rich than the Earth's after the accretion and core formation. The initial temperature distribution after the core formation is not necessarily convectively unstable: The viscosity is extremely sensitive to the temperature and uncertainties in the initial thermal state easily cover the transition from conductive to convective regimes. Convection and conduction-convection transition are parameterized for the temperature-, pressure- and stress-