the specific information symbols are chosen uniform randomly from the message block. Finally, the selected information symbols are XORed to form the code symbol. The Prioritized LT code construction includes an additional restriction that code symbols formed by a relatively small number of XORed information symbols select some of these information symbols from the pool of high-priority data. Once high-priority data are fully covered, encoding continues with the conventional LT approach where code symbols are generated by selecting information symbols from the entire message block including all different priorities. Therefore, if code symbols derived from high-priority data experience an unusual high number of erasures, Prioritized LT codes can still reliably recover both high- and low-priority data. This hybrid approach decides not only "how to encode" but also "what to encode" to achieve UEP. Another advantage of the priority encoding process is that the majority of high-priority data can be decoded sooner since only a small number of code symbols are required to reconstruct high-priority data. This approach increases the likelihood that high-priority data is decoded first over low-priority data.

The Prioritized LT code scheme achieves an improvement in high-priority data decoding performance as well as overall information recovery without penalizing the decoding of low-priority data, assuming high-priority data is no more than half of a message block. The cost is in the additional complexity required in the encoder. If extra computation resource is available at the transmitter, image, voice, and video transmission quality in terrestrial and space communications can benefit from accurate use of redundancy in protecting data with varying priorities.

This work was done by Simon S. Woo and Michael K. Cheng of Caltech for NASA's Jet Propulsion Laboratory. For more information, contact iaoffice@jpl.nasa.gov. NPO-46653

Fast Image Texture Classification Using Decision Trees

The algorithms used can be applied to robotics, image retrieval for Web searching, and computer vision for electronic devices.

NASA's Jet Propulsion Laboratory, Pasadena, California

Texture analysis would permit improved autonomous, onboard science data interpretation for adaptive navigation, sampling, and downlink decisions. These analyses would assist with terrain analysis and instrument placement in both macroscopic and microscopic image data products. Unfortunately, most state-of-the-art texture analysis demands computationally expensive convolutions of filters involving many floating-point operations. This makes them infeasible for radiation-hardened computers and spaceflight hardware.

A new method approximates traditional texture classification of each image pixel with a fast decision-tree classifier. The classifier uses image features derived from simple filtering operations involving integer arithmetic. The texture analysis method is therefore amenable to implementation on FPGA (field-programmable gate array) hardware.

Image features based on the "integral image" transform produce descriptive and efficient texture descriptors. Training the decision tree on a set of training data yields a classification scheme that produces reasonable approximations of optimal "texton" analysis at a fraction of the computational cost. A decision-tree learning algorithm employing the traditional k-means criterion of inter-cluster variance is used to learn tree structure from training data. The result is an efficient and accurate summary of surface morphology in images.

This work is an evolutionary advance that unites several previous algorithms (k-means clustering, integral images, decision trees) and applies them to a new problem domain (morphology analysis for autonomous science during remote exploration). Advantages include order-of-magnitude improvements in runtime, feasibility for FPGA hardware, and significant improvements in texture classification accuracy.

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Constraint Embedding Technique for Multibody System Dynamics

This approach is applicable to multibody dynamics modeling of vehicles and robots.

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Multibody dynamics play a critical role in simulation testbeds for space missions. There has been a considerable interest in the development of efficient computational algorithms for solving the dynamics of multibody systems. Mass matrix factorization and inversion techniques and the $O(N)$ class of forward dynamics algorithms developed using a spatial operator algebra stand out as important breakthrough on this front. Techniques such as these provide the efficient algorithms and methods for the application and implementation of such multibody dynamics models. However, these methods are limited only to tree-topology multibody systems.

Closed-chain topology systems require different techniques that are not as efficient or as broad as those for tree-topolgy systems. The closed-chain forward dynamics approach consists of treating the closed-chain topology as a tree-topology system subject to additional closure constraints. The resulting forward dynamics solution consists of: (a) ignoring the closure constraints and using the $O(N)$ algorithm to solve for the "free" unconstrained accelerations for the system; (b) using the tree-topology solution to compute a correction