performance of the communication system as quantified in the word-error rate and the undetected-error rate as functions of the SNRs and the total latency of the interleaver and inner code. The method is embodied in equations that describe bounds on these functions. Throughout the derivation of the equations that embody the method, it is assumed that the decoder for the outer code corrects any error pattern of t or fewer errors, detects any error pattern of s or fewer errors, may detect some error patterns of more than s errors, and does not correct any patterns of more than t errors. Because a mathematically complete description of the equations that embody the method and of the derivation of the equations would greatly exceed the space available for this article, it must suffice to summarize by reporting that the derivation includes consideration of several complex issues, including relationships between latency and memory requirements for block and convolutional codes, burst error statistics, enumeration of error-event intersections, and effects of different interleaving depths.

In a demonstration, the method was used to calculate bounds on the performances of several communication systems, each based on serial concatenation of a (63,56) expurgated Hamming code with a convolutional inner code through a convolutional interleaver. The bounds calculated by use of the method were compared with results of numerical simulations of performances of the systems to show the regions where the bounds are tight (see figure).

This work was done by Bruce Moision and Samuel Dolinar of Caltech for NASA's Jet Propulsion Laboratory. Further information is contained in a TSP (see page 1). NPO-44652

Parameterizing Coefficients of a POD-Based Dynamical System

This parameterization enables accurate prediction of temporal evolution of certain flow dynamics.

Goddard Space Flight Center, Greenbelt, Maryland

A method of parameterizing the coefficients of a dynamical system based of a proper orthogonal decomposition (POD) representing the flow dynamics of a viscous fluid has been introduced. (A brief description of POD is presented in the immediately preceding article.) The present parameterization method is intended to enable construction of the dynamical system to accurately represent the temporal evolution of the flow dynamics over a range of Reynolds numbers.

The need for this or a similar method arises as follows: A procedure that includes direct numerical simulation followed by POD, followed by Galerkin projection to a dynamical system has been proven to enable representation of flow dynamics by a low-dimensional model at the Reynolds number of the simulation. However, a more difficult task is to obtain models that are valid over a range of Reynolds numbers. Extrapolation of low-dimensional models by use of straightforward Reynolds-number-based parameter continuation has proven to be inadequate for successful prediction of flows.

A key part of the problem of constructing a dynamical system to accurately represent the temporal evolution of the flow dynamics over a range of Reynolds numbers is the problem of understanding and providing for the variation of the coefficients of the dynamical system with the Reynolds number. Prior methods do not enable capture of temporal dynamics over ranges of Reynolds numbers in low-dimensional models, and are not even satisfactory when large numbers of modes are used.

The basic idea of the present method is to solve the problem through a suitable parameterization of the coefficients of the dynamical system. The parameterization computations involve utilization of the transfer of kinetic energy between modes as a function of Reynolds number. The thus-parameterized dynamical system accurately predicts the flow dynamics and is applicable to a range of flow problems in the dynamical regime around the Hopf bifurcation. Parameter-continuation software can be used on the parameterized dynamical system to derive a bifurcation diagram that accurately predicts the temporal flow behavior.

This work was done by Virginia L. Kalb of Goddard Space Flight Center. For further information, contact the Goddard Innovative Partnerships Office at (301) 286-5810. GSC-15131-1

Confidence-Based Feature Acquisition

Selective acquisition of data values enables higher classification performance at lower cost.

NASA's Jet Propulsion Laboratory, Pasadena, California

Confidence-based Feature Acquisition (CFA) is a novel, supervised learning method for acquiring missing feature values when there is missing data at both training (learning) and test (deployment) time. To train a machine learning classifier, data is encoded with a series of input features describing each item. In some applications, the training data may have missing values for some of the features, which can be acquired at a given cost. A relevant JPL example is that of the Mars rover exploration in which the features are obtained from a variety of different instruments, with different power consumption and integration time costs. The challenge is to decide which features will lead to increased classification performance and are therefore worth acquiring (paying the cost).

To solve this problem, CFA, which is made up of two algorithms (CFA-train and CFA-predict), has been designed to greedily minimize total acquisition cost (during training and testing) while aiming for a specific accuracy level (specified as a confidence threshold). With this method, it is assumed that there is a non-empty subset of features that are "free;" that is, every instance in the data set includes these features initially for zero cost. It is also assumed that the feature acquisition (FA) cost associated with each feature is known in advance, and that the FA cost for a given feature is the same for all instances. Finally, CFA requires that the base-level classifiers produce not only a classification, but also a confidence (or posterior probability).

CFA trains an ensemble of classifiers $M_0 \ldots M_f$ that use successively larger subsets of the features to classify instances. M_0 uses only the "free" (zero cost) features, and M_1 additionally incorporates costly features F_1 through F_i. CFA reduces FA cost in that model M_i is trained only on instances that cannot be classified with sufficient confidence by model M_{i-1}. Therefore, values for feature F_i are acquired only for the instances that require it. At test time, each test instance is successively classified by M_0, M_1, $M_2 \ldots$ until its classification is sufficiently confident (i.e., until the confidence of the prediction reaches the confidence threshold). Again, features are acquired for the new instance only as required. In an empirical comparison with an existing method (Cost-Sensitive Naive Bayes) that makes acquisition decisions only during test time (and therefore requires that all training items be fully acquired), CFA achieves the same (or higher) level of performance at a much reduced cost (by at least an order of magnitude).

This work was done by Kiri L. Wagstaff of Caltech and Marie desJardins and James MacGlashan of the University of Maryland for NASA's Jet Propulsion Laboratory. For more information, contact iaoffice@jpl.nasa.gov. NPO-46886

Algorithm for Lossless Compression of Calibrated Hyperspectral Imagery

NASA's Jet Propulsion Laboratory, Pasadena, California

A two-stage predictive method was developed for lossless compression of calibrated hyperspectral imagery. The first prediction stage uses a conventional linear predictor intended to exploit spatial and/or spectral dependencies in the data. The compressor tabulates counts of the past values of the difference between this initial prediction and the actual sample value. To form the ultimate predicted value, in the second stage, these counts are combined with an adaptively updated weight function intended to capture information about data regularities introduced by the calibration process. Finally, prediction residuals are losslessly encoded using adaptive arithmetic coding.

Algorithms of this type are commonly tested on a readily available collection of images from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) hyperspectral imager. On the standard calibrated AVIRIS hyperspectral images that are most widely used for compression benchmarking, the new compressor provides more than 0.5 bits/sample improvement over the previous best compression results.

The algorithm has been implemented in Mathematica. The compression algorithm was demonstrated as beneficial on 12-bit calibrated AVIRIS images.

This work was done by Aaron B. Kiely and Matthew A. Klimesh of Caltech for NASA's Jet Propulsion Laboratory. For more information, contact iaoffice@jpl.nasa.gov. NPO-46547

Universal Decoder for PPM of any Order

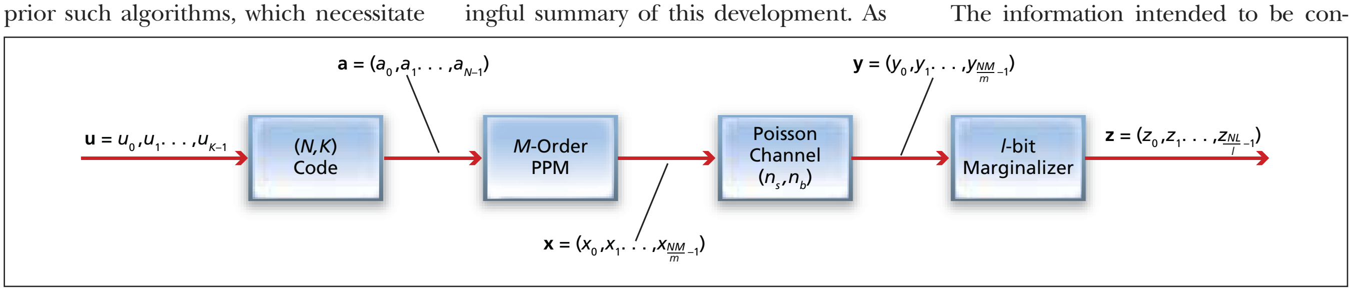
Complexity can be reduced and flexibility increased, at small cost in performance.

NASA's Jet Propulsion Laboratory, Pasadena, California

A recently developed algorithm for demodulation and decoding of a pulse-position-modulation (PPM) signal is suitable as a basis for designing a single hardware decoding apparatus to be capable of handling any PPM order. Hence, this algorithm offers advantages of greater flexibility and lower cost, in comparison with prior such algorithms, which necessitate the use of a distinct hardware implementation for each PPM order. In addition, in comparison with the prior algorithms, the present algorithm entails less complexity in decoding at large orders.

An unavoidably lengthy presentation of background information, including definitions of terms, is prerequisite to a meaningful summary of this development. As an aid to understanding, the figure illustrates the relevant processes of coding, modulation, propagation, demodulation, and decoding. An M-ary PPM signal has M time slots per symbol period. A pulse (signifying 1) is transmitted during one of the time slots; no pulse (signifying 0) is transmitted during the other time slots.

The information intended to be con-



Processing of Information in an M-ary PPM communication system includes the sequence of steps depicted here. The l-bit marginalizer is a feature of the innovation reported here; the other features are typical of PPM systems in general.