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.

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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 nonempty subset of features that are "free;" that is, every instance in the data set in-