

mate reference sets of weight coefficients for weighted sums of the SAMP features that correspond to known words and/or phrases.

Once training has been done, a SAMP that includes an unknown word is sampled and processed by the SPT, the SPT outputs are used to construct a matrix, the matrix is decomposed into cells, and

neural-network analysis is performed, all in the same manner as that of training. The weight coefficients computed during training are used to determine whether there is a sufficiently close match between an unknown word in the SAMP and a known word in the training database. If such a match is found, the word is deemed to be recognized.

This work was done by C. C. Jorgensen and D. D. Lee of Ames Research Center. Further information is contained in a TSP (see page 1).

This invention is owned by NASA and a patent application has been filed. Inquiries concerning rights for the commercial use of this invention should be addressed to the Ames Technology Partnerships Division at (650) 604-2954. Refer to ARC-15040-1.

➤ Physical Principle for Generation of Randomness

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A physical principle (more precisely, a principle that incorporates mathematical models used in physics) has been conceived as the basis of a method of generating randomness in Monte Carlo simulations. The principle eliminates the need for conventional random-number generators.

The Monte Carlo simulation method is among the most powerful computational methods for solving high-dimensional problems in physics, chemistry, economics, and information processing. The Monte Carlo simulation method is especially effective for solv-

ing problems in which computational complexity increases exponentially with dimensionality. The main advantage of the Monte Carlo simulation method over other methods is that the demand on computational resources becomes independent of dimensionality. As augmented by the present principle, the Monte Carlo simulation method becomes an even more powerful computational method that is especially useful for solving problems associated with dynamics of fluids, planning, scheduling, and combinatorial optimization.

The present principle is based on coupling of dynamical equations with the corresponding Liouville equation. The randomness is generated by non-Lipschitz instability of dynamics triggered and controlled by feedback from the Liouville equation. (In non-Lipschitz dynamics, the derivatives of solutions of the dynamical equations are not required to be bounded.)

This work was done by Michail Zak of Caltech for NASA's Jet Propulsion Laboratory. For further information, contact iaoffice@jpl.nasa.gov. NPO-43822

➤ DSN Beowulf Cluster-Based VLBI Correlator

Software architecture is scalable to meet faster processing needs for future data processing.

NASA's Jet Propulsion Laboratory, Pasadena, California

The NASA Deep Space Network (DSN) requires a broadband VLBI (very long baseline interferometry) correlator to process data routinely taken as part of the VLBI source Catalogue Maintenance and Enhancement task (CAT M&E) and the Time and Earth Motion Precision Observations task (TEMPO). The data provided by these measurements are a crucial ingredient in the formation of precision deep-space navigation models. In addition, a VLBI correlator is needed to provide support for other VLBI related activities for both internal and external customers.

The JPL VLBI Correlator (JVC) was designed, developed, and delivered to the DSN as a successor to the legacy Block II Correlator. The JVC is a full-capability VLBI correlator that uses software processes running on multiple computers to cross-correlate two-antenna broadband noise data. Components of this new system (see Figure 1)

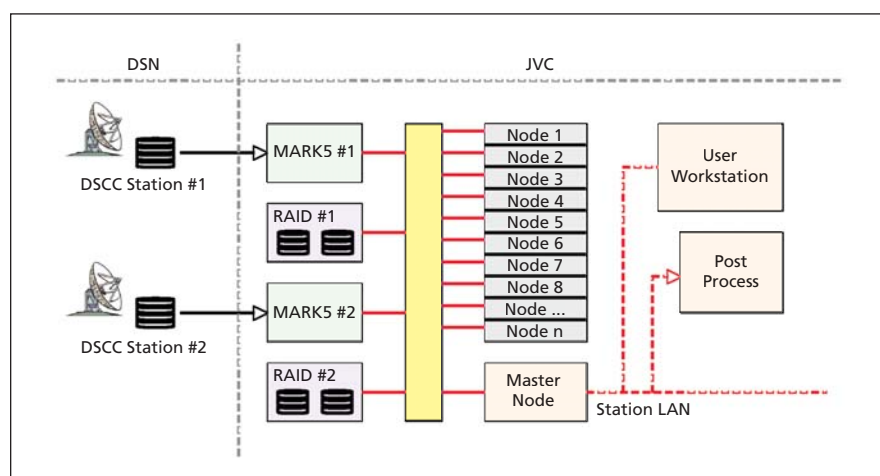


Figure 1. Components of the New Correlator are shown in this simplified block diagram.

consist of Linux PCs integrated into a Beowulf Cluster, an existing Mark5 data storage system, a RAID array, an existing software correlator package (SoftC) originally developed for Delta DOR

Navigation processing, and various custom-developed software processes and scripts.

Parallel processing on the JVC is achieved by assigning slave nodes of the

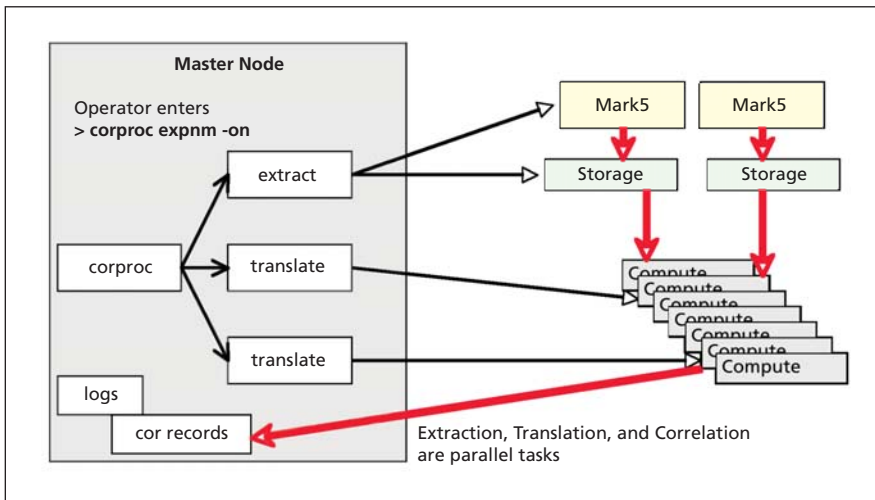


Figure 2. **Extraction, Translation, and Correlation** are run as parallel tasks.

Beowulf cluster to process separate scans in parallel until all scans have been processed. Due to the single-stream sequential playback of the Mark5 data, some ramp-up time is required before all nodes can have access to required scan data. Core functions of each processing step are accomplished using optimized C programs. The coordination and execution of these programs across the cluster is accomplished using Pearl scripts, PostgreSQL

commands, and a handful of miscellaneous system utilities.

Mark5 data modules are loaded on Mark5 Data systems playback units, one per station. Data processing is started when the operator scans the Mark5 systems and runs a script that reads various configuration files and then creates an experiment-dependent status database used to delegate parallel tasks between nodes and storage areas (see Figure 2). This script forks into three

processes: extract, translate, and correlate. Each of these processes iterates on available scan data and updates the status database as the work for each scan is completed.

The extract process coordinates and monitors the transfer of data from each of the Mark5s to the Beowulf RAID storage systems. The translate process monitors and executes the data conversion processes on available scan files, and writes the translated files to the slave nodes. The correlate process monitors the execution of SoftC correlation processes on the slave nodes for scans that have completed translation.

A comparison of the JVC and the legacy Block II correlator outputs reveals they are well within a formal error, and that the data are comparable with respect to their use in flight navigation. The processing speed of the JVC is improved over the Block II correlator by a factor of 4, largely due to the elimination of the reel-to-reel tape drives used in the Block II correlator.

This work was done by Stephen P. Rogstad, Andre P. Jongeling, Susan G. Finley, Leslie A. White, Gabor E. Lanyi, John E. Clark, and Charles E. Goodhart of Caltech for NASA's Jet Propulsion Laboratory. For more information, contact iaoffice@jpl.nasa.gov. NPO-46279

Hybrid NN/SVM Computational System for Optimizing Designs

The NN and the SVM help each other “learn” in an iterative process.

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A computational method and system based on a hybrid of an artificial neural network (NN) and a support vector machine (SVM) (see figure) has been conceived as a means of maximizing or minimizing an objective function, optionally subject to one or more constraints. Such maximization or minimization could be performed, for example, to optimize solve a data-regression or data-classification problem or to optimize a design associated with a response function. A response function can be considered as a subset of a response surface, which is a surface in a vector space of design and performance parameters. A typical example of a design problem that the method and system can be used to solve is that of an airfoil, for which a response function could be the spatial distribution of pressure over the airfoil. In this example, the response surface would describe the pressure distribu-

tion as a function of the operating conditions and the geometric parameters of the airfoil.

The use of NNs to analyze physical objects in order to optimize their responses under specified physical conditions is well known. NN analysis is suitable for multidimensional interpolation of data that lack structure and enables the representation and optimization of a succession of numerical solutions of increasing complexity or increasing fidelity to the real world. NN analysis is especially useful in helping to satisfy multiple design objectives. Feedforward NNs can be used to make estimates based on nonlinear mathematical models. One difficulty associated with use of a feedforward NN arises from the need for nonlinear optimization to determine connection weights among input, intermediate, and output variables. It can be very expensive to train an NN in

cases in which it is necessary to model large amounts of information.

Less widely known (in comparison with NNs) are support vector machines (SVMs), which were originally applied in statistical learning theory. In terms that are necessarily oversimplified to fit the scope of this article, an SVM can be characterized as an algorithm that (1) effects a nonlinear mapping of input vectors into a higher-dimensional feature space and (2) involves a dual formulation of governing equations and constraints. One advantageous feature of the SVM approach is that an objective function (which one seeks to minimize to obtain coefficients that define an SVM mathematical model) is convex, so that unlike in the cases of many NN models, any local minimum of an SVM model is also a global minimum.

In the SVM approach as practiced heretofore, underlying feature-space co-