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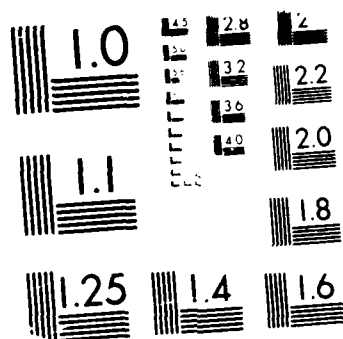
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Signal processing computational needs

Jeffrey M. Speiser
Naval Ocean Systems Center
San Diego, CA 92152

Abstract

Previous reviews of signal processing computational needs and their systolic implementation have emphasized the need for a small set of matrix operations, primarily matrix multiplication, orthogonal triangularization, triangular backsolve, singular value decomposition, and the generalized singular value decomposition. Algorithms and architectures for these tasks are sufficiently well understood to begin transitioning from research to exploratory development. Substantial progress has also been reported on parallel algorithms for updating symmetric eigensystems and the singular value decomposition. Another problem which has proved to be easier than expected is inner product computation for high-speed high resolution predictive analog-to-digital conversion. Although inner product computation in a general setting will require $O(\log n)$ time via a tree, the special structure of the prediction problem permits the use of a systolic transversal filter, producing a new predicted value in time $O(1)$.

Problem areas which are still in an early stage of study include parallel algorithms for the Wigner-Ville Distribution function, L_1 norm approximation, inequality constrained least squares, and the total least squares problem.

Introduction

Representative areas of modern signal processing which have substantial computational requirements for real-time implementation include beamforming, direction finding, spectrum analysis, and image processing. An important area which has received less attention is intelligent analog-to-digital conversion.

Beamforming and direction finding

Classical frequency-domain beamforming is the spatial equivalent of a matched filter. To form a beam in one direction at one frequency, it is necessary to form the inner product of the vector of complex amplitudes at the sensor array elements with a steering vector for the specified look direction.¹ If the processing bandwidth is small compared to the center frequency, then the number of operations (complex multiply-adds) required per second to realize the beamforming by matrix-vector multiplication will be $B \cdot W \cdot E$, where B is the number of beams (more generally the number of cells in direction/focus depth), W is the bandwidth in Hertz, and E is the number of elements in the array. For a limited number of special array geometries and corresponding special choices of look directions, it is possible to reduce the number of operations by using spatial convolutions or discrete Fourier transforms (DFTs) realized via the Fast Fourier Transform (FFT).¹ However, general matrix multiplication will be needed for randomly time-varying array geometries as well as for arrays subject to flexure or required to conform to special surface shapes.

Several interference cancellation techniques require the solution of linear least squares problems: An adaptive combiner using pre-formed beams requires the solution of an unconstrained linear least squares problem. Minimum variance distortionless response (MVDR) beamforming requires the solution of a least squares problem with one linear constraint.^{2,3} More recent versions use multiple linear constraints to avoid the formation of deep nulls in directions too close to the look directions.^{4,5} Although least squares adaptive beamformers have frequently been implemented using gradient descent and similar iterative methods, such methods can suffer from slow convergence when the interference is strong compared to the signal and noise, and the data covariance matrix therefore has a large condition number. Since the cost of computation is continually decreasing relative to the cost of aperture in space or time, it is desirable to avoid statistical iteration, and rather to provide at each time the best least squares solution possible with the available data. Although the signal processing textbooks describe such a solution in terms of direct inversion of the sample covariance matrix,² it is numerically far preferable to solve the least squares problem directly with the data matrix, using either the singular value decomposition (SVD) or orthogonal triangularization techniques such as Givens rotations, Householder reflections, or the modified Gram-Schmidt method.⁶ Some authors have proposed parallel architectures based on hyperbolic rotations or a hyperbolic version of the Householder transformation. Such transformations are not unitary, and are not guaranteed to have the good numerical stability of true unitary transformations. For MVDR implemented via orthogonal-triangularization, with a number of look directions greater than the number of elements in the array, and with the adaptive weights updated for each data sample, the number of arithmetic operations required per second will be approximately $B \cdot W \cdot E \cdot E$, or larger than the requirement for classical beamforming by about a factor of E , the number of elements in the array.

While adaptive interference cancellation techniques incorporate a-priori information in the form of the assumption of point sources of interference, eigenvector and eigenvalue-eigenvector based direction finding methods use two covariance matrices: prior knowledge (perhaps in the form of a model) of the noise spatial covariance structure, and measurement of the total signal-plus-noise spatial covariance matrix. A survey of such methods through mid 1985 is available.⁷ Although a quantitative theory of the performance of such methods remains difficult, many stimulation studies and a few experimental ones have shown that when the prior information is correct, eigenvector based direction finding can provide resolution many times finer than the Rayleigh limit. A representative eigenvector based direction method is the MUSIC algorithm of R. Schmidt.⁸⁻¹¹ MUSIC requires the following sequence of calculations: a) Solution of a generalized eigenvalue problem. b) Estimating the number of sources from the multiplicity of the smallest generalized eigenvalue. (With finite sample size, this will actually be a cluster of small generalized eigenvalues). c) Determining the "noise subspace" - computing an orthonormal basis for the generalized eigenvectors corresponding to the smallest (or small) generalized eigenvalues. d) Forming the so-called "direction-of-arrival spectrum," or equivalently searching for look directions whose steering vectors are orthogonal or nearly orthogonal to the noise subspace. e) Estimation of the source covariance matrix to determine source powers and to associate multiple arrivals from a single source.

In order to accurately compute small generalized eigenvalues and corresponding generalized eigenvectors, it is preferable to solve the generalized eigenvalue problem via the generalized singular value decomposition (GSVD) of Van Loan.^{12,13}

For most eigenvector-based direction finding techniques, the most computationally burdensome step will be the computation of the DOA spectrum. Although this requires only matrix-vector multiplications, it requires a very large number of them — unless fast search techniques are developed, it will require one matrix-vector product for each resolvable point in the array manifold. For a two-dimensional antenna array with elements sensing diverse polarizations, the required number of matrix-vector multiplications per frequency bin update is the product of the number of resolvable two-dimensional angles times the number of resolved polarizations. One recent eigenvector based direction finding method, the ESPRIT technique of Paulraj and Kailath,¹⁴ avoids the computationally expensive DOA spectrum calculation, but is only applicable for very special array geometries and noise fields.

Spectrum analysis

Most beamforming/direction finding techniques have direct analogs for the problem of spectrum analysis,¹⁵ due to the similarity of beamforming for a uniformly spaced line array and spectrum analysis for a stationary random sequence. An extensive survey of modern spectrum estimation techniques is available.^{15a} One class of methods that should receive special attention from a computation point of view is the linear predictive techniques.^{16,15} Frequently, these methods are implemented using fast Toeplitz equation solvers, such as the Levinson-Trench method or Durbin's method to solve the prediction problem. Although such methods save arithmetic operations, they can produce poor numerical results when the covariance matrix is ill-conditioned. Such ill conditioning will occur, when there are strong spectral lines — exactly the case where the random process has an all pole spectrum as assumed by linear predictive methods. Improvement of linear predictive methods by using the SVD to solve the prediction equations has been reported.^{17,18}

Dense matrix computation needs for beamforming, direction finding, and spectrum estimation

Beamforming, direction finding, and spectrum analysis lead to requirements for a fairly complete set of linear algebra operations for dense matrices: In principle one needs matrix-vector multiplication, matrix multiplication, linear equation solution, matrix inversion, least squares solution, orthogonal triangularization, solution of Hermitian symmetric eigensystems, singular value decomposition, and the generalized singular value decomposition. The above list can be reduced to a) matrix-vector multiplication, b) orthogonal triangular decomposition, c) the SVD, d) the generalized SVD.

Matrix computations in image processing

The above list of matrix operations also suffices for many types of image processing. The SVD is especially suitable for imagery with unknown or time-variant statistics, since it generates a best reduced rank approximation to a data block, thus constructing a transform basis matched to the current data block.^{18a} An eigenvector based image registration technique has been reported which uses signal subspace methods quite similar to the MUSIC algorithm.¹⁹⁻²¹

Image restoration problems will require a wider range of minimization techniques than unconstrained and linearly constrained least squares solution. Promising methods include least squares (possibly damped or regularized) with nonnegativity or other nonlinear constraints²²⁻²⁵ and L1 norm minimization.²⁶ The use of L1 norm minimization has also been described for deconvolution with improved tolerance of noise bursts²⁷ and for spectrum estimation with improved tolerance of outliers.²⁸

Predictive analog-to-digital conversion

Techniques have been proposed for improving the dynamic range and accuracy of analog to digital converters (A/Ds) by incorporating a linear prediction using coarsely quantized past samples.³⁰ To implement such converters with high sample rates it is necessary to minimize the computational latency in the predictor, since the allowable latency will be less than the sampling interval. Predictors using weights which are independent of the data statistics (other than bandwidth) have been described by Brown³¹ and Splettstosser.^{32,33} Such methods require a digital inner product computation with a fixed weight vector for each new data sample. The multiplications needed for such an isolated inner computation can be performed in parallel, so only one multiplication is needed. However, if the summation is performed by a binary tree of adders, $\log_2(N)$ addition times are required, so a lower latency method for inner product computation or summation would be useful, even at the cost of decreased efficiency. Since the predictor output may be viewed as the result of convolving the previously quantized values with a fixed set of filter coefficients, the latency may be reduced to approximately one multiply/add time by using a systolic convolver. Several suitable designs have been discussed by H.T. Kung.²⁹

Parallel matrix algorithms and architectures: non-iterative

Highly efficient multiplication of matrices may be performed using a rectangular systolic array in the "engagement processor" mode.^{34,35} An engagement processor provided with multiple planes of memory can also efficiently perform the partitioned multiplication of large matrices,^{34,35} or the partitioned inversion of strongly nonsingular matrices. Gentleman and Kung have described an efficient triangular systolic architecture for orthogonal reduction of matrices to triangular form via Givens' rotations and its use for least squares solution when combined with a linear systolic array for triangular backsubstitution.³⁶ This architecture can also efficiently update such a reduction when an additional row is added, or indeed can continuously update with new rows corresponding to new data. Its application to constrained least squares solution for MVDR beamforming has been described,³⁷ including efficient implementation of complex arithmetic and full triangular array emulation by a subarray. A variant of the triangular systolic array has been described which permits direct formation of the MVDR output without requiring a separate backsolve array.^{38,39} However it appears difficult to efficiently apply this array to problems requiring the formation of multiple simultaneous beams. A difficulty with the solution of least squares problems by present systolic arrays for orthogonal triangularization is that they are unable to provide for column pivoting. Therefore, if the data matrix has less than full rank, the triangularized matrix can be singular, and the triangular backsolve will break down. In the case of near rank deficiency, the triangularized matrix will be close to singular, and the backsolve may exhibit poor numerical performance. While more complicated architectures may provide pivoting for matrices of fixed size, many least squares signal processing applications will require continuous updating. Harper Whitehouse has suggested that the triangularized problem be solved via the SVD.⁴⁰ This avoids the need for

pivoting in the orthogonal triangularization, and permits solution of the least squares problem via the pseudoinverse of the triangularized matrix. Regularization may easily be provided. Orthogonal triangularization via the Gentleman-Kung and similar arrays requires the computation of a Givens rotation before the rotation coefficients can be propagated and applied to a pair of rows of the matrix. Application of a rotation to a pair of elements requires only multiplications and additions, but computation of the rotation requires square roots, and can limit the speed of the processor. Several approaches to this problem have been proposed: a) implementing the square root cell using a faster technology than is used for the interior cell, b) use of on-line arithmetic⁴¹ to speed the computation of square roots, c) use of scaled Givens rotations,^{42,43} also known as "fast Givens" or "square root free Givens." The last approach requires special care to select a stable version of the algorithm, to avoid underflow, and also leads to a significantly more complicated control structure for the array.

Parallel matrix algorithms and architectures: iterative

For matrices larger than 4×4 , the computation of eigensystems, the SVD, and their generalization is necessarily iterative. There are three generally applicable classes of numerically stable methods for the dense symmetric eigensystem and the SVD for which parallel implementations have been proposed: a) Jacobi methods,⁴⁴⁻⁴⁹ b) QR methods,⁵⁰⁻⁵⁴ and c) the recently introduced tearing methods.⁵⁵⁻⁵⁶ The Jacobi methods are far superior in terms of simplicity, regularity, and need for only local communication and control. The QR methods (QR or QL eigensystem and Golub-Reinsch SVD) are significantly faster on a uniprocessor, but introduce several new problems: a) The need for a preliminary reduction to tridiagonal form for the eigensystem problem or to bidiagonal form for the SVD, b) greatly increased communication and control complexity, c) the possibility of required decomposition of the problem into subproblems, possibly of different sizes, when implicit shifts are used. The tearing methods are in an early stage of study, but may be the most efficient of all, and may be used in combination with the other two methods.

The difficult problem of systolic computation of the GSVD by a fully numerically stable method has now been solved.⁵⁷

While nearly optimally efficient systolic architectures are known for the dense, non-iterative matrix computations, that stage of development has not yet been reached for the eigensystem problem and the SVD. Other areas of current research include efficient communication between systolic subarrays and higher level language support for parallel processors.

Updating eigensystem solutions and the SVD

In many signal processing applications, data is received essentially continuously, and it is necessary to update previously computed eigensystem decompositions or singular value decompositions. Such problems frequently occur in beamforming, direction finding, and spectrum estimations. Although efficient updating techniques have long been known for orthogonal-triangular factorization, the more difficult problem of updating eigensystems has only recently been addressed.⁵⁸⁻⁵⁹

L1 norm model fitting and deconvolution

Traditionally, model fitting and deconvolution in signal processing has used the L2 norm. However, it has long been known in the statistical literature that L1 regression is far more robust with respect to outliers - bad observations or long-tailed error distributions. For this reason, L1 norm model fitting is beginning to receive attention in the signal processing community for deconvolution and model-fitting methods of spectral analysis.⁶⁰⁻⁶¹ On traditional computers, L1 model fitting has usually been performed via variants of the simplex algorithm. The simplex algorithm requires a great deal of testing, branching, and data movement, and does not seem to be well suited to implementation on systolic arrays. However, L1 norm fitting may also be performed via iteratively reweighted least squares techniques⁶²⁻⁶³ using extensions of current parallel algorithms and architectures for orthogonal triangularization and singular value decomposition.

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