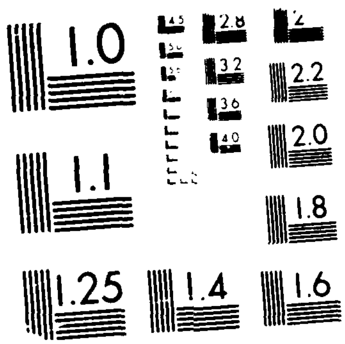
AD-A191 756   SIGNAL PROCESSING COMPUTATIONAL NEEDS(U) NAVAL OCEAN   1/1
SYSTEMS CENTER SAN DIEGO CA   J M SPEISE   NOV 87

UNCLASSIFIED   F/G 12/5   NL



MICROCOPY RESOLUTION TEST CHART

DTIC FILE COPY

AD-A191 756

REPORT DOCUMENTATION PAGE

1a REPORT SECURITY CLASSIFICATION: UNCLASSIFIED	1b RESTRICTIVE MARKINGS
2a SECURITY CLASSIFICATION AUTHORITY	3 DISTRIBUTION / AVAILABILITY OF REPORT: Approved for public release; distribution is unlimited.
2b DECLASSIFICATION / DOWNGRADING SCHEDULE	
4 PERFORMING ORGANIZATION REPORT NUMBER(S)	5 MONITORING ORGANIZATION REPORT NUMBER(S)
6a NAME OF PERFORMING ORGANIZATION: Naval Ocean Systems Center; 6b OFFICE SYMBOL (If applicable): NOSC	7a NAME OF MONITORING ORGANIZATION: Naval Ocean Systems Center
6c ADDRESS (City, State and ZIP Code): San Diego, CA 92152-5000	7b ADDRESS (City, State and ZIP Code): San Diego, CA 92152-5000
8a NAME OF FUNDING / SPONSORING ORGANIZATION: Office of Naval Research; 8b OFFICE SYMBOL (If applicable): ONR	9 PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER
8c ADDRESS (City, State and ZIP Code): 800 North Quincy Street, Arlington, VA 22217	10 SOURCE OF FUNDING NUMBERS

PROGRAM ELEMENT NO	PROJECT NO	TASK NO	AGENCY ACCESSION NO
61153N	EE55	RR01509	DN088 669

11 TITLE (Include Security Classification)

Signal Processing Computational Needs

12 PERSONAL AUTHOR(S)

J.M. Speiser

13a TYPE OF REPORT	13b TIME COVERED	14 DATE OF REPORT (Year, Month, Day)	15 PAGE COUNT
Professional Paper	FROM Aug 1986 TO Aug 1986	November 1987	

16 SUPPLEMENTARY NOTATION

DTIC ELECTE MAR 2 1 1988 S E D

17 COSATI CODES		
FIELD	GROUP	SUB-GROUP

18 SUBJECT TERMS (Continue on reverse if necessary and identify by block number)

covariance matrix
matrix-vector multiplication
Spatial equivalent

19 ABSTRACT (Continue on reverse if necessary and identify by block number)

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 0(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 0(1).

Problem areas which are still in an early stage of study include parallel algorithms for the Wigner-Ville Distribution function, L1 norm approximation, inequality constrained least squares, and the total least squares problem.

20 DISTRIBUTION / AVAILABILITY OF ABSTRACT: ☐ UNCLASSIFIED/UNLIMITED ☒ SAME AS RPT ☐ DTIC USERS	21 ABSTRACT SECURITY CLASSIFICATION: UNCLASSIFIED
22a NAME OF RESPONSIBLE INDIVIDUAL: J. M. Speiser	22b TELEPHONE (Include Area Code): (619)225-2686 — 22c OFFICE SYMBOL: Code 743

DD FORM 1473, 84 JAN — 83 APR EDITION MAY BE USED UNTIL EXHAUSTED. ALL OTHER EDITIONS ARE OBSOLETE

UNCLASSIFIED
SECURITY CLASSIFICATION OF THIS PAGE

DISCLAIMER NOTICE

THIS DOCUMENT IS BEST QUALITY PRACTICABLE. THE COPY FURNISHED TO DTIC CONTAINED A SIGNIFICANT NUMBER OF PAGES WHICH DO NOT REPRODUCE LEGIBLY.

Presented at SPIE conference on Advanced Signal Processing Algorithms and Architectures, San Diego, CA, Aug.19-20, 1986
To appear in Proc. SPIE, Vol.696, paper 696-01

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 0(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 0(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*W*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 preformed 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 appproximately B*W*E*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 constraints[22–25] and L1 norm minimization.[26] The use of L1 norm minimization has also been described for deconvolution with improved tolerance of noise bursts[27] 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 convertors 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 Brown[31] 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 arithmetic[41] 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 X 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 algorithms 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 techniques[62-63] using extensions of current parallel algorithms and architectures for orthogonal triangularization and singular value decomposition.

Acknowledgments

The author is pleased to acknowledge the support of the Office of Naval Research, Mathematical Sciences Division (Dr. Richard Lau) and the NOSC IR program.

References

1. Speiser, J.M., H.J. Whitehouse, and N.J. Berg, "Signal Processing Architectures using Convolutional Technology," in Real-Time Signal Processing, Proc. SPIE Vol. 154, paper 154-10, SPIE International Technical Conference, Aug. 28-29, 1978, San Diego, CA.

2. Monzingo, R.A., and T.W. Miller, "Introduction to Adaptive Arrays," John Wiley & Sons, New York, 1980.

3. Haykin, S. (editor), "Array Signal Processing," Prentice-Hall, 1985, (Individual chapters cover beamforming/direction finding techniques in exploration seismology, sonar, and radar, as well as imaging techniques for radio telescopes and tomography. See chapter by N. Owsley for MVDR beamforming.

4. Steele, A.K., "Comparison of directional and derivative constraints for beamformers subject to multiple linear constraints," IEE Proc., Vol. 130, parts F and H, No. 1, Feb. 1983, pp. 41-45.

5. Er, M.H., and A. Cantoni, "Derivative Constraints for Broad-Band Element Space Array Processors," IEEE Trans. on Acoustics, Speech, and Signal Processing, Vol. ASSP 31, No. 6, Dec. 1983, pp. 1378-1393.

6. Lawson, C.L., and R.J. Hanson, "Solving Least Squares Problems," Prentice-Hall, Inc., Englewood Cliffs, N.J., 1974.

7. Speiser, Jeffrey M., "Progress in Eigenvector Beamforming," in Real-Time Signal Processing VIII, SPIE Proceedings, Vol. 564, paper 564-01, San Diego, CA, Aug. 22-23, 1985.

8. Schmidt, R.O., "Multiple Emitter Location and Signal Parameter Estimation," first published in Proceedings of the RADC Spectrum Estimation Workshop, held in October 1979 at Griffiss Air Force Base, NY. Reprinted in IEEE Trans. on Antennas and Propagation, Vol. AP-34, No. 3, March 1986, pp. 276-280.

9. Schmidt, R.O., and R.E. Franks, "Multiple Source DF Signal Processing: An Experimental System," IEEE Trans. on Antennas and Propagation, Vol. AP-34, No. 3, March 1986, pp. 281-290.

10. Ferrara, E.R., and T.M. Parks, "Direction Finding with an Array of Antennas Having Diverse Polarizations," IEEE Trans. on Antennas and Propagation, Vol. AP-31, No. 2, March 1983.

69 3 01

11. Schmidt, R.O., "A Signal Subspace Approach to Multiple Emitter Location and Spectral Estimation," Ph.D. dissertation, Dept. of Electrical Engineering, Stanford University, Nov. 1981.

12. Golub, G.H., and C.F. Van Loan, "Matrix Computations," The Johns Hopkins University Press, 3rd Printing (with corrections), Baltimore, Maryland, 1985.

13. Speiser, J.M., and C. Van Loan, "Signal Processing Computations using the Generalized Singular Value Decomposition," Real-Time Signal Processing VII, Proc. SPIE, Vol. 485, paper 495-32, pp. 47-55, 1984.

14. Paulraj, A., R. Roy, and T. Kailath, "Estimation of Signal Parameters via Rotational Invariance Techniques – Esprit," IEEE Asilomar Conference Proceedings, Nov. 1985. (A MUSIC-like direction finding technique which avoids the computationally expensive DOA spectrum computation – but is applicable only for special arrays). See also Roy, R., A. Paulraj, and T. Kailath, "Direction-of Arrival Estimation by Subspace Rotation Methods – ESPRIT," in ICASSP 86, Tokyo, Japan, April 7-11, 1986, IEEE Catalog No. 86CH2243-4 Vol. 4, paper 47.2, pp. 2495–2498.

15. Haykin S, (editor), "Nonlinear Methods of Spectral Analysis," Springer-Verlag, 1983.

15a. Kay, S.M., and S.L. Marple, Jr., "Spectrum Analysis – A Modern Perspective," Proc. IEEE, Vol. 69, No. 11, November 1981, pp. 1380–1419.

16. Makhoul, J., "Linear Prediction, A Tutorial Review," Proc. IEEE, Vol. 63, pp. 561–580, April 1975, correction in Proc. IEEE, Vol. 64, p. 285, Feb. 1976.

17. Tufts, D.W., and R. Kumerasan, "Singular Value Decomposition and Improved Spectral Estimation using Linear Prediction," IEEE Trans. on Acoustics, Speech, and Signal Processing, Vol. ASSP-30, pp. 671–675, Aug. 1982.

18. De Groat, R.D., and R.A. Roberts, "Accurate Frequency Estimation with Short Data Records," Conference Record, Eighteenth Asilomar Conference on Circuits, Systems & Computers, held at Pacific Grove, CA, Nov. 5–7, 1984, pp. 158–162, IEEE Catalog No. 85CH2200-4.

18a. Andrews, H.C. and C.L. Patterson, "Singular Value Decompositions and Digital Image Processing," IEEE Trans. on Acoustics, Speech, and Signal Processing, Vol. ASSP-24, No. 1, Feb. 1976, pp. 26–53.

19. Barry, P.E., and M. Klop, "Jitter suppressing: a data processing approach," in Modern Utilization of Infrared Technology VIII, SPIE International Technical Conference, San Diego, CA, Aug. 26–27, 1982, SPIE Proceedings, Vol. 366.

20. Barry, P.E., M. Klop, and J.D. Huisman, "Image Registration: The Undersampled Case," Optical Society of America – Winter Topical Conference on Signal Recovery, Lake Tahoe, CA, Jan. 12–14, 1983.

21. Hulsman, J.D., and P.E. Barry, "An Eigenvectoe Procedure for Eliminating Line-of-Sight Jitter Induced Noise from Staring Mosaic Sensors," Conference Record, 19th Asilomar Conference on Circuits, Systems and Computers, Nov. 1985.

22. Ichioka, Y., and N. Nakajimi, "Iterative image restoration considering visibility," J. Optical Society of Maerica, Vol. 71, No. 8, August 1981, pp. 983–988.

23. Rabbani, M., and B.E.A. Saleh, "Restoration of bilinearly distored images. 3: Constrained least squares method," Applied Optics, Vol. 22, No. 22, 15 Nov. 1983, pp. 3549–3554.

24. Maeda, J., "Image restoration by an iterative damped least-squares method with non-negativity constraint," Applied Optics, Vol. 24, No. 6, 15 March 1985, pp. 751–757.

25. Maeda, J., " Restoration of bandlimited images by an iterative damped least-squares method with adaptive regularization," Applied Optics, Vol. 24, No. 10, 15 May 1985, pp. 1421–1425.

26. Abdelmalek, N.N., and N. Otsu, "Restoration of images with missing high-frequency components by minimizing the L1 norm of the solution vector.

27. Bednar, J., R. Yarlagadda, and T. Watt, "L1 deconvolution and its application to seismic signal processing," Proceedings of ICASSP 85 (IEEE International Conf. on Acoustics, Speech, and Signal Processing) held at Tampa, Florida, March 26–29, 1985, Vol. 1, paper 12.6, pp. 453–460. IEEE Catalog No. 85CH2118-8.

28. Figueras, A.R. and others, L1-norm versus L2-norm minimization in parametric spectrum analysis: a general discussion," paper 9.1, pp. 304–307 in Proceedings of ICASSP 85 (IEEE International Conf. on Acoustics, Speech, and Signal Processing) held at Tampa, Florida, March 26–29, 1985, Vol. 1, IEEE Catalog No. 85CH2118-8.

29. Kung, H.T., "Why Systolic Architectures," IEEE Computer, Jan. 1982, pp. 37–46.

30. McKnight, W.H., J.M. Speiser, and H.J. Whitehouse, to appear

31. Brown, J.L., "Uniform Linear Prediction of Bandlimited Processes from Past Samples," IEEE Trans. of Information Theory, Vol. IT-18, pp. 662–664 (1972).

32. Splettstosser, W., "On the Prediction of Band-Limited Signals from Past Samples," Information Sciences, Vol. 28, pp. 115–130 (1982).

33. Mugler, D.H., and W. Splettstosser, "Difference Methods and Round-off Error Bounds for the Prediction of Bandlimited Functions from Past Samples," Frequenz-Zeitschrift fur Telekommunikation, Band 39, Ausgabe 7-8, Juli/August 1985, pp. 182–187 (paper is in English).

34. Speiser, J.M., and H.J. Whitehouse, "Parallel processing algorithms and architectures for real-time signal processing," in Real-Time Signal Processing IV, Proc. SPIE Vol. 298 (1981), pp. 2–9.

35. Whitehouse, H.J., J.M. Speiser, and K. Bromley, "Signal Processing Applications of Concurrent Array Processor Technology," Chapter 2 of VLSI and Modern Signal Processing, edited by S.Y. Kung, H.J. Whitehouse, and T. Kailath, Prentice-Hall, Inc., Englewood Cliffs, N.J., pp. 25–41.

36. Gentleman, W.M., and H.T. Kung, "Matrix Triangularization by Systolic Arrays," in Real-Time Signal Processing IV, Proc. SPIE, Vol. 298, 1981.

37. Schreiber, R., and P.J. Kuekes, "Systolic Linear Algebra Machines in Digital Signal Processing," Chapter 22 of VLSI and Modern Signal Processing, edited by S.Y. Kung, H.J. Whitehouse, and T. Kailath, Prentice-Hall, Inc., Englewood Cliffs, N.J., pp. 389–405

38. McWhirter, J.G., "Recursive Least Squares Minimization using a Systolic Array," in Real-Time Signal Processing VI, Proc. SPIE Vol. 431, paper 431-15, pp. 105–112, 1983.

39. Ward, C.P., P.J. Hargrave, and J.G. McWhirter, "A Novel Algorithm and Architecture for Adaptive Digital Beamforming," IEEE Trans. on Antennas and Propagation, Vol. AP-34, No. 3, March 1986, pp. 338–346.

40. Whitehouse, H.J., Naval Ocean Systems Center, San Diego, CA 92152, (private communication).

41. Ercegovac, M.D., "On-Line Arithmetic: an Overview," Real-Time Signal Processing VII, Proc. SPIE Vol. 495, paper 495-10, pp. 86–93.

42. Ipsen, I., "A Parallel QR Method Using Fast Givens' Rotations," Research Report RR-299, Dept. of Computer Science, Yale University, Jan. 1984.

69 01

43. Barlow, J.L., and I. Ipsen, "Parallel Scaled Givens Rotations for the Solution of Linear Least Squares Problems," Research Report RR-310, Dept. of Computer Science, Yale University, March 1984.

44. Brent, R.P., and F.T. Luk, "A systolic architecture for the singular value decomposition," Technical Report TR-CS-82-522, Dept. of Computer Science, Cornell University, 1983.

45. Brent, R.P., F.T. Luk, and C.F. Van Loan, "Computation of the singular value decomposition using mesh-connected processors," Technical Report TR-CS-528, Dept. of Computer Science, Cornell University, 1983.

46. Schreiber, R., "On the Systolic Arrays of Brent, Luk, and Van Loan," Real-Time Signal Processing VI, Proc. SPIE, Vol. 431, paper 431-10, pp. 72-76, Aug. 1983.

47. Moreno, J., "Analysis of Alternatives for a Singular Value Decomposition Processor," M.S. Thesis, Dept. of Computer Science, University of California at Los Angeles, 1985, Report CSD-850035.

48. Luk, Franklin T., "A Triangular Processor Array for Computing the Singular Value Decomposition," Report TR 84-625, July 1984, Dept. of Computer Science, Cornell University, Ithaca, NY 14853 to appear in the Journal of "Linear Algebra and its Applications," special issue on parallel computations, 1986.

49. Schimmel, David E., and Franklin T. Luk, "A New Systolic Array for the Singular Value Decomposition," Technical Report EE-CEG-85-7, *School of Electrical Engineering, Cornell University, Ithaca, NY 14853, (to appear in Proc. of Fourth MIT Conf. on* Advanced Research on VLSI).

50. Ipsen, I.C.F., "Singular Value Decomposition with Systolic Arrays," Research Report RR-291, Dept. of Computer Science, Yale University, Nov. 1983.

51. Ipsen, I.C.F., "Singular Value Decomposition with Systolic Arrays," ICASE Contractor Report No. 84-30, July 1984, Institute for Computer Applications in Science and Engineering, NASA Langley Research Center, Contract No. NAS1-17070.

52. Ipsen, I.C.F., "Singular Value Decomposition with Systolic Arrays," Real-Time Signal Processing VII, Proc. SPIE Vol. 495, paper 495-04, pp. 13-21, Aug. 1984.

53. Schreiber, R., "Systolic Arrays for eigenvalue computation," SPIE Technical Symposium East, Proc. SPIE Vol. 341, May 1982.

54. Schreiber, R., "Bidiagonalization and Symmetric Tridiagonalization by Systolic Array," Nov. 1985, Saxpy Computer Corporation, 255 San Geronimo Way, Sunnyvale, CA 94086, research performed at Stanford University, supported under Office of Naval Research Contract N00014-83-K-4311. Submitted to the journal "Linear Algebra and its Applications.

55. Krishnakumar, A.S., and M. Morf, "A Tree Architecture for the symmetric eigenvalue problem," Real-Time Signal Processing VI, Proc. SPIE Vol. 431, paper 431-11, pp. 77-83.

56. Dongarra, J.J., and D.C. Sorensen, "A Fast Algorithm for the Symmetric Engenvalue Problem," (1985 or early 1986), Mathematics and Computer Science Division, Argonne National Laboratory, 9700 Cass Avenue, Argonne, Illinois 60439. (This may be the *first numerically stable method to be faster than the QR eigensystem method, at least for large matrices).*

57. Luk, Franklin T., "A Parallel Method for Computing the Generalized Singular Value Decomposition," Journal of Parallel and Distributed Computing, Vol. 2, pp. 250-260 (1985).

58. De Groat, R.D., and R.A. Roberts, "Highly Parallel Eigenvector Update Methods with Application to Signal Processing," Proc. SPIE Vol. 696, paper 696-09, San Diego, CA, Aug. 1986.

59. Schreiber, R., "Implementation of Adaptive Array Algorithms," IEEE Transactions on Acoustics, Speech, and Signal Processing, Vol. ASSP-34, No. 5, Oct. 1986, pp. 1038-1045 (updating MVDR solution and eigensystems).

60. Schroeder, J., and R. Yarlagadda, "Linear Predictive Spectral Analysis via the Lp Norm," ICASSP 86 Proceedings, paper 5.9, IEEE Order No. CH2243-4/86.

61. Figueras-Vidal, A.R., et al., "L1 Norm versus L2 Norm Minimization in Parametric Spectrum Analysis: A General Discussion," ICASSP 85 Proceedings, paper 9.1, IEEE Order No. CH2118-8/85.

62. Bednar, J.B., R. Yarlagadda, and T. Watt, "L1 Deconvolution and its Applications to Seismic Signal Processing," ICASSP 85 Proceedings, paper 12.6, IEEE Order No. CH2118-8/85.

63. Yarlagadda, R., et al., "Fast Algorithms for Lp Deconvolution," IEEE Trans. on Acoustics, Speech, and Signal Processing," Vol. ASSP-33, No. 1., Feb. 1985.

END
DATE
FILMED
5-88
DTIC