Recursive Principal Components Analysis Using Eigenvector Matrix Perturbation

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1. INTRODUCTION

Principal components analysis is an important and well-studied subject in statistics and signal processing. The literature has an abundance of algorithms for solving this problem, where most of these algorithms could be grouped into one of the following three approaches: adaptation based on Hebbian updates and deflation, optimization of a second-order statistical criterion (like reconstruction error or output variance), and fixed point update rules with deflation. In this paper, we take a completely different approach that avoids deflation and the optimization of a cost function using gradients. The proposed method updates the eigenvector and eigenvalue matrices simultaneously with every new sample such that the estimates approximately track their true values as would be calculated from the current sample estimate of the data covariance matrix. The performance of this algorithm is compared with that of traditional methods like Sanger’s rule and APEX, as well as a structurally similar matrix perturbation-based method.

Principal components analysis is a well-known statistical technique that has been widely applied to solve important signal processing problems like feature extraction, signal estimation, detection, and speech separation [1, 2, 3, 4]. Many analytical techniques exist, which can solve PCA once the entire input data is known [5]. However, most of the analytical methods require extensive matrix operations and hence they are unsuited for real-time applications. Further, in many applications such as direction of arrival (DOA) tracking, adaptive subspace estimation, and so forth, signal statistics change over time rendering the block methods virtually unacceptable. In such cases, fast, adaptive, on-line solutions are desirable. Majority of the existing algorithms for PCA are based on standard gradient procedures [2, 3,6, 7, 8, 9], which are extremely slow converging, and their performance depends heavily on step-sizes used. To alleviate this,
subspace methods have been explored [10, 11, 12]. However, many of these subspace techniques are computationally intensive. The recently proposed fixed-point PCA algorithm [13] showed fast convergence with little or no change in complexity compared with gradient methods. However, this method and most of the existing methods in literature rely on using the standard deflation technique, which brings in sequential convergence of principal components that potentially reduces the overall speed of convergence. We recently explored a simultaneous principal component extraction algorithm called SIPEX [14] which reduced the gradient search only to the space of orthonormal matrices by using Givens rotations. Although SIPEX resulted in fast and simultaneous convergence of all principal components, the algorithm suffered from high computational complexity due to the involved trigonometric function evaluations. A recently proposed alternative approach suggested iterating the eigenvector estimates using a first-order matrix perturbation formalism for the sample covariance estimate with every new sample obtained in real time [15]. However, the performance (speed and accuracy) of this algorithm is hindered by the general Toeplitz structure of the perturbed covariance matrix. In this paper, we will present an algorithm that undertakes a similar perturbation approach, but in contrast, the covariance matrix will be decomposed into its eigenvectors and eigenvalues at all times, which will reduce the perturbation step to be employed on the diagonal eigenvalue matrix. This further restriction of structure, as expected, alleviates the difficulties encountered in the operation of the previous first-order perturbation algorithm, resulting in a fast converging and accurate subspace tracking algorithm.

This paper is organized as follows. First, we present a brief definition of the PCA problem to have a self-contained paper. Second, the proposed recursive PCA (RPCA) algorithm is motivated, derived, and extended to non-stationary and complex-valued signal situations. Next, a set of computer experiments is presented to demonstrate the convergence speed and accuracy characteristics of RPCA. Finally, we conclude the paper with remarks and observations about the algorithm.

2. PROBLEM DEFINITION

PCA is a well-known algorithm and is extensively studied in the literature as we have pointed out in the introduction. However, for the sake of completeness, we will provide a brief definition of the problem in this section. For simplicity, and without loss of generality, we will consider a real-valued zero-mean, n-dimensional random vector \( \mathbf{x} \) and its \( n \) projections \( y_1, \ldots, y_n \), such that \( y_j = w_j^T \mathbf{x} \), where \( w_j \)'s are unit-norm vectors defining the projection dimensions in the \( n \)-dimensional input space.

The first principal component direction is defined as the solution to the following constrained optimization problem, where \( \mathbf{R} \) is the input covariance matrix:

\[
\mathbf{w}_1 = \arg \max_{\mathbf{w}} \mathbf{w}^T \mathbf{R} \mathbf{w} \quad \text{subject to} \quad \mathbf{w}^T \mathbf{w} = 1. \quad (1)
\]

The subsequent principal components are defined by including additional constraints to the problem that enforce the orthogonality of the sought component to the previously discovered ones:

\[
\mathbf{w}_j = \arg \max_{\mathbf{w}} \mathbf{w}^T \mathbf{R} \mathbf{w}, \quad \text{s.t.} \quad \mathbf{w}^T \mathbf{w}_l = 1, \; l < j. \quad (2)
\]

The overall solution to this problem turns out to be the eigenvector matrix of the input covariance \( \mathbf{R} \). In particular, the principal component directions are given by the eigenvectors of \( \mathbf{R} \) arranged according to their corresponding eigenvalues (largest to smallest) [5].

In signal processing applications, the needs are different. The input samples are usually acquired one at a time (i.e., sequentially as opposed to in batches), which necessitates sample-by-sample update rules for the covariance and its eigenvector estimates. In this setting, this analytical solution is of little use, since it is not practical to update the input covariance estimate and solve a full eigendecomposition problem per sample. However, utilizing the recursive structure of the covariance estimate, it is possible to come up with a recursive formula for the eigenvectors of the covariance as well. This will be described in the next section.

3. RECURSIVE PCA DESCRIPTION

Suppose a sequence of \( n \)-dimensional zero-mean wide-sense stationary input vectors \( \mathbf{x}_k \) are arriving, where \( k \) is the sample (time) index. The sample covariance estimate at time \( k \) for the input vector is\(^1\)

\[
\mathbf{R}_k = \frac{1}{k} \sum_{i=1}^{k} \mathbf{x}_i \mathbf{x}_i^T = \frac{(k-1)}{k} \mathbf{R}_{k-1} + \frac{1}{k} \mathbf{x}_k \mathbf{x}_k^T. \quad (3)
\]

Let \( \mathbf{R}_k = \mathbf{Q}_k \mathbf{A}_k \mathbf{Q}_k^T \) and \( \mathbf{R}_{k-1} = \mathbf{Q}_{k-1} \mathbf{A}_{k-1} \mathbf{Q}_{k-1}^T \), where \( \mathbf{Q} \) and \( \mathbf{A} \) denote the orthonormal eigenvector and diagonal eigenvalue matrices, respectively. Also define \( \mathbf{a}_k = \mathbf{Q}_k^T \mathbf{x}_k \). Substituting these definitions in (3), we obtain the following recursive formula for the eigenvectors and eigenvalues:

\[
\mathbf{Q}_k (k \mathbf{A}_k) \mathbf{Q}_k^T = \mathbf{Q}_{k-1} [(k-1) \mathbf{A}_{k-1} + \mathbf{a}_k \mathbf{a}_k^T] \mathbf{Q}_{k-1}^T. \quad (4)
\]

Clearly, if we can determine the eigendecomposition of the matrix \( [(k-1) \mathbf{A}_{k-1} + \mathbf{a}_k \mathbf{a}_k^T] \), which is denoted by \( \mathbf{V}_k \mathbf{D}_k \mathbf{V}_k^T \), where \( \mathbf{V} \) is orthonormal and \( \mathbf{D} \) is diagonal, then (4) becomes

\[
\mathbf{Q}_k (k \mathbf{A}_k) \mathbf{Q}_k^T = \mathbf{Q}_{k-1} \mathbf{V}_k \mathbf{D}_k \mathbf{V}_k^T \mathbf{Q}_{k-1}^T. \quad (5)
\]

\(^1\)In practice, if the samples are not generated by a zero-mean process, a running sample mean estimator could be employed to compensate for this fact. Then this biased estimator can be replaced by the unbiased version and the following derivations can be modified accordingly.
By direct comparison, the recursive update rules for the eigenvectors and the eigenvalues are determined to be

$$Q_k = Q_{k-1} V_k,$$

$$\Lambda_k = \frac{D_k}{k}. \tag{6}$$

In spite of the fact that the matrix \([k-1)\Lambda_{k-1} + a_i a_i^T]\) has a special structure much simpler than that of a general covariance matrix, determining the eigendecomposition \(V_k D_k V_k^T\) analytically is difficult. However, especially if \(k\) is large, the problem can be solved in a simpler way using a matrix perturbation analysis approach. This will be described next.

### 3.1. Perturbation analysis for rank-one update

When \(k\) is large, the matrix \([k-1)\Lambda_{k-1} + a_i a_i^T]\) is strongly diagonally dominant; hence (due to the Gershgorin theorem) its eigenvalues will be close to those of the diagonal portion \((k-1)\Lambda_{k-1}\). In addition, its eigenvectors will also be close to identity (i.e., the eigenvectors of the diagonal portion of the sum).

In summary, the problem reduces to finding the eigen-decomposition of a matrix in the form \((\Lambda + aa^T)\), that is, a rank-one update on a diagonal matrix \(\Lambda\), using the following approximations: \(D = \Lambda + P_\Lambda\) and \(V = I + P_V\), where \(P_\Lambda\) and \(P_V\) are small perturbation matrices. The eigenvalue perturbation matrix \(P_\Lambda\) is naturally diagonal. With these definitions, when \(VDV^T\) is expanded, we get

$$VDV^T = (I + P_V)(\Lambda + P_\Lambda)(I + P_V)^T$$

$$= \Lambda + \Lambda P_V + P_\Lambda + P_\Lambda P_V + P_\Lambda P_V + P_V \Lambda$$

$$+ P_V \Lambda P_V + P_V P_\Lambda P_V + P_\Lambda P_V + P_V P_\Lambda P_V$$

$$= \Lambda + P_\Lambda + DP_V + P_V D$$

$$+ P_V \Lambda P_V + P_V P_\Lambda P_V. \tag{7}$$

Equating (7) to \(\Lambda + aa^T\), and assuming that the terms \(P_V \Lambda P_V^T\) and \(P_V P_\Lambda P_V^T\) are negligible, we get

$$aa^T = P_\Lambda + DP_V + P_V D. \tag{8}$$

The orthonormality of \(V\) brings an additional equation that characterizes \(P_V\). Substituting \(V = I + P_V\) in \(VV^T = I\), and assuming that \(P_V P_V^T \approx 0\), we have \(P_V = -P_V^T\).

Combining the fact that the eigenvector perturbation matrix \(P_V\) is antisymmetric with the fact that \(P_\Lambda\) and \(D\) are diagonal, the solutions for the perturbation matrices are found from (8) as follows: the \(i\)th diagonal entry of \(P_\Lambda\) is \(a_i^2\) and the \((i, j)\)th entry of \(P_V\) is \(a_i a_j/(\lambda_j + a_j^2 - \lambda_i - a_i^2)\) if \(j \neq i\), and 0 if \(j = i\).

### 3.2. The recursive PCA algorithm

The RPCA algorithm is summarized in Algorithm 1. There are a few practical issues regarding the operation of the algorithm, which will be addressed in this subsection.

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**Algorithm 1:** The recursive PCA algorithm outline.

1. Initialize \(Q_0\) and \(\Lambda_0\).
2. At each time instant \(k\) do the following.
   a. Get input sample \(x_k\).
   b. Set memory depth parameter \(\lambda_k\).
   c. Calculate \(a_k = Q_k^T x_k\).
   d. Find perturbations \(P_\Lambda\) and \(P_V\) corresponding to \((1 - \lambda_k)\Lambda_{k-1} + \lambda_k a_i a_i^T\).
   e. Update eigenvector and eigenvalue matrices:
      \(\tilde{Q}_k = Q_{k-1} (I + P_V)\)
      \(\tilde{\Lambda}_k = (1 - \lambda_k)\Lambda_{k-1} + P_\Lambda\).
   f. Normalize the norms of eigenvector estimates by \(Q_k = \tilde{Q}_k T_k\), where \(T_k\) is a diagonal matrix containing the inverses of the norms of each column of \(\tilde{Q}_k\).
   g. Correct eigenvalue estimates by \(\Lambda_k = \tilde{\Lambda}_k T_k^{-2}\), where \(T_k^{-2}\) is a diagonal matrix containing the squared norms of the columns of \(Q_k\).

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**Selecting the memory depth parameter**

In a stationary situation, where we would like to weight each individual sample equally, this parameter must be set to \(\lambda_k = 1/k\). In this case, the recursive update for the covariance matrix is as shown in (3). In a nonstationary environment, a first-order dynamical forgetting strategy could be employed by selecting a fixed decay rate. Setting \(\lambda_k = \lambda\) corresponds to the following recursive covariance update equation:

$$R_k = (1 - \lambda)R_{k-1} + \lambda x_k x_k^T. \tag{9}$$

Typically, in this forgetting scheme, \(\lambda \in (0, 1)\) is selected to be very small. Considering that the average memory depth of this recursion is \(1/\lambda\) samples, the selection of this parameter presents a trade-off between tracking capability and estimation variance.

**Initializing the eigenvectors and the eigenvalues**

The natural way to initialize the eigenvector matrix \(Q_0\) and the eigenvalue matrix \(\Lambda_0\) is to use the first \(N_0\) samples to obtain an unbiased estimate of the covariance matrix and determine its eigendecomposition \((N_0 > n)\). The iterations in step (2) can then be applied to the following samples. This means in step (2) \(k = N_0 + 1, \ldots, N\). In the stationary case \((\lambda_k = 1/k)\), this means in the first few iterations of step (2) the perturbation approximations will be least accurate (compared to the subsequent iterations). This is simply due to \((1 - \lambda_k)\Lambda_{k-1} + \lambda_k a_i a_i^T\) not being strongly diagonally dominant for small values of \(k\). Compensating the errors induced in the estimations at this stage might require a large number of samples later on.

This problem could be avoided if in the iteration stage (step (2)) the index \(k\) could be started from a large initial value. In order to achieve this without introducing any bias...
to the estimates, one needs to use a large number of samples in the initialization (i.e., choose a large \( N_0 \)). In practice, however, this is undesirable. The alternative is to perform the initialization still using a small number of samples (i.e., a small \( N_0 \)), but setting the memory depth parameter to \( \lambda_k = 1/(k + (\tau - 1)N_0) \). This way, when the iterations start at sample \( k = N_0 + 1 \), the algorithm thinks that the initialization is actually performed using \( y = \tau N_0 \) samples. Therefore, from the point of view of the algorithm, the data set looks like

\[
\{x_1, \ldots, x_{N_0}\}, \ldots, \{x_1, \ldots, x_{N_0}\}, \{x_{N_0+1}, \ldots, x_N\}. \tag{10}
\]

The corresponding covariance estimator is then naturally biased. At the end of the iterations, the estimated covariance matrix is

\[
R_{N,\text{biased}} = \frac{N}{N + (\tau - 1)N_0} R_N + \frac{(\tau - 1)N_0}{N + (\tau - 1)N_0} R_{N_0}, \tag{11}
\]

where \( R_M = (1/M) \sum_{i=1}^M x_i x_i^T \). Consequently, we conclude that the bias introduced to the estimation by tricking the algorithm can be asymptotically diminished (as \( N \to \infty \)).

In practice, we actually do not want to solve for an eigen-decomposition problem at all. Therefore, one could simply initialize the estimated eigenvector to identity (\( Q_0 = I \)) and the eigenvalues to the sample variances of each input entry over \( N_0 \) samples (\( \Lambda_0 = \text{diag} R_{N_0} \)). We then start the iterations over the samples \( k = 1, \ldots, N \) and set the memory depth parameter to \( \lambda_k = 1/(k + \gamma) \). Effectively this corresponds to the following biased (but asymptotically unbiased as \( N \to \infty \)) covariance estimate:

\[
R_{N,\text{biased}} = \frac{N}{N + \gamma} R_N + \frac{\gamma}{N + \gamma} \Lambda_0. \tag{12}
\]

This latter initialization strategy is utilized in all the computer experiments that are presented in the following sections.\(^1\)

In the case of a forgetting covariance estimator (i.e., \( \lambda_k = \lambda \)), the initialization bias is not a problem, since its effect will diminish in accordance with the forgetting time constant any way. Therefore, in the nonstationary case, once again, we suggest using the latter initialization strategy: \( Q_0 = I \) and \( \Lambda_0 = \text{diag} R_{N_0} \). In this case, in order to guarantee the accuracy of the first order perturbation approximation, we need to choose the forgetting factor \( \hat{\lambda} \) such that the ratio \( (1 - \lambda)/\hat{\lambda} \) is large. Typically, a forgetting factor \( \lambda < 10^{-2} \) will yield accurate results, although if necessary values up to \( \lambda = 10^{-1} \) could be utilized.

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\(^1\)A further modification that might be installed is to use a time-varying \( \gamma \) value. In the experiments, we used an exponentially decaying profile for \( \gamma, \gamma = \gamma_0 \exp(-k/\tau) \). This forces the covariance estimation bias to diminish even faster.

### 3.3. Extension to complex-valued PCA

The extension of RPCA to complex-valued signals is trivial. Basically, all matrix-transpose operations need to be replaced by Hermitian (conjugate-transpose) operators. Below, we briefly discuss the derivation of the complex-valued RPCA algorithm following the steps of the real-valued version.

The sample covariance estimate for zero-mean complex data is given by

\[
R_k = \frac{1}{k} \sum_{i=1}^k x_i x_i^H = \frac{(k - 1)}{k} R_{k-1} + \frac{1}{k} x_k x_k^H, \tag{13}
\]

where the eigendecomposition is \( R_k = Q_k \Lambda_k Q_k^H \). Note that the eigenvalues are still real-valued in this case, but the eigenvectors are complex vectors. Defining \( \alpha_k = Q_k^H \theta_k \) and following the same steps as in (4) to (8), we determine that \( P_V = -P_V \). Therefore, as opposed to the expressions derived in Section 3.1, here the complex conjugation * and magnitude \( | \cdot | \) operations are utilized. The \( i \)th diagonal entry of \( P_A \) is found to be \( |\alpha_i|^2 \) and the \( (i, j) \)th entry of \( P_V \) is \( \alpha_i \alpha_j^*/(\lambda_j + |\alpha_j|^2 - \lambda_i - |\alpha_i|^2) \) if \( j \neq i \) and 0 if \( j = i \). The algorithm in Algorithm 1 is utilized as it is except for the modifications mentioned in this section.

### 4. NUMERICAL EXPERIMENTS

The PCA problem is extensively studied in the literature and there exist an extensive variety of algorithms to solve this problem. Therefore, an exhaustive comparison of the proposed method with existing algorithms is not practical. Instead, a comparison with a structurally similar algorithm (which is also based on first-order matrix perturbations) will be presented [15]. We will also comment on the performances of traditional benchmark algorithms like Sanger's rule and APEX in similar setups, although no explicit detailed numerical results will be provided.

#### 4.1. Convergence speed analysis

In the first experimental setup, the goal is to investigate the convergence speed and accuracy of the RPCA algorithm. For this, \( n \)-dimensional random vectors are drawn from a normal distribution with an arbitrary covariance matrix. In particular, the theoretical covariance matrix of the data is given by \( AA^T \), where \( A \) is an \( n \times n \) real-valued matrix whose entries are drawn from a zero-mean unit-variance Gaussian distribution. This process results in a wide range of eigen-spreads (as shown in Figure 1), therefore the convergence results shown here encompass such effects.

Specifically, the results of the 3-dimensional case study are presented here, where the data is generated by 3-dimensional normal distributions with randomly selected covariance matrices. A total of 1000 simulations (Monte Carlo runs) are carried out for each of the three target eigenvector estimation accuracies (measured in terms of degrees between the estimated and actual eigenvectors): 10°, 5°, and 2°. The convergence time is measured in terms of the number of iterations.
of iterations it takes the algorithm to converge to the target eigenvector accuracy in all eigenvectors (not just the principal component). The histograms of convergence times (up to 10000 samples) for these three target accuracies are shown in Figure 2, where everything above 10000 is also lumped into the last bin. In these Monte Carlo runs, the initial eigenvector estimates were set to the identity matrix and the randomly selected data covariance matrices were forced to have eigenvectors such that all the initial eigenvector estimation errors were at least 25°. The initial γ value was set to 400 and the decay time constant was selected to be 50 samples. Values in this range were found to work best in terms of final accuracy and convergence speed in extensive Monte Carlo runs.

It is expected that there are some cases, especially those with high eigenspreads, which require a very large number of samples to achieve very accurate eigenvector estimations, especially for the minor components. The number of iterations required for convergence to a certain accuracy level is also expected to increase with the dimensionality of the problem. For example, in the 3-dimensional case, about 2% of the simulations failed to converge within 10° in 10000 on-line iterations, whereas this ratio is about 17% for 5 dimensions. The failure to converge within the given number of iterations is observed for eigenspreads over 5 × 10^6.

In a similar setup, Sanger’s rule achieves a mean convergence speed of 8400 iterations with a standard deviation of 8. The forgetting factor is set to a constant λ = 10^-6. The two parameters of the first-order perturbation method were again set to ε = 10^-3/6.5 and δ = 10^-2, the results of 30 Monte Carlo runs were averaged to obtain Figure 4.

4.3. Direction of arrival estimation

The use of subspace methods for DOA estimation in sensor arrays has been extensively studied (see [14] and the references therein). In Figure 5, a sample run from a computer simulation of DOA according to the experimental setup described in [14] is presented to illustrate the performance of the complex-valued RPCA algorithm. To provide a benchmark (and an upper limit in convergence speed), we also performed this simulation using Matlab’s eig function several times on the sample covariance estimate. The latter typically converged to the final accuracy demonstrated here within 10–20 samples. The RPCA estimates on the other hand take a few hundred samples due to the transient in the y value. The main difference in the application of RPCA is that typical DOA algorithm will convert the complex PCA problem into a structured PCA problem with double the number of dimensions, whereas the RPCA algorithm works directly with the complex-valued input vectors to solve the original complex PCA problem.

4.4. An example with 20 dimensions

The numerical examples considered in the previous examples were 3-dimensional and 12-dimensional (6 dimensions in complex variables). The latter did not require all the eigenvectors to converge since only the 6-dimensional signal subspace was necessary to estimate the source directions; hence the problem was actually easier than 12 dimensions. To demonstrate the applicability to higher-dimensional situations, an example with 20 dimensions is presented here. The PCA algorithms generally cannot cope well with high-dimensional problems because the interplay between two
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Figure 2: The convergence time histograms for RPCA in the 3-dimensional case for three different target accuracy levels: (a) target error $= 10^\circ$, (b) target error $= 5^\circ$, and (c) target error $= 2^\circ$.

Figure 3: The average eigenvector direction estimation errors, defined as the angle between the actual and the estimated eigenvectors, versus iterations are shown for the first-order perturbation method (thin dotted lines) and for RPCA (thick solid lines).

competing structural properties of the eigenspace makes a compromise from one or the other increasingly difficult. Specifically, these two characteristics are the eigenspread (max $\lambda_i$/min $\lambda_i$) and the distribution of ratios of consecutive eigenvalues ($\lambda_n/\lambda_{n-1}, \ldots, \lambda_2/\lambda_1$) when they are ordered from largest to smallest (where $\lambda_n > \cdots > \lambda_1$ are the ordered eigenvalues). Large eigenspreads lead to slow convergence due to the scarcity of samples representing the minor components. In small-dimensional problems, this is typically the dominant issue that controls the convergence speeds of PCA algorithms. On the other hand, as the dimensionality increases, while very large eigenspreads are still undesirable due...
to the same reason, smaller and previously acceptable eigenspread values too become undesirable because consecutive eigenvalues approach each other. This causes the discriminability of the eigenvectors corresponding to these eigenvalues diminish as their ratio approaches unity. Therefore, the trade-off between small and large eigenspreads becomes significantly difficult. Ideally, the ratios between consecutive eigenvalues must be identical for equal discriminability of all subspace components. Variations from this uniformity will result in faster convergence in some eigenvectors, while others will suffer from almost spherical subspaces indiscriminability.

In Figure 6, the convergence of the 20 estimated eigenvectors to their corresponding true values is illustrated in terms of the angle between them (in degrees) versus the number of on-line iterations. The data is generated by a 20-dimensional jointly Gaussian distribution with zero mean, and a covariance matrix with eigenvalues equal to the powers (from 0 to 19) of 1.5 and eigenvectors selected randomly. This result is typical of higher-dimensional cases where major components converge relatively fast and minor components take much longer (in terms of samples and iterations) to reach the same level of accuracy.

5. CONCLUSIONS

In this paper, a novel approximate fixed-point algorithm for subspace tracking is presented. The fast tracking capability is enabled by the recursive nature of the complete eigenvector matrix updates. The proposed algorithm is feasible for real-time implementation since the recursions are based on well-structured matrix multiplications that are the consequences of the rank-one perturbation updates exploited in the derivation of the algorithm. Performance comparisons with traditional algorithms as well as a structurally similar perturbation-based approach demonstrated the advantages of the recursive PCA algorithm in terms of convergence speed and accuracy.

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REFERENCES

[1] R. O. Duda and P. E. Hart, Pattern Classification and Scene Analysis, John Wiley & Sons, New York, NY, USA, 1973.
[2] S. Y. Kung, K. I. Diamantaras, and J. S. Taur, “Adaptive principal component extraction (APEX) and applications,” IEEE Trans. Signal Processing, vol. 42, no. 5, pp. 1202–1217, 1994.
[3] J. Mao and A. K. Jain, “Artificial neural networks for feature extraction and multivariate data projection,” IEEE Transactions on Neural Networks, vol. 6, no. 2, pp. 296–317, 1995.
[4] Y. Cao, S. Sridharan, and A. Moody, “Multichannel speech separation by eigendecomposition and its application to co-talker interference removal,” IEEE Trans. Speech and Audio Processing, vol. 5, no. 3, pp. 209–219, 1997.
[5] G. H. Golub and C. F. Van Loan, Matrix Computations, Johns Hopkins University Press, Baltimore, Md, USA, 1983.
[6] E. Oja, Subspace Methods for Pattern Recognition, John Wiley & Sons, New York, NY, USA, 1983.
[7] T. D. Sanger, “Optimal unsupervised learning in a single-layer linear feedforward neural network,” Neural Networks, vol. 2, no. 6, pp. 459–473, 1989.
[8] J. Rubner and K. Schulten, “Development of feature detectors by self-organization: a network model,” Biological Cybernetics, vol. 62, no. 3, pp. 193–199, 1990.
[9] J. Rubner and P. Tavan, “A self-organizing network for principal-component analysis,” Europhysics Letters, vol. 10, no. 7, pp. 693–698, 1989.
[10] L. Xu, “Least mean square error reconstruction principle for self-organizing neural-nets,” Neural Networks, vol. 6, no. 5, pp. 627–648, 1993.
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Jose C. Principe is a Distinguished Professor of Electrical and Computer Engineering and Biomedical Engineering at the University of Florida, where he teaches advanced signal processing, machine learning, and artificial neural networks (ANNs) modeling. He is BellSouth Professor and the Founder and Director of the University of Florida Computational NeuroEngineering Laboratory (CNEL). His primary area of interest is processing of time-varying signals with adaptive neural models. The CNEL has been studying signal and pattern recognition principles based on information theoretic criteria (entropy and mutual information). Dr. Principe is an IEEE Fellow. He is a Member of the ADCOM of the IEEE Signal Processing Society, Member of the Board of Governors of the International Neural Network Society, and Editor in Chief of the IEEE Transactions on Biomedical Engineering. He is a Member of the Advisory Board of the University of Florida Brain Institute. Dr. Principe has more than 90 publications in refereed journals, 10 book chapters, and 200 conference papers. He directed 35 Ph.D. dissertations and 45 Master’s theses. He has recently wrote an interactive electronic book entitled Neural and Adaptive Systems: Fundamentals Through Simulation published by John Wiley and Sons.
Special Issue on

Advanced Signal Processing and Computational Intelligence Techniques for Power Line Communications

Call for Papers

In recent years, increased demand for fast Internet access and new multimedia services, the development of new and feasible signal processing techniques associated with faster and low-cost digital signal processors, as well as the deregulation of the telecommunications market have placed major emphasis on the value of investigating hostile media, such as powerline (PL) channels for high-rate data transmissions.

Nowadays, some companies are offering powerline communications (PLC) modems with mean and peak bit-rates around 100 Mbps and 200 Mbps, respectively. However, advanced broadband powerline communications (BPLC) modems will surpass this performance. For accomplishing it, some special schemes or solutions for coping with the following issues should be addressed: (i) considerable differences between powerline network topologies; (ii) hostile properties of PL channels, such as attenuation proportional to high frequencies and long distances, high-power impulse noise occurrences, time-varying behavior, and strong inter-symbol interference (ISI) effects; (iv) electromagnetic compatibility with other well-established communication systems working in the same spectrum, (v) climatic conditions in different parts of the world; (vii) reliability and QoS guarantee for video and voice transmissions; and (vi) different demands and needs from developed, developing, and poor countries.

These issues can lead to exciting research frontiers with very promising results if signal processing, digital communication, and computational intelligence techniques are effectively and efficiently combined.

The goal of this special issue is to introduce signal processing, digital communication, and computational intelligence tools either individually or in combined form for advancing reliable and powerful future generations of powerline communication solutions that can be suited with for applications in developed, developing, and poor countries.

Topics of interest include (but are not limited to):

- Multicarrier, spread spectrum, and single carrier techniques
- Channel modeling
- Channel coding and equalization techniques
- Multiuser detection and multiple access techniques
- Synchronization techniques
- Impulse noise cancellation techniques
- FPGA, ASIC, and DSP implementation issues of PLC modems
- Error resilience, error concealment, and Joint source-channel design methods for video transmission through PL channels

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Special Issue on
Numerical Linear Algebra in Signal Processing Applications

Call for Papers
The cross-fertilization between numerical linear algebra and digital signal processing has been very fruitful in the last decades. The interaction between them has been growing, leading to many new algorithms.

Numerical linear algebra tools, such as eigenvalue and singular value decomposition and their higher-extension, least squares, total least squares, recursive least squares, regularization, orthogonality, and projections, are the kernels of powerful and numerically robust algorithms.

The goal of this special issue is to present new efficient and reliable numerical linear algebra tools for signal processing applications. Areas and topics of interest for this special issue include (but are not limited to):

- Singular value and eigenvalue decompositions, including applications.
- Fourier, Toeplitz, Cauchy, Vandermonde and semi-separable matrices, including special algorithms and architectures.
- Recursive least squares in digital signal processing.
- Updating and downdating techniques in linear algebra and signal processing.
- Stability and sensitivity analysis of special recursive least-squares problems.
- Numerical linear algebra in:
  - Biomedical signal processing applications.
  - Adaptive filters.
  - Remote sensing.
  - Acoustic echo cancellation.
  - Blind signal separation and multiuser detection.
  - Multidimensional harmonic retrieval and direction-of-arrival estimation.
  - Applications in wireless communications.
  - Applications in pattern analysis and statistical modeling.
  - Sensor array processing.

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Special Issue on
Human-Activity Analysis in Multimedia Data

Call for Papers

Many important applications of multimedia revolve around the detection of humans and the interpretation of human behavior, for example, surveillance and intrusion detection, automatic analysis of sports videos, broadcasts, movies, ambient assisted living applications, video conferencing applications, and so forth. Success in this task requires the integration of various data modalities including video, audio, and associated text, and a host of methods from the field of machine learning. Additionally, the computational efficiency of the resulting algorithms is critical since the amount of data to be processed in videos is typically large and real-time systems are required for practical implementations.

Recently, there have been several special issues on the human detection and human-activity analysis in video. The emphasis has been on the use of video data only. This special issue is concerned with contributions that rely on the use of multimedia information, that is, audio, video, and, if available, the associated text information.

Papers on the following and related topics are solicited:

- Video characterization, classification, and semantic annotation using both audio and video, and text (if available).
- Video indexing and retrieval using multimedia information.
- Segmentation of broadcast and sport videos based on audio and video.
- Detection of speaker turns and speaker clustering in broadcast video.
- Separation of speech and music/jingles in broadcast videos by taking advantage of multimedia information.
- Video conferencing applications taking advantage of both audio and video.
- Human mood detection, and classification of interactivity in duplexed multimedia signals as in conversations.
- Human computer interaction, ubiquitous computing using multimedia.
- Intelligent audio-video surveillance and other security-related applications.

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| Publication Date             | 1st Quarter, 2008  |

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Special Issue on

Advanced Signal Processing and Pattern Recognition Methods for Biometrics

Call for Papers

Biometric identification has established itself as a very important research area primarily due to the pronounced need for more reliable and secure authentication architectures in several civilian and commercial applications. The recent integration of biometrics in large-scale authentication systems such as border control operations has further underscored the importance of conducting systematic research in biometrics. Despite the tremendous progress made over the past few years, biometric systems still have to reckon with a number of problems, which illustrate the importance of developing new biometric processing algorithms as well as the consideration of novel data acquisition techniques. Undoubtedly, the simultaneous use of several biometrics would improve the accuracy of an identification system. For example the use of palmprints can boost the performance of hand geometry systems. Therefore, the development of biometric fusion schemes is an important area of study. Topics related to the correlation between biometric traits, diversity measures for comparing multiple algorithms, incorporation of multiple quality measures, and so forth need to be studied in more detail in the context of multibiometrics systems. Issues related to the individuality of traits and the scalability of biometric systems also require further research. The possibility of using biometric information to generate cryptographic keys is also an emerging area of study. Thus, there is a definite need for advanced signal processing, computer vision, and pattern recognition techniques to bring the current biometric systems to maturity and allow for their large-scale deployment.

This special issue aims to focus on emerging biometric technologies and comprehensively cover their system, processing, and application aspects. Submitted articles must not have been previously published and must not be currently submitted for publication elsewhere. Topics of interest include, but are not limited to, the following:

- Fusion of biometrics
- Analysis of facial/iris/palm/fingerprint/hand images
- Unobtrusive capturing and extraction of biometric information from images/video
- Biometric identification systems based on face/iris/palm/fingerprint/voice/gait/signature
- Emerging biometrics: ear, teeth, ground reaction force, ECG, retina, skin, DNA
- Biometric systems based on 3D information
- User-specific parameterization
- Biometric individuality
- Biometric cryptosystems
- Quality measure of biometrics data
- Sensor interoperability
- Performance evaluation and statistical analysis

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| Final Manuscript Due         | December 1, 2007 |
| Publication Date             | 1st Quarter, 2008 |

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Special Issue on
Information Theoretic Methods for Bioinformatics

Call for Papers

Information theoretic methods for modeling are at the center of the current efforts to interpret bioinformatics data. The high pace at which new technologies are developed for collecting genomic and proteomic data requires a sustained effort to provide powerful methods for modeling the data acquired. Recent advances in universal modeling and minimum description length techniques have been shown to be well suited for modeling and analyzing such data. This special issue calls for contributions to modeling of data arising in bioinformatics and systems biology by information theoretic means. Submissions should address theoretical developments, computational aspects, or specific applications. Suitable topics for this special issue include but are not limited to:

- Normalized maximum-likelihood (NML) universal models
- Minimum description length (MDL) techniques
- Microarray data modeling
- Denoising of genomic data
- Pattern recognition
- Data compression-based modeling

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| Manuscript Due            | February 1, 2007 |
|---------------------------|------------------|
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| Final Manuscript Due      | July 1, 2007     |
| Publication Date          | 3rd Quarter, 2007|

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IEEE ICME 2007 Call for Papers

2007 International Conference on Multimedia & Expo (ICME)

July 2-5, 2007
Beijing International Convention Center, Beijing, China

Sponsored by: Circuits and Systems Society, Communications Society, Computer Society, and Signal Processing Society.

IEEE International Conference on Multimedia & Expo is a major annual international conference with the objective of bringing together researchers, developers, and practitioners from academia and industry working in all areas of multimedia. ICME serves as a forum for the dissemination of state-of-the-art research, development, and implementations of multimedia systems, technologies and applications. ICME is co-sponsored by four IEEE societies including the Circuits and Systems Society, the Communications Society, the Computer Society, and the Signal Processing Society. The conference will feature world-class plenary speakers, exhibits, special sessions, tutorials, and paper presentations.

Prospective authors are invited to submit a four-page paper in double-column format including authors’ names, affiliations, and a short abstract. Only electronic submissions will be accepted. Topics include but are not limited to:

- Audio, image, video processing
- Virtual reality and 3-D imaging
- Signal processing for media integration
- Multimedia communications and networking
- Multimedia security and content protection
- Multimedia human-machine interface and interaction
- Multimedia databases
- Multimedia computing systems and appliances
- Hardware and software for multimedia systems
- Multimedia standards and related issues
- Multimedia applications
- Multimedia and social media on the Internet

A number of awards will be presented to the Best Papers and Best Student Papers at the conference. Participation for special sessions and tutorial proposals are encouraged.

**SCHEDULE**

- Special Session Proposals Due: December 1, 2006
- Tutorial Proposals Due: December 1, 2006
- Regular Paper Submissions Due: January 5, 2007
- Notification of Acceptance: March 19, 2007
- Camera-Ready Papers Due: April 16, 2007

Check the conference website [http://www.icme2007.org](http://www.icme2007.org) for updates.

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