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## ABSTRACT

An improved iterative scheme, which optimizes both poles and residues, is developed for approximating a function by a sum of exponentials. In the pole optimization, the damped least squares Taylor method keeps pole increments small, while pole constraints are employed to insure stability. A more direct matrix inversion technique simplifies the residue optimization.

## INTRODUCTION

In a recent paper by Chatterjee and Fahmy ${ }^{[I]}$, an iterative scheme was presented for approximating a desired impulse response $f(t)$ by a finite sum of exponentials of the form $\sum_{i=1}^{n} \alpha_{i} \exp \left(-q_{i} t\right)$ where $\alpha_{i}$ and $q_{i}$ are real and $q_{i}>0$. The performance index used was the mean square error, and it was minimized by optimizing both the poles ( $q_{i}$ ) and the residues ( $\alpha_{i}$ ). At the risk of oversimplification, this iterative procedure may be described as follows. First, the least squares Taylor method $[z]$ is utilized to obtain optimum pole locations with residues fixed a priori. Second, the optimum residues are obtained by using the well-known Kautz orthonormal set [3]. Once an initial pole is chosen judiciously, the iterative cycle continues until the preassigned number of poles and iterations are achieved.

Since this iterative technique optimizes both the poles and the residues it yields a lower performance index than that obtained by the Kautz method [3]. However, inherent in this approach is the lack of control over pole inerements; hence, for large numbers of poles un-
stable solutions ( $q_{i} \leqq 0$ ) may emerge, and assumptions for the least squares Taylor method may be violated. Moreover, a rigorous proof for the convergence of the iterative technique has not been given. The purpose of this correspondence will be to (I) amend the pole optimization so as to preclude intemperate pole increments and unstable solutions, (2) reformulate the residue optimization so that optimal residues are obtained without making use of the rather involved Kautz orthonormal set, and (3) verify the convergence of this technique.

## PROBLEM FORMULATION

For comparision purposes, the nomenclature of Chatterjee and Fahmy ${ }^{[1]}$ will be used in this paper. It is ciesired to employ an iterative process to approximate $f(t)$ on $I_{2}[0, \infty)$ by the exponential function

$$
\begin{equation*}
g_{\ell, m}(t)=\sum_{i=1}^{n} \alpha_{i}(\ell)_{\exp }\left(-q_{i}(m)_{t}\right), \tag{I}
\end{equation*}
$$

where $\ell$ and $m$ denote the respective iterations on the residues and poles. The error functional to be minimized is

$$
\begin{equation*}
J[g]=\int_{0}^{\infty}[f(t)-g(t)]^{2} d t . \tag{2}
\end{equation*}
$$

POLE OPTTMIZATION:

If

$$
\begin{equation*}
q_{i}(k+1)=q_{i}(k)+\Delta q_{i}(k) \tag{3}
\end{equation*}
$$

and the $\Delta q_{i}{ }^{(k)}$ are small, a linear approximation may be used so that

$$
\begin{equation*}
g_{k, k+1}(t) \approx g_{k, k}(t)+\sum_{i=1}^{n} \frac{\partial g_{k, k}(t)}{\partial q_{i}(k)} \Delta q_{i}(k) \tag{4}
\end{equation*}
$$

Using the damped least squares Taylor method ${ }^{[4]}$ to minimize $J[g]$ as
well as the pole increments, $\Delta q_{i}(k)$, the error criterion

$$
\begin{equation*}
E=\int_{0}^{\infty}\left[f(t)-g_{k, k}(t)-\sum_{i=1}^{n} \frac{\partial q_{k, k}(t)}{\partial q_{i}(k)} \Delta q_{i}(k)\right]^{2} d t+\lambda^{2} \sum_{i=I}^{n}\left(\Delta q_{i}(k)\right)^{2} \tag{5}
\end{equation*}
$$

will be used, where $\lambda^{2}$ is a positive constant. This insures that the linear approximation in Eq. (4) remains valid duxing the iteration.

To minimize E with respect to $\Delta q_{j}(k)$, the equations

$$
\begin{align*}
\frac{\partial E}{\partial\left(\Delta q_{j}(k)\right)}= & \int_{0}^{\infty} 2\left[f(t)-g_{k, k}(t)-\sum_{i=1}^{n} \frac{\partial g_{k, k}(t)}{\partial q_{i}(k)} \Delta q_{i}(k)\right]\left[-\frac{\partial g_{k, k}(t)}{\partial q_{j}(k)}\right] d t \\
& +2 \lambda^{2} \Delta q_{j}(k)=0 \quad j=1, \ldots, n \tag{6}
\end{align*}
$$

must be satisfied. Rewriting Eq. (6) gives

$$
\begin{equation*}
\left({\underset{\sim}{A}}^{(k)}+\lambda^{2} \underset{\sim}{I}\right) \underset{\sim}{q}(k)={\underset{\sim}{b}}^{(k)} \tag{7}
\end{equation*}
$$

where I denotes the nom identity matrix and $\underset{\sim}{A}(k)$ is an won real symmetric matrix with elements

$$
\begin{equation*}
a_{j i}^{(k)}=\frac{2 \alpha_{j}^{(k)} \alpha_{i}^{(k)}}{\left(q_{j}^{(k)}+q_{i}^{(k)}\right)^{3}} \tag{8}
\end{equation*}
$$

$\Delta q_{\sim}^{(k)}$ and $\underset{\sim}{b}{ }^{(k)}$ are the column vectors described by

$$
\Delta_{\sim}^{(k)}=\left[\begin{array}{llll}
\Delta q_{1}^{(k)} \Delta q_{2}^{(k)} & \ldots & \Delta q_{n}^{(k)} \tag{9}
\end{array}\right]^{T}
$$

and

$$
b_{j}^{(k)}=\frac{\sum_{i=1}^{n} \alpha_{j}^{(k)} \alpha_{j}^{(k)}}{\left(q_{j}^{(k)}+q_{i}(k)\right)^{2}}-\alpha_{j}^{(k)} \int_{0}^{\infty} t f(t) \exp \left(-q_{j}^{(k)} t\right) d t
$$

or

$$
\begin{equation*}
b_{j}^{(k)}=\frac{\sum_{i=1}^{n}{\alpha_{j}}^{(k)}{\alpha_{i}}^{(k)}}{\left(q_{j}^{(k)}+q_{i}(k)\right)^{2}}+\left.\alpha_{j}^{(k)} \frac{d}{d s} F(s)\right|_{s=q_{j}}(k) \quad j=1, \ldots, n, \tag{10}
\end{equation*}
$$

if $f(t)$ is Laplace transformable.
(k)

By inspecting its principal minors it can be show that $\underset{\sim}{A}$ is
a positive definite matrix; thus $\underset{\sim}{A}(k)+\lambda^{2} \underset{\sim}{I}$ is positive definite also.

Eq. (7) then yields the solution

$$
\begin{equation*}
\underset{\sim}{\Delta q}(k)=\left({\underset{\sim}{A}}^{(k)}+\lambda^{a}{\underset{\sim}{I}}^{-1}{\underset{\sim}{b}}^{(k)}\right. \tag{11}
\end{equation*}
$$

Now let us inspect the $\underset{\sim}{\sim}{\underset{\sim}{(k)}}_{(\mathrm{k})}^{\text {given in Eq. (II). Consider the rate }}$ of change of E as ${\underset{\sim}{q}}^{(k)}$ migrates in the direction of $\Delta{\underset{\sim}{c}}^{(k)}$, i.e.,

where $\beta$ is a positive scalar $[5]$. Since $\left[A^{(k)}+\lambda^{2} \underset{\sim}{I}\right]$ is positive definite, $\left[\underset{\sim}{A}(k)+\lambda^{2} I\right]^{-1}$ is also, so it follows from Eq. (12) that E decreases in the direction $\Delta q^{(k)}$ defined in Eq. (II); the downhill behavior of $E$ is assured. Since ${\underset{\sim}{A}}_{(k)}^{(k)}$ is positive definite it is an even simpler matter to show that the least squares Taylor method $(\lambda=0)^{[I]}$ also converges provided the $\Delta q_{i}{ }^{(k)}$ are small. Note that the minimization of the error criterion E given in Eq. (5) indeed guarandes the minimization of the error functional $J[g]$ given in $E q$. (2).

To insure the stability of the approximation, the constraints []

$$
\begin{equation*}
q_{\min }<{\underset{\sim}{q}}^{(k)}+\Delta q_{\sim}^{(k)}<q_{\max } \tag{13}
\end{equation*}
$$

are imposed on the minimization procedure. For a stable RC realization $q_{\min }$ may be set equal to zero and $q_{\text {max }}^{*}$ some convenient positive number so that the poles are confined to the negative real axis of the complex plane. Such constraints are only used as a check at the end of each iteration. That is, if a pole is found to violate one of its bounds it is set equal to the extreme value
allowed and frozen there for a fixed number of iterations.

RESIDTJE OPTIMIZATION:

The pole optimization yields

$$
\begin{equation*}
g_{k, k+1}(t)=\sum_{i=1}^{n} \alpha_{i}^{(k)} \exp \left(-q_{i}{ }^{(k+1)} t\right) \tag{4}
\end{equation*}
$$

Let

$$
\begin{equation*}
g_{k+1, k+1}(t)=\sum_{i=1}^{n} \alpha_{i}^{(k+1)} \exp \left(-q_{i}^{(k+1)} t\right) \tag{15}
\end{equation*}
$$

be the best least squares approximation to $f(t) \in I_{2}[0, \infty)$ from among the linear combinations of $h_{i}=\exp \left(-q_{j}(k+1) t\right)$, which are linearly independent. It is well-known ${ }^{[7]}$ that the optimal residues $\alpha_{i}(k+1)$
are obtained by solving the normal equations:

$$
\begin{array}{r}
\alpha_{1}^{(k+1)}\left(h_{1}, h_{j}\right)+\alpha_{2}^{(k+1)}\left(h_{2}, h_{j}\right)+\cdots+\alpha_{n}^{(k+1)}\left(h_{n}, h_{j}\right)=\left(f, h_{j}\right) \\
t j=1, \ldots, n . \tag{16}
\end{array}
$$

Rewriting Eq. (16) gives

$$
\begin{equation*}
{\underset{\sim}{H}}^{(k+1)} \underset{\sim}{\alpha}(k+1){\underset{\sim}{d}}^{(k+1)}, \tag{17}
\end{equation*}
$$

where $\underset{\sim}{\underset{\sim}{H}}{ }^{(k+1)}$ is an nxn real symmetric Gram matrix with elements

$$
\begin{equation*}
\left(h_{j}, h_{i}\right)=\int_{0}^{\infty} h_{j i} h_{i} d t=\frac{1}{q_{j}^{(k+1)}+q_{i}(k+1)} \tag{18}
\end{equation*}
$$

$\underset{\sim}{\alpha}{ }^{(k+1)}$ and $\underset{\sim}{d}(k+1)$ are the column vectors described by

$$
{\underset{\sim}{\alpha}}^{(k+1)}=\left[\begin{array}{llll}
\alpha_{1} & \alpha_{2}^{(k+1)} & \ldots \alpha_{n}^{(k+1)} \tag{Iq}
\end{array}\right]^{(k+1}
$$

and

$$
d_{j}^{(k+1)}=\int_{0}^{\infty} f(t) \exp \left(-q_{j}(k+1) t\right) d t
$$

or

$$
\begin{equation*}
d_{j}^{(k+1)}=\left.F(s)\right|_{s=q_{j}}(k+1) \quad j=1, \ldots, n \tag{20}
\end{equation*}
$$

if $f(t)$ is Laplace transformable.

$$
\text { Since } \underset{\sim}{H}(k+1) \text { is a positive definite matrix, Eq. (17) }
$$

yields

$$
\begin{equation*}
{\underset{\sim}{\alpha}}^{(k+1)}=\left[{\underset{\sim}{H}}^{(k+1)}\right]^{-1}{\underset{\sim}{d}}^{(k+1)} . \tag{21}
\end{equation*}
$$

Although the resulting ${\underset{\sim}{\alpha}}_{(k+1)}^{(s)}$ is me as that obtained from the Kautz orthonormal set, Eq. (21) uses a more direct computation.

Thus, the $(k+1)$ th cycle of the iteration is completed and
the performance index is evaluated from

$$
\begin{aligned}
\text { PoI. } & =\int_{0}^{\infty}\left[f(t)-g_{k+1, k+1}(t)\right]^{2} d t \\
& =\int_{0}^{\infty}[f(t)]^{2} d t-2[\underset{\sim}{\alpha}(k+1)]^{T} d_{\sim}^{(k+1)}+\left[{\underset{\sim}{\alpha}}_{(k+1)}^{\sim}\right]_{\sim}^{T}(k+1)[\underset{\sim}{\alpha}(k+1)] .
\end{aligned}
$$

If the performance index exceeds the specified tolerable exmor for the preassigned number of iterations, distant poles are succossively added to improve the approximation.

## CONCIUSION

A. flow chart of the algorithm for computing the optimum approximating function is given in Fig. I. It incorporates all the refinements presented here. A subsequent paper will cover this material in more detail and discuss a method of optimizing the poles and residues simultaneously; various numerical results will also be given.
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Fig. 12


Fig. Ib

$$
\begin{aligned}
Q & =\text { Pole } \\
\alpha & =\text { Residue } \\
M & =\text { Maximum number of iterations to be performed } \\
N P & =\text { Maximum number of poles to be tried } \\
M F & =\text { Multiplying factor } \\
\delta & =\text { Tolerable error } \\
\epsilon & =\text { Ditto } \\
P I & =\text { Performance index } \\
I & =\text { Pole count } \\
K & =\text { Iteration count } \\
\Delta Q & =\text { Pole increment } \\
P I N T & =\int_{0}^{\infty}[f(t)]^{2} d t \\
D Q(I) & =\int_{0}^{\infty} f(t) \exp \left(-q_{i} t\right) d t \\
D T Q(I) & =\int_{0}^{\infty} t f(t) \exp \left(-q_{i} t\right) d t
\end{aligned}
$$

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