An Algebraic Approach for Identifying Operating Point Dependent Parameters of Synchronous Machines Using Orthogonal Series Expansions

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***Abstract*—This paper presents a method for identifying armature and field parameters of synchronous machines from Digital Fault Recorder (DFR) data. The method uses operational properties of orthogonal series expansions such as the Hartley, Walsh and Fourier series to transform a set of differential equations into linear algebraic equations. The algebraic formulation and use of operational calculus reduce the problem of identifying parameters to the manipulation of matrices that may be easily performed in such computational packages as Matlab. The variation of machine parameters with operating point is considered.**

***Index Terms*—Hartley series, least squares, maximum likelihood, operational matrices, parameter estimation, synchronous machines.**

I. Introduction

THE PROBLEM of on-line identification of synchronous generator parameters has particular importance in interconnected power systems, and this topic has received considerable attention [1], [2]. The main application areas are in detecting incipient failures, and accurate dynamic modeling of interconnected systems. The general approach is to use $dq0$ variables. A list of selected on-line identification algorithms [3] is given in Table I. The extended Kalman filter (EKF) deserves special mention among these techniques: in this approach the unknown parameters are included in the state vector. The EKF lends itself to nonlinear problems.

In the area of synchronous machines, maximum likelihood algorithms have been applied with good results [4]–[9]. It is important to add that the latter algorithms use an additional Kalman filter to facilitate the *observation* of the states and the error covariance [7]. The previously mentioned approaches are recursive approaches that allow for efficient computer implementations.

In this paper a different approach is adopted: the approach uses orthogonal series expansions to approximate the expected value of dynamic behavior and system parameters. More traditional methods of estimation of machine parameters convert the problem of *parameter* estimation into a problem of *state* estimation. In the method described below, this process is reversed: the state estimation problem is converted into parameter estimation. The key points of the method are the use of operational calculus and a matrix of coefficients common to all orthogonal series expansions. The problem is formulated as a nonlinear optimization problem subject to linear equality constraints. The Hartley series is illustrated in applications; however the similar results may be achieved with different kernels such as Fourier or Walsh functions. Using the operational matrix of integration, P, the need for the difficult differentiation of stochastic processes is overcome [10]. The original differential input/output model is converted to a linear algebraic model convenient for a direct (or least squares) solution. The method also permits the identification of unknown initial conditions simultaneously with the parameter identification that may be time varying. To ensure the accuracy of the estimated parameters, effects of damping windings, present in transient conditions, are taken into account.

TABLE I
SELECTED PARAMETER IDENTIFICATION APPROACHES

Domain	Method
Time	Modified on-line cross-correlation
Time	First order stochastic approximation
Time	Second order stochastic approximation (extended least squares)
Time, frequency	On-line maximum likelihood algorithm
Time, frequency	Maximum a posteriori probability algorithm
Time	Extended Kalman filter
Time, frequency	Generalized least squares algorithm
Frequency	Fourier analysis
Time	Instrumental variable algorithm
Time, parameter space	Random search

II. Orthogonal Series Expansions

In this section general background on approximation using orthogonal series expansions and operational matrices that is relevant for the material that follows is presented. The notation of presentation is kept general in order to include all possible domains. Most time functions of common engineering interest $f(t)$ may be approximated to arbitrary accuracy using

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orthogonal series expansions. The common feature of orthogonal series is that the basis functions used in the series are orthogonal to each other, that is when a pair of basis functions is integrated, the integral is zero if the two functions are different, and nonzero if they are the same. This property is used to find the coefficients of the series easily. Orthogonal series expansions also share other properties known as operational properties. In spite of having many common properties, orthogonal series expansions are different in their respective kernel or basis functions. While the kernel function of a complex Fourier series is $e^{-j\omega t}$, the Hartley series utilizes $\cos(\omega t)+\sin(\omega t)$, also known as the *cosine-and-sine* function or $\mathrm{cas}(\omega t)$. There exist orthogonal series expansions where the kernels are step functions such as Walsh series, block-pulse series or the basic Haar wavelet. Some kernels are aperiodic, some are transient, and some are polynomial in form. The challenge is to select a kernel that results in low computation, few terms in the series representation of $f(t)$, and low error.

If the vector of basis functions, $T(t)$, is used to include a particular set of basis kernels and denoted as (note that the prime notation indicates transposition),

$$T(t) = [\, T_{-n} \quad \cdots \quad T_{-1} \quad T_0 \quad T_1 \quad \cdots \quad T_n \,]' . \tag{1}$$

Thus a function can be approximated as

$$f(t) = FT'(t) \qquad F = [\, F_{-n} \quad \ldots \quad F_{-1} \quad F_0 \quad F_1 \quad F_n \,] . \tag{2}$$

Each coefficient of vector F, F_n is calculated using inner product in (3) (this is the orthogonal property),

$$F_n = k \int_0^{T_p} f(t)T(t)\, dt. \tag{3}$$

The operational properties of the orthogonal series may be written in terms of operational matrices of integration and differentiation. The main concept is that the integral of a orthogonal series may also be expressed as a orthogonal series. The same can be stated for orthogonal series and their derivatives. In general terms the operational matrix of integration and differentiation may by defined as

$$\int_0^t \cdots \int_0^t T(\tau)\, d\tau = P^n T(t) \qquad \frac{d^n T(t)}{dt^n} = D^n T(t).$$

Note that P and D are operational matrices of integration and differentiation, respectively.

It is convenient to define two additional important matrices that are derived from properties of orthogonal series expansions. These matrices are not referred as operational matrices because they are not related to the integration and differentiation operators but they are nevertheless related to the multiplication operator. The two additional matrices are the *product matrix* and the *matrix of coefficients*. The product of the orthogonal series basis vector and its transpose is called the *matrix product*, $\Pi(t)$, namely

$$\Pi(t) = T'(t)T(t).$$

The matrix of coefficients is defined in terms of the product matrix and the orthogonal series basis vector as a matrix that satisfies,

$$[c]T(t) = \Pi(t)c.$$

Matrix $[c]$ is the matrix of coefficients given in vector c. The product and coefficient matrices are properties that make possible analytical solutions for time varying systems and that they were found for the first time in the Walsh domain [13]. Appendix A shows the derivation of the operational matrices D and P and the product and coefficient matrices in Hartley domain.

In general, algebraic methods of operational matrices are a unified approach independent of the type of orthogonal series used to solve a problem. The particularities of each domain are reflected in the numerical characteristics of matrices P, D, $\Pi(t)$, $[c]$ and the vector of coefficients F. The structures of P, D, $\Pi(t)$, and $[c]$ of different domains vary. The sparsity of the matrices is also different which make some formulations more efficient than others for applications such as optimal control and system analysis. In terms of approximations, the selection of domain is relevant. For instance, a single term Walsh series may be used in a given application to represent a switching function in a power converter, but the same signal may require a long Hartley series to achieve the same accuracy.

III. Synchronous Machine Modeling

Continuous measurement of stator and field voltage and currents are available and will be used as state variables in the current model [14]. A major problem in the identification of parameters in Park's equation is the fact that some measurements may be unavailable. To overcome the problem, an observer for damping currents may be suggested but the problem is complicated because damper parameters are also unknown. Although EKF methods may be useful to solve this nonlinear problem and because monitoring field parameters is the main objective, a simplified alternative is proposed. If armature and field parameters are the main subject of the estimation algorithm, only the overall effect of the damper windings is required. The current model may be simplified for identification purposes as,

$$\begin{aligned} v_d &= -\, ri_d - \omega L_q i_q - L_d p i_d - kM_F p i_{fd} - v_1 \\ v_q &= \omega L_d i_d - ri_q + \omega k M_F i_{fd} - L_q p i_q - v_2 \\ -v_{fd} &= -\, r_{fd} i_{fd} - kM_F p i_d - L_F p i_{fd} - v_3 \end{aligned} \tag{4}$$

where v_1, v_2 and v_3 are time functions that model the effects that damping windings may have on the direct and quadrature axis voltages. Instead of estimating (or "observing") damper currents, the simpler problem of observing damper winding *effects* is adopted. In other words v_1, v_2 and v_3 are artificial variables that contain information on both damper currents and damper parameters.

The measurements available for parameter estimation include line currents i_a, i_b and i_c, the line-line voltages v_{ab}, v_{bc} and v_{ca}, the field current and voltage i_{fd} and v_{fd}. The machines under study were instrumented to measure power angle δ. Measurements are transformed for identification purposes. In these

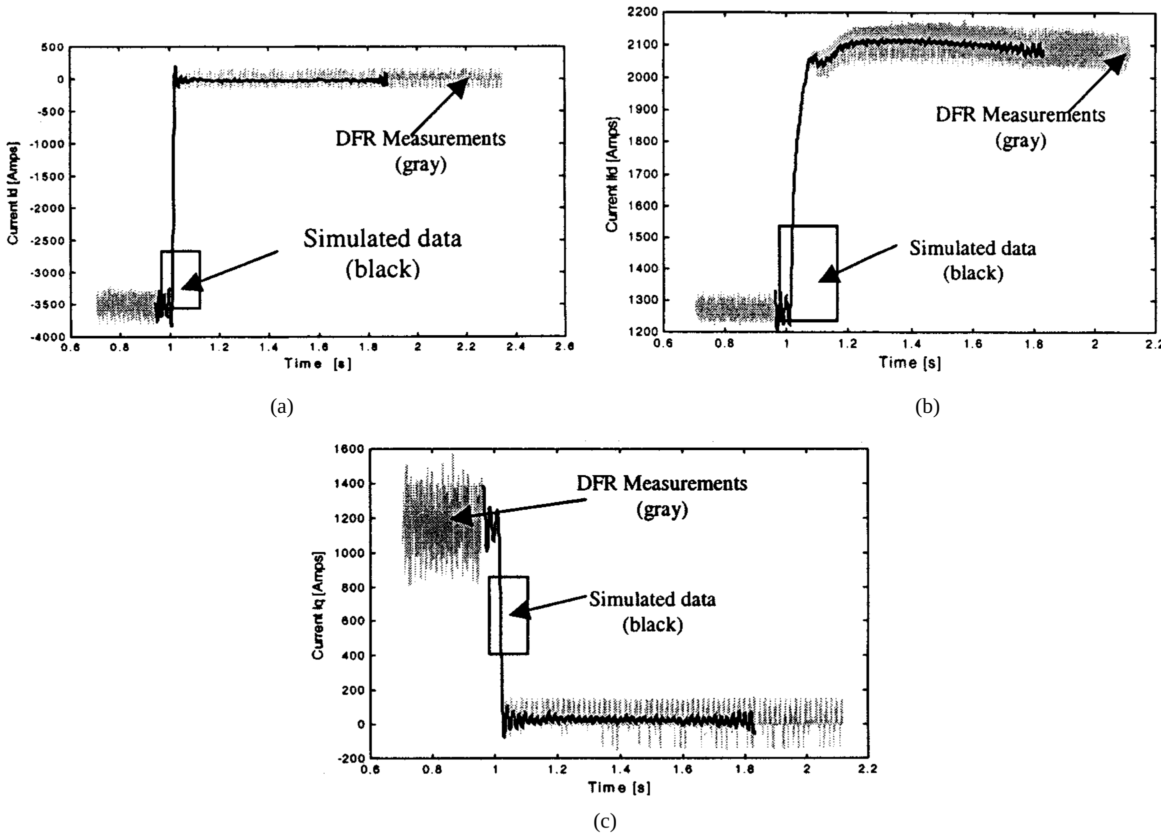

Fig. 1. Measurements (highly varying gray trace) vs. simulations (smoother black trace) for a large disturbance: tripped unit. (a) Current $i_d(t)$. (b) Current $i_{fd}(t)$. (c) Current $i_q(t)$.

system the electric frequency, ω, varies very little from the rated line frequency. These conditions allow for the simpler abc to $dq0$ transformation. Simple expressions for active and reactive power, voltage and current at the machine terminals are used to perform this transformation (see [11] for details). Fig. 1 shows typical results after applying the abc to the $dq0$ transformation. Fig. 1 shows that the system migrates between various steady states conditions. The estimated parameters must then satisfy the steady state equations of the machine during those periods. Taking this into account, the estimation problem is an optimization problem subject to equality constraints. The Hartley (or any other orthogonal series) expansions of these signals have the effect of low pass filtering the signal. The approach presented here focuses on approximating the mean as the basis of the orthogonal series expansions.

IV. The Algebraic Estimator

Because of the use of orthogonal series expansions and operational matrices to transform (4) into an algebraic equation, the estimator is termed an algebraic estimator and it is developed as follows: consider the approximations,

$$\begin{aligned} v_d(t) &= V_d T(t) \qquad v_q(t) = V_q T(t) \\ v_{fd}(t) &= V_{fd} T(t) \end{aligned} \tag{5}$$

and similar expressions for i_d, i_q, i_{fd}, v_1, v_2, v_3. A transient is a collection of operating points and the machine may travel between saturated and unsaturated states. Accordingly, all inductors in model (4) are considered time varying may be also approximated by an orthogonal series as $M_F T(t)$, $L_d T(t)$, $L_q T(t)$, $L_{fd} T(t)$. At this point, is possible to transform each Equation in (4) into an algebraic expression. For simplicity the procedure is shown only for excitation voltage v_{fd}. The transformation starts by transforming the differential equation into and integration formula, i.e.,

$$\begin{aligned} &-\int_0^t v_{fd}(\tau)\,d\tau + i_{fd}^0 \\ &\quad = -\int_0^t r_{fd} i_{fd}(\tau)\,d\tau - kM_F T(t) i_d(t) - L_{fd} T(t) i_{fd}(t) \\ &\qquad -\int_0^t v_3(\tau)\,d\tau. \end{aligned} \tag{6}$$

In this paper the authors have decided to use the integration formula owing to the fact that differentiation of a signal decreases the signal to noise ratio because noise generally fluctuates more rapidly than the command signal. Sometimes the signal to noise ratio may be decreased by several times by a single differentiation process.

Using an approximation in (6),

$$\begin{aligned} -V_{fd} PT(t) + i_{fd}^0 eT(t) = &- r_{fd} I_{fd} PT(t) - kM_F T(t) I_d T(t) \\ &- L_{fd} T(t) I_{fd} T(t) - V_3 PT(t) \end{aligned}$$

which, after applying the properties of the product and coefficients matrices, becomes (e is an elemental row vector)

$$\begin{aligned} -V_{fd} PT(t) + i_{fd}^0 eT(t) = &- r_{fd} I_{fd} PT(t) - kM_F [I_d] T(t) \\ &- L_{fd} [I_{fd}] T(t) - V_3 PT(t). \end{aligned} \tag{7}$$

It is clear, from (7), that time dependence may be dropped from our formulation to produce an algebraic equation in the frequency domain. Following the same procedure for all dynamic equations the following equation may be written.

$$p = \theta Q \tag{8}$$

where

$$\begin{aligned} p &= [\, r_{fd} \;\; M_F \;\; L_d \;\; L_q \;\; L_{fd} \;\; i_d^0 \;\; i_{fd}^0 \;\; i_q^0 \;\; V_1 \;\; V_2 \;\; V_3 \,] \\ p &= [\, V_d P \quad -V_{fd} P \quad V_q P \,] \end{aligned} \tag{9}$$

and

$$Q = \begin{bmatrix} 0 & -I_{fd}P & 0 \\ -[I_{fd}] & -[I_d] & \omega[I_{fd}]P \\ -[I_d] & 0 & \omega[I_d]P \\ -\omega[I_q]P & 0 & -[I_q] \\ 0 & -[I_{fd}] & 0 \\ e & 0 & 0 \\ 0 & e & 0 \\ 0 & 0 & e \\ -P & 0 & 0 \\ 0 & -P & 0 \\ 0 & 0 & -P \end{bmatrix}.$$

The parameters may be "solved" using pseudoinverse, denoted "+," estimating θ,

$$\widehat{\theta} = pQ^{+}. \tag{10}$$

V. The Optimization Problem

A feature that substantially improves the quality of the estimates is that of including additional constraints to the problem of least squares. In this paper the additional constraints are related to the fact that the estimated parameters must satisfy the steady state equations of the machine during the steady state conditions shown in Fig. 1 (e.g., $t > 1.2$ s). The steady state equation of the synchronous machine is written as

$$\begin{bmatrix} V_d \\ V_q \end{bmatrix} = -\begin{bmatrix} I_d & & & \omega I_q \\ I_q & -\omega k I_F & -\omega I_d & \end{bmatrix} \begin{bmatrix} r \\ M_F \\ L_d \\ L_q \end{bmatrix} \tag{11}$$

or in compact form

$$p_{ss} = \theta Q_{ss}. \tag{12}$$

With the equality constraints taken into consideration the estimation problem is written as a nonlinear optimization problem, minimizing pp^t over the steady states 1 through n. There are several tools to solve this nonlinear problem. In this paper

TABLE II
ESTIMATED PARAMETERS

Parameter		Estimated (data set 1)	Estimated (data set 2)
r_{fd}	(Ohms)	0.046	0.046
kM_F	(mH)	22.7	21.7
L_d	(mH)	4.9	5.9
L_q	(mH)	4.9	4.8
L_{fd}	(mH)	11.9	7.6

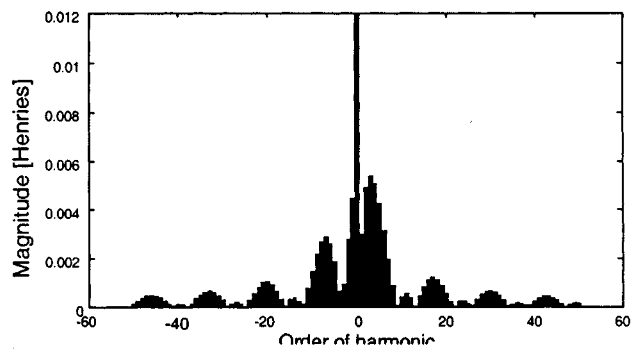

Fig. 2. Frequency spectrum of parameter L_{fd} given in henries. The horizontal scale is the harmonic of 60 Hz.

the authors include the equality constraints in the estimation problem. Thus the augmented estimator may be expressed as

$$[\, p \quad p_{ss}^1 \quad \cdots \quad p_{ss}^n \,] = \theta [\, Q \quad Q_{ss}^1 \quad \cdots \quad Q_{ss}^n \,]. \tag{13}$$

VI. Parameter Estimation From Operating Measurements

In this section the method described above is used to estimate armature and field parameters of two large generators operating under different conditions. The generators are connected a large electric network and measurements were taken with a DFR. The measurements include line currents, line–line voltages at terminals as well as current and voltages at the excitation field. For both machines it was also possible to have a device for measuring power angle. The abc quantities can be converted to $dq0$ axis using procedure presented in Section III.

Fig. 1 illustrates the agreement between DFR measurements and simulated responses of the machine. If test data used to identify machine parameters and damper response (i.e., the training data) capture a given range of operating conditions, the model built using these identified parameters behaves like actual DFR recorded traces. This occurs for new operating conditions not included in the training data—but contained within the range of given operating conditions. This agreement is observed provided that L_{fd} does not change materially between the training data set and the new operating condition. Table II shows the estimated parameters for disturbance shown in Fig. 2. The tabulated values except the field resistance correspond to the dc component of the Hartley series used to approximate the time dependant parameters. The field inductance was found the most sensitive estimated parameter to the operating point.

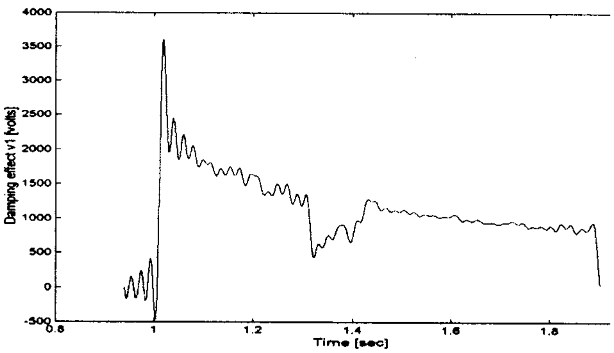

Fig. 3. Time evolution of damping effect $v_1(t)$ for a 5% change in V_f at $t = 1$ s.

Fig. 2 shows the spectral content of inductance L_{fd}. Although a dominant dc component is observed the presence of other components will caused the inductance to be sensitive to the operating point. Similar results were found for several data sets. Fig. 3 shows the time evolution of $v_1(t)$. It shows a characteristic damping effect at about $t = 1$ s. When a new steady state is reached the effect goes to zero. Note that the present form of the algorithm can not be used to model the damper winding parameters.

VII. Conclusions

In this paper, a method for estimating armature and field parameters from DFR measurements taken from actual network transients has been presented. The method has been validated and its accuracy has been shown comparing DFR measurements and simulations using the identified models. The results are in very good agreement. Two important features of the methods deserve special mention. Although rotor body parameters are not estimated at this point, its effects are taken into account using artificial variables that contain mixed information of parameters and damping currents. The other feature is that the method allows for taking into account the dependence of the parameters with respect to the operating point.

Appendix A
The Hartley Series and its Operational Properties

In this appendix a brief review of the Hartley series is given. It can be stated that the kernel function of the familiar Fourier transform and Fourier series is the complex exponential, $e^{-j\omega t}$. The Hartley transform and series utilize a similar frequency based kernel, the function $\cos(\omega t) + \sin(\omega t)$, also known as the *cosine-and-sine* function or $\text{cas}(\omega t)$. Thus Hartley technology does not employ complex numbers. Reference [13] is a definitive work on the subject. The Hartley series basis function $T(t)$ is denoted as (note that the prime notation indicates transposition),

$$\begin{aligned} T(t) &= [T_{-n} \quad \cdots \quad T_{-1} \quad T_0 \quad T_1 \quad \cdots \quad T_n]' \\ T_n &= \text{cas}(nvt) = \cos(nvt) + \sin(nvt). \end{aligned}$$

Thus a periodic function of period T_p can be approximated by a $2n+1$ term Hartley series as

$$\begin{aligned} f(t) &= FT(t) \\ F &= [F_{-n} \quad \cdots \quad F_{-1} \quad F_0 \quad F_1 \quad \cdots \quad F_n]_{(1,\,2n+1)}. \end{aligned}$$

Each coefficient of vector F, F_n is calculated using (A1),

$$F_n = \frac{1}{T_p}\int_0^{T_p} f(t)\text{cas}(nvt)\,dt. \tag{A1}$$

Similar to other orthogonal series expansions, the Hartley series possesses operational properties, namely an operational matrix of integration and differentiation. These can be defined as follows: consider the integral,

$$\int_0^t T_0(\tau)\,d\tau = \int_0^t d\tau = t \tag{A2}$$

$$\int_0^t T_n(\tau)\,d\tau = \int_0^t \text{cas}(nv\tau)\,d\tau = \frac{1}{2n\pi}(1 - \text{cas}(-nvt)). \tag{A3}$$

Use of the Hartley series for approximating (A2) and (A3) is done in [12] yielding that the integral of a basis function can be also expanded in a Hartley series,

$$\int_0^t T(\tau)\,d\tau = PT(t)$$

$$P = \frac{1}{2\pi}\begin{bmatrix} & & & & -\frac{1}{n} & & & & \frac{1}{n} \\ & & & & \vdots & & & \iddots & \\ & & & & -\frac{1}{2} & & \frac{1}{2} & & \\ & & & & -1 & 1 & & & \\ \frac{1}{n} & \cdots & \frac{1}{2} & 1 & \pi & -1 & -\frac{1}{2} & \cdots & -\frac{1}{n} \\ & & & -1 & 1 & & & & \\ & & -\frac{1}{2} & & \frac{1}{2} & & & & \\ & \iddots & & & \vdots & & & & \\ -\frac{1}{n} & & & & \frac{1}{n} & & & & \end{bmatrix}. \tag{A4}$$

Following a similar procedure to that described in previous section, an operational matrix for differentiation may be found,

$$\begin{aligned} \frac{dT_0(t)}{dt} &= 0 \\ \frac{dT_{-n}(t)}{dt} &= -nv\text{cas}(nvt) \quad \frac{dT_n(t)}{dt} = nv\text{cas}(-nvt). \end{aligned} \tag{A5}$$

In (A5), the notation ν is used to denote frequency in radians per second. The ν notation is used to distinguish the Hartley from

$$[c]=\begin{bmatrix} c_0 & c_{-1}+c_1 & c_{-2}+c_2 & 2c_{-3} & c_{-2}-c_2 & c_{-1}-c_1 & 0 \\ c_{-1}+c_1 & 2c_0 & c_{-1}+c_1+c_{-3}-c_3 & 2c_{-2} & c_{-1}-c_1+c_{-3}+c_3 & 0 & c_1-c_{-1} \\ c_{-2}+c_2 & c_{-1}+c_1+c_{-3}-c_3 & 2c_0+c_{-2}-c_2 & 2c_{-1} & c_{-2}+c_2 & c_{-1}-c_1+c_{-3}+c_3 & c_2-c_{-2} \\ 2c_{-3} & 2c_{-2} & 2c_{-1} & 2c_0 & 2c_1 & 2c_2 & 2c_3 \\ c_{-2}-c_2 & c_{-1}-c_1+c_3+c_{-3} & c_{-2}+c_2 & 2c_1 & 2c_0+c_2-c_{-2} & c_{-1}+c_1+c_2-c_{-2} & c_2+c_{-2} \\ c_{-1}-c_1 & 0 & c_1-c_{-1}+c_3-c_{-3} & 2c_2 & c_1+c_{-1}+c_3-c_{-3} & 2c_0 & c_{-1}+c_1 \\ 0 & c_{-1}-c_1 & c_{-2}+c_2 & 2c_3 & c_{-2}+c_2 & c_{-1}+c_1 & 2c_0 \end{bmatrix}$$

the Fourier domain. If n frequencies are considered, in [12] it is shown that

$$\frac{dT(t)}{dt}=DT(t)$$

$$D=\begin{bmatrix} & & & & & & -nv \\ & & & & & \cdot^{\cdot^{\cdot}} & \\ & & & & -v & & \\ & & & 0 & & & \\ & & v & & & & \\ & \cdot^{\cdot^{\cdot}} & & & & & \\ nv & & & & & & \end{bmatrix}.$$

In the Hartley domain the product matrix becomes

$$T(t)=[\,\text{cas}(-\nu t)\quad 1\quad \text{cas}(\nu t)\,]\begin{bmatrix}\text{cas}(-\nu t)\\ 1 \\ \text{cas}(\nu t)\end{bmatrix}$$

$$=\left[\begin{array}{l|l|l} \text{cas}(-2\nu t)+ & \text{cas}(-\nu t)+ & \text{cas}(-2\nu t)+ \\ \text{cas}(0)+ & \text{cas}(-\nu t)+ & \text{cas}(0)- \\ \text{cas}(0)+ & \text{cas}(\nu t)- & \text{cas}(0)+ \\ \text{cas}(2\nu t) & \text{cas}(ot) & \text{cas}(2\nu t) \\ \hline \text{cas}(-\nu t)+ & \text{cas}(0)+ & -\text{cas}(-\nu t)+ \\ \text{cas}(\nu t)+ & \text{cas}(0)+ & -\text{cas}(\nu t)+ \\ \text{cas}(-\nu t)- & \text{cas}(0)- & \text{cas}(\nu t)+ \\ \text{cas}(\nu t) & \text{cas}(0) & \text{cas}(\nu t) \\ \hline \text{cas}(-2\nu t)+ & -\text{cas}(-\nu t)+ & \text{cas}(-2\nu t)+ \\ \text{cas}(0)- & \text{cas}(\nu t)+ & \text{cas}(0)+ \\ \text{cas}(0)+ & \text{cas}(\nu t)+ & \text{cas}(0)- \\ \text{cas}(2\nu t) & \text{cas}(-\nu t) & \text{cas}(2\nu t) \end{array}\right]. \tag{A6}$$

The coefficient matrix is found by multiplying the product matrix in (A6) by the vector $c=[\,c_{-1}\quad c_0\quad c_1\,]'$, and then factorizing harmonic functions. The coefficient matrix for a c vector of 6×1 has the form as shown at the top of the page. Finding the same matrix for higher dimensions makes apparent a pattern that is used to design a computational program that generates the coefficient matrix in a very efficient way. The authors have written Matlab functions to generate coefficient matrices of any dimension for several domains. Selection of the adequate domain for signals involve becomes apparent from pattern of matrix $[c]$. Signals that will require a large number of coefficients will yield highly populated matrices.

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