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TRANSIENT PLASMA ESTIMATION: A NOISE CANCELLING/IDENTIFICATION APPROACH

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Transient Plasma Estimation: A Noise Cancelling/Identification Approach

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Abstract

In this paper we discuss the application of a noise cancelling technique to extract energy storage information from sensors occurring during fusion reactor experiments on the Tandem Mirror Experiment-Upgrade (TMX-U) at the Lawrence Livermore National Laboratory (LLNL). We show how this technique can be used to decrease the uncertainty in the corresponding sensor measurements used for diagnostics in both real-time and post-experimental environments. We analyze the performance of the algorithm on the sensor data and discuss the various tradeoffs. The algorithm suggested is designed using **SIG**, an interactive signal processing package developed at LLNL.

Background

Controlled *fusion* of heavy isotopes of hydrogen (deuterium and tritium) would enable virtually limitless energy [1] and therefore provide a solution to the dwindling supply of conventional energy sources. Ultimately, deuterium, which occurs naturally in water, represents a fuel reserve that would last for billions of years. Fusion reactions occur when ions of the hydrogen isotopes, heated to sufficient temperatures, collide and overcome the electrical forces of separation. When the nuclei fuse, enormous amounts of energy are released in the form of neutrons and protons from a relatively small amount of matter. The basic requirement for controlled fusion is to heat a plasma (or ionized gas) to high temperatures, in excess of 10^8 degrees, and confine it for times long enough that a significant number of fusion events occur. In order to confine, heat, sustain, and maintain purity the hot plasma must be isolated in a vacuum from contact with the surrounding vessel walls. One method of accomplishing this is call *magnetic confinement*.

The magnetic confinement method presently used at Lawrence Livermore National Laboratory (LLNL) is the result of over 30 years of research [2,3], starting with a single magnetic mirror cell and evolving to a tandem mirror with thermal barriers [4-6], the Tandem Mirror Experiment - Upgrade (TMX-U) experiment. Results from this experiment are leading to design principles for a commercial reactor. In Fig. 1 we show a schematic of the TMX-U experiment presently operating at LLNL. As shown in the figure, the tandom mirror consist of a large sausage-shaped region (*central cell*) with a *mirror cell* at each end. Here the magnetic forces confine the plasma within the reacting region until after many collisions they eventually escape. The confining magnetic fields are produced by 24 water cooled coils requiring 20 MW of power to generate peak fields of 2.2T. A target plasma is generated by electrical breakdown of deuterium gas with intense beams of microwaves. The high power microwaves, 800 KW at 24 GHz, also heat the electrons by electron cyclotron resonance heating (ECRH) to temperatures in excess of 50 KeV. Hot deuterium ions are created by ionization and charge exchange with the target plasma of neutral deuterium atoms injected at 15 KeV using a neutral beam system consisting of up to 24 neutral beams producing 5 MW of power for 80 msec pulses. Additional heating of ions can be obtained by ion cyclotron resonance heating (FeRH) using rf power injection of 200 KW in the frequency range of 1.5-4.0 MHz. This electrical environment requires specialized diagnostic sensors and processing techniques to accurately measure plasma parameters without perturbing the confined plasma.

A parameter of significant importance to magnetically confined plasmas is the diamagnetism of the plasma. This is a measure of the energy density stored in the hot particles. It is also used to determine the *beta*, β, the ratio of kinetic pressure (nKT) to magnetic field pressure ($B^2/2\mu_0$) indicating the efficiency of utilization of applied magnetic fields. A single-turn loop transformer is used as the sensor for the plasma diamagnetism [7-10]. As the plasma particle pressure increases due to heating, it will exclude magnetic field lines from inside thus increasing the apparent magnetic field around the plasma column. The single-turn transformer has $d\phi/dt$ generated as its output. Thus, time integration of this waveform can be used to calculate the plasma, β. On TMX-U we expect values of β up to 0.5 in the end-cell regions. This paper is concerned with the dynamic estimation of the plasma diamagnetism.

In the TMX-U plasma, a number of noise sources are present which make the estimation of β difficult. Variations of the magnetic field used to contain the plasma are present because of feedback circuits and ripple currents in the main power system. In many cases the signal that is used to determine the plasma diamagnetism is so badly corrupted with coherent frequency noise (ripple) that the plasma perturbation due to diamagnetism is not even visible. The present noise removal process involves subtraction of a short block of signal that represents the noise component only from data during the time that plasma is present. The noise reference block is aligned in phase with each of the signal plus noise data blocks so that the offending ripple component is removed. The result is integrated and a measure of the plasma diamagnetism is obtained. When the signals are approaching the noise level, or when the feedback control system has introduced a linear trend to the data, this approach is no longer satisfactory. A more sophisticated technique must be used for the processing of the measured signals. It must incorporate trend removal with the capability of removing the coherent noise without affecting the frequency content of the plasma perturbation itself. In this paper we will show how the problem can be viewed as a noise cancelling problem which can be solved using an identification approach.

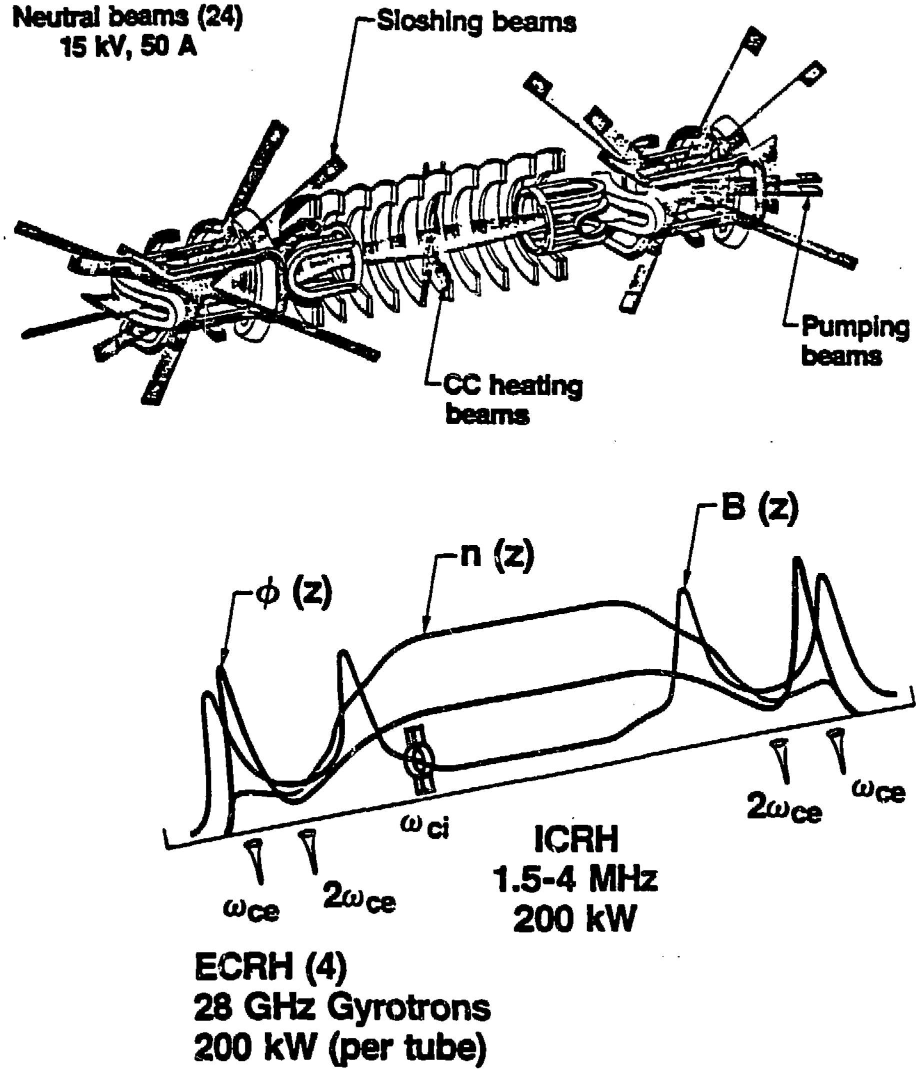

Figure 1 Tandom Mirror Experiment-Upgrade (TMX-U)

In the next section we develop the noise canceller using a system identification approach. Next we summarize the algorithm implementation using a solution to the generalized Levinson problem, then we discuss the design of the processor for the plasma estimation problem and summarize the results in the final section.

Noise Cancelling Via System Identification

In this section we develop the algorithm for the noise canceller using an identification approach. The concept of noise cancelling evolves naturally from applications in the biomedical (EKGs, patient monitoring, speech, etc.) and seismological areas [11-13]. Ideally, for noise cancelling to be effective the measured data contains little or no signal information for a period of time so that the only information recorded is the noise, therefore, when the signal occurs it is uncorrelated with the reference noise (e.g. pulses in radar, etc.). The initial algorithms developed were adaptive requiring long data records in order for the algorithm to converge, new approaches eliminate this requirement [13,14]. Variations from the ideal case still met with success. For example, even if signal information is present in the reference record, a reasonable signal estimate can still be obtained. Also, independent measurements can be used rather than the same data record partitioned into reference and signal plus reference. The removal of 60 Hz disturbances can be accomplished by measuring the line voltage as the reference, for instance. In any case, the plasma diagnostics required for monitoring fusion reaction is an ideal candidate for cancelling, since the reference noise can be obtained directly from the measured signal plus noise record, the signal is uncorrelated with the noise, and the onset of the plasma is known.

The fundamental noise cancelling problem is depicted in Fig. 2. Here we assume that the noise corrupting the signal is passed through a linear system,

$$y(t) = s(t) + h_1(t) * n(t) + v_1(t), \tag{1}$$

$$r'(t) = h_2(t) * n(t) + v_2(t) \tag{2}$$

where

y is the measured data

s is the signal

n is the disturbance or noise

v is the random disturbance or noise

r' is the measured reference noise, and

h is the sensor or measurement system dynamics.

The convolution operation * is defined by

$$h(t) * n(t) = \sum_{i=1}^{N} h(i)n(t-i) = \sum_{i=1}^{N} h(i)q^{-i}n(t) = H(q^{-1})n(t)$$

for

$$H(q^{-1}) = h(0) + h(1)q^{-1} + \cdots + h(N)q^{-N},$$

and **q** is a shift or delay operator (i.e., $q^{-i}n(t) = n(t-i)$).

Thus, using these relations the convolution equations of (1,2) can be expressed as

$$y(t) = s(t) + H_1(q^{-1})n(t) + v_1(t), \tag{3}$$

$$r'(t) = H_2(q^{-1})n(t) + v_2(t). \tag{4}$$

The noise cancelling problem can be defined in terms of a parameter estimation problem by eliminating **n** from the above relations, i.e., if we assume that H_2 is invertible (exists), then we have

$$n(t) = H_2^{-1}(q^{-1})r'(t) - H_2^{-1}(q^{-1})v_2(t).$$

Substituting for n in the measurement equation, we obtain

$$y(t) = s(t) + H_1(q^{-1})H_2^{-1}(q^{-1})\left[r'(t) - v_2(t)\right] + v_1(t),$$

or more simply,

$$y(t) = s(t) + H(q^{-1})r(t) + v(t) \tag{5}$$

where $H(q^{-1}) = H_1(q^{-1})H_2^{-1}(q^{-1})$, $r(t) = r'(t) - v_2(t)$, and $v(t) = v_1(t)$.

Equation (5) defines an input/output model for the noise cancelling problem with the input sequence given by $\{r(t)\}$ and the output by $\{y(t)\}$. Using this formulation, we can state the corresponding **noise estimation problem** as

> **Given** the model of (5), measurement sequence $\{y(t)\}$, and the noise reference sequence $\{r(t)\}$, **Find** the *best* (minimum error variance) estimate of the noise, n(t).

This problem differs from the classical signal estimation problem† because more information about the characteristics of the noise is available in the reference data. Using the solution to this problem, the canceller is constructed as depicted in Fig. 2. We see at the output of the canceller, that the estimated or filtered response is given by

$$\hat{z}(t) = y(t) - \hat{n}(t). \tag{6}$$

The minimum variance estimate, $\hat{n}(t)$, removes or cancels the reference noise, as is easily seen by substituting the estimator,

$$\hat{n}(t) = \hat{H}(q^{-1})r(t) \tag{7}$$

† Actually this estimation problem is a system identification problem as noted by Ljung [11]

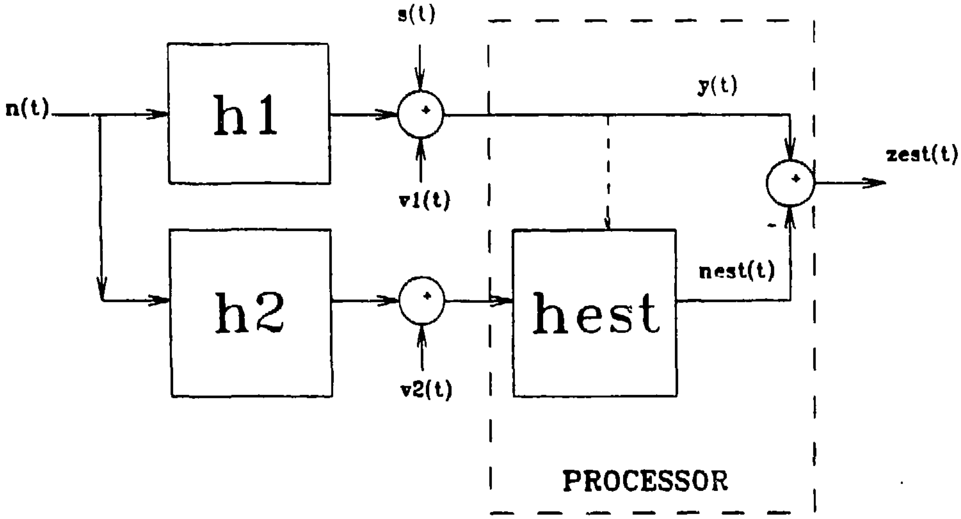

Figure 2 Noise Cancelling Processor

above and using (5) for y(t) to obtain

$$\hat{z}(t) = s(t) + \Big[H(q^{-1}) - \hat{H}(q^{-1})\Big]r(t) + v(t). \tag{8}$$

Clearly, as $\hat{H} \rightarrow H$ then $\hat{z} \rightarrow s + v$. If the random measurement noise, $v(t)$ were minimal (small variance), then $\hat{z} \rightarrow s$, i.e., the estimator would provide the minimum variance estimate of s as well, however, for v significant, further processing must be used to obtain the minimum variance estimate of s.

Thus, we see that noise cancelling can be viewed as a two step process:

1. Obtain the minimum variance estimate of the noise, $n(t)$, and
2. Subtract the estimated noise, $\hat{n}(t)$, from the measured data, $y(t)$.

If we define the criterion function,

$$J(t) = E\{\epsilon^2(t)\}$$

where the error is given by $\epsilon(t) = y(t) - \hat{n}(t)$, then the minimum variance estimator is obtained by finding the $H(q^{-1})$ that minimizes the criterion, i.e.,

$$min_H J(t).$$

The solution to this problem is obtained by differentiating J with respect to each of the $h(i)$, setting the result to zero and solving the resulting set of equations, i.e.,

$$\begin{aligned}\frac{\partial J(t)}{\partial h(k)} &= \frac{\partial}{\partial h(k)} E\{\epsilon^2(t)\} \\ &= 2E\{\epsilon(t)\frac{\partial \epsilon(t)}{\partial h(k)}\}\end{aligned}$$

The error gradient is found by substituting Eqn. 7 for $\hat{n}(t)$ to obtain

$$\frac{\partial \epsilon(t)}{\partial h(k)} = -r(t-k),$$

and therefore,

$$\begin{aligned}\frac{\partial J(t)}{\partial h(k)} &= -2E\{(y(t) + \sum_{i=1}^{N} h(i)r(t-i))r(t-k)\}, \\ &= -2\Big(E\{y(t)r(t-k)\} - \sum_{i=1}^{N} h(i)E\{r(t-i)r(t-k)\}\Big), \quad k = 1, \cdots, N.\end{aligned}$$

Setting this expression to zero and solving, we obtain the so-called *normal equations*

$$-R_{yr}(k) = \sum_{i=1}^{N} h(i) R_r(k-i), \;\; k = 1, \cdots, N. \tag{9}$$

Carrying out the summations, we obtain the set of linear vector-matrix equations,

$$-\begin{pmatrix} R_{yr}(1) \\ \vdots \\ R_{yr}(N) \end{pmatrix} = \begin{pmatrix} R_r(0) & R_r(-1) & \cdots & R_r(1-N) \\ \vdots & \vdots & \ddots & \vdots \\ R_r(N-1) & R_r(N-2) & \cdots & R_r(0) \end{pmatrix} \begin{pmatrix} h(1) \\ \vdots \\ h(N) \end{pmatrix},$$

or solving for $\mathbf{h}$ we obtain

$$\underline{\hat{h}}(N) = -\mathbf{R_r}^{-1} \underline{R}_{yr}(N) \tag{10}$$

It is straightforward to show that the corresponding error variance, $\tilde{R}$, is given by

$$\tilde{R} = R_r(0) - \underline{R}'_{ry}(N) \mathbf{R_r}^{-1} \underline{R}_{yr}(N) \tag{11}$$

This set of linear equations can be solved using standard techniques in linear algebra or since the covariance matrix to be inverted has a Toeplitz structure, a more efficient technique employing the generalized Levinson approach discussed in the next section.

Generalized Levinson Recursion

The noise cancelling problem requires the solution of the set of linear equations given in Eqn. 10, where $\mathbf{R_r}$ is a Toeplitz matrix. Efficient algorithms to invert Toeplitz matrices recursively were developed by Levinson [15,16], and extended to the so-called "generalized" case by Wiggins and Robinson [17]. In this section, we develop the **LWR** for this problem. The **LWR** recursion can be developed in two steps. The first establishes the basic recursion, and the second is the standard Levinson recursion for inverting Toeplitz matrices. We will use the notation $\{h_i^k\}$ to denote the i^{th} coefficient of the k^{th} order filter and the corresponding *autocorrelation* as $R_j = E\{x(t)x(t+j)\}$ and *crosscorrelation* as $g_j = E\{x(t)y(t+j)\}$. In this notation, Eqn. 10 becomes

$$\underline{\hat{h}}(N) = -\mathbf{R}^{-1} \underline{g}(N) \tag{12}$$

Let us assume that we have the k^{th} order filter that satisfies the set of *normal equations*,

$$\begin{bmatrix} R_0 & \cdots & R_k \\ \vdots & \ddots & \vdots \\ R_k & \cdots & R_0 \end{bmatrix} \begin{bmatrix} h_0^k \\ \vdots \\ h_k^k \end{bmatrix} = -\begin{bmatrix} g_0 \\ \vdots \\ g_k \end{bmatrix} \tag{13}$$

and we want the $(k+1)^{th}$ order solution given by

$$\begin{bmatrix} R_0 & \cdots & R_{k+1} \\ \vdots & \ddots & \vdots \\ R_{k+1} & \cdots & R_0 \end{bmatrix} \begin{bmatrix} h_0^{k+1} \\ \vdots \\ h_{k+1}^{k+1} \end{bmatrix} = - \begin{bmatrix} g_0 \\ \vdots \\ g_{k+1} \end{bmatrix} \tag{14}$$

Suppose the optimum solution for the $(k+1)^{th}$ order filter is is given by the k^{th} order, then $\underline{h}'(k+1) = [\ \underline{h}'(k)\ \vdots\ 0\ ]$ and $\underline{g}'(k+1) = [\ \underline{g}'(k)\ \vdots\ \nabla_k\ ]$ with $\nabla_k = g_{k+1}$. We can rewrite Eqn. 14 as

$$\begin{bmatrix} R_0 & \cdots & R_k & R_{k+1} \\ \vdots & \ddots & \vdots & \vdots \\ R_k & \cdots & R_0 & R_1 \\ R_{k+1} & \cdots & R_1 & R_0 \end{bmatrix} \begin{bmatrix} \underline{h}(k) \\ \cdots \\ 0 \end{bmatrix} = - \begin{bmatrix} \underline{g}(k) \\ \cdots \\ \nabla_k \end{bmatrix} \tag{15}$$

where $\nabla_i = \sum_{j=0}^{i} h_j^i R_{i-j+1}$.

We must perform operations on Eqn. 15 to assure that $\nabla_k = g_{k+1}$ for the correct solution. Let us assume there exists a solution $\{\alpha_i^{k+1}\}$ such that †

$$\begin{bmatrix} R_0 & \cdots & R_{k+1} \\ \vdots & \ddots & \vdots \\ R_{k+1} & \cdots & R_0 \end{bmatrix} \begin{bmatrix} \alpha_0^{k+1} \\ \vdots \\ \alpha_{k+1}^{k+1} \end{bmatrix} = - \begin{bmatrix} v_{k+1} \\ \vdots \\ 0 \end{bmatrix} \tag{16}$$

Now by elementary manipulations, we can reverse the order of the components, multiply by a constant, K_{k+1} and subtract the result from Eqn. 15, that is,

$$\begin{bmatrix} R_0 & \cdots & R_{k+1} \\ \vdots & \ddots & \vdots \\ R_{k+1} & \cdots & R_0 \end{bmatrix} \left\{ \begin{bmatrix} h_0^k \\ \vdots \\ h_k^k \\ 0 \end{bmatrix} - K_{k+1} \begin{bmatrix} \alpha_{k+1}^{k+1} \\ \vdots \\ \alpha_1^{k+1} \\ \alpha_0^{k+1} \end{bmatrix} \right\} = - \left\{ \begin{bmatrix} g_0 \\ \vdots \\ g_k \\ \nabla_k \end{bmatrix} - K_{k+1} \begin{bmatrix} 0 \\ \vdots \\ 0 \\ v_{k+1} \end{bmatrix} \right\}$$

or

$$\begin{bmatrix} R_0 & \cdots & R_{k+1} \\ \vdots & \ddots & \vdots \\ R_{k+1} & \cdots & R_0 \end{bmatrix} \left\{ \begin{bmatrix} h_0^k - K_{k+1}\alpha_{k+1}^{k+1} \\ \vdots \\ h_k^k - K_{k+1}\alpha_1^{k+1} \\ -K_{k+1}\alpha_0^{k+1} \end{bmatrix} \right\} = \left\{ - \begin{bmatrix} g_0 \\ \vdots \\ g_k \\ \nabla_k - K_{k+1}v_{k+1} \end{bmatrix} \right\} \tag{17}$$

† Note that this the solution to this set of equations results in the standard Levinson-Durbin recursion of linear prediction theory [13]

Here the multiplier K_{k+1} is selected so that

$$\nabla_k - K_{k+1} v_{k+1} = g_{k+1}$$

By identifying the coefficients $\underline{h}(k+1), \underline{g}(k+1)$ from Eqn. 17 with $\alpha_0^i = 1$, we obtain the first part of the recursion

$$\begin{aligned} Initialize: \quad v_1 &= R_0 - r_1^2/R_0, \nabla_0 = R_1 \\ For \quad i &= 1, \cdots, k \\ \nabla_i &= \sum_{j=0}^{i} h_j^i R_{i-j+1} \\ K_{i+1} &= \frac{\nabla_i - g_{i+1}}{v_{i+1}} \\ h_{i+1}^{i+1} &= -K_{i+1} \\ h_j^{i+1} &= h_j^i - K_{i+1} \alpha_{i-j+1}^{i+1} \quad for \quad 1 \leq j \leq i \end{aligned} \tag{18}$$

In order to satisfy the recursion, we must also obtain a recursion for the predictor, $\{\alpha_i^{k+1}\}$, and v_{k+1} from the solution of Eqn. 16. This can be accomplished using the well-known *Levinson-Durbin* recursion [13] for the $\{\alpha_j^i\}$ as:

$$\begin{aligned} Initialize: \quad v_0 &= R_0, \quad \Delta_0 = R_1, \quad K_1^* = -R_1/R_0 \\ For \quad i &= 1, \cdots, k \\ \Delta_i &= \sum_{j=0}^{i} \alpha_j^i R_{i-j+1} \\ K_{i+1}^* &= \frac{\Delta_i}{v_i} \\ \alpha_{i+1}^{i+1} &= -K_{i+1}^* \\ \alpha_j^{i+1} &= \alpha_j^i - K_{i+1}^* \alpha_{i-j+1}^i \quad for \quad 1 \leq j \leq i \\ v_{i+1} &= v_i - K_{i+1}^* \Delta_i \end{aligned} \tag{19}$$

This completes the solution to the Toeplitz inversion u ing the generalized Levinson algorithm. The noise cancelling algorithm is implemented using **SIG** [18], by first performing the generalized Levinson recursion to estimate the optimal noise cancelling filter $\hat{h}$, filtering the reference noise r, to provide the estimated noise $\hat{n}$, and subtracting it from the signal plus noise data. The design and application of the processor are discussed in the next section.

Plasma Estimation Using the Noise Canc

In this section, we analyze the acquired diamagne ic loop (DML) sensor measurements and show how the data can be processed to retain the essential information required for post-experimental analysis. The measured DML data is analog (anti-alias) filtered and digitized at a 25 KHz sampling rate (40 μ sec sample interval). A typical experiment generates a transient signal (plasma) which is recorded for approximately 650 msec. Preprocessed data (decimated etc.) and the frequency spectrum are shown in Fig. 3 along with an expanded section of the transient pulse and noise. We note that the raw data is contaminated with a sinusoidal drift, linear trend, and random noise as well as sinusoidal disturbances at harmonics of 60 Hz, the largest at 360 Hz caused by the feedback circuits and ripple currents in the main power system. The pulse is also contaminated by these disturbances. We also note that some of the plasma information appears as high energy spikes(pulses) *riding* on the slower plasma build-up pulse.

A processor must be developed to eliminate these disturbances, yet preserve all of the essential features of the transient plasma pulse and associated energy spikes. This application is ideally suited for *noise cancelling*. The basic requirements of the data are that a reference file of noise and of the signal and noise are available. For best results, the signal and noise should not be correlated. These conditions are satisfied by the DML measurement data, since the onset of the measurement consists only of the disturbances (trend and sinusoids), and the signal is available at the time of the transient plasma pulse.

During the operation of the TMX experiment a "shot" (injection of a plasma into the reactor) terminates after a few seconds, during this time data are collected and displayed so that the experimenter can adjust process parameters and criteria and perform another shot within a five (5) minute time period. So we see that even though the processor need not be on-line, it still must function in a real-time enviroment. Clearly, post-experimental analysis creates no restrictions on the processor design and alloted computational time. So we analyzed the performance of the processor to function for both real-time and post-experimental modes of operation. We studied the performance of the processor by varying its length **N** . The real-time processor must perform reasonably well enough to enable the experimenter to make the necessary decisions regarding the selection of process parameters for the next shot.

After some preliminary runs of the processor over various data sets we decided to use $\mathbf{N} = \mathbf{512}$ weights for the post-experimental design since it produced excellent results. Using the post-experimental design as a standard we then evaluated various designs for

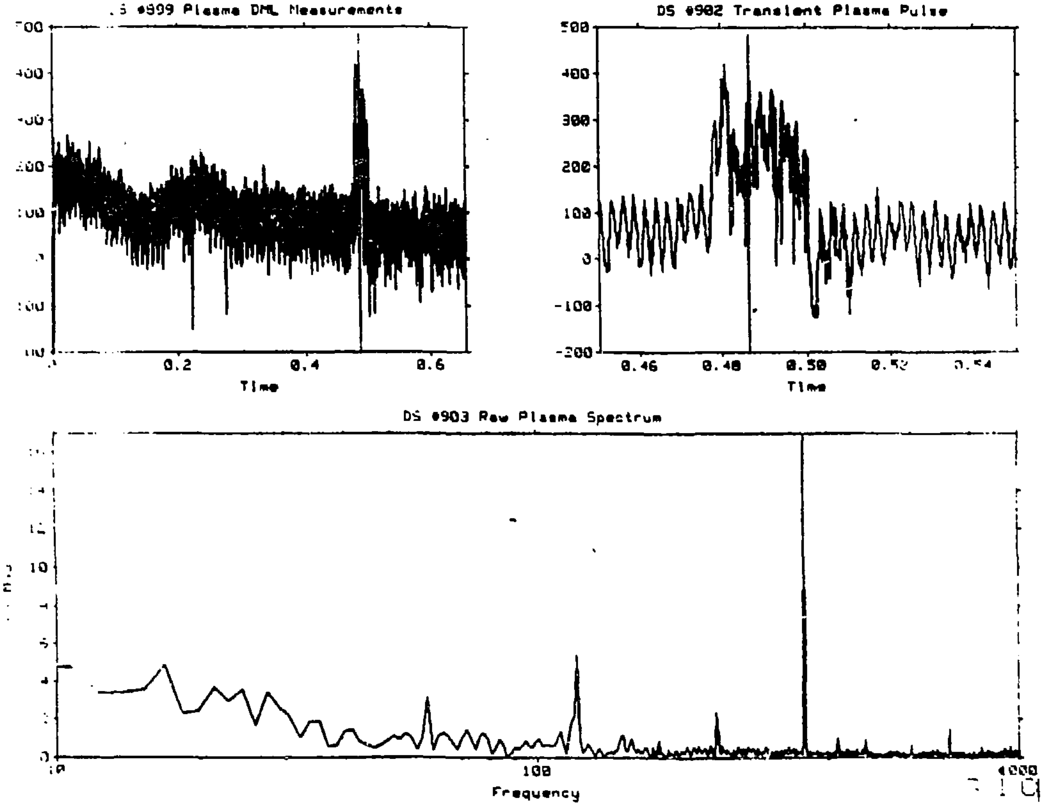

Figure 3 Preprocessed Diamagnetic Loop Measurement Data and Spectrum

weights in the range of $8 < N < 512$. Before we discuss the comparisions, let us consider the heuristic operation of the processor. Investigating the block diagram of Fig. 2, we see that the crucial step in the design of the canceller is the estimation of the optimal noise filter $\hat{h}$ which is required to produce the minimum variance estimate of the noise, $\hat{n}$. In essence we expect the filter to spectrally match the corresponding noise spectrum in magnitude and phase. This means that we expect the optimal filter to pass the spectral peaks of the noise and attenuate any signal information not contained in the reference file. These results are confirmed as shown by the performance of the 512-weight filter shown in Fig. 4a. Here we see that the filter passbands enable most of the noise resonances to pass while signal energy is attenuated. The real-time design is shown below in Fig. 4b. Here we see that the 64-weight filter still passes much of the noise energy but does not spectrally match the noise as well as the 512-weight filter since there are fewer weights. These results are again confirmed in Fig. 5 where the estimated and actual noise spectra are shown. Again we see that the 512-weight produces a much better spectral match than the 64-weight design due to its increased resolution. Note that the highest energy noise spectral peaks were matched by both processors reasonably well thereby eliminating these disturbances in the cancelling operation. Intermediate designs for the real-time processor fall in between these results where selecting higher number of weights the resulted in better processor performance.

It should be mentioned that we chose to use the FIR (all-zero) solution to this problem, rather than the IIR (pole-zero) as suggested in [11] or [14] because initial attempts at identifying the optimal noise filter were unsatisfactory primarily because of the high resonances (sinusoids) in the data. The IIR identifiers could identify the frequencies but always overestimated the damping which proved detrimental when the estimated noise was cancelled (subtracted) from the signal plus noise measurements.

The noise canceller algorithm was constructed using various commands in SIG discussed previously. Both the post-experimental and real-time designs were run on the data set described in Fig. 3 and the results are show in Fig. 6 and 7 for the post and real-time processors, respectively. Here we see the raw and processed data and corresponding spectra. Note that the sinusoidal disturbances and trend have been eliminated (spectrum). A closer examination of the estimated transient pulse shows that not only have the disturbances been removed, but that the integrity of the pulse has been maintained and all of the high frequency energy spikes have been preserved. We see that the 512-weight processor has clearly eliminated the trends and sinusoidal disturbances and retained the transient plasma information quite well while the real-time (64-weight) processor has not performed as well as evidenced by some remaining (though small) sinusoidal disturbances. However, for the real-time requirements it is satisfactory.

Once these disturbances have been removed, the processed signal can be integrated to remove or deconvolve the effects of the differentiating DML probe and provide an estimate of the stored energy build-up in the machine.

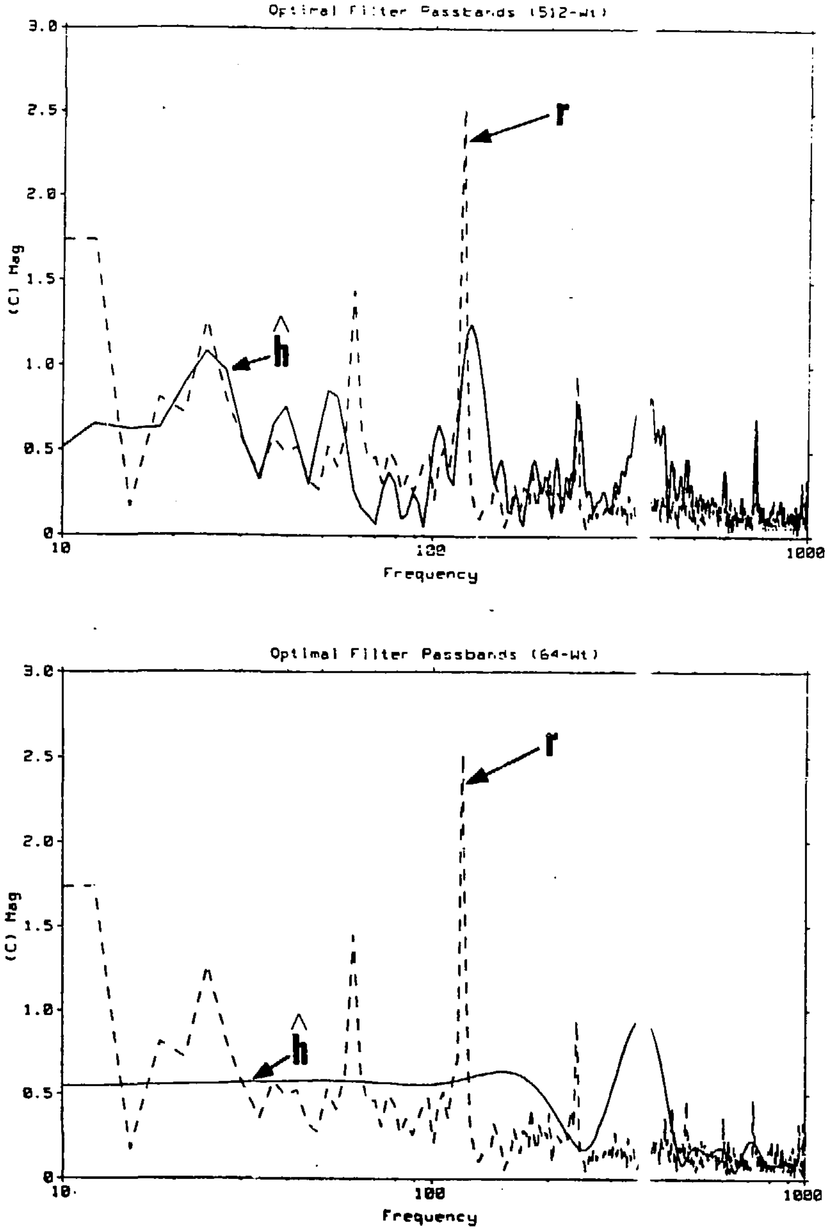

Figure 4 Optimal Noise Filter and Noise Spectra: (a) Post Filter and (b) Real-Time Filter

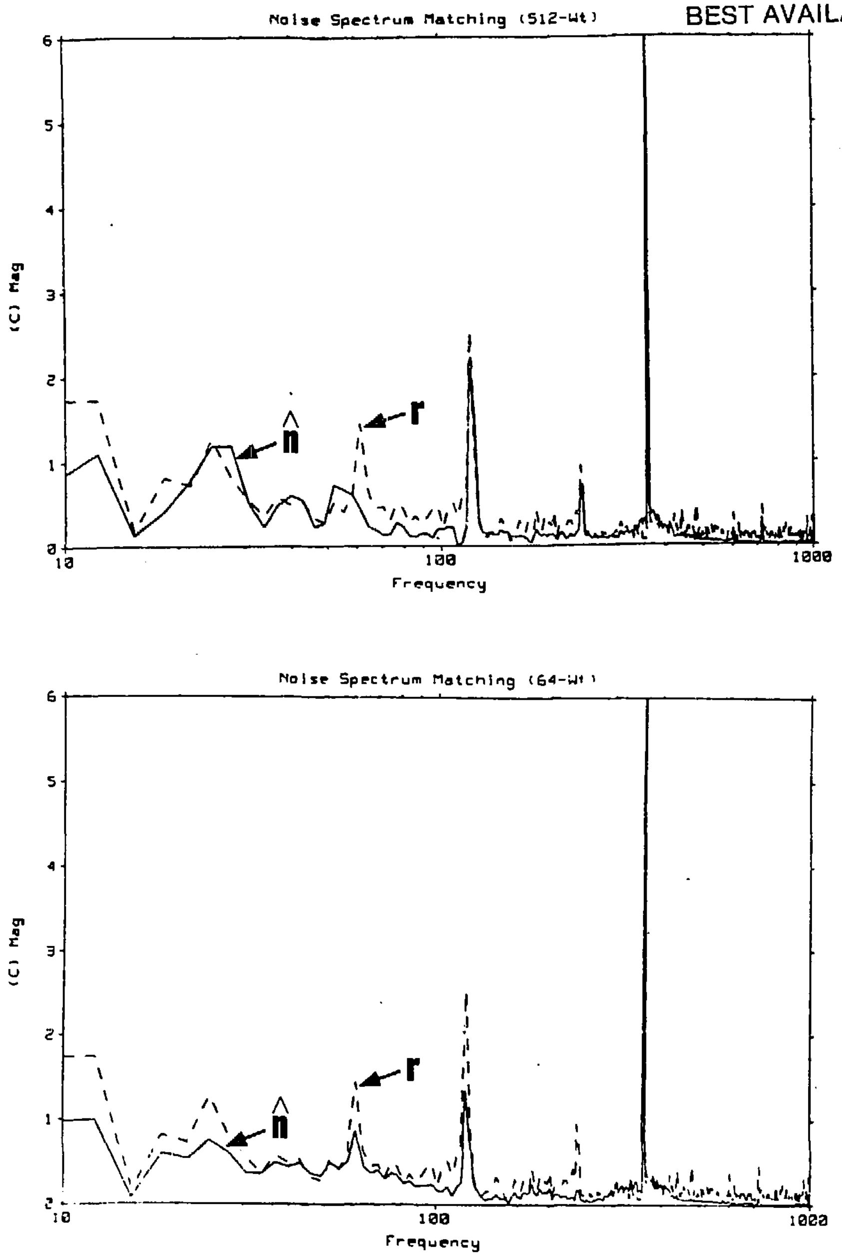

Figure 5 Optimal Noise Spectral Matching: (a) Post Filter; and (b) Real-Time Filter

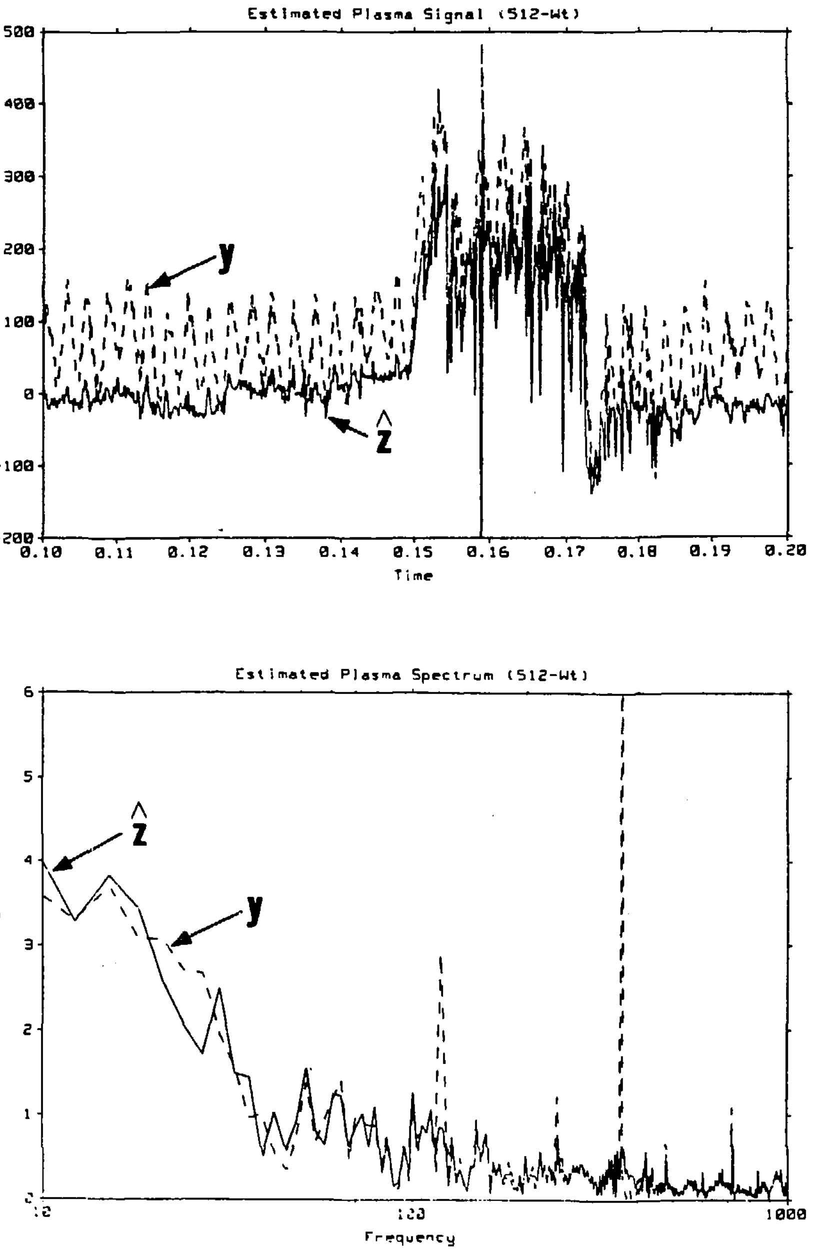

Figure 6 Post-Experiment Noise Canceller Design: (a) Plasma Pulse; and (b) Spectra

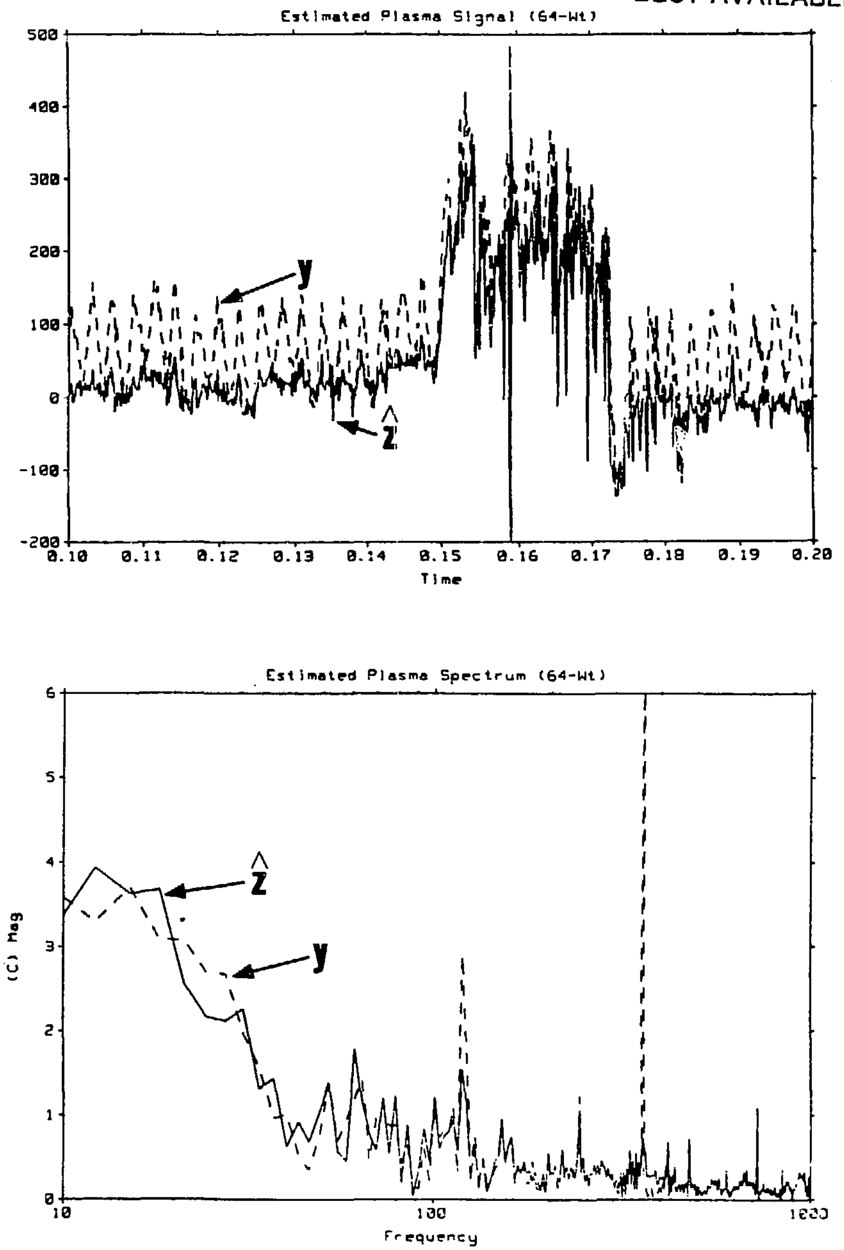

Figure 7 Real-Time Noise Canceller Design: (a) Plasma Pulse; and (b) Spectra

Summary

In this paper we have developed a noise cancelling algorithm using the system identification approach and applied it to the problem of estimating a transient plasma pulse for the magnetic fusion experiment (TMX-U). We have developed solutions for both post-experimental analysis and real-time processing and analyzed the performance of the corresponding processors. More effort will continue in developing processors for the experiments and they will utilize model-based signal processing ideas [19].

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