The Separation of Control Variables in an H⁻ Ion Source*

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Abstract

This paper describes a successful methodology that was used to classify a series of waveforms that were taken as a 100 mA H⁻ ion source at Los Alamos was perturbed by adjusting its control parameters. The series of 260 waveforms was divided into a "training" set and a "test" set. A sequence of mathematical transformations was performed on the training waveform data then it was subjected to discriminant analysis. The analysis generated a set of filters that allowed classification of an unknown waveform in the test set as to which of the control parameters had been perturbed. The probability of successful classification using this methodology was 87%.

Introduction

As accelerator costs continue to rise (e.g., an estimation of several billion dollars for the construction of the Superconducting Super Collider), the cost of an idle facility also continues to grow. Thus, reduction in time spent to tune these machines and bring them into production status will also reduce the operating costs. Further, the use of accelerators in the industrial and medical worlds is on the increase. These machines must be built so they can be operated in simple, straightforward ways. It is unreasonable to expect that machines of the future would require the skills of today's accelerator operators. The first problem that must be solved when automating any device is to discover which of the many parameters that might be real process control parameters are the true process control parameters. This has been a particularly difficult problem with ion sources since the physics of the process itself is not well understood. The approach we take to discover how to control the process is based on an analysis of the consequences of changes to these parameters rather than a firm understanding of the underlying process.

Methodology

A supervisory control system that was built for the High Current Test Stand and that has been reported on elsewhere[1] provided control for the ion source. Waveforms were obtained from eight-bit waveform digitizers which captured 4096 samples of waveform data at a sampling rate of 2 MHz. Four waveforms were synchronously collected: extraction voltage, arc current, arc voltage, and ion beam current. The first three were obtained from power supplies, while the ion beam current was obtained from the output of a Faraday cup.

The data that were gathered characterizes the system in various modes of stability. We were constrained by prior design to use as control parameters the three that had been instrumented: arc voltage, hydrogen gas flow rate, and the plasma chamber temperature. All beams were extracted at 14.5 kv.

The 4X ion source[2] was brought to an operational point by an experienced ion source physicist. He then manually controlled each of the three parameters, one at a time, in both the positive and negative direction from the optimal point until either a plasma instability was reached or the power supply being changed had reached the limit of adjustment. After most of the changes, the four waveforms mentioned above were acquired and stored. In fact two sets were acquired at each point to provide for both the training and the test sets. This provided 260 sets of four waveforms, which were used in the subsequent analysis.

Data Analysis

Visual inspection of the waveforms seemed to indicate a plethora of information. The technique of choice was to subject the training set to discriminant analysis, which would generate a vector that would group the waveforms into the three sets as we indicated they should be grouped. This vector would then be applied to the test set to see how well it per-

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formed on a set of unknown data. Since our concern was with the identification of waveforms during the arc pulse, we decided to include in the analysis 2500 points of the 4096 obtained in a waveform which was just that data obtained while the arc was on. Figure 1(a) shows a representative sample of a waveform of the arc-voltage when the source was operating in its optimal region. The 2500 points mentioned are indicated by the two vertical lines in 1(a). In the Fourier transform of the arc-voltage, we found a great deal of broadband process noise that interfered with the analysis. This broadband noise indicates that the arc voltage is randomly distributed with respect to time so we removed time from the data by generating a histogram of the amplitudes found in the 2500 point waveform. The histogram corresponding to the waveform shown in 1(a) is pictured in 1(b) in a way that shows the projection of the values of the voltage into the histogram. Because the waveform data came from an eight-bit waveform digitizer, the generated histogram contains 256 bins. The Fourier transform of the histogram was then generated and analyzed using multivariate discriminant analysis. Figure 1(c) is the Fourier transform of the histogram in 1(b). For a theoretical basis of the use of the Fourier transform of a histogram, see Kendall[3]. The SPSS[4] software package provided the discriminant analysis. The Fourier transform is an array of 128 numbers so that what started out to be the analysis of 2500 data points has been reduced to the analysis of 128 data points.

Results

The results of running the analysis using the arc voltage data for discrimination are as follows: for three groups, the training set had a success rate of 96.4%, while the test set had a success rate of 87.0%. These success rates indicate the ratio of correct classification to misclassification of waveforms into the proper sets. Discriminant analysis produces a vector of coefficients called a classification function, one for each group in the training set. The classification function which belongs to a particular group is then multiplied, in an inner product fashion, by the vector of the Fourier transform coefficients. The number produced by this multiplication is a score. The largest score that is produced when the Fourier transform vector is multiplied by each of the classification functions indicates to which group that data set belongs. The number of non-zero elements in the generated classification function which is, by the way also the dimensionality of the classification function was 20. This means that rather than using all 128 elements of the Fourier transform, the classification uses just 20.

Figure 2 shows a scatter plot of how the discriminant functions group the waveforms. A visual inspection of all of the raw waveforms that were misclassified shows that in almost every case one can see one to several large anomalous voltage excursions in the waveforms. It seems that the discriminant analysis is seeing the variances due to these anomalies and consequently misclassifying the waveforms. It is also worthwhile to reemphasize that the classification into these groupings can be done from information extracted from the arc-voltage waveform only. For the purposes of control, we need to monitor just that one waveform and monitor it in a noninvasive manner.

Conclusions

We have developed a method, using discriminant analysis, that allows us to noninvasively monitor a single waveform from an ion source and extract
sequent readings. In fact, it seems that if monitoring a source that is subject to the anomalous behavior that we have noted, decisions should be based on several waveforms taken in sequence.

References

[1] R. Wright, "The High-Current Test Stand Control and Data Acquisition System (Steps on the Way to One-Button Control of an Accelerator Source)," Los Alamos National Laboratory Report #LAUR-87-1147.

