STEEL CHARACTERIZATION USING BAYESIAN ANALYSIS OF BARKHAUSEN NOISE

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ABSTRACT. Changes in the crystaline structures of steels (indicative of damage) can be inferred from Barkhausen noise data. Barkhausen noise is created by the random changes of magnetic axis orientation of groups of adjacent atoms (called magnetic domains). Current practice is to examine the noise spectrum by using the Fast Fourier Transform [FFT], averaged over several cycles of magnetization of the sample, to infer damage to the metallic structure (Vokurka, 1982) (Foderaro, 1989). Maximum Entropy spectral estimates of the noise are shown to provide useful information for sample identification. Bayesian analysis is applied to aspects of the identification problem.

1. The Problem

A large class of industrial problems centers on the need to make a decision about the acceptability of a part; often, this decision must be made in very little time, based on less information than could be gathered by a more detailed testing. Some industrial testing of steel uniformity utilizes the Barkhausen effect.

Vokurka observed that the probability of observing a Barkhausen noise pulse was greatest immediately following another Barkhausen noise pulse (while changing the imposed magnetic field uniformly). The longer the interval since the last observed Barkhausen pulse, the less likely is one to observe yet another pulse. The analytic form of the probability density for pulse occurence was determined to be exponential, of form

$$p(\tau|\mathbf{H}) \propto e^{-\alpha\tau} \tag{1}$$

τ = time since last pulse

α = a parameter characteristic of steel domains

$\mathbf{H}$ = hypothesis of probability density having exponential dependence

It is worth noting that this form is convenient for future computations. Either fitting of experimental observations for the probability density of pulse occurence to an exponential

W. T. Grandy, Jr. and L. H. Schick (eds.), Maximum Entropy and Bayesian Methods, 147–152.

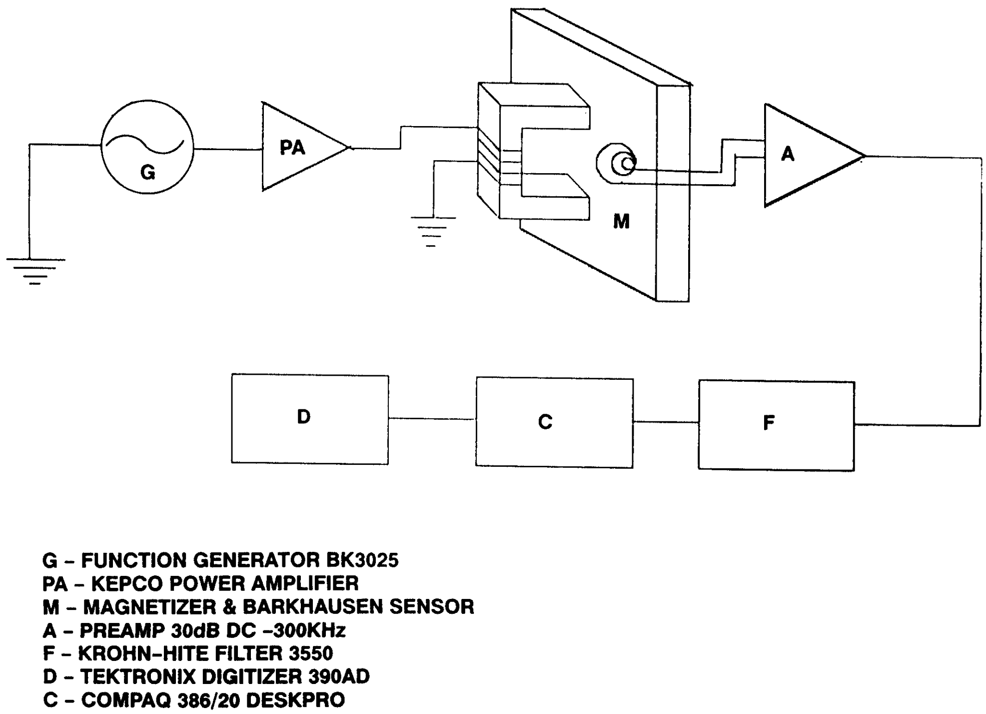

Fig. 1. Apparatus for observing Barkhausen noise.

model (or indeed, using the experimental measurement of pulse density directly) gives us a Bayesian prior.

2. The Method

The apparatus used to observe the Barkhausen noise is described in Figure 1. The magnetic field intensity is impressed upon the steel sample using a low reluctance yoke. The yoke is magnetized by a low frequency current source (below 1 Hertz). An air wound coil serves to pick up the Barkhausen noise. The noise is amplified and passes through a low pass filter to eliminate any aliasing due to frequency components of the signal which are higher than half the sampling frequency of the digitizer. Two sources of data communication, low frequency filtering to eliminate the exciting signal and high frequency filtering to eliminate the aliasing, have been introduced by the filtering.

Unless the high frequency filtering is far above the frequency content of the signal, an apparent decrease in proximate pulses will be observed. This is due to the inability of pulse waveforms to rapidly change amplitude, as a result of the filtering of the signal, rather than the physical occurance of the actual domain transitions.

Though the probability density ties together the correlation function, and indeed the power spectral density, each observation is made with a contamination of the information. The probability density suffers from the instrumentation limitations just mentioned. If we examine all pulse peaks, then the question of whether the pulses arise from the same region (as lower amplitude peaks may originate from more distant regions) is raised. If we restrict ourselves to larger peaks (say, larger than the RMS value of the noise voltage), then the pulses are more widely separated, and the assumed interaction mechanism due to adjacent domain transitions is in question. Further, observing only the peaks throws away information contained in the noise data between peaks. If we use the correlation function instead, then all the data are used. However, correlation is an integrating or smoothing operation, again averaging out information about local variation. Let us first assure ourselves that the noise data, when constrained by experimental low and high frequency cutoffs, still contains useful information.

A curve showing the typical data, and the Fast Fourier Transform of that data (2048 points) is shown in Figures 2 and 3.

It is clear that little information is revealed on the corner frequency of the power spectrum (as shown by the FFT). For that reason, industrial practice is to average together several spectral estimates from Barkhausen noise data sets. In contrast, the Maximum Entropy Method [MEM] of spectral estimation (Burg, 1975) can be used to determine the one pole model for frequency estimation. A curve showing the frequency of cutoff, determined by a single pole MEM estimate, normalized, for 20 samples of steel, is shown in Figure 4. The frequency determination is based on 2048 points, also.

From the grouping of samples, we see that we have an easily computed parameter which differentiates between sample groups. That information is contained in the data is evident from the grouping. Though the information is imbedded in the data, it is spread throughout the data.

If we apply Bayes's theorem to answer the question, "what is the parameter α that best describes the hypothesized exponential probability density?", we get a very precise answer. The result, shown on a logarithmic scale in Figure 5, appears as a delta function. Though the value is precisely determined, the parameter α shows little variation (less than 5%) among all 20 samples. Whether one examines the probability density versus interval separation for all peaks or just major peaks, only small variations of the probability density are observed between samples. A similar observation is made if the correlation function is used in lieu of the probability density function. A tight fit to a simple model is possible, but little differentiation between samples results. The reason is partly due to the loss of information previously discussed. A more important reason is the failure to ask the proper question. The question should not have been "what is the best parameter value for the model?", but instead, "given the data represented by the other 19 samples, which fall into 4 known classes of samples, what is the probability that the given sample came from class 1, 2, 3, or 4?" Bayes's theorem (Bretthorst, 1988), for the case of the probability density of sample #1 being tested for belonging to class 2 is:

$$p(\mathbf{H}|D,I) = p(\mathbf{H}|I)p(D|\mathbf{H},I)/p(D|I)$$

where $\mathbf{H}$ = hypothesis that sample #1 was extracted from the class described by samples 6, 7, 8, 9, and 10 (*i.e.*, class 2) I = the prior information of Barkhausen probability density

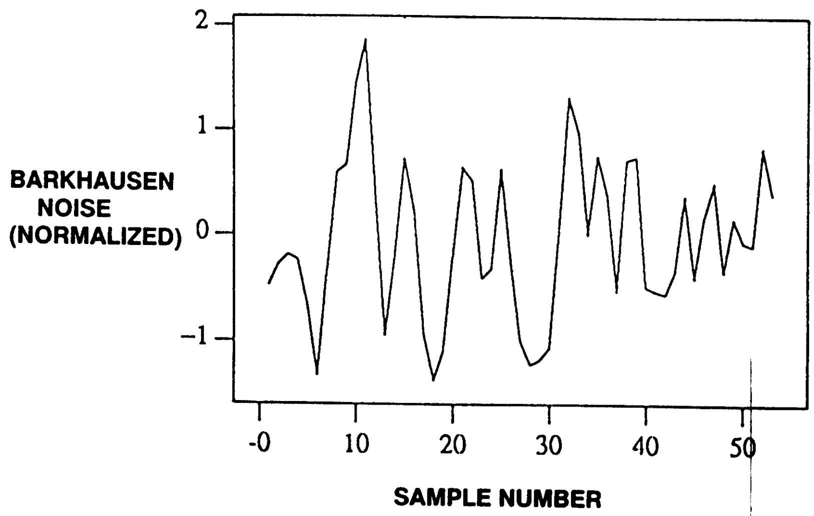

Fig. 2. Typical data curve.

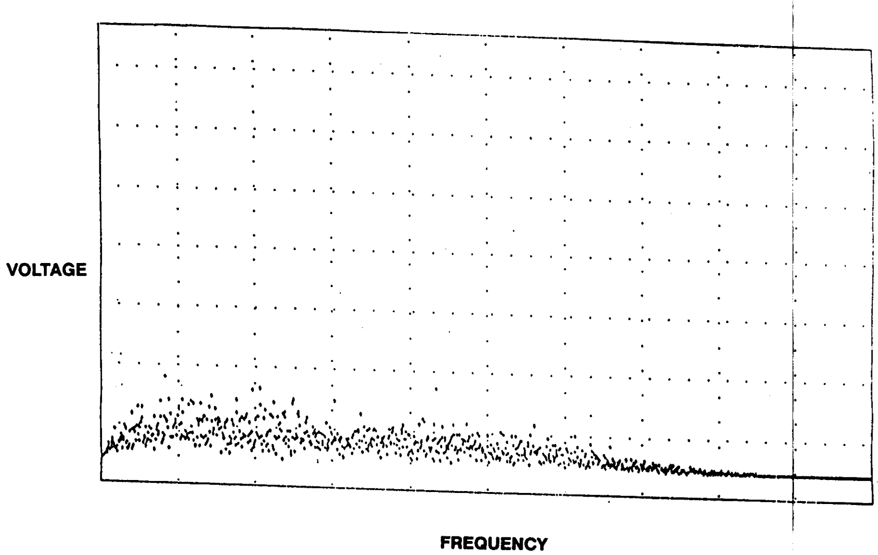

Fig. 3. FFT of the data.

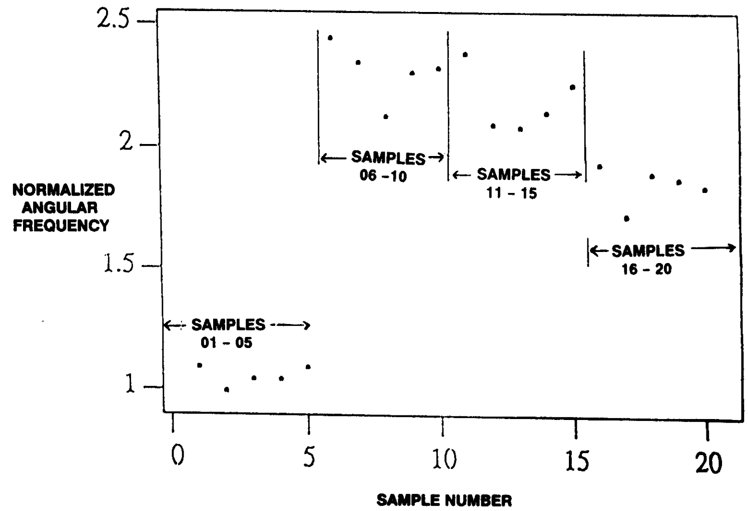

Fig. 4. Curve showing the cutoff frequency.

form. D = the data, is taken as the observed density of pulses versus interval between pulses. Substituting for a gaussian dependence of $p(D|\mathbf{H},I)$ as the least restrictive assumption,

$$p(D|\mathbf{H},I)\frac{1}{\sqrt{2\pi}\sigma}\, e^{\frac{-\Sigma(d_i-f_i)^2}{2\sigma^2}} \tag{2}$$

where σ = standard deviation of the sequence $(d_i - f_i)$.

The function, f, against which the data are compared, is the Bayesian prior (the average measured pulse density for samples 6, 7, 8, 9, and 10). Here, the Bayesian prior serves as both the prior (of course) and the function against which the data are compared. Since the last term, $p(D|I)$, is independent of the hypothesis, $\mathbf{H}$, we can concentrate on the proportionality

$$p(D|\mathbf{H},I) \propto p(\mathbf{H}|I)p(D|\mathbf{H},I). \tag{3}$$

We convert the proportionality to an equation by noting that 100% of the samples must fit the 4 classes, as no other choice is offered. All terms are now known. The probability density measured (averaged) for each class of samples serves as the Bayesian prior. The data is the computed probability density for the given sample. The standard deviation, σ, is computed for the difference of data compared to the prior. This is repeated for each class of objects. Though the probability density contains only a few (6, typically) non-zero values, correct sample class identification is obtained in 2/3rds of the cases. Perhaps one can attribute this poor showing (compared to our hopes) to the paucity of information in the probability density curve, rather than a weakness of the analytic approach. However, high speed computation and decision making have been objects of this study. With limited non-zero data, limited computational effort is required, allowing these results to be achieved rapidly.

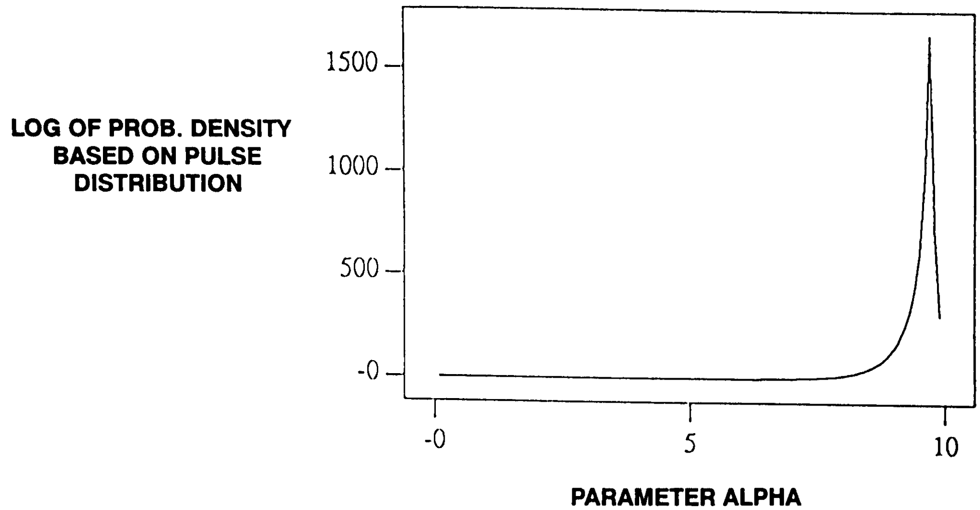

Fig. 5. Logarithmic plot of α.

3. The Conclusion

The frequency content determination using Maximum Entropy worked reasonably well; the use of the probability density curve was marginal in practice. Some better combination of parameters, all derived from the Barkhausen noise data, are needed to make rapid decisions in real time. What was shown is significantly better than current industrial practice. Room for much improvement remains.

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