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Level-Independent Detection of Signal Saturation in Sensor Data

Terry E. Riemer, Marc W. Losh, and Russell E. Trahan

Department of Electrical Engineering, University of New Orleans, Lakefront, New Orleans, Louisiana 70148

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A new technique has been developed which accurately identifies signal saturation in sensor data regardless of the level at which it occurs. This capability is of particular value when sensor or preamp/signal conditioner saturation is a possibility, which may cause clipping to appear at some unanticipated voltage level. In addition, the sensitivity of the technique may be adjusted to identify clipping which exhibits some variability, such as when soft limiting is used. This method may find application in either a digital or analog implementation; a digital signal processing approach is demonstrated here. This technique does not require any *a priori* knowledge of the amplitude dynamics of the signal.

1. INTRODUCTION

When processing digitized data, the problem of signal saturation is one which must be addressed either by the analog signal processing equipment, which may be designed to minimize or eliminate clipping prior to digital conversion, by a software preprocessor, which must obviously be relegated to the role of detecting clipping, or, preferably, by a combination of both. This becomes especially necessary in instances where the signal is subject to a wide amount of variability in dynamic range. Clipping may also be deliberately incurred as the cost of taking maximum advantage of the resolution capabilities of the analog-to-digital (A/D) converter.

To date, efforts to detect the occurrence of clipping have been minimal, at best [1–4]. Typically, software clipping detection techniques consist of a simple check for the A/D converter rail voltage (upper and lower A/D converter quantization limits). This approach assumes that clipping will only occur in the input section of the A/D converter, an assumption which is incomplete. Clipping may occur at any stage in the signal path, including the sensor itself, or the sensor signal conditioner, and thus may manifest itself at any voltage level within the excursion range of the signal.

Furthermore, in the case of signals with a broad dynamic range, soft limiting is sometimes employed just prior to the A/D converter input section to protect the converter from excessive voltage excursions which may damage it and to prevent saturation of the input stage. To do this, the soft limiter will usually be adjusted so that its output will remain just within the resolvable input capability of the A/D converter [5]. Figures 1 and 2 illustrate the nature of the problem under discussion. These figures are taken from an undistorted analog recording of a rock group which was sampled and then clipped by a software routine designed to simulate soft clipping. The remaining illustrations in this document are based on this data.

2. DEVELOPMENT AND DESCRIPTION OF METHOD

To detect data anomalies such as those described above, a software preprocessor was developed [6] which proved quite effective in identifying clipping, even that caused by soft limiters, which introduce some variability in clipped signal regions. At the outset, several design considerations were felt to be important.

First, the clip detection technique should be able to detect clipping at any voltage level where it occurs. The problem with using a simple voltage level detector is that clipping may occur at any stage in a signal

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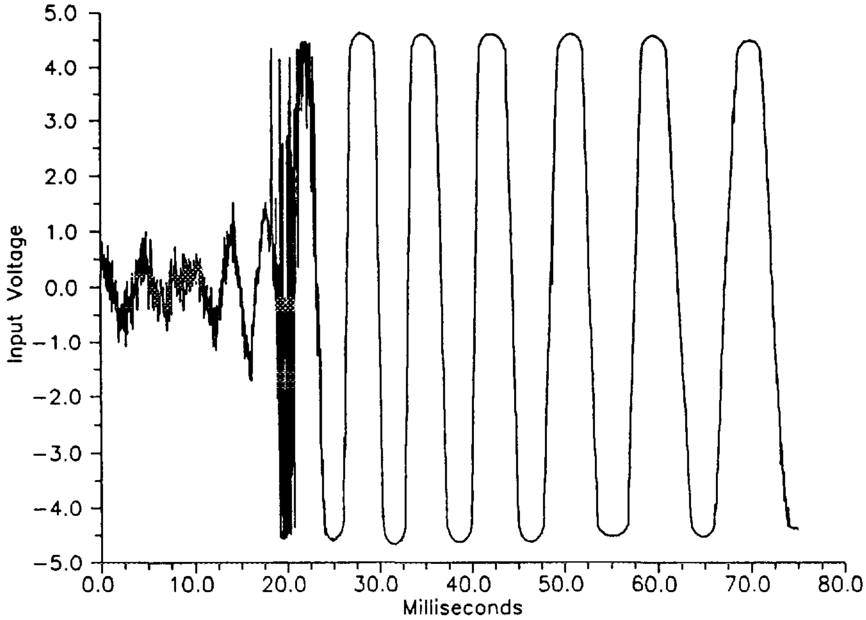

FIG. 1. An example of clipped digitized audio data.

path and, thus, the level where clipping will occur cannot be predicted. Furthermore, setting such a level, even one at or near the rail, will inevitably flag perfectly good data as being clipped. Secondly, the software must be able to distinguish between a clipped signal region and a region in which a signal is merely undergoing little change. A detection scheme which simply looks for small changes in voltage per unit time will not be able tell the difference between a signal which is actually clipped and one which is merely temporarily exhibiting little dynamic activity.

Further complicating the clip detection process is the use of soft limiting to prepare the signal prior to sending it to the A/D converter. It is not unusual for data clipped by soft limiting to exhibit variability of as much as 0.1 V (for a signal which occupies more than 50% of the dynamic range of an A/D converter with an input capability of ±10 V). Obviously, this poses a problem of significantly more difficulty than the detection of hard clipping alone.

To accommodate these considerations, the preprocessor was designed to pass digitized data through

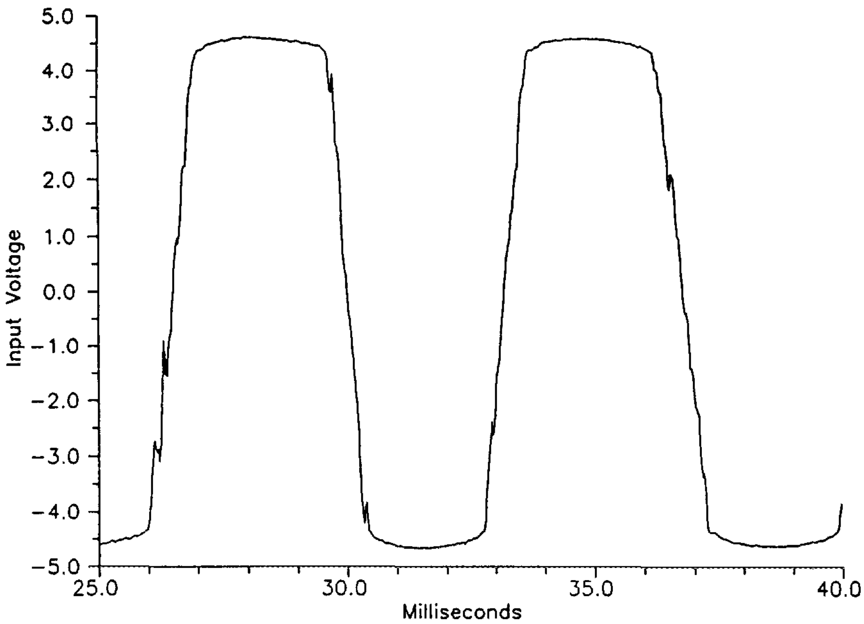

FIG. 2. A closer examination of a section from Fig. 1 showing the nature of the clipping problem.

four distinct blocks (Fig. 3). These blocks will be discussed in detail later, but a brief discussion of each first will provide an overview of the technique. Block 1 could best be described as a differentiation type operation. It was found that an ideal differentiator, the $j\omega$ operator, introduced unacceptable oscillations in the resulting time derivative of the signal. The method developed here, while not an ideal differentiator, performs suitably without oscillation.

Block 2 normalizes the resultant derivative from the first block to a value which is determined to bound the amount of variability encountered in suspected clipped regions. Thus normalized, the derivative is then raised to a high power. The effect of normalization and exponentiation in this fashion is to drive those derivatives from signal regions which are clipped closer to zero, while greatly augmenting derivatives of regions of unclipped signal, thereby simplifying the detection process.

Block 3 examines the treated derivatives for sequences where the average value is below the variability bound, recording such sequences in a histogram of clip candidates. As the data is processed, a histogram is compiled of the number of clip candidates at each quantization level, and a separate record is kept of where they occur in the data. The histogram is employed as a mechanism to exclude good data which exhibit clip-like features from being classified as clipped. Examples of such clip-like features are the plateaus and ledges which routinely occur in signals which may be modelled as a sum of random processes.

Upon completion of all derivative computation and processing, Block 4 performs analysis of the histogram. First, it determines the existence of clipping events by examining the normalized probability density function developed from the histogram for regions where there are statistically significant concentrations of clip candidates. If such concentrations cannot be found, it is concluded that clipping did not occur. If clipping is determined to exist, those quantization levels corresponding to the clipping concentrations identified in the density function would be flagged, and only clip candidates quantized at those levels would be excluded from further processing. A clip detection method using a differentiator without a histogram would result in significantly more good data being flagged as clipped than the method which incorporates the histogram.

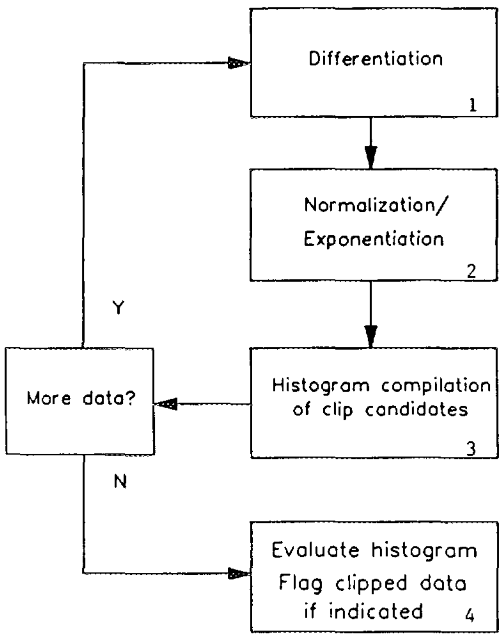

FIG. 3. Block diagram of the data clip detection algorithm.

2.1. *Differentiation*

The differentiation process itself, as previously mentioned, is not ideal differentiation when viewed in the frequency domain. The $j\omega$ operator yields an infinite impulse response. To minimize the high frequency oscillations which appear around signal time discontinuities, while simultaneously preserving the linear slope of the differentiator in the frequency range of the signal, a filter block is needed which performs approximate differentiation with a finite impulse response.

An examination of the difference equation

$$y(k) = \frac{1}{T}[x(k) - x(k-1)], \tag{1}$$

where $y(k)$ is the differential, $x(k)$ is the signal, T is the sample time interval, and k is the sample time, yields a Z-domain transfer function,

$$H(z) = \frac{1}{T}[1 - z^{-1}]. \tag{2}$$

The frequency response of $H(z)$ may ultimately be expressed as

$$H(e^{j\omega T}) = j\omega\left(\frac{\sin(\omega T/2)}{(\omega T/2)}\right)e^{-j(\omega T/2)} \tag{3}$$

or

$$H(e^{j\omega T}) = j\omega \operatorname{sinc}\left(\frac{\omega T}{2}\right)e^{-j(\omega T/2)}. \tag{4}$$

For small ωT, the sinc and exponential terms in (4) are near one and $H(z)$ provides a reasonable approximation for a perfect differentiator, $j\omega$, as may be seen in Fig. 4. This accomplishes the necessary time differentiation of the signal. For signals with broad spectral content, the approximation becomes less accurate, but this is not of particular concern. Clipped regions generally possess mostly low frequency spectra, and the assumption of ωT being small is satisfied. Thus, in these regions the numerical differentiator in (1) is a good approximation to an actual differentiator and so fall under the linear region of the differentiator.

The simple first order differentiator approximation given in (1) can be even further simplified by normalizing the sample time T to a value of one. This effectively scales the derivative by the value of T. However, this has no effect on the use of the derivative values. All of the data presented here have been processed with an assumption of $T = 1$ s.

A high frequency spectral region corresponds to an unclipped time signal region, by definition. The pseudodifferentiator of equation (1) is much more computationally efficient than a true differentiator. A more accurate approximation to the differentiation process requires many more terms than (1); however, this first order difference equation yields good results. A result of using this differentiation technique on the data of Fig. 1 is shown in Fig. 5. Note that the clipped regions yield differentials which are small, but nonzero.

2.2. *Normalization and Exponentiation*

The method developed to process the derivatives is meant to exaggerate the differences between clipped and unclipped data. The result of this stage may be expressed as

$$\left[\frac{|y(n)|}{\beta}\right]^{\rho}, \tag{5}$$

where $y(n)$ is the differential from Eq. (1) and ρ is the integer exponent to which the normalized differential is raised. β is an empirically determined parameter which is found by examining clipped data generated by the system being used for the maximum voltage difference between adjacent sampled data points. The absolute value of this figure is defined to be the *variability bound,* β.

The choice of the bound to which the differential is normalized is one determinant of the overall clip detection sensitivity. If known clipped data were differentiated and, separately, known good data were also differentiated, with the resulting absolute values of the respective derivatives plotted together on a histogram, two distributions would be observed. In systems with only hard clipping, an impulse would appear at or very near zero for the clipped data derivatives, with the unclipped data derivatives having some multirate distribution. In most cases, however, some variability will occur in the clipped data, with a corresponding expansion of the distribution of associated derivatives. There will be some overlapping of these two distribution regions, as illustrated in Fig. 6.

The selection of the bound will result in the initial classification of those derivatives of lesser value as clipped and those derivatives with greater value as unclipped. It may be seen that the more positive the bound, the more sensitive the clip detection. The cost of establishing the bound too great is increased iden-

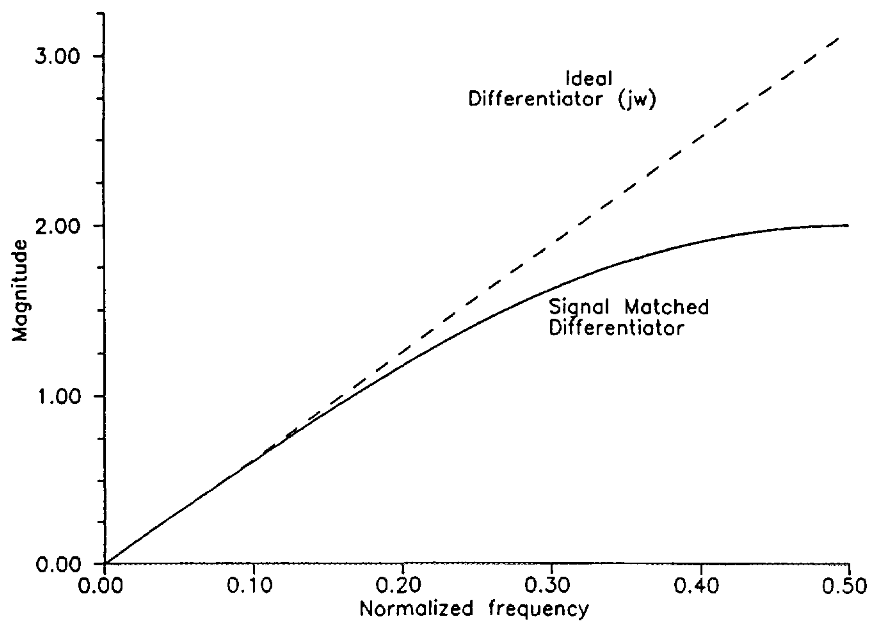

FIG. 4. Frequency response of the difference equation compared with that of an ideal differentiator, the $j\omega$ operator.

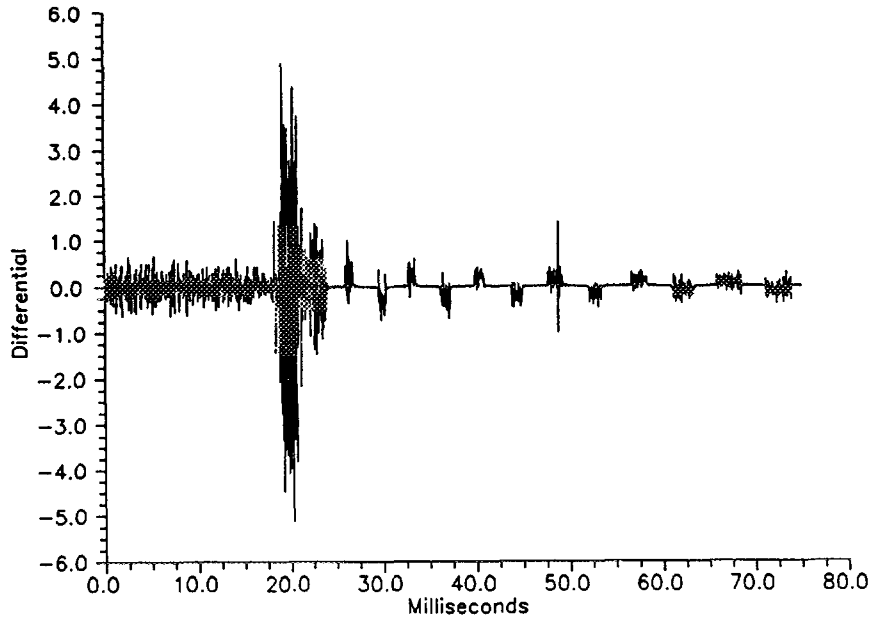

FIG. 5. Differentiated audio data from Fig. 1.

tification of good data as clipped. On the other hand, establishing the bound too small results in an increase in the amount of clipped data identified as good. The selection of the bound is a critical step in the process of clip detection.

Selection of the exponent to which the normalized differential is raised is important, but somewhat less critical than the determination of the variability bound. Generally, the value of the exponent should not be any higher than necessary due to the high computational cost of exponentiation. This step has the effect of driving the values of subbound differentials (differentials below the value of variability bound, β) closer to zero while greatly increasing the values of the overbound differentials. In conjunction with a clip window, described below, this step better defines the edges of clipped signal regions, with a resultant improvement of classification performance. The effect

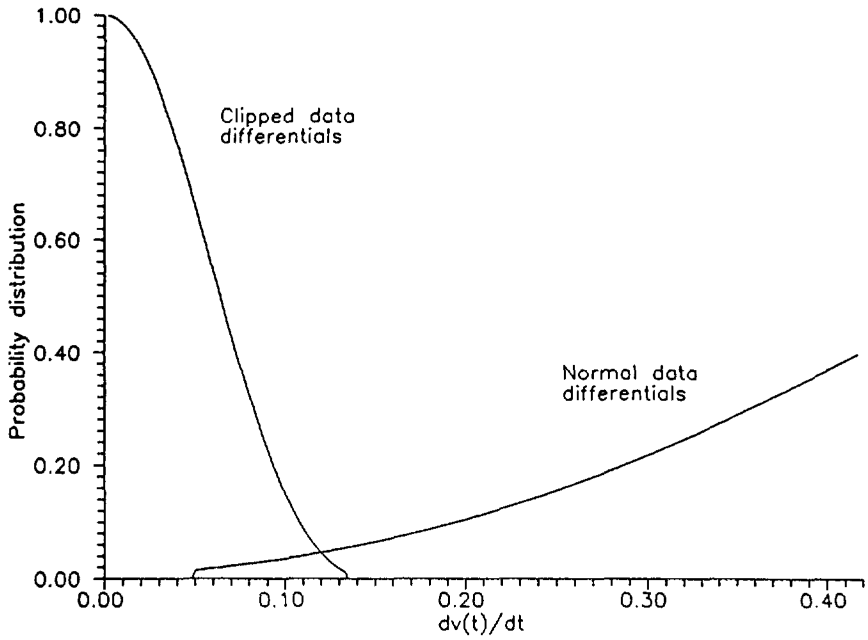

FIG. 6. Distributions of normal and clipped data differentials. Selecting the variability bound within the area of distribution overlap leads to a tradeoff of clip detection sensitivity vs classification of good data as clipped.

of this process is shown in Fig. 7, which is the result of normalizing and differentiating the differentials shown in Fig. 5.

As mentioned previously, the histogram is used to minimize the erroneous classification of unclipped data as clipped. Let $\{x(k), k = 1, \ldots, N\}$ be the set of data points comprising a digitized unclipped audio signal. The subset of $\{x(k)\}$ which contains those points which produce differentials of less than β is defined by

$$\mathcal{S} = \{x(k), x(k-1) \| x(k) - x(k-1)| \leq \beta\}. \quad (6)$$

A histogram is compiled from subset $\mathcal{S}$ and the corresponding subset of data points from clipped data which produce subbound differentials (SBDs). If analysis of the histogram determines that clipping occurred (by finding significant nonnormal behavior at the extrema of the probability density function computed from the histogram), data points which produced SBDs and were digitized at the quantization levels where clipping was determined to occur are flagged to exclude them from further processing. The elements of subset $\mathcal{S}$ which will fall into this class (i.e., good data points which will be classified as clipped) can be defined as subset Q where

$$Q = \{x(k) \in \mathcal{S} \mid |x(k)| \geq q_0\}. \quad (7)$$

The parameter q_0 is the minimum quantization level where the onset of clipping is detected. The probability that good data will be classified as clipped is found by integrating the probability density function (pdf) computed for subset $\mathcal{S}$ from q_0 to the end of the pdf. The probability that a pair of unclipped data points will be contained in subset $\mathcal{S}$ may be expressed as

$$P_r\{x(k), x(k-1) \in \mathcal{S}\} = P_r\{|x(k) - x(k-1)| \leq \beta\}. \quad (8)$$

Further, the probability that such data will fall in a quantization region that ultimately will be flagged as a region where clipping occurs is (assuming zero mean, normal distribution for good data, and that clipping will occur at the maximum and/or minimum quantization regions of the distribution)

$$P_r\{x(k), x(k-1) \in Q\} = \frac{1}{\sigma\sqrt{2\pi}} \int_{q_0}^{q_{max}} e^{(-q^2/2\sigma^2)}\, dq, \quad (9)$$

where q_0 is the minimum quantization level for a distribution concentration where clipping is detected, q_{max} is the maximum quantization level of the clipped distribution concentration, and σ^2 is the variance of the pdf of the $x(k) \in \mathcal{S}$. For the lower end of the distribution, the integral limits become q_{min} to q_0. From this discussion, it can be seen that use of the histogram reduces the amount of data lost due to false classification.

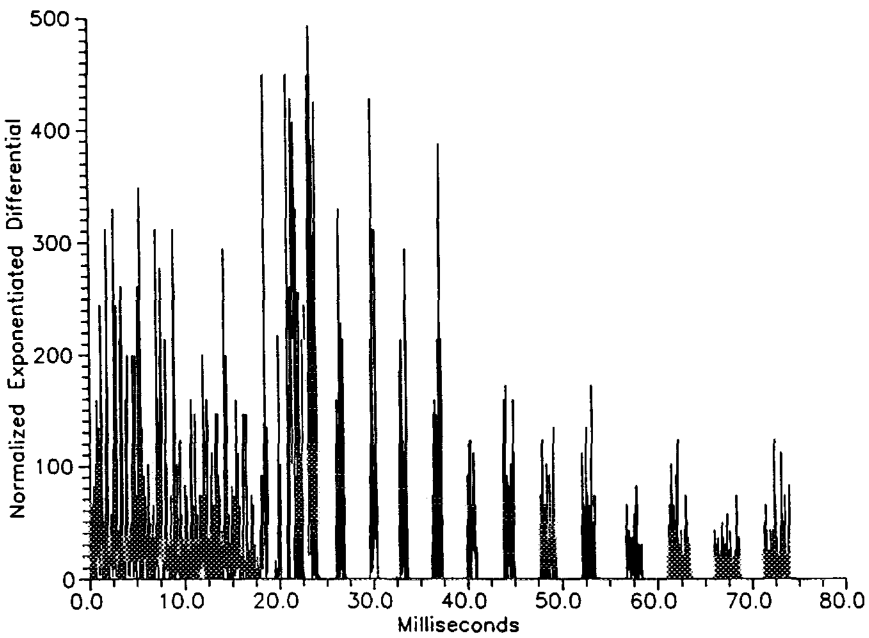

FIG. 7. Normalized and exponentiated differentials computed from data of Fig. 1.

2.3. *Compiling the Histogram*

By incrementing a sum at the related quantization level each time an SBD occurs, a histogram may be compiled of all such detections for the data. Clipping will occur in a relatively limited range of values at the excursion extrema, while the SBD's of good data, assuming a zero-mean random process, will span the range of quantization levels used in the digitization process in decreasing concentrations from zero. Thus, only a small percentage of SBDs from good data will fall in quantization levels where clipped data SBDs occur.

Admission to the histogram may be further restricted by utilizing a clip window whose boundaries define the minimum number of contiguous data points which can constitute a clip candidate. This window is used to examine the normalized and exponentiated (or "processed") derivatives. The probability that any two adjacent points in an unclipped portion of an audio signal may differ by an amount less than the variability bound cannot be based on an assumption that the amplitudes of adjacent sample points are statistically independent of each other. However, an approximation of the probabilities can be realized by assuming statistical independence between sample intervals. The probability of a classification error as defined in Eq. (8) for a single point is upper bounded by β for a single interval. Thus, by multiplying the individual probabilities of classification error for each interval by $(n - 1)$ adjacent intervals an approximation of the probability that a contiguous sequence of unclipped data points may be classified as clipped is given by

$$P_r\{x(k), \ldots, x(k-n) \in \mathcal{S}\} = [P_r\{x(k) - x(k-1) \leqslant \beta\}]^{n-1}, \quad (10)$$

where n is the number of contiguous data points associated with the clip window. While the actual probability may be somewhat greater than the probability given by Eq. (10), it is clear that the use of a window dramatically reduces the chances of classifying good data as clipped for a given β. Thus, the variability bound may be established, with some confidence, such that it is just greater than the maximum amount of variability present in clipped data.

As the window is moved along the processed derivatives, associated data points would not be considered clip candidates unless the average of all processed derivatives within the window was subbound. Implicitly, the window would be wider than one differential, so, under this consideration, single SBDs would not be compiled in the histogram unless the adjacent data points yield processed derivatives which are near enough to the bound to produce an average which, in combination with an SBD, is subbound.

Considerations for choosing the number of adjacent points which constitute a clip would include the frequency content of the signal and the sample rate, as well as the recovery time of the amplifier stages from a saturation condition and the type of clipping encountered. The fact that any two adjacent data points may differ by an amount less than the bound of variability has little impact on the signal characteristics, and no harm is done by assuming that any single occurrence of an SBD is associated with good data.

2.4. *Evaluating the Histogram*

As previously mentioned, evaluation of the histogram involves identifying statistically significant distributions of SBD concentrations and flagging the associated quantization levels to exclude clip candidates quantized at those levels from further processing. This may be accomplished by computing a normalized probability density function from the clipping histogram and examining it for significant values. A normalized probability density function (normalized in that it possesses unit area), as shown in Fig. 9, is easily found by differentiating the probability distribution function (Fig. 8) of clip candidates, which is itself computed from the histogram. Figures 8 and 9 were compiled from data from which Fig. 1 was taken. Use may be made of the fact that clipping occurs at the maximum and/or minimum quantization levels to exclude interior distributions from consideration as clip levels, if necessary. Figure 10 shows the results of applying the algorithm to the data of Fig. 1.

3. RESULTS AND CONCLUSIONS

This technique was implemented on audio data digitized at a 44.1-kHz sample rate. The original data was a recording of a track which was subsequently processed by a routine based on the arctan function to produce simulated clipping in the signal. Examination of the data showed that clipping was occurring at about ±4.6 V, with a variability of up to 0.1 V in clipped regions. The variability bound β was established empirically at 0.021 V. The frequency content of the signal was virtually confined to under 20 kHz. This led to the definition of a clip as being

$$\frac{1}{3} \sum_{j=1}^{3} \frac{|y_{i+j}|^{\rho}}{\beta} \leqslant 1, \quad (11)$$

where y is the differential of Eq. (1). The exponent ρ was set to a value of 4 and was used to weight the

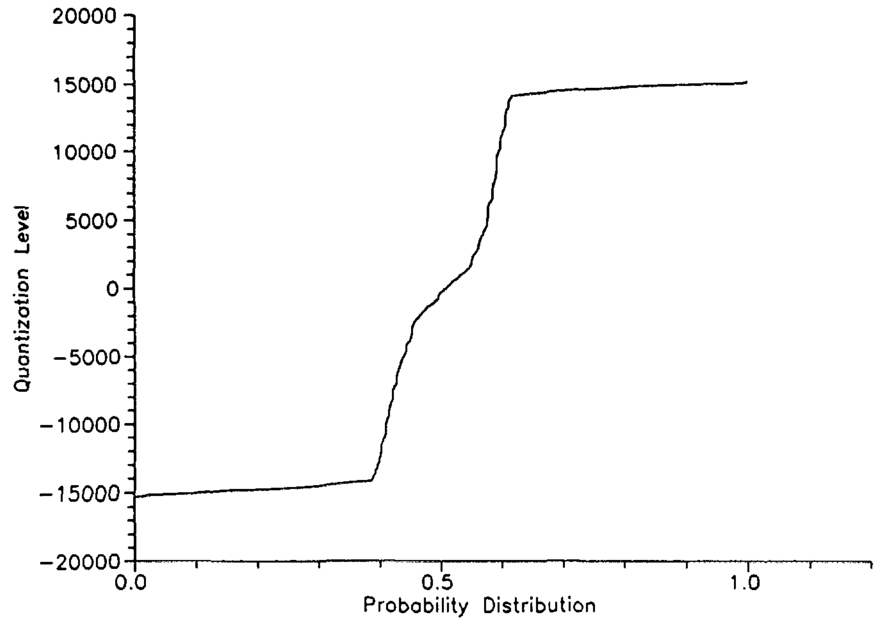

FIG. 8. Probability distribution function computed from histogram.

normalized differential result. The method successfully identified clipped data where it occurred, while not classifying any unclipped data as clipped.

In conclusion, it must be noted that this treatment can be computationally intensive, somewhat militating against its use where clipping is only a minor problem. However, in an effort to get maximum use of the A/D converter's dynamic range, it is often acceptable to incur some significant clipping in order to obtain maximum signal resolution. In cases such as this, especially when the signal is highly variable, some form of clipping detection must be employed if subsequent signal processing is to have any validity. Clip detection does not necessarily have to add appreciably to the duration of the overall process. If digitization is performed on a platform with sufficiently high performance, it would be possible to compile the histogram of clip candidates on line during digitization, leaving only histogram analysis and clip record development to be accomplished upon completion of digitization.

It has been demonstrated that the method presented here vastly outperforms simple level detection. In addition to clipping detection, other possible appli-

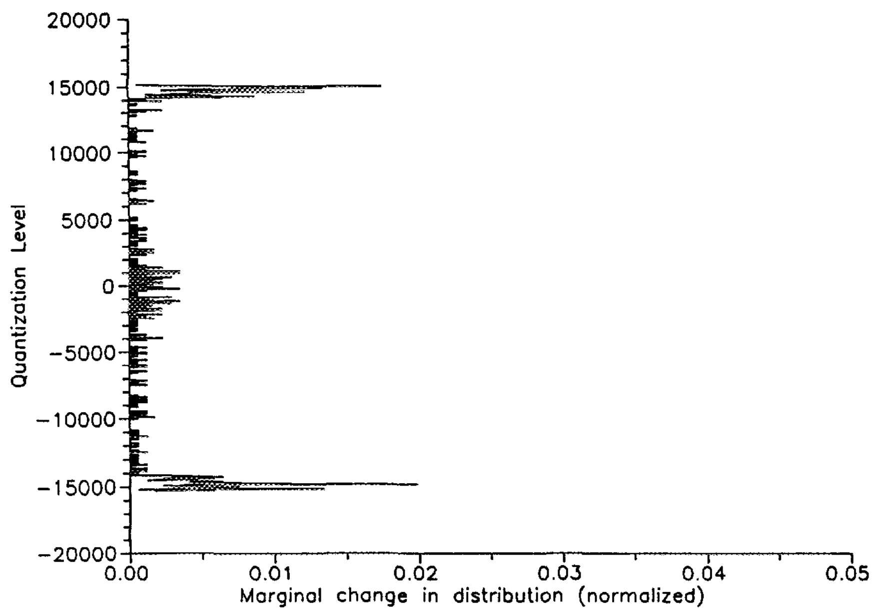

FIG. 9. Normalized probability density function computed from the probability distribution function of Fig. 8.

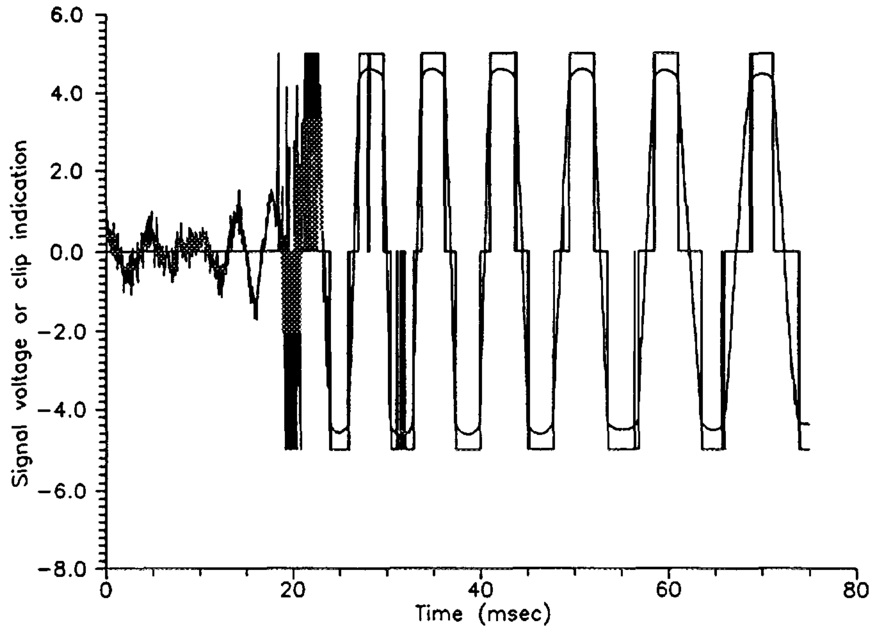

FIG. 10. Results of clip detection algorithm applied to Fig. 1. Levels of 5 or −5 indicate clipping was identified, while levels of 0 indicate unclipping signal.

cations of this technique became apparent. The probability distribution function may be examined for data irregularities aside from clipping.

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RUSSELL E. TRAHAN, JR. received his B.S. and M.S. degrees in engineering sciences from the University of New Orleans in 1970 and 1973, respectively. He received a Ph.D. in electrical engineering from the University of California, Berkeley, in 1977, with a specialization in optimization and control. Since 1977 he has held a faculty position in the Department of Electrical Engineering at the University of New Orleans, and he now has the rank of Professor of Electrical Engineering. In 1980 he returned to the University of California, Berkeley, as a Visiting Assistant Professor. During the summers of 1986 through 1989 he was an ASEE Summer Faculty Research Fellow at the Naval Research Laboratory-Stennis Space Center, MS. His current research interests are in the areas of controls, optimization, and signal processing. Dr. Trahan is a senior member of IEEE and is active in the New Orleans Section of IEEE. He was named the *Outstanding Engineering Educator* in Region 3 of IEEE in 1991. He is also a member of ASEE, ISA, Eta Kappa Nu, Phi Kappa Phi, and Omicron Delta Kappa.

TERRY E. RIEMER received his BSEE and MSEE degrees from Tulane University, New Orleans, Louisiana, and the Ph.D. in electrical engineering from Purdue University, Lafayette, Indiana. From 1970 to 1974 he was a graduate researcher at the Laboratory for the Application of Remote Sensing (LARS), Purdue University, and an instructor in electrical engineering at Purdue University. From 1974 to 1975 he was employed at the Bellaire Research Laboratory of Texaco, Inc., Houston, Texas, where he was involved in the development of seismic data processing algorithms based upon signal and image processing techniques. In 1975 he joined the faculty of the University of New Orleans where he is presently associate professor of electrical engineering. Dr. Riemer's teaching and research interests lie in the areas of audio electronics, analog and digital communications, and the application of digital signal processing techniques to biomedicine, geophysics, speech and audio. He is a member of IEEE, AES, and Eta Kappa Nu.

MARC W. LOSH received the M.S. in Engineering from the University of New Orleans in 1991. He was employed as a research assistant at the Naval Biodynamics Laboratory, New Orleans, LA from June 1990 to August, 1991. He is currently manager of the Network Products Group, Bay Technical Associates, Bay St. Louis, MS. His research interests include signal estimation and digital communications.