EXPLOITING RMS TIME-FREQUENCY STRUCTURE FOR DATA COMPRESSION IN EMITTER LOCATION SYSTEMS

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Abstract: An effective way to locate RF transmitters is to measure the time-difference-of-arrival (TDOA) and the frequency-difference-of-arrival (FDOA) between pairs of signals received at geographically separated sites, but this requires that samples of one of the signals be sent over a data link. Often the available data link rate is insufficient to accomplish the transfer in a timely manner unless some form of lossy data compression is employed. A common approach in data compression is to pursue a rate-distortion criterion, where distortion is the mean-square error (MSE) due to compression. This paper shows that this MSE-only approach is inappropriate for TDOA/FDOA estimation and defines a more appropriate, non-MSE distortion measure. This measure is based on the fact that in addition to the inverse dependence on SNR, the TDOA accuracy also depends inversely on the signal's RMS (or Gabor) bandwidth and the FDOA accuracy also depends inversely on the signal's RMS (or Gabor) duration. The paper discusses how the wavelet transform can be used to exploit this measure.

Key Words: Data Compression, Emitter Location, Time-Difference-of-Arrival, TDOA, Frequency-Difference-of-Arrival, FDOA

1. INTRODUCTION

An effective way to locate electromagnetic emitters is to measure the time-difference-of-arrival (TDOA) and frequency-difference-of-arrival (FDOA) between pairs of signals received at geographically separated sites [1],[2],[3]. The measurement of TDOA/FDOA between these signals is done by coherently cross-correlating the signal pairs [2],[3], and requires that the signal samples of the two signals are available at a common site, which is generally accomplished by transferring the signal samples over a data link from one site to the other site. An important aspect of this that is not widely addressed in the literature is that often the available data link rate is insufficient to accomplish the transfer within the time requirement unless some form of lossy data compression is employed. For the case of Gaussian signals and noises, Matthiesen and Miller [4] established bounds on the rate-distortion performance for the TDOA/FDOA problem and compared them to the performance achievable using scalar quantizers, where distortion is measured in terms of lost SNR due to the mean square error (MSE) of lossy compression. However, these results are not applicable when locating radar and communication emitters because the signals encountered are not Gaussian.

The two signals to be correlated are the complex envelopes of the received RF signals having RF bandwidth B. The complex envelopes can then be sampled at $F_s \geq B$ complex-valued samples per second; for simplicity here we will assume critical sampling, for which $F_s = B$. The signal samples are assumed to be quantized using $2b$ bits per complex sample (b bits for the real part, b bits for the imaginary part), where b is large enough to ensure fine quantization. The two noisy signals to be correlated are notated as

$$\begin{aligned} \hat{s}(k) &= s(k) + n(k) \\ &= [s_r(k) + js_i(k)] + [n_r(k) + jn_i(k)] \\ \hat{d}(k) &= d(k) + v(k) \\ &= [d_r(k) + jd_i(k)] + [v_r(k) + jv_i(k)] \end{aligned} \tag{1}$$

where $s(k)$ and $d(k)$ are the complex baseband signals of interest and $n(k)$ and $v(k)$ are complex white Gaussian noises, each with real and imaginary parts notated as indicated. The signal $d(k)$ is a delayed and doppler-shifted version of $s(k)$. The signal-to-noise ratios (SNR) for these two signals are denoted *SNR* and *DNR*, respectively[1].

To cross correlate these two signals one of them (assumed to be $\hat{s}(k)$ here) is compressed, transferred

[1] SNR (non-italic) represents an acronym for signal-to-noise ratio; *SNR* (italic) represents the SNR for $\hat{s}(k)$.

to the other site, and then decompressed before cross-correlation. Signal $\hat{s}(k)$ has SNR of $SNR_q < SNR$ after lossy compression/decompression [5], and the output SNR after cross-correlation is given by

$$SNR_o = \frac{WT}{\frac{1}{SNR_q} + \frac{1}{DNR} + \frac{1}{SNR_q DNR}} \triangleq WT \times SNR_{eff} \qquad (2)$$

where WT is the time-bandwidth product (or coherent processing gain), with W being the noise bandwidth of the receiver and T being the duration of the received signal and SNR_{eff} is a so-called effective SNR [3]. The accuracies of the TDOA/FDOA estimates are governed by the Cramer-Rao bounds (CRB) given by [3]

$$\sigma_\tau \geq \frac{1}{2\pi B_{rms}\sqrt{SNR_o}}$$
$$\sigma_\nu \geq \frac{1}{2\pi D_{rms}\sqrt{SNR_o}}, \qquad (3)$$

where B_{rms} is the signal's RMS (or Gabor) bandwidth in Hz given by

$$B_{rms}^2 = \frac{\int f^2 |S(f)|^2 df}{\int |S(f)|^2 df}$$

with $S(f)$ being the Fourier transform of the signal $s(t)$ and D_{rms} is the signal's RMS (or Gabor) duration in seconds given by

$$D_{rms}^2 = \frac{\int t^2 |s(t)|^2 dt}{\int |s(t)|^2 dt}.$$

2. NON-MSE DISTORTION CRITERIA

To ensure maximum performance it is necessary to employ a compression method that is designed specifically for this application. However, much of the past effort in developing general lossy compression methods has focused on minimizing the MSE due to compression; furthermore, even compression schemes developed for TDOA/FDOA applications have also limited their focus to minimizing the MSE [4],[5],[7]. But when the goal is to estimate TDOA/FDOA, the minimum MSE criterion is likely to fall short because it fails to exploit how the signal's structure impacts the parameter estimates. In such applications it is crucial that the compression methods minimize the impact on the TDOA/FDOA estimation performance rather than stressing minimization of MSE as is common in many compression techniques.

Achieving significant compression gains for the emitter location problem requires exploitation of how signal characteristics impact the TDOA/FDOA accuracy. For example, the CRBs in (3) show that the TDOA accuracy depends on the signal's RMS bandwidth and that the FDOA accuracy depends on the signal's RMS duration. Thus, compression techniques that can significantly reduce the amount of data while negligibly impacting the signal's RMS widths have potential. We briefly show in the next section that for the TDOA-only case it is possible to exploit this idea through simple filtering and decimation together with quantization to meet requirements on data transfer time that can't be met through quantization-only approaches designed to minimize MSE. These results are encouraging because it is expected that non-MSE approaches more advanced than simple filtering and decimation will enable even larger improvements in performance, and this motivates the results presented in Section 4, where the use of the wavelet transform for exploiting the time-frequency structure of the signal is explored.

3. JOINT DECIMATION & QUANTIZATION

In this section we consider minimizing σ_{TDOA} while adhering to a fixed data link rate constraint. If we consider that the signals are collected for T seconds, then the total number of bits collected is $2bBT$. System requirements often specify a fixed length of time for the data transmission. Thus, if the transfer is constrained to occur within T_l seconds and the data link can transfer bits at the rate R_l bits/second then the total number of bits collected is constrained to satisfy $2bBT \leq R_l T_l$. Equivalently, if we define $R = R_l T_l / T$ as a fixed effective rate and assume equality in the constraint (i.e., fully utilize the allocated data link resources) we get

$$R = 2Bb. \qquad (4)$$

This requirement may be achieved in various ways by selecting appropriate values of B and b, where different values of B would be obtained by filtering and decimating to a lower sample rate, and different values of b would be obtained through coarse quantization. A subtle aspect here is that strict application of Equation (4) implies that bandwidth B is allowed to increase without bound as b decreases; however, the signal itself imposes an upper bound on this bandwidth.

Under this rate constraint, we investigate the optimal trade-off between decimation and quantization. Let the received signals be filtered and decimated to a bandwidth of W_f. After filtering and decimation, the signal to be transmitted is quantized using $2b$ bits per complex sample (b bits for the real part and b bits for the imaginary part).

For simplicity we consider using ideal lowpass filters operating on the complex-valued baseband signal and we do not restrict the decimation factor to rational values, as would be done in practice. Thus, if we choose the filter such that the bandwidth is reduced by some factor γ with $0 < \gamma < 1$ then we can reduce the sampling rate by the factor γ also. Obviously, for practical signals, as we change the filter's cutoff we will change the signal's SNR and its RMS bandwidth; how these quantities change with the cutoff depends on the signal's spectral shape. For simplicity yet insight, we will assume that the signal's spectrum is flat, so that the effective SNR of the filtered signals will not change with the cutoff frequency. In practice though, since the signal's spectrum typically trails off at high frequency, the effective SNR will vary to some degree as the signal is filtered. If the filter has cutoff frequency $W_f/2$, then the RMS bandwidth becomes $2\pi B_{rms} = 1.8 W_f$, the time-bandwidth product becomes TW_f, and the output SNR becomes $SNR_o(W_f) = TW_f \times SNR_{eff}$. The decimated and quantized signal has SNR given by [5]

$$SNR_q(b) = \frac{SNR}{1 + \alpha^2 \; SNR \left(\dfrac{2^{-2b}}{3}\right)}, \qquad (5)$$

where α is the signal's peak factor (i.e., the ratio of the signal's peak value to its RMS value). Using these results in (2), the output SNR depends on the filtered bandwidth and the quantization level according to

$$SNR_o(W_f, b) = W_f T \; SNR_{eff}(b). \qquad (6)$$

Using Equation (6) in Equation (3) gives a bound on TDOA accuracy that depends on the amounts of decimation and quantization, and is given by

$$\sigma_{TDOA}(W_f, b) \geq \frac{1}{1.8\, W_f^{3/2} \sqrt{T \; SNR_{eff}(b)}}. \qquad (7)$$

This result has no constraint on the effective rate; it simply shows the impact of W_f and b on the TDOA accuracy. However, we wish to consider the rate constrained case, so the effective rate constraint gives $W_f = R/2b$, which after use in (7) removes the dependence on W_f and gives

$$\sigma_{TDOA}(b) \geq \frac{2^{3/2}}{1.8 R^{3/2} \sqrt{T}} \left[\frac{b^{3/2}}{\sqrt{SNR_{eff}(b)}} \right], \qquad (8)$$

where it is really the bracketed term that is of interest here, since it shows the tradeoff between decimation and quantization, and can be considered as a decimation-quantization performance factor (for which smaller is better). It is important to remember that (8) includes the rate constraint, so for a fixed R, increasing b necessarily decreases W_f, and vice versa. The nonbracketed term in (8) just scales the result up or down depending on the values of the system parameters R and T.

Finding the minimum of the bracketed term in (8) as a function of b, provides the value of b that optimally trades between decimation and quantization. Note that the value of R does not affect these curves; therefore, the optimal level of quantization is *not* set by the allowable data rate. Once this optimal number of bits b is determined, the appropriate amount of decimation is determined using $W_f = R/2b$, given the allowable effective rate R. To investigate the characteristics of this result we consider the following. Say we have the following signal scenario: α = 3.5, T = 1 s, the signal's available bandwidth is B = 4 kHz, the original signal samples were done with b = 10 bits, the data link rate is R_l = 2.4 kbps and the link time constraint is T_l = 10 s, then the effective rate is R = 24 kbps. Plots of the rate-distortion (R-D) curves for the two cases of (1) *SNR*=30 dB and *DNR*=60 dB, and (2) *SNR*=10 dB and *DNR*=20 dB are given in Figure 1 and Figure 2. R-D curves are given for the cases of using quantization only, decimation only, and joint quantization and decimation.

For the high SNR case in Figure 1 we see that the quantize/decimate method uniformly outperforms both quantize-only and decimate-only (except at rates above 48 kbps where quantize-only and quantize/decimate are equivalent because the quantize/decimate method uses the full signal BW for those rates). It should also be observed that for the high SNR case, decimate-only is better than quantize-only at low rates but not at high rates. Thus, for the high SNR case we see that, both mathematically and practically, the quantize/decimate approach is favored at all effective rates. For the low SNR case, however, the rate-distortion curves in Figure 2 seem to indicate that quantize-only is nearly uniformly preferred over quantize/decimate and decimate-only. However, it is important to recognize that in this case the effective rates at which quantize-only is clearly better are precisely those rates at which the mathematics calls for excessive quantization (below 4 bits) to meet the rate constraint, and the resulting severe nonlinearities can be detrimental to TDOA in ways not captured by (7). Thus, from a practical viewpoint, quantize/decimate is preferred at these lower rates. Stated another way, quantize/decimate gives a viable means for meeting the lower rate constraints without suffering excessive nonlinearity effects from quantization. Thus, even in the low SNR case, the quantize/decimate approach is an effective way to meet the imposed rate constraint. For further discussion of this approach see [6].

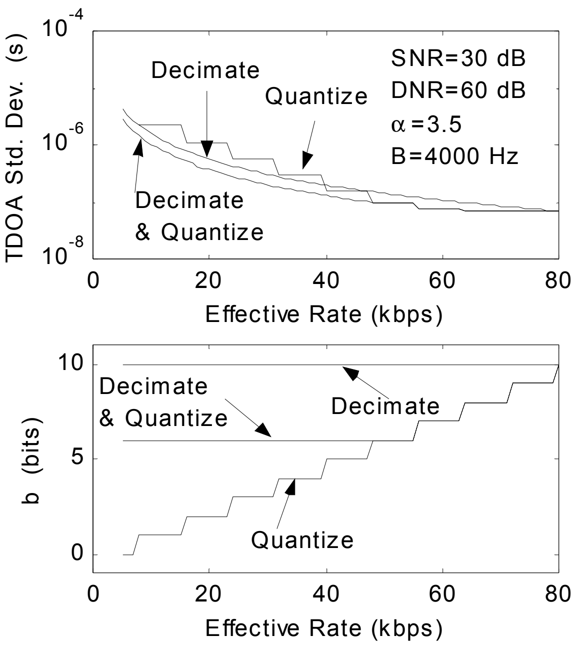

Figure 1: R-D Curve for High SNR

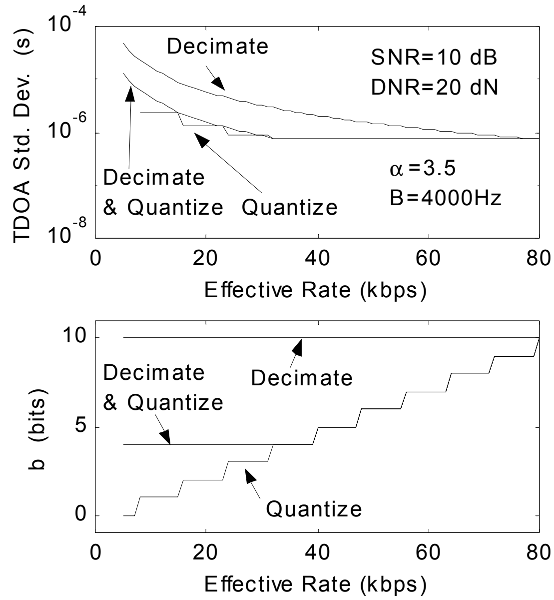

Figure 2: R-D Curve for Low SNR

4. WAVELET TRANSFORM METHOD

Obviously, lowpass filtering and decimation used above is the simplest way to exploit the RMS bandwidth's effect on TDOA accuracy. These results point the way to more general filtering/decimation approaches for TDOA-only as well as the use of the wavelet transform to exploit the joint effect of RMS bandwidth and RMS duration for systems that supplement TDOA with frequency-difference-of-arrival (FDOA).

The wavelet transform has been found to be very useful for signal and image compression [9]. It is an extension of the Fourier transform (FT) in the sense that it provides a decomposition of a signal in terms of a set of component signals. However, the wavelet transform decomposes a signal into a weighted sum of component signals that are localized in time as well as in frequency; this allows them to provide a more efficient representation of signals with time varying spectra. Accordingly, each wavelet coefficient conveys how much of the signal's energy is in a specific time-frequency cell. A simple example of such cells are shown in Figure 3. The rectangles in Figure 3 represent where each of the wavelet coefficients is positioned in the time-frequency plane. A particular characteristic of the wavelet transform is that it yields broad frequency resolution and narrow time resolution at high frequencies while giving narrow frequency resolution and broad time resolution at low frequencies. Thus, the highest frequency wavelet coefficients contain information about the content of the signal in the upper half of the signal's bandwidth; the lowest frequency wavelet coefficients contain information about the content of the signal over its entire duration. Wavelet-based compression based on a MSE criterion exploits the fact that a signal may be concentrated in this time-frequency plane. Signals typically have their energy concentrated in specific areas of the time-frequency plane, while large regions of the time-frequency plane may contain only very little or none of the signal's energy. A small number of bits is then spent encoding these small energy time-frequency regions, while a large number of bits is spent encoding the regions that exhibit large energy concentrations.

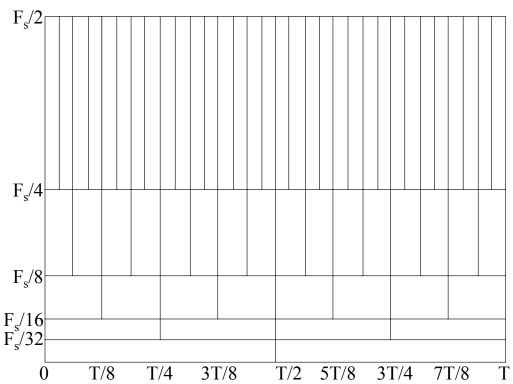

Figure 3: Wavelet Time-Frequency Cells

The wavelet transform compression algorithm [7] consists of breaking the signal into blocks of $N = 2^p$ samples, applying an L-level wavelet transform to each block for $L<p$ (i.e., stopping the cascade of wavelet transform filter bank stages at the level where the filter outputs have $N_B = N/2^L$ elements [9]), grouping the resulting N wavelet coefficients into $K = 2^L$ subblocks of $N_B = 2^{p-L}$ samples each, and adaptively quantizing each of these subblocks. For the complex baseband signals used here, this procedure is applied independently to the real and the imaginary components.

The subblocks of the wavelet coefficients are formed within wavelet scale levels as follows: the $N/2$ wavelet transform coefficients from the first filter bank stage are grouped into 2^{L-1} subblocks of 2^{p-L} coefficients each, the $N/4$ wavelet transform coefficients from the second filter bank stage are grouped into 2^{L-2} subblocks of 2^{p-L} coefficients each, . . ., and finally the 2^{p-L} wavelet transform coefficients from the last filter bank stage form a single subblock, and the 2^{p-L} scaling coefficients from the last stage also form a single subblock.

Each one of these subblocks is quantized with a quantizer designed to achieve the desired level of quantization noise. The choice of these quantizers is made easy by the fact that the wavelet transform preserves energy; this property can be used to show that the proper choice of the quantizer cell width is given by

$$\Delta = \sqrt{\frac{12\ P_x}{SQR}}\ ,$$

where SQR is the desired signal-to-quantization noise ratio and P_x is the power of the input signal $x(n)$ (in this case, either $\hat{s}_r(k)$ or $\hat{s}_i(k)$). Thus, to obtain a desired SQR, the quantizers $\{Q_1, Q_2, \ldots Q_K\}$ should each have a quantization step size given by Δ. Then the number of bits B_k used by the k^{th} quantizer is chosen to assure that the resulting quantizer covers the range of the k^{th} subblock. This leads to the rule

$$B_k = \lceil_0 \left(\log_2 \left[\max\{|W_x^k|\} \right] - \log_2 \Delta + 1 \right),$$

where the maximum is taken over the wavelet coefficients in the k^{th} block and the operator $\lceil_0(a)$ means Athe smallest integer not less than 0 that is larger than a ;@ this means that when the expression in parentheses in the equation for B_k is negative we set $B_k = 0$.

In addition to sending the quantized wavelet coefficients, this scheme requires sending side information to the receiver about the number of bits used for each quantizer as well as the step size used. If the maximum number of bits used by any of the subblocks is B_{max} , then the allowable quantizers are those that use between 0 and B_{max} bits, for a total of $B_{max} + 1$ different quantizers; the number of bits required to specify which of these is used for a specific subblock is $\log_2(B_{max} + 1)$ bits. Since this must be done for each of the K subblocks, we require $K \log_2(B_{max} + 1)$ bits of side information; side information on the quantizer step size also must be sent, which will be no more than the number of bits to which the original signal is quantized (we have assumed 8 bits here). So the total amount of side information is

$$R_{side} = K \text{ x } \log_2(B_{max} + 1) + 8 \text{ (bits)} .$$

Simulations have shown that it is possible to limit $B_{\max}$ to 7 bits.

In this approach, the wavelet transform is used together with bit allocation to provide a means of reducing the number of bits per (real or imaginary) sample with negligible degradation of the TDOA/FDOA accuracy. This scheme accepts a specific desired signal-to-quantization ratio (SQR) and attempts to minimize the number of bits needed to achieve that SQR value. In practice, the desired SQR can be set either (i) to be roughly equal to the estimated SNR of the signal to ensure that the impact of the compression on the TDOA/FDOA accuracy is negligible, or (ii) to some fixed *a priori* value.

An algorithm parameter that can be adjusted is called B_{min}; it is possible to set to zero all values of B_k, as determined above, that are below some specified value B_{min}. This helps to eliminate wavelet coefficients that contain only noise, and thus helps to reduce the amount of information that must be transmitted. Increasing B_{min} causes a larger number of coefficients to be set to zero and can therefore increase the compression ratio with only a small impact on accuracy.

Simulations are used to demonstrate the performance of this wavelet transform method. These simulations also made use of the compression-correction method proposed in [8], in which prior to sending the compressed signal it is cross-correlated with its original version and the location of the peak of this correlation surface is then sent to the other platform where it is subtracted from the peak locations of the surface computed there. Such an approach is very effective at removing bias imparted by the compression method.

The results presented here are for the case of a radar pulse train whose samples between pulses have been removed by a pre-compression detection procedure; timing pointers are also sent to allow reassembling the pulses into their original timing relationships. The pulse trains are complex baseband linear FM signals having a pulse width of 4 µs and a frequency deviation of ±0.7 MHz, and consisted of 4096 samples generated at 4 MSPS using 8 bits/sample for the real samples and 8 bits/sample for the imaginary samples. The signal that was not compressed had an SNR of DNR = 40 dB; the signal that was compressed had SNRs prior to compression in the range $SNR \in [10,40]$ dB.

The wavelet transform method used a transform size of N = 2048 and L = 8 levels. Thus, the number of subblocks per transform was 256, each having 8 samples per subblock. The values SQR = 10 dB and B_{min} = 2 were used.

Figure 4 shows three plots. Each plot shows two curves: using no compression (dashed curve) and using the wavelet transform (WT) compression (solid curve). The first two plots show the achieved TDOA and FDOA accuracies (each normalized by the "no compression" value attained at SNR = 10 dB), respectively, as a function of the compressed signal's *SNR*. The third plot shows the achieved compression ratios vs. the compressed signal's *SNR*. The wavelet method achieved a compression ratio of around 6:1 with a slight degradation in TDOA accuracy but with virtually no degradation in the FDOA accuracy.

The wavelet compression method described above has focused on minimizing the MSE due to compression. However, because the goal is to estimate TDOA/FDOA, the minimum MSE criterion is not the most appropriate one because it fails to fully exploit how the signal's structure impacts the parameter estimates. Because TDOA/FDOA accuracy depends not only on SNR but also on the signal's rms bandwidth and rms duration (see (3)), compression approaches that can reduce the amount of data while negligibly impacting the signal's rms widths are desired. Accordingly, one effect of increasing B_{min} in the wavelet method is to remove small wavelet coefficients that may contribute insignificantly to the signal's rms widths. The wavelet transform approach is a natural tool to enable removing time-frequency components of the signal that contribute very little to the signal's rms widths.

Obviously, it is desirable to find a means to optimally remove time-frequency components so as to maximize compression while minimizing the impact on accuracy. Such a goal is made difficult by the interlinked impact of such removal on SNR and the RMS widths. However, it is possible to demonstrate the potential of such an RMS-width-based approach via an ad hoc removal method. As an experiment we set the odd-indexed quantizer sizes B_k to zero. Because these 256 quantizers are spread throughout the time-frequency plane, this has the effect of creating a (nonuniform) checkerboard-like pattern of zero-valued wavelet coefficients throughout the time-frequency plane. Such an approach ensures that along any vertical line drawn at a time instant, not all of the coefficients are thrown away, and similarly along any horizontal line. Therefore, except for signals with sparse wavelet transforms, this approach should be effective at preserving RMS widths while allowing a large number of wavelet coefficients to be removed.

The signal used here has a normalized RMS bandwidth of 0.15 and a normalized RMS duration of

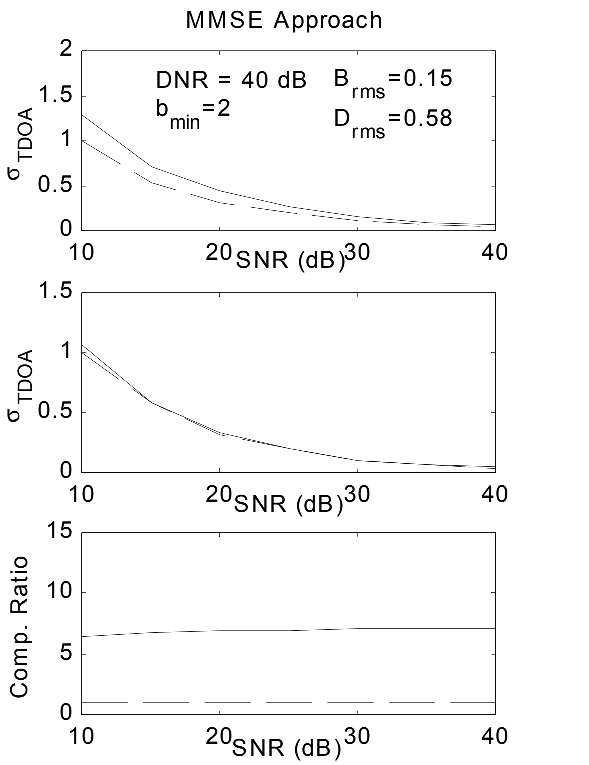

Figure 4: MSE-Based WT Method. Solid = WT Results; Dashed = No Compression

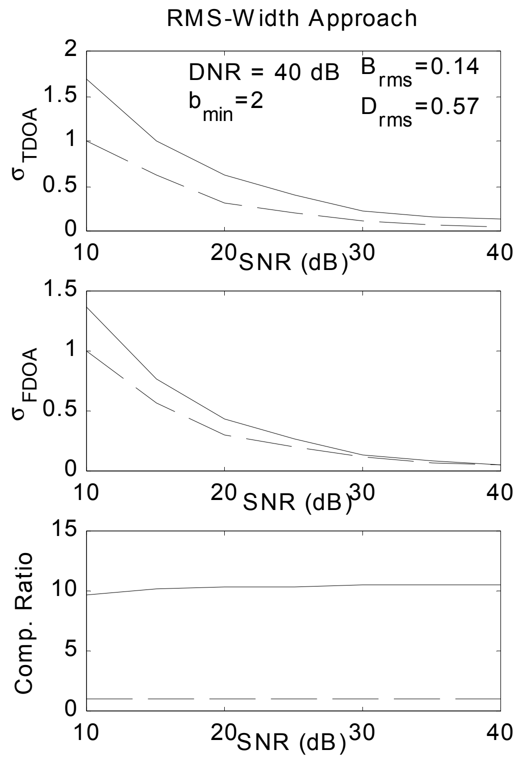

Figure 5: RMS-Width WT Method. Solid = WT Results; Dashed = No Compression

0.58, normalized to frequency range of [-1,1] and time range of [-1,1], respectively. The legend in Figure 4 indicates that after the MSE wavelet compression approach (with B_{min} = 2) that the RMS widths are unchanged.

Simulation results using this RMS-width approach are shown in Figure 5, where the legend shows the negligible impact on the RMS widths of zeroing out odd-indexed quantizers. These results also show the large increase in compression ratio due to throwing away such a large number wavelet coefficients. The accuracy of TDOA and FDOA are seen to be degraded, however not by an unreasonable amount, given the high level of compression achieved. Figure 6 shows the original noisy signal (SNR = 25 dB) and the resulting signal after the MSE WT method and the RMS-width WT method, from which it is clear that the RMS-width approach results in a signal that looks very much unlike the original, and therefore suffers a large decorrelation loss, which is likely the source of the TDOA/FDOA accuracy degradations. This source of degradation needs further consideration to improve the RMS-width approach. None the less, it is remarkable that it is possible to remove so much of the signal, resulting in a very poor replica of the original signal (from a MSE viewpoint), and still preserve the ability to obtain fairly accurate TDOA/FDOA estimates. It is this characteristic and potential that motivates our interest in refining this method.

5. CONCLUSIONS

We have investigated the potential for using a non-MSE based distortion criterion for data compression when computing TDOA/FDOA for emitter location systems. This criterion is motivated by the dependence of the TDOA/FDOA accuracies on the signal's RMS bandwidth and duration. It was argued that methods that increase the compression ratio but do not reduce these RMS widths have potential. Towards this end we proposed, analyzed, and demonstrated a simple way to balance the MSE and RMS bandwidth effects through the use of quantization and decimation. It was argued that the wavelet transform provides a useful means to reduce signal data quantity without significantly reducing the RMS widths. An ad hoc means of eliminating wavelet coefficients was shown via simulation to result in a large improvement in compression ratio; however, the

TDOA/FDOA accuracies did suffer noticeable degradation. However, given the fact that the resulting signal was so severely perturbed from the original, the accuracies achieved are indeed remarkable and motivate further investigation into non-ad hoc approaches.

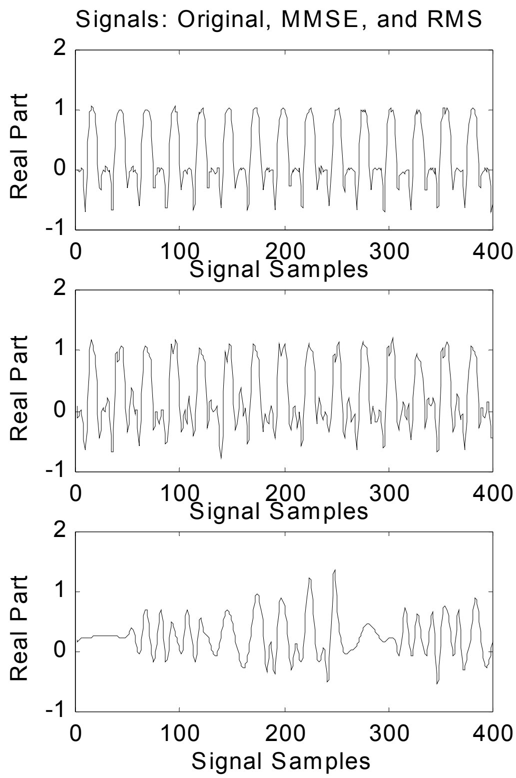

Figure 6: Original signal compared to those arising from MSE and RMS approaches

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7. AUTHOR BIOGRAPHY

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