URINE ACTIVATED PAPER BATTERIES FOR BIOSYSTEMS

ABSTRACT A spatial noise shaping (SNS) method based on human visual sensitivity is presented. The method exploits the capability of frequency domain linear prediction for spatial envelope retrieval. It effectively shapes (or hides) the noise of an image in areas which are not sensitive to human vision so that the resultingimage is more pleasant to human eyes. The noise comes from the processing of the image, and it can be either separable like the additive noise pattern in image watermarking or non separable like the quantization noise in image coding. An application of the algorithm is demonstrated in the paper by using it to enhance image coders. Images decoded from the SNS incorporated coders have superior perceived quality than those without using SNS.

I. INTRODUCTION

NOISE appearance has always been unwelcome in many speech, audio, and image applications. Many studies have been done in the field of noise reduction, ranging from conventional median or Wiener filter types of algorithms [1] to recent wavelet denoising techniques [2], [3]. Although these methods are able to eliminate or reduce the amount of noise, some useful information in the host signal may be damaged by them as well, and the damage is usually proportional to the amount of noise reduced. This tradeoff constitutes the major challenge for these methods, and limits their usage. Noise shaping techniques are another approach of removing perceptible noise, and have been widely employed in many applications, such as coding (compression) [4], data hiding, and watermarking [5]. Unlike noise reduction methods, the purpose of all these techniques is not to reduce the noise but rather to shape the structure of the noise so that it becomes less perceptible in the final signal. Most of them shape noise by altering its spectrum, and hence called spectral noise shaping methods. These methods may be called spectral noise shaping methods. Many of them are application specific, and not applicable to other methods. Recently, a novel temporal noise shaping (TNS) method [6] was proposed, which adapts the temporal structure of the quantization noise to that of the host signal, therefore the masking effects of the human auditory system can be exploited. As a result, this new approach effectively reduces the pre-echo problem caused by the spread of quantization noise in the time domain within a transform window. It has been shown that TNS has contributed to the high performance of MPEG advanced audio coder (AAC) [7]. A few attempts [8]-[10] were reported with some success in shaping quantization noise spatially for image compression. A larger part of the noise could be spatially distributed to the textured part of the image by using filtered noise distribution makes it difficult to control the noise distribution accurately. The problem appeared to be resolved by optimizing the perceptual weighted quantization noise feedback [9], [10]. In addition, all these methods [8]-[10] were specifically developed for transform image coders, especially distributed to the textured part of the image by using filtered quantization noise feedback. However, the lack of known relationship between filter coefficients and noise distribution makes it difficult to control the noise distribution accurately. The problem appeared to be resolved by optimizing the perceptual weighted quantization noise feedback [9], [10]. The algorithm was shown to be effective in reducing mosquito noise in a JPEG image. However, since it is an iterative method, the computationis expensive. In addition, all these methods [8]-[10] were specifically developed for transform image coders, especially JPEG, but not directly applicable to other image processing applications, such as watermarking. In this paper, a generic spatial noise shaping (SNS) method has been developed for images to hide processing related noise (e.g., quantization) in areas which are not sensitive to human visual perception. Similar to TNS, the algorithm shapes the spatial structure of the processing noise to directly comply with human visual sensitivity. SNS runs open-loop linear prediction (LP) in the frequency domain instead of in the time domain, as compared to the conventional LP used in speech and image processing. It is well known that the operation of the conventional LP is in the time domain and it captures and/or shapes the spectrum of the signal (or noise). Conversely, SNS operates in the frequency domain, and shapes the spatial structure of the signal (or noise). The underlying principle or techniques developed for the algorithm is generic and SNS is applicable to various noise shaping tasks. The application of SNS to image coders is demonstrated in this paper. SNS can be conveniently used as an embedded or ad-hoc process in an image coder, although an embedded system will certainly provide a better result. This predictive analysis/synthesis process over frequency possesses two important properties which result in a decoded image with superior quality compared to the one without SNS. The first property is that since the analysis filter of SNS preserves some desirable spatial structure of the image in the filter, such as edges, so that they will not be damaged by the image coder and will be restored to the decoded image at the synthesis stage ofNS. The other unique property of SNS is that it effectively adapts the spatial structure of the quantization noise to that of the image masking profile, therefore, allows more efficient use of masking. As a result, given the same compression ratio, images produced by the coder with SNS possesses a cleaner and sharper appearance than those produced by the coder without SNS. This paper is organized as follows. The duality between the spectral and temporal noise shaping using linear prediction is discussed in Section II. The spatial shaping of noise according to human visual sensitivity is presented in Section III. The application of SNS is demonstrated and discussed in Section IV. Finally, the conclusion is given in Section V.

II. SPECTRAL VERSUS

TEMPORAL NOISE SHAPING

It has been shown [6] that given a real signal, x(t) the square of its Hilbert envelope

e(t) = ^{jx©.X\*(^-f)d^}(i)

If x(f) is the Fourier Transform of x(t) then X(f) is the Fourier Transform of its analytic signal i.e., X(f) is a single sided spectrum defined as

{ 0, f<0

X(f) = { X(f) , f=0 (2)

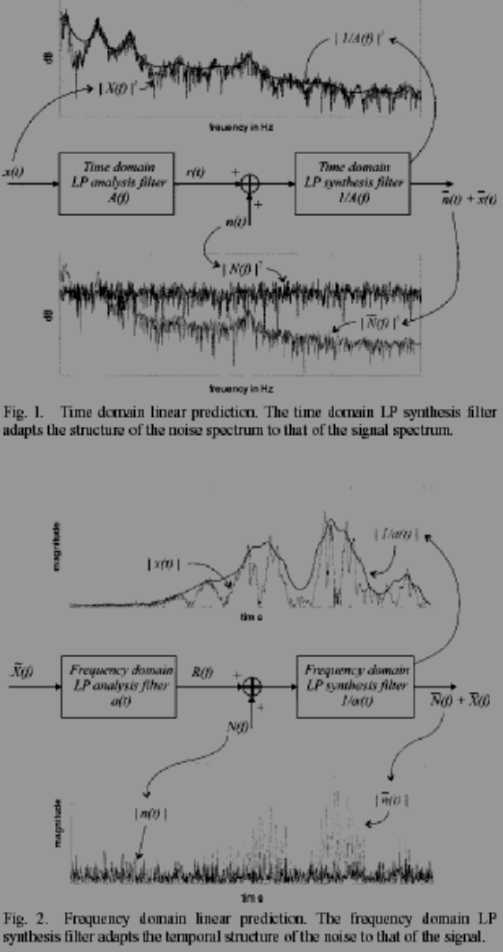
{ 2X(f) , f>0

Equation (1) shows that the signal envelope directly relates to the autocorrelation function of its single sided spectrum, X(f). This relationship is the dual to the following well-known formula which relates the power spectrum density of a signal, Sxx(f) to its autocorrelation function in the time domain

Sxx(f)= ^(Ix(x). x\*(x-t)dx} (3)

By taking advantage of this duality, some  
well-established theories in time domain  
linear prediction (LP) can be applied to the  
frequency domain case. One of them is that  
linear prediction coefficients (LPC) of the  
time signal x(t) provide a good estimate of  
its power spectrum, Sxx(f). As shown at the  
topof Fig. 1, the time domain LP synthesis  
filter which is an IIRfilter using LPC as the  
filter taps captures the spectrum structure of  
the host signal x(t). A nice property

of this filter is thatit can adapt the spectral structure of the processing noise, n(t) to that of the host signal, which is shown in the bottom of Fig. 1. Based on the duality of (1) and (3), the following deduction canbe made: If we apply the frequency domain linear prediction on the coefficients of X(f) which is the single sided spectrum of theAll opera-tions of the time domain LP, Fig. 1, are implemented in the time domain, but the noise shaping property is happening in the fre-quency domain. Conversely, all the operations of the frequency domain LP, Fig. 2, are carried out in the frequency domain,



time signal x(t) the resulting frequency domain LPC will provide a good estimate of the envelope of the time signal x(t) This is shown at the top of Fig. 2. As shown at the bottom ofFig. 2, the frequency domain LP synthesis filter can adapt thetime structure of the processing noise to that of the host signal x(t) Note that Figs. 1 and 2 are duals to each other.

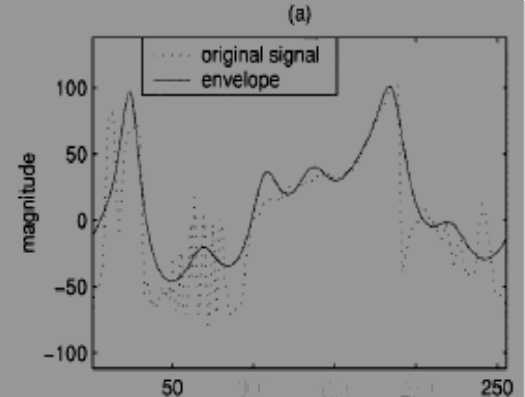
Figure 3 (a)



original signal

signal roughness

roughness Envelope



IOC 150 £00 Time (samples)

100

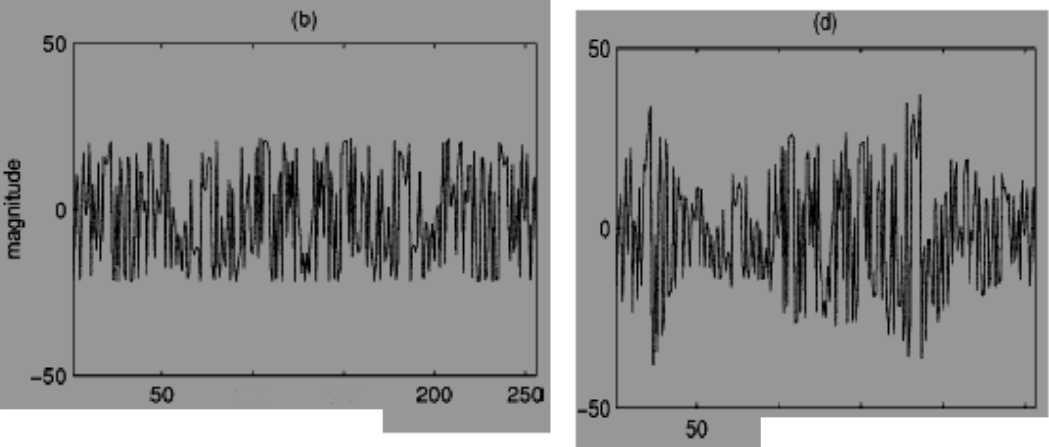
50

-50 -100

100 150 £00 250

Figure 3(b)

, but the noise shaping property is happening in the time domain. This technique is also temporal noise shaping (TNS) in MPEG AAC [7]. Note that in order to avoid complex arithmetic, real fil-terbanks, such as discrete cosine transform (DCT) or modified DCT (MDCT), are best used with this noise shaping technique. TNS is directly applicable to one-dimensional (1-D) speech or audio signals, but not to two-dimensional (2-D) image signals. By taking signal coding (compression) as an example, Fig. 3(a) shows a time signal and its envelope which is the time response of the LPsynthesis filter noise shaping filter, without and with respectively If the signal in Fig. 3(a) is a

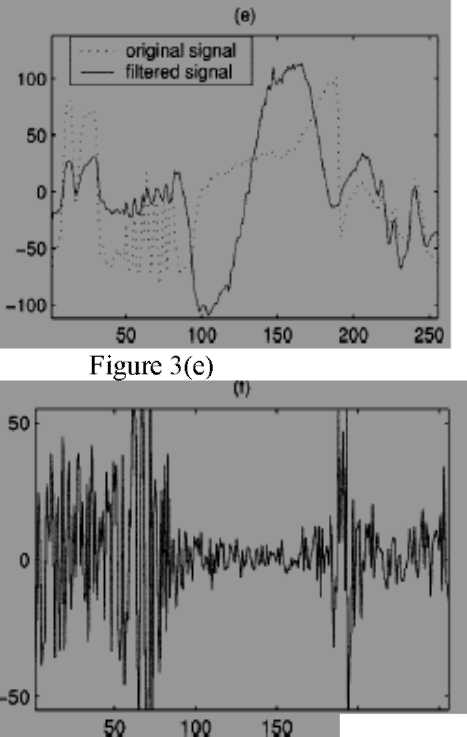


100 150 Time- (samples)

Figure 3(c)

100 150 £00 ?50 Figure 3(d)

figure 3(f)



200 ?W

piece of music, then in audio coding, the shaped noise shown in Fig. 3(d) can be successfully masked by the high magnitude attack-like signal. This is in contrast with the case where the coding noise without being shaped by the filter, as shown in Fig. 3(b), may be clearly heard in the decoded signal. However, this noise shaping filter is not directly applicable to image coding, because



it may result in more visible noise in bright flat areas. Fig. 3(a) is in fact the 250th row of the 256 X 256 Lena image in Fig. 4. The high amplitude area in Fig. 3(a) belongs to obtained in the frequency domain. Fig. 3(b) and (d) show the resulting coding noise the bright and smooth shoulder area in the image. Such shaped noise results in lots of visible noise in the area as seen in Fig. 5(a), as well as other bright and flat areas. Some areas of the resulting image is in fact worse than the one without using the noise shaping filter, as shown in Fig. 5(b). Therefore, unlike the case in speech/audio processing, in image processing we cannot simply adapt the structure of the processing noise to that of the signal envelope. As it will become clear in the following paragraphs, the proposed SNS has to be developed in such a way that the. processing noise is shaped according to the sensitivity of the human visual system

III. SNS Based on Human Visual Sensitivity

The human visual system (HVS) is more sensitive to detecting noise in flat (smooth) regions than it is in textural regions, that is, texture and edge areas have bigger masking capability with respect to noise. In other words, the sensitivity of the human visual system is proportional to the flatness of the image, that is, the rougher the image, the more masking. In order to make the most of these locally space-dependent masking thresholds, we have to shape the coding noise according to the roughness (textures and edges) of the image, not to the overall image amplitude envelope. This can be accomplished by first weighting the spectral coefficients before deriving the LPC. The weighting function is a high-pass type window as shown in Fig. 6, which is a rough approximation of the inverse human visual modulation transfer function (MTF) [4]. This weighting function can be expressed as

{ 0, if 0 < r < 1V W(fx,fy) = { sin ( 8n/13 (r -%)),

if V < r < 15/16  
{ 1, if 15/16 < r < 1

(4)

where r = V(fx2+ fy2) and fx and fy are normalized spatial frequencies between ±1. Let us once again use the Lena image and its 250th row as an example. Fig. 7 is the spatial response of the windowed spectral coefficients, and Fig. 3(c) is its 250th row plotted along with its original signal. Clearly, it contains only the roughness information of the image, all the information associated with flat regions has been removed. Fig. 7 can be considered the masking profile based on the roughness (textures and edges) of the image. Therefore, the corresponding LPC derived from the spectral coefficients of the profile will preserve only the roughness structure of the image. This can be seen by plotting the spatial response of the SNS synthesis filter in Fig. 3(c). Hence, in the SNS synthesis stage, the structure of the coding noise can be effectively adapted according to the roughness of the image as shown in Fig. 3(f). The superior quality of the resulting image can be clearly observed in Fig. 8. The edges are sharper, and the flat regions or backgrounds are much cleaner. The corresponding errors of the decoded image with and without using SNS are shown in Fig. 9(a) and (b), respectively. The error image clearly shows the capability that SNS can shape (or hide) the noise in those visually insensitive regions. In addition, the masking profile can be further modified to accommodate other visual sensitivity factors. For instance, it has been shown [4] that the HVS is less sensitive to changes (or noise) in regions of high and low luminance. One way to add this luminance sensitivity to the masking profile is as follows: 1 ) filter the host Lena image by a low-pass filter such that only low frequency luminance contents are kept in the resulting image;

1. map each pixel of the resulting image by a mapping function which is an inverse of the luminance sensitivity function [4]; the result can be called luminance masking profile for the host image;
2. add this luminance masking profile to the roughness masking profile, Fig. 7, to form a new masking profile for the host Lena image, which reflects the roughness and luminance sensitivities of the HVS.

For the proposed SNS filter, we found that the following two modules can effectively stabilize the filter. One is to cyclically pad the spectrum of the image masking profile as shown in Fig. 10 before applying the 2-D covariance method [11] to derive the LPC. Since this periodic repetition of the spectrum represents more precisely the nature of the space-limited image signal, it enables us to calculate the correlation function more accurately during LPC retrieval. The other technique we use to stabilize the filter is to weight LPC in the following way: a(k,l) = a(k,l) XyAV(k2+F) , 0 < y < 1

(5)

where a(k,l) are the original LPC derived by the 2-D covariance method. This weighting operation is similar to that of the 1-D case, in that the poles of the synthesis filter are pulled toward the origin, resulting a more stable filter. For image coding applications, the value of could be determined by optimization so it results in the highest SNR

of the decoded image. The other implementation detail is that the dc value the input image is first removed before applying the spectral transformation and the subsequent SNS. In other words, the mean value of the input image should be made to be zero.

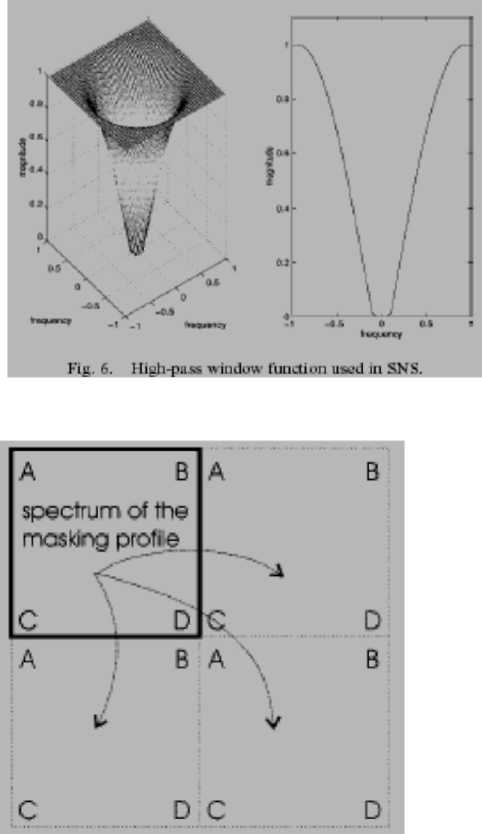


Figure 10 Cyclically repitition of the

spectrum of image masking profile.

The result is used to derive the LPC for the

SNS filter.



Figure 8 Resultant decoded image using SNS based on human visual sensitivity



Figure 7 masking profile based on image roughness

IV. CONCLUSION

A generic SNS technique for images is proposed for hiding quantization (or processing related) noise in areas which are not sensitive to human visual perception. A solution to resolve the stability issue of 2-D linear prediction is also presented. The algorithm is applicable to various tasks and the application for enhancing image coders is demonstrated. SNS can be used as embedded or ad-hoc processing. For coding typical images like Lena which is a combination of flat, edge and texture regions, SNS can effectively hide the coding noise in perceptually insensitive areas (such as texture and edges) and at the same time preserve sharp edges. Hence, given the compression rate, images produced by the coder with SNS possesses a superior perceived quality than those produced by the coder without SNS.

REFERENCES

[1] A. K. Jain, Fundamentals of Digital Image Processing. Englewood Cliffs, NJ: Prentice-Hall, 1989.

[2] D. L. Donoho, "De-noising by soft-thresholding," IEEE Trans. Inform. Theory, vol. 41, pp. 613-627, May 1995.

[3] N. Jayant, J. Johnston, and R. Safranek, "Signal compression based on models of human perception," Proc. IEEE, vol. 81,

Oct. 1993.

[4] J. Herre and J. D. Johnston, "Enhancing the performance of perceptual audio coding by using temporal noise shaping (TNS)," in Proc. 101st AES Conv., Los Angeles, CA,

Nov. 1996, Preprint 4384 [Online]. Available:

(<http://www.aes.org/publications/preprints>).

[5] B. Girod, U. Horn, and Y. Xiancheng, "Spatial shaping: A fully compatible improvement of DCT coding," in Proc. Picture Coding Symp., 1993.