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On Optimum and Nearly Optimum Data Quantization for Signal Detection

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Abstract—**The application of companding approximation theory to the quantization of data for detection of coherent signals in a noisy environment is considered. This application is twofold, allowing for greater simplicity in both analysis and design of quantizers for detection systems. Most computational methods for designing optimum (most efficient) quantizers for signal detection systems are iterative and are extremely sensitive to initial conditions. Companding approximation theory is used here to obtain suitable initial conditions for this problem. Furthermore, the companding approximation idea is applied to design suboptimum quantizers which are nearly as efficient as optimum quantizers when the number of levels is large. In this design, iteration is not needed to derive the parameters of the quantizer, and the design procedure is very simple. In this paper, we explore this approach numerically and demonstrate its effectiveness for designing and analyzing quantizers in detection systems.**

I. Introduction

In recent years there have been several studies of problems relating to the quantization of data for use in signal detection systems [1]–[6]. These studies include both analytical and numerical treatment of the problem of optimal data quantization for the detection of deterministic (coherent) signals [1], [2] and purely stochastic signals [5], and analytical treatments of quantization within more general signal detection formulations [3]–[6]. In particular, Kassam [1] has considered this problem for the coherent detection case and has developed a design technique for this situation based on the solution to a system of nonlinear equations in the quantizer parameters. He showed that quantizers derived in this manner have maximum efficacy (i.e., are most efficient) among all quantizers with a fixed number of output levels. It is interesting to compare Kassam's quantizer to those optimized by a criterion not specifically for signal detection purposes; for instance, the minimum-distortion quantizer [7], which minimizes the mean-squared error between data and its quantized version, coincides with the optimum quantizer based on Kassam's detection criterion [1] only for Gaussian noise.

In the alternative context of quantizing data for minimum distortion, approximations to the minimum-distortion nonuniform quantizer which are of practical interest have been proposed. Bennett [8] modeled a nonuniform quantizer by a compressor, followed by a uniform quantizer and an expander (compander). With this companding model, Panter and Dite [9] presented a useful approximation to minimum-distortion quantizers. Later, Algazi [10] used the companding approximation to obtain results on optimal quantizers for a general class of error criteria (Algazi estimated distortion due to optimally quantizing data in the minimum mean-squared error sense; see also Gersho [11]).

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In this paper, we apply the companding approximation theory to signal detection problems. First, we use the companding approximation to help in solving Kassam's system of nonlinear equations for the optimum quantizer parameters (see also Bucklew and Gallagher [12]). Then, we present a scheme to design a quantizer which in a sense estimates Kassam's optimum quantizer using a companding approximation. The performance of detection systems using these companding quantizers is compared to that of Kassam's optimum quantizer detector. Also, the exact performance of the optimum system is compared to its approximate performance predicted by the companding model. These issues are explored numerically for a wide range of noise distributions, including both Gaussian and non-Gaussian cases.

II. Preliminaries

The model we consider is based on a standard additive noise assumption. In particular, we assume that we have a sequence of data samples $x = \{x_i;\ i = 1, 2, \cdots, n\}$ from a random sequence $X = \{X_i;\ i = 1, 2, \cdots, n\}$ which can obey one of the two possible statistical hypotheses:

$$H_0: X_i = N_i, \quad i = 1, 2, \cdots, n \tag{2.1}$$

versus

$$H_1: X_i = N_i + \theta s_i, \quad i = 1, 2, \cdots, n$$

where $\{N_i;\ i = 1, 2, \cdots, n\}$ is an independent, identically distributed (i.i.d.) zero-mean noise sequence with known common univariate probability density and distribution functions f and F, respectively. Throughout this work, the noise probability density function f is assumed to be symmetric about the origin. The parameter θ is a positive signal-to-noise ratio (SNR) parameter and $\{s_i;\ i = 1, 2, \cdots, n\}$ is a known coherent (i.e., deterministic) signal sequence. As a practical case, we wish to consider the weak signal case ($\theta \to 0^+$), since this is the situation in which the design is most critical. Therefore, rather than maximizing the detection probability (β) for a fixed false alarm probability (α), we consider the locally optimum detector for H_0 versus H_1 which maximizes the slope of the power function $(\partial\beta(\theta)/\partial\theta)$ at $\theta = 0$ while keeping a fixed false-alarm probability. Within mild regularity conditions, the locally optimum test statistic for our detection problem is given by

$$W = \sum_{i=1}^{n} s_i g_{lo}(X_i) \tag{2.2}$$

where the locally optimum nonlinearity $g_{lo}(\cdot)$ is given by

$$g_{lo}(x) \triangleq -\frac{f'(x)}{f(x)} \tag{2.3}$$

Noise Reduction in Image Sequences Using Motion-Compensated Temporal Filtering

ERIC DUBOIS, MEMBER, IEEE, AND SHAKER SABRI, MEMBER, IEEE

Abstract—**Noise in television signals degrades both the image quality and the performance of image coding algorithms. This paper describes a nonlinear temporal filtering algorithm using motion compensation for reducing noise in image sequences. A specific implementation for NTSC composite television signals is described, and simulation results on several video sequences are presented. This approach is shown to be successful in improving image quality and also improving the efficiency of subsequent image coding operations.**

I. INTRODUCTION

NOISE introduced in television signals degrades both the image quality and the performance of subsequent image coding operations. This noise may arise in the initial signal generation and handling operations, or in the storage or transmission of these signals. The effect of additive noise on potential image coding performance is illustrated by considering a uniformly distributed noise with values −1, 0, 1 out of 256, giving an SNR of 45.8 dB. Although this added noise is barely perceptible, it has an entropy of 1.58 bits/sample, clearly limiting the image coding compression factor. Thus, there is great interest in reducing the noise level in the input signal in order to get maximum coding efficiency.

Noise reduction in image sequences is possible to the extent that image and noise components have different characteristics. For stationary random processes, the classical method of noise reduction is Wiener filtering, based on the image and noise power spectra. However, images are not well modeled by stationary random processes, and other approaches based on improved image models are sought. A major distinguishing feature between the noise and signal in image sequences is that the noise is uncorrelated from frame to frame, while the image is highly correlated, especially in the direction of motion. By performing a low-pass temporal filtering in the direction of motion, the noise component can be attenuated without affecting the signal component.

Noise reduction using temporal filtering to give improved image quality has been described in [1]–[3]. These systems use motion detection, as opposed to motion estimation; temporal filtering is only applied in the nonchanging parts of the picture. This is accomplished either by explicitly segmenting into changing and nonchanging areas, or by a nonlinear filtering approach (to be discussed later). These algorithms have the disadvantage that noise cannot be reduced in moving areas without modifying the image detail, and noise can appear and disappear as objects begin and stop moving. Although noise in moving areas is masked to some extent by the motion, it will still be visible in slowly moving areas.

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The concept of motion-compensated temporal filtering has been described by Huang and Hsu [4]. In this approach, the displacement at each picture element is estimated, and a temporal averaging is performed along the trajectory of motion. Reference [4] describes nonrecursive linear and median temporal filters, both with and without motion compensation. However, the amount of noise reduction which can be attained with low-order nonrecursive filters is quite limited. Also this approach can introduce artifacts in areas where motion is not tracked and in newly exposed areas.

In this paper, the nonlinear recursive filtering approach of [2], [3] is extended by the application of motion compensation techniques. A specific noise reducer for use with NTSC composite television signals is then described, and computer simulation results of its performance on several video sequences are presented. It is shown that this approach is successful in improving image quality, while also improving the performance of subsequent image coding operations.

II. MOTION-COMPENSATED TEMPORAL FILTERS FOR NOISE REDUCTION

A. Theory of Motion-Compensated Temporal Filtering

Let $u(\mathbf{x}, t)$ be the image intensity at spatial location $\mathbf{x} = (x_1, x_2)$ and time t, and let $\mathbf{d}(\mathbf{x}, t)$ be the displacement of the image point at $(\mathbf{x}, t)$ between time $t - T$ and t. The vector field $\mathbf{d}(\mathbf{x}, t)$ is called the *displacement field*. If the intensity of the object point has not changed over the time T, then

$$u(\mathbf{x}, t) = u(\mathbf{x} - \mathbf{d}(\mathbf{x}, t), t - T). \tag{1}$$

Note that $\mathbf{d}$ is not defined in newly exposed areas, i.e., for those picture elements (pels) which were not visible in the previous field. For background and stationary objects, $\mathbf{d}(\mathbf{x}, t) = 0$, while for an object in translational motion, $\mathbf{d}(\mathbf{x}, t)$ is a constant over the object. In general, $\mathbf{d}(\mathbf{x}, t)$ is a slowly varying function of space, except for discontinuities at the edges of moving objects.

The value over time of the image sequence at a given *object point* forms a one-dimensional signal, defined on the time interval for which this point is visible in the scene. This signal is assumed to be the sum of an image component and an additive noise component. The variation in the image component is solely due to change in the luminance of the object point, caused by changes in illumination or orientation of the object. This change is relatively slow, so that the image component is a low bandwidth signal. The noise is assumed to be white and uncorrelated with the signal. By performing a low-pass filtering operation on this signal, the noise component can be significantly attenuated, with a minimal effect on the image component.

In practice, the image sequence is sampled spatially, and it is not precisely possible to filter the sequences corresponding to given object points. However, the principle of performing a temporal filtering or averaging operation along the trajectory of motion is feasible. This filtering can be of either the recursive or nonrecursive type. Since greater selectivity can be obtained for a given filter order with recursive filters, this type of filter has been chosen for this application. This is especially important in temporal filtering, where each increase by one in filter order requires an additional frame memory.

A block diagram of a first-order recursive temporal filter with motion compensation is shown in Fig. 1 (assume for now that the output of the block NL is a constant value α). The basic operation of this filter is described by

$$v(\boldsymbol{x}, t) = \alpha u(\boldsymbol{x}, t) + (1-\alpha)\tilde{v}(\boldsymbol{x} - \hat{\boldsymbol{d}}(\boldsymbol{x}, t), t - T) \quad (2)$$

where v is the output of the filter, $\hat{\boldsymbol{d}}$ is an estimate of $\boldsymbol{d}$, and $\tilde{v}$ is an estimate of v at a non-grid point obtained by spatial interpolation. The signal $\hat{u}(\boldsymbol{x}, t) = \tilde{v}(\boldsymbol{x} - \hat{\boldsymbol{d}}, t - T)$ is called the *prediction* and $e = u - \hat{u}$ is called the *prediction error*. This filter requires a frame memory in order to be able to form the prediction. A module for estimating the displacement field is also required. This estimation can be performed using any of a number of algorithms which have been proposed in the literature [5]–[8]. The displacement estimator can use the input signal as well as any of the signals available in the noise reducer to perform the estimate.

An indication of the ability of this filter to reduce noise can be obtained by considering its performance in stationary areas where $\boldsymbol{d} = 0$. In this case, the filter reduces to a standard one-dimensional temporal recursive filter with transfer function

$$H(z) = \frac{\alpha}{1-(1-\alpha)z^{-1}}. \quad (3)$$

It can easily be shown that for a white noise input, the noise power is reduced by $10 \log_{10}((2-\alpha)/\alpha)$ dB. Due to the spatial interpolation error, the performance in moving areas will be slightly different, even if the displacement estimate is perfectly accurate.

A number of modifications are required to make this scheme work in practice. The major change is based on the observation that the displacement field is not defined for the newly exposed parts of the image, and that the displacement estimate may not always be accurate, especially in regions where (1) is violated. These regions are characterized by a large value of prediction error. Since the movement is not being followed in these regions, it is preferable to disable the filtering operation. This can be accomplished by varying the value of α as a function of the prediction error, which is equivalent to passing the prediction error e through a memoryless nonlinearity $y = \alpha(e)\cdot e$. A typical piecewise-linear characteristic for the function $\alpha(e)$ is shown in Fig. 2. It is given by

$$\alpha(e) = \begin{cases} \alpha_b, & \text{if } |e| \leqslant P_b; \\ \dfrac{\alpha_b - \alpha_e}{P_b - P_e}|e| + P_b\alpha_e - P_e\alpha_b, & \text{if } P_b < |e| \leqslant P_e; \\ \alpha_e, & \text{if } |e| > P_e. \end{cases} \quad (4)$$

In areas where the motion is tracked, $e(\boldsymbol{x}, t)$ is small (of the order of the noise level), and a linear temporal filtering with parameter $\alpha = \alpha_b$ is performed. In areas where the motion is not being tracked and $e(\boldsymbol{x}, t)$ is large, a temporal filtering with parameter α_e is performed. To avoid introducing artifacts in these regions, α_e is typically set to unity. For values of e between P_b and P_e, $\alpha(e)$ varies linearly between α_b and α_e, to provide a smooth transition between regions where motion is tracked and where it is not. The choice of values of P_b and P_e to be used depends on the noise level and the appearance of artifacts.

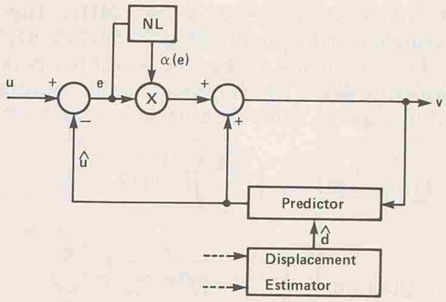

Fig. 1. First-order recursive temporal filter with motion compensation.

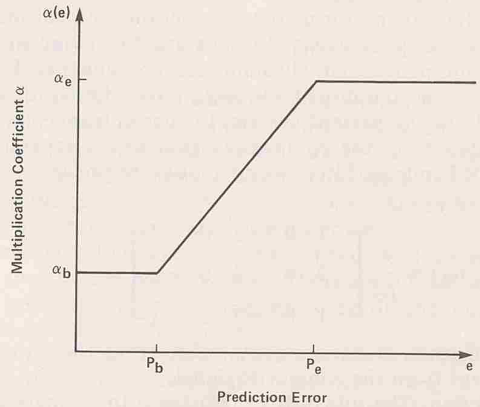

Fig. 2. Nonlinear function for multiplier coefficient α.

The digital noise reducers which have been described in the literature [1]–[3] are basically obtained by setting the displacement estimate to zero, and filtering only in the stationary areas. This can be accomplished by explicitly segmenting into changed and unchanged areas, and filtering with a linear temporal filter in the unchanged areas, or by using a nonlinear temporal filter with the nonlinearity as described above. In either case, the noise in the moving or changed areas can only be reduced at the expense of image detail. (Note that higher noise level in changing areas is permissible to a certain extent because the movement or change will mask the noise). With this system, noise can abruptly appear in areas which were fixed and then begin to move. If an accurate displacement estimate is available, these effects can be reduced. Clearly, a displacement estimator which is robust in the presence of noise is required.

B. A Motion-Compensated Noise Reducer for NTSC Composite Video Signals

This section describes a particular nonlinear temporal filter with motion compensation suitable for noise reduction in NTSC composite video signals. This noise reducer must specifically account for the properties of the NTSC composite signal, namely, the modulation of the chrominance information on a subcarrier, and the 2:1 line-interlaced scanning. The issues related to displacement estimation and prediction from NTSC composite signals are discussed in [8]. The techniques described here can easily be adapted to component processing of color video signals.

The NTSC Signal: The NTSC signal has the form

$$U(t) = Y(t) + C(t) = Y(t) + I(t)\cos(2\pi f_{sc}t + 33°) + Q(t)\sin(2\pi f_{sc}t + 33°) \quad (5)$$

where Y is the luminance component and I and Q are the chrominance components, quadrature-modulated on a sub-

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