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신호패턴 종속잡음 채널을 위한 신호검출

Signal Detection for Pattern Dependent Noise Channel

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요 약

고밀도의 저장기록장치 채널의 주요 신호검출 오류의 원인은 천이 지터잡음이다. 이러한 채널환경에서 최적의 신호검출기 구현을 위해서는 고도의 복잡도가 요구되는데 이는 지터잡음이 신호와 상관관계가 있고 잡음간에도 상관관계가 존재하기 때문이다. 본 논문에서는 계산량과 하드웨어 복잡도 관점에서 효율적인 두 가지 종류의 신호검출기에 대해서 설명한다. 이는 전통적인 비터비 복호기의 가지값을 변화시킨 형태이며 같은 이진데이터 값의 반복을 제한하는 부호와 함께 결합하여 일반적인 PR 채널에 적용된다. 기존의 비터비 알고리즘의 복잡도와 비교하면 비터비 트렐리스에서 각각의 가지값을 계산할 때 추가적으로 하나의 곱셈기 혹은 덧셈기의 증가가 요구된다.

Abstract

Transition jitter noise is one of major sources of detection errors in high density recording channels. Implementation complexity of the optimal detector for such channels is high due to the data dependency and correlated nature of the jitter noise. In this paper, two types of hardware efficient sub-optimal detectors are derived by modifying branch metric of Viterbi algorithm and applied to partial response (PR) channels combined with run length limited modulation coding. The additional complexity over the conventional Viterbi algorithm to incorporate the modified branch metric is either a multiplication or an addition for each branch metric in the Viterbi trellis.

Key words : Modified branch metric, partial response channels, transition jitter noise, Viterbi algorithm.

1. Introduction

As linear densities for digital magnetic storage channels increase, the medium noise becomes one of the major sources of impairments to the reliable retrieval of the stored data. One of the important sources of medium noise is non-ideal magnetic transitions. The transition positions vary randomly around the nominal position due to the zig-zag geometry of magnetic transitions written in thin film media [1]. Since the transitions imply binary information in digital recording, the noise is data-dependent. In other words, the statistics of the transition jitter noise is highly correlated with data patterns stored in the magnetic medium. Various types of sequence detection methods have been proposed to achieve the maximum likelihood sequence detection (MLSD) performance by utilizing the statistical nature of the transition noise [2][3]. In one approach each factor of the likelihood function is represented by a conditional probability density function (PDF) of an observation sample conditioned by a channel input sequence [2]. In the other approach each factor of the likelihood function is derived from a PDF of an observation sample conditioned by both a channel input sequence and past observation samples (channel output sequence) [3]. Without any complexity constraints, both methods result in the same optimal detection performance. However, a direct implementation of the MLSD may not be feasible due to the complexity depending on the noise characteristics in the channel. As a sub-optimum solution, noise prediction filters are used to reduce the jitter noise in the observation sample [4]. Path memories are used to obtain noise estimate and to reduce the implementation complexity. Different sets of noise prediction coefficients are used to cancel the data-dependent noise associated with different branches in the trellis. As a compromised solution between detection performance and implementation complexity, the correlation between neighboring noise samples is ignored and a factorized likelihood function is obtained in [5], where each factor of the likelihood function is a conditional PDF of an observation sample conditioned by a channel input sequence. The detector implementation requires additional hardware (a multiplier and an adder for each branch metric calculation) over the conventional Viterbi algorithm tuned to additive white Gaussian noise.

In this paper, two types of computationally efficient sub-optimum sequence detection schemes are proposed to improve the performance under the transition jitter noise dominant channel. We first derive the proposed schemes beginning with the optimum detection branch

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metric. Next, one of the partial response channels is taken as an example and is used to describe the details how the modified branch metric is applied to high density channels. Finally bit-error-rate simulations results follow with conclusions.

2. Optimized Branch Metric

For a data dependent noise channel, the maximum likelihood (ML) detector finds a noiseless channel output sequence **y** which maximizes the likelihood function:

$$f(\mathbf{z}\,|\,\mathbf{y}) = \frac{1}{\sqrt{(2\pi)^N|\mathbf{C}|}}\exp(-\frac{(\mathbf{z}-\mathbf{y})^T\mathbf{C}^{-1}(\mathbf{z}-\mathbf{y})}{2}) \quad (1)$$

where the noise distribution is assumed to be Gaussian, **z** is observation, N is the size of the observation sample and **C** is the data dependent noise covariance matrix which depends on the sequence **y**. The ML detector implementation for such channel requires large number of states in the Viterbi trellis and matrix multiplications for each branch metric calculation. It can be shown that the branch metric to implement the MLSD based on autoregressive (AR) noise model can be represented as the following form [2]:

$$\ln(\sigma_k^2) + (\sum_{i=0}^{L}\rho_{k,i}[z_{k-i} - y_{k-i}])^2 / \sigma_k^2 \quad (2)$$

where $\rho_{k,i}$ is the noise prediction filter coefficients whose values are dependent on the input data pattern, L is the Markov memory length of the noise, σ_k^2 is the noise variance, z_k is an observation sample and y_k is a noiseless channel output at time k. This metric is also a good approximation for channel based on the non-AR model (e.g. moving average (MA) noise model) when L is large enough. The implementation complexity depends on L and the span of the channel intersymbol interference (ISI). In [4] the data dependent scaling term σ_k^2 and the $\ln\sigma_k^2$ term in (2) is ignored and the path memory in the Viterbi trellis is used instead of increasing the number of states to reduce the implementation complexity. Another compromised solution is proposed in [5], where off-diagonal elements of the covariance matrix which represent correlation between neighboring observation samples, are ignored in the metric calculation. The resulting modified branch metric is defined by

$$\ln(\sigma_k^2) + (z_k - y_k)^2 / \sigma_k^2. \quad (3)$$

This branch metric is degenerate case of (2) where prediction filter is delta function. The calculation of the metric shown in (3) requires additional multiplication and addition over the conventional Viterbi algorithm tuned to additive white Gaussian noise.

In this paper, two modified branch metrics are proposed using a multiplication or an addition term only. These additional terms are optimized to reflect the amount of the variance of the pattern dependent noise. Decomposing the noise variance σ_k^2 into two components, data-independent additive noise part σ_e^2 and jitter noise part $\sigma_{m,k}^2$, and considering only scaling term $1/\sigma_k^2$, (3) can be represented by

$$(z_k - y_k)^2/(1+\sigma_{m,k}^2/\sigma_e^2) = (z_k - y_k)^2/(1+c_k\gamma) \quad (4)$$

where the constant term $1/\sigma_e^2$ is ignored and the ratio of noise powers is decomposed into data-dependent term c_k and data-independent term γ. Instead of using multiplicative term, an additive term can be used to incorporate the pattern dependent noise variance. The resulting branch metric is given by

$$(z_k - y_k)^2 - c_k\alpha \quad (5)$$

where c_k is a data-dependent term and α is a data-independent term. Proposed modified branch metrics described above allows more noise margin for the observation samples associated with more transition noise by scaling or subtracting with larger value. The scaling operation effectively changes the shape of the conditional probability function given some data sequence. The subtraction operation also shifts the decision boundaries between different symbols associated with different set of data sequences.

3. Application to Partial Response Channel

In this section, proposed detection schemes are applied to the channel which is suitable for high-density storage system. For the analytical derivation purposes, it is assumed that transition noise is modeled as random position jitter around the nominal transition. Although the example described here is based on a specific noise model, we can also apply the proposed modified branch metrics to other noise model or experimental readback signal if we can measure the relative variance of the transition noise.

The transition response with a small amount of transition jitter noise can be approximated by a first order Taylor series [6]:

$$\begin{aligned} r(t) &= \sum_k a_k h(t - kT + \Delta_k) + n(t) \\ &= \sum_k a_k h(t-kT) + \sum_k a_k \Delta_k h'(t-kT) + n(t) \end{aligned} \quad (6)$$

where $r(t)$ is the readback signal, a_k is the channel input data which takes "±1" or "0" value where "±1" represents existence of transition, $h(t)$ is the isolated transition response, $n(t)$ is additive noise, and Δ_k is the amount of position jitter which is assumed to be white Gaussian. It can be shown that the observation sample z_k at the output of the equalizer can be represented as

$$z_k = a_k * p_k + \Delta_k a_k * p_k * q_k + n'_k \tag{7}$$

where $*$ is the discrete time convolution operation, p_k is equalization target response, n'_k is the additive noise sample and q_k is the derivative of the sinc function:

$$q_k = [\pi^2 k \cos(\pi k) - \sin(\pi k)]/(\pi k)^2 \tag{8}$$

In (6) and (7) the assumption is made that $h(t)$ is an ideally band-limited pulse (in high density magnetic channel, most of signal energy is concentrated within the Nyquist band). The same assumption is also made for the equalization response.

For an EEPR4 channel [7], $P(D)=1+3D+3D^2+D^3$ and the jitter noise response $P(D)Q(D)$ can be well approximated by $1+D-D^2-D^3$ ignoring a scaling factor and small residual tails (see Fig. 1). It can be also shown that the jitter noise variance is proportional to the number of transitions in the past four symbol periods. The variance of the jitter noise $\sigma^2_{m,k}$ can be represented in terms of channel parameters as follows:

$$\begin{aligned} \sigma^2_{m,k} &= \mathrm{E}|\Delta_k a_k * p_k * q_k|^2 \\ &\approx \mathrm{E}|\Delta_k a_k + \Delta_{k-1} a_{k-1} - \Delta_{k-2} a_{k-2} - \Delta_{k-3} a_{k-3}|^2 \\ &= \mathrm{E}|\Delta_k|^2 \{|a_k|^2 + |a_{k-1}|^2 + |a_{k-2}|^2 + |a_{k-3}|^2\} \end{aligned} \tag{9}$$

where Δ_k and a_k are assumed to be statistically independent to each other. From these observations, we can see that $\sigma^2_{m,k}$ mainly depends on the current and the last three transitions and approximately proportional to the number of transitions within the last four symbol intervals. For the parameter setting, c_k in (4) and (5) is set equal to the number of transitions associated with the corresponding trellis branch. Once we obtain the relative variance for different data pattern, optimization of the detector performance with new branch metrics involves only adjusting a single parameter α or γ.

4. Simulation Results

For performance comparisons, bit-error-rate (BER) simulations have been conducted for an EEPR4-equalized Lorentzian channel combined with the time varying maximum transition run code with rate 8/9 [8]. User bit density is Du=2.5. SNR is defined as the ratio of squared isolated transition pulse peak amplitude to the total noise power within the Nyquist band at symbol density Ds=2.0 assuming all "1" data patterns are written in the media [9]. In the simulations, it is assumed that 90% of the total noise power comes from transition position jitter noise and the 10% from additive noise. The number of states in the Viterbi detector is 16 for all schemes and the branch metric modification is made based on past four and current input NRZ binary data symbols. For comparison purposes the detection scheme using branch metric shown in (3) is also tested. The variance term σ_k^2 in (3) has been estimated for each trellis-branch. The measurement for the relative values of the noise variance for different input data sequence can be done either in analytical way assuming specific noise model as described in the previous section or by direct measurement. The number of transitions (0, 1, 2 or 3) in the past 4 symbol periods is used for c_k in (4) and (5) following the analysis in the previous section. The parameter γ in (4) and α in (5) are tuned to get the optimal BER performance. In this simulations they are set to 5.6 and 1.3, respectively. As shown in Fig. 2, Viterbi detectors with the modified branch metrics with additional multiplicative (MUL) and additive (ADD) term have about 1.0 dB gain at BER=10^{-6} over the conventional Viterbi detector and show the performance gain comparable to Viterbi detector with branch metric in (3) which is labeled as VAR in Fig. 2.

5. Conclusion

Sub-optimum sequence detection schemes are proposed for jitter noise dominant channels. Application to the PR channel suitable for high-density systems shows large performance gains without significant increase of the implementation complexity. Comparisons to other sub-optimum solution under the same constrained size of the trellis have also been made and show comparable performance with less computational load.

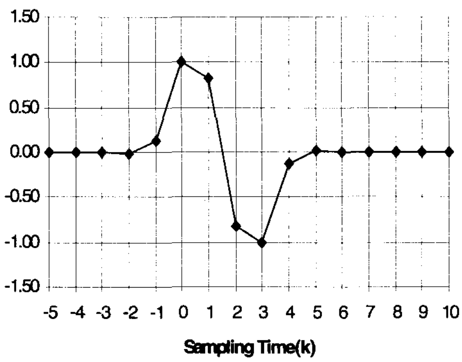

Fig. 1. Transition response to the jitter noise ($p_k * q_k$) for EEPR4 equalized channel (amplitude of the response is normalized to the value at sampling time k=0).

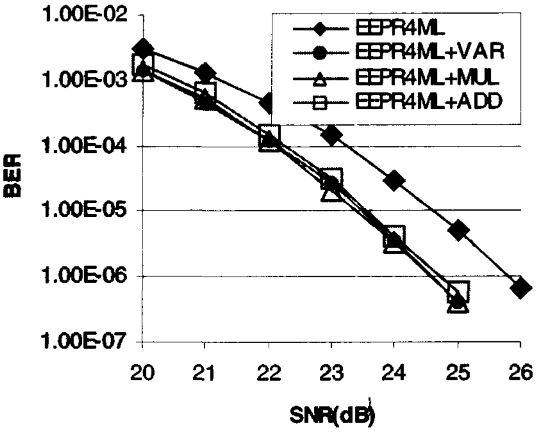

Fig. 2. BER curves for a Lorentzian channel at Du=2.5 with 90% jitter and 10% additive noise (VAR, MUL and ADD represent the schemes with modified branch metrics described in (3), (4) and (5), respectively).

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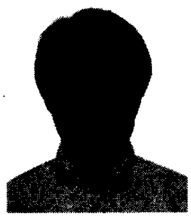

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