SUPPORT VECTOR MACHINES BASED DATA DETECTION FOR HOLOGRAPHIC DATA STORAGE SYSTEMS

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ABSTRACT

Nonlinear nature of Holographic Data Storage Systems (HDSS) suggests that nonlinear equalization and detection techniques may be beneficial. Complexity involved in nonlinear methods does not often make them practical solutions. Support Vector Machines (SVMs) are recently being studied for pattern recognition applications. We investigated linear SVM *detection* and observed that the Bit Error Rate (BER) using SVM for data detection on Linear Minimum Mean Squared Error (LMMSE) equalized holographically recorded and retrieved 2-D data pages is about 17% better than the simple threshold detection on unequalized pages.

1. INTRODUCTION

For data storage systems in general, and for Holographic Data Storage Systems (HDSS) in particular, efficient equalization and detection techniques have proved to be immensely useful [1] for reducing the raw Bit Error Rates (BERs). Their goal is to improve the storage density by mitigating the effects of intersymbol interference (ISI) and noise. Equalization is one means for compensating or reducing the ISI in the system. Data detection refers to the method of converting retrieved analog values (e.g., from the output camera in a HDSS) to bits (i.e., 1s and 0s).

Nonlinearity in the holographic data storage channel is evident from the fact that the camera in the output plane detects the light intensity, which is the magnitude squared of the light amplitude which is linearly related to the input page [2]. Nonlinear equalization and detection schemes may thus offer benefits for HDSS. An important aspect of the holographic data storage system is that the 2-D Fourier transforms (FTs) of the input pages get stored in the medium. To reduce the amount of storage medium used for storing the data, apertures are placed in the frequency plane. Decreasing the frequency plane aperture size leads to an increase in the areal density, but at the expense of increased ISI in the output camera plane since smaller frequency plane apertures result in broader impulse responses (called point spread functions in 2-D). Other impairments such as non-full fill factor of the input plane pixels and the output camera pixels, finite contrast ratio (i.e., the input pixel representing bit 0 really does not have zero light amplitude) and non-uniformity of the input pixel array, optical and electronic noise, cause increase in the BER of the channel.

Support Vector Machine (SVM) technique, a popular pattern recognition method, was recently proposed as a method for performing nonlinear equalization in communication systems [3]. This idea is adapted and investigated for HDSS in this paper. We also investigate the benefits of using the Linear Minimum Mean Squared Error (LMMSE) equalization as an aid to SVM.

The rest of this paper is organized as follows. In Section 2, the formulation of SVM for data detection is discussed. Section 3 addresses the use of LMMSE equalization prior to SVM for detection. Section 4 provides the results obtained using SVM for data detection, LMMSE equalization followed by SVM detection and some observations about the choice of SVM kernel function and size. Finally, our conclusions are presented in Section 5.

2. SVM FOR DATA DETECTION

Equalization and detection together can be viewed as a pattern classification problem [3, 4]. In essence, we are converting analog samples or sample sequences to bits or bit sequences. Translating this to 2-D holographically stored data pages, contiguous pixel areas of size $n \times n$ in the data page are treated as vectors in the pattern space to be classified. It is a mapping of n^2-sized vectors to bit 0 or 1. The size of the pixel neighborhood chosen depends on the expected amount of ISI in the system. A two-step procedure of equalization and detection, shown in Fig. 1a, effectively reduces to a one-step pattern classification problem shown in Fig. 1b. The intermediate analog values of equalization are not of consequence since they will be converted to bits eventually and thus in most cases the latter method is sufficient Moreover, nonlinear equalization often becomes unmanageably complex and computationally intensive.

Some techniques for nonlinear equalization are Volterra filters [5] and neural networks [4]. We apply SVM to data detection [3]. The effectiveness of applying SVM to a pattern classification problem involving large datasets has been demonstrated in literature [6].

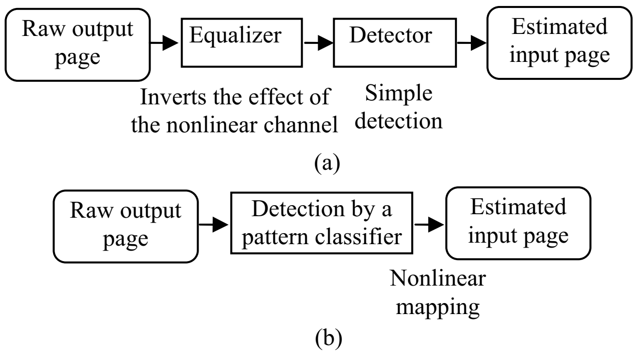


Fig. 1. (a) Two-step channel equalization and detection and (b) Single-step detection by a pattern classifier.

2.1. SVM detection formulation

The main idea behind SVM is to separate classes with a decision surface that maximizes the margin between them [7]. Different generalization bounds exist motivating different algorithms, e.g., optimizing the maximal margin, the margin distribution, the number of support vectors etc. The most common one aims at training a SVM to obtain the maximum margin classifier and this can be shown to be equivalent to the problem of minimizing the norm of the weight vector.

The training and testing datasets used and the SVM formulation pertaining to our application is described in this section. InPhase Technologies provided the data pages we use in experiments. It consists of 60 binary input pages of size 1024x1280 pixels and their corresponding real holographically stored and retrieved pages. Pages 1 through 60 were recorded in the same order in time, with page 1 being the first page recorded and page 60 the last one. Page 60 is used as the training data page to determine the SVM decision function parameters because it is the last page recorded, hence unlike the other pages it has no or very little erasure [1]. The remaining 59 pages were tested using the decision boundaries determined from the training page. These pages are processed block wise, i.e., the data page is divided into blocks of size 64×64 and each block is processed independently. This is because the channel response is not spatially stationary. Due to the nature of optics of the system, there is more ISI at the edges of the field of view than in the center.

A decision function $f_{\lambda}(\mathbf{x})$ needs to be determined for each of these blocks in the page. The known example set $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_n, y_n)$ from each block in the training data page is used to determine this function, where λ is a set of abstract parameters, $\mathbf{x}_i$ is the $n \times n$ pixel neighborhood of each pixel in the i^{th} block of the real retrieved data page and y_i is the corresponding true bit (0 or 1). For linearly separable training samples, there exists a pair ($\mathbf{w}$, b) such that:

$$\begin{aligned} \mathbf{w}.\mathbf{x}_i + b &\geq 1 \qquad \forall y_i = 1 \\ \mathbf{w}.\mathbf{x}_i + b &\leq -1 \qquad \forall y_i = 0 \end{aligned} \tag{1}$$

Given an input vector $\mathbf{x}$ an SVM classifies it according to

$$f_{\mathbf{w},b}(\mathbf{x}) = \mathrm{sign}(\mathbf{w}.\mathbf{x} + b)\,. \tag{2}$$

The hyperplane ($\mathbf{w}$, b) that solves the optimization problem with constraints for normalized weight vector $\mathbf{w}$, additional set of variables that measure the amount of violation of constraints for a non-separable linear SVM case and extension to nonlinear decision surfaces and kernel functions used for them are described in [7].

3. LMMSE EQUALIZATION AND SVM BASED DETECTION

Unlike many conventional storage channels, the HDSS channel is inherently nonlinear because the output camera detects intensity. Linear Minimum Mean Squared Error (LMMSE) equalization is established to be a practical solution [8] for HDSS. In this paper we combine LMMSE equalization and SVM-based detection and show that this linear equalization in fact aids the detection process.

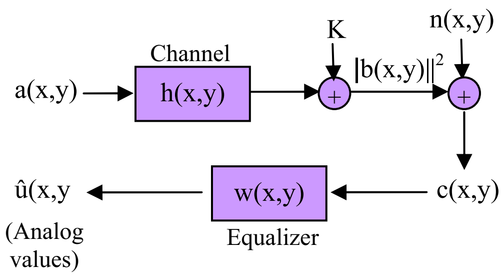


Fig. 2. Nonlinear channel and equalizer model

A schematic of the nonlinear channel model of HDSS and the role of the equalizer is shown in Fig. 2. The analog outputs $\hat{u}(x, y)$ are the LMMSE equalized values. They are the inputs to the SVM detector. In Section 4, we show that LMMSE, which minimizes the mean squared error between the channel output $c(x, y)$ and the input $a(x, y)$, complements the linear SVM; which minimizes the norm of the weight vector $\mathbf{w}$, effectively increasing the margin of separation between the two classes (i.e., 0s and 1s).

4. RESULTS AND DISCUSSION

In this section, we present our results for data detection on real data pages using SVM. Section 4.1 compares the BER with SVM detection compared to the threshold detection. In section 4.2 results using LMMSE equalization prior to SVM is presented. Finally, choice of SVM kernel type and the required kernel size for our dataset from InPhase Technologies is discussed in Section 4.3. A simple choice of linear SVM of size 3×3 combined with LMMSE equalization using a 3×3 kernel and a bias constant K is seen to be sufficient.

4.1. Performance of SVM for detection

The SVM decision boundaries for each block of size 64×64 segmented from a data page are determined using the training page 60. These boundaries are used in the test pages 1 through 59 to make decisions of bit 0 or 1. Similarly, the thresholds to obtain the best BER in each of these blocks of the training page are determined and utilized in the test pages. For this test, a linear SVM of kernel size 3×3 was used. Some additional SVM parameters were assigned specific values for all the simulations. Cost of constraints violation C, in non-separable linear SVM case is chosen to be 1. Choice of this parameter is a current research area. Another assumption is that we use linear violation in the constraints for the non-separable case.

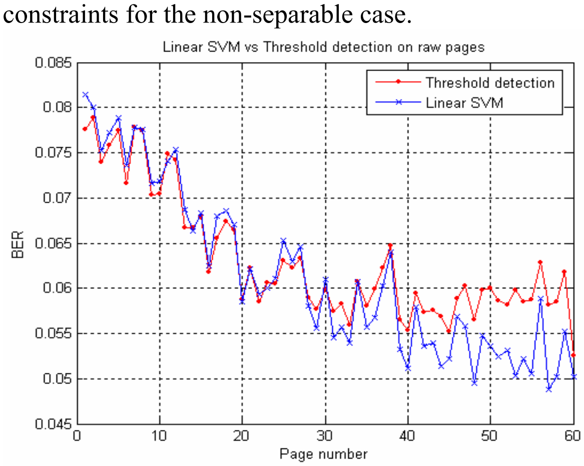


Fig. 3. Performance of linear SVM versus threshold detection

SVM performs slightly better than threshold detection on the real read back pages 30 to 60 and for the rest of the pages, the BER is similar to threshold detection. This is illustrated is Fig. 3. In the training page 60, the BER using threshold detection is 0.0525 and using linear SVM it is 0.0502. BER reduced by about 4.4% by using SVM rather than the threshold detection. In the test pages, use of SVM reduced the error rate by about 10.5% in page 59 and increased by 5% in page 4.

Computing the SVM decision boundaries from the training data requires about 3.2 seconds compared to the 0.08 seconds to determine the best threshold, for a block size of 64×64 pixels in training data page on our computer setup using Matlab 6.5 on a Dell Dimension 4600 Series, Intel Pentium 4 Processor at 3.4 GHz and 1024 MB DDR SDRAM at 333MHz. However, for SVM detection for the test pages that use the boundaries determined from the training page, the number of seconds required for a 64×64 pixel block is 1.08. So, clearly using the SVM involves more computational complexity.

4.2. LMMSE equalization prior to SVM detection

The real retrieved page is equalized using LMMSE equalizer prior to applying SVM detection on it. Essentially the raw page is equalized using a set of filter coefficients and a bias constant derived based on the minimum mean squared error criterion between them and the input binary pattern (see Fig. 2) [8]. We use a filter size of 3×3. In these pages there is very little ISI and hence bigger size filters are not necessary. Hence, there are 10 parameters determined from the LMMSE equalization that essentially invert the effect of the linear ISI in the channel.

Linear SVM is applied to these equalized pages and the BER obtained is compared to the BERs obtained using the LMMSE equalization and the threshold detection combination. The results for both are shown in Fig. 4.

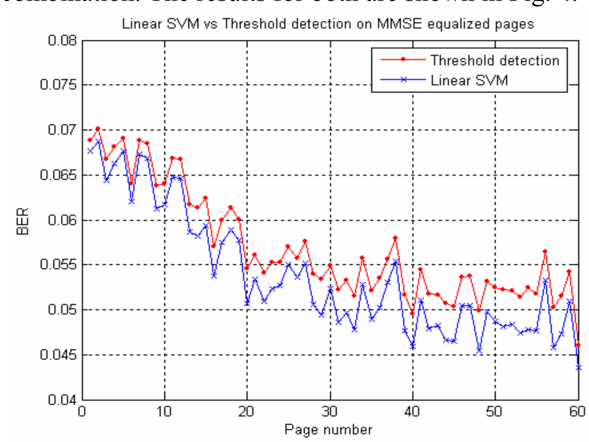


Fig. 4. Performance of LMMSE equalization prior to linear SVM/ threshold detection

	Threshold detection	Linear SVM
Training page 60	0.0460	0.0436
Test page 59	0.0542	0.0509
Test page 4	0.0681	0.0662

Table 1. Comparison of linear SVM and threshold detection on LMMSE equalized pages

LMMSE equalization in itself reduces the BER for both SVM and threshold detection by about 13% and 12% (in training page 60) respectively over that of the detection without LMMSE equalization. Detection using linear SVM in particular seems to have produced a greater advantage from LMMSE equalization (17% reduction in BER in the training page 60, 17.5% in test page 59 and 12.7% in test page 4).

Comparison between the BER using linear SVM and threshold detection on LMMSE equalized pages is shown in Table 1. BER using linear SVM on LMMSE equalized pages is about 0.0436 in the training page 60 which is slightly less than 0.0460, the BER using threshold detection on the equalized pages.

4.3. Choice of SVM kernel type and size

The choice of kernel function is important for SVM detection. There are several options available such as the Radial Basis Function (RBF), polynomials, the multilayer perceptron etc. [7]. These were applied and evaluated for our problem. The results are shown in Table 2.

RBF kernel function works best with the training page. However, linear SVM offers better generalization capability and performs comparably to the other kernels for the test pages. As seen in Table 2, linear SVM performs quite similarly to the other kernels for the test pages 59 and 4. Similar observation can be made for the rest of the test pages as well.

	Linear	Polynomial (Degree 2)	Polynomial (Degree 3)	RBF
Training page 60	0.0436	0.0387	0.0343	0.0321
Test page 59	0.0509	0.0490	0.0520	0.0500
Test page 4	0.0662	0.0638	0.0656	0.0632

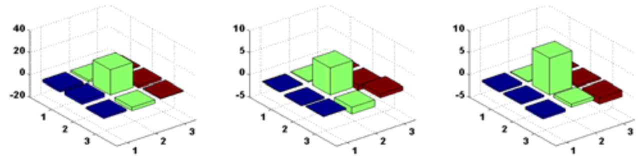
Table 2. Comparison of performance of different kernel functions for SVM detection on LMMSE equalized pages

Suitable size of the SVM kernel also needs to be determined. Based on the amount of ISI in the system, the choice of the kernel size is made. BER for various kernel sizes of linear SVM is shown in Table 3. We observe from this table that there is no significant improvement in the BER by using bigger kernel sizes of 5×5 and 7×7.

	3×3	5×5	7×7
Training page 60	0.0436	0.0412	0.0394
Test page 59	0.0509	0.0497	0.0501
Test page 4	0.0662	0.0663	0.0666

Table 3. Comparison of kernel sizes for linear SVM on LMMSE equalized pages

The amount of ISI in the system can be visualized by observing the 3×3 LMMSE and SVM correlation kernels. A 3-D bar plot of these correlation kernels is in Fig. 5. Linear SVM kernel for the raw data is seen in Fig. 5a. It is evident that there is very little ISI in the system. The LMMSE kernel for the raw pages and the SVM kernel for the LMMSE equalized pages are seen in Figs. 5b and c. They reflect the same observation.



(a) (b) (c)

Fig. 5. (a) 3×3 SVM kernel for raw data, (b) 3×3 LMMSE kernel for raw data, (c) 3×3 SVM kernel for LMMSE equalized data

5. CONCLUSIONS

Some useful inferences can be drawn from our investigation of the 60 input binary pages and their real retrieved pages provided by InPhase Technologies. It is evident from the simulations that the BER using SVM for data detection on LMMSE equalized pages is about 17% better than simple threshold detection on the raw pages. Among the different SVM kernel functions tested we observed that a simple choice of linear SVM of size 3×3 is sufficient for this problem.

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