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Channel Modeling and Detector Design for Dynamic Mode High Density Probe Storage and Nano-imaging Applications ⋆

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Abstract:
In this paper, we provide a consolidated summary of the work reported in [1], [2], [3], [4] which is based on probe based high density storage and nano-imaging using atomic force microscopy (AFM) setup. In probe based high density storage, we consider a data storage system that operates by encoding information as topographic profiles on a polymer medium. A cantilever probe with a sharp tip (few nm radius) is used to create and sense the presence of topographic profiles, resulting in a density of few Tb per in.^{2}. The high quality factor dynamic mode operation, that is less harsh on the media and the probe, is analyzed. The read operation is modeled as a communication channel which incorporates system memory due to inter-symbol interference and the cantilever state. Next, the solutions to the maximum likelihood sequence detection problem and maximum a posterior (MAP) symbol detection problem based on the Viterbi algorithm and BCJR algorithm respectively are devised. Experimental results demonstrate that the performance of the Viterbi and BCJR detectors are several orders of magnitude better than the performance of other existing schemes.
Nano-imaging has played a vital role in basic sciences as it enables interrogation of material with sub-nanometer resolution. In this paper, we also present a high speed one-bit imaging technique using dynamic mode AFM with a high quality factor cantilever. Experimental results demonstrate that our proposed algorithm provides significantly better image resolution compared to current nano-imaging techniques at high scanning speed.

1. INTRODUCTION

Currently high density storage devices are primarily based on magnetic, optical and solid state technologies. Advanced signal processing and detection techniques such as partial-response max-likelihood have played an important role in the design of all data storage systems [5, 8].

In this paper, we have considered a promising high density storage methodology which utilizes a sharp tip at the end of a micro cantilever probe to create, remove and read indentations (see [12]). A bit of information is represented by the presence/absence of an indentation. The main advantage of this method is the significantly higher areal densities compared to conventional technologies that are possible. Recently, experimentally achieved tip radii near 5 nm on a micro-cantilever were used to create areal densities close to 1 Tb/in^2 [12].

A particular realization of a probe based storage device that uses an array of cantilevers, along with the static mode operation is provided in [7]. However, there are fundamental drawbacks of this technique. In the static mode operation, the cantilever is in contact with media throughout the read operation which results in large vertical and lateral forces on the media and the tip. Moreover, significant information content is present in the low frequency region of the cantilever deflection and it can be shown experimentally that the system gain at low frequency is very small. Therefore, in order to overcome the measurement noise at the output, the interaction force between the tip and the medium has to be large. This degrades the medium and the probe over time, resulting in reduced device lifetime.

The dynamic mode operation can partly address the problem of tip and media; particularly when a cantilever with a high quality factor is employed. In the dynamic mode operation, the cantilever is forced sinusoidally using a dither piezo. The oscillating cantilever gently taps the medium and thus the lateral forces are reduced which decreases the media wear [15]. Using cantilever probes that have high quality factors leads to high resolution, since the effect of a topographic change on the medium on the oscillating cantilever lasts much longer (approximately Q cantilever oscillation cycles, where each cycle is $1/f_0$ seconds long and Q and f_0 is the quality factor and the resonant frequency of the cantilever respectively). Moreover, the SNR improves as $\sqrt{Q}$ [13]. However, this also results in severe inter-symbol-interference, unless the topographic changes are spaced far apart. Spacing the changes far apart is undesirable from the storage viewpoint as it implies lower areal density. Another issue is that the cantilever exhibits complicated nonlinear dynamics. For example, if

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there is a sequence of hard hits on the media, then the next hit results in a milder response, i.e., the cantilever itself has inherent memory, that cannot be modeled as ISI. Conventional dynamic mode methods described in [9], that utilize high-Q cantilevers are not suitable for data storage applications. This is primarily because they are unable to deal with ISI and the nonlinear channel characteristics. The current techniques can be considered analogous to peak detection techniques in magnetic storage [6].

In this paper, we have demonstrated that these issues can be addressed by modeling the dynamic mode operation as a communication system and developing high performance detectors for it. Note that corresponding activities have been undertaken in the past for technologies such as magnetic and optical storage [14], e.g., in magnetic storage, PRML techniques, resulted in tremendous improvements. In this work, the main issues are, (a) developing a model for the cantilever dynamics that predicts essential experimental features and remains tractable for data storage purposes, and (b) designing high-performance detectors for this model, that allow the usage of high quality cantilevers, without sacrificing areal density. As discussed in the sequel, several concepts such as Markovian modeling of the cantilever dynamics and Viterbi detection in the presence of noise with memory [5], play a key role in given approach.

Atomic force microscopy (AFM) has also played a vital role in controlling, manipulating and interrogating matter at the atomic scale. In nano-imaging, the samples, to be imaged, are mostly soft which requires the use of the dynamic mode AFM with a high quality factor cantilever as against contact mode AFM. The dynamic mode operation provides less sample wear [15]. In the current state of art, various imaging techniques such as amplitude imaging [16], root mean square imaging [17] and LMP imaging [2] are available for the dynamic mode AFM setup. However, current imaging techniques are too slow to be useful in high fidelity imaging of chemical and biological processes that evolve at fast time scales. In nano-imaging work, the main issues are, (a) developing an imaging algorithm which can provide high fidelity imaging of biological and chemical processes evolving at fast time scales and (b) incorporating a learned input prior in the imaging algorithm for better feature detection.

In this paper, we provide a consolidated summary of the work reported in [1], [2], [3], [4]. This paper will motivate the use of control and communications techniques in probe based high density storage and nano-imaging. The summary of the work is as follows. We have researched a dynamic mode read operation where the probe is oscillated and the media information is modulated on the cantilever probe's oscillations. We have demonstrated that an appropriate level of abstraction is possible that obviates the need for an involved physical model. The read operation is modeled as a communication channel which incorporates the system memory due to inter-symbol interference and the cantilever state that can be identified using training data. Using the identified model, the solutions to the maximum likelihood sequence detection (MLSD) and maximum a posterior (MAP) symbol detection problem based on the Viterbi algorithm and BCJR algorithm respectively are devised. The developed detectors can also be used

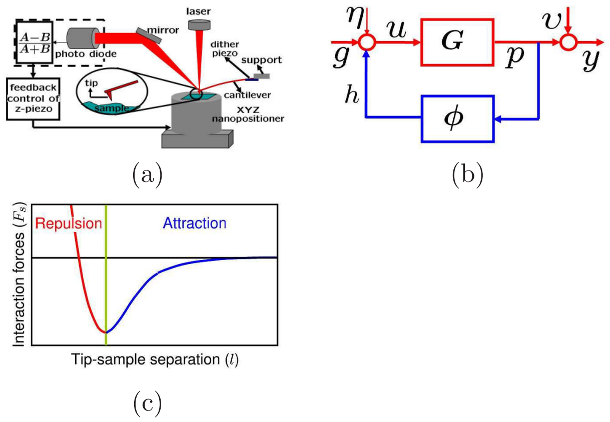

Fig. 1. (a) Shows the main components of a probe based storage device. (b) Shows a block diagram representation of the cantilever system. (c) Shows the typical tip-media interaction forces of weak long range attractive forces and strong repulsive short range forces [1].

for one-bit nano-imaging imaging. The BCJR imaging algorithm is presented which incorporates a learned prior from the previous scan line while detecting the features on the current scan line. Experimental results which corroborate the analysis of the detector, demonstrate that the performance of the BCJR and Viterbi decoding is several orders of magnitude better than the performance of other existing schemes and confirm performance gains that can render the dynamic mode operation feasible for high density data storage purposes. Experimental results for nano-imaging show that the BCJR imaging provides significantly better image resolution compared to current nano-imaging techniques at high scanning speed.

The paper is organized as follows. In Section 2, background and related work of the probe based data storage system is presented. Section 3 deals with the problem of designing and analyzing the data storage unit as a communication system and finding efficient detectors for the channel model. Section 4 discusses the imaging algorithms used for nano-imaging applications. Section 5 reports results from experiments. Section 6 provides the main findings of this paper and future work.

2. BACKGROUND AND RELATED WORK.

Probe based high density data storage devices employ a cantilever beam that is supported at one end and has a sharp tip at another end as a means to determine the topography of the media on which information is stored. The information on the media is encoded in terms of topographic profiles. A raised topographic profile is considered a high bit and a lowered topographic profile is considered a low bit. There are various means of measuring the cantilever deflection. In the standard atomic force microscope setup, which has formed the basis of probe based data storage, the cantilever deflection is measured by a beam-bounce method where a laser is incident on the back of the cantilever surface and the laser is reflected from the cantilever surface into a split photodiode. The photodiode collects the incident laser energy and provides a measure of the cantilever deflection (see Figure 1(a)).

2.1 Models of cantilever probe, the measurement process and the tip-media interaction

A first mode approximation of the cantilever is given by the spring mass damper dynamics described by

$$\ddot{p} + \frac{\omega_0}{Q}\dot{p} + \omega_0^2 p = \mathfrak{f}(t),\ y = p + v, \tag{1}$$

where $\ddot{p} = \frac{d^2p}{dt^2}$, $p, \mathfrak{f}$, y and v denote the deflection of the tip, the force on the cantilever, the measured deflection and the measurement noise respectively whereas the parameters ω_0 and Q are the first modal frequency (resonant frequency) and the quality factor of the cantilever respectively. The input-output transfer function with input $\mathfrak{f}$ and output p is given as $G = \frac{1}{s^2 + \frac{\omega_0}{Q}s + \omega_0^2}$. The cantilever model described above can be identified precisely (see [10]).

The interaction force, h, between the tip and the media depends on the deflection p of the cantilever tip. Such a dependence is well characterized by the Lennard-Jones like force that is typically characterized by weak long-range attractive forces and strong short range repulsive forces (see Figure 1(c)). Thus, the probe based data storage system can be viewed as an interconnection of a linear cantilever system G with the nonlinear tip-media interaction forces in feedback (see Figure 1(b) and note that $p = G(h + \eta + g)$ with $h = \phi(p)$ [11]).

2.2 Cantilever-Observer Model

A state space representation of the filter G can be obtained as $\dot{\overline{x}} = A\overline{x} + B\mathfrak{f}$, $y = C\overline{x} + v$ where $\overline{x} = [p\ \dot{p}]^T$ and $\mathfrak{f} = \eta + g$ (assuming no media forces h) and A, B and C are given by,

$$A = \begin{bmatrix} 0 & 1 \\ -\omega_0^2 & -\omega_0/Q \end{bmatrix},\quad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix},\quad C = [\,1\ \ 0\,]$$

Based on the model of the cantilever, an observer to monitor the state of the cantilever can be implemented (see Figure 2) [9]. The observer dynamics and the associated state estimation error dynamics is given by,

$$\overbrace{\begin{aligned} \dot{\hat{\overline{x}}} &= A\hat{\overline{x}} + Bg + L(y - \hat{y}); \hat{\overline{x}}(0) = \hat{\overline{x}}_0, \\ \hat{y} &= C\hat{\overline{x}}, \end{aligned}}^{Observer}$$

$$\overbrace{\begin{aligned} \dot{\tilde{\overline{x}}} &= A\overline{x} + B(g + \eta) - A\hat{\overline{x}} - Bg - L(y - \hat{y}), \\ &= (A - LC)\tilde{\overline{x}} + B\eta - Lv, \\ \tilde{\overline{x}}(0) &= \overline{x}(0) - \hat{\overline{x}}(0), \end{aligned}}^{State\ Estimation\ Error\ Dynamics}$$

where L is the gain of the observer, $\hat{\overline{x}}$ is the estimate of the state $\overline{x}$ and g is the external known dither forcing applied to the cantilever. The error in the estimate is given by $\tilde{\overline{x}} = \overline{x} - \hat{\overline{x}}$, whereas the error in the estimate of the output y is given by, $e = y - \hat{y} = C\tilde{\overline{x}} + v$.

As described in [9], the discretized model of the cantilever dynamics is given by

$$\begin{aligned} x_{k+1} &= Fx_k + G(g_k + \eta_k) + \delta_{\theta,k+1}\nu\ , \\ y_k &= Hx_k + v_k, k \geq 0\ , \end{aligned} \tag{2}$$

where the matrices F, G, and H are obtained from matrices A, B and C using the zero order hold discretization at a desired sampling frequency and $\delta_{i,j}$ denotes the dirac delta function. θ denotes the time instant when the impact between the cantilever tip and the media occurs and ν signifies the value of the impact. The impact results in an instantaneous change or jump in the state by ν at time instant θ. When a Kalman observer is used, the profile in the error signal due to the media can be pre-calculated as,

$$e_k = y_k - \hat{y}_k\ = \Gamma_{k;\theta}\ \nu + n_k\ , \tag{3}$$

where $\{\Gamma_{k;\theta}\ \nu\}$ is a known dynamic state profile with an unknown arrival time θ defined by $\Gamma_{k;\theta} = H(F - L_K H)^{k-\theta}$, for $k \geq \theta$. L_K is the Kalman observer gain, n_k is a zero mean white noise sequence which is the measurement residual had the impact not occurred and θ is assumed to be equal to 0 for simplicity.

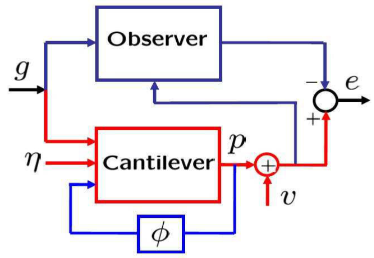

Fig. 2. An observer architecture for the cantilever system shown in Figure 1(b) [1].

3. CHANNEL MODEL AND DETECTORS

3.1 Reformulation of state space representation

It is to be noted that although we have modeled the cantilever system as a spring-mass-damper model (second order system with no zeros and two stable poles)(see (1)), the experimentally identified channel transfer function that is more accurate in practice has right half plane zeros that are attributed to delays present in the electronics. Given this scenario, the state space representation used in [9] leads to a discrete channel with two inputs as seen in (3) because the structure of B is no longer in the form of $[0\ 1]^T$. However, source information enters the channel as a single input as the tip-medium interaction force. The problem can be reformulated as one of a channel being driven by a single input by choosing an appropriate state space representation [2]. In this paper, the single source model is used as it simplifies the detector structure and analysis substantially.

3.2 Channel Model

We have modeled the cantilever based data storage system as a communication channel as shown in Figure 3 [3]. The components of this model are explained below in detail.

Shaping Filter ($b(t)$): The model takes as input the bit sequence $\bar{a} = (a_0,\ a_1 \ldots\ a_{N-1})$ where $a_k, k = 1, \ldots, N-1$ is equally likely to be 0 or 1. In the probe storage context, '0' refers to the topographic profile being *low* and '1' refers to the topographic profile being *high*. Each bit has a duration of T seconds. This duration can be found based on the length of the topographic profile specifying a single bit and the speed of the scanner. The height of the high bit is denoted by A. The cantilever interacts with the media by gently tapping it when it is high. When the media is low, typically no interaction takes place. We model the effect of the medium height using a filter with impulse response

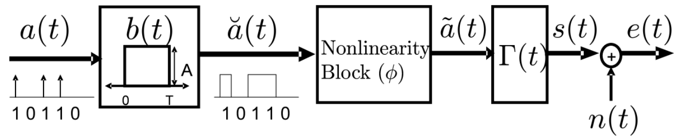

Fig. 3. Continuous time channel model of probe based data storage system [1].

$b(t)$ (shown in Figure 3) that takes as input, the input bit impulse train $a(t) = \sum_{k=0}^{N-1} a_k \delta(t-kT)$. The output of the filter is given by $\breve{a}(t) = \sum_{k=0}^{N-1} a_k b(t-kT)$.

Nonlinearity Block (ϕ): The cantilever oscillates at frequency f_0 which means that in each cantilever cycle of duration $T_c = 1/f_0$, the cantilever hits the media at most once if the media is high during a time T_c. Due to the dynamics of the system it may not hit the media, even if it is high. The magnitude of impact on the media is not constant and changes according to the state of the cantilever prior to the interaction with the media. We note that a very accurate modeling of the cantilever trajectory will require the solution of complex nonlinear equations corresponding to the cantilever dynamics and knowledge of the bit profile so that each interaction is known. In this work we model the impact values of the tip-media interaction by means of a probabilistic Markov model that depends on the previous bits. This obviates the need for a detailed model. We assume that in each high bit duration T, the cantilever hits the media q times (i.e. $T = qT_c$) with varying magnitudes. Therefore, for N bits, the output of the nonlinearity block is given by, $\tilde{a}(t) = \sum_{k=0}^{Nq-1} \nu_k(\bar{a})\delta(t-kT_c)$, where ν_k denotes the magnitude of the k^{th} impact of the cantilever on the medium. Here, we approximate the nonlinearity block output as a sequence of impulsive force inputs to the cantilever. The strength of the impulsive hit at any instant is dependent on previous impulsive hits; precisely because the previous interactions affect the amplitude of the oscillations that in turn affect how hard the hit is at a particular instance. The exact dependence is very hard to model deterministically and therefore we chose a Markov model, as given below for the sequence of impact magnitudes for a single bit duration,

$$\bar{\nu}_i = \bar{\mathfrak{G}}(a_i, a_{i-1}, \ldots, a_{i-m}) + \bar{\mathfrak{b}}_i \tag{4}$$

where $\bar{\mathfrak{G}}(a_i, a_{i-1}, \ldots, a_{i-m})$ is a function of the current and the last m bits and $\bar{\nu}_i = [\nu_{iq}\ \nu_{iq+1} \ldots \nu_{(i+1)q-1}]^T$. Here m denotes the system memory and $\bar{\mathfrak{b}}_i$ is a zero mean i.i.d. Gaussian vector of length q. The appropriateness of the model will be demonstrated by our experimental results.

Channel Response ($\Gamma(t)$): The Markovian modeling of the output of the nonlinearity block as discussed above allows us to break the feedback loop in Figure 2 (see also [9]). The rest of the system can then be modeled by treating it as a linear system with impulse response $\Gamma(t)$. $\Gamma(t)$ is the error between the cantilever tip deflection and the tip deflection as estimated by the observer when the cantilever tip is subjected to an impulsive force. It can be found in closed form for a given set of parameters of cantilever-observer system (see (3)).

Channel Noise ($n(t)$): The measurement noise (from the imprecision in measuring the cantilever position) and thermal noise (from modeling mismatches) can be modeled by a single zero mean white Gaussian noise process ($n(t)$) with power spectral density equal to V.

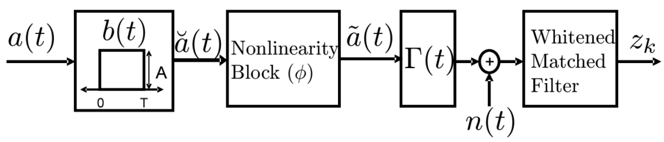

Fig. 4. Discretized channel model with whitened matched filter [1].

The continuous time innovation output $e(t)$ becomes, $e(t) = s(t, \bar{\nu}(\bar{a})) + n(t)$, where $s(t, \bar{\nu}(\bar{a})) = \sum_{k=0}^{Nq-1} \nu_k(\bar{a})\Gamma(t-kT_c)$ and $\bar{\nu}(\bar{a}) = (\nu_0(\bar{a}),\ \nu_1(\bar{a}) \ldots\ \nu_{Nq-1}(\bar{a}))$.

3.3 Sufficient Statistics for Channel model

In [1], we have proved that the output of the discretized output of whitened matched filter shown in Figure 4 forms the sufficient statistics for the channel model. We shall denote the discretized output of whitened matched filter as z_k, such that $z_k = \sum_{k_1=0}^{I} \nu_{k-k_1}(\bar{a})h_{k_1} + n_k$, where the filter $\{h_k\}_{k=0,1,\ldots,I}$ denotes the effect of the whitened matched filter and the sequence $\{n_k\}$ represents the Gaussian noise with variance V.

3.4 Viterbi Detector Design

We can formulate the maximum likelihood (ML) detection strategy as,

$$\begin{aligned} \hat{\bar{a}} &= \arg \max_{\bar{a} \in \{0,1\}^N} f(\bar{z}|\bar{a}) \\ &= \arg \max_{\bar{a} \in \{0,1\}^N} \Pi_{i=0}^{N-1} f(\bar{z}_i|\bar{a}, \bar{z}_0^{i-1}) \end{aligned} \tag{5}$$

where $\bar{z} = [z_0\ z_1 \ldots z_{Nq-1}]^T$, $\bar{z}_i$ is the received output vector corresponding to the i^{th} input bit, i.e., $\bar{z}_i = [z_{iq}\ z_{iq+1} \ldots z_{(i+1)q-1}]^T$ and $\bar{z}_0^{i-1} = [\bar{z}_0^T\ \bar{z}_1^T \ldots \bar{z}_{i-1}^T]^T$. This detector can be simplified using dependency graph and a closed form solution for the detector metric can be found in [1].

3.5 MAP Symbol Detector

The a posteriori probability (APP) of a symbol, a_k is defined as, $APP(a_k) = f(a_k|\bar{z})$. In MAP symbol detection, the symbol a_k is found which maximizes the $APP(a_k)$. This detector can also be derived in closed form using physically motivated assumptions and dependency graph [4].

3.6 LMP, GLRT and Bayes Detector

In [2], we proposed various detectors for hit detection like locally most powerful (LMP), generalized likelihood ratio test (GLRT) and Bayes detector. These detectors also ignore the system memory and perform detection of single hits. Subsequently a majority type rule is used for bit detection. These detectors perform well only when the hits are sufficiently apart.

4. HIGH SPEED FEATURE DETECTION IN NANO-IMAGING

The channel modeling and detector design for dynamic mode AFM can also be used for various applications such as nano-imaging. In [4], we have considered one-bit

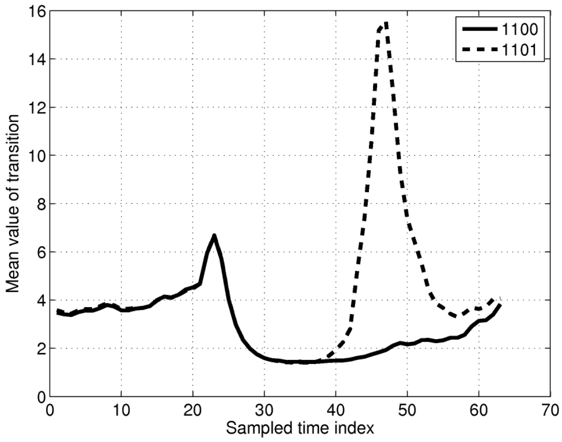

Fig. 5. Mean vector for 2 state transitions for 300 μs bit width from experimental data where '1100' and '1101' represents transition from state '110' to state '100' and '101' respectively [1].

imaging, i.e., the presence/absence of a feature is detected. In one-bit imaging technique, the raster scan is used for the imaging which means that the image is subdivided into a sequence of horizontal scan lines and each scan line is imaged using AFM system scanner. The channel model for the high quality factor cantilever system which was developed for the dynamic mode probe storage is used for one-bit imaging. But the Viterbi detection algorithm based on equiprobable input prior cannot be used as the images will have different priors depending upon the features present in the image. Thus, the imaging problem is posed as one of finding the maximum a posteriori (MAP) symbol detector for this model. This is solved by adapting the BCJR algorithm for the channel model. Furthermore, we have proposed an improved MAP symbol detector in [4] that incorporates a learned prior from the previous scan line while detecting the features on the current scan line.

5. EXPERIMENTAL RESULTS

5.1 Dynamic Mode Probe Storage

In experiments, a cantilever with resonant frequency $f_0 = 71.78$ KHz and quality factor $Q = 67.55$ is oscillated near its resonant frequency. A freshly cleaved mica sheet is placed on top of a high bandwidth piezo. This piezo can position the media (mica sheet) in z-direction with respect to cantilever tip. A random sequence of bits is generated through an FPGA board and applied to the z-piezo. The bit width can be changed using FPGA controller from $60-350\,\mu s$. An observer is implemented in another FPGA board which is based on the cantilever's free air model and takes dither and deflection signals as its input and provides innovation signal at the output. The innovation signal is used to detect bits by comparing various bit detection algorithms. The experiments were performed on Multimode AFM, from Veeco Instruments.

The BER for different bit widths from all the detectors is shown in Figure 6. It can be clearly seen that Viterbi and BCJR decoding gives remarkable results on experimental data as compared to the LMP and the GLRT detector. The Viterbi and BCJR detector exploits the cantilever

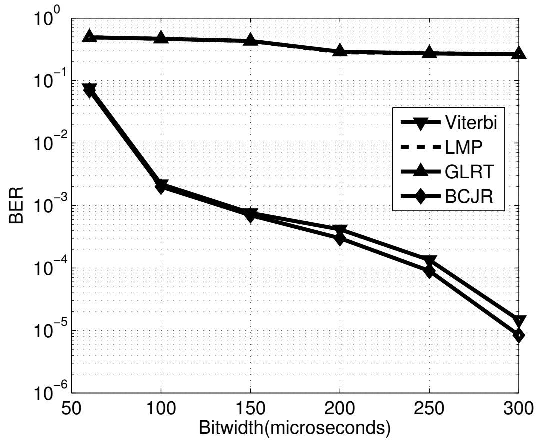

Fig. 6. BER for BCJR, Viterbi, LMP and GLRT for different bit widths varying from 60 μs to 300 μs for experimental data. There is a marginal difference between LMP and GLRT curve which is not visible in the graph but LMP performs better than GLRT [1].

dynamics by modeling the mean and covariance matrix for different state transitions. We have plotted the mean vectors for 2 state transitions with 300 μs bit width in Figure 5. There are around 21 hits in one bit duration. The Viterbi decoding contains 8 states and 16 possible state transitions. In Figure 5, there is a clear distinction in mean vectors for different transitions which makes the Viterbi detector quite robust. Thresholding detectors like LMP and GLRT perform very badly on experimental data. It is interesting to see that BCJR decoding performs better than Viterbi decoding for larger bitwidths but they perform equally well for smaller bitwidths.

5.2 Nano-imaging Experiments

We performed the experiments for one-bit imaging with a cantilever with resonant frequency $f_0 = 74.73$ KHz and quality factor $Q = 140.68$. The test pattern shown in Figure 7 (a), that is of dimension 2.7 μm$\times$ 10μm is considered. In the first set of experiments, the scan rate is taken such that each pixel remains high or low for 120 μsec which means cantilever will hit around 8 times if the topographic profile is high. The scan rate in this case is 182.44 μm/sec. In Figure 7, the performance of current state of the art techniques is compared with BCJR imaging technique at 182.44 μm/sec imaging speed. In order to see the improvement provided by BCJR imaging method, the images are zoomed in for showing the spatial features in Figure 8. BCJR algorithm cleanly resolves all the spatial features present in the image whereas other state-of-the-art imaging techniques cannnot. It is evident that the proposed technique has much better fidelity providing better resolution even at high scan speeds.

6. CONCLUSIONS AND FUTURE WORK

We presented the dynamic mode operation of a cantilever probe with a high quality factor and demonstrated its applicability to a high-density probe storage system. We modeled the system as a communication system by modeling the cantilever interaction with media. The bit detection problem is solved by posing it as a MLSD and

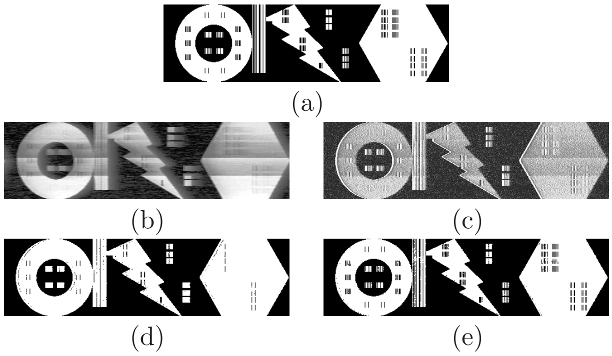

Fig. 7. Comparison of imaging techniques at a scan rate of 182.44 μm/sec scan rate. (a) Reference test pattern, (b) Amplitude imaging (c) Root mean square imaging (d) LMP imaging (e) BCJR Imaging [4].

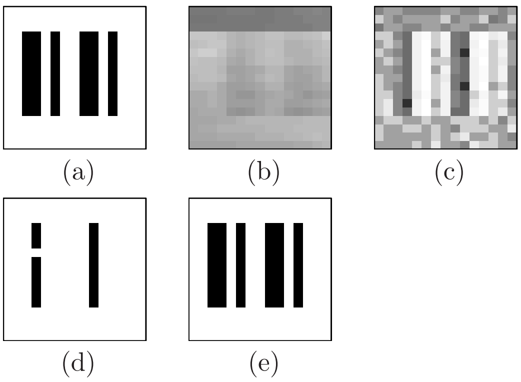

Fig. 8. Comparison of the feature resolution provided by different techniques at scan rate of 182.44 μm/sec. A zoomed image is provided for facilitating visual comparison. (a) Reference test pattern, (b) Amplitude imaging (c) Root mean square imaging (d) LMP imaging (e) BCJR Imaging [4].

MAP symbol detection followed by Viterbi and BCJR decoding respectively. Experimental results show that the Viterbi and BCJR detectors outperform LMP, GLRT and Bayes detector and give remarkably low BER in storage. In future, it is expected to achieve even lower BER by using appropriate coding techniques. We have also shown the application of the abstracted channel model for the cantilever based nano-imaging system. We proposed the BCJR imaging algorithm for the raster scan imaging which incorporates the input prior from previous line scan while detecting the features on the current line scan. Experimental results demonstrate that proposed algorithm provides better image resolution compared to current imaging techniques at high scanning speed. In future, these techniques will enable video rate imaging of molecular scale phenomenon.

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