Journal of Magnetic Resonance 195 (2008) 17–22

Contents lists available at ScienceDirect

Journal of Magnetic Resonance

journal homepage: www.elsevier.com/locate/jmr

Real time exponentially weighted recursive least squares adaptive signal averaging for enhancing the sensitivity of continuous wave magnetic resonance

C.J. Cochrane, P.M. Lenahan *

The Pennsylvania State University, 101 EES Building, University Park, PA 16802, USA

ARTICLE INFO

Article history:
Received 14 March 2008
Revised 8 August 2008
Available online 20 August 2008

Keywords:
Signal processing
Semiconductor reliability
Electrically detected magnetic resonance
Signal averaging
Signal to noise

ABSTRACT

This study involves the use of adaptive signal processing techniques to improve the sensitivity of continuous wave electrically detected magnetic resonance. The approach should be of widespread utility in continuous wave magnetic resonance experiments of all kinds. We utilize adaptive signal averaging to expedite the averaging process usually performed in magnetic resonance experiments. We were capable of reducing the noise variance in a single trace by a factor of 11.3 which is equivalent to reduction in time by the same factor. This factor can be quite significant especially when signal averaging must be performed over the span of many hours to days. This technique may also be tailored to conventional electron spin resonance experiments and other techniques where signal averaging is utilized. The approach may offer promise in the eventual development of spin based quantum computing.

1. Introduction

This paper describes a real time exponentially weighted recursive least squares adaptive signal averaging technique which greatly decreases the amount of time needed for signal averaging of continuous wave magnetic resonance measurements. The technique provides a very low cost means to achieve a quite significant improvement in signal to noise ratio and data acquisition time. The technique is utilized in electrically detected magnetic resonance (EDMR) via spin dependent recombination (SDR) [1,2] in individual transistors [3,4]. However, the approach should be widely applicable in continuous wave magnetic resonance measurements.

EDMR typically involves SDR. EDMR in general and SDR in particular are electron spin resonance (ESR) techniques [5] in which a spin dependent change in current provides a very sensitive measurement of paramagnetic defects. Without special application of digital signal processing techniques, EDMR measurements involving SDR are about seven orders of magnitude more sensitive than conventional ESR. The techniques are therefore particularly useful in studies of imperfections in the semiconductor devices utilized in integrated circuits. In such devices, the dimensions are quite small and can have very low defect densities. SDR detected EDMR can be utilized in fully processed devices such as metal oxide semiconductor field effect transistors (MOSFETs), bipolar junction transistors (BJTs), and diodes [3,4]. With some additional improvements, the technique's very high sensitivity may make it potentially useful for single spin detection and quantum computing. However, the sensitivity EDMR is not currently high enough to detect a single spin in the presence of the noise encountered with present day EDMR spectrometers in a reasonable amount of time. The purpose of this study is to improve the signal to noise ratio and thus the rate of data acquisition in such sensitive EDMR measurements.

Continuous wave magnetic resonance typically utilizes a sinusoidal modulation of the applied magnetic field, thereby encoding the signal in a sinusoid. The amplitude of the modulated signal is a measure of the EDMR and therefore, a measure of the number of defects within the device. A lock-in amplifier (LIA) is then used to demodulate the amplitude modulated EDMR signal to DC, thus exploiting the sensitivity enhancement available from the phase and frequency detection. This widely used method effectively attenuates much of the noise associated with the 1/f noise typically observed with a DC current produced by the diode or transistor utilized in the EDMR measurement. However, lock-in detection alone is not always sufficient to achieve a reasonable signal-to-noise ratio (SNR), so signal averaging is also often utilized. In very small devices with very low defect densities, the EDMR signal to noise ratios can be low. Therefore, extensive signal averaging may be required to achieve a reasonable SNR for the EDMR spectra.

Though work has been performed to remove noise observed in related fields via software, such as nuclear magnetic resonance (NMR) [8], not much has been done in any area of ESR including EDMR. There are many things can be done to improve EDMR SNR in terms of hardware such as proper grounding, minimizing cable length to reduce stray capacitance, and utilizing low noise preamplifiers. However, the focus of this paper will be on the advancements that we made in software.

* Corresponding author. Fax: +1 814 863 7967.
E-mail addresses: corey.cochrane@gmail.com (C.J. Cochrane), pmlesm@engr.psu.edu (P.M. Lenahan).

1090-7807/$ - see front matter © 2008 Elsevier Inc. All rights reserved.
doi:10.1016/j.jmr.2008.08.004

We performed our measurements on 4H SiC lateral n-channel MOSFETs fabricated by Cree Corporation. These devices had a gate area of $200 \times 200\ \mu m^2$ and a thickness of 500 Å. These devices received a thermal ONO gate growth process. All EDMR measurements were made with the sample at room temperature and were performed with a fixed gate voltage. All EDMR spectra reported here were taken with the magnetic field orientation parallel to the SiC/oxide surface normal which is nearly parallel to the crystal's *c*-axis. EDMR measurements were made with a modulation frequency of 1400 Hz and quite low modulation filed amplitude (<0.1 G). The EDMR measurements were made on a custom built EDMR spectrometer which utilizes a Resonance Instruments 8330 X-band bridge, TE_{102} cavity, and magnetic field controller, a Varian E-line century 4 in. magnet, and power supply. We use a Stanford Research Systems SR570 current preamplifier to prefilter and amplify the device currents. We have implemented a virtual lock-in amplifier using Labview (version 8.2) with the NI PCI 6259 M series DAQ card. This VLIA is just as good, if not better, than any of the off the shelf commercial lock-in amplifiers. All software is implemented in Labview and is run on a Dell Optiplex GX270 desktop computer with a 3.2 GHz processor and 1 GB of RAM.

Some of the noise sources that are associated with our EDMR measurements include quantization noise, the ambient noise from the surrounding hardware, and most importantly, the internal shot, thermal, and flicker noise arising from within the device under observation [6,7]. Fig. 1 illustrates the signal path in a typical EDMR spectrometer and shows the types of noise introduced to the signal as well as where it is added. The sampler represents the last contribution of noise because noise cannot be added to the signal once it is digitized. As mentioned earlier, we utilize a digital lock-in amplifier which removes most of the preamp and ambient noise but adds quantization noise (because it digitizes the signal before it is processed). The noise due to sources internal to the device are not entirely removed at the lock-in stage because this noise is to some extent present at the modulation frequency and lock-in phase. Therefore, it is the noise internal to the device that primarily determines the SNR at the output of the lock-in amplifier.

Fig. 2 illustrates current noise spectra from a MOSFETs configured as a gate controlled diode for three different biasing conditions. The top figure represents the condition with 0 V applied to the source and drain of the MOSFET; the current flowing through the device is thus essentially zero, therefore, this indicates that the noise spectrum observed in this case is the noise generated by the preamp. Note that this is more or less a white spectrum, meaning that the noise variance at all frequencies is the same. The middle figure represents the condition in which a small forward bias is applied to the source and drain of the MOSFET, yielding a dc current of 0.002 μA. The bottom figure illustrates a condition in which a large forward bias is applies to the source and drain yielding a dc current of 5 μA. This latter configuration corresponds to the biasing condition which results in maximum recombination and the operating point of our EDMR experiments. Note that this spectrum is significantly different than the other two. The reason for this is because of the significant flicker and shot noise that is introduced with larger dc currents [6]. This indicates that the dominating source of noise in the EDMR experiment is due to flicker and shot noise and that the noise from the preamp only becomes a problem when smaller devices (smaller currents) are being used.

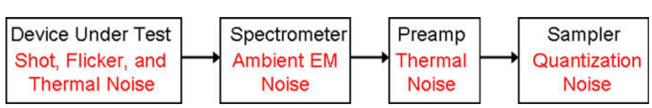

Fig. 1. Signal path in our EDMR spectrometer illustrating the types of introduced as well as the sources.

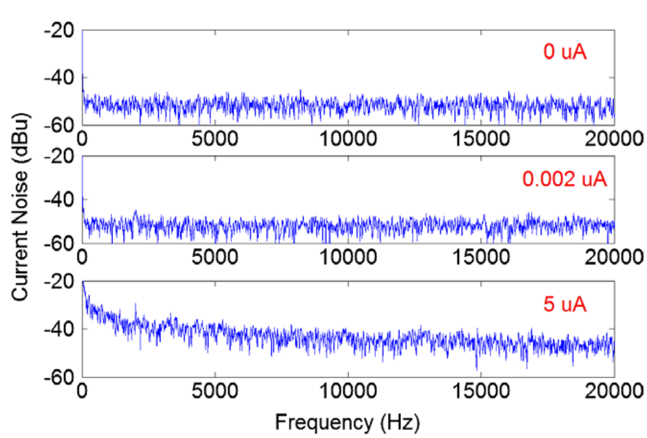

Fig. 2. Current noise spectra from a 4H SiC MOSFET configured in a gated controlled diode biased with three different voltages.

Initially, we attempted to reduce the noise observed in the EMDR experiments with adaptive noise cancellation techniques with a field programmable gate array (FPGA) before lock-in detection. The logic of processing EDMR signals before lock-in detection was the hope that a better representation (ie: improved SNR) of the amplitude modulated input signal would result in an improved SNR signal at the output of the LIA. It turned out that only minimal improvement was achieved because, as mentioned earlier, the majority of the noise in the EDMR measurement arises from the device under study and not the surrounding ambient noise. Also, lock-in detection itself is an extremely effective means of removing noise because it is not only frequency sensitive, but it is sensitive to phase as well. Therefore, the only noise that contaminates the post-lock-in EDMR signal is the noise with a frequency content near that of the modulation frequency. As a result, we decided to move our search to the output of the LIA for an effective way to enhance the sensitivity of EDMR.

In some cases, the devices under study have very few defects which make signal acquisition very difficult and time consuming. We have developed a way to expedite the averaging process by utilizing the predictability of the autoregressive noise features at the output of the LIA. (The time constant of the LIA determines the correlation between successive samples and hence, the predictability). We term this tool an adaptive signal averager (ASA) which utilizes adaptive linear prediction as illustrated in Fig. 2. It works by using the conventional scan average as the desired response in an adaptive linear prediction configuration. The linear predictor $\boldsymbol{w}_n$ is a finite impulse response (FIR) filter of length *p*and the input to the linear predictor is the tapped delayed noisy EDMR vector $\boldsymbol{x}(n)$ also of length *p*, where *n* is the present time index. These vectors are represented as column vectors which are indicated by the transpose operators *T*. The input samples $x(n)$ of the vector $\boldsymbol{x}(n)$ are composed of the desired EDMR signal $d(n)$ and an arbitrary noise component $u(n)$.

$$\boldsymbol{w}_n = [w_n(1), w_n(2), \ldots, w_n(p)]^{\mathrm{T}} \tag{1}$$

$$\boldsymbol{x}(n) = [x(n-1), x(n-2), \ldots, x(n-p)]^{\mathrm{T}} \tag{2}$$

The tapped delayed input vector $\boldsymbol{x}(n)$ is analogous to a shift register. First, the vector is initialized to the first *p* samples of the EDMR signal. Then, when a new sample is acquired, the samples are shifted to make room for the present sample. As a result, the oldest sample is forced out of the input array. This shifting process is then continued until the end of the scan. The present sample of the tapped delayed input vector is represented by the term $x(n-1)$ which is counterintuitive because this notation implies that it is the first past sample. This notation is used because we are attempting to predict the future sample $d(n)$ based on past values of the noisy input sam-