Thermal Hysteresis Characterization Through Blind Deconvolution

Eduardo F. Simas Filho
Electromechanical Systems Research Group
Federal Institute of Education, Science and Technology
Simões Filho, Bahia, Brazil
esimas@ifba.edu.br

Diego B. Haddad
Telecommunications Department
CEFET-RJ
Rio de Janeiro, Brazil
diego@pads.ufrj.br

Luiz A. L. de Almeida
Institute of Humanities, Arts and Science
Federal University of Bahia
Salvador, Bahia, Brazil
lalberto@ufba.br

*Abstract***— Vanadium dioxide (VO_2) thin films are applied in optical detection and modulation sensors. As these films exhibit hysteresis in the temperature-resistance characteristic, proper thermodynamic characterization is required. Temperature sensors usually present slow dynamic responses, and thus, when characterizing thermal hysteresis, the result is a distorted version of the real curve. One way to avoid this problem is to perform thermodynamic characterization by applying a very low temperature ramp. This procedure is time consuming and cannot be repeated for a large number of films. In this work is proposed an unsupervised signal processing procedure to remove the distortion introduced by the measurement channel. For this, a blind deconvolution algorithm is applied to estimate both the measurement channel and the real temperature signal, using only the measured temperature version. The proposed methodology does not require the time-consuming quasi-static measurement and achieves low mean-square error values.**

Keywords: Blind deconvolution; Unsupervised sinal processing; Thermo-electrical characterization; VO_2 thin films.

I. INTRODUCTION

Vanadium dioxide (VO_2) thin films (typical thickness of 1 μm) are applied in thermo-optical switching applications. The speed of the switches can be as fast as 3 ms [1]. VO_2 thin films undergo a semiconductor to metal phase transition at about 68 °C [2]. At low temperature, the VO_2 is a semiconductor. It transforms into metal at high temperature. The phase transition is accompanied with drastic changes in its optical and electrical properties. Considering the temperature - electrical resistance characteristic (T x R), hysteresis loops appear in the semiconductor - metal transition region (for 35°C < T < 60°C), as illustrated in Figure 1.

Using VO_2 thin films at the semiconductor-metal transition is interesting as, at this region, it presents high sensibility (large resistance variations for small temperature changes). In order to use the transition region, proper characterization of the hysteresis curve is required. A problem that appears during the thermo-dynamical characterization is that the delay introduced by the temperature measurement system produces severe distortion on the hysteresis curve (see Figure 2).

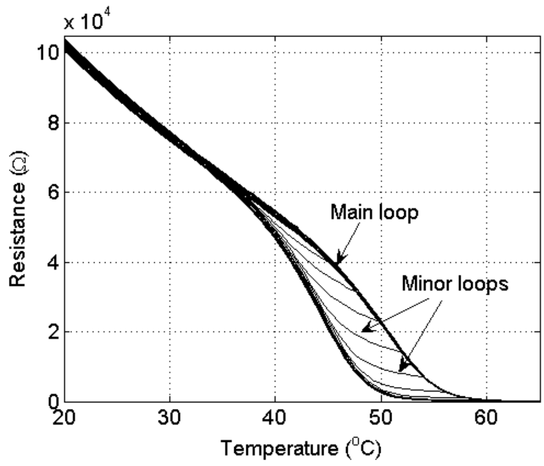

Figure 1 - VO_2 thin film hysteresis curve

One way of minimizing the temperature measurement channel effects is to perform the thermo-dynamical characterization at very low temperature gradient (dT/dt). The hysteresis curve obtained through this procedure is called quasi-static and is the best approximation available for the real curve. The quasi-static measurement is time consuming and requires a sophisticated experimental setup. Considering this, it cannot be performed for a large number of films.

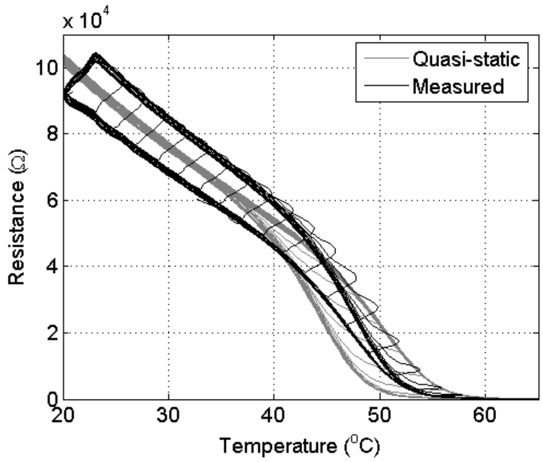

Figure 2 - Measured (distorted) and quasi-static hysteresis curves.

In a previous work [3], the measurement channel inverse transfer function was estimated through a neural network [4] fed from the measured (distorted) temperature (T_M) and using as target the quasi-static temperature (T_{QS}). Once the inverse transfer function is obtained by the neural network it can be used for characterization of other films. In this work, an unsupervised signal processing technique is proposed to remove the distortion introduced by the measurement channel. A blind deconvolution algorithm [5] was applied to estimate both, the measurement channel inverse transfer function and the real temperature by using only the measured signal. Through the proposed methodology small error was obtained and there is no more need to perform the time consuming quasi-static measurement, as the only information required is the measured temperature (T_M).

II. Proposed Method

A. Blind Deconvolution

Deconvolution is a signal processing technique applied to remove the effects of convolution between a signal (*s(n)*) and a propagation channel (transfer function *h(n)*). The observed (or measured) signal is defined as:

$$x(n) = \sum_{i=-\infty}^{\infty} h(i) s(n-i) \ . \quad (1)$$

If *h(n)* and *x(n)* are known, the signal *s(n)* can be easily recovered through an inverse model.

In blind deconvolution (BD) [5], the channel *h(n)* and the source signal *s(n)* are not known a priori and both need to be estimated using only the observed data sequence *x(n)* as illustrated in Figure 3 (some BD algorithms estimate the inverse transfer function $w(n)=h^{-1}(n)$ instead of *h(n)*). This is a much complicated scenario and blind deconvolution can only be solved approximately. Compared to the source, the estimated signal (y(n)) may be modified by undetermined scaling factor and time delay.

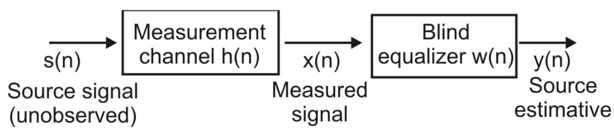

Figure 3 - Diagram of bilnd deconvolution technique.

BD is closely related to another signal processing problem called blind signal separation (BSS) [6]. In the last years, algorithms have been proposed to solve both BD and BSS [5, 6]. Applications of BD and BSS can be found respectively in [7, 8].

B. NGBDe Algorithm

While blind source separation algorithms can estimate distorced versions of the sources, in blind deconvolution (BD) algorithms the time structure of the signals must be preserved. This propertie makes BD attractive for our purposes.

In [9] there is a proposal of a blind deconvolution algorithm that uses a sort of natural gradient. This algorithm usually performs better than the Original Natural Gradient Blind Deconvolution algorithm [10], because of an extra truncation step, which guarantees that the coefficient updates depend only on the input signal samples that appear in its cost function. In this paper, we aim at the monochannel version of the NGBD enhanced (NGBDe) algorithm.

If the *L*-order FIR equalizator is given by *w*(*n*):

$$\mathbf{w}(n) = [w_0(n)\ w_1(n)\ ...\ w_L(n)], \quad (2)$$

and $\mathbf{x}(n) = [x(n)\ x(n\text{-}1)\ ...\ x(n\text{-}L)]^T$ (where ^{T} is the transpose operator), we have that the *n*-th equalizator output sample is:

$$y(n) = \mathbf{w}(n)\mathbf{x}(n). \quad (3)$$

Since $\mathbf{w}(n)$ is adapted in a on-line iterative manner, the *n* index indicates the iteration number. The NGBDe algorithm requires a (possibly inexact) statistical knowledge about the distribution of the source samples, which are supposed to be iid – independent and identically distributed. This is the *nuisance* parameter of the algorithm [11]. Let *p*(*s*) be the pdf that models the source samples. The *f* function is the derivative of the logarithm of *p(s)*. When the source is supergaussian, we usually use the *tanh* choice for *f*. In the case of subgaussian signals, we often choice the y^3 function.

Let $\mathbf{R}(n)$ be the autocorrelation matrix of the coefficients $w_i(n)$, written as:

$$\mathbf{R}(n) = \begin{bmatrix} r_n(0) & r_n(1) & \cdots & r_n(L) \\ r_n(-1) & r_n(0) & \ddots & r_n(L-1) \\ \vdots & \ddots & \ddots & \vdots \\ r_n(-L) & r_n(-L+1) & \cdots & r_n(0) \end{bmatrix}, \quad (4)$$

where $r_n(l) = \sum_{p=0}^{L-|l|} w_p(n) w_{p+|l|}(n)$. If $\mathbf{z}(n) = \mathbf{R}(n)\mathbf{x}(n)$, the NGBDe update equation can be exposed as:

$$\mathbf{w}(n+1) = w(n) + \mu[\mathbf{w}(n) - f(y(n))\mathbf{z}^T(n)] . \qquad (5)$$

III. RESULTS

The experimental setup is composed by a thermo-electric module and a temperature controller, able to perform precisely both low and high rate temperature ramping. The experimental data was collected through two different procedures. Initially, in order to obtain a target signal to evaluate the performance of the algorithm, the temperature was varied in a very low rate ($dT/dt \cong 0$). This signal (T_{QS} - quasi-static temperature) is the best approximation available for the real temperature, as while using $dT/dt \cong 0$ the measurement channel effects are minimized. The quasi-static measurement is only needed in the development phase for performance evaluation. The proposed system does not require this information in the operational phase. In the following, the temperature was measured at high dT/dt, producing the distorted (T_M – measured temperature) data. Figure 4 shows a scatter plot of T_M x T_{QS}.

The NGBDe algorithm was applied to the distorted temperature signal in order to remove the measurement channel effects. It is known that, in our particular problem, the source signal (quasi-static temperature) is subgaussian. Considering this, it was used $f(y)=y^3$ in Eq. 5. A limitation inherit to the blind deconvolution method is that the estimated signal $y(n)$ might be modified by unknown scaling factor α and time delay δ. These indeterminations may prevent the application of the proposed method. In order to estimate the parameters α and δ, the following procedure was adopted:

1. The estimated signal is normalized;

$$y(n) \leftarrow y(n) - E\{y(n)\}, \qquad (6)$$

$$y(n) \leftarrow y(n)/\max\{y(n)\}. \qquad (7)$$

2. The maximum ($max\{T_M\}$) and mean ($E\{T_M\}$) values of the measured temperature are computed and used to re-scale $y(n)$;

$$y(n) \leftarrow (\max\{T_M\} - E\{T_M\}) \times y(n) + E\{T_M\}. \qquad (8)$$

3. The estimation of the time delay δ is performed during the temperature measurement at high dT/dt. The time interval between the instant when the temperature of the thermoelectric module reaches its maximum and the measured temperature (T_M) stabilizes, also at its maximum value, is used as an approximation of δ.

The temperature signal estimated through the proposed method $y(n)$ is compared to the quasi-static measurement in Figure 5. It can be seen that $y(n) \cong T_{QS}(n)$. The hysteresis curve obtained after blind deconvolution is illustrated in Fig.6

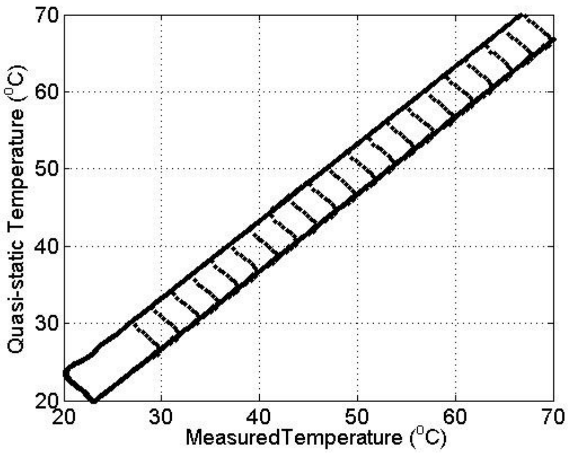

Figure 4 – Measured versus quasi static temperatures

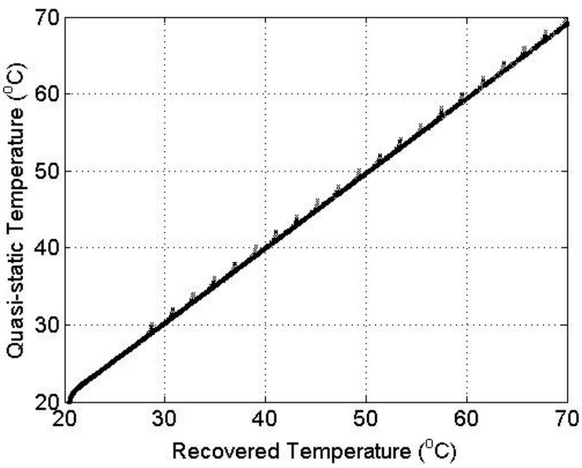

Figure 5 – Post-processed (recovered) versus quasi-static temperatures

The quasi static curve and the recovered one are almost superposed.

The results obtained through the proposed system are compared to other methods in Table 1. In a previous work [3], a neural network was supervised trained to approximate the measurement channel inverse transfer function. The quasi-static temperature was used as target output. A different blind deconvolution algorithm (Constant Modulus Bussgang algorithm) was also applied in [12] to estimate the real temperature. It can be seen that the supervised method (Neural Network) obtained smallest error. Comparing the blind deconvolution algorithms, using NGBDe produces smaller error. The great advantage of using unsupervised learning techniques is that there is no need to perform the time consuming quasi-static measurement. Considering the mean square errors, it can be seen that supervised and non-supervised methods present the same order of magnitude.

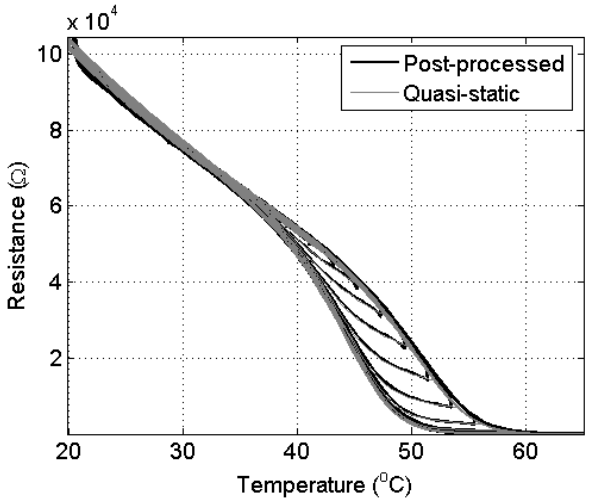

Figure 6 - Post-processed and quasi-static hysteresis curves

TABLE I. MEAN SQUARE ERROR FOR DIFFERENT TECHNIQUES

Mean Square Error (°C)		
Neural Network	*Bussgang BD*	*NGBDe*
1,0	5,4	3,2

IV. CONCLUSIONS

Thermal characterization of vanadium dioxide thin films at the semiconductor-metal transition region is important to produce more sensible optical-electrical devices. Proper characterization of VO_2 films usually requires an excessively time consuming procedure (quasi-static measurement) used to avoid the effects of the slow time response introduced by the temperature measurement systems. In order to minimize the distortion introduced by the measurement channel, in this work is proposed the application of blind deconvolution technique. Through the proposed unsupervised signal processing chain it was possible to approximately recover the real hysteresis curve, reducing drastically the processing time.

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