Enhancing Reflectometry Systems with CHIRP-OMTDR and Compressed Sensing: A Study on Signal Recovery Quality

Yosra Gargouri, Nicolas Ravot, Mariem Ben Hadj Abdallah, Mickaël Cartron

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Yosra GARGOURI
Universite Paris-Saclay, CEA, List,
F-91120, Palaiseau, France
yosra.gargouri@cea.fr

Nicolas RAVOT
Universite Paris-Saclay, CEA, List,
F-91120, Palaiseau, France
nicolas.ravot@cea.fr

Mariem SLIMANI
Universite Paris-Saclay, CEA, List,
F-91120, Palaiseau, France
mariem.slimani@cea.fr

Mickael CARTRON
Universite Paris-Saclay, CEA, List,
F-91120, Palaiseau, France
mickael.cartron@cea.fr

***Abstract*—This paper investigates the application of Compressed Sensing (CS) in Orthogonal Multi-tone Time-Domain Reflectometry (OMTDR) using a specific signal known as CHIRP-OMTDR. The Random Demodulator (RD) has been chosen as the Analog-to-Information Converter (AIC) in the acquisition chain. The study focuses on the influence of RD's filter selection, signal length, and compression factors on signal recovery quality. The results demonstrate that reconstruction quality improves with longer signal lengths, and that the choice of low-pass filter type and order has minimal impact. The findings contribute to the enhancement of reflectometry systems based on Compressed Sensing.**

***Index Terms*—OMTDR, CHIRP-OMTDR, Random Demodulator, Reflectometry, Compressed Sensing.**

I. Introduction

Reflectometry is a nondestructive sensing system used to identify and characterize electrical faults in cables or transmission lines. It involves transmitting a signal through a medium and analyzing the reflections caused by impedance changes. Reflectometry has also other applications such as detecting damage in photovoltaic systems, characterizing nanostructures, and evaluating moisture content in soils [1].

A significant challenge in reflectometry is enhancing the accuracy of locating and characterizing impedance discontinuities, which contain valuable information. This task requires the use of high-frequency Analog-to-Digital Converter (ADC). However, the cost, power consumption, and complexity associated with very high-frequency ADCs introduce significant limitations. As a result, alternative solutions like compressed sensing have emerged to overcome these challenges [2].

Compressed sensing theory enables accurate signal recovery with fewer samples than what the Nyquist-Shannon theorem dictates. This reduction in required samples allows for a decrease in sampling frequency and memory requirements. Previous studies [2] have demonstrated promising results in detecting impedance discontinuities using compressed sensing on linear chirp signals. This study goes a step further by investigating OMTDR signals and examining the impact of filter selection, signal length, and compression factors on the quality of the reflected signal reconstruction. The findings will contribute to a better understanding of the factors influencing signal reconstruction, ultimately improving the accuracy and reliability of CS-based reflectometry systems.

II. THEORY OF COMPRESSED SENSING

A. *Principle of Compressed Sensing*

In traditional Digital Signal Processing, signals are typically sampled uniformly following the Nyquist-Shannon theorem, where the sampling rate is at least twice the signal bandwidth. Compressed Sensing, also known as Compressive Sensing, Compressive Sampling or CS, is a data acquisition technique that aims to capture signals directly in a compressed form with nonadaptive measurements.

The main idea behind CS is that many real-world signals exhibit sparsity, meaning that they can be represented by a sparse or compressible set of coefficients in a suitable basis. By leveraging the knowledge of signal sparsity, the compressed measurements obtained through CS can be efficiently reconstructed using advanced signal processing algorithms. It becomes possible to accurately reconstruct the original signal at a significantly lower rate than the Nyquist rate. This reduction in sampling rate has various advantages, including reduced storage requirements, data transmission bandwidth, and power consumption during acquisition [3].

B. *Analog-to-Information Converter (AIC)*

The concept of compressed sensing has led to the development of a new type of converter known as the Analog-to-Information Converter (AIC) [4]. AICs differ from conventional ADCs in that they can operate at lower sampling rates than those dictated by the Nyquist-Shannon theorem thanks to the CS techniques. Prominent AIC architectures include the Non-Uniform Sampler (NUS), Random Demodulator (RD), and Random Modulator Pre-Integrator (RMPI) [3].

III. CS-BASED REFLECTOMETRY ARCHITECTURE

A. *Conventional reflectometry vs CS-based reflectometry*

The conventional reflectometry chain is depicted in Fig.1. A signal is injected into the device under test (DUT) using a

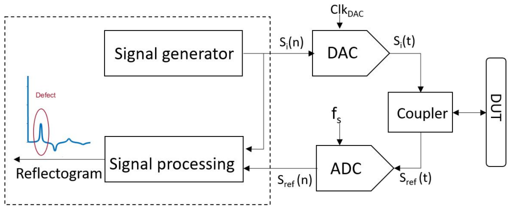

Fig. 1. Schematic diagram of conventional reflectometry architecture

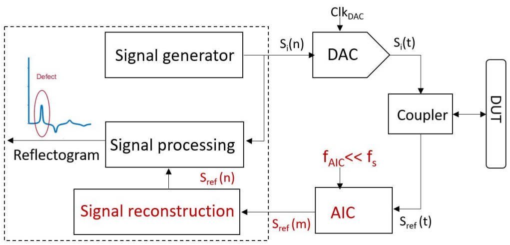

Fig. 2. Schematic diagram of CS-based reflectometry architecture

digital-to-analog converter (DAC). This injected signal propagates through the medium and reflects upon encountering impedance discontinuities. The reflected signal is then acquired using an analog-to-digital converter (ADC) operating at a sampling frequency f_s. Following the acquisition, signal processing techniques are employed for fault detection and localization purposes.

By utilizing CS, the ADC operating at f_s in the conventional chain will be replaced by an Analog-to-Information Converter (AIC) operating at a lower frequency, $f_{AIC} < f_s$. This change necessitates a signal reconstruction phase, which is followed by signal processing for fault detection and location, as shown in Fig. 2.

In this study, we will focus on exploring the feasibility of implementing Compressed Sensing technology specifically for OMTDR method.

B. OMTDR and CHIRP-OMTDR

Reflectometry-based techniques are categorized based on the injected waveforms and the methods used for analyzing the reflected signal. The analysis of the reflected signal can be performed in either the time domain (Time Domain Reflectometry) or the frequency domain (Frequency Domain Reflectometry). Various well-known reflectometry methods are reviewed in [5].

Previous studies on CS-based reflectometry mainly focused on Time-Domain Reflectometry (TDR) methods using linear chirp signals [2]. In this paper, we will explore the Orthogonal Multi-Tone Time Domain Reflectometry (OMTDR) method.

OMTDR offers not only real-time diagnosis capabilities but also facilitates data transmission in complex wiring networks [6]. In OMTDR, a signal consisting of multiple tones or frequencies is transmitted, with these tones being encoded using the M-phase shift keying (M-PSK) digital modulation technique to carry information [5].

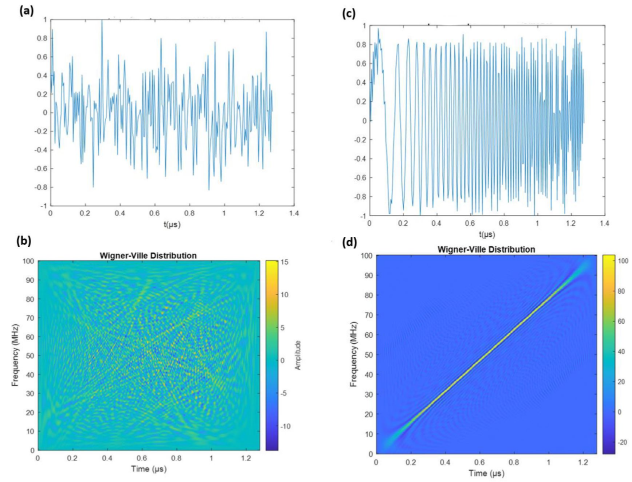

Fig. 3. (a) The time representation of the classical OMTDR signal. (b) the time-frequency representation of the classical OMTDR signal. (c) the time representation of the OMTDR signal in chirp form (d) the time frequency representation of the OMTDR signal in chirp form.

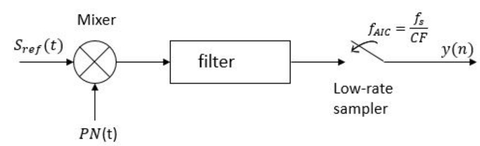

Fig. 4. Block diagram for the Random Demodulator.

However, the classical OMTDR signal is not sparse in the time domain (Fig. 3(a)), frequency domain, or time-frequency domain (Fig. 3(b)). This poses a challenge since CS requires signals to exhibit sparsity in a known domain.

To address this challenge, we have developed a specific OMTDR signal, referred to as CHIRP-OMTDR (Fig. 3(c)), which follows the M-PSK modulation and features a compressible chirp waveform in the time-frequency domain (Fig. 3(d)). Detailed information on generating this signal can be found in patent application [7]. The CHIRP-OMTDR signal format enables us to explore the application of Compressed Sening in OMTDR-based reflectometry systems and delve deeper into its potential benefits.

IV. AIC Architecture Modeling

A. Choice of the AIC architecture

We have chosen the Random Demodulator as the AIC architecture in the acquisition chain. The choice of this architecture is motivated by its efficiency on compressible signals in the time-frequency domain for linear chirp waves [2] and its relative simplicity of implementation compared to an RMPI architecture.

The RD architecture, depicted in Fig.4, comprises three main components: a mixer, a filter, and an ADC.

In the RD-based AIC, the reflected signal (S_{ref}) is demodulated at the device's input using a pseudo-random sequence

(PN) composed of +1 and -1 values. This demodulation process operates at a frequency that is equal to or higher than the Nyquist frequency. Subsequently, the demodulated signal is filtered and then sub-sampled using an ADC clocked at a frequency f_{AIC}, where f_{AIC} equals f_s/CF (CF denotes the compression factor employed).

B. Choice of filter and compression factor

In the literature, various types of filters have been employed in Random Demodulator. Historically, early filters utilized integrator designs [8] [9]. Butterworth filters have also been utilized, including second-order Butterworth low-pass filters [10] and fourth-order Butterworth low-pass filters [11].

In order to determine the appropriate filter for our architecture, we simulate different filters including the integrator and Butterworth filters of orders one to six. We compare their reconstruction accuracy based on the Signal-to-Error Ratio (SER). Additionally, we investigate the impact of signal lengths, and compression factor on the system's performance. To achieve this, we proceed as follows:

1) During the emission phase, we generate the CHIRP-OMTDR signal with a variable length (N, ranging from 128 to 2048 samples) at a frequency of 200 MHz.
2) The signal is injected and propagated into a coaxial cable.
3) The reflected signal passes through the AIC block: it is multiplied by a pseudo-random sequence at 200 MHz.
4) Next, it undergoes filtering. We explore different filter choices, including an integrator filter and Butterworth filters ranging from the first to the sixth order.
5) Subsequently, the filtered signal is downsampled using compression factors of 2, 4, and 8.
6) Finally, we reconstruct the signal and evaluate the reconstruction accuracy (SER) using the general formula. $SER = 20 \cdot \log_{10}\left(\frac{\|R_{CV}\|_2}{\|(R_{CV}-R_{CS})\|_2}\right)$ where R_{CV} represents the reflectogram of a conventional reflectometry chain and R_{CS} represents the reflectogram of a CS-based reflectometry chain.

Figures 5, 6 and 7 illustrate the variation of SER as a function of the signal length N and the nature of the filter for compression factors 2, 4 and 8, respectively.

We observe that irrespective of the filter type and its order, there is a consistent trend in terms of reconstruction quality, with the results being very similar. Therefore, what matters most from our standpoint is not necessarily having a high-fidelity low-pass filter, but rather having a filter with a stable impulse response. This is crucial due to the sensitivity of the Random Demodulation (RD) technique to distortion introduced by the low-pass filter component [11].

Furthermore, we observe that, for the same compression factor CF, the reconstruction quality (SER) improves as the signal length N increases. This finding aligns with the state of the art in CS, which suggests that the minimum measurement requirement for accurate reconstruction scales approximately logarithmically with the signal size. In other words, as the signal length increases, the number of required measurements for accurate reconstruction also increases, but at a slower rate than a linear relationship.

However, it is worth noting that the reconstruction quality deteriorates when using a compression factor (CF) of 8. We will exclude this compression factor and instead focus on CF = 2 and CF = 4.

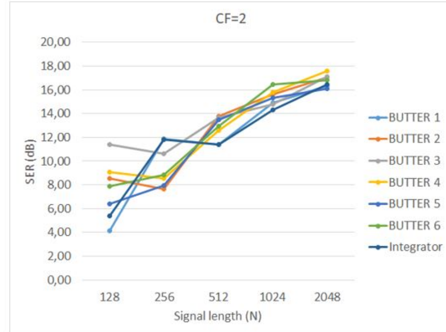

Fig. 5. Evaluation of the SER as a function of the number of signal points and the nature of the filter (cutoff frequency f_c=50 MHz for Butterworth filters) for a compression factor of 2.

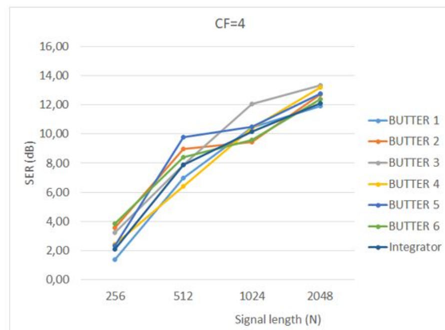

Fig. 6. Evaluation of the SER as a function of the number of signal points and the nature of the filter (f_c=25 MHz for Butterworth filters) for a compression factor of 4.

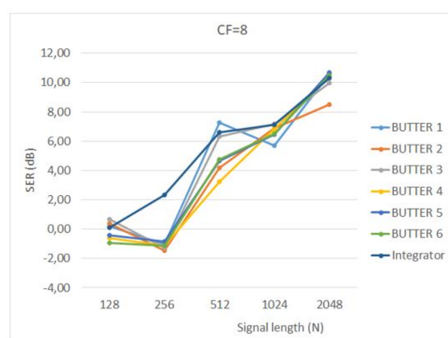

Fig. 7. Evaluation of the SER as a function of the number of signal points and the nature of the filter (f_c=12.5 MHz for Butterworth filters) for a compression factor of 8.

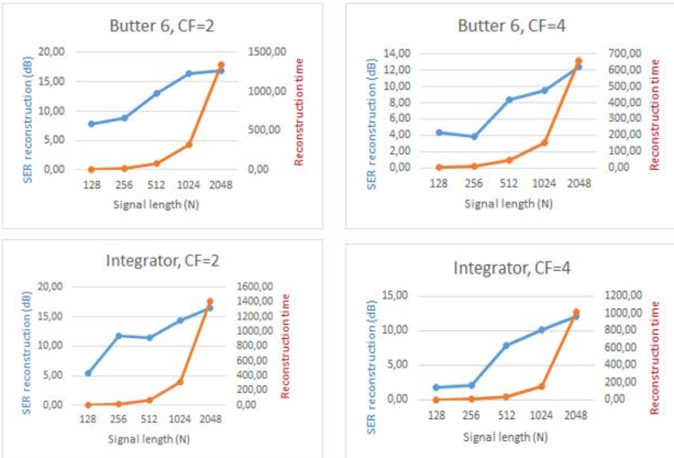

Fig. 8. Signal Length Estimation.

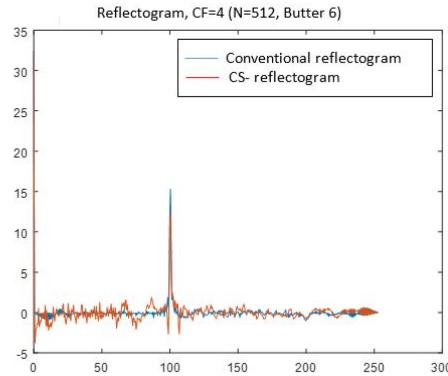

Fig. 9. Reflectogram generated with the conventional reflectometry architecture at 200 MHz (blue curve), reflectogram generated with the reflectometry architecture based on CS at 50 MHz (N=512 samples, CF=4, Butterworth filter of order 6 and f_c=25 MHz).

C. Choice of the length of the injection signal

To determine the optimal signal length N, two factors must be considered: signal reconstruction error precision (SER) and the time required for signal reconstruction. To determine the optimal signal length, we conducted a statistical analysis of 30 simulations using two filter types (an integrator and a 6th-order Butterworth) and two compression factors (CF=2 and CF=4). By applying Compressed Sensing with varying signal lengths (ranging from 128 to 2048), we reconstructed the signal, measured the reconstruction time, and evaluated the SER.

Our observations revealed that increasing the signal length improves signal reproduction accuracy, resulting in a higher SER. However, longer sequences also lead to longer execution times during the reconstruction phase. To strike a balance between SER and reconstruction time, we found that selecting N=512 points provides a well-balanced compromise.

Fig. 9 illustrates an example of the reconstructed reflectogram quality with a reconstruction precision of 8.42 dB compared to a standard reflectogram without CS. This reconstruction precision was evaluated after applying CS to a 512-point signal, using a 6th-order Butterworth filter and subsampling by a compression factor of 4, as compared to the standard case.

V. Conclusion

In conclusion, our study has demonstrated the effectiveness of a CS-based reflectometry architecture in accurately recovering reflected signals in the context of OMTDR. By employing a compressed factor of 4 and a 512-point CHIRP-OMTDR signal, we achieved reliable signal recovery. Furthermore, our findings indicate that the selection of low-pass filter type and order has negligible influence on the reconstruction quality. After completing the phase of simulations and testing, our next step involves conducting an experimental test bench using evaluation boards. The ultimate goal is to develop an analog reflectometry printed circuit board (PCB) based on Compressed Sensing.

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