Electric arc detection using compressive sensing

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Résumé – Dans ce papier nous étudions la détection et la reconstruction des signaux d'arcs électriques reçus par un capteur de surveillance d'un réseau de panneaux photovoltaïques. Un des problèmes de ces capteurs est la perte éventuelle des données qui peut être due aux aléas de fabrication mais aussi au niveau variable des perturbations entre les sources des arcs et le capteur acoustique. Pour compenser ces pertes de données, nous proposons un algorithme simple basé sur le concept *compressive sensing*. Ce concept est appliqué dans le domaine de représentation temps-fréquence. Pour la reconstruction nous utilisons la S-method pour améliorer la localisation de la source d'arcs électriques.

Abstract – In this paper, we analyze the detection and reconstruction of the electric arc received at a sensor while surveilling photovoltaic power systems. We assume that an acoustic signal was transmitted, and, due to some failure in the system, it is received with some missing measurements. The missing measurements can be for various reasons, like having malfunctions on the sensor or the distance between the transmitter and receiver is large. A simple yet effective compressive sensing (CS) algorithm was used for the reconstruction of the missing measurements for a better localization of the electric arc. The basic time-frequency representation, the short-time Fourier transform (STFT), will be used as the analyzed transformation domain. After reconstruction, the S-method is applied on the obtained STFT for a better localization of the source.

1 Introduction

The electrical power systems must be continuously supervised in order to be aware of the environment and analyze the electrical faults. The energy demand is growing, so the need of an increased production, together with an extended distribution system, is a problem concerning the energetic field all over the world. These demands make photovoltaic systems very useful.

One of the major problems are the arc faults that appear in the photovoltaic systems. Over the years, the demand of photovoltaic power systems is growing. To be able to isolate the electrical faults that appear in these systems, it is crucial to detect and localize them correctly. These faults are very sensitive problems and must be surveilled permanently to keep the system safe [1–5]. Because the faults appear in the system very often, the need for surveilling the system, as well as detecting, localizing and limiting the faults, are of major concern for the entire energetic system.

The signals could be located within much smaller regions using appropriate time-frequency representations [6–8]. The basic representation in time-frequency analysis is the short-time Fourier transform (STFT), which will be used in this paper. If the time-frequency (TF) domain consists of only few components which are nonzero, compared to the total number of coefficients, then the signal is said to be sparse in the TF domain. Following compressive sensing (CS) framework, a signal that is sparse in a certain domain can be reconstructed from a reduced set of measurements (signal samples) than it is required by the standard sampling theorem [9–13].

The reduced set of measurements occurs for various reasons. It can be the desired sampling technique or it can also be a hardware constraint, that will produce the signal with some highly corrupted measurements, which are better omitted for the calculations. Since the idea of CS considers the acquisition of the signal, it can be used in many everyday areas. In this paper, we will analyze the detection and reconstruction of the received electric arc by using the CS theory. We assume a hardware problem in the case of a malfunctioned sensor, which will produce a signal with missing measurements. Another reason for the effect of missing measurements is in having a sensor that is far away, so that the signal is not received accurately.

In the signal processing sense, the electric arcs are transient signals (that occur as dielectrical breakdowns). It is well known that the time-scale analysis is a very powerful tool in detecting transient signals [2]. Also, the recurrence plot analysis was shown as an interesting tool for partial discharge detection and localization [3]. In this paper, we will focus on improving the time-frequency analysis in the CS sense, which will improve the overall performance in a non-ideal environment.

The paper is organized as follows. Section 2 briefly describes the theory of compressive sensing, Section 3 presents the method used for recovery, and in Section 4 results are shown. Section 5 concludes the paper.

2 Compressive Sensing Background

Consider a general form of a non-stationary multicomponent signal $x(n)$. We will assume that the signal is sparse in the short-time Fourier transform (STFT) domain, as it is the mostly used time-frequency representations domain. The STFT of a discrete-time signal is

$$STFT(n,k) = \sum_{m=-N/2}^{N/2-1} x(n+m)w(m)e^{-j\frac{2\pi}{N}mk} \tag{1}$$

at a time instant n and a frequency k. In the vector form, the STFT of the signal is

$$\mathbf{S}_N(n) = [STFT(n,0), STFT(n,1), \ldots, STFT(n,N-1)]^T.$$

In this paper, the window function $w(m)$ of length N is assumed to be a Hamming window described by

$$w(m) = \frac{1+\cos(2\pi m/N))}{2}. \tag{2}$$

With a proper window overlapping, the recovery of the whole signal, based on the STFT is straightforwardly done [6–8]. A K-sparse windowed signal $x(n,m) = x(n+m)w(m)$ has K non-zero components in the STFT domain, i.e.

$$x(n,m) = \sum_{i=1}^{K} A_i(n)e^{j2\pi mk_i/N}. \tag{3}$$

According to the compressive sensing theory, if a signal is said to be K-sparse in a transformation domain (in our case the STFT domain), it can be reconstructed by a reduced set of N_A measurements [9–12], where $K \ll N_A < N$. For a given n, the available signal samples are at the positions $n+m \in \mathbb{N}_A$, where $\mathbb{N}_A = \{n+m_1, n+m_2, ..., n+m_{N_A}\}$.

The available samples of the windowed signal are

$$\mathbf{y}_n = [x(n+m_1)w(m_1), ..., x(n+m_{N_A})w(m_{N_A})]^T \tag{4}$$

or in a matrix form

$$\mathbf{y}_n = \mathbf{A}\mathbf{S}_N(n), \tag{5}$$

where $\mathbf{A}$ is the partial inverse DFT matrix which corresponds to the positions of the available samples

$$\mathbf{A} = \begin{bmatrix} \psi_0(m_1) & \psi_1(m_1) & \cdots & \psi_{N-1}(m_1) \\ \psi_0(m_2) & \psi_1(m_2) & \cdots & \psi_{N-1}(m_2) \\ \vdots & \vdots & \ddots & \vdots \\ \psi_0(m_{N_A}) & \psi_1(m_{N_A}) & \cdots & \psi_{N-1}(m_{N_A}) \end{bmatrix} \tag{6}$$

with coefficients

$$\psi_k(m) = \frac{1}{N}e^{j2\pi mk/N}. \tag{7}$$

The main goal of compressive sensing is to reconstruct the missing samples of the received sparse signal from the available samples, by minimizing its sparsity

$$\min \|\mathbf{S}_N(n)\|_0 \text{ subject to } \mathbf{y}_n = \mathbf{A}\mathbf{S}_N(n). \tag{8}$$

The problem (8) is more theoretical because it is very sensitive to noise and computationally not feasible. That is why, in practice, the closest convex form is used as the general expression for the CS formulation as

$$\min \|\mathbf{S}_N(n)\|_1 \text{ subject to } \mathbf{y}_n = \mathbf{A}\mathbf{S}_N(n). \tag{9}$$

In most practical cases, according to [11], the solutions from (8) and (9) are the same. In recent years, many solutions to this problem were derived. In this paper, we will use a simple and effective method, based on estimation of the positions of nonzero components and calculating the unknown signal amplitudes based on the known samples.

3 Reconstruction Algorithm

The initial step of the reconstruction is in calculating the STFT using the available samples

$$S_{N0}(n,k) = \sum_{i=1}^{N_A} x(n+m_i)w(m_i)e^{-j\frac{2\pi}{N}m_ik} \tag{10}$$

$$\mathbf{S}_{N0}(n) = N\mathbf{A}^H\mathbf{y}_n \tag{11}$$

where H is the Hermitian transpose.

From the initial estimate, we can find the position of the largest component as

$$k_1 = \arg\max\{\mathbf{S}_{N0}\}. \tag{12}$$

Then, matrix $\mathbf{A}_1$ is formed from matrix $\mathbf{A}$ from (6) by omitting all rows except the row corresponding to the found position k_1. The first STFT reconstruction estimate is found as

$$\mathbf{S}_{N1}(n) = (\mathbf{A}_1^H\mathbf{A}_1)^{-1}\mathbf{A}_1^H\mathbf{y}_n. \tag{13}$$

The signal is reconstructed and subtracted from the original signal at that position

$$\mathbf{y}_{n1} = \mathbf{y}_n - \mathbf{y}_{r1} \tag{14}$$

where $\mathbf{y}_{r1}$ is the reconstructed signal from (13).

The reconstruction is implemented in an iterative way, repeating the previous steps [13, 14]. The STFT is calculated again with the signal (14) and its maximum position is found at k_2. A new set of positions of components $\mathbb{K} = \{k_1, k_2\}$ is formed with the corresponding matrix $\mathbf{A}_2$. The new estimate $\mathbf{S}_{N2}(n)$ is calculated and the signal $\mathbf{y}_{r2}$ is reconstructed and subtracted. The procedure is repeated K times with the last iteration being

$$\mathbf{S}_{NR}(n) = (\mathbf{A}_K^H\mathbf{A}_K)^{-1}\mathbf{A}_K^H\mathbf{y}_n. \tag{15}$$

where $\mathbf{A}_K$ is now a $K \times N_A$ matrix, with columns corresponding to the found positions, i.e.

$$\mathbf{A} = \begin{bmatrix} \psi_{k_1}(m_1) & \psi_{k_2}(m_1) & \cdots & \psi_{k_K}(m_1) \\ \psi_{k_1}(m_2) & \psi_{k_2}(m_2) & \cdots & \psi_{k_K}(m_2) \\ \vdots & \vdots & \ddots & \vdots \\ \psi_{k_1}(m_{N_A}) & \psi_{k_2}(m_{N_A}) & \cdots & \psi_{k_K}(m_{N_A}) \end{bmatrix}. \tag{16}$$

The reconstructed signal STFT is $\mathbf{S}_{NR}(n)$.

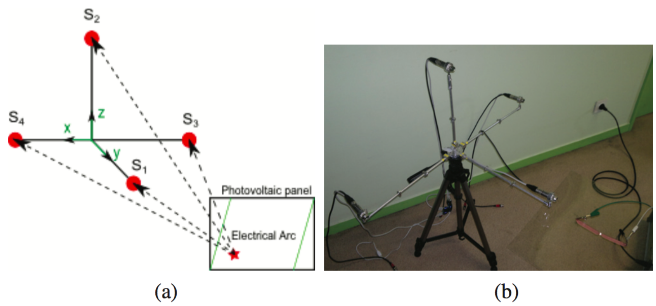

FIGURE 1 – Set-up configuration : experimental (a) ; implementation (b)

TABLE 1 – PSNR results for various sparsity levels

K	**1**	**3**	**5**	**7**	**9**	**11**
PSNR [dB]	21.33	26.11	31.30	33.02	33.40	33.71

This method is then applied this reconstruction of the signal with missing samples, for an easier localization of the electric arcs, presented in the next section.

4 Results

We will analyze the electric arc received at a detector composed of four acoustic sensors. The set-up of the sensors is shown in Fig. 1. The nearest sensor (sensor 1) is taken as the reference, since it has the greatest signal-to-noise ratio (SNR). The arc received at sensor 1 (the reference sensor) is shown in Fig. 2 (top). The original arc received at sensor 2 is shown in Fig. 2 (bottom).

When assumed that the sensor 2 is malfunctioning, the signal received is shown in Fig. 3 (top). It is noticeable that the missing measurements destroy the time-frequency representation and that the arc is hard to follow. Using the algorithm mentioned in Section 3, the arc from Fig. 3 (top) is reconstructed. The recovered arc is presented in Fig. 3 (bottom).

4.1 Error calculation

We use the peak signal-to-noise ratio (PSNR)

$$\text{PSNR}_{dB}(\mathbf{I}_o, \mathbf{I}_R) = 10\log_{10}\left(\frac{1}{\text{mean}\left(|\mathbf{I}_o - \mathbf{I}_R|^2\right)}\right) \tag{17}$$

for a quantitative comparison between the signals. The values $\mathbf{I}_o$ and $\mathbf{I}_R$ present normalized reference signal and normalized considered signal, respectively. Assuming that half of the samples are missing, we calculate the PSNR between the received STFT and the reconstructed STFT at sensor 2. The results for various sparsity levels are given in Table 1. We can see that $K = 7$ is enough for a successful reconstruction, since the reconstruction performance does not change significantly.

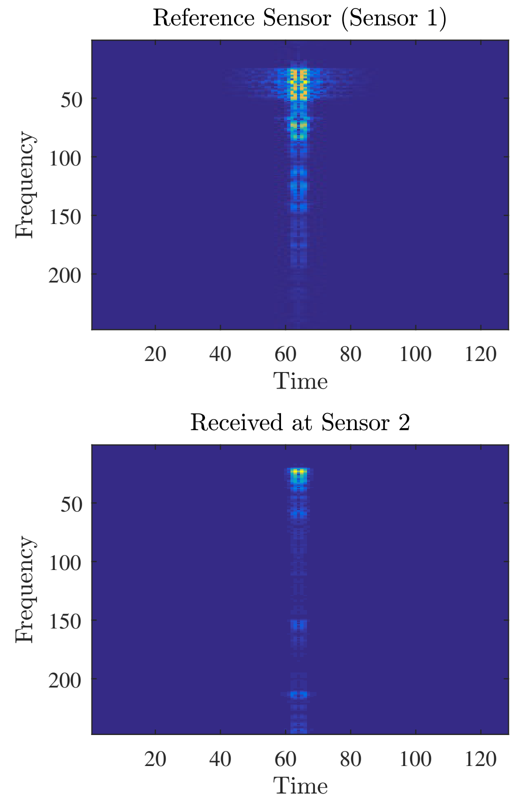

FIGURE 2 – STFTs of the received signals at : sensor 1 (top) and sensor 2 (bottom)

4.2 S-method representation

For an improved concentration, time-frequency analysis using the S-method representation domain will be used. For the S-method, we need the short-time Fourier transform (STFT) of signal. The S-method is calculated as [8]

$$SM(k,n) = \sum_{p=-L}^{L} STFT(n,k+p)STFT^*(n,k-p), \tag{18}$$

where $2L+1$ is the window width, which, in our case, is $L = 15$. For the comparison, the recovered STFT is presented in Fig. 4 (top) and the S-method of the recovered signal is shown in Fig. 4 (bottom).

5 Conclusions

In this paper, the reconstruction of a signal received at a malfunctioned sensor is considered for an easier detection of the electric arc. It is assumed that a transmitted acoustic signal is received with some missing measurements. A simple and effective compressive sensing algorithm was used for the reconstruction. The signal is analyzed using the time-frequency STFT representation domain as the basic representation. Also, the reconstruction is smoothed with the S-method for improving the localization of the source.

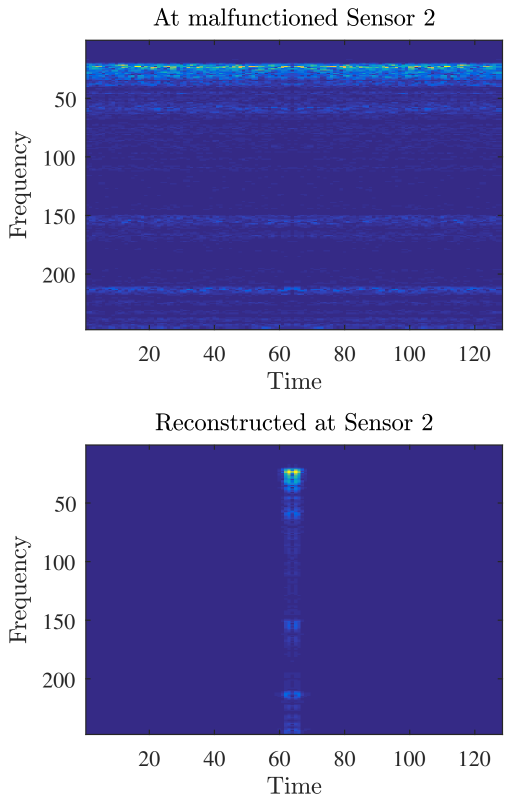

FIGURE 3 – Malfunctioned (top) and reconstructed (bottom) STFT at sensor 2

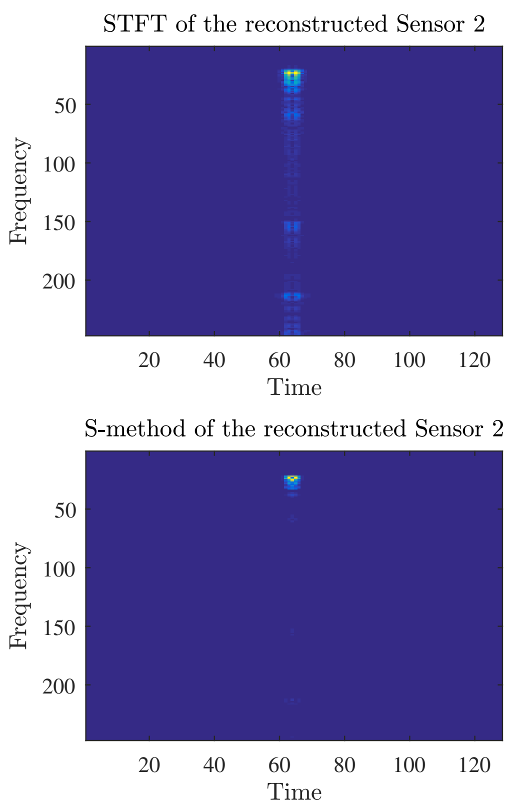

FIGURE 4 – Reconstructed STFT (top) and S-method (bottom)

In future work, some aspects of the localization and the classification of the source of electric arc failure will be analyzed. The localization can be potentially improved by improving the compressive sensing algorithms. Also, more robust compressive sensing theory can be applied on these signals.

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