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Adaptive de-noising and smoothing technique for signal in the monitoring of laser welding

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Abstract

Laser weld monitoring is usually based on the feedback from photodiodes able to provide information about radiation from plume, the reflected laser light and the thermal condition of the melt. By using the optical emissions, it is possible to evaluate laser process quality, in particular, to find out the relationship between emission characteristics and weld quality characteristics. The optical signals detected during the laser welding are typically contaminated by different kind of noises that affect the photo-detector. To avoid this phenomenon, it is necessary to smooth and de-noise the signal for getting a "clean" signal. One of the most effective methods of dealing with noise contamination is to filter the noise out of the signal while retaining as much as possible of the region of interest in the frequency spectrum. Advanced filtering techniques such as discrete wavelet transforms, Wiener filtering have been used to that end. Although these methods have proven useful, their main drawback is the complexity of devising an automatic and systematic procedure, i.e., a mother wavelet function must be selected when using discrete wavelet transforms, the filtering function parameters must be chosen when using the Wiener filter, etc. This work presents an alternative to the digital filtering methods. It is a non-parametric technique based on principles of multivariate statistics. The original time series is decomposed into a number of additive time series, each of which can be easily identified as being part of the signal, or as being part of the random noise. The proposed technique significantly improves components localization. For giving practical applicability to the proposed method, we compare the methods by analyzing signals detected during the laser welding, demonstrating the expected advantages.

Keywords: Singular spectrum analysis; transient signal analysis

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1. Introduction

Laser welding is increasingly used in industrial applications, because of the advantages it offers, such as high speed, high accuracy, low heat input and low distortion. As for any other fusion welding process, weld imperfections can occur.

In the automotive industry, for instance, the demand for real-time monitoring methods has become increasingly urgent since for reducing vehicle weight and improve fuel efficiency and safety, the development of lightweight and high-strength vehicles has prompted an increased use of advanced high strength steels (AHSS). These steels are galvanized in order to improve the surface corrosion resistance for automotive parts. It is still a great challenge the laser weld of galvanized steels in a zero-gap lap joint configuration. When laser welding of galvanized steels in a zero-gap lap-joint configuration, the zinc coating at the contact interface will vaporize; due to the lower boiling point (906 ^{0}C) of zinc as compared to the melting temperature of steel (above 1500 ^{0}C), the highly pressured zinc vapour expels the liquid metal out of the weld pool, resulting in blowholes and pores which dramatically decrease the mechanical properties of the weld [1].

Most common techniques in use today for process monitoring, employ photo-diode sensors to record electromagnetic (EM) signals arising from the molten pool during welding, with the objective of correlating the output from the sensor to features such as weld penetration, the occurrence of pin holes, or weld shape. These systems have been developed to monitor laser welding in real-time and generally examine the laser-to-metal interactions to infer the quality of the weld itself. By using different types of sensors, responding to different wavelengths of light, different aspects of the process or weld can be monitored, such as the weld pool temperature, the plasma above the weld pool and the level of back reflection, for instance. Different detectable emissions can be used as the process signals:

a) the reflected laser, originated from the amount of the laser source radiation which is not absorbed by the material
b) radiation emitted from the metal vapour and the molten pool
c) acoustic emissions, originated from the stress waves induced by changes in the internal structure of a work piece.

By using the optical emissions, it is possible to evaluate laser process quality, in particular, to find out the relationship between emission characteristics and weld quality characteristics. Since these techniques are indirect, they require accurate signal interpretation and processing to infer information about the actual condition of the weld: the more accurate signal analysis technique, the better weld quality characterization. Several scientific fields, such as signal processing, statistics and neural networks have been used for condition monitoring [2, 3, 4, 5, 6, 7, 8].

The optical signals detected during the laser welding, however, are typically contaminated by different kind of noises that affect the photo-detector. To avoid this phenomenon, it is necessary to smooth and de-noise the signal for getting a “clean” signal. Although several methods have been developed to reduce the effect of noise, one of the most effective methods of dealing with noise contamination is to filter the noise out of the signal while retaining as much as possible of the region of interest in the frequency spectrum.

The traditional method to de-noise process signals is to use digital Butterworth filters. Nonetheless, more advanced filtering techniques such as discrete wavelet transforms, Wiener filtering have also been used to that end. Although these methods have proven useful, their main drawback is the complexity of devising an automatic and systematic procedure, i.e., a mother wavelet function must be selected when using discrete wavelet transforms, the filtering function parameters must be chosen when using the Wiener filter, etc.

Singular spectrum analysis (SSA) is a novel non-parametric technique based on principles of multivariate statistics. The original time series is decomposed into a number of additive time series, each of which can be easily identified as being part of the signal, or as being part of the random noise. This way it's possible to get a clean signal without noise.

The SSA method is based on two parameters, window length and number of eigenvectors, which has to be set before starting the de-noising procedure. Certain choices of window lengths and number of eigenvectors (grouping strategy) lead to poor separation between trend and noise in the signal, i.e., trend components become mixed with noise components in the reconstruction of the signal.

The modified singular spectrum analysis (MSSA) method, presented in the paper, has been developed to overcome the previous drawbacks and is intended to be a valid alternative to traditional digital filtering methods.

1.1 Singular Spectrum Analysis (SSA)

The main purpose of SSA is to decompose the original series into a sum of series, so that each component in this sum can be identified as either a trend, periodic or noise. This is followed by a reconstruction the original series. The SSA technique consists of two complementary stages: decomposition and reconstruction and both of which include two separate steps.

At the first stage we decompose the series and at the second stage we reconstruct the original series and use the reconstructed series which is without noise. We provide a discussion on the methodology of the SSA technique [9, 10, 11, 12].

We consider the real-valued nonzero time series of sufficient length T $Y_T = (y_1 \dots . y_T)$. Fix L $(L \leq T/2)$, the window length, and let $K = T - L + 1$.

Step 1 - Computing the trajectory matrix (Embedding)

This transfer a one-dimensional time series $Y_T = (y_1 \dots .. y_T)$ into the multi-dimensional series $X_1 \dots \dots X_K$ with vectors $X_i = (y_i \dots . y_{i+L+1}) \in \mathrm{R}^{\mathrm{L}}$, where $K = T - L + 1$. The single parameter of the embedding is the *window length L*, an integer such that $2 \leq \mathrm{L} \leq \mathrm{T}$. The result of this step is the trajectory matrix:

$$\boldsymbol{X} = \left(x_{i,j}\right)_{i,j=1}^{L,K} = \begin{pmatrix} y_1 & y_2 \dots .. & y_K \\ y_2 & y_3 \dots .. & y_{K+1} \\ \dots \dots & \dots \dots & \dots \dots \\ y_L & y_{L+1} \dots .. & y_T \end{pmatrix}$$

Note that the trajectory matrix $\boldsymbol{X}$ is a Hankel matrix, which means that all the elements along the diagonal $i + j = const$ are equal.

Step 2 - Singular value decomposition of the trajectory matrix

It can be proved that the trajectory matrix (or any matrix of that type) may be expressed as the sum of d rank-one elementary matrices $\boldsymbol{X} = E_1 + E_2 + \dots . E_d$, where d is the number of non-zero eigenvalues in decreasing order, $\lambda_1, \lambda_2, \dots \lambda_d$ of the LxL matrix $\mathbf{S} = \boldsymbol{X} \cdot \boldsymbol{X^T}$. The elementary matrices are given by:

$$\boldsymbol{E_i} = \sqrt{\lambda_i} \cdot \boldsymbol{U_i V_i^T}$$

for $i = 1,2, \dots ., d$, with $\boldsymbol{U_1}, \boldsymbol{U_2}, \dots, \boldsymbol{U_d}$ being the corresponding eigenvectors, and the vectors $\boldsymbol{V_i}$ being given by:

$$V_i = X^T \cdot \frac{U_i}{\sqrt{\lambda_i}}$$

for $i = 1,2, \ldots, d$ .The contribution of the first elementary matrices $\boldsymbol{E_i}$ to the norm of $\boldsymbol{X}$ is much greater than that of the last matrices. Therefore, it is likely that these last matrices represent noise in the signal. The plot of eigenvalues in decreasing order is called the singular spectrum, and gives the method its name.

Step 3 - Grouping

The next step consists in partitioning the set of indices $\{1, \ldots, d\}$ into m disjoint subsets: $I_1, \ldots, I_m$. Let $\boldsymbol{I} = i_1, \ldots, i_b$ be one of these partitions. Then, the trajectory matrix $\boldsymbol{E_I}$ corresponding to the set $\boldsymbol{I}$ is defined as $E_I = E_{i1} + +E_{i2} + \cdots E_{ib}$. Once the matrices have been calculated for the partitions established, $I_1, \ldots, I_m$, the original time series trajectory matrix can be expressed as the sum of the trajectory matrices corresponding to each partition: $\boldsymbol{X} = E_I = E_{I1} + E_{I2} + \cdots E_{Ib}$.

Step 4 - Reconstruction (diagonal averaging)

In this step, each trajectory matrix $\boldsymbol{E_i}$ is transformed into a principal component of length $\boldsymbol{N}$ by applying a linear transformation known as diagonal averaging or Hankelization.
To reconstruct each principal component, the average along the diagonals $i + j = const$ is calculated. The diagonal averaging algorithm (golyandina) is as follow: let Y be any of the elementary matrices $\boldsymbol{E_i}$ of dimension LxK, the elements of which are y_{ij} , with $1 \leq i \leq L$, $1 \leq j \leq K$.
The time series $\boldsymbol{G}$ (principal component) corresponding to this elementary matrix is given by:

$$g_k = \begin{cases} \frac{1}{k+1} \sum_{m=1}^{k+1} y_{m,k-m+2} & for\ 0 \leq k < L^* - 1 \\ \frac{1}{L^*} \sum_{m=1}^{L^*} y_{m,k-m+2} & for\ L^* - 1 \leq k < K^* \\ \frac{1}{N-k} \sum_{m=k-K^*+2}^{N-K^*+1} y_{m,k-m+2} & for\ K^* \leq k < N \end{cases}$$

where $L^* = min(L, K)$, $K^* = max(L, k)$, and $N = L + K - 1$.

It can be shown [9, 10] that the squared norm of each elementary matrix equals the corresponding eigenvalue, and that the squared norm of the trajectory matrix is the sum of the squared norms of the elementary matrices. The largest eigenvalues in the singular spectrum represent the high-amplitude components in the decomposition. Contrariwise, the low-amplitude noise components of the signal are represented in the singular spectrum by the smallest eigenvalues.

1.2 Modified Singular Spectrum Analysis (MSSA)

One of the drawbacks of SSA is the lack of a general criterion to select the values of the parameters L (window length) and the grouping strategy used in the algorithm.

Certain choices of window lengths and grouping strategy lead to poor separation between trend and noise in the signal, i.e., trend components become mixed with noise components in the reconstruction of the signal.

To overcome the uncertainty in what value L to select, we apply sequentially the Singular Value Decomposition step, starting from L=3:

- for each iteration, the RMS between the current and previous eigenvalue is calculated

$$RMS(1) = rms(\lambda_1 : \lambda_2)$$

$$RMS(2) = rms(\lambda_2 : \lambda_3)$$

$$RMS(L-1) = rms(\lambda_{L-1} : \lambda_L)$$

- the minimum and its position is calculated based on defined halt criterion at iteration

$$[min, posmin] = min(RMS(1: L-1)) < \varepsilon = 1/100$$

The convergence of this sequential procedure is such in that the percentage RMS difference between the current and previous signals in a given iteration is sufficiently small.

1.3 Application to laser welding process signals

The aim of this section is to demonstrate how the proposed method effectively smooths the signals detected during the laser welding. The Data acquisition was performed with a NI CompactRIO multi-channel data acquisition board. Two different materials have been used for the trials. For each signal we firstly apply the Singular Spectrum Analysis, highlighting its own drawback, after that we demonstrate the effectiveness of the modified version.

Example #1 – Welding of High Strength Steel DP600 – overlapped samples, sampling frequency 32768 Hz

Figure 1 displays the signal (up) detected during the laser welding of overlapped HSS samples and the relative spectrum (bottom), where the noise spectral band is highlighted (red line).

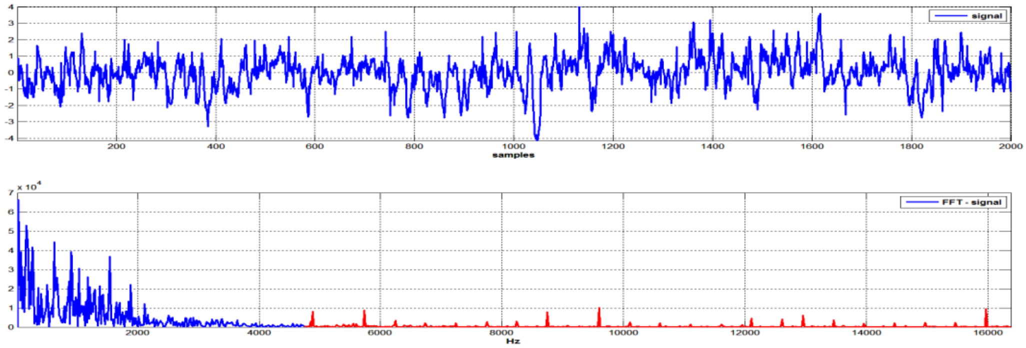

Fig.1. up) signal, bottom) spectrum

Figure 3 displays: de-noised signal (up-left) and the relative spectrum (bottom-left), residual noise (up-right) and relative spectrum (bottom-right).

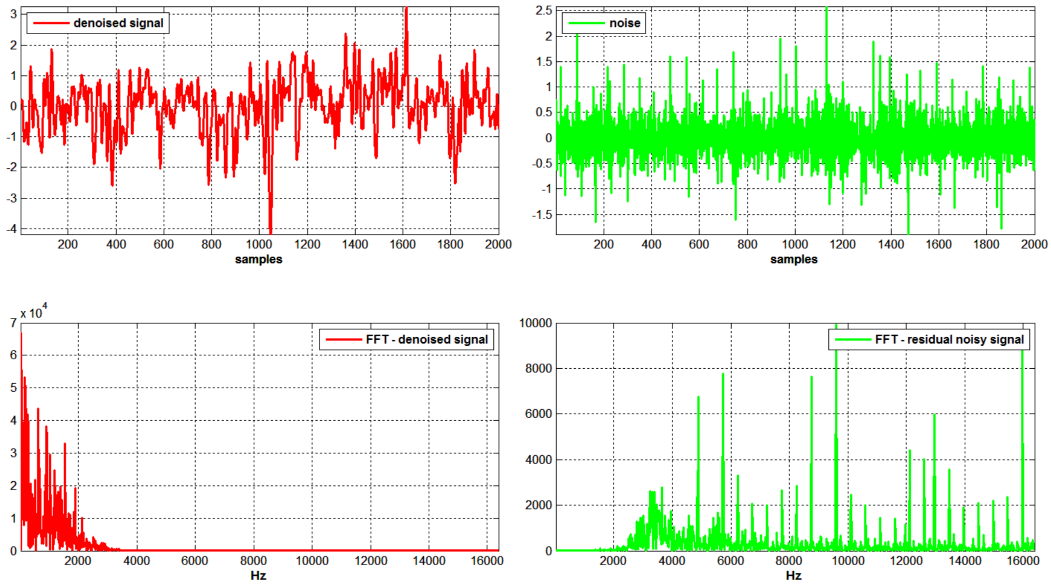

Fig.2. up-left) de-noised signal, bottom-left) de-noised signal spectrum, up-right) residual noise, bottom-right) noise spectrum

Example #2 – Welding of Titanium alloys - overlapped samples, sampling frequency 95000 Hz

Figure 3 displays the signal (up) detected during the laser welding of Titanium alloy Ti64 samples and the relative spectrum (bottom), where the noise spectral band is highlighted (red line).

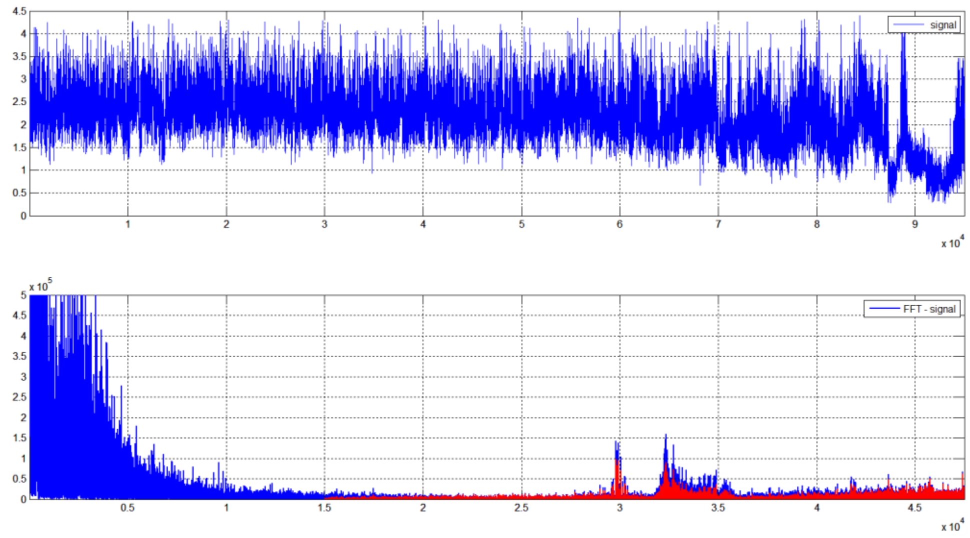

Fig. 3. up) signal, bottom) spectrum

Figure 4 displays: de-noised signal (up-left) and the relative spectrum (bottom-left), residual noise (up-right) and relative spectrum (bottom-right).

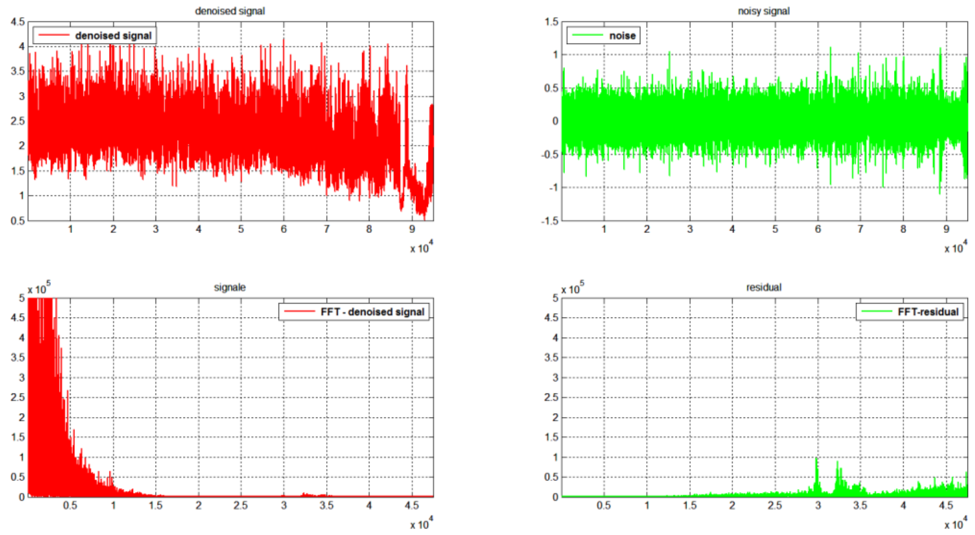

Fig.4. up-left) de-noised signal, bottom-left) de-noised signal spectrum, up-right) residual noise, bottom-right) noise spectrum

It should be noted, looking at the spectra shown in figure 2 and figure 4, the separation between the spectra. This condition ensures that the de-noised signal is not contaminated by noise. The Modified Singular Spectrum analysis method allows the smoothing of the signal without fixing any initial conditions.

1.4 Conclusions

This paper introduces a Modified Singular Spectrum Analysis for de-noising signals detected, as example, during the laser welding process. The proposed method is derived from the well-established Singular Spectrum Analysis, a novel non-parametric technique for smoothing and de-noising the detected signals. The proposed method aims to overcome the uncertainty in what window length value to select and what number of eigenvectors to choose. The examples have demonstrated the effectiveness of the proposed method.

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