IET Generation, Transmission & Distribution

Research Article

Accurate identification and characterisation of transient phenomena using wavelet transform and mathematical morphology

ISSN 1751-8687
Received on 16th January 2019
Revised 12th May 2019
Accepted on 25th June 2019
E-First on 9th September 2019
doi: 10.1049/iet-gtd.2019.0101
www.ietdl.org

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Abstract: Electric transient events are recurrent phenomena in electrical installations and distribution systems or grids; hence, the identification of these kinds of phenomena has become an important topic for researchers. This work presents a methodology to identify and accurately delimit transients in current signals of non-residential buildings. The proposed method firstly analyses the signal using the wavelet transform to pre-visualise the transients, and then opening and closing morphological operators are applied to the signal to find the beginning and ending of the transient; furthermore, the highest point of the transient and its location is obtained. The experimentation is performed with real current signals measured in a non-residential building. The results indicate that the proposed method can precisely identify and delimit transients, even when the transients are very close to each other.

1 Introduction

Transient events in electrical installations and grids are power quality disturbances caused by the action of different electronic devices, RLC circuits and compensation circuits with capacitors. In general, power quality disturbances (PQD) is an interesting topic for the researchers and it is possible to find standards and reviews that define the different power quality disturbances [1, 2]. These disturbances are possible to detect through the analysis of the voltage and current signals, which in an ideal condition are sinusoidal, periodic and stationary, and it is possible to analyse them with techniques like the discrete Fourier transform (DFT) and fast Fourier transform (FFT).

However, in a real environment the electric signals are prone to polarity changes, waveform distortions, and noise contamination; for these reasons the use of DFT and FFT is not recommended to analyse the non-stationary effects on electric signals [3]. Other techniques, such as the short-time Fourier transform (STFT), have been used to analyse electric disturbances [4, 5] resulting acceptable for time–frequency analysis or harmonic disturbances, and with a small window length these methods are able to detect some transients but with a high computational effort. Due to this, several works are focused on developing methodologies applying different techniques for the detection of different disturbances and their classification [6–9]; some of the most applied techniques are the Gabor transform, S-transform, Hilbert–Huang transform, wavelet transform, other less recurrent techniques are support vector machines and mathematical morphology, even in some cases the researchers combine two different techniques to make the identification or classification [10–12].

The wavelet transform is used in different ways for the transient event identification; for instance, Thirumala *et al.* [10] presented an estimation of time-varying PQ indices based on the empirical wavelet transform to improve the assessment of PQD using IEEE recording waveforms and laboratory measured signals; thus the empirical wavelet transform can be used in real-time estimation. Marques *et al.* [13] presented a methodology for the identification and discrimination of the internal fault condition in power transformers, this method uses discrete wavelet transform and detail coefficients to identify transients during the fault condition to discriminate between different types of internal faults and inrush currents transients. Naik and Kundu [14] used the same technique proposed for a PQD index using simulated signals created with automated theorem proving (ATP)/electromagnetic transients program (EMTP) software in the index creation and laboratory signals for the method validation; the results show that the proposed index is useful in the identification and quantification of the deviation degree from the desired pure signal. Costa *et al.* [15] implemented the discrete wavelet transform to decompose a signal in the wavelet coefficient energy and boundary scaling to develop an overcurrent protection in distribution systems with distributed generation; they modelled the distributed system in a real-time digital simulator to validate the method. In a similar way, Medeiros *et al.* [16] proposed a method for the differential protection in power transformers based on the discrete wavelet transform by detecting critical faults with overdamped transients and simulations for the validation; they conclude that the method can be implemented in digital signal processors. Santos *et al.* [17] presented an algorithm for high-impedance fault identification on distribution networks; the discrete wavelet transform is used in the monitoring of frequency voltage components and to find transients. Chen *et al.* [18] used the wavelet transform to extract high-impedance fault features and detect high-impedance faults as inrush currents and capacitor switching transients in distribution networks. The results from the measured and simulated data show that the detection can discriminate between high-impedance faults and other typical transient disturbances.

However, some works report the use of mathematical morphology for the transient identification; for instance, Pathirana *et al.* [11] developed a sensor to detect high-frequency transients based on a ferrite core, the results of the detection are compared with wavelet transform and mathematical morphology using synthetic signals created in a laboratory. Gush *et al.* [19] proposed a method to detect and locate faults in microgrids using mathematical morphology and recursive least-square techniques; their method applies mathematical morphology to detect faults and the location is estimated by applying recursive least squares and their results are validated in MATLAB/Simulink. Morais *et al.* [20] presented an algorithm for fault detection in transmission lines, as in [16] they used mathematical morphology to detect faults, but they used differential equations for locating the fault; their

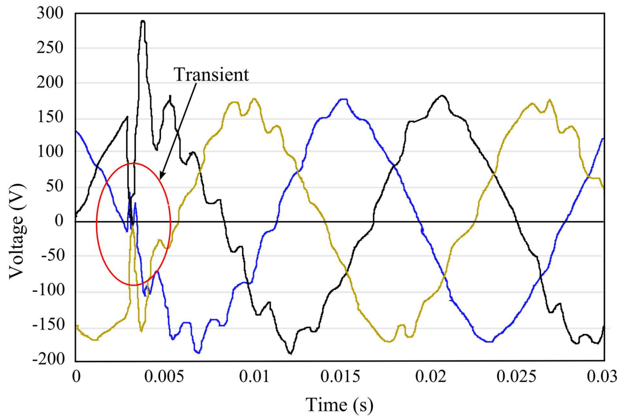

Fig. 1 *Oscillatory transient in a sinusoidal signal [2]*

algorithm seems to be robust for different fault scenarios. Gautam and Brahma [21] presented a method based on mathematical morphology to detect high-impedance faults in power distribution systems over the current waveform, and, Wu *et al.* [22] proposed a scheme using mathematical morphology to discriminate between internal faults and inrush currents in power transformers using morphological gradient in the current discrimination; they concluded that the computation of mathematical morphology is faster than the Fourier algorithm and it is easier to implement in hardware. Farhan and Shanti Swarup [23] developed a methodology for the detection of islanding condition in microgrids by using a filter based on dilated and erode difference to determine a ratio index and use it to track the islanding condition. Lopez-Ramirez *et al.* [24] developed a hardware PQD sorter based on mathematical morphology and singular value decomposition; the sorter is implemented in a field-programmable gate array and the results show efficacy in the PQD classification.

The aforementioned works used wavelet transform or mathematical morphology to identify transients and detect faults in specific elements connected to an electrical installation or grid; however, their methods are focused on identifying the transient for a known phenomenon or instrument. Furthermore, the wavelet transform presents some problems to identify the beginning and ending of a transient phenomenon, overall when two or more transients are closer to each other. On the other hand, mathematical morphology is efficient in the identification of the transient beginning and ending but in the case of oscillatory transients the size of the data window must be variable to make the identification. The accurate characterisation of the transient attributes as indicated that the standard is important when the transient identification is used to detect a pattern in the signal or to diagnose a fault in electric equipment.

This work presents a methodology to accurately locate and delimit transients in a non-residential building. The methodology proposes to analyse the current signal to preliminary locate transient events and then apply mathematical morphology no matter the data window size; the morphological opening and closing are used to find the transient beginning and ending accurately. Finally, the difference between the upper and lower transient values is used to obtain the amplitude of the transient. The results show an accurate identification of the transient beginning and ending even when two different transients are closer to each other.

2 Theoretical background

The IEEE international standard [2] includes terminology and definitions of power quality phenomena including transient events. A space transform maps and compares a function of certain domain against another function that projects it to a different domain. Mathematical morphology is a set of procedures commonly implemented in the image processing; however, due to its mathematical nature these procedures can be applied in any set of data.

2.1 Transient phenomena

Transients are phenomena defined as a sudden frequency change in the steady-state condition of current, voltage or both. An oscillatory transient consists of a voltage or current whose instantaneous value changes its polarity rapidly.

Generally electronic devices, RLC circuits, switching power instruments and physical phenomena can produce oscillatory transients; furthermore, the energisation of capacitor banks results in the creation of oscillatory transients along the electrical installation.

A transient with a primary frequency component <5 kHz and a duration from 0.3 to 50 ms is considered a low-frequency transient. This category of phenomena is frequently encountered on sub-transmission and distribution systems and it is caused by many types of events, primarily capacitor bank energisation. The charging of capacitor banks results in an oscillatory voltage transient with a primary frequency between 300 and 900 Hz. ‘The transient has a peak magnitude that can approach 2.0 pu, but it is typically 1.3–1.5 pu, with durations between 0.5 cycles and 3 cycles of the fundamental, depending on the system damping’ [2] (Fig. 1).

2.2 Mathematical morphology

Mathematical morphology is a set of procedures and definitions used for processing and modeling data, in this work two procedures called morphologic opening and morphologic closing are used [25]. To understand the definition of opening and closing, it is necessary to define the morphological erosion and dilatation.

First is necessary define two sets (X, λB) where $X \in \mathbb{R}$ and $\lambda B \in \mathbb{R}$. Now according to (1) the morphological erosion of set X by the set λB (structural element) is given by

$$\varepsilon_{\lambda B}(X) = X \ominus \lambda \check{B} \tag{1}$$

From the geometric point of view, the set X erosion by a set λB is the place of centres of the structural element when it is totally included in X [25].

Using the pre-defined sets X and λB, the morphological dilatation of set X by the set λB (structural element) is given by

$$\delta_{\lambda B}(X) = X \oplus \lambda \check{B} \tag{2}$$

From the geometric point of view, the set X dilatation by a set λB is the place of centres of the structural element when it touches the set X.

The morphologic opening is defined in (3) as the sequential application of an erosion (ε) and dilatation (δ) of the sets X and λB [25], it is given by

$$Y_{\lambda B}(X) = \left(X \ominus \lambda \check{B}\right) \oplus \lambda B = \delta_{\lambda \check{B}}(\varepsilon_{\lambda B}(X)) \tag{3}$$

Fig. 2 shows an example of morphologic opening applied in a signal.

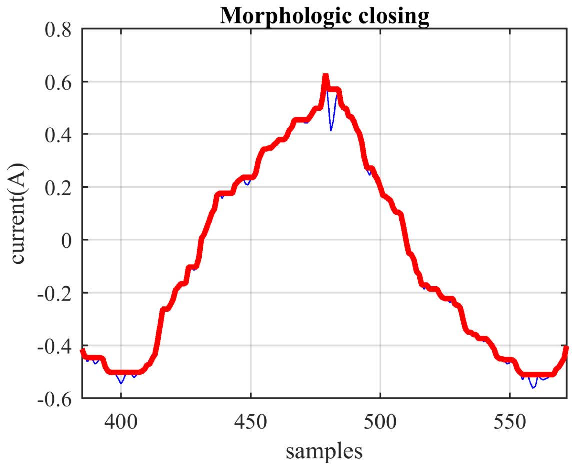

Fig. 2 *Morphologic closing, the signal in blue is the original signal and the signal in red is the resulting morphologic enclosing*

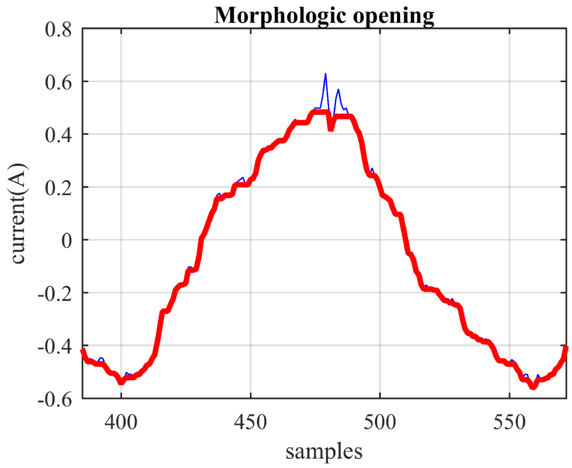

Fig. 3 *Morphologic opening, the signal in blue is the original one and the signal in red is the resulting morphologic opening*

The morphologic closing is defined in (4) as the sequential application of a dilatation (δ) and erosion (ε) of the sets X and λB [25] it is given by

$$\varphi_{\lambda B}(X) = \left(X \oplus \lambda \check{B}\right) \ominus \lambda B = \varepsilon_{\lambda \check{B}}(\delta_{\lambda B}(X)) \tag{4}$$

Fig. 3 shows an example of morphologic closing applied in a signal.

2.3 Wavelet transform

A space transform is a projection of one function from one domain to another and commonly defined by

$$X(s) = \int_{-\infty}^{\infty} K(s,t)x(t)\mathrm{d}t \tag{5}$$

where $X(s)$ is the transformed space, $K(s, t)$ is the transformation kernel in the time t and $x(t)$ is the original space [26].

The wavelet transform decomposes a signal into different signals named components and these components correspond to different frequency bands in the original signal. This way is possible to make a frequency and amplitude analysis in a noisy signal. A mother wavelet is a variating time function with adjustable ρ scale. This scalable function is compared along the original function and a wavelet transform is obtained, for each p scale.

The definition of a wavelet transform [26] is

$$X(s,p) = \int_{-\infty}^{\infty} K(s,p,t)x(t)\mathrm{d}t \tag{6}$$

where $X(s, p)$ is the wavelet transform of p scale, $w(s, p, t)$ is the mother wavelet of p scale in the t time and $x(y)$ is the original space.

The high number of vanishing moments and the shapes used in the Daubechies filter for wavelets is the better option to implement the wavelet transform in the acquired current signals and make the transient first identification

3 Methodology

The main purpose of this work is to present a method to accurately detect and delimit transient through the combination of the discrete wavelet transform and mathematical morphology. The proposed methodology is depicted in Fig. 4.

In the first stage, ~24 h of measured signal is processed in time stamps of 10 min. For this task, an order 10 Daubechies wavelet with four decomposition levels is used as a pre-process to broadly find transient events in the current signal. In this case, the wavelet transform is useful due to its lower computation cost and the reliability to find transient events. Furthermore, Daubechies wavelets' waveforms are very similar with the waveform expected in the transient events in the electrical signal. When a transient is found that part of the signal is isolated and stored in a binnacle to be processed later by using mathematical morphology. In the second stage the isolated signal is analysed with two different processes, in the first one the morphologic erosion and dilatation is applied according to (3) to obtain the morphologic opening of the signal, in the second one the morphologic dilatation and erosion is applied by following (4) to obtain the morphologic closing of the signal. In this way, the opening is used to identify the transient upper part and the closing to identify the transient lower part. Once the morphologic opening and closing are obtained, the next step consists in to compute the difference between opening and closing to find the transient amplitude and the transient limits, when the transient begins and when the transient finishes. Finally, with the transient amplitude and limits it is possible to determine accurately the transient parameters.

4 Experimentation

The experimentation is carried out in a non-residential building. Data acquisition is done with a proprietary data acquisition system (DAS) able to store all the waveforms of current and voltage signals during a long period of time.

The DAS is located on the main board CG6 as shown in Fig. 5 due to the different load kinds presented in this board. The acquired signal processing is done in 24 h intervals, using an order 10 Daubechies wavelet with four decomposition levels and an aperture and closing with a size window of one. Daubechies wavelet is used due to the waveform similitude with the transients of interest in the analysed signal. Some clarifications about the experimental setup are detailed in the Appendix.

5 Results

The results of the transient preliminar identification are shown in Fig. 6, where the red signal is the original current signal and the blue one is the first level of the wavelet decomposition, from the blue signal the location of transients is evident.

The morphological opening and closing of two different transients are shown in Fig. 7. The signal in red of Fig. 7*b*

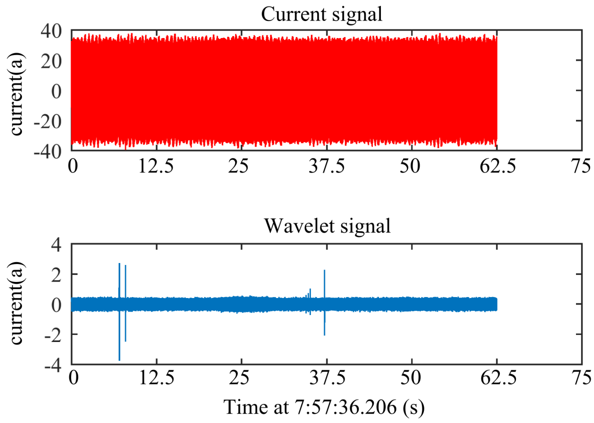

Fig. 4 *Wavelet transient identification, the red one is the original current signal and the blue one is the event wavelet identification*

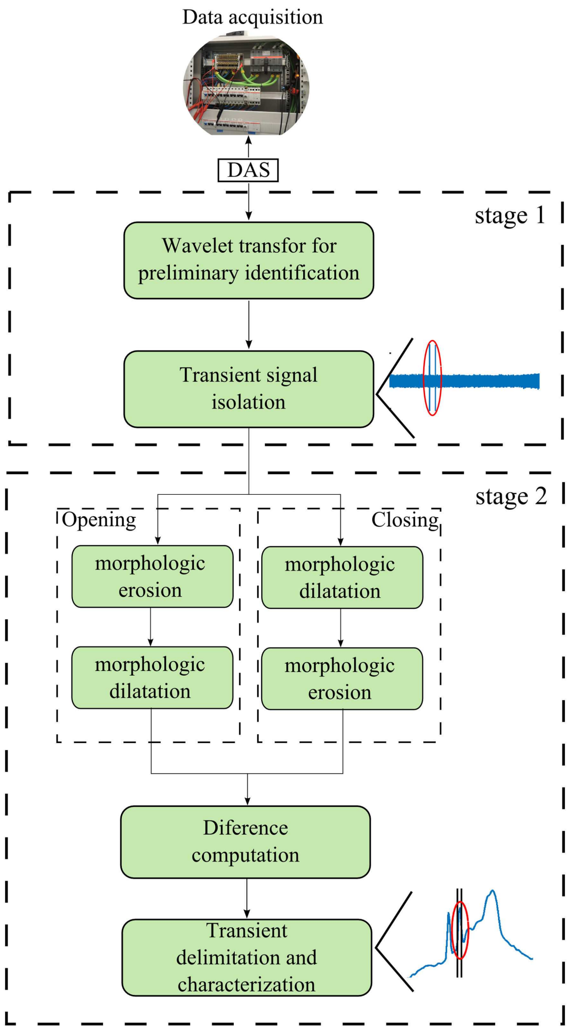

Fig. 5 *Proposed methodology for the accurate identification and characterisation*

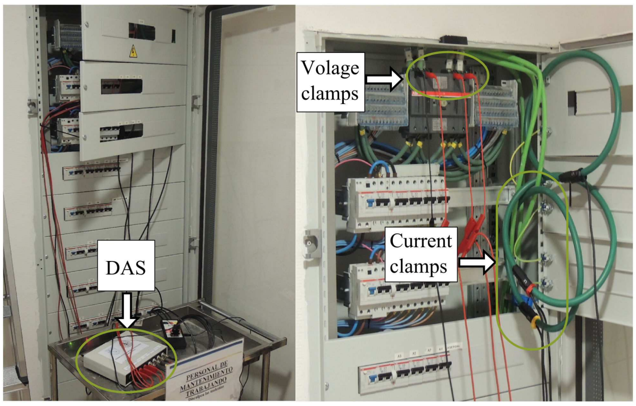

Fig. 6 *DAS installation at the main board CG6 with three voltage clamps and three current clamps*

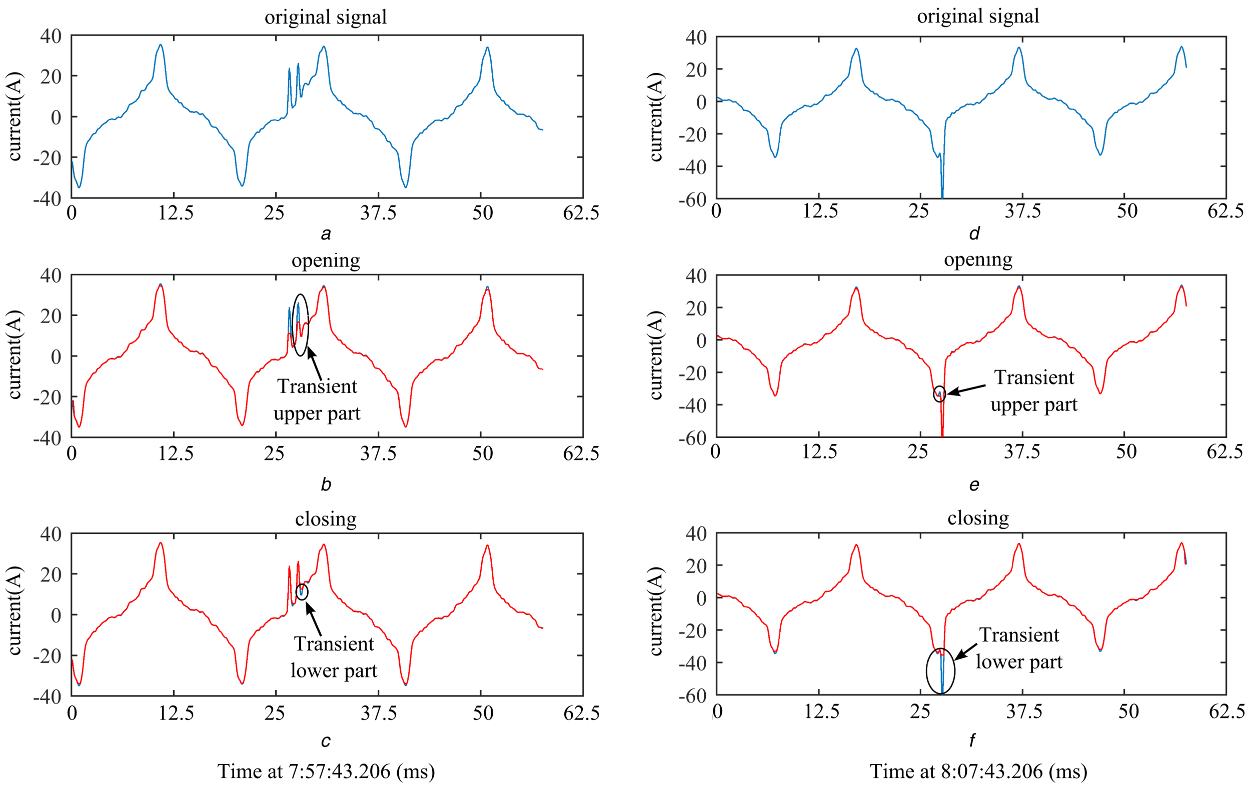

Fig. 7 *Wavelet transient identification:*
(a) Original signal transient 1, ***(b)*** Morphologic opening transient 1, ***(c)*** Morphologic closing transient1, ***(d)*** Original signal transient 2, ***(e)*** Morphologic opening transient 2 and ***(f)*** Morphologic closing transient 2

represents the opening of the original signal and it is possible to see the zones in which the upper part of the transients is identified; furthermore, it is important to notice that the opening can be distinguished between the two closer transients. Fig. 7*e* shows the identification of a different transient with a small portion of the upper part. Similarly, Figs. 7*c* and *f* show the lower part of the transients where the first one is less evident than the second one.

The difference between the morphological opening and closing to know accurately the limits of the transients is shown in Fig. 8, this difference is useful to establish the beginning and ending of a transient; furthermore, it indicates the amplitude and their location in the original signal. Figs. 8*b* and *e* show how the limits for the transients are illustrated clearly and which is the location and the value for the highest point in the transient signal in Figs. 8*c* and *f* the delimitation of the transients in the original signal according to the results of Figs. 8*b* and *e* is shown.

In contrast with the identification using wavelet and mathematical morphology, Fig. 9 shows the transient identification using three different methods. Fig. 9*a* shows the current signal with the transients of interest. Fig. 9*b* shows the transient identification using only the wavelet identification, in this case it can be observed that the wavelet transform identifies the two transients as if they were a single transient whereas using both techniques as in Fig. 8*c* the transients are identified and delimited individually. Fig. 9*c* shows the transient identification using multiple signal classification (MUSIC) with 1024 bits resolution, 60% overlapping and a 30-order filter, in this case the identification is ambiguous and difficult to locate the beginning and ending of the transient; furthermore, is not possible establish the decay time and the transient amplitude. Fig. 9*d* shows the transient identification using short-time fast fourier transform (SFFT) with a window length of 8, hop size of 1 and 4 points for the FFT, in this case it is possible to observe the identification of the two closer transients but as in MUSIC is very difficult the identification of the amplitude and decay time.

A different case of transient identification with different techniques is shown in Fig. 10, where, the original signal Fig. 10*a* is a single transient in the negative side of the waveform. Fig. 10*b* shows the identification using only the wavelet transform, in this case the identification is clear, but the delimitation of the transient beginning and ending is out of the real values. Fig. 10*c* shows the identification using MUSIC with 1024 bits resolution, 60% overlapping and a 30-order filter, in this case the identification is better than the one in Fig. 9*c*, but the transient limits identification

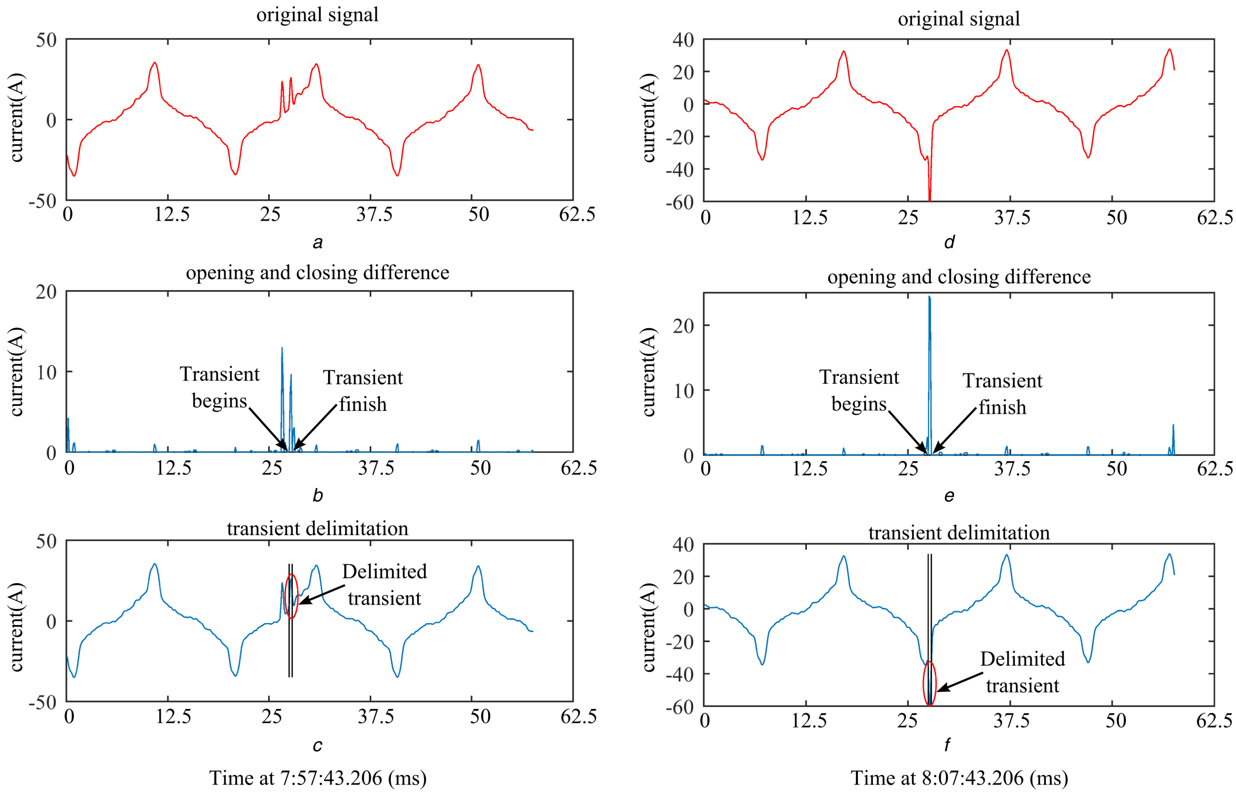

Fig. 8 *Morphologic transient delimitation:*
(a) Original signal transient 1, ***(b)*** Opening and closing difference for the transient delimitation, ***(c)*** Transient Delimitation in the original signal, ***(d)*** Original signal transient 2, ***(e)*** Opening and closing difference for the transient delimitation and ***(f)*** Transient delimitation in the original signal

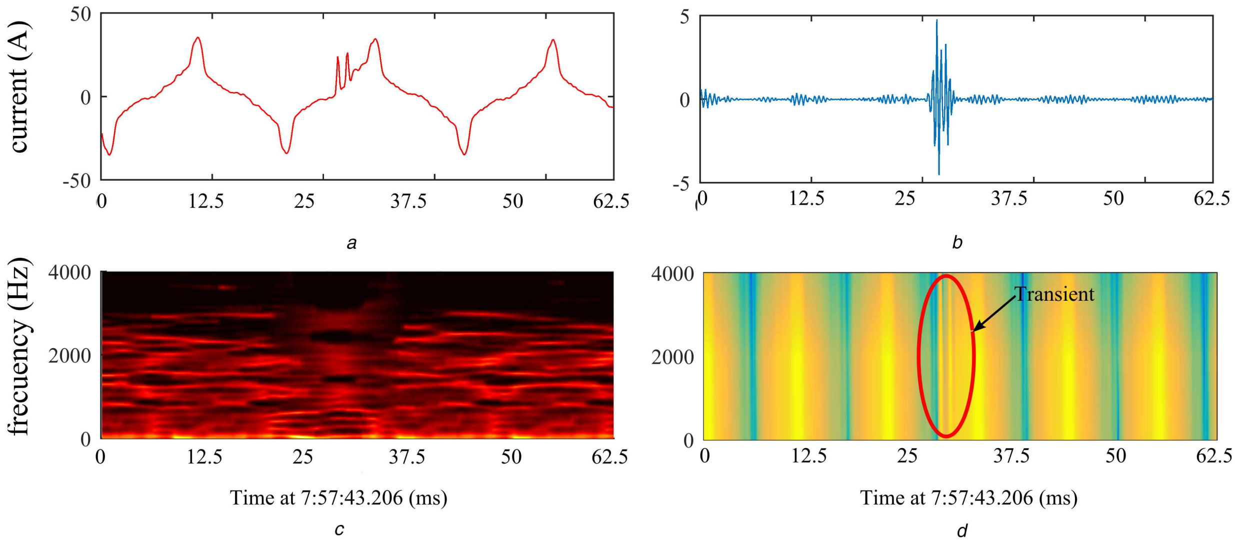

Fig. 9 *Identification of two closer transients:*
(a) Original signal, ***(b)*** Wavelet signal at the first decomposition, ***(c)*** MUSIC method identification ***(d)*** SFFT identification

remains difficult to be made. Fig. 10*d* shows the transient identification using SFFT with a window length of 8, hop size of 1 and 4 points for the FFT, in this case the identification looks clear and the transient delimitation could be done; however, due to the nature of the SFFT the identification depends entirely of the user and the transient amplitude cannot be done directly from the SFFT.

For the example shown in Fig. 9*a* and to contrast with the example in Fig. 8*a* some attributes as energy, amplitude and decay time are computed from both examples, the results are shown in Table 1.

From Table 1, it is possible to see the differences in the computation of different transient attributes where the differences between each other are evident; in this case these differences can result in an incorrect diagnosis or transient classification for the analysed event.

6 Conclusions

In this paper, a methodology combining wavelet transform and mathematical morphology to identify accurately transient phenomena is presented. Owing to the preliminary transient identification done through the wavelet transform, the proposed methodology allows the mathematical morphology focused on a specific area of the signal to accurately establish the limits and the higher value of the transient, no matter if it is positive or negative.

The combination of wavelet transform with morphological opening and morphological closing with a window size of 1, allows identifying and delimiting transients accurately, even though they are closer to each other. Furthermore, in some cases the use of only the wavelet transform can result deficient to identify transients when they are closer to each other. Moreover, the problem of the wavelet transform to identify the transient beginning and ending is

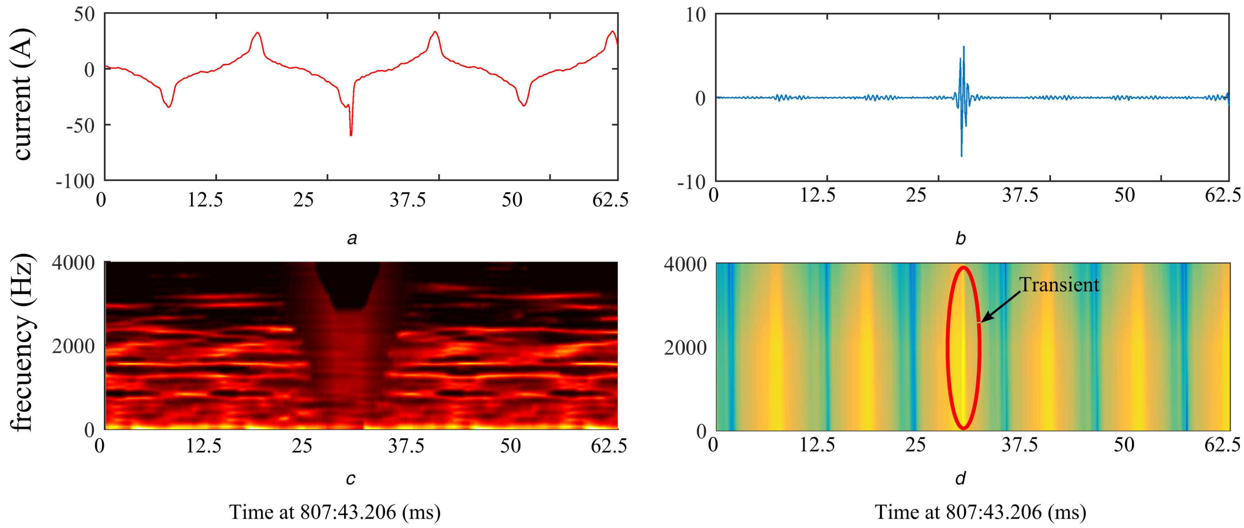

Fig. 10 *Identification of a single transient:*
(a) Original signal, ***(b)*** Wavelet signal at the first decomposition, ***(c)*** MUSIC method identification ***(d)*** SFFT identification

Table 1 Attributes contrast

Attribute	Wavelet and morphology	Wavelet	MUSIC	SFFT
energy	499.8	5632.2	—	499
amplitude, A	9.7	13.1	—	—
decay time, ms	0.37	2.3	—	—

resolved with the implementation of mathematical morphology and, the window size for the mathematical morphology analysis can be constant due to the preliminar transient identification with the wavelet transform. In the case of MUSIC, the transient identification is ambiguous and it is very difficult delimiting the transient beginning and ending; furthermore, the amplitude and decay time is not possible to be calculated. With the SFFT method it is possible delimiting the transient beginning and ending even when there are two closer transients; however, the resulting identification with SFFT needs the interpretation of an experimented user. Additionally, to compute the amplitude and decay time further analysis over the original signal would be necessary.

7 Acknowledgments

The authors want to thank the Administration Board of Sanidad de Castilla y Leon (SACYL) for providing the access to the healthcare facilities. This project was supported in part by the National Council of Science and Technology (CONACYT), Mexico, under scholarship 48762; SEP-CONACyT 222453-2013 grant, FOMIX QRO-2014-C03-250269 grant, and FOFIUAQ-FIN201819 grant.

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9 Appendix

The details about the experimental setup are presented in this section.

The non-residential building is a healthcare facility that is a modern hospital with a three-floor construction in 115,147 m^2 surface and over 600 beds. The electrical installation is divided in six main boards that feed different regions inside the hospital. The main board CG6 feeds different zones like emergencies, hospitalisation, infirmary, dining rooms, medical zones, halls and informatic racks.

Data acquisition is done with a proprietary DAS, this equipment can measure seven simultaneous signals at 8000 samples per second with a 16-bit resolution. The seven measured signals are four of 1–1000 A current data (15.25 mA of resolution), one for each phase in a three-phase installation and the neutral line, and three 100–600 V of voltage data (9.15 mV of resolution). DAS is able to store all the waveforms of current and voltage signals during a long period using a flash drive.

The acquired signal processing is done in 24 h intervals with a 10 min window, using an order 10 Daubechies wavelet with four decomposition levels and an aperture and closing with a size window of one.