Validation of a Wavelet Algorithm Implemented in a Fixed-Point DSP for Detection and Analysis of Electrical Transients

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Abstract: In this work we develop an on-line algorithm to detect and classify transients produced in capacitor buses during connection and disconnection. The algorithm was implemented in a Blackfin® BF-535 Processor. Transients are modeled as an oscillation modulated in amplitude by an exponential decay. The detection process consists in detecting the transient's onset, while the classification consists in measuring the oscillation frequency and decay parameters. Two validations were performed, one against a database of simulated transients and the other with a database of experimental signals. In the last case, as no gold standard is available, we assessed the degree of agreement against an off-line algorithm implemented in a PC. The algorithm performed good in onset detection, where the absolute error was under 1 ms. Also exhibited good performance in frequency classification, where the global relative error was under 1.8%. In contrast, the τ parameter classification relative error only reached an overall range under the 22%. This motivated future improvements in this aspect.

Key–Words: Wavelets, Multiresolution, Fixed-point, DSP, Transients

1 Introduction

The capacitor banks used to correct the power factor reduce the reactive power increasing the power transmission capacity. In this work we studied oscillatory transients caused by capacitors switching, specially the short time and high frequency transients in voltage over capacitors buses. The transient frequency (f_O) is between 400 and 2000 Hz, depending on the ratio between the fault power and the bank capacitor power. Meaning that this frequency corresponds to the serial resonance frequency that involves the bank capacity and the system inductance at the connection bus. The overshoot voltage varies from 1.3 to 1.8 times but could rise up to 4 times in case that more capacitors are connected [1]. When a high frequency overvoltage transient appear, failures on electronic devices, such as PLCs, control systems, measurements devices, etc, might happen. These problems motivated the development of an algorithm to detect and analyze these transients [2]. Once this off-line algorithm is validated in a PC simulation software like Matlab®, it could be ported to another architecture most appropriate to achieve on-line processing, like a DSP processor, probably in a handheld device. These kind of processors have an optimized architecture that fits exactly in applications that use mathematical and data management resources intensively [3]. On the other hand, algorithms implemented in fixed-point DSP processors requires more development time (for example than Matlab scripts or C/C++ for PC) mainly because problems related to finite precision and algorithm validation is not a trivial problem [4]. The objective of this work is to port an algorithm simulated in Matlab to a fixed-point DSP architecture, and perform a validation of its performance.

2 Methods

2.1 Experimental Scheme

In this work we used a signal data base from a previous work [2]. This data base consists in 27 voltage signals sampled at 15 kHz, over an inductive load connected to a 2 kVA transformer (with it's own Joule's looses) during the manual connection of a back to back capacitor bank. The resultant transient over an industrial frequency voltage carrier, corresponds to a exponentially decaying oscillation. It was proposed a simplified model which consists of: oscillation frequency (f_O), exponential decay (τ) and transient's onset (T_{on}). These signals were transmitted to the DSP, and the results of the detection and classification process were sent back to assess the degree of agreement with the off-line algorithm, since it was not available a gold standard measurement about the three parameters.

Due to wide bandwidths and short lengths of electrical transients under study, the wavelet transform was used.

2.2 Wavelet Transform Analysis

The algorithm implemented in this work is based on the well known wavelet transform (WT) under a multiresolution scheme (MR)[5]. The WT is a powerful tool to detect short transients and discontinuities in continuous signals, like power line signals. MR can be performed with Mallat's algorithm[6], which is a fast implementation based on digital (decomposition) filters followed by dyadic decimators (Fig. 1).

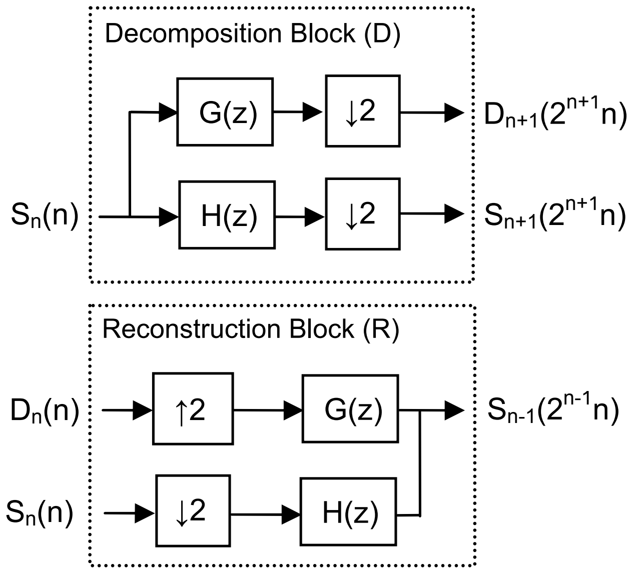

Figure 1: Decomposition and reconstruction filter blocks.

Those decomposition and recomposition filters belong to the Daubechies's wavelets (Daub) families. The low pass output can be followed by another section as many times as needed, obtaining one successive detail D_n (high pass output) and approximation coefficients S_n(low pass output) (Fig. 2). The inverse wavelet transform (iWT) is performed in a reciprocal manner, dyadic interpolators followed by digital (reconstruction) filters (Fig. 1). The analysis consists of the localization of events in time at different decreasing dyadic frequency bands.

As the frequency bands become narrower, time uncertainty increases and vice versa (Fig. 3). Transients studied in this paper correspond to high frequency ranges ($f > 375Hz$).

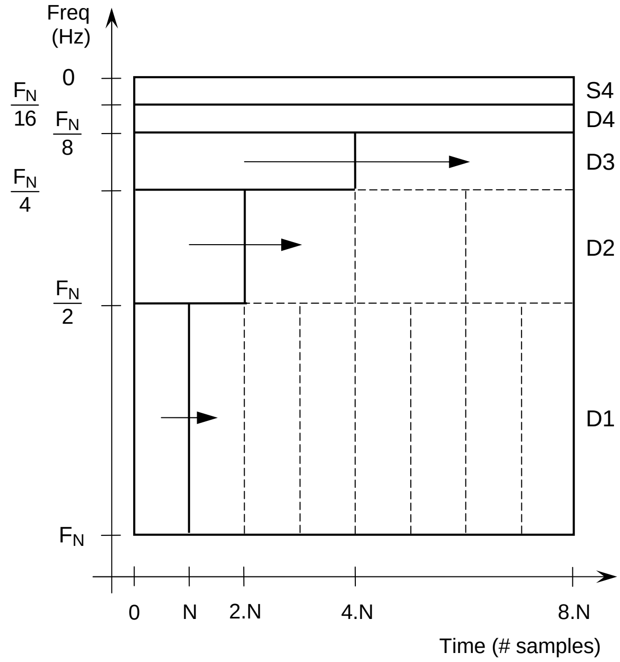

Figure 3: Time-frequency plane showing the trade off relation between time and frequency resolution in wavelets analysis. We used F_N for Nyquist frequency, and N for filter kernel size. Horizontal arrows show the translation in time of the time-frequency window in dyadic steps.

2.3 Wavelet Selection Criteria

When the aim of an algorithm is transient's detection, a convenient balance between computational burden and time resolution is found with wavelets $Daub_4$ and $Daub_6$ [2]. However those wavelets do not provide reliable information about waveform characteristic (pattern recognition) because of its lack of frequency resolution.

The lower the filter kernel is, the better the resolution in time, but the worst resolution in frequency. As an example, Fig. 4 shows in dash line the $Daub_4$ (8 coefficients) and in solid line the $Daub_{10}$ (20 coefficients) wavelet's frequency response (FR). The downslope measured from the frequency where the FR is equal to -3 dB is 70 dB/decade for $Daub_4$, while 170 db/decade for $Daub_{10}$.

The Daubechies's wavelets from $Daub_4$ to $Daub_{14}$ were tested against 280 simulated transients, based on 10 realizations of 7 f_O steps and 4 different τ with the off-line algorithm. The τ parameter was measured using a statistical tool known as pseudoinverse [7], which fits an exponential decay with least mean square (LMS) error. The reliability of pattern recognition is imposed by the time-frequency resolution which belongs to the chosen wavelet. The most suitable wavelet is the one which achieves minimum

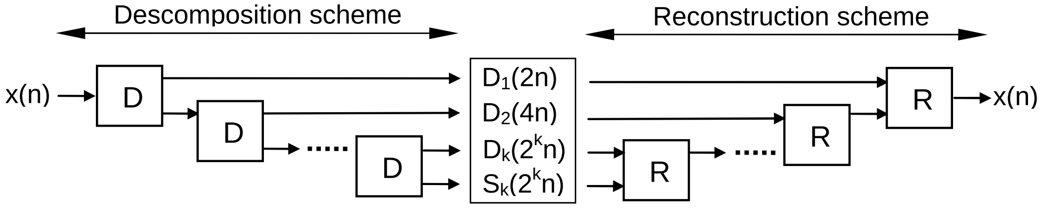

Figure 2: Multiresolution scheme using decomposition and reconstruction blocks (figure 1). The details D_n and the last approximation S_n are shown in the center of the scheme within a box.

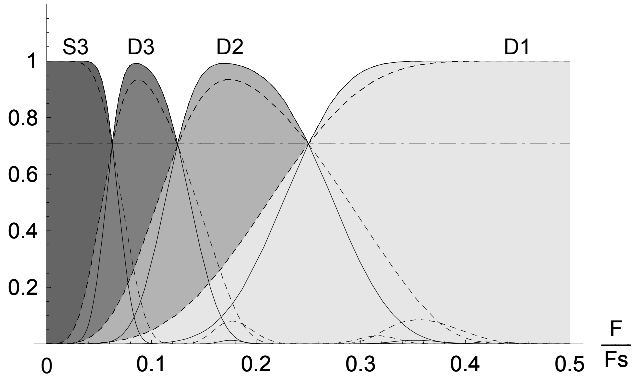

Figure 4: $Daub_4$ and $Daub_{10}$ Frequency Response

square error in τ measurement. The LMS error vs. $Daub_i$ families results are shown in Fig. 5, having f_O as parameter. As can be seen in this figure, $Daub_{10}$ provide the most reliable τ measurement along the whole range of transients.

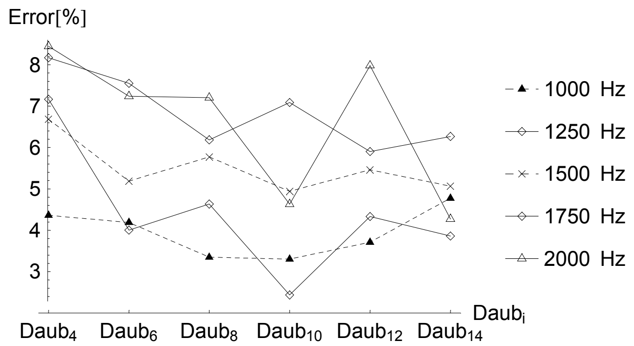

Figure 5: Performance of Daubechies wavelets measuring τ parameter.

2.4 Algorithm description

The T_{on} detection is performed by thresholding the smaller detail levels, where the time resolution is higher (Fig. 3). This threshold can be adapted to different signal to noise ratio (SNR) scenarios. Once the transient was detected, reconstruction is performed with higher frequency coefficients ($f > 375Hz$) discarding the last approximation ($f < 375Hz$). By this manner, most of the transient's energy is separated from the power line signal and ready to be classified.

The measurement of τ was performed by detecting the relative maxima modulus values of the oscillation, and then performing an ad-hoc fitting algorithm that iteratively minimize the square error. After that, f_O is measured by averaging the intervals between relative maxima modulus of the same sign.

2.5 Algorithm Validation

The MR algorithm validation was done in Matlab, using the Fixed Point Toolbox, and contrasted against Wavelets Toolbox functions. We started implementing MR algorithm in Matlab in order to minimize as much as possible debugging in the DSP environment. It means that any Matlab specific feature was avoided, trying to code scripts as similar as C language as possible. This eased the posterior language translation process. Once algorithm reached a stable version in the DSP platform, we need to validate the correct behavior and study error distribution in detection and classification process. Those steps are entirely related each other, and were carried out together. Error analysis was studied with simulated transients that were transmitted with a PC to the DSP. Once detection and classification process finished, results were sent back to the PC for statistical analysis. This process was repeated for the whole frequency range from 400 to 2000 Hz in steps of 100 Hz, with durations from 3 to 15 periods of the corresponding frequency (1.5 to 37.5 ms). This kind of parameterization was adopted since the classification algorithm strongly depends on the amount of detected cycles. The beginning of each transient was determined by a uniformly distributed random function, to test the algorithm's performance in a wide range of situations.

2.6 DSP Processor

It was used an Analog Devices (AD) Blackfin® BF535 to develop the algorithm. Blackfin DSP processors (DSP) have most important and powerful features of modern DSP's, like dual 16 bits multiply and accumulators (MACs), 40 bits arithmetic and logic unit (ALUs), data address generators (DAGs), direct memory access (DMA) peripheral controller, cache memory organized in two layers, and a RISC pipelined architecture clocked at 500Mhz [3]. Before start working with the DSP development environment (AD Visual® DSP++ 4.0 IDDE), the detection algorithm was simulated with Matlab's Fixed Point Toolbox. Then Matlab scripts were translated into C language, a supported language in VDSP++. We used BF535 EZ-Kit Lite for firmware development in combination with VDSP++ IDDE. The DSP algorithm could be controlled through a serial (RS-232) terminal either by a human operator or an external device, like a PC. The DMA controller managed the RS-232 serial controller in order to free the Blackfin core from this work. The result was that the core took care only of data processing and management tasks, reducing drastically overhead work. For data processing purposes all architectural features of the core were used via built-in functions implemented in C language. Those built-in functions are available in the VDSP++ Run-Time library.

2.7 Statistical Analysis

We used Bland and Altman method [8] to study the agreement between the simulated off-line algorithm and the real-time implementation, since we did not know the actual values to be measured (gold standard). In order to express the limits of agreement, we analyzed first the normality of the difference between methods with Kolmogorov-Smirnov test [9]. For normal distributions we used two standard deviations (SD) from the mean of the differences as limit of agreement. While for not normal distributions we used a scheme similar to boxplot, upper and lower whiskers as limits of agreement. Upper and lower whiskers are calculated as 1.5 times the distance between quartile 75 and 25, away from the median.

3 Results

3.1 Simulation Results

The results of the simulation are summarized in Fig.6. For transients longer than 3 periods the median of the f_O relative errors was under 1%, since for shorter transients this reached the 3.5% (Fig. 6). The same happened with τ parameter, reaching a maximum relative error of 45% for short transients and less than 15% for longer transients. The onset detection was achieved in all cases with an absolute error smaller than 1 ms. In tables 1 and 2 the error distributions are showed in more detail for f_O and τ parameters. The relative error is under 1.8% in the whole range for f_O parameter, but for τ parameter in the same range the relative error is under the 22%.

3.2 Experimental Results

The degree of agreement between on-line and off-line implementations is shown in figure 7 for τ and f_O parameters. As can be seen in the τ parameter panel, the degree of agreement is very low since the distance between limits of agreement is large respect to the mean of the measurements. Whereas in the frequency panel the agreement rises, as the distance of agreement decreases.

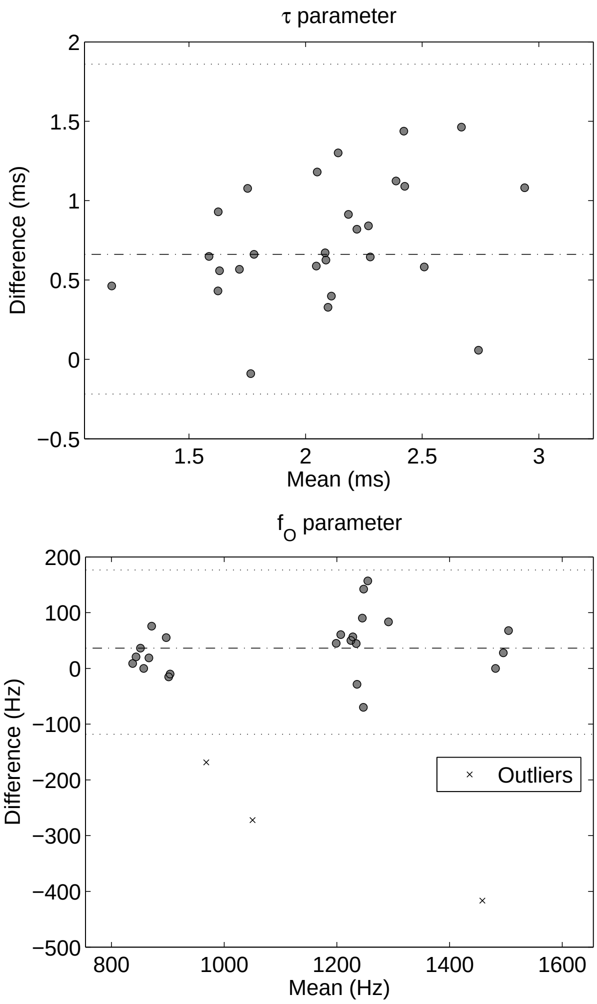

Figure 7: Bland and Altman plots shows the degree of agreement between experimental results obtained with on-line and off-line algorithms. As none of the difference datasets presented a normal distribution, median is shown in dash dotted line and limits of agreement in dotted lines.

4 Conclusion

In this work we validated a real-time implementation of an algorithm developed for detection and classification of electric transients. The transient's object detection was achieved with less than 1 ms of error,

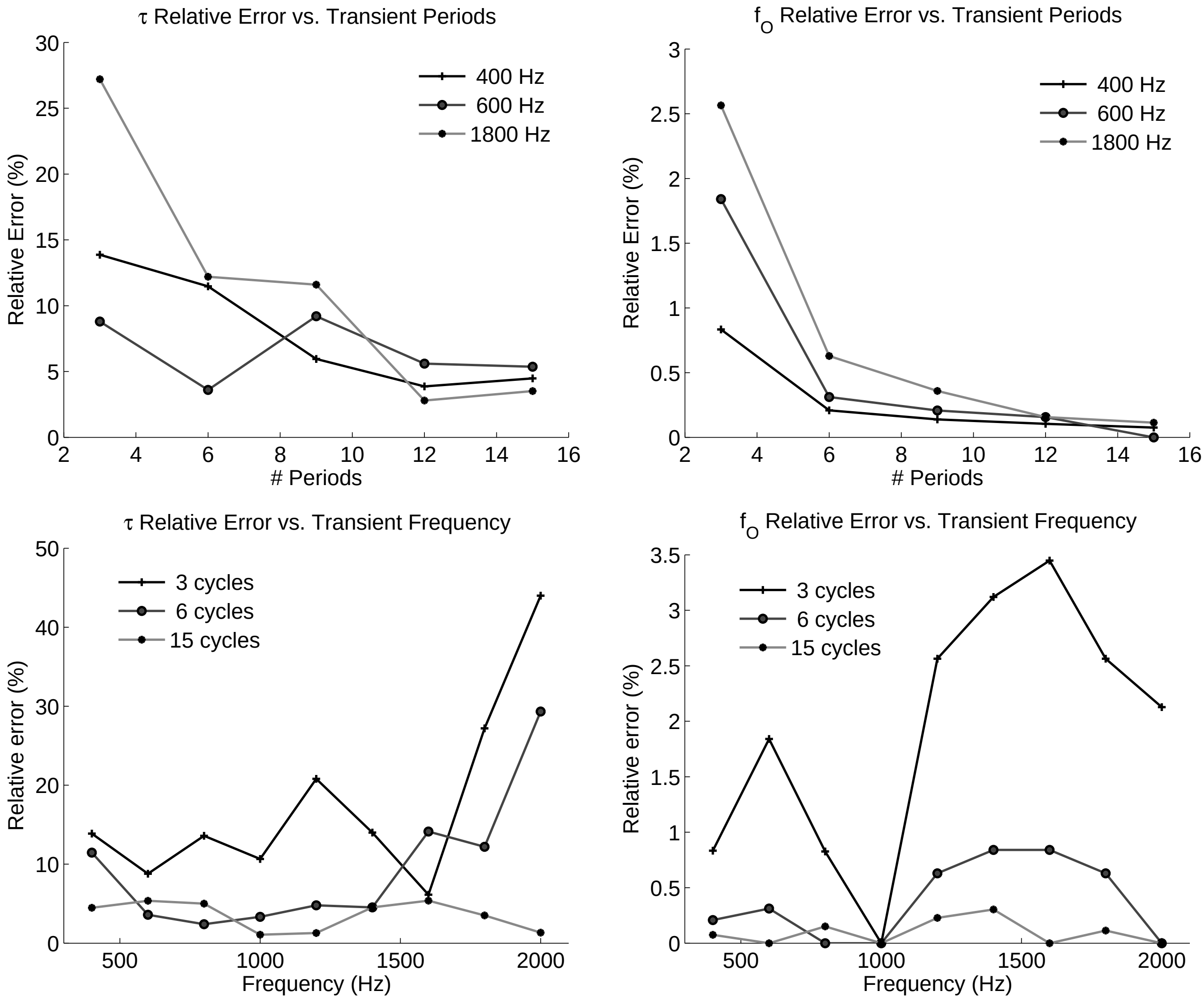

Figure 6: Relative error as a function of transient duration and frequency. For longer transients the error decreases asymptotically, as well as for lower f_O.

this feature makes it very useful for fail logging purposes. The f_O parameter is measured with a relative error smaller than 3.5% during simulation. This error is strongly correlated with transient's length (Fig. 6), is quite simple to note that as the amount of periods increases the algorithm has more data to measure, and better measurements are made. This is applicable for τ parameter in the same manner, but the classification performance of this parameter is by far the worst (table 2). We used the pseudoinverse method in the off-line algorithm, and as can be seen in table 2, the τ_{Ps} parameter achieves better performance for shorter transients. Error ranges obtained were acceptable but since the model of transient used in our simulation was very simple, actual performance was somewhat worst. In the experimental analysis, important discrepancies were seen when measuring the τ parameter. This was caused mainly by limitations of the on-line fitting algorithm and the transient model. This limitation can be improved by making better model of transient and an ad-hoc measurement algorithm, like pseudoinverse method. In spite of algorithm and transient's model simplicity, the results discussed before are satisfactory enough as a first solution.

5 Limitations and future works

The inherent limitation of the WT is in its intrinsic nature, since it is a time-frequency transform, a memory buffer is necessary to be sampled in order to be performed. So the algorithm on line response is limited to the time required to fill a buffer. The smaller the time to fill an observation buffer, the higher on-line response of the algorithm but the poorer the capability of long transients classification. As it can be seen, the transients duration range to be analyzed, the on-line response of the algorithm and the memory and processing performance of the DSP are related in a trade-

Table 1: Summary of the measurements error for f_O, τ and T_{on} for different transient frequencies in the range from 400 to 2000 Hz. The table shows the relative error for f_O and τ parameter, while the absolute error for T_{on}, expressed in ms. In all cases lower whisker (LW), median (M) and upper whisker (UW) are respectively shown for each condition.

	Transient Frequency Range (Hz)											
	400-700			700-1400			1400-2000			400-2000		
	LW	M	UW	LW	M	UW	LW	M	UW	LW	M	UW
f_O	0.0	0.2	0.8	0.0	0.3	1.6	0.0	0.4	2.1	0.0	0.3	1.8
τ	0.3	6.0	17.1	0.0	3.6	14.1	0.0	6.1	38.7	0.0	5.2	21.6
T_{on} (ms)	0.5	0.5	0.7	0.7	0.8	0.8	0.3	0.8	0.8	0.4	0.7	0.8

Table 2: Summary of the measurement error for f_O, τ and T_{on} for different transient durations in the range from 1.5 to 37.5 ms. The table shows the relative error for f_O and τ parameter, while the absolute error for T_{on}, expressed in ms. The τ_{Ps} parameter is measured with the pseudoinverse method. In all cases lower whisker (LW), median (M) and upper whisker (UW) are respectively shown for each condition.

	Transient Duration Range (# periods)											
	3			6-9			12-15			3-15		
	LW	M	UW	LW	M	UW	LW	M	UW	LW	M	UW
f_O	0.0	2.1	3.9	0.0	0.4	1.1	0.0	0.1	0.5	0.0	0.3	1.8
τ	0.8	16.0	44.0	0.0	5.6	20.0	0.0	2.6	9.9	0.0	5.2	21.6
τ_{Ps}	0.4	5.8	22.6	0.5	7.2	17.6	2.2	5.7	14.1	0.4	6.0	20.0
T_{on} (ms)	0.6	0.8	0.8	0.6	0.8	0.8	0.1	0.5	0.8	0.4	0.7	0.8

off relation. In this work we limited the time observation window to 2048 samples. It means that information is updated at a 7 Hz rate and the maximum transient duration is 100 ms (5 periods of 50Hz). As future improvements to this work we will study the effect of lifting scheme to improve algorithm's speed, the use of pseudoinverse fitting method to improve τ classification accuracy, another methods of transient's spectral content measurement like FFT, and a more general transient model to take into account other sources of perturbations.

Acknowledgements: This work was partially supported by Fundación Antorchas and Semak S.A., Argentina.

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