Adaptive Transient Event Detection for Industrial Applications

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Abstract Foreign elements may destroy sensitive parts of mobile industrial machines such as harvesters. When such undesired transient events shall be detected, varying machine noise scenarios demand adaptive algorithms that allow for a robust detection performance. Moreover, a detection system that is too responsive reduces the machine's speed of operation. We have evaluated three algorithms that are capable of detecting transient events, and that allow for timely precautionary measures. Two of the methods apply a fixed and adaptive threshold to the short-time energies of the high-pass filtered sensor signal, respectively, while a new method employs linear prediction-based filtering and an adaptive frame-energy threshold, and incorporates the variance of the high-frequency frame content enabling the distinction between events resulting from foreign elements and events originated by the machine. The algorithms were applied to four types of transient events that were combined with a set of machine noise recordings at different signal-to-noise-ratio (SNR) levels. Our results show that the new method provides 95% correct detections down to a SNR of -1 dB, and that all methods provide a very low rate of misdetected events.

1 Introduction

In the feeding process, harvesting machines can seriously be damaged by foreign elements that are collected together with the crop. To avoid such an undesired failure, a detection system is needed to allow for an early detection of these foreign elements, thus enabling an automatic machine stop on time. The objective of this work was to develop an adaptive algorithm that allows for the detection of

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transient events due to foreign elements based on knock sensor signals. This adaptive algorithm should tolerate potential transients resulting from the cropping process, and thus avoid false alarms.

This paper is structured as follows. Section 2 briefly reviews related work in the field of transient detection. In Section 3, we present three algorithms for transient detection which we will experimentally evaluate and compare. The evaluation setup is described in Section 4, and the results are presented in Section 5. Finally, we conclude our findings in Section 6.

2 Related Work

The problem of detecting transients has been explored in various fields. Wang and Willett (Wang & Willett, 2000) tested the performance of different approaches to detect transients in noise in the realm of process-monitoring by acoustic emission. The authors have tested the performance of the detection of unknown transient signals in white Gaussian noise. Their results suggest that unsophisticated methods such as “Nuttall's Power-Law Detector”' (Nuttall, 1994) give reliable results. As an example for transient detection in the biomedical area, Nenadic and Burdick (Nenadic & Burdick, 2005) tested a spike detection algorithm based on the Continuous Wavelet Transform. Their method allows for nearly real-time performance. In musical signal processing, Masri and Bateman (Masri & Bateman, 1996) presented a technique to cope with transient phases in analysis-resynthesis models. Time-scale modification of audio requires the detection and particular processing of transient events, especially if large modification factors are used. Bonada (Bonada, 2000) proposes to detect fast changes and keep them as they are. His system for change detection involves bank filter energies, Mel cepstrum coefficients and their deltas. Verma and Meng (Verma & Meng, 2000) extended spectral modeling synthesis (Serra & Smith, 1990) by a model for the transient parts of sounds. Their transient modeling system first analyzes the sinusoidal parts of the sound signal, resynthesizes those components and detects transients based on the energies of the resynthesized signal and the first-order residual signal, i.e. the original signal minus the resynthesized signal. Nsabimana and Zölzer (Nsabimana & Zölzer, 2007) use a transients plus sinusoids and noise approach. They detect transients by applying a linear prediction error signal and an adaptive threshold based on the envelope. Gnann and Spiertz (Gnann & Spiertz, 2009) use the absolute discrete group delay as a measure to detect transients in sounds. In combination with a maximum order filter, their method works well both on percussive and tonal-percussive sounds. Glover et al. (Glover, et al., 2001) compare seven algorithms for musical onset detection. These algorithms are based on signal frame energy differences, spectral difference of consecutive frames, a detection function using combined magnitude and phase information, three detection functions that are based on linear prediction, and a method that is based on the differences of peak amplitudes using a sinusoidal model.

3 Transient Detection Algorithms

The aim of this work is to develop a transient detection algorithm that provides reliable detection results in a computationally efficient manner. In this section, we present two variants of a simple transient detection algorithm (SITRA). In the first implementation, a fixed threshold is used, while the second implementation features an adaptive threshold. Then, we introduce a more sophisticated algorithm that incorporates linear prediction-based filtering, an adaptive threshold and the incorporation of the variance of the high-frequency content of candidate frames.

In each of these algorithms, the sensor signal is sampled at 20 kHz and divided into frames of 256 samples that overlap by 50%.

3.1 SITRA with Fixed Threshold

As a simplest means of transient detection, an algorithm called SITRA (Simple transient detection) has been developed. This algorithm is schematically shown in Figure 1.

As the machine noise mostly consists of low-frequency energy, the framed sensor signal is high-pass filtered at 200 Hz first (3rd-order Butterworth). Then, the frame energy is calculated. If the energy level exceeds a certain fixed threshold, a foreign element is detected.

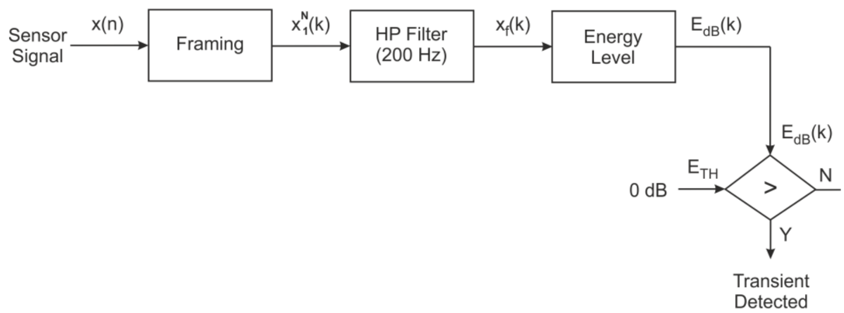

Figure 1. SITRA block diagram (fixed threshold).

An example for this variant of SITRA is given in Figure 2. The upper plot shows the energy of the filtered sensor signal frames, while the bottom plot illustrates the detected events and ground truth data. The last three events cannot be detected due to their low energy.

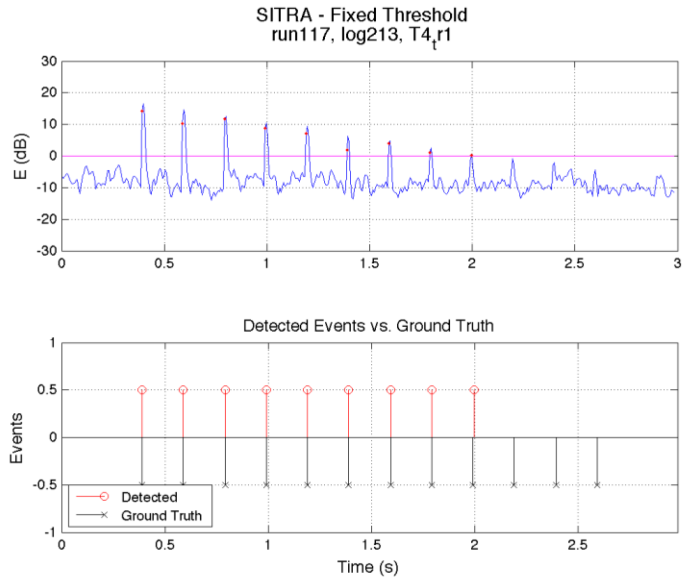

Figure 2. Example for SITRA Transient Detection with a fixed threshold.

3.2 SITRA with Adaptive Threshold

Varying operating conditions require an appropriate degree of flexibility with regard to the threshold level. Hence, we have extended the previous method by introducing an adaptive threshold which is derived by calculating the median of the previous 20 frame energy levels and adding a fixed threshold offset (10 dB). Again, a transient is detected as soon as the energy level of the actual frame exceeds the threshold. This procedure is depicted in Figure 3.

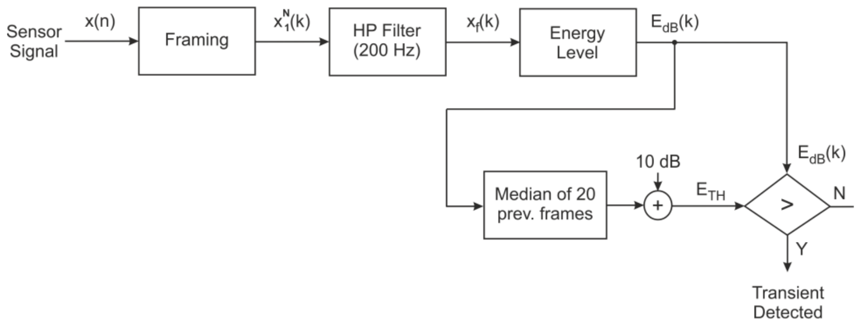

Figure 3. SITRA block diagram (adaptive threshold).

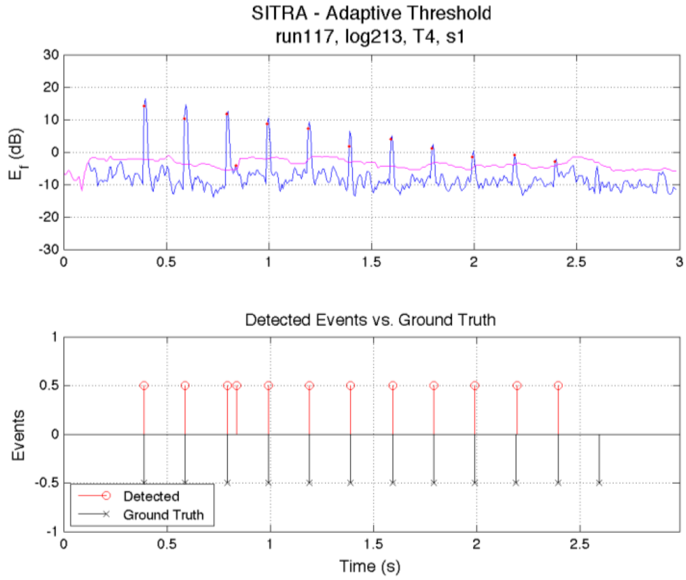

Figure 4. Example for SITRA transient detection with an adaptive threshold.

Figure 4 presents an example of the adaptive version of SITRA using the same signal as before. Again, the upper plot illustrates the signal frame energy, while the bottom plot shows the detected and ground truth events. While this algorithm detects almost all transients, a misdetection occurs after the third event.

3.3 Linear Prediction-based Method

Except for a certain amount of cropping noise, the spectral characteristics of the harvester machine noise usually remain stable within a certain operation mode. Therefore, we utilize linear prediction (LP), (Makhoul, 1975), to remove this kind of noise as illustrated in Figure 5.

First, the input sensor signal is windowed, the LPC-coefficients $A(z)$ are calculated using the model order of 128, and the frame is FIR-inverse-filtered by directly applying $A(z)$. This results in a residual signal in which the machine noise has been removed to a great extent. In the next step, the signal frame energy is calculated and a threshold $E_{\mathrm{TH}}(k)$ is derived based on previous energy values as described in the following.

As a basis, the median of the frame energy levels of the previous 20 frames (including the current), $\tilde{E}_{20}(k)$, is calculated:

$$\tilde{E}_{20}(k) = median\{E_f(k - 19 \dots k)\} \qquad \textit{Equation 1}$$

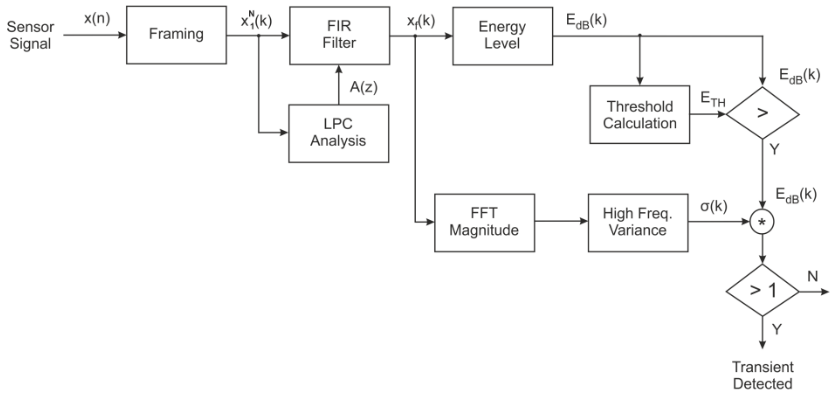

Figure 5. Block diagram of the LPC-based transient detection algorithm. The calculation of the threshold energy is described in the text.

Then, $\tilde{E}_{20}(k)$ is subtracted from the current filtered frame energy level $E_{\mathrm{f}}(k)$

$$\delta E(k) = E_f(k) - \tilde{E}_{20}(k), \qquad \textit{Equation 2}$$

and the standard deviation $\sigma_{\delta\mathrm{E}}(k)$ of the previous five level differences (excluding the current) is derived as follows:

$$\sigma_{\delta E}(k) = std(\delta E(k-5 \ldots k-1)). \qquad \textit{Equation 3}$$

Finally, the energy threshold $E_{\mathrm{TH}}(k)$ is calculated:

$$E_{TH}(k) = \tilde{E}_{20}(k) + 2 \cdot \sigma_{\delta E}(k) \qquad \textit{Equation 4}$$

Threshold $E_{\mathrm{TH}}(k)$ is compared with the actual frame energy level in order to identify transient *candidates*. If the actual frame is a candidate, a novel Transient Detection Function (*TDF*) is derived by multiplying the candidate frame energy level with the variance $\sigma_{\mathrm{HF}}(k)$ of its high-frequency energy content (5-10 kHz).

$$TDF(k) = E_{TH}(k) \cdot \sigma_{HF}(k) \qquad \textit{Equation 5}$$

If $TDF(k) > 1$, candidate frame k is defined as a transient event.

This detection process is illustrated in Figure 6. The top plot shows the energy level $E(k)$ of the unfiltered sensor signal frames. The second plot presents the filtered frame energy $E_{\mathrm{f}}(k)$ and the adaptive energy threshold $E_{\mathrm{TH}}(k)$. For each frame of which the filtered frame energy exceeds the threshold, the high-frequency variance is calculated (third graph). The fourth plot shows the *TDF* and its threshold. In the bottom plot, the detected events and the ground truth events are presented.

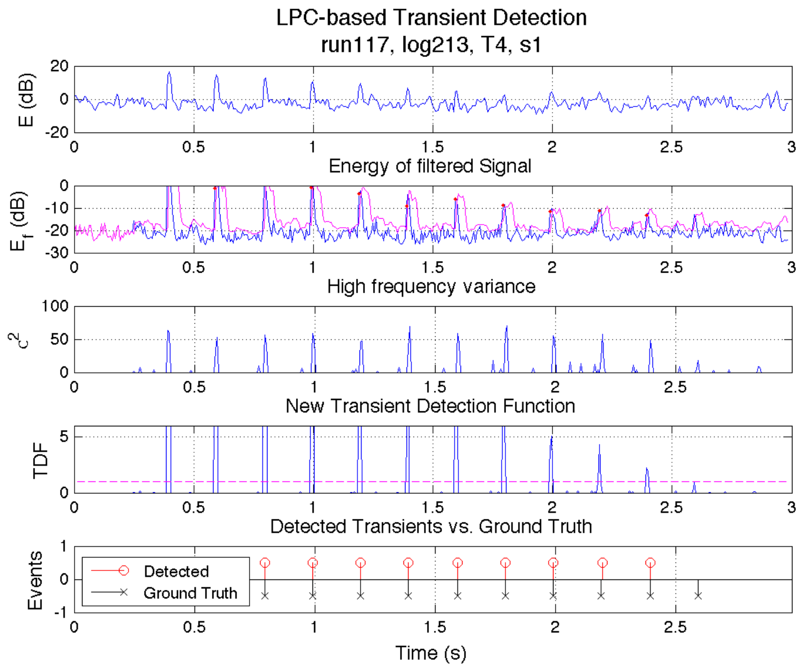

Figure 6. Example for linear prediction-based transient detection.

In Figure 7, we present the result of the LPC-based filtering in terms of the spectrograms of an original signal (top) and its filtered version (bottom). These plots illustrate the elimination of the machine noise while preserving the low-frequency transient information. In the SITRA methods, this information is highly reduced by the use of the high-pass filter.

4 Evaluation

In order to be able to carry out a structured evaluation of the detection algorithms, we have combined two types of signals, namely (i) transient signals and (ii) feeding noise signals. The transient signals were acquired in the laboratory using the test setup schematically illustrated in Figure 8, while the feeding noise signals were logged at a harvesting machine.

As transient events may exhibit different spectral characteristics, we have used the following objects to generate the test signals:

- Rubber hammer (low frequency bumps)
- Book back (low/mid frequency bumps)
- Stone (broadband noise)
- Metal object (broadband noise)

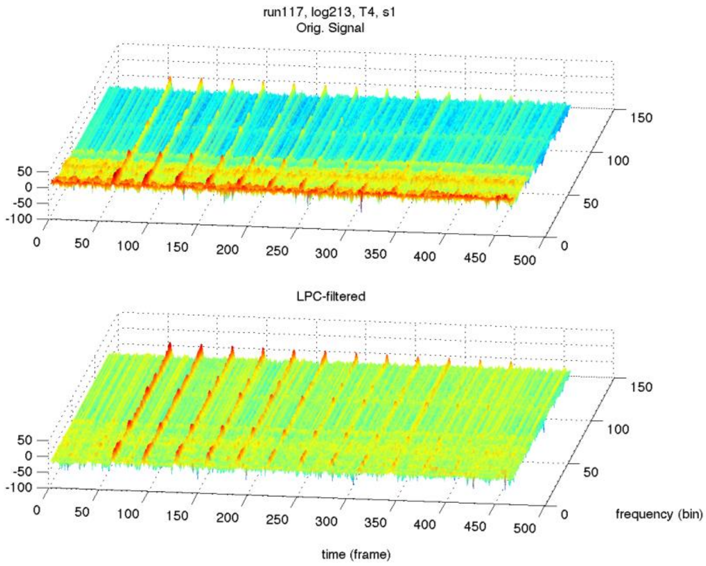

Figure 7. LPC-based transient detection: Spectrograms of original (top) and filtered (bottom) signal. Low-frequency transient information is preserved.

The knock sensor was mounted on the shaker and connected to a data acquisition card by which the sensor data has been recorded. The four objects were hit upon the shaker using different levels of force. From the resulting signals, we have extracted five transient events per object for further processing.

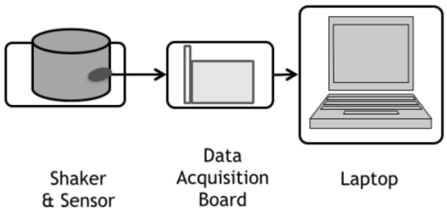

Figure 8. Experimental Setup for the acquisition of the transient signals.

For our study, we have combined 16 fragments of the harvester noise signal (three seconds duration) with the four types of transient signals by adding 12 repetitions of a particular transient every 200 ms starting at 400 ms with the amplitude energy decreasing by 2 dB per repetition. In addition, 20 implementations of these repetitions were generated by consecutively adding a time shift of 20 ms to the transient events per implementation. Hence, the total number of samples is 16 noise samples x 4 transient types x 5 transients per type x 20 implementations = 6400 samples containing a total of 76800 transients.

As the transients exhibit varying decay behavior, we have calculated the SNR levels of the individual transient signals based on the first *N*=100 signal samples $E_{\mathrm{t}}(n)$, and the respective samples of the noise signal $E_{\mathrm{n}}(n)$ as follows:

$$SNR = 10 \cdot log_{10}\left(\frac{\sum_{n=1}^{N} E_t(n)}{\sum_{n=1}^{N} E_n(n)}\right) \qquad \textit{Equation 6}$$

Considering a minimum occurrence of 500 realizations at SNR steps of 2 dB, 97% of the transients ranged between an *SNR* of -31 dB and 33 dB.

The samples were fed to the three transient detection algorithms and the detection performance was evaluated by means of a confusion matrix. Transients that were detected one frame before or after the ground truth transient position were tolerated. The performance with regard to the correctly detected transients (true positives) was analysed in detail and the respective cumulative distribution function has been calculated as a function of the SNR level.

5 Results

Figure 1 presents the results of the evaluation of the three transient detection algorithm in terms of the cumulative distribution functions (cdfs) with regard to the true positives, i.e. the correctly detected transients, versus the SNR level. The SITRA method with a fixed threshold provides 95% correctly detected transient events down to an SNR of 7 dB, while the corresponding SNR level equals 3 dB for the adaptive SITRA version. The novel method performs best, providing at least 95% true positives down to an SNR of -1 dB. From an SNR perspective, at an SNR level of 0 dB, fixed SITRA, adaptive SITRA and the LPC-method provide 78%, 92.7%, and 96% correctly detected events, respectively.

Finally, Table 1 presents the confusion matrix of the overall performance of the algorithms based on the entire dataset. The rate of correctly detected events (true positives) increases from 48% for the fixed threshold SITRA to 61% for the adaptive SITRA method, and to 72% for the new linear prediction-based approach. In turn, the rates of actual transients not being detected (false negative) are decreasing from 51% (SITRA-FT) via 38% (SITRA-AT) to 27.6% (LPC). As the false positive rates suggest, misdetections rarely occur in general. Hence, in this respect, all of our methods provide a high degree of robustness.

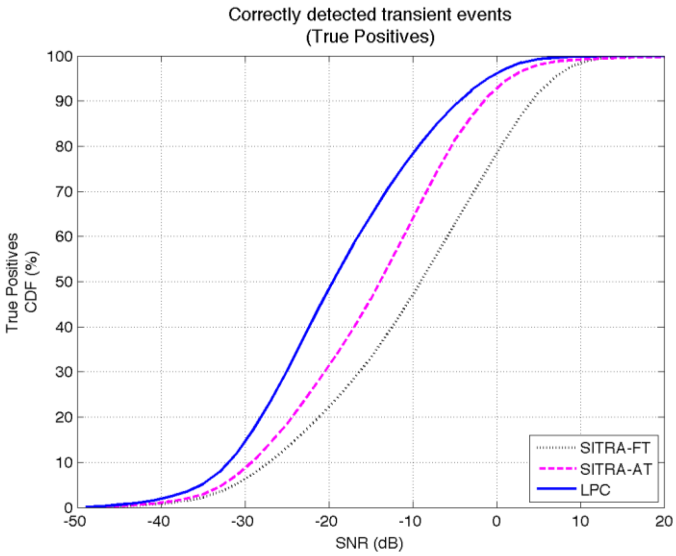

Figure 9. Cumulative distribution function (CDF) plots with regard to the correctly detected transients (true positives).

Table 1. Confusion matrix of the overall performance.

Rate (%)	**SITRA-FT**	**SITRA-AT**	**LPC**
True Positive	48.15	61.82	72.36
False Negative	51.85	38.18	27.64
True Negative	99.76	99.22	99.74
False Positive	0.24	0.78	0.26

6 Conclusions

We have presented three frame-based algorithms for the detection of transient events and evaluated their performance based on four different transient types. Our results show that the novel LPC-based algorithm provides 95% correct detections down to an SNR level of -1 dB. Taking the simplicity of SITRA into account, it provides good results, especially when an adaptive threshold is employed.

In future work, the detection algorithm may be designed in a more tolerant way regarding consecutive transient events as to prohibit unnecessary misdetections.

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