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Detection of alarms and warning signals on an digital in-ear device

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ABSTRACT

A majority of workers in industrial environments must wear hearing protection devices. While these hearing protectors provide increased safety in terms of auditory health, in some conditions they also have the adverse effect of preventing individuals from hearing alarm and warning signals which seriously compromises their safety.

Recent advances in the field of microelectronics allow the integration of tiny digital signal processors inside hearing protection devices. This paper develops new algorithms to automatically detect alarm signals in the digitized audio stream fed to the processor. This detection is performed in real-time with low latency to quickly inform the user of a dangerous situation. The algorithms were also optimized to require low computational resources due to the limited processing power of typical embedded electronic devices.

The proposed algorithms detect periodicity of the signal amplitude in a determined frequency bandwidth. The system was simulated with a database of alarm signals from a major North-American manufacturer of industrial alarms and warning signals, mixed with typical environmental noises at signal-to-noise ratios ranging from 0 to 15 dBA. The results show an average true-positive recognition rate of 95% for pulsed alarms compliant to the ISO 7331 standard. The system can be optimized for specific alarms which results in near 100% true positive and 0.2% false positive recognition rates.

Relevance to industry: Alarms and warning signals are widely use in industry to promptly alert workers of events that can compromise their safety. In practice, however, their efficiency can be dramatically affected by several factors, among which the use of hearing protectors by workers is the most severe. Designing digital hearing protectors with built-in alarms and warning signal detectors may considerably improve the situation.

1. Introduction

In workplaces, acoustic warning signals are necessary to promptly alert workers of events that can compromise safety. Although several standards exist for the design of proper warning signals (like SAE International (2009) or International Organization for Standardization (2005)), they are unfortunately in practice poorly installed or implemented. Besides, these standards are basically prescribing a minimal signal-to-noise ratio, but the extremely complex interaction between noise characteristics, hearing protector attenuation and hearing status may in practice precludes predicting the ability to perceive warning signals in a given workplace by a worker or group of workers. Some recent research exists for the proper installation of warning signals (see Laroche et al., 2007)) by taking into account specific parameters of the background noise, worker's hearing sensitivity and hearing protector's attenuation. In practice however, such approach requires fixed location for the warning signals and may be less useful when dealing with more dynamic work environments that are frequent in industrial workplaces. For example, the limitations of such optimized and dedicated approach would appear clearly when dealing with the construction trades: the background noise may be highly variable within the same construction site, the workers have a wide range of hearing status, depending on their duties, employers, demographics, etc. and finally the hearing protectors may also greatly vary between individuals. Such apparently *extreme* scenario can however not be underestimated: the construction industry continues to account for a disproportionate share of work-related injuries and illnesses in North-America (Waehrer et al., 2007) that are caused by a large amount by the non-perception of warning signals or alarms.

The proposed is to develop a simple but reliable alarm and warning signal detection algorithm that could be later implemented in an electronic hearing protector. The requirements on

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this algorithm are that it could be implemented on a low-power digital signal processor (DSP), such as the one used in hearing aid devices, and that it could in real-time, with a limited latency, trigger the speak-through function of the hearing protector in order to let the user perceive clearly the warning signal at a reasonable level.

1.1. Literature review

Acoustic warning signals are necessary to promptly alert workers of events that can compromise safety. The nature of the danger signal in the workplace shall be such that workers in the facility must hear and react to the signal intended. Several standards exist for the proper audio design of warning signals. The ISO 7731:2003 (International Organization for Standardization, 2005) standard specifies the physical principles of design, ergonomic requirements and the corresponding test methods for danger signals for public and work areas in the signal reception area and gives guidelines for the design of the signals. In this ISO standard, the temporal characteristics of the danger signal are defined to be an intermittent signal with a repetition frequency ranging from 0.5 to 4 Hz while the danger signal spectrum is to include frequency components ranging from 500 to 2500 Hz, with general recommendation of two dominant components between 500 and 1500 Hz. Unfortunately, the proper use of warning signals in industry is poorly regulated and enforced. As a consequence, these systems are submitted to intuitive installation practices, often with little regard to the many factors contributing to an efficient use: the audibility of the warning signals depends not only of the frequency components and temporal characteristics of the warning sounds, but also on the individual's hearing status (auditory thresholds, frequency selectivity), on the noise characteristics (level, spectrum) in the workplace, and – when applicable – on the attenuation of the hearing protectors.

There are still some areas of today's industry where warning signals are strictly enforced: backup alarm signal are mandatory per most national regulations and such warning signal are ubiquitous in the construction industry and in any modern workplace. The acoustical properties of the backup alarm signal may also be clearly specified (like the Society of Automotive Engineers standard J994b-2009 (SAE International, 2009)). As an illustration, this SAE standard specifies six types of backup alarms according to their overall A-weighted level and also specifies the nature of the frequency spectrum for the backup alarm signal: the dominant frequencies of the backup alarm signal must fall between 700 and 2800 Hz with a duty-cycle (cyclic pulsation rate) comprised between 0.8 and 1.8 Hz.

Despite the omnipresence of these backup alarms, the number of injuries and fatalities for backup accidents is still very high, making the effectiveness of existing backup alarms questionable. Furthermore, it is often not enough to simply detect the backup alarm signals: construction workers who are exposed to backing vehicles should also perceive the signal's direction and distance to be able to evade the backing vehicle and avoid injury (Alali, 2011).

The use of hearing protection devices (HPD) is also common in noisy workplaces, especially in the construction industry, where noise reduction at the source is rarely feasible in practice. Several studies clearly showed that the use of HPD only make things worse, both from a detection point of view (since the warning signal might be below the protected threshold of the user (Laroche and Sabourin, 2007; Giguère et al., 2009)) and from the localization point of view (since most circum- and supra-aural devices are dramatically altering the user's ability to localize a sound source (Alali, 2011; Casali et al., 2004; Alali and Casali, 2011; Christian, 1999)).

Considering the practical design challenges that are faced in the proper design of alarms in highly dynamic work environments, and considering that HPD are to be worn in theses noisy environments, it would be very tempting to consider designing an HPD that would make these warning signal be both *detectable* and *localizable* by the wearer. Very few attempts have been conducted at designing electronic detection modules for alarm signals. The most recent one found (Ellis, 2001) deals with the problem of alarm detection for the hearing impaired using two different approaches. The first approach is a neural-net that involves a classification system that is still today too expensive in terms of memory and computational costs to be implemented in an embedded device. The second approach, a sinusoid model system, offers some implementation advantages in term of simplicity but also appears to have limited performances in terms of alarm detection capability.

1.2. Proposed approach

The envisioned electronic hardware that will be embedded in the HPD is illustrated in Fig. 1. It features one miniature external microphone that is connected to the audio input of an ultra-low-power DSP optimized for audio applications, such as the Voyager GA3280 (Corporation, 2006). This DSP offers more than 42 Million instructions per second (MIPS) equivalent processing available for a 2 MHz clock or more than 35 Million Multiply-ACcumulate operations per second (MMAC) for a 2 MHz clock, while maintaining a minimum of 20-bit quantification in the entire audio path. A miniature loudspeaker is connected to the audio output of the DSP and will be used to playback the warning signals, when detected, at an appropriate level. The playback level is automatically adjusted within the DSP's audio amplification stage by monitoring the sound pressure level in the occluded ear using the second audio input of the DSP. The proposed electronic hardware offers a versatile configuration since the DSP can also be reprogrammed in the field: it would therefore be feasible to reprogram the unit for very specific alarm signals if needed to further improve the alarm detection rate, as it will be discussed in Section 6.2. The audio processing DSP also enables various audio treatments of the detected alarm signal, such as removal of the background noise and enhancement of the warning signal by applying known digital signal processing treatments, while staying within the processing power offered by the processor, as presented in Section 4.

2. Types of alarms and warning signals

Alarm and warning signals are generally designed to emerge from the background noise and get the attention of individuals in the vicinity of the sound source. Although there are standards to define the warning signals characteristics to better attain these objectives, in real life, the nature of alarm and warning signals vary greatly.

Therefore, we define here three types of alarm and warning signals:

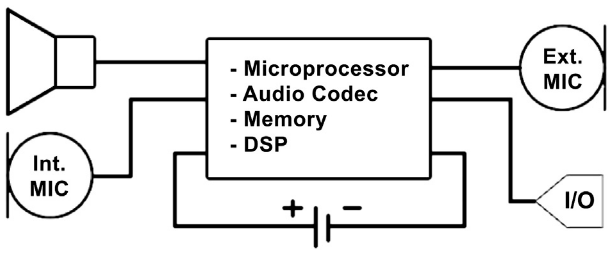

Fig. 1. Schematic overview of the low-power, versatile, field-programmable electronic hardware to be embedded in hearing protection devices.

- *Pulsed* alarm signals consist of a repetition of the same sound with a silence gap between each occurrence. The frequency content of the repeated sound is constant.
- *Siren* alarm signals consist of sounds in which the tonality continuously changes, also known as frequency sweeping. Sirens can also be pulsed.
- *Alternating* alarm signals consist of two different alternating tones with no silence gap between them.

The spectrogram of samples of these three types of alarms are shown in Fig. 2.

The proposed system was designed to automatically detect pulsed alarm signals, compliant to the ISO 7731 standard, as they are the type of warning signals most often found in industrial environments.

3. Proposed detection system

The block diagram of the proposed system is shown in Fig. 3. The system is designed to detect pulsed alarm signals by evaluating the periodicity of sound amplitude in a determined bandwidth. The input signal, $s(n)$, is assumed to be captured by a microphone and digitally converted. The sampling frequency f_s and quantization resolution are assumed sufficiently high for their effect to be ignored in this paper. The system continuously processes the input signal in real-time and provides a decision with low latency (within two cycles of the pulsed alarm signal).

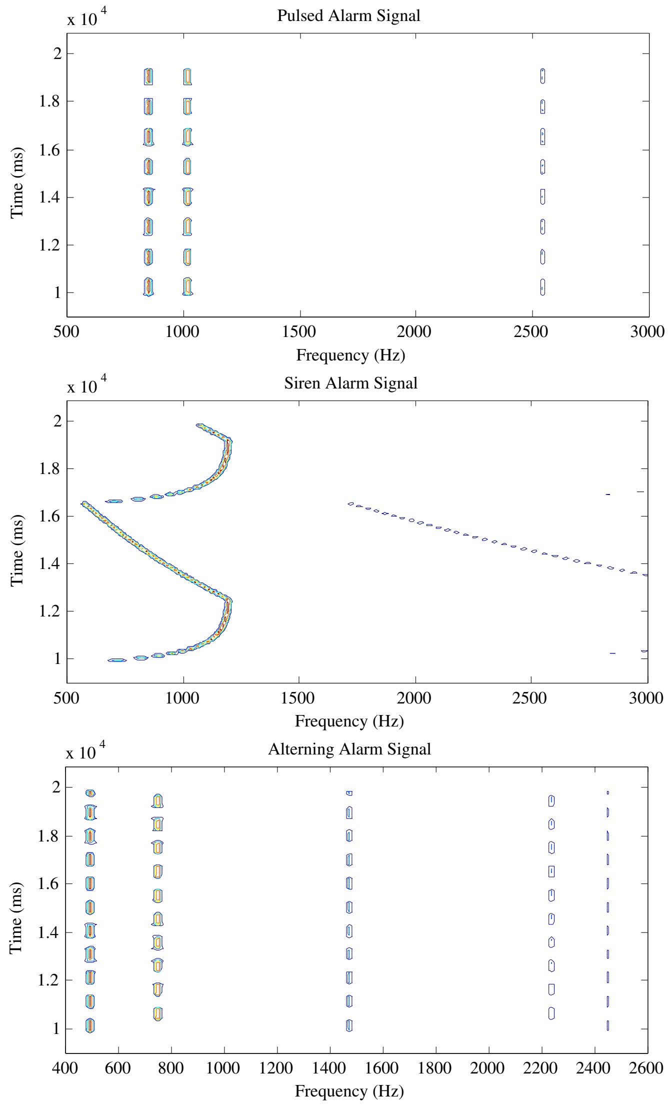

Fig. 2. Example spectrograms of three types of warning signals.

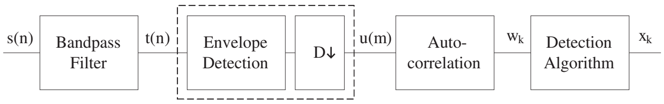

Fig. 3. Block diagram of the alarm sound detection system

The system is composed of the following signal processing blocks, which are detailed in the next subsections:

- A bandpass filter, centered around the fundamental frequencies of sound of the alarms to be detected.
- An envelope detector, which generates a signal proportional to the amplitude level of the input signal.
- An autocorrelation computing block, to evaluate the periodicity of the signal envelope.
- A detection algorithm, which analyzes the autocorrelation of the signal envelope and applies decision rules to determine if the input signal should be considered an alarm signal.

Each block was optimized for real-time implementation using low computational complexity.

3.1. Bandpass filter

The bandpass filter is of the infinite impulse response (IIR) form. It applies the following transfer function to the input signal $s(n)$ (Proakis and Manolakis, 1996):

$$H(z) = \frac{\sum_{j=0}^{M} b_j z^{-j}}{1 + \sum_{j=1}^{N} a_j z^{-j}} \quad (1)$$

The coefficients $b_{1,\ldots,M}$ and $a_{1,\ldots,N}$ are determined to obtain a 3-dB bandwidth, from from f_{b1} to f_{b2}, which should include the fundamental frequencies of all the alarm sounds that needs to be detected. Increasing this bandwidth allows the detection of a larger class of alarm sounds, but also increases the rate of false detections in the presence of background noise. As stated in Section 2, an approximate bandwidth for this filter should cover frequencies from 500 to 1500 Hz.

3.2. Envelope detection

The periodicity test is performed on the envelope of the signal, at a significantly lower rate than the input signal sampling frequency f_s.

While the Hilbert transform is typically used for the envelope detection in linear systems (Ipatov, 2005), an envelope detector based on the filtered absolute value of the input signal is preferred for this application due to its low computational power implementation. Low-pass filtering is performed by integration using a digital accumulator. Every D samples, the output of the accumulator is transferred to $u(m)$ and the accumulator is reset. The envelope detector thus performs the following operation:

$$u(m) = \sum_{n=1}^{D} |t(n)| \quad (2)$$

This integrate-and-dump function filters the envelope while providing decimation by a factor D.

3.3. Autocorrelation

The autocorrelation of the signal envelope provides the relevant information to evaluate periodicity. The autocorrelation is performed on a window comprising the last L samples of the decimated envelope signal $u(m)$. The parameter L is empirically determined as a compromise between latency and detection performances with the constraint that the time window $L \cdot D$ must be long enough to contain at least two periods of the cycling alarm signal. The following operation is performed:

$$\mathbf{w}_k(\tau) = \sum_{l=1}^{L-\tau} u(l)u(l+\tau) \tag{3}$$

which returns a vector $\mathbf{w}_k$ with each element τ being the autocorrelation of $u(m)$ at lag τ.

3.4. Detection algorithm

For pulsed alarm signals, the autocorrelation of the signal envelope exhibits peaks at lag delays corresponding to the alarm repetition rate, as shown in Fig. 4. Between these peaks, the autocorrelation takes a negative value. This means that for a given alarm period, the autocorrelation will exhibit a determined number of zero-crossings (ZCs). On the other hand, any typical sound environment will exhibit an autocorrelation rapidly decaying around zero because of its non-periodic nature. This will increase the occurrence of ZCs for a given time window.

Any algorithm that can identify the presence of equally-spaced peaks or ZCs in vectors $\mathbf{w}_k$ could be used for this application. A ZC is easily detected in hardware as a change of sign between two samples. Therefore, a hardware-efficient algorithm based on ZCs characterization was designed for this application. Fig. 5 schematizes this algorithm.

At each sample k, the number of ZCs, Z_k, is detected as the number of sign changes in the vector w_k. The number of ZCs indicates whether the periodicity of the signal is within the desired range. A minimum and maximum period $T_{\min}$ and $T_{\max}$ is set based on the repetition rate of the alarms to be detected. Taking into account that each repetition generates 2 ZCs, the number of ZCs in w_k must be within this range:

$$2\frac{DL}{f_s T_{\max}} - 1 \geq Z_k \geq 2\frac{DL}{f_s T_{\min}} + 1 \tag{4}$$

Due to the random nature of sound environments, the characteristics of some signal excerpts will satisfy Eq. (4) without the presence of alarm sounds thus triggering false positive detections. By tracking past decisions of the detection algorithms, the number of false positive errors can be dramatically reduced. The variability of the number of ZCs in the previous P windows is used as a measure of reliability of the detector. The consistency test in Fig. 5 performs the following equation:

$$\Delta = \sum_{p}^{P} |Z_p - Z_{p-1}| \tag{5}$$

The consistency test is positive if $\Delta \leq \Delta_{\max}$. An efficient value of parameter $\Delta_{\max}$ was empirically found to be 4 with $P = 6$.

The improvement in recognition rate based on consistency could also be obtained simply by taking larger windows (i.e. increasing parameter L). However, to obtain significant improvements, L must be increased by several orders of magnitude, which significantly increases latency. The proposed consistency test was found to be a better compromise between recognition performances and latency.

Finally, since most errors were isolated, a simple test waits for two consecutive positive decisions before generating a positive decision.

A more performant tracking algorithm, based for instance on Kalman filtering (Weng et al., 2006), could be used. The evaluation of the trade-off between recognition rate, latency and computational requirements is beyond the scope of this paper.

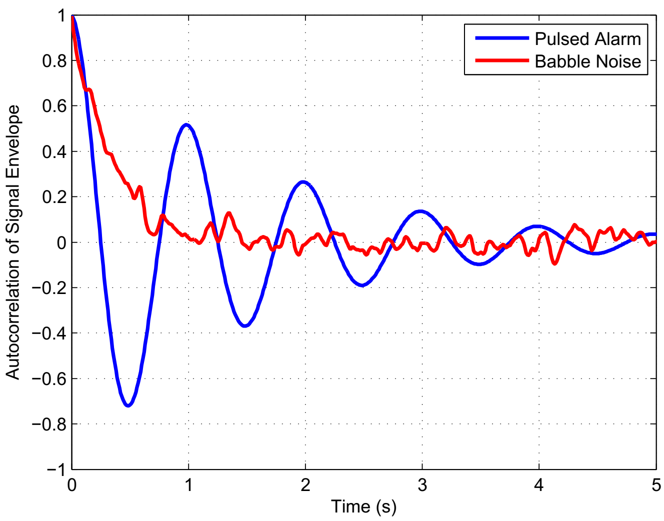

Fig. 4. Typical results for the autocorrelation of the signal envelope for a pulsed alarm signal and noise from a crowd of talking people.

4. Resource requirements

The algorithm is designed to minimize computing resources as to be implemented in a low-power DSP, embedded in a hearing protector. This section sums up the arithmetic operation cost of the proposed algorithm.

The bandpass filter and the envelope detector operate at the sampling frequency (f_s) of the incoming audio stream. The number of operations per second is thus proportional to f_s for these two blocks. The resource requirement analysis is performed with $f_s = 22.05$ kHz which is the expected sampling frequency of the analog-to-digital converter.

It should be noted that since the maximum fundamental frequency of the alarm signals is 2.5 kHz, a sampling frequency of $f_s = 5$ kHz could be used, provided an anti-aliasing filter is available.

4.1. Bandpass filter

The results presented in Section 5 were obtained with a sixth order bandpass filter as it was found to be a good compromise between computational requirements and performance. This implementation requires 12 multiplications and 12 additions per sample.

4.2. Envelope detector

The envelope detector is implemented using a simple accumulator, as in Eq. (2). On each sample, one addition is required for the accumulator, and one equivalent multiplication is required for the absolute value. Two additions are also required for the counter and comparator to the decimation value D.

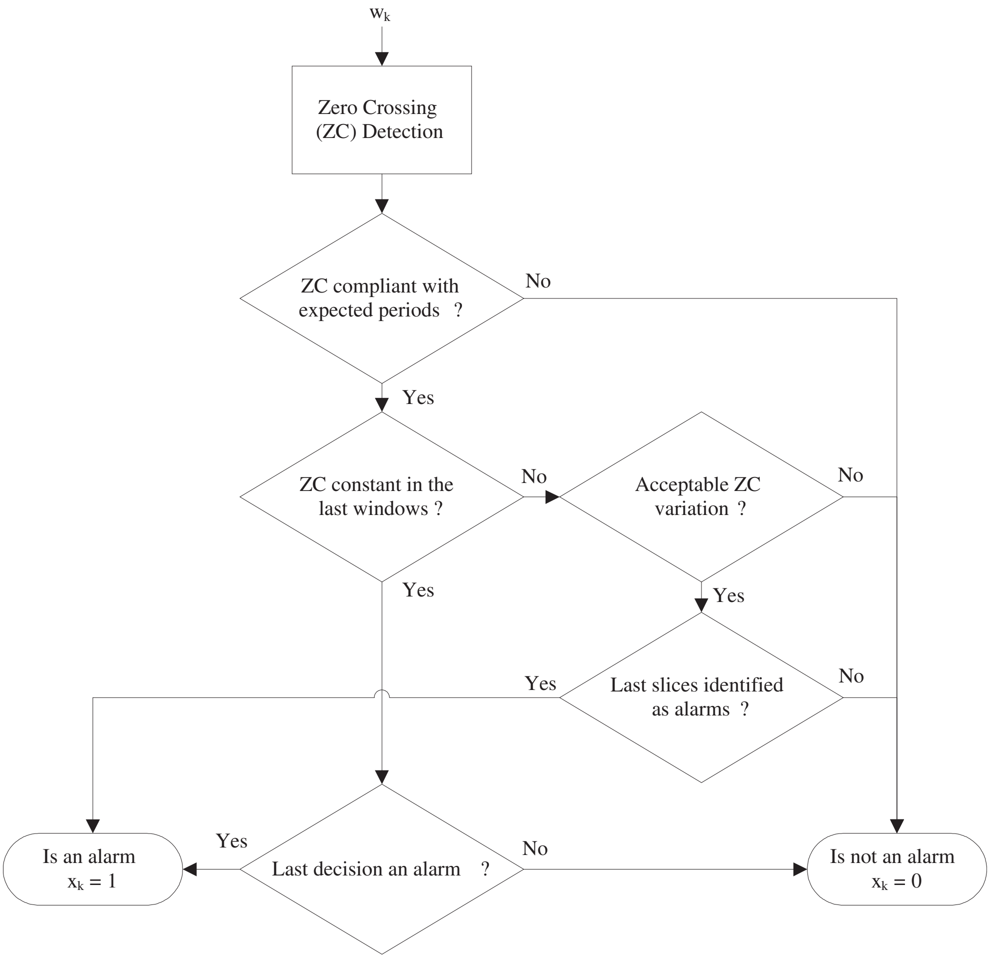

Fig. 5. Alarm detection algorithm.

4.3. Autocorrelation

In order to clearly identify the periodicity in the autocorrelation of the signal envelope, the signal must be zero-mean. This calculation is performed each time the autocorrelation is calculated, i.e. every D sample of the incoming sound stream. The number of needed arithmetic operations to calculate the mean of the signal is L additions and one multiplication. Another addition is required to remove the mean on each sample $u(m)$, which results in $2L$ additions and one multiplication on each sample.

By itself, the autocorrelation as expressed in Eq. (3) is a sliding window which gets shorter as it advances. For $\tau = 0$, it requires L additions and L multiplications. For $\tau = 1$, it requires $L-1$ additions and $L-1$ multiplications. Therefore, the autocorrelation requires $(L^2 + L)/2$ additions and multiplications.

4.4. Detection algorithms

The detection algorithms also run at frequency f_s/D. It is mainly conditions and simple arithmetic (ZC detection) and is thus considered insignificant in terms of resource requirements, when compared, for instance, with the bandpass filter operating at f_s.

4.5. Summarized resource requirements

The number of additions and multiplications per second are calculated using the parameter values used in Section 5 to validate the system. In this case, $f_s = 22{,}050$ Hz, $D = 2205$, and $L = 30$. Therefore, the autocorrelation and detection algorithm runs at 10 Hz which allows a response time (minimum latency) of 100 ms while detecting periodicity in windows of length 3000 ms. Table 1 details the resource requirement calculation.

The number of addition and multiplication per second is 627,310, which is compatible with the targeted DSP chip that offers 42 MIPS. This leaves significant margin for other processing functions.

5. Validation of the proposed algorithm

5.1. Database of warning signals

To validate the proposed algorithm, a database of warning signals was constructed. Given the importance in this work of the representativity of the warning signals encountered in real world situations, the warning signals had to be realistic, i.e. real recordings of existing devices, and had to cover the wide range of real life

Table 1
Resource requirements calculation with $f_s = 22{,}050$ Hz, $D = 2205$ and $L = 30$.

Processing block	Add. per sample	Mult. per sample	Frequency	Op. per second
Bandpass filter	12	12	22,050	529,200
Envelope detector	3	1	22,050	88,200
Mean removal	60	1	10	610
Autocorrelation	465	465	10	9300
Total				627,310

applications, from backup alarms to evacuation signals. After several attempts at contacting the manufacturers of such alarms devices and warning apparatus, a comprehensive database was finally found to be freely available on the website of Federal Signals Corporation, a leader in "*advancing security and well-being for communities and workplaces*" (sic) (Federal, 2012). From this comprehensive database, 27 warning signals were selected, based on their representativity of the industrial workplace, and ensuring that they would differ in the frequency content and the periodicity of their auditory signals. These warning signals were then classified based on their types: *pulsed*, *siren* or *alternating*, as defined in Section 2.

Furthermore, these warning signals were also classified as either *compliant* or *non-compliant* to the ISO 7731 standard, based on their period and frequency content. *Compliant* warning signals are those with a period within 0.5–2 s and with frequency components between 500 and 1500 Hz; *non-compliant* alarms signals are those with period or frequency content out of these ranges.

This classification yields:

- 10 *Pulsed* warning signals: six compliant and four non-compliant.
- 10 *Sirens* warning signals: four compliant and six non-compliant.
- 7 *Alternating* warning signals: all compliant.

These signals are listed in Table 2 with the original filename from the website database, for convenience.

5.2. Database of background noises

To further evaluate the performance of the proposed alarm detector in industrial workplace, realistic background noises were also required. Given the very wide range of background noises

Table 2
Details and classification of the audio files used for the construction of the test database.

Original Filename	Description	Period (s)	Type	ISO 7731 Compliance
TM1.wav	Police car siren long	1.7	Siren	No
TM2.wav	Police car siren short	0.4	Siren	No
TM3.wav	Two tones alternating	1.0	Alternating	Yes
TM4.wav	Pulsed electronic bell	1.0	Pulsed	Yes
TM5.wav	Repeated sweep down tone	1.6	Siren	Yes
TM7.wav	Pulsed tone	0.9	Pulsed	Yes
TM8.wav	Pulsed tone	0.6	Pulsed	No
TM9.wav	Pulsed siren	3.5	Pulsed	No
TM11.wav	Pulsed sweeping tone	1.2	Pulsed	No
TM13.wav	80's Synthesizer	0.2	Siren	No
TM15.wav	Pulsed electronic bell	1.2	Pulsed	Yes
TM16.wav	Fast anti theft alarm	0.5	Alternating	Yes
TM17.wav	Two tones alternating	1.5	Alternating	Yes
TM18.wav	Fast anti theft alarm	1.0	Siren	No
TM19.wav	Pulsed siren	0.2	Siren	Yes
TM20.wav	Two tones alternating	0.5	Alternating	Yes
TM21.wav	Anti theft alarm short period	0.4	Siren	Yes
TM22.wav	Pulsed tone sweeping up	3.3	Siren	No
TM23.wav	Pulsed tones	1.0	Pulsed	Yes
TM25.wav	Two tones alternating	1.6	Alternating	Yes
TM26.wav	Pulsed tone	0.2	Pulsed	No
TM27.wav	Repeat sweeping tones	1.0	Siren	Yes
252_253_Alarms.wav	Truck backing up alarm	0.7	Pulsed	Yes
AlternateSteady.wav	Two tones alternating	1.2	Alternating	Yes
LP4_1.wav	Two tones alternating	0.5	Alternating	Yes
LP5_8r.wav	Repeat tone sweeping	1.0	Siren	Yes
PulsedSteady.wav	Pulsed polyphonic tone	1.2	Alternating	Yes

encountered in the real world, any attempt to find *representative* noise samples is a challenge in its own. Nevertheless, the NOISEX92 database (NOISEX-92, 2012) is a commonly used noise database for that purpose and three noisy environments were selected among the available recorded signals: buccaneer, destroyer engine and babble noises. Two of these noises are stationary (buccaneer and destroyer engine noise) and the most common in industrial environment, and one is non-stationary and pseudo-periodic which is the babble noise.

5.3. Generation of the test signals

To test the performance of the proposed detection algorithm, a test database was created, using each of the 27 warning signals in each of the three background noises. Each test sample was constructed by mixing a 10 s recording of the alarm signal to 30 s of background noise. The alarm signal starts at $t = 10$ s and ends at $t = 20$ s, as illustrated in Fig. 6. The signal-to-noise ratio (SNR) between the warning signal and the different background noises was computed by applying an A-weighted filter on both the alarm and the background noises. Four SNRs were used in the validation test: 0 dBA, 5 dBA, 10 dBA and 15 dBA.

This results in 324 scenarios (27 alarms, 3 noises, 4 SNRs). Furthermore, since the noise samples from the Noisex92 database are longer than the 30 s required for the test, to increase the statistic relevance, each test was repeated 10 times using random excerpts of the background noise. Ultimately the test database thus contained 3240 test signals.

5.4. Recognition rates of the detection algorithm

To assess the performance of the detection algorithm, the number of true positives (see Fig. 6 for definition) is computed for each of the test signal. True positives (TP) are detections that occur from the first rising edge after $t = 10$ s until the end of the alarm signal at $t = 20$ s, meaning an alarm is detected when it is present. False positives (FP) are detections that occur outside of the interval of the alarm.

The following parameters, described in Section 3 were used:

- Bandpass filter corner frequencies, $f_{b1} = 500$ Hz and $f_{b2} = 1500$ Hz.
- Alarm period limits, $T_{min} = 500$ ms and $T_{max} = 2000$ ms.
- Decimation rate after envelope detection, $D = 2250$.
- Number of samples for autocorrelation calculation, $L = 30$.

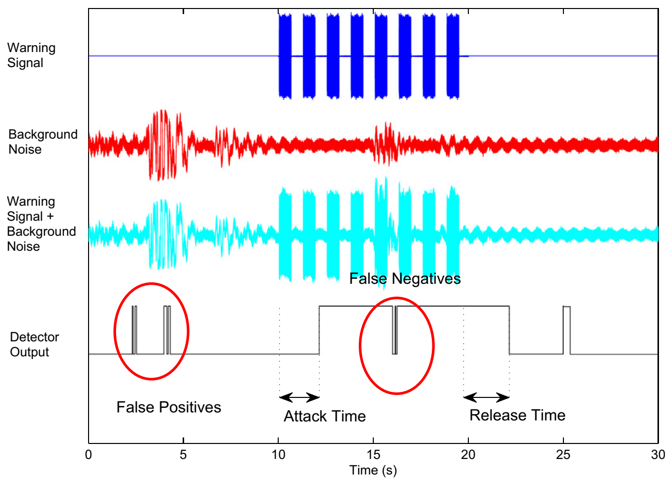

Fig. 6. Construction of the test database.

based on the ISO 7731 standard and are thus considered general-purpose parameters to detect a wide range of alarm signals.

The average TP rates are plotted as a function of the SNRs in Fig. 7 for the *compliant* warning signals, and in Fig. 8 for the *non-compliant* warning signals. These results are also summarized in Table 3.

As it can be seen in Fig. 7, the average rate of true positives exceeds 50% for all the compliant alarms and can reach above 90% for the pulsed alarms. For the alternating and siren alarm types, the TP rate increases with the increase of the SNR. What is important is that for low SNRs, where the human ear would not be able to detect the presence of a warning signal, the proposed detection algorithm still offers very decent TP rates, that are above 50%. It can also be seen in Fig. 8 that the TP rate is very low for all the non-compliant alarms, and does not really exceed 10% on average in the three background noise. This poor performance is no surprise, since it is caused by the proposed detector being tightly tuned to the ISO 7731 specifications and that the non-compliant alarms have periods outside the 0.5–2.0 s window or their frequency content is outside of the 500–1500 Hz bandwidth. Nevertheless, it will be shown in Section 6.2 that an optimization is still possible for these non-compliant alarms by *tuning* the detection parameters described in Section 3 to these alarms characteristics.

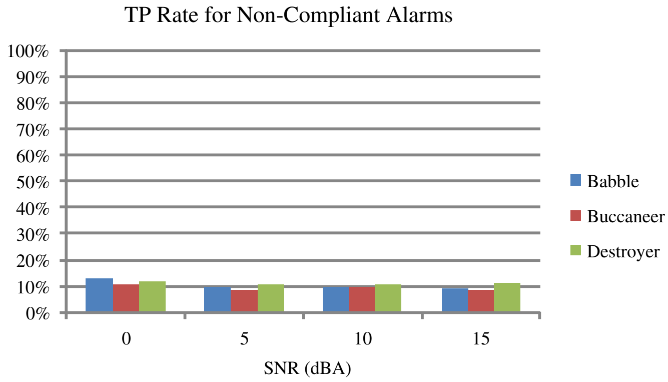

Fig. 8. True-positive (TP) rates as a function of SNR for all ISO 7731 non-compliant alarms in the presence of the three types of background noise.

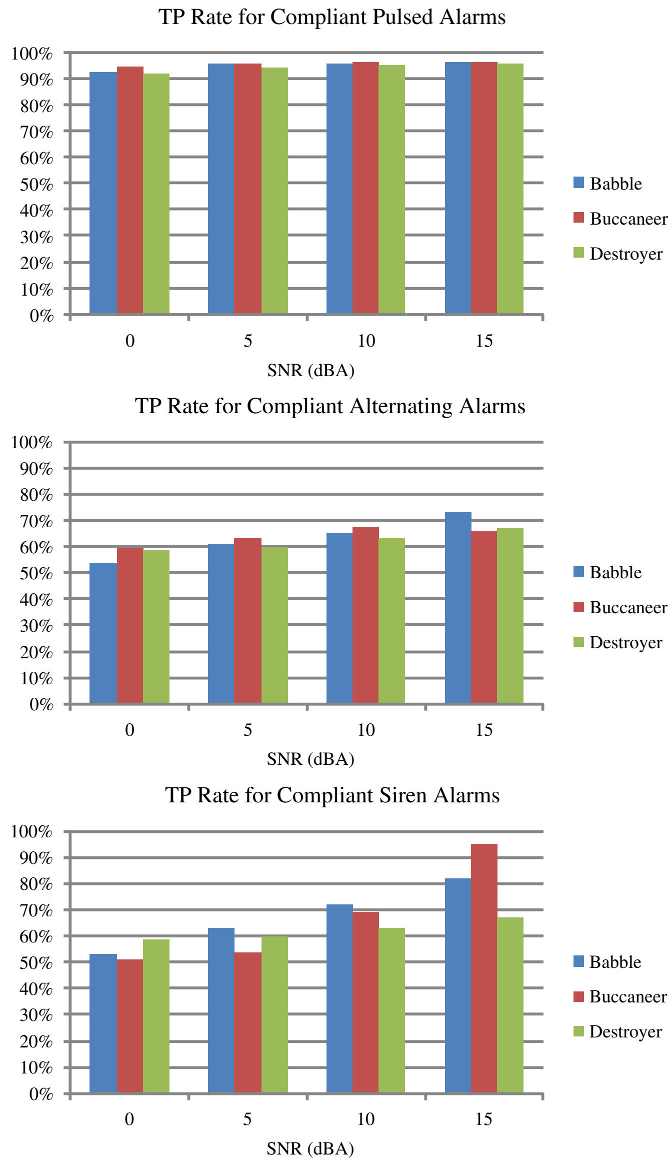

Fig. 7. True-positive (TP) rates as a function of SNR for ISO 7731-compliant pulsed, siren and alternating alarms in the presence of the three types of background noise.

The FP rate can also be computed, using the entire background noise audio files, without any alarm (the presence of alarm signal is irrelevant for this test) to increase statistical relevance. Fig. 9 shows the results. The FP rate is greatest in the presence of destroyer noise, which will be discussed later in Section 6.1.

5.5. *Detection speed*

The performance of the proposed detection algorithm is inherently tied to the latency of the system: the faster the system can detect the presence of the warning signal the better. To evaluate this other performance parameter, the attack and the release times were computed. The attack time is defined as the time at which the first detection is made, once the signal is present (at $t = 10$ s) while the release time is defined as the time between the end of the alarm (at $t = 20$ s) and the falling edge of the detection flag. These attack and release times are also presented in Table 3.

The attack, i.e., the latency before the first TP detection of the alarm signal ranges strictly between 1.0 and 3.0 s for all the alarms in all the background noises. Comparing these results with the intrinsic periodicity of the warning signals it can be seen that most of the time only the first appearance (or pulse) of the warning signal is left undetected. Finally, the average release time is ranging between 0.1 and 2.1 s for all the detected alarms in all the background noises. For alarm signals with TP rate lower than 10%, the system is considered unable to properly detect the alarm and the latency becomes an irrelevant measure.

6. Discussions

6.1. *Limits*

The results presented in Section 5.4 are using two types of background noise that are representative of a typical industrial background noise: these noises are indeed caused by reciprocating engines covering a wide frequency range, while still offering strong periodic components. As such, another type of industrial background noise has not been covered by this study: it would be the wideband random noise that can be created by non-periodic processes, like burning furnace, stream of vapor, water or sand, etc. Such a background noise was not available in the NOISEX-92 database (NOISEX-92, 2012) and was further believed to be trivial to work with given the fact that the proposed alarm detector uses

Table 3
Summarized results for the proposed algorithm. Greyed rows indicate ISO 7731-compliant alarms. The TP rate is given as an average for the three types of background noise.

Original filename	Description	Period (s)	Type	Average TP rate			
				0 dBA	15 dBA	Attack (s)	Release (s)
TM1.wav	Police car siren long	1.7	Siren	6%	7%	NR	NR
TM2.wav	Police car siren short	0.4	Siren	5%	1%	NR	NR
TM3.wav	Two tones alternating	1.0	Alternating	98%	98%	2.11	0.93
TM4.wav	Pulsed electronic bell	1.0	Pulsed	92%	100%	1.35	1.25
TM5.wav	Repeated sweep down tone	1.6	Siren	19%	92%	1.92	0.39
TM7.wav	Pulsed tone	0.9	Pulsed	90%	93%	1.25	0.97
TM8.wav	Pulsed tone	0.6	Pulsed	1%	1%	NR	NR
TM9.wav	Pulsed siren	3.5	Pulsed	12%	9%	NR	NR
TM11.wav	Pulsed sweeping tone	1.2	Pulsed	62%	59%	1.90	0.49
TM13.wav	80's Synthesizer	0.2	Siren	0%	0%	NR	NR
TM15.wav	Pulsed electronic bell	1.2	Pulsed	97%	100%	1.57	2.13
TM16.wav	Fast anti theft alarm	0.5	Alternating	49%	97%	2.55	0.17
TM17.wav	Two tones alternating	1.5	Alternating	94%	93%	1.71	0.67
TM18.wav	Fast anti theft alarm	1.0	Siren	0%	0%	NR	NR
TM19.wav	Pulsed siren	0.2/1.25	Siren	98%	99%	1.68	0.23
TM20.wav	Two tones alternating	0.5	Alternating	2%	31%	2.97	0.11
TM21.wav	Anti theft alarm short period	0.4	Siren	8%	0%	NR	NR
TM22.wav	Pulsed tone sweeping up	3.3	Siren	14%	11%	NR	NR
TM23.wav	Pulsed tones	1.0	Pulsed	93%	93%	1.17	0.75
TM25.wav	Two tones alternating	1.6	Alternating	99%	100%	1.77	1.52
TM26.wav	Pulsed tone	0.2	Pulsed	10%	6%	1.50	0.10
TM27.wav	Repeat sweeping tones	1.0	Siren	79%	99%	1.76	1.15
252_253_Alarms.wav	Truck backing up alarm	0.7	Pulsed	92%	94%	1.01	1.67
AlternateSteady.wav	Two tones alternating	1.2	Alternating	6%	0%	2.67	0.03
LP4_1.wav	Two tones alternating	0.5	Alternating	11%	31%	2.20	0.11
LP5_8r.wav	Repeat tone sweeping	1.0	Siren	12%	66%	2.50	0.19
PulsedSteady.wav	Pulsed polyphonic tone	1.2	Alternating	98%	99%	1.71	1.28

ISO 7731 compliant; NR, not recognized.

the periodicity of the alarm signal for its detection, as detailed in Section 3.

The TP rates presented in Table 3 do not show a clear trend in terms of which alarms are easier to detect in the various background noises at the different SNRs. It is important to note however that for the lowest SNR, of 0 dBA, the proposed detection algorithm still offers detection rate between 50% and 60% for alternating and sirens alarm that would have been otherwise undetected by many worker with poor hearing or for workers wearing hearing protectors.

The FP rate is greatest in the presence of destroyer noise, as seen in Fig. 9. This is no surprise considering that this noise is created by reciprocating engine that has dominant harmonics in the 500–1500 Hz frequency range and that may also features amplitude modulation that may be interpreted by the proposed detection algorithm as on-purpose pulsation. Nevertheless, improvements can be made by the precise tuning of the detection algorithm in these very unique environments, using the approach described hereafter in Section 6.2.

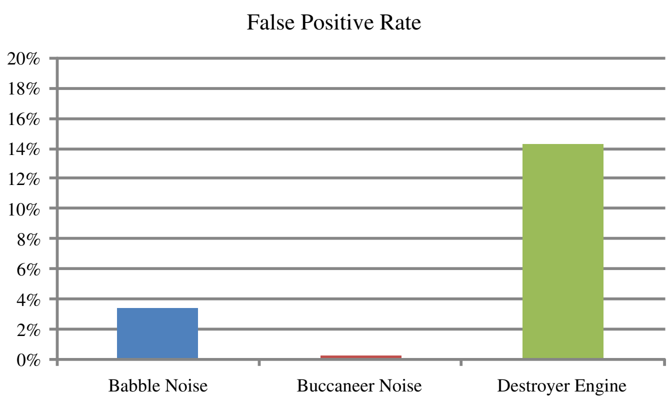

Fig. 9. False-positive (FP) rate for the three types of background noise.

6.2. Possible optimization

The recognition rates shown in Section 5 were obtained using general-purpose settings, to be compliant with the ISO 7731 standard and detect a variety of different alarm types. Better results can be obtained in terms of detection rate, latency and FP rate by adjusting two sets of parameters in the algorithm: the bandpass filter bandwidth (f_{b1} and f_{b2}) and the alarm period limits (T_{min} and T_{max}) for a specific alarm signal.

The same tests as in Section 5 were conducted for three alarm signals to assess the gain performance that can be obtained by optimizing the bandpass filter bandwidth and alarm period limits. The results for the alarm-specific optimized system are summarized in Table 4.

The alarm signal 252_253_alarms.wav (typical pulsed alarm sound for a backing truck) fundamental frequency is 1.2 kHz and its period is 800 ms. The corner frequencies of the bandpass filter were therefore adjusted to $f_{b1} = 1100$ Hz and $f_{b2} = 1300$ Hz. The limit periods were set to $T_{min} = 700$ ms and $T_{max} = 1300$ ms.

This alarm performed well with the general settings (95% TP rate for SNR = 15 dBA). However, as can be seen in Table 4, optimizing

Table 4
Comparison of TP recognition rate using general-purpose and alarm-specific parameters for the bandpass filter and alarm period limits.

Original filename	Description	Type	General purpose parameters		Alarm-specific Parameters	
			0 dBA	15 dBA	0 dBA	15 dBA
252_253_Alarms.wav	Truck backing up alarm	Pulsed	92%	94%	98%	100%
AlternateSteady.wav	Two tones alternating	Alternating	6%	0%	100%	100%
LP5_8r.wav	Repeat tone sweeping	Siren	12%	66%	100%	100%

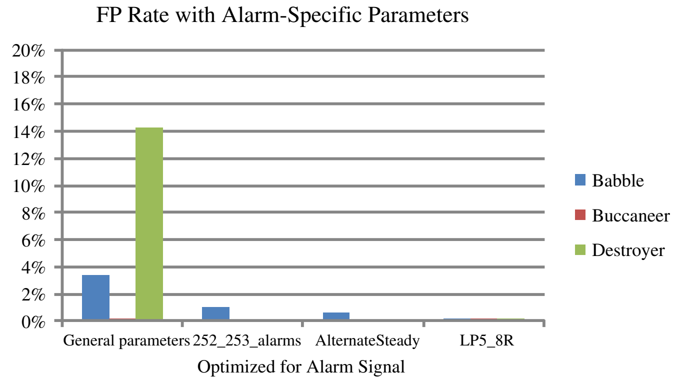

Fig. 10. FP rate when using alarm-specific parameters for three different alarm signals.

the system for this specific alarm increased the TP rate from 92% to 98% at SNR = 0 dBA, and maintened 100% TP rate for SNR = 15 dBA.

Alternating warning signals are generally not recognized by the proposed algorithm because the signal amplitude is constant (no silence gap). By adjusting the bandpass filter to exclude the fundamental frequency of one of the tones, the filtered signal envelope $u(m)$ exhibits characteristics which are similar to pulsed alarm signals and thus becomes recognizable by the proposed algorithm. Adjusting the expected period also increases the performances of the system.

This optimization was applied to the alternating alarm signal AlternateSteady.wav, which showed low recognition rates with the general-purpose settings. The filter corner frequencies were set to $f_{b1} = 900$ Hz and $f_{b2} = 1100$ Hz, while the expected period was set to $T_{min} = 1000$ ms and $T_{max} = 1600$ ms. The recognition rate was significantly improved, as shown in Table 4. For instance, the TP rate increased from 6% to 100% at 0 dBA SNR.

Siren warning signals can also be optimized the same way as alternating signals. Because sirens are a repetition of frequency sweeps, by adjusting the bandpass filter to reject a significant portion of the swept frequencies, a periodic envelope is observed. This has been done for siren signal LP5_8R.wav which, also, performed poorly with the general settings. The filter corner frequencies were set to $f_{b1} = 1600$ Hz and $f_{b2} = 1800$ Hz, the expected period was set to $T_{min} = 900$ ms and $T_{max} = 1400$ ms. Again, this resulted in significant improvements, as shown in Table 4 (100% TP rate).

Finally, the FP rate is also improved using the alarm-specific parameters because the detection conditions are tighter. For instance, the FP rate for the destroyer, which was problematic with the general parameters went from 14.3% to less than 0.2% for the three alarm-specific optimized parameters. These results are summarized in Fig. 10.

7. Conclusions

This paper presented new digital signal processing algorithms to automatically detect alarm and warning signals in real-time, for implementation in a low-power DSP embedded in hearing protection devices. The system is composed of a bandpass filter to select fundamental frequencies of typical alarm signals, an envelope detector and a periodicity evaluation algorithm. This system was designed to detect pulsed alarm signals which are common in industrial workplaces.

The proposed system was validated with a database of recorded alarm signals and noises. The system performs generally well with pulsed alarms with frequency content and cyclic period which are compliant to the ISO 7331 standard. The average true-positive recognition rate is 95% and the average latency is 1.27 s, which is usually within two cycles of the periodic alarm sound. The proposed system is not efficient at identifying sirens and two-tone alternating alarms. However, it was shown that by optimizing parameters, the system can recognize these types of alarms with near 100% accuracy. Although this optimization will reject other types of alarm signals, the implemented detection system could run several of these detection algorithms in parallel, including the general-purpose parameters and specific problematic alarms to increase the overall detection performances.

Further optimization of the required computational resources are expected at the stage of the real-time implementation of the algorithms on the targeted DSP platform. Future research might also include investigation of the integration of budget machine learning algorithms to automatically optimize the parameters of the system in a given work environment.

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