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# Zwicker's Annoyance model implementation in a WASN node

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## ABSTRACT

**Wireless Acoustic Sensor Network (WASN) nodes for noise measurement and acoustic environment description is a common use in the environmental measurement within the Smart City. The implementation of the psycho-acoustic parameters in each WASN node is a tricky problem and currently is the battle horse in the automatic acoustic environment description. In this work, the implementation and the improvement of the algorithms used for each psycho-acoustic parameter is described and the performance of the implementation measured.**

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## 1. INTRODUCTION

Noise is a problem in urban environments that influences on the health of citizens, ranging from children's cognition, cardiovascular diseases, insomnia, etc. to simple headaches and lack of concentration [1]. Recognizing this as a major problem, the European Commission adopted in 2002 an Environmental Noise Directive (END) 2002/49/EC [2], requiring main cities with more than 250.000 inhabitants, to gather real data on noise exposure in order to produce local action plans and to provide accurate mappings of noise pollution levels.

These measurements are mainly based on the equivalent sound pressure level (called $L_{eq}$). However, $L_{eq}$ is not enough in terms of Psycho-Acoustic Annoyance (PA) due to the fact that similar values for $L_{eq}$ can lead to different feelings of the noise, perceived by different people, so failing to provide information related to the subjective annoyance [3] and their psychoacoustic properties. This is due to the lack of information from $L_{eq}$ regarding the frequency characteristics. In addition, there are many sources of noise with low levels of $L_{eq}$ that produce a disgusting annoyance and even worse than the ones with high values of $L_{eq}$, for instance an isolated tone from a mechanic vibration. To define metrics based on the human hearing system, different studies and techniques have been carried out and different methods have been defined in order to estimate the subjective annoyance (such as Zwicker's [4], Moore's [5]...). Nevertheless, all of them require high computational costs due to the complexity of the analysis and required signal processing. In particular one of the most commonly used and accurate is the Zwicker's model, that provides enhanced indexes, such as Loudness (L), Sharpness (S), Fluctuation Strength (FS) and Roughness (R), that allow the estimation of an accurate and precise subjective PA, recently regulated by ISO 12913 [6] [7], instead of just considering $L_{eq}$.

In this scenario, Wireless Acoustic Sensor Networks (WASN) based on Internet of Things (IoT) are a very interesting tool, for instance to deploy a distributed sensor systems on smart cities for urban noise monitoring, allowing the identification of acoustically problematic areas and critical sound sources in real time, as well as the possibility to react efficiently against such health hazards. But with these systems, the number of samples both in time and space increase, as well as the computational complexity, making the construction of these mentioned subjective maps a tough and complex task. Thus, WASNs fail if we want to process the previous parameters in near real time for an accurate soundscape profiling. Thus, the goal of this paper is focused on an efficient and accurate implementation of these indexes or psycho-acoustic parameters to monitor PA within this scenario, that is WASN and IoT.

The rest of the paper is structured as follows. Section 2 discusses the state of the art. Section 3 expounds the Zwicker's annoyance model. Section 4 describes the implementation steps. Section 5 exhibits the results obtained. Section 6 concludes the paper.

## 2. STATE OF THE ART

Psychoacoustic research has been widely studied and several standards for evaluating subjective annoyance and calculating psychoacoustic parameters have been defined in [8] [9]. For instance, regarding Psycho-Acoustic Annoyance (PA) models, in [10], the Zwicker's annoyance model [4] is used for soundscape categorization to determine how an acoustic environment sounds like, using manually collected noise samples.

In addition, several works have already considered the use of WASN for noise monitoring. In [11] and [12], the authors evaluate a WASN to monitor road traffic noise measured by the $L_{eq,T}$ [13]. In [14] and [15] show a WASN deployed in Ostrobothnia (Finland), reporting different tests to evaluate the noise impact. Other references such as [16], [17] and [18] use the mobile phones for noise pollution monitoring. Although the results are interesting, in our opinion the lack of information about the recording conditions prevents getting accurate noise measurements. When assessing noise indicators, the location of the measuring devices must follow defined rules [2]. In the previous references [11] - [18], the measurements are based on the $L_{eq,T}$, even with the A-weighting filter (ITU-R 468) with $L_{eqA,T}$, that is a frequency-selective filter picking up the frequency range around 3-6 kHz, to which the human ear is most sensitive. These parameters are measured in dB and dBA respectively. Nevertheless, these parameters do not provide information about the subjective annoyance from the point of view of human perception [4] [10] [19].

## 3. ZWICKER'S PSYCHOACOUSTIC MODEL

Psycho-acoustic metrics are an alternative to express people's feelings by subjective measures. In this section, we describe the Zwicker's annoyance model [4] for a general purposes by measuring Psycho-Acoustic Annoyance (PA),Loudness (L), Sharpness (S), Fluctuation Strength (FS) and Roughness (R). This model is based on the anatomy of the human hearing. When complex sounds are being considered, the frequency spectrum of the psycho-acoustic metrics is made in terms of Critical Bands (CB) [20], that refers to the frequency bandwidth of the *auditory filter* created by the *cochlea*, the sense organ of hearing within the inner ear. The human hearing combines the sound stimuli which are situated in close proximity of each other in terms of frequency into particular CB. When serializing these CBs, two different frequency scales are created, called the CB rate scales, one measured in the unit *Bark* and the other one measured in *Equivalent Rectangular Bandwidth* (*ERB*) [4]. The *Bark* scale is defined as the mapping from the physical frequency scale to the CB rate scale from 1 to 28. The *ERB* scale is closely related to the CB as well, but it is defined analytically and more smoothly behaved than the *Bark* scale.

Next, we show the numerical expressions used to estimate the different parameters within the Zwicker's Psychoacoustic Model, defined to measure PA, L, S, R and F [4]. The signal processing that these parameters require, is out of the scope of this paper although the detail of their implementations are shown in the next Section 4. It must be stressed that these parameters are measured using different temporal window sizes over the audio signal.

$$L = \sum_{z=0}^{28Bark} L(z) \cdot \Delta z \tag{1}$$

Loudness (L) as shown in equation 1, is the value that deals with the sound volume (intensity sensations), measured in *Sones* with a linear scale. It is standardized in ISO 532B and DIN45631. The process used to calculate L is based on the Specific Loudness ($L(z)$ or L contribution for each CB, where $z$ identifies the CB number), measured in *Sone/Bark*. The total $L$ is the result of the different contributions. $\Delta z$ is the bandwidth of each *Bark*. In Figure 1 we show a flow diagram of this parameter, that it will explained in the next section.

$$S = 0.11 \cdot \frac{\sum_{z=0}^{28Bark} L(z) \cdot e^{0.171 \cdot z} \cdot z \cdot \Delta z}{L} \tag{2}$$

Sharpness (S) as shown in equation 2, is a value of sensory human perception of unpleasantness in sounds that is caused by high frequency components. It is measured in *Aures* in a linear scale.

$$R = 1.596 \cdot \sum_{i=0.5}^{33\,ERB} (g(z_i) \cdot m_i \cdot k_{i-2} \cdot k_i)^2 \tag{3}$$

Roughness (R) as shown in equation 3, it describes the perception of the sound fluctuation even when L or $L_{eq,T}$ remains unchanged. It analyzes the effects with different degrees of frequency modulations (around 70Hz) in each CB. The basic unit for R is *Asper*. In this case, this parameter is better described in *ERB*. Thus for each *ERB* $i$, $g(z)$ is an arbitrary weighting function, $m$ is the modulation depth of each *ERB* and $k$ is the cross-correlation between the envelopes of the *ERB* with indexes $i$ and $i-2$. In Figure 2 we show a flow diagram of this parameter, that it will explained in the next section.

$$F = 0.3493 \cdot \sum_{i=0.5}^{33\,ERB} (g(z_i) \cdot m_i \cdot k_{i-2} \cdot k_i)^2 \tag{4}$$

Fluctuation Strength (F) as shown in equation 4, it describes how strongly or weakly sounds fluctuate. It depends on the frequency and depth of the L fluctuations, around 4 Hz in each *ERB*. It is measured in *Vacils*.

$$PA = L(1 + \sqrt{(\frac{3(S-1.75)log(L+10)}{4})^2 + (\frac{2.18(0.4F+0.6R)}{L^{0.4}})^2}) \tag{5}$$

Finally, with all of them we can estimate the Psycho-acoustic Annoyance (PA) as shown in equation 5, it is a perceptual attribute that allows an objective quantification from the physical characteristics of the signal, based on the mean values of L, S, R and F.

A flow diagram of the implementation of L can be seen in Figure 1. Also, Figure 2 shows the flow diagrams for R. The details are given in the next section.

## 4. MODEL IMPLEMENTATION

To improve the calculation of the different psycho-acoustics parameters, all of them have been broken down into simpler steps in order to find out similarities between them. As a result of this analysis, we made a classification between the parameters calculated in time domain (in particular R and F) and the ones calculated in frequency domain (in particular L and S). As result of this classification, it has been decided to use two different types of windows. On one side Blackmann windows are used for time processing and on the other side Hanning windows are used for frequency processing.

The model used for the L calculation is shown in Figure 1, according to the DIN-45631. In this figure the input signal is sampled and windowed each second with a Hanning window. Then a Frequency Fourier Transform (FFT) is applied to get the sound pressure levels, that latter are filtered out with $\frac{1}{3}$ octave filters to obtain these levels, named $P(z)$ being $z$ each *Bark*. Then, these outputs are processed according the DIN-45631 to calculate the specific loudness, named $L(z)$ per *Bark*. Notice that in order to speed the

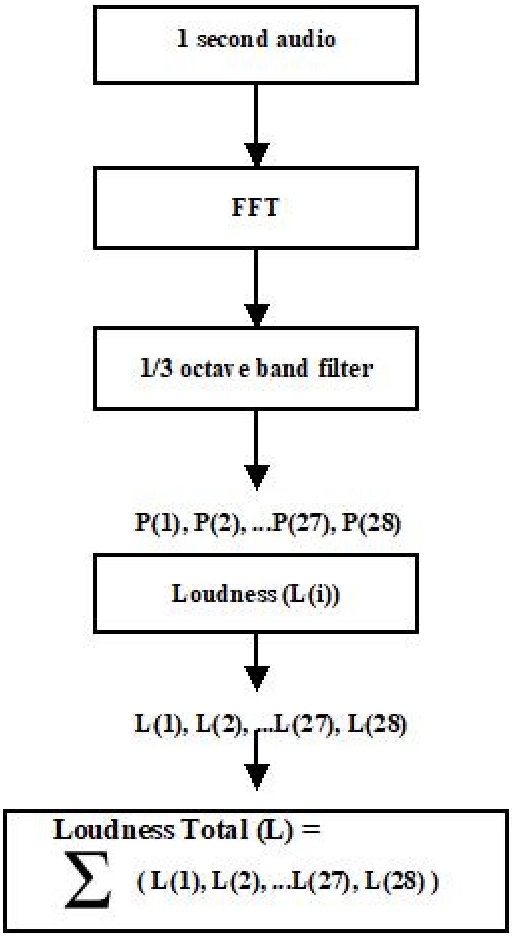


*Figure 1: Loudness (L) algorithm standarized by ISO-532B and DIN-45631*

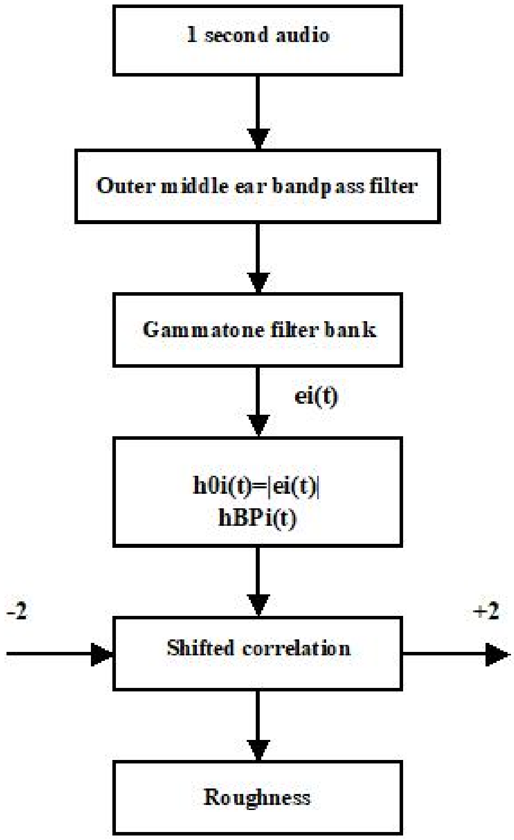


*Figure 2: Roughness (R) algorithm*

calculation of L, the conversion of the signal to $\frac{1}{3}$ octave bands has been done performing a filtering, which turns out to be a matrix multiplication due to the frequency domain.

Once we know L and the specific loudness, named $L(z)$ per *Bark*, following the equation 2, it allows the calculation of S with a near null computational cost, since it is enough to apply the S formula to the specific loudness.

The model used for the R is the defined by V.Jourdes [21] based on the Optimised Model of P. Daniel and R. Weber [22] and shown in Figure 2. The main characteristic of this model is the use of the *ERB* scale (instead of *Barks*) using Gammatone filters. In this figure the input signal is sampled and windowed each second with a Blackmann window, that then it is filtered by the outer middle ear bandpass filter. Then this is processed using Gammatone filter banks to obtain 33 *ERB*, named $e_i(t)$, being $i$ each *ERB*. Then for each band $i$, we calculate each continuous value (DC) called $h0_i$ as well as the envelope of each $e_i(t)$ called $hBP_i(t)$, that is a BandPass (BP) using an Infinite Impulse Response (IIR) weighthing function. From these values for each band $i$, we calculate $m_i$ that is the modulation depth using the Root Mean Square (RMS) as follows:

$$m_i = RMS\left(\frac{hBP_i(t)}{h0_i}\right) \qquad (6)$$

This modulation depth then is calibrated according to each band $i$. Finally, we perform a shifted correlation between their modulation depths to obtain cross-correlation $k_i$, between the envelopes of the *ERB* with indexes $i$ and $i-2$. Finally, using the equation 3, we calculate R.

Making use of the similarities between R and F, it is possible to adjust the R model to calculate the F, by changing only the Infinite Impulse Response (IIR) weighthing function above mentioned for R calculation, and then following the equation 4. This weighting function has been extracted from the proposed model by Osses Vecchi [23].

Notice that in order to speed these parameters (R and F), the initial steps, from the input signal till the Gammatone filter bank, are equal and they are calculated once. Thus, once this is done, we apply the weighting function according to each model as explained above, and calculate the corresponding modulation depths $m$ and cross correlation factors $k$ for each psycho-acoustic parameter R and F.

It must be highlighted that another improvement for the calculation of R and F, can be done in the shifted correlation shown in Figure 2. This function shifts the signals in order to see the shift produced by the Gammatone filter bank. This is done by doing shifts of 10 samples and performing the correlation in order to find out the maximum value. Just in case, the value found is 1 or almost 1 (for instance 0.999) we stop searching other shifts, as the maximum has already been achieved.

## 5. RESULTS

In this section, we evaluate the implementation of the Zwicker's annoyance model [4] on different platforms and languages.

Regarding the platforms, on one hand, we use small board computers (SBC), in particular on RaspBerry Pi models 3B and 3B+. These models have 4 cores. Notice that these models could fit in a WASN for psycho-acoustic annoyance monitoring. On the other hand, we use a computer as a baseline. This computer is an i7-7700HQ @ 3.5GHz and 16GB DDR4 of RAM with 8 cores. The RPi 3B uses a ARM Cortex-A53 @ 1.2GHz and 1GB LPDDR2 of RAM and RPi 3B+ uses a ARM Cortex-A53 @ 1.4GHz and 1GB LPDDR2 of RAM. All these platforms uses a Linux 64bit operating system. It must be stressed that for a fair comparison between the different platforms above mentioned, we will use always only 4 core in each processor for the different alternatives.

Regarding the languages used, the different algorithms have been written in C++/Python and Matlab of The Mathworks Inc. In this case, Matlab is interpreted language used as a baseline. Python is an interpreted language and a reference in IoT research. C++ is a compiled and efficient language in terms of computational time. It must be noticed that in the C++/Python option, the main program is based on Python and we use C++ in order to implement a Python library that performs all the tough processing from each pyscoacoustic parameter, in an efficient way by using the linear algebra library called Armadillo [24]. Python also is in charge of capturing audio and showing the results. With this combination C++/Python, we get a fast and powerful program due to the C++ at the same time we maintain the flexibility of Python.

Table 1 and Table 2 show a performance comparison in terms of computational time per each second of audio recording between Matlab and C++/Python running on the computer and the C++/Python implementation running of RPi for the different psycho-acoustic parameters. In order to obtain the most realistic results, 100 random samples of daily sounds of one second of duration have been used. Furthermore, as the C++ compiler has the possibility to choose the level of optimisation that runs, it has been decided to perform the calculations, both the optimisation disabled (enabled by option `-O0` and shown in Table 2), and the optimisation completed (enabled by option `-O3` and shown in Table 1). These adjustments lead to use a single core (disabled, option`-O0`) or the use of all of them in parallel (option `-O3`). Notice that the code has not been programmed using threads or any kind of parallelization. This is one of the outcomes of using Armadillo library.

We have managed to overcome the calculation in real time in both Matlab and C++ using a modern computer as well as running it using Raspberry Pi family. The best performance computing time is shown for the C++ implementation using the complete optimisation option.

*Table 1: Time comparison between different devices and programming languages, without optimization enabled*

| | L | S | R & F | Total | R | F |
|---|---|---|---|---|---|---|
| Linux | 0.081 | 0.000 | 0.527 | 0.534 | 0.298 | 0.240 |
| RPi3B | 0.047 | 0.000 | 5.617 | 5.664 | 3.258 | 2.431 |
| RPi3B+ | 0.041 | 0.000 | 4.851 | 4.891 | 2.803 | 2.093 |

*Table 2: Time comparison between different devices and programming languages, with optimization*

| | L | S | R & F | Total | R | F |
|---|---|---|---|---|---|---|
| Matlab | 0.058 | 0.000 | 0.638 | 0.699 | 0.288 | 0.404 |
| Linux | 0.003 | 0.000 | 0.235 | 0.238 | 0.128 | 0.235 |
| RPi3B | 0.018 | 0.000 | 1.462 | 1.479 | 0.849 | 0.742 |
| RPi3B+ | 0.017 | 0.000 | 1.389 | 1.406 | 0.794 | 0.694 |

## 6. CONCLUSIONS

In this paper we have introduced an accurate implementation of the Zwicker's Psychoacoustic model, to monitor the Psycho-Acoustic Annoyance. This model is one of the most commonly used and accurate. Nevertheless, as it is stated and shown in the paper, it requires high computational costs due to the complexity of the analysis and required signal processing. Due to this complexity, it fails if we want to run it one Wireless Acoustic Sensor Network using low cost platforms or small board computers, such as RaspBerry Pi family. For this reason, we have shown an extremely efficient and optimized code implementation of this model.

However, it must be noticed that while the results in this paper showed the feasibility of the implementation of the Zwicker's Psychoacoustic model on the RPi platforms, they also illustrated the practical limitations and outcomes of these platforms. But these outcomes can be overcame by using new trends based on edge and fog computing as well as using clustering techniques that are suggested as future work.

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