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Measuring and identifying background noises in offices during work hours

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Abstract

Acoustical comfort inside open-plan offices is necessary for optimal work performance. In fact, it is well known that productivity is closely related to the acoustic conditions of the working environment. Noise inside offices is basically due to two kinds of sources: mechanical sources (HVAC devices, office equipment like printers, phones, etc.) and human activities (human activity noise). The combined effect of these noise sources may play a key role in privacy metrics, e.g. the STI and its spatial decay. Therefore some technique is needed to identify and separate the contribution of each kind of source. The data for the present work are a set of short-Leq values acquired over long-term sound pressure levels recordings. Noise sources are identified using a two-step statistical technique: at first the blind Gaussian Mixture Model (GMM) is used to segment the sources, then each source is classified using a customary statistical analysis. It is shown that the probability distribution of each source can be identified, conferring a different sound pressure level to each one. In order to investigate the dynamic behaviour of privacy criteria, these analyses are carried out for each octave band frequency.
Keywords:open plan office, background noise, source separation

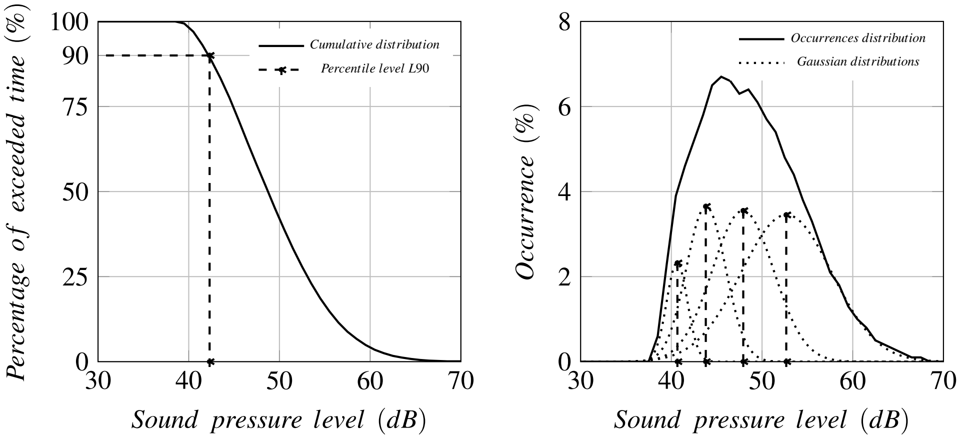
1 INTRODUCTION

Acoustic comfort in offices is an important aspect to provide a high level of productivity and quality of work. Background noise is an important factor influencing privacy in offices and it can be seen as the most important parameter for the acoustical office design[1]. Colle and Welsh highlighted that distraction in the work place is not strictly related to the sound pressure level but to the speech intelligibility value [2]. Thus, if the noise carries information, like the speech from neighbors in the office, there's a lack of productivity [3]. The speech intelligibility is defined in IEC 60268-16 [4] by the Speech Transmission Index (STI). It depends on the acoustical conditions of the room and the background noise. The calculation of this criterion can be adjusted in post processing selecting a more specific background noise condition, so the measurement of the latter is very important. Since noise reduces speech intelligibility of other people's communications, it can be considered as a fundamental criterion to improve the work flow. For this reason, the background noise should be neither too low nor too high [5]. ISO 3382-3 [6] specifies the parameters which describe the acoustical state like the distraction distance (r_D) and the spatial decay rate of speech per distance doubling ($D_{2,S}$). All these parameters are connected to the noise sources, so analyzing them means understanding how the acoustic conditions influence the comfort. The sound field in an enclosed space is different if it is in the occupied or unoccupied state so a sound source could have more than one behavior. In addition, in the occupied state there are further sound sources, i.e. the equipment and the human activities. In the project phase of an open plan office, the ability to distinguish between sources of a different nature is important to suggest specific interventions. The background noise (L_B) due to HVAC could be controlled by interventions on single devices, whereas the human activity noise (L_S) could be influenced by L_B and by the distance from the devices, that contribute to trigger the Lombard effect [7].

Hodgson et al. [8] suggested a method to measure the background noise into classrooms with a statistical technique, differentiating the student activity during lecture from the speech level of the speaker. Dehlbæk et al. [9] applied this method in order to measure the human activity noise in open-plan offices. Measuring for a whole working day with a sound level meter, the occupied and unoccupied state of an office can be analyzed. Basic statistical techniques find out the most common SPLs. Iterative statistical algorithms permit to point out the sound levels attributable to the various sources in the office. In the present work, noise sources are identified using a two-step statistical technique: at first the blind Gaussian Mixture Model (GMM) is used to segment the sources, then each source is classified using a customary statistical analysis. It is shown that the probability distribution of each source can be identified, conferring a different sound pressure level to each one. In order to investigate the dynamic behavior of privacy criteria, these analyses are carried out for each octave band frequency. This newer technique is compared with the standard percentile levels technique to evaluate the background noise.

2 STATISTICS OF SOUND PRESSURE LEVELS

A statistical analysis of the data collected by a sound level meter, distributes the sound pressure levels basing on their occurrences. In this way it is possible to highlight the most frequent levels during the work day. If the frequency (in the statistical sense) of a sound pressure level is high, it means that there is a sound source working at that level continuously.



(a) Percentile Levels Technique

(b) Gaussian Mixture

Figure 1. Two statistical methods used in the present work. In figure (a) the continuous line represent the cumulative distribution of the recorded SPL of a sound level meter. In figure (b) the continuous line represents the occurrences distribution of the same measurement. The asymmetrical distribution was decomposed in four Gaussian curves. The mean values of Gaussian curves indicated with $*$ correspond to the sound sources.

Studying the occurrences in each octave band is useful to distinguish the kind of sound source which is operating. Two statistical methods were used for the survey: percentile levels (PL) and Gaussian Mixture Model (GMM).

Regarding the percentile, it is worth remembering that in statistics, the rank r of a percentile q of N observations is defined as:

$$r(q) = \frac{q}{100}(N+1) \tag{1}$$

Consequently, the value of the *acoustic* percentile level L_q of a certain dataset is equal to the rank r of 100-q. For a large number of observations, if the occurrence curve is represented by $f(x)$, the value q can be expressed as:

$$q = P(x > L_q) = \int_{r(100-q)}^{\infty} f(x)dx. \tag{2}$$

Gaussian Mixture Model decomposes the original model data in a sum of gaussian curves. The clusters, represented by the gaussian curves, and their points are defined via Maximum Likelihood method. With *Rstudio* [10] is possible estimate via Expectation - Maximization (EM) [11] iterative algorithm the Maximum Likelihood of the recorded SPL.

Let X be a set of independent observations, $x_1, \ldots, x_n$, drawn from a mixture of Gaussian distributions; the density $f(x_i)$ can be written in the form

$$f(x_i; \psi) = \sum_{k=1}^{K} \pi_k f_k(x_i; \theta_k) \quad i = 1, \ldots, n, \quad \psi = \{\theta, \pi\} \tag{3}$$

where the $f_k(x_i, \theta)$s are the Gaussian densities with parameter vector $\theta_k = \{\mu_k, \sigma_k^2; k = 1, \ldots, K\}$ and π_k are the so called *mixing proportions*, non-negative quantities that sum to one; that is, $0 \leq \pi_k \leq 1 \quad (k = 1, \ldots, K)$ and $\sum_{k=1}^{K} \pi_k = 1$ [12]. The likelihood function for a mixture model with K univariate Normal components is:

$$\mathscr{L}(\psi|x) = \prod_{i=1}^{n} \sum_{k=1}^{K} \pi_k f_k(x_i|\theta_k) = \prod_{i=1}^{n} \sum_{k=1}^{K} \pi_k \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_i-\mu_k)^2}{2\sigma_k^2}}. \tag{4}$$

Detailed information on the samples collected can then be obtained through statistical analysis. Three successive steps of analysis are identified: the distribution of the occurrences of the measured SPL, for each octave band (125 Hz - 4000 Hz), the segmentation of the occurrences in Gaussian curves as possible sources constituting the background noise and finally the identification of human (L_S) and mechanical (L_B) contribution (figure 2).

3 METHOD

A small open-plan office, with four workplaces, was used as case study in this preliminary study (figure 5). Sound pressure levels were recorded for an entire work day with a sound level meter with 0.1 seconds of sample time for acquisition. The sample population was hypothesized large enough to identify Gaussian curves. For the GMM method the algorithm was set as "random", which means that the number of the Gaussian curves was calculated automatically in order to optimize the fit. The number of Gaussian curves obtained and the corresponding standard deviation were extracted. The standard deviation (s.d.) permits to identify the nature of the source: if the s.d. is low (say < 5 dB) it belongs to a mechanical sources, if it is greater ($\geq$ 5 dB) it belongs to human activities. In this study a s.d. value of 5 dB is considered the threshold to discern the type of source according to the literature [13, 14, 15]. Afterwards, the sound pressure levels of the office have been calculated using the diffuse field formula:

$$L_{P,S,i} = L_{W,S,i} + 10log\frac{4}{A} - 11 \tag{5}$$

where $L_{W,S}$ is the sound power level of (normal) speech as the ISO 3382-2 [6] suggests, A is the equivalent absorbent area of the room and $i = (1, ..., 6)$ represent the range of octave band from 125 Hz to 4000 Hz. To verify the tendency of the sound pressure levels of the human activity noise, the measured values have been compared with the calculated ones. L_{eq} and the percentile level L_{90} were extracted as the standard procedures require. This analysis was conducted for each octave band from 125 Hz to 4000 Hz.

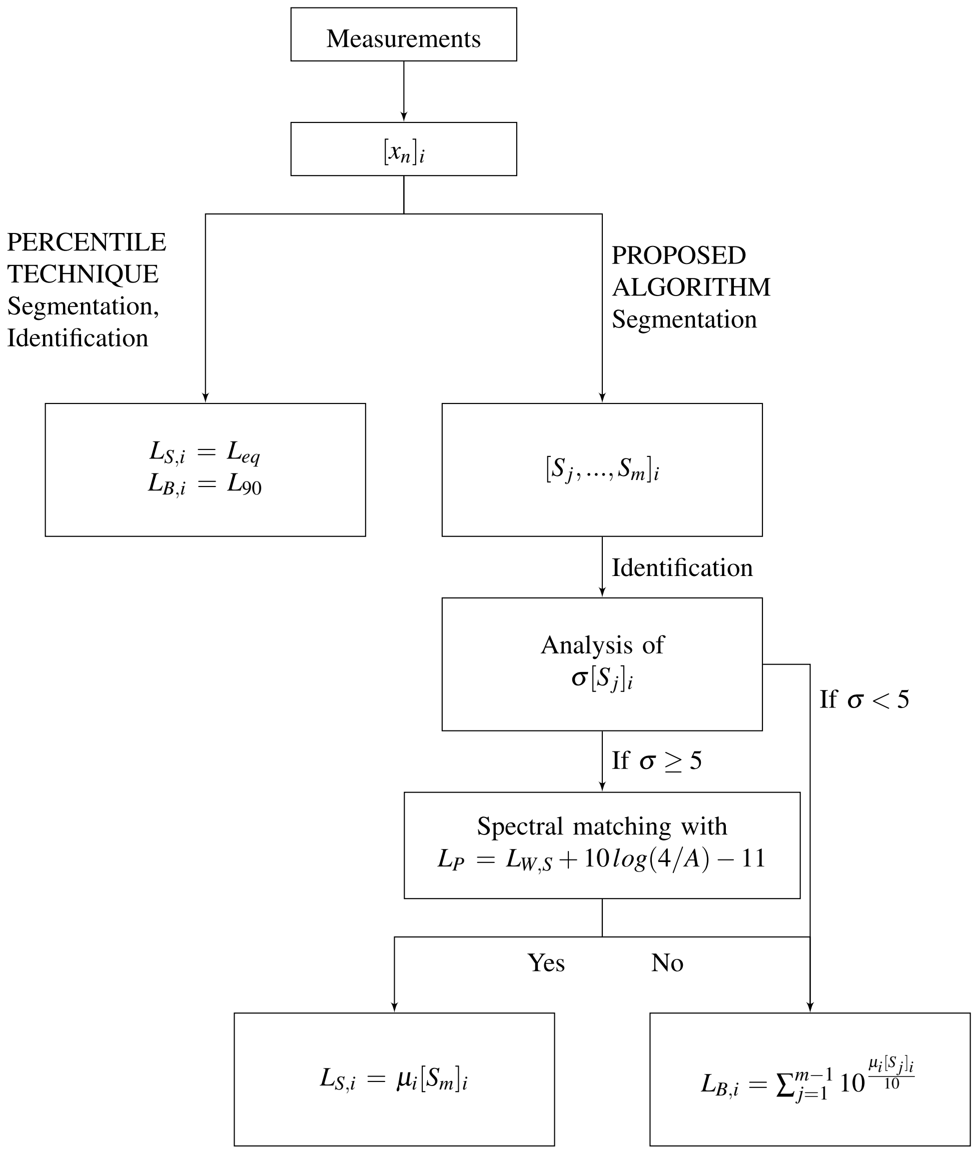


Figure 2. Step of the analysis made by Percentile Levels and made by Gaussian Mixture Model. $i = (1, ..., 6)$ is the range of the octave band (125Hz - 4000Hz) and $S_j = (1, ..., m)$ are the noise sources individuated by the proposed algorithm (EM algorithm in this study). In this study $S_j = (1, ..., m-1)$ are assumed as mechanical sources and S_m is assumed as human activity source.

4 RESULTS

The results for the two techniques are shown in table 1 for the percentile levels method and in table 2 for the Gaussian Mixture Model analysis. In table 2, for the GMM technique, the human activity source is in bold style. In figure 3 the mean values of the GMM analysis are plotted in function of the standard deviation, for each octave band. The means corresponding to the mechanical noise (in black) are distribute in the left part, with s.d less than 4 dB and L_P values between 15–45 dB, with little differences between them. The means of the human noise (in white) with a s.d. grater than 6 dB and L_P values greater than 35 dB, represent outliers from the others values.

Table 1. Identification and segmentation of L_{eq} and L_{90} (in dB) with percentile levels technique.

Percentile level (dB)		Frequency octave band (Hz)					
		125	250	500	1000	2000	4000
Mechanical	L_{90}	29.5	26.7	23.7	19.9	17.5	20.7
Human activity	L_{eq}	**32.6**	**34.1**	**36.2**	**30.1**	**24.6**	**20.3**

Table 2. Identification of the possible sound sources and segmentation into mechanical and human noise with GMM technique. The means and the standard deviations (s.d.) are shown.

Sound level of the n-th segmented noise source	Frequency octave band (Hz)					
(dB)	125	250	500	1000	2000	4000
1	–	–	–	–	17.2 (0.4)	19.0 (0.4)
2	–	–	–	–	17.9 (0.3)	20.8 (0.3)
3	–	–	23.5 (1.2)	–	18.6 (0.4)	21.2 (0.2)
4	–	26.8 (1.4)	25.7 (1.1)	19.7 (1.0)	19.6 (0.6)	21.7 (0.2)
5	–	28.5 (1.0)	27.9 (1.0)	21.3 (0.8)	21.1 (0.9)	22.1 (0.3)
6	–	30.5 (1.0)	30.2 (1.1)	23.1 (1.1)	23.2 (1.2)	22.8 (0.7)
7	31.1 (1.9)	32.9 (1.4)	33.1 (1.7)	25.9 (1.9)	26.3 (1.7)	24.4 (1.6)
8	34.6 (3.3)	36.2 (2.6)	37.1 (2.9)	31.2 (3.9)	30.4 (3.0)	27.9 (3.2)
9	**44.2 (6.9)**	**45.2 (6.8)**	**46.3 (7.9)**	**39.0 (8.3)**	**35.8 (7.1)**	**34.2 (6.0)**
			Levels' sum of sources			
Mechanical	36.2	39.3	39.7	33.3	33.3	32.4
Human activity	**44.2**	**45.2**	**46.3**	**39.0**	**35.8**	**34.2**

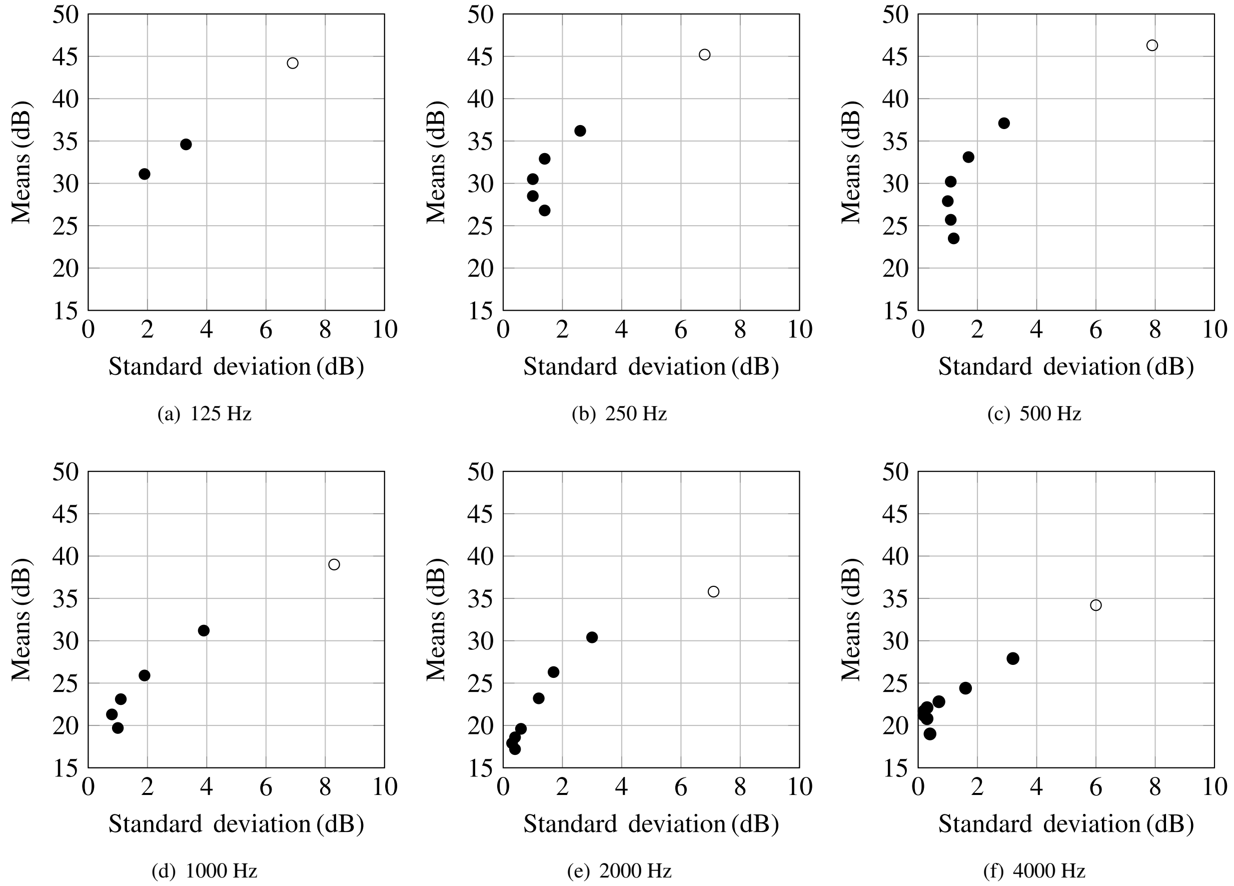


Figure 3. Relationship between means obtained by the GMM clustering and the standard deviation for each octave band.

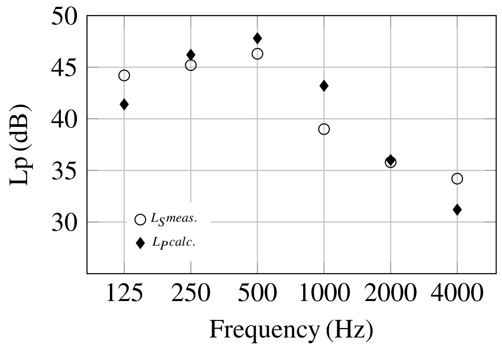


Figure 4. Spectral matching between the measured values of the noise source hypothesized as human and diffuse speech level in the room under study (equation 5).

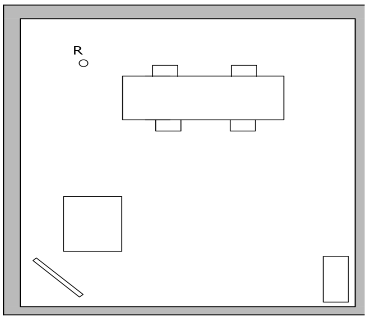


Figure 5. Layout of the office with the position of the sound level meter.

5 DISCUSSIONS

The more complex statistical approach with the Gaussian Mixture Model allows to highlight every sound source in an enclosed space regardless of its nature, mechanical or human. Results show how GMM brings back more values than PL. The random algorithm permits to extract a certain number of clusters, thereafter the distance between the means and their standard deviations can be re-conducted to a specific kind of noise source. Little differences between the means could be connected to the same source while a tiny standard deviation indicates the mechanical nature of the source. In fact, a little standard deviation means that a source produces a specific sound pressure level continuously during time. Quite the opposite, a high standard deviation means a more accidental nature of the source, like the human activity. The comparison between the mean values identified as human source and the diffuse speech levels characteristic of the office under study shows the same trend with differences of up to 4 dB. This result confirm, with good approximation, the threshold chosen for the standard deviation and it could be implemented, for a more accurate similarity, with a neural network. Thus GMM is a stronger method than the percentile levels one, since, in order to obtain the same results with this latter, is necessary to know the percentage of exceeded time for each noise source.

6 CONCLUSIONS

Identifying sound sources in a work space is an important aspect in order to attain a high acoustical comfort and improve the productivity. This study compares two statistical techniques to highlight their differences in distinguishing the various sources. The percentile levels technique is a standard method of analysis; it is used here for comparison with the Gaussian Mixture Model, which represents a newer approach to the statistical data obtained by a sound level meter. This latter method allows to identify not only the number of noise sources in the space but their nature too. In fact, properly using the standard deviation it is possible to identify the kind of source: if the s.d. is high then the source works in a larger range of sound pressure levels, thus it can't be considered as mechanical source but more random like the human activity. This approach of analysis allows a potential deeper understanding of the acoustical field in an enclosed space in order to operate more accurately in the correction of the criteria which describe the acoustical quality of the space, e.g. the STI, and the design interventions to achieve a better comfort of the work flow.

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