

Real-time urban traffic noise maps: the influence of Anomalous Noise Events in Milan Pilot area of DYNAMAP

Giovanni ZAMBON¹; Roberto BENOCCI¹

1 Dipartimento di Scienze dell'Ambiente e del Territorio e di Scienze della Terra (DISAT), Università di Milano-Bicocca, Piazza della Scienza 1, 20126 Milano, Italy.

Ferran ORGA², Rosa Maria ALSINA-PAGÈS², Francesc ALÍAS², Joan Claudi SOCORÓ²

2 GTM - Grup de recerca en Tecnologies Mèdia, La Salle - Universitat Ramon Llull, C/Quatre Camins, 30, 08022 Barcelona, Spain.

ABSTRACT

The DYNAMAP project is expected to provide the traffic noise mapping of the city of Milan with an updating interval down to 5 minutes, thanks to a network of real-time noise monitoring stations. As the noise displayed by the maps should be exclusively attributed to the traffic noise, the recorded data need to be analyzed before the map updating process in order to exclude the presence of possible non-traffic events (e.g. sirens, horns, speech, doors, aircrafts,...), which are denoted as Anomalous Noise Events (ANE). To that effect, an Anomalous Noise Event Detection algorithm (ANED) has been designed and adjusted to deal with the identification of ANE within the Milan pilot area, where the mapping system is expected to be in operation in 2017. In this work, we present a comparative analysis of the ANE identification and classification considering the output of the ANED and the results obtained from the manual recognition of ANE by skilled personnel. The comparative takes into account the typology and duration of ANE (with their noise level distribution). In addition, their influence on the measured Leq,5min levels is evaluated for both methods by statistically analyzing the differences between the processed (without ANE) and non-processed (with ANE) Leq,5min.

Keywords: Noise, Traffic, Acoustic Maps, Anomalous Noise Events I-INCE Classification of Subjects Number(s): 51.4

1. INTRODUCTION

The DYNAMAP project (Dynamic Acoustic Mapping - Development of low cost sensors networks for real time noise mapping) is a LIFE project aimed to develop a dynamic noise mapping system able to detect and represent in real time the acoustic impact of road infrastructures. Scope of the project is the European Directive 2002/49/EC relating to the assessment and management of environmental noise (END) [1], [2], enforcing Member States to provide and update noise maps every five years in order to report about changes in environmental conditions (mainly traffic, mobility and urban development) that may have occurred over the reference period. The DYNAMAP project foresees the development of an automatic noise mapping system delivering short-term (real-time dynamic noise maps), as well as long-term noise assessments (annual evaluations). Despite real time noise maps are not explicitly required by the END, their automatic generation is estimated to lower the cost of noise mapping by 50%, with added significant benefits for noise managers and receivers [18][19], such as the possibility of providing updated information to the public through appropriate web tools or the opportunity to

abate noise with alternative measures based on traffic control and management.

The main project idea is focused on the research of a technical solution able to ease and reduce the cost of noise mapping, through an automatic monitoring system, based on customized low-cost acoustic sensors and a software tool implemented on a general purpose GIS platform, performing the update of noise maps in real time (dynamic noise maps) [3].

The update of noise maps is accomplished by scaling pre-calculated basic noise maps, prepared for different arches of roads. Basic noise maps are selected and scaled using the information retrieved from low-cost sensors continuously measuring the sound pressure levels of the primary noise sources present in the mapping area. A complete basic noise map covering the entire survey area is calculated and saved for each group of sources. Scaled basic noise maps of each group of sources are then energetically summed-up to provide the overall noise map of the area.

The feasibility of this approach will be proven implementing the system in two pilot areas with different territorial and environmental characteristics: an agglomeration and a major road. The first pilot area is located in the city of Milan, in the northern part of the town (district 9), where different type of roads and acoustical scenarios are present. The second pilot area is located along a major road, the motorway A90, which encircles the city of Rome.

Automating the update of noise maps through the DYNAMAP system entails several consequences. One of them deals with the content of the detected equivalent noise level (Leq), which can include, in addition to the main noise source, i.e. the road traffic, the contribution of other noise sources present in the mapping area. Consequently, the resulting maps would not constitute a faithful reflection of the acoustic impact of road infrastructures [10].

For this reason, it is necessary to endow the DYNAMAP system with the ability to discern between road traffic noise and other types of acoustic events (e.g., aircrafts, industries, works on the road, etc.) denoted as Anomalous Noise Events (ANE), to exclude them from the noise level computation. To that end, an Anomalous Noise Events Detection (ANED) algorithm has been developed [10][15]. In this work, we present a comparative analysis of the ANE identification and classification considering the output of the ANED and the results obtained from the manual recognition of ANE by skilled personnel. The comparative takes into account the typology and duration of ANE (with their noise level distribution). In addition, their influence on the measured Leq,5min levels is evaluated for both methods by statistically analyzing the differences between the processed (without ANE) and non-processed (with ANE) Leq,5min.

2. THE DYNAMAP PROJECT IN MILAN

Given the large number of roads present inside the city of Milan, a statistical approach was applied to size the monitoring network. Thus, roads having similar traffic flow conditions and, consequently, similar noise trends were grouped together after an extensive measurement campaign that involved the acquisition of daytime and nighttime noise levels from 93 monitoring stations distributed all over the city. The data achieved from the monitoring campaign were then analyzed and two main clusters with different noise trends and traffic flow were identified.

In order to estimate the noise behavior of the unmonitored roads, a statistical model, based on traffic features, was finally implemented [4-9]. In this model the estimate of the noise level is given by a linear combination of two quantities, named $\delta 1(h)$ and $\delta 2(h)$, i.e. the normalized mean hourly noise values related to clusters 1 and 2:

$$\delta i(h) = \beta 1 \, \delta I(h) + \beta 2 \, \delta 2(h) \tag{1}$$

where βI and $\beta 2$ are weighting factors calculated as a function of a traffic parameter (X):

$$\beta I = PI(X) / (PI(X) + P2(X))$$
 (2)

$$\beta 2 = P2(X) / (P1(X) + P2(X))$$
 (3)

X is the logarithm of the total daily traffic flow (X=LogT_T) and P1(x) and P2(x) are the distribution functions of X related to the two clusters. Therefore, the weighting factors $\beta 1$ and $\beta 2$ provide an estimate of the probability of a road stretch to belong to cluster 1 and 2.

In order to define the number of basic noise maps to be prepared and of the monitoring stations to be installed, the parameter X was further analyzed with the aim to split the total range of X values in a reasonable number of groups with similar traffic characteristics. In the end, a total of six groups were found. Each group includes more or less the same number of roads and identifies the corresponding basic noise map. For each group, the mean value of X was also calculated, together with the weighting factors βI and βZ . These parameters were then used to determine the reference noise level of each group, to be updated in real time as a function of the sound pressure level detected on site by the monitoring stations, placed on locations having an hourly traffic flow similar to the mean value of each group. Four monitoring stations were identified for each group, leading to a total of 24 measurement points.

In order to keep the error of the noise level estimate roughly the same (i.e. around 2 dB), the update of the noise maps will be delivered with a different time frequency as a function of the day period: 5 minutes from 7 to 21 hours, 15 minutes from 21 to 01 hours and 60 minutes from 01 to 07 hours [5].

.

3. DETECTION OF ANOMALOUS NOISE EVENTS

In this section, we detail the two methods used to eliminate the contribution of the anomalous events to the calculation of the equivalent value Leq. The automatic method (ANED), which works on the raw signal that the microphones pick up, is firstly detailed, and works with the spectral components of the signal. The manual method, applied by expert professionals, should be applied off-line measurements, and is based on the Leq1sec instantaneous value and on the spectrogram analysis of the received signal.

3.1 The Anomalous Noise Event Detection Algorithm

According to the DYNAMAP project specifications, an automatic detector has to be integrated in the evaluation system to prevent ANE to be computed in the GIS-based road-traffic noise map. The ANED algorithm is implemented as a binary classifier designed to differentiate between ANE and Road Traffic Noise (RTN) (see Figure 1). The ANED follows a classic machine learning approach, composed of two key processes: the parametrization of the input audio signal and the classification.

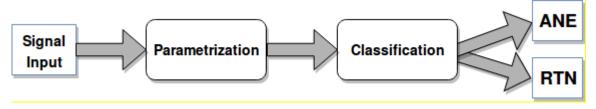


Figure 1. Block diagram of the ANED algorithm.

The audio parametrization, also known as feature extraction, provides a meaningful compact description of the input audio frame. In this case, referring to spectra. Mel Frequency Cepstral Coefficients (MFCC) [11] or Gammatone Cepstral Coefficients (GTCC) [12] have been studied in this environment to conduct the parametrization module of the ANED [10].

The classification module of the ANED has been implemented by means of a binary classification scheme, considering only two classes: ANE and RTN. Several machine learning techniques have been used for the binary classifier at the frame level, such as k-Nearest Neighbor (k-NN) [17] or

Fisher's Linear Discriminant (FLD) [16], since they provide a measure of the similarity between the input frame under study with respect to the previously trained RTN and ANE classes.

At execution time, each input audio is windowed every 30 ms and labelled as ANE or RTN. The decisions at the frame level are subsequently integrated every second by means of majority voting scheme to generate the final ANED output in order to satisfy the 1-sec decision of the DYNAMAP information chain [15] (see Figure 2).

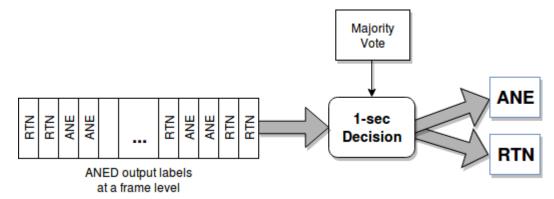


Figure 2, Block diagram of the ANED majority voting decision stage. The binary input provided at every second, and the binary output is provided every second.

3.2 The Manual Anomalous Noise Event Detection

The manual identification of the anomalous events has been done by competent staff: for each measurements it is based on the comparison and analysis of variation of the amplitude of the Leq,1s and the sonograms. Sonograms are graphic representations of a sequence of spectra in time, where the sound pressure level, in a chromatic scale, is expressed in function of time and frequency (an example is depicted in Figure 3).

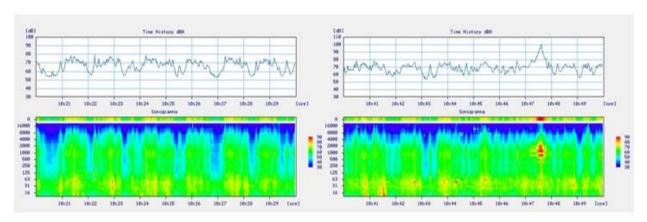


Figure 3. Leq,1s and sonograms related to road traffic in normal conditions (leftmost figures) and in the presence of an anomalous event (ambulance siren) (rightmost figures).

4. ANOMALOUS NOISE EVENTS ASSESSMENTS

In this section, we analyze the detection and impact of anomalous noise events, and we define a procedure for their removal from the recorded time series. We have evaluated the performance of the manual method (using three different users) and the ANED results for the aforementioned dataset.

4.1 Leq evaluation in presence of ANEs

The removal on anomalous events from a recorded time series may modify the equivalent level of the time interval considered for the calculation. Here, we present the results of the unaltered equivalent level and the equivalent level as calculated by removing the anomalous events inside the integration time τ (5). In this case, the equivalent level attributed to the time interval τ is calculated over interval:

$$\tilde{\tau} = \tau - \tau_A NE$$
 (4)

where τ _ANE represents the time interval of in which the anomalous event occurred. In Figure 4 the described procedure is illustrated.

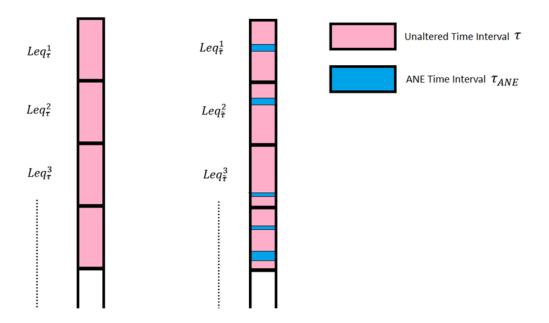


Figure 4: time series divided into τ (5 minutes) intervals. On the left, the unaltered time series. On the right, time series with ANE and corresponding τ _ANE. The equivalent level attributed to the time interval τ is calculated according to eq. (4) and denoted as $[\![\text{Leq}]\!]$ ($\tilde{\tau}$ _) $^{\hat{\iota}}$ with (i=1, 2,..., n).

4.2 Description of the real-life data under evaluation (La Salle)

In this section, we give a brief description of the real-life dataset used to conduct the experiments.

Table 1 shows the key information of the real-life recording campaign conducted in the DYNANAP's pilot area of Milan, considering its two clusters. As it can be observed, both clusters present similar recording conditions as well as number of anomalous noise events. However, it is worth noting that cluster 2 has a slightly greater accumulated ANE duration although the recording time is less.

	Cluster 1	Cluster 2	Total
Number of recordings	4	5	9
Total recording time	2h 4min	1h 53min	3h 57min
Accumulated ANE duration	20min 30s	24min 47s	45min 17s

Table 1. Recording information of the Milan pilot area divided in clusters.

Concerning the typology of the collected ANEs, the longest accumulated duration of cluster 1 belongs to the tramway category, with a 6% of the total duration in relation to the total recording time of this cluster. In addition, people talking, sirens, birds, brakes and horns can be heard frequently, among others. In cluster 2, people talking represent 3% of the total duration, while train pass-bys 2%. In addition, thunders, door sounds and airplanes are often heard in this cluster. For a detailed analysis of the nature of the ANEs of the DYNAMAP Milan's pilot area, the reader is referred to [14].

The ground truth (GT) of the presented dataset h was obtained following the process described in [14]. Several experts labelled with the suitable information the raw recorded data. For that purpose, they used a combination of visual and acoustic information. They had both the Leq1sec, the raw audio data and the spectrograms of the recorded files to observe, but all the decisions were made using also the acoustic information of the recordings, together with manual annotations of the technicians recording. The labelling was conducted using the maximum information of the real-life raw acoustic data to increase its reliability.

4.3 Analysis of the results of the ANE classification vs manual experts annotations

In this section, both ANE detection procedures, that is, the expert-based manual labelling and the automatically derived ANED output, are compared in terms of the standard evaluation metrics. Specifically, we compute the classification *precision* (i.e., the ratio between the number of correctly detected ANEs with respect to all the detected elements), *recall* (i.e., the ratio between the number of correctly detected ANEs in relation to all the real ANEs) and *F1 measure* (i.e., the harmonic mean of *precision* and *recall*). These values are obtained in comparison with the ground truth annotation.

Table 2: Precision, recall and F1 measure of the ANED and the manual annotations for each cluster (1 and 2) and altogether (All).

Criterion	Cluster	Precision	Recall	F1
Manual	1	58.3%	2.1%	4.0%
Manuai 1	2	60.5%	1.8%	3.5%
	All	59.5%	1.9%	3.7%
Manual 2	1	67.5%	0.4%	0.7%
	2	61.5%	0.2%	0.3%
	All	64.2%	0.3%	0.5%
Manual 3	1	63.8%	1.2%	2.3%
	2	50.9%	0.5%	1.0%
	All	56.6%	0.8%	1.6%
ANED	1	37.0%	63.3%	43.2%
	2	42.3%	59.1%	41.0%
	All	39.9%	61.0%	41.9%

Table 2 shows the precision, recall and F1 measures of the automatic and manual annotation of ANEs divided in the two clusters [13]. As the reader may observe, the precision of the manual annotations is around 60% for manual annotations and around 40% for ANED. The difference can be explained by the higher sensitiveness of the ANED algorithm than the manual counterpart annotations, provoking more false positives than the manual annotations since they are only built from visual inspection of the Leq-1s and sonogram values and evolution. Therefore, the competent annotators are more precise than the automatic detection since they only label clearly-distinguishable events.

On the contrary, the recall for ANED is around 60%, while nearly none of the manual annotations are higher than 2%. The reason for these results are mainly due to the presence of some ANEs that are deeply mixed with the background traffic noise, i.e. they are not visually salient, thus, very difficult to observe by the competent staff. In these regions, the ANED takes the most from the frame-based spectral parameterization, as it is specifically trained to identify all ANEs regardless of their equivalent noise level. The F1 measure is also influenced for the lower values of the recall, and its values follow the results of the recall measurement.

Figure 5 shows a couple of examples of the performance of bot the manual and automatic annotation for illustrative purposes. Figure 5.a shows a situation where the three competent staff annotate an ANE around second 27, whereas this region should be labelled as RTN according to the ground truth. The manual annotation may have detect a change in the Leq1s value, concluding that it is due an ANE incorrectly. Nevertheless, the ANED, which takes into account the spectral information of the input audio data, concludes that this audio region does not belong to the ANE class. Despite that correct evaluation, there are two more evaluations in the Figure 5.a example where the ANED yields to false positive ANE detections: the first, around second 5 and the second around second 60. The second example, in Figure 5.b, two of the manual annotations detect correctly an ANE starting around second 12 and finishing around second 40. The ANE is actually longer in time according to the ground truth. The ANED also detects the presence of an anomalous noise event, but its 1-second decisions are noisier than the two manual annotations.

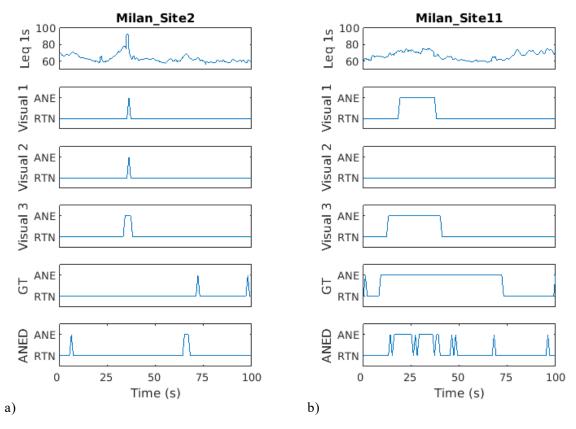


Figure 5a – 5b. Two case examples of manual and ANED evaluation in comparison with ground truth (GT). The left one was captured in Site 2 on 20th May 2015 at 13:54h (belongs to cluster 2), and the one in the right belongs to Site 11 recording on 21th May 2015 at 15:55h (belonging to cluster 2).

4.4 Influence on the measured levels of the two methods

In this section, we evaluate the quality of the annotation for both annotation methods according to their impact in the final Leq5m. Any detection method should guarantee that an ANE producing an impact in the Leq5m greater than ±2dB has to be removed from the measurement in order to provide a reliable

picture of the road traffic noise level within that 5 minutes period.

In figure 6, we can observe the Leq5m trajectories corresponding to representative examples. The figure depicts the Leq5m evaluated without removing any ANE, the Leq5m removing all the ANEs indicated by the ground truth (reference), and the Leq5m after removing the ANE according to the three manual annotations and the ANED algorithm output. If we observe the Leq5min curves obtained after removing the ANEs according to both annotation methods, it can be concluded that they mostly fit within the ±2dB deviation range with respect to the ground truth Leq5m curve (depicted as a shaded area in the figure). The ANED algorithm obtains the closest values to the ground truth Leq5m trajectory, despite its performance is influenced by a large number of false positive evaluations. For instance, in the rightmost part of figure 6, the Leq5min derived ANED curve is below the ground truth reference. This is due to deletion of some audio regions that have been annotated as ANE instead of RTN, i.e. false alarms. The manually derived curves are usually noisier, i.e. the three skilled personnel detect different ANEs within each piece of audio, showing their curves generally higher Leq5min values than the ground truth. This is due to the elision of some relevant ANEs. Finally, it can be observed that the ANED is more stable in terms of performance along time for both examples. A maximum difference between the ground truth evaluation and the Leq5m with all ANE is observed to be of +2.5 dB and +4.5 dB for each example, respectively. In both cases, the curves from the second manually derived labels are very similar to the Leq5m trajectory obtained from "Leq with all ANEs" curve, except for minute 25 in the second example, which unveils the difficulty to detect ANEs for this annotator. The reader may also observe the difference between manual annotations in the first example, e.g. minute 15, where there are near 3 dB of difference between the second and the third annotator, showing the first one an intermediate value. On the contrary, in the second example, the competent staff present very similar Leq5m patterns between them and with respect to the Leq5min curve without removing the ANEs (except in minutes 20 and 25).

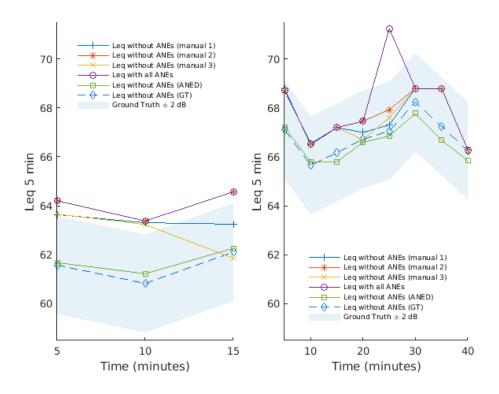


Figure 6: Two examples of the impact of removing the ANEs from the Leq5min for the different annotated approaches. Both recordings were obtained on the 20th May 2015, Site 4 in Via Privata Mario Galli (it belongs to cluster 2) at 16:33h and Site 5 in Viale Fulvio Testi (belonging to cluster 1) at 17:22h.

5. CONCLUSIONS

Both manual and automatic ANE identifications lead to a better estimation of the Leq5min value. The automatic ANED has a better recall in terms of results due to the fact that it uses spectral information to identify whether each frame is ANE or RTN. The manual annotations, despite being conducted by experts, only have the Leq1sec and the spectrograms. It is worth highlighting that the performance of the ANED can be better assessed through recall measure, as it is devoted to identify the presence of ANEs.

Automatic event recognition has the advantage that it can work in the sensor with the raw data coming from the microphones. The manual identification cannot be implemented in a real-time monitoring system. The data recorded in Milano show how in certain moments is necessary to eliminate the influence of ANE to perform the Leq5min measurements; their value would be more than 2dB difference from the one measured with the ground truth.

This work will continue about the duration and the saliency of each ANE, in terms of their impact to the Leq5min value and consequently ANED recognition capability will be calibrated.

ACKNOWLEDGEMENTS

This research has been partially funded by the European Commission under project LIFE13 ENV/IT/001254 DYNAMAP.

The Grup de recerca en Tecnologies Mèdia would like to thank the Secretaria d'Universitats i Recerca del Departament d'Economia i Coneixement (Generalitat de Catalunya) under grant ref. 2014-SGR-0590. Ferran Orga thanks the support of the European Social Fund and the Secretaria d'Universitats i Recerca del Departament d'Economia i Coneixement of the Catalan Government for the pre-doctoral FI grant No. 2017FI_B00243.

REFERENCES

- 1. Directive 2002/49/EC of the European Parliament and of the Council of 25 June 2002 relating to the assessment and management of environmental noise. Official Journal of the European Communities, L189/12, (2002).
- 2. D.Lgs. 08/19/2005 n.194. Attuazione della direttiva 2002/49/CE relativa alla determinazione e alla gestione del rumore ambientale, Gazzetta ufficiale della Repubblica Italiana n° 222, (2005).
- 3. Bellucci P., Peruzzi L. The Life Dynamap project: towards the future of real time noise mapping. Proc of the 22nd International Congress on Sound and Vibration; Florence, Italy, 12-16 July, (2016).
- 4. Zambon G., Benocci R., Brambilla G. Statistical Road Classification Applied to Stratified Spatial Sampling of Road Traffic Noise in Urban Areas. Int. J. Environ. Res. 2016; 10(3):411-420.
- 5. Zambon G., Benocci R., Brambilla G. Cluster categorization of urban roads to optimize their noise Monitoring. Environ. Monitoring Assessment 2016; 188(26): DOI 10.1007/s10661-015-4994-4
- 6. Zambon, G., Benocci, R., Bisceglie A., 2015. Development of optimized algorithms for the classification of networks of road stretches into homogeneous clusters in urban areas. In: The 22nd ICSV, Florence, Italy, 2015.
- 7. Zambon, G., Benocci, R., Angelini, F., Brambilla, G., Gallo, V., 2014. Statistics-based functional classification of roads in the urban area of Milan. In: The 7th Forum Acusticum, Krakow, Poland, 2014.
- 8. Zambon, G., Benocci, R., Bisceglie A., Roman, H. E., 2016. Milan dynamic noise mapping from few monitoring stations: Statistical analysis on road network. In: The 45th INTERNOISE, Hamburg, Germany, 2016.

- 9. Zambon G. et Al. Traffic noise monitoring in the city of Milan: construction of a representative statistical collection of acoustic trends with different time resolutions, Proceedings of the 23rd International Congress on Sound and Vibration, Florence, Italy, 12–16 July, (2015).
- 10. Socoró J.C., Ribera G., Sevillano X., Alías F. Development of an anomalous noise event detection algorithm for dynamic road traffic noise mapping, Proceedings of the 23rd International Conngress on Sound and Vibration, Florence, Italy, 12–16 July, (2015).
- 11. Mermelstein, P.: Distance measures for speech recognition--psychological and instrumental. Pattern Recognition and Artificial Intelligence, 374--388 (1976)
- 12. Valero, X., Alias, F.: Gammatone Cepstral Coefficients: Biologically Inspired Features for Non-Speech Audio Classification. IEEE Transactions on Multimedia 14 (6), 1684--1689 (2012)
- 13. Orga, F.; Socoró, J.C.; Alías, F.; Alsina-Pagès, R.M.; Zambon, G.; Benocci, R.; Bisceglie, A. Anomalous Noise Events Considerations for the Computation of Road Traffic Noise Levels: the DYNAMAP's Milan case study, *Proceedings of the 24th International Congress on Sound and Vibration*, London (UK), July 2017 (to appear).
- Alías, F.; Socoró, J.C. Description of Anomalous Noise Events for Reliable Dynamic Traffic Noise Mapping in Real-Life Urban and Suburban Soundscapes. Applied Sciences, vol. 7, pp. 146, www.mdpi.com/2076-3417/7/2/146, (2017).
- 15. Xavier Sevillano, Joan Claudi Socoró, Francesc Alías, Patrizia Belucci, Laura Peruzzi, Simone Radaelli, Paola Coppi, Luca Nencini, Andrea Cerniglia, Alessandro Bisceglie, Roberto Benocci and Giovanni Zambon; "DYNAMAP Development of low cost sensors networks for real time noise mapping", Noise Mapping (Special Issue on Environmental noise aspects in EU funded projects), Volume 3, Issue 1, pp. 172-189, (De Gruyter Open), May
- 16. Creixell, E.; Haddad, K.; Song, W.; Chauhan, S.; Valero, X. A method for recognition of coexisting environmental sound sources based on the Fisher's Linear Discriminant classifier. Proceedings of INTERNOISE, 2013, Innsbruck (Austria).
- 17. M.L. Zhang, and Z.H. Zhou. *A k-nearest Neighbor Based Algorithm for Multi-label Classification*. 2005 IEEE international conference on granular computing. Vol. 2. IEEE, 2005.
- 18. Bellucci P., Peruzzi L. Zambon G. Dominguez X. S., Basic secondary aspects of the Life Dynamap project. Proc of the 22nd International Congress on Sound and Vibration; Florence, Italy, 12-16 July, (2016).
- 19. Bellucci P., Peruzzi L. Zambon, G., LIFE DYNAMAP: an overview of the project after two years working. In: the 45th INTERNOISE Congress, Hamburg, Germany, (2016).