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Cross-calibration of participatory sensor networks for environmental noise mapping

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ABSTRACT

Participatory measurements appear as a promising technique for performing noise mapping and monitoring. However, the confidence in the quality of raw data collected through participatory measurements controls the faithfulness of the output noise maps. In this paper, a cross-calibration method is proposed, which aims at both selecting the best candidate sensors and improving the furnished raw data. The method rests upon four steps: (i) an outlier detection, (ii) the crowd sensors-based correction, (iii) a fixed sensors-based correction, and (iv) the L_{den} estimation. The efficiency of the approach for different characteristics of the network of mobile sensors is evaluated on its ability to reconstruct an artificial reference sound field, which consists of the one-month L_{10s} evolution, on a twenty streets network. The main conclusions are: (i) the systematic errors of the sensors can be efficiently corrected by a cross-calibration method, and thus do not affect the L_{den} estimation, (ii) the fixed sensor network helps estimating the average error of the network of mobile sensors, (iii) the dispersion in an individual sensor measurements, which is due for example to the operator, stands for a much more critical concern and should be flagged by a rigorous outlier detection method, as the one proposed in this paper, (iv) although individual measures are improved by the proposed cross-calibration, some errors remain on the L_{den} estimation because of the shortness of the collected samples, (v) increasing the number of sensors does not improve the L_{den} estimation as long as individual measurements dispersions remain too large.

1. Introduction

The knowledge of urban sound levels is a crucial step towards the proposal of noise mitigation plans. The Directive 2002/49/EC, which requires that European cities of more than 100 000 inhabitants elaborate and broadcast strategic noise maps, contributes to this knowledge [1]. Although noise maps are currently mainly obtained through noise sources (road traffic, trains, aircrafts and industries) and sound propagation modelling [2,3], participatory noise measurement is increasingly considered as a possible alternative to these traditional approaches. Such measurements are made possible by the wide development of smartphone technologies, which integrate on the same apparatus multiple sensors including a Global Position System (GPS) and a microphone. Thereby participatory noise measurement would potentially offer three main advances: (i) the expected high number of volunteers guarantees both good spatial and temporal coverages, (ii) measures are sensible to all the noise sources that compose urban sound environments while traditional methods are restrained to the modelled sources (excluding voices, birds, human activities, wind, fountains, helicopters, etc.), (iii) participatory measurements give the opportunity for the citizen to play a dual role of consumer and producer of environmental information.

In view of these new potentialities, numerous smartphone applications were recently developed for the purpose of acoustic data acquisitions, e.g. NoiseTube [4,5], WideNoise [6], NoiseSpy [7], NoizCrowd [8], EarPhone [9,10], etc. The possibility to build noise maps based on participatory sensing is now proven [5]. However the quality of the collected data has not been regarded sufficiently yet, limiting the level of confidence of the maps already produced. The use of smartphones for the purpose of acoustic measurements gives rise indeed to several metrological questions, in particular about the directivity and the accuracy of the microphones, and representativeness questions because of the shortness of the measurement samples, which make them hardly representative of the sound environments [11,12]. Participants themselves stand for a key point of the measurement protocol. The acquisition

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can be triggered at a time when the smartphone is held in the palm in good measurement configuration or, on the contrary, buried in a pocket, or worn by the user in communication situation. To avoid these difficulties, a set of modules based on signal processing to capture measurement configuration information was designed in [13]. Even when the measure is undertaken under good condition, it is sensitive to the protocol followed by the operator [14].

For all the above reasons, a high dispersion can be observed in measurements if different devices and noise measurement applications are used [13]. This dispersion could theoretically be reduced thanks to calibration processes. An individual calibration was shown to be efficient in [15], restraining however measurements to the case when identical smartphones and applications are used by all the participants. Nonetheless, the calibration offset can even differ with identical mobile phones and applications [10]. Moreover, individual calibration is an expensive and time consuming process, which loses in efficiency if apparatus deviate with time or produce dispersed data. Finally, dispersion linked to the operator seems difficult to handle.

In this paper, a noise sensors cross-calibration method is proposed, which aims at working on a network of mobile sensors that is not necessarily previously calibrated. The sensors considered are typically smartphones, but could be as well low cost noise sensors from consumer electronics, which are gaining interest in noise monitoring [16]. The hypothesis that each individual measure can be calibrated relatively to the measures given by the network of mobile sensors, is investigated through the reconstruction of a noise map, which aims to be as similar as possible to a reference one. The difficulty encountered for evaluating the accuracy of the produced noise maps stands in that it would theoretically require knowing the actual noise levels at every point of the map at given periods, which is of course an unavailable information. In this paper, a simulated urban sound field is created, which is conceived to follow real urban sound levels space and time variations. Thus, reference noise levels are made artificially available at every point of the map and at each instant. Raw data post-treatments methods are then assessed on their ability to satisfactorily estimate the reference noise map, for different characteristics of the network of mobile sensors (number of sensors, accuracy, dispersion, etc.). Section 2 explains the artificial sound field conception and details the study. Section 3 proposes an outlier detection method. Section 4 compares the sensor cross-calibration methods. Section 5 gives practical results about the convergence of the noise maps produced. Lastly, Section 6 discusses the results and the required further researches.

2. Principle

The study consists in the estimation of a noise map, which aims to be as similar as possible to the reference artificial sound field detailed in Section 2.1. The noise maps produced rely on both a network of mobile sensors (detailed in Section 2.2) and a network of fixed sensors (detailed in Section 2.4). The measurement process described in Section 2.3, and the indicators used to test the quality of the produced maps are detailed in Section 2.5. The post-treatment of the raw data collected and the noise maps elaboration are described in Section 2.6.

2.1. Creation of a reference artificial sound field

The urban area simulated consists of a 500 m × 500 m square, made of 10 horizontal streets and 10 vertical streets, distant by 50 m. Each street is discretized with a spatial resolution of 25 m, constituting a map of 297 points. A reference urban sound field is created, which represents at each of these 297 points the $L_{Aeq,10s}$ evolution for a duration of 30 days. An aggregation time of 10 s is chosen, which is supposed to be the minimum measurement length and is compatible with usual mobile measurements time resolution [17,18].

The sound field does not follow classical emission and propagation calculations, but is constructed instead by summing the expected contribution on overall sound levels of permanent sources (mainly road traffic, but also additional sources such as birds and voices) and episodic sources (schools, working zones, air-traffic), with respect to the usual sound levels time variations observed in urban areas [12].

First, the contribution of the permanent sources is simulated as follows:

– The daily average 1 h-noise pattern R_u of each of the 20 streets u is generated randomly, as a linear combination between R_{min} and R_{max}, with:

$$R_u = \alpha_u R_{max} + (1-\alpha_u) R_{min}, \tag{1}$$

where α_u is a uniform random number between 0 and 1. R_{min} and R_{max} are designed following classical urban street characteristics, R_{max} corresponding to a busy ring road and R_{min} to a calm residential street [12,19], as depicted in Fig. 1;

– The daily average 1 h-standard deviation pattern $\sigma_{Leq,10s,u}$ of each street u is generated randomly, as a linear combination between $\sigma_{Leq,10s,min}$ and $\sigma_{Leq,10s,max}$, with:

$$\sigma_{Leq,10s,u} = \alpha'_u\ \sigma_{Leq,10s,max} + (1-\alpha'_u)\ \sigma_{Leq,10s,min}, \tag{2}$$

where σ'_u is a uniform random number between 0 and 1. $\sigma_{Leq,10s}$ represents the standard deviation of the $L_{Aeq,10s}$ values corresponding to the permanent sources, for a given 1 h time-slot. This deviation is due to the combination of the randomness of the traffic flow (speed and flow rate variations, noisy vehicles...) and additional noise sources (birds, voices, human activities, etc.). $\sigma_{Leq,10s,min}$ and $\sigma_{Leq,10s,max}$ comply with classical urban street noise deviations, as depicted in Fig. 1 [12];

– The 1-h time-series of sound levels $L_{Aeq,1h}$ are generated at each point, with $L_{1h} = R_u + \mu_{1h}$, where μ_{1h} is a series of normal random numbers with a standard deviation of 1, to account for the time-series variation from one day to the other.

– Finally, the time-series contribution of the permanent sources $L_{Aeq,10s,perm}$ is generated at each point, as $L_{Aeq,10s,perm} = L_{1h} + \mu_{10s,perm}$, where $\mu_{10s,perm}$ is a series of normal random numbers with a standard deviation of $\sigma_{Leq,10s,u}$.

Then, the contribution of 7 additional episodic sources is simulated, which aim at mimicking particular urban sound sources, namely schoolyards, air-traffic (e.g. helicopters) and working zones. The modelling of these source contributions is really simplified, but conceived to add a spatiotemporal sound levels variability that is usually observed in urban areas and that complicates the elaboration of noise maps based on participatory measurements. Each source is defined by its location, period of the day and duration, and produces a time series $L_{Aeq,10s,\ source} = L_{source} + \mu_{source}$, where μ_{source} is a series of normal random numbers with a standard deviation of σ_{source}, with source = {1...7}. The characteristics of the 7 sources are detailed in Table 1. Three similar schoolyards and working zones are simulated introducing surface sources with a radius of 50 m and are not supposed to affect the zone outside the defined circles. Each of these sources is located at a fixed position, which is chosen randomly among the locations where $L_{Aeq,8h\text{-}18h,perm} < 70$ dB. This simplified modelling is preferred to a theoretical geometric attenuation calculation, as it increases the influence of the source on the spatial sound levels variability. Air-traffic sources are defined as punctual sources, which impact the surroundings $L_{10s,P}$ time series at each point P of the simulated