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Airport take-off noise assessment aimed at identify responsible aircraft classes

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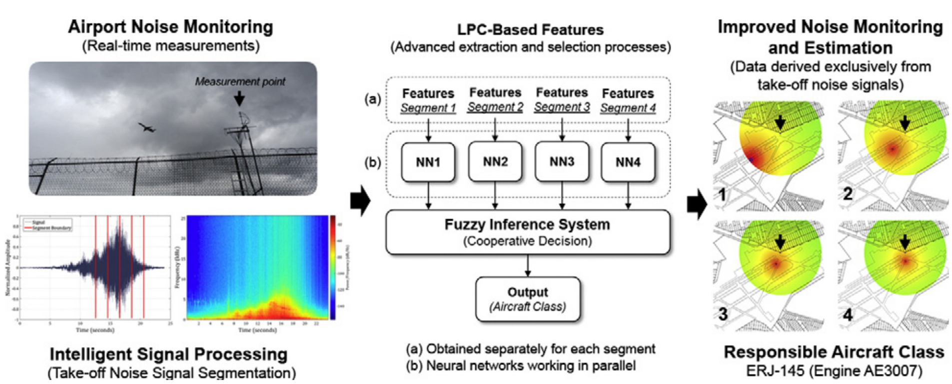
HIGHLIGHTS

- Support for airport noise monitoring
- Airport take-off noise assessment
- Real time environmental noise measurements
- Intelligent digital processing of take-off noise signals
- Aircraft class recognition using a neural-fuzzy model

GRAPHICAL ABSTRACT



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ABSTRACT

Assessment of aircraft noise is an important task of nowadays airports in order to fight environmental noise pollution given the recent discoveries on the exposure negative effects on human health. Noise monitoring and estimation around airports mostly use aircraft noise signals only for computing statistical indicators and depends on additional data sources so as to determine required inputs such as the aircraft class responsible for noise pollution. In this sense, the noise monitoring and estimation systems have been tried to improve by creating methods for obtaining more information from aircraft noise signals, especially real-time aircraft class recognition. Consequently, this paper proposes a multilayer neural-fuzzy model for aircraft class recognition based on take-off noise signal segmentation. It uses a fuzzy inference system to build a final response for each class p based on the aggregation of K parallel neural networks outputs O_p^k with respect to Linear Predictive Coding (LPC) features extracted from K adjacent signal segments. Based on extensive experiments over two databases with real-time take-off noise measurements, the proposed model performs better than other methods in literature, particularly when aircraft classes are strongly correlated to each other. A new strictly cross-checked database is introduced including more complex classes and real-time take-off noise measurements from modern aircrafts. The new model is at least 5% more accurate with respect to previous database and successfully classifies 87% of measurements in the new database.

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1. Introduction

Assessment of aircraft noise has become a major concern for airports and aeronautical authorities (ICAO, 2007; ICAO, 2008a,b; DCA Nighttime Noise Rule MWAA, 1981; MASSPORT, 2015a), which is part of the efforts to fight environmental noise pollution, especially given the growing proximity between major cities and airports (López-Pacheco et al., 2014; Sánchez-Fernández, 2011; Sánchez-Fernández et al., 2013). This evaluation commonly requires noise monitoring or estimation around the airport and depends on matching noise levels to the generating aircraft class (SAE, 2012a,b). In this respect, many major airports have built noise monitoring systems using permanent or moving measurement positions since airport noise regulations and charges are very strict (MWAA, 2015; MASSPORT, 2015b). Generally, these systems require external non-related noise inputs for matching noise levels at certain position with the responsible aircraft class, i.e., the noise signal is only used for computing statistical indicators. Also, multiple models for computing noise contours around airports have been defined (SAE, 1986; ICAO, 2008c; ECAC, 2005a,b; FAA, 2013). In this case, the noise estimation is based on single events modeling according to default or typical operations. That is to say, a subset of the total airport traffic is defined using an expected number of operations by aircraft class so that the flight path, mass and operating procedure are considered identical within the subset. Then, the noise level at the observer location is computed based on tabulations of the maximum instantaneous level (L_{max}) or exposure level (L_E) as functions of propagation distance d for specific airplane types, variants, flight configurations and power settings P. Likewise, these models do not use the aircraft noise signal produced by real events. In this sense, many approaches have been considered in order to obtain more information from the aircraft noise recorded and either build self-contained noise monitoring systems or improve noise estimation around airports.

One of the aforesaid approaches is the real-time aircraft class recognition based on features obtained from the take-off noise signal, i.e., now real-time measurements not only make available noise levels calculation but also provide the airplane type producing it (Sánchez-Fernández et al., 2007; Rojo Ruiz et al., 2008). Also, a passive acoustic method for aircraft states estimation based on the Doppler Effect is proposed in Martin et al. (2014). A microphone array is also used for aircraft tracking in Martín et al. (2013), active control of aircraft fly-over sound transmission through an open window in Pàmies et al. (2014) and a thrust reverse noise detection system in Asensio et al. (2013). Likewise, geo-referenced flight path estimation during take-off can be done by means of aircraft noise measurements using a microphone array as demonstrated in Sánchez-Pérez et al. (2014), something of particular interest for noise certifications procedures where the correlation between aircraft class, flight path and noise level at certain points has to be performed without using aircraft navigation systems data (http://www.gpo.gov/fdsys/granule/CFR-2011-title14-vol1/CFR-2011-title14-vol1-part36). Moreover, discrimination between aircraft noise and non-aircraft sources have been explored in Genescà et al. (2009), Genescà et al. (2013) and Asensio et al. (2010), examining the direction of arrival of the recorded signals. In fact, the Metropolitan Washington Airports Authority (MWAA) maintains an aircraft noise monitoring system displaying community noise level at monitor locations splitting overflights from non-aircraft sources (MWAA, 2015).

Although some of the previous information might be obtained from cooperative airport authorities, airlines, airplanes equipped with ADS-B (Richards et al., 2010) or advanced radar data, the methods and algorithms aforesaid are applicable to other environmental issues such as the light rapid transit noise impact or those problems where noise signals are the only source of information such as gunshot localization and weapon identification (George and Kaplan, 2013; Sallai and Hedgecock, 2011; Donzier and Cadavid, 2005). Besides, since aircraft noise monitoring systems analyze the signals in order to compute statistical indicators, using models and methods for getting more information from those signals adds potentiality and robustness without excluding the possibility of validation from multiple information sources.

Concerning aircraft class recognition, models based on the feature extraction from K adjacent take-off noise signal segments have proven to outperform those using the whole signal (Sánchez-Pérez et al., 2013). Neural networks have been used with excellent results in Sánchez-Fernández et al. (2007), ,Sánchez-Pérez et al. (2013), Sánchez Fernández et al., 2013 and Márquez-Molina et al., 2014). Moreover, the pattern recognition model introduced in Sánchez-Pérez et al. (2013), which is based on signal segmentation in time, uses a neural network NN_k regarding each segment k for evaluating LPC-based features (Linear Predictive Coding). Additionally, human auditory features such as MFCC (Mel Frequency Cepstral Coefficients) and 1/24 Octave Bands are concurrently evaluated in Márquez-Molina et al. (2014) by two parallel neural networks. All models include an aggregation algorithm to build a final response from the multiple outputs produced by all neural networks. Aggregation in Sánchez-Pérez et al. (2013) is based on a dynamic weighting of the output O_p^k for class p from the neural network NN_k regarding signal segment k. However, weights w_p^k for output O_p^k are the same for all aircraft classes $p = 1,2,\ldots,P$. On the other hand, aggregation in (Márquez-Molina et al., 2014) is based on the weighted sum $\sum_k w_p^k O_p^k$, but weights w_p^k are static and do not change according to context (in this case k represents the feature type used). Outputs aggregation is highly important given that involves weighting several answers over the same space $p = 1,2,\ldots,P$ including misclassifications. So far the algorithms proposed in Sánchez-Pérez et al. (2013), Sánchez Fernández et al. (2013) and Márquez-Molina et al. (2014) only allow weighting each class p separately, so that associations between outputs O_p^k and O_{p+n}^k from same neural network NN_k are not considered. Moreover, earlier algorithms are not design to offset the best individual classifier with respect to class p (i.e. the highest weighted) when it outputs an erroneous high value for that same class p. In this paper a multilayer neural-fuzzy model for aircraft class recognition based on signal segmentation is proposed. The model uses neural networks and fuzzy logic sequentially, taking advantage of generalization and fuzzy inference under cognitive uncertainty regarding neural networks performance. It uses fuzzy aggregation of multiple outputs O_p^k for building a final output with respect to class p.

The remainder of the paper is organized as follows. Section 2 gives a detailed explanation of the proposed multilayer neural-fuzzy model based on signal segmentation and the theoretical and practical justification. Section 3 reports extensive experiments of the proposed model and existing models over real-world take-off noise measurements, followed by the conclusions drawn in Section 4.

2. Proposed model

Aircraft take-off noise is a non-stationary signal that varies both in frequency and amplitude during a take-off. This variation mainly depends on the take-off flight path and a particular combination of factors such as the sound generating mechanisms, Doppler Effect, atmospheric attenuation, lateral attenuation (SAE, 2006), among others. A complete review of the aircraft take-off noise can be found in Sánchez-Pérez et al. (2013).

Since aircraft class recognition using take-off noise signals have been mainly associated with spectral analysis, using the whole signal could involve masking certain temporal features. Signal segmentation is equivalent to split the aircraft take-off into different flight stages containing unique temporal features. Fig. 1 illustrates the abovementioned through the spectrogram of an Airbus A320-211 take-off noise signal, measured with sampling rate of 51.2 kHz and 24-bit resolution during 24 s. The model presented in this paper uses the signal segmentation described next. A further analysis of the take-off noise signal segmentation is provided in Sánchez-Pérez et al. (2013).