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Dynamic hierarchical aggregation of parallel outputs for aircraft take-off noise identification

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ABSTRACT

Assessment of airport noise pollution mainly depends on the correlation between aircraft class, noise measured and flight path geometry. Regulation, evaluation and especially certification procedures generally establish that previous correlation cannot be carried out using aircraft navigation systems data. Additionally, airport noise monitoring systems generally use aircraft noise signals only for computing statistical indicators. Consequently, methods to acquire more information from these signals have been explored so as to improve noise estimation around airports. In this regard, this paper introduces a new model for aircraft class recognition based on take-off noise signal segmentation and dynamic hierarchical aggregation of K parallel neural networks outputs O_p^k. A single hierarchy is separately defined for every class p, mainly based on the recall and precision of neural network $NN_k|k=1,2,\ldots,K$. Similarly, the dynamics proposed is also particular to each class p. The performance of the new model is benchmarked against models in literature over a database containing real-world take-off noise measurements. The new model performs better on the abovementioned database and successfully classifies over 89% of measurements.

1. Introduction

Noise pollution around airports is a growing concern for aeronautical authorities (ICAO, 2007, 2008a, 2008b; MASSPORT, 2015b), which has been addressed in the same way as other environmental issues in order to lower noise contamination in large cities (Elmenhorst et al., 2012; López-Pacheco et al., 2014; Sánchez-Fernández, 2011; Sánchez-Fernández et al., 2013). For instance, a noise regulation at the Ronald Reagan National Airport in Washington D.C. restricts nighttime operations of aircraft classes that do not comply with certain noise certification levels (MWAA, 1981). Additionally, the International Civil Aviation Organization (ICAO) encourages noise-related charges associated with landing fees, possibly by means of surcharges or rebates (ICAO, 2012). In this respect, several major airports have implemented monitoring systems to assess environmental noise pollution (MASSPORT, 2015a; MWAA, 2015). Furthermore, multiple models for computing noise contours around airports have been defined (ECAC, 2005a, 2005b; FAA, 2013; ICAO, 2008c; SAE, 1986, 2012a, 2012b). Previous approaches correlate noise statistical indicators such as the equivalent continuous sound level (L_{eq}) or the effective perceive noise level (L_{EPN}) with the aircraft class responsible by means of single events modeling according to default or typical operations.

In any of the above cases, aircraft noise signals are only used for computing statistical indicators. In this sense, many approaches have been designed so as to obtain more information from these signals. For example, methods to identify the aircraft class using feature extraction from take-off noise signals have been developed (Márquez-Molina et al., 2014; Rojo Ruiz et al., 2008; Sánchez-Fernández et al., 2007, 2013; Sánchez-Pérez et al., 2013). In addition, microphone arrays have been used for creating a passive acoustic method for aircraft states estimation based on the Doppler Effect in Martin et al. (2014), a trust reverse noise detection system in Asensio et al. (2013) and active control of aircraft fly-over sound transmission through an open window in Pàmies et al. (2014). Similarly, a method to estimate the georeferenced flight path during take-off is introduced in Sánchez-Pérez et al. (2014), something relevant for noise certification procedures, where the flight path determination in order to correlate noise

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levels produced by a particular aircraft class at certain points, must be performed without the aircraft navigation system data (FAA and DOT, 2014). Also, discrimination between aircraft noise and non-aircraft sources has been explored in Asensio et al. (2010) and Genescà et al. (2013, 2009). In this sense, the Metropolitan Washington Airports Authority (MWAA) holds an aircraft noise monitoring system displaying community noise levels splitting overflights from non-aircraft sources (MWAA, 2015).

Concerning aircraft class identification, models based on feature extraction from adjacent take-off noise signal segments have proven to outperform recognition using the whole signal (Sánchez-Pérez et al., 2013). The motivation for segmentation arises from considering the aircraft take-off noise as a non-stationary process with a dynamic spectrum. Its main goal is splitting the signal into K segments with different spectral characteristics. Neural networks have been used with excellent results in order to identify aircraft classes based on supervised training using patterns containing features extracted from the take-off noise signal (Márquez-Molina et al., 2014; Sánchez-Pérez et al., 2013; Sánchez Fernández et al., 2013). Moreover, the pattern recognition model introduced by Sánchez-Pérez et al. (2013) uses a neural network NN_k for each signal segment k and LPC-based features (Linear Predictive Coding). Also, 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 neural networks. Both models define an aggregation algorithm for weighting the multiple outputs produced by all neural networks. Aggregation in Sánchez-Pérez et al. (2013) is based on a dynamic weighting of output O_p^k with respect to class p from the neural network NN_k, which is trained to deal with LPC-based features from signal segment k. However, weight w_p^k for output O_p^k is the same for every aircraft class $p=1,2,\dots,P$. 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 weight w_p^k is static and does not change according to context (in this case k represents the feature type used). Moreover, the previous aggregation methods are not designed to offset the best classifier with respect to class p when it outputs a false positive for that same class p. What is more, weight w_p^k is computed taking into account only true positives with respect to class p.

In this paper a new model for aircraft class identification based on take-off noise signal segmentation and dynamic hierarchical aggregation of K parallel neural networks outputs O_p^k is proposed. The model dynamically weighs each output O_p^k from neural network NN_k with respect to class p based on a neural network hierarchy. The hierarchy is determined based on a ranking criterion separately defined for every class p according to the validation performance during training. The ranking criterion introduced in this paper is based on the score F_β which uses recall and precision measures with respect to each class p.

The remainder of the paper is organized as follows. Section 2 reviews aircraft class recognition based on take-off noise signal segmentation. Section 3 provides a detailed theoretical and practical definition of the new model. Section 4 presents the new model results along with the comparison against the literature model followed by the conclusions drawn in Section 5.

2. Review

Aircraft class identification using take-off noise signals has been mainly based on the extraction of features related to the signal spectrum. However, the aircraft noise signal is a non-stationary process that leads to a variable spectrum during take-off. In this respect, a take-off noise signal segmentation method is introduced by Sánchez-Pérez et al. (2013). Its motivation arises from assuming that using the whole signal could involve masking certain temporal features. The earlier segmentation method extracts two segments of two second on both sides of T_{mid} ($K=4$), which is a common point for all signals determined as the time instant corresponding to the local maximum, higher or equal to 0.85[max $E(q)$] with highest $Z(q)$ value, where $E(q)$ is the energy profile calculated using (1) and $Z(q)$ is the zero crossing profile computed using (2) and (3).

$$E(q) = \sum_{x=l}^{l+S_E} |y(x)|^2 \tag{1}$$

$$F(x) = \begin{cases} 1, & \text{sign}[y(x)] \neq \text{sign}[y(x+1)] \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$Z(q) = \sum_{x=l}^{l+S_E-1} F(x) \tag{3}$$

$$\forall q \mid q = 1,2,\cdots,\left\lfloor \frac{(N-S_E)}{S_E(1-O_{S_E}/100)} \right\rfloor;$$

$$l = (q-1)\left(S_E\left(1-\frac{O_{S_E}}{100}\right)\right)$$

where q denotes a fragment of the signal $y(x)$, S_E represents the q fragment length, N denotes the signal length, sign[] symbolizes the sign operator, O_{S_E} indicates the overlapping percentage, and $\lfloor\rfloor$ denotes the lower nearest integer.

The recognition model introduced by Sánchez-Pérez et al. (2013) defines a neural network NN_k for each signal segment k. In this work, outputs from NN_k with respect to each aircraft class $p=1,2,\dots,P$ are referred as O_p^k. The foregoing model introduces the dynamic hierarchical weighting of outputs O_p^k according to (4) and (5). The predicted label y for an input $\{x_1,\dots,x_K\}$ is estimated after neural network NN_k has evaluated pattern x_k resulting in ,O_p^k which is dynamically weighted by $w_k+f(k)$. Value of w_k is computed with (6) based on the validation error e_k of neural network NN_k during training, while function $f(k)$ returns an adjustment factor α_k according to the two prior lower ranked networks outputs $O_p^{i|\vec{r}_{(i)}=\vec{r}_{(k)}-2}$ and $O_p^{j|\vec{r}_{(j)}=\vec{r}_{(k)}-1}$. Value α_k is calculated using (7). Vector $\vec{r}$ represents neural networks $NN_k|\ k=1,2,\dots,K$ ranks according to weights $w_k \mid k=1,2,\dots,K$ so that $\vec{r}_{(k)}$ contains the ascendant sorted position of weight w_k as revealed in (8) and (9). Therefore, component $\vec{r}_{(k)}$ denotes the rank of neural network NN_k where a higher value indicates a higher importance and rank.

$$y(x_1,\dots,x_K) = \underset{p=1,2,\dots,P}{\operatorname{argmax}} \left\{ \left(\begin{bmatrix} O_1^1 & O_1^2 & \cdots & O_1^K \\ O_2^1 & O_2^2 & \cdots & O_2^K \\ \vdots & \vdots & & \vdots \\ O_P^1 & O_P^2 & \cdots & O_{p=P}^{k=K} \end{bmatrix} \begin{bmatrix} w_1+f(1) \\ w_2+f(2) \\ \vdots \\ w_{k=K}+f(K) \end{bmatrix} \right) \right.$$

$$\left. \times \left(1/\sum_{k=1}^{K}(w_k+f(k)) \right) \right\} \tag{4}$$