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Aerospace Science and Technology
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A two-step approach for the prediction of dynamic aircraft noise impact

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ARTICLE INFO

Article history:
Received 6 January 2015
Received in revised form 11 March 2016
Accepted 14 October 2016
Available online xxxx

Keywords:
Differential flatness
Neural networks
Aircraft noise level

ABSTRACT

Noise impact on surrounding areas of airports has become an important issue with direct consequence on their potential of development. Accurate predictions of the noise levels generated all around an airport area by approaching, landing and departing aircraft are necessary for the effective evaluation of the noise impact of new traffic scenarios as well as new departure/approach procedures. The noise levels associated to traffic scenarios have been computed in general using static models while applying an arbitrary night penalty to compute a daily noise impact index. In this communication a two-step approach to get predictions of the aircraft noise level time series at a given location is described. The proposed approach is based on the dynamic relations between aircraft flight parameters and the corresponding flyable 4D trajectories. First, the differential flatness property of flight guidance dynamics is used to generate from the considered 4D trajectories, the successive values of the main aircraft noise causal factors. These values are then submitted to a neural estimator which generates the prediction of the noise level evolution produced at a given location by an aircraft. Then summing up the effects of each nearby aircraft, the evolution of noise levels at the location can be predicted. The approach can easily be extended to a grid of points, thus providing noise levels estimation at any location in an airport vicinity.

1. Introduction

The accurate prediction of noise exposure levels in the vicinity of airports resulting from traffic scenarios is necessary in order to search for strategies to restrain noise impact over the nearby population. This is specially important in the case of airports which are subject to fast increasing traffic or are introducing new aircraft and/or operational procedures. The estimation of noise exposure levels around airports has been done until recently through static models such as the Integrated noise model – INM [1]. Based on traffic scenarios, such software draw average noise exposure level curves around airports providing data mainly used to support airport traffic management studies and land use planning around airports. There a flight is considered as a succession of static situations and an estimation is performed by summing up the effects of these situations for each flight along day and night periods. In this approach, the time history of the noise level at given locations is not built and therefore not considered while it is known [2] that noise level history at a given point is a relevant input to compute an effective estimation of the resulting annoyance for people at this location. In this paper the problem of assessing the annoyance generated by noisy activities around airports such as aircraft landing and departing is not developed, see for that authors such as [3] and [4].

The generation, propagation and reception of aircraft noise result in a complex process subject to local conditions characterizing the considered area (topography, vegetation, buildings, etc.) and the weather at that time (humidity, wind, temperature, etc.). In standard conditions, the causal factors related to noise generation at a given location are relatively few. They are mainly related with the evolution of flight parameters such as aircraft attitude, angle of attack, airspeed and thrust regime, as well as changes in its surface such as the deployment of landing gear and high lift devices.

The proposed approach sketched in Fig. 1 is based on the differential flatness property [5] of the guidance flight dynamics of an aircraft with respect to its trajectory. This implies that it is theoretically possible, given a 4D trajectory to be followed by the aircraft, to compute the corresponding control inputs. These inputs associated with the flight conditions are characteristic of the generated noise. Then, a numerical input–output device, based on a multilayer neural network (NN), can be built to predict, using these

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http://dx.doi.org/10.1016/j.ast.2016.10.017
1270-9638/

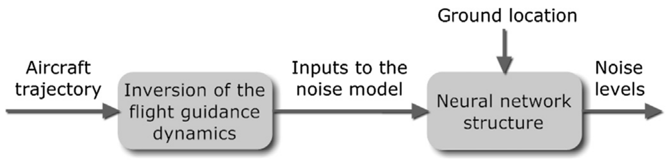

Fig. 1. Two-step approach for dynamic noise levels estimation.

computed control inputs, the corresponding noise level produced by an aircraft flying nearby a reference location. Such an approach should provide accurate predictions of the noise level histories at selected locations resulting from given traffic scenarios, providing then relevant noise data for annoyance estimation.

The paper is organized as follows: In Section 2, differential flatness is defined and some typical applications are discussed. In Section 3 the flight guidance dynamic equations are considered and analyzed. Section 4 discusses the feasibility of the inversion of flight guidance dynamics according to the differential flatness property. Section 5 describes the construction and validation of the neural noise estimator. Section 6 shows results of the comparison different approach procedures while Section 7 develops the prediction of the evolution of global noise impact at a given location. Conclusions are drawn in Section 8.

2. Differential flatness

In this section the definition of differential flatness is presented and a brief discussion of some main applications is provided.

2.1. Definitions

Consider a system whose dynamics can be described by a general analytical state equation:

$$\dot{\underline{x}} = f\left(\underline{x}, \underline{u}\right) \qquad \underline{x} \in \mathbb{R}^n, \quad \underline{u} \in \mathbb{R}^m \tag{1}$$

where $\underline{x}$ is the state vector and $\underline{u}$ is the control vector. The output vector $\underline{y}$, $\underline{y} \in \mathbb{R}^m$, is supposed to be such as:

$$\underline{y}_i = h_i\left(\underline{x}, \underline{u}\right), \quad i = 1, \ldots, m \tag{2}$$

The output vector $\underline{y}$, is said to be differentially flat for system (1) over a non-empty domain Δ if the state vector, the control vector and the output vector with a finite number of its derivatives δ, satisfy a relation such as:

$$G\left(\underline{x}, \underline{u}, \underline{y}, \dot{\underline{y}}, \ldots, \underline{y}^{(\delta)}\right) = 0 \tag{3}$$

where G is locally invertible with respect to $\underline{x}$ and $\underline{u}$ over the non-empty domain Δ [6]. If the components of the state vector $\underline{x}$ and of the control vector $\underline{u}$ can be expressed as functions of the flat outputs $\underline{y}$ and a finite number of their derivatives, i.e.:

$$x_i = \Phi_i\left(y_1, y_1^1, \ldots, y_1^{\mu_{i,1}}, y_m, \ldots, y_m^{\mu_{i,m}}\right) \quad i = 1, \ldots, n \tag{4}$$

$$u_j = \Psi_j\left(y_1, y_1^1, \ldots, y_1^{\nu_{j,1}}, y_m, \ldots, y_m^{\nu_{j,m}}\right) \quad j = 1, \ldots, m \tag{5}$$

where $\mu_{i,k}$ $i = 1, \ldots, n, k = 1, \ldots, m$ and $\nu_{j,h}$ $j = 1, \ldots, m$ and $h = 1, \ldots, m$, are integers, then $\underline{y}$, is said to be a *fully explicit flat* output vector for system (1).

When general condition (3) and condition (4) are satisfied while condition (5) is not, $\underline{y}$, is said to be a *control implicit flat* output vector for system (1). When general condition (3) and condition (5) are satisfied while condition (4) is not, $\underline{y}$, is said to be a *state implicit flat* output vector for system (1). Finally, when general condition (3) is satisfied while conditions (4) and (5) are not, $\underline{y}$, is said to be a *fully implicit flat* output vector for system (1).

2.2. Control of differential flat systems

The differential flatness theory has been developed to cope more efficiently with the control of a large class of nonlinear systems. The causal relationship between the input vector and the outputs is expressed by Equations (1) and (2) while the flatness property expressed by Relation (3) or in some cases by (4) and (5) provided that the inputs of the system for every instant of time can be found once feasible trajectories for the flat outputs are given. Then the flatness property gives warranty of the existence of an open loop control law making the flat outputs to follow a nominal trajectory. When flatness is fully explicit, this control law gets an analytical form (Relation (5)) while in a control implicit situation numerical devices such as neural networks must be used to perform the inversion and compute the corresponding control inputs [7]. It is important to notice that the local inversion characterizes the theoretical controllability of the non-linear system, although if the signals determined through the inversion go beyond physical limitations of the actuators, the proposed output trajectory will not be feasible. In general mathematical models of dynamic systems encompass approximations while the physical system may be subject to disturbances which are not considered in the modeling process. Thus, the flat control law must include a correction loop to account for the differences between the effective outputs and the expected ones, due to the effects of modeling errors and disturbances, and assure the stability of the outputs along their nominal trajectories.

The differential flatness property allows the representation of the state variables as a function of the outputs and their derivatives (see Equation (4)) and provides grounds for system monitoring. As an example, internal variables possess operational limitations such as maximum temperature and pressure, among others, on which it is possible to verify the feasibility of an output trajectory related to these restrictions. Considering also that Relation (4) corresponds to an analytical redundancy constraint, once the flat outputs and some of the state vector components are measured, the comparison between these values and those expected from this relation provides a basis to failure detection in non-linear systems.

In the present study, the differential flatness property is used to generate the values of the flight variables of an aircraft which are related to the noise it generates along its trajectory and distributes all around it.

3. Flight dynamics model

In this section are introduced the equations describing the guidance dynamics of transportation aircraft which are of main interest in this study [8,9]. These equations describe the relation between the aircraft attitude and total engine thrust and the trajectory followed by the aircraft.

The ground speed components of the aircraft in a local Earth frame are given by:

$$\dot{x} = V_a \cos\psi \cos\gamma + w_x \tag{6}$$

$$\dot{y} = V_a \operatorname{sen}\psi \cos\gamma + w_y \tag{7}$$

$$\dot{z} = -V_a \operatorname{sen}\gamma + w_z \tag{8}$$

where $(x, y, z)^T$ is the aircraft position (m), V_a is the air speed, ψ is the heading of the aircraft (rad), γ is the path angle (rad), w_x, w_y and w_z are the local wind components in the Earth's frame (m.s^{-1}).

The inertial speed V (m.s^{-1}) of the aircraft, the wind speed W (m.s^{-1}) and the air speed V_a (m.s^{-1}) of the aircraft are given respectively by: