Statistical Estimation of Aircraft Infrared Signature Dispersion

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1. Introduction

Knowledge of aircraft InfraRed Signature (IRS) is indispensable for assessing their detection probability, and thus their survivability in an hostile environment. By signature, we mean all the quantities for predicting the signal that would be observed by an optronic sensor when the aircraft is in its surroundings. For many reasons, the experimental approach is generally not feasible to evaluate the IRS dispersion. Computer programs, which enable to evaluate the IRS of aircraft and backgrounds, are therefore extremly valuable tools. Existing computer simulations of aircraft IRS [1] do not account for the dispersion induced by uncertainty on input data, such as aircraft aspect angles and meteorological conditions. As a result, they are of little use to estimate the detection performance of IR optronic systems: in that case, the scenario encompasses a lot of possible situations, that must indeed be addressed, but can not be singly simulated.
In this paper, a three-step methodological approach for predicting simulated IRS dispersion of poorly known aircraft is proposed. The first step is a sensitivity analysis, which identifies inputs that have negligible influence on the IRS and can be set at a constant value. The second step consists in a Quasi-Monte Carlo survey of the code output dispersion. In the last step, a metamodel of the IRS simulation code is constructed. This method is illustrated in a typical scenario, namely a daylight air-to-ground full-frontal attack by a generic combat aircraft flying at low altitude, and gives a satisfactory estimation of the infrared signature dispersion.

2. Sensitivity analysis with a fractional factorial design

A black box representation is associated to the IRS computer simulation code. We focus on a scalar response: the sensor differential irradiance between target and background. In order to simplify the analysis, only the 3-5 μm spectrally integrated target intensity is considered. Some inputs are set at a constant value by the scenario: they can not induce any uncertainty in IRS and are not taken into account in this statistical study. For our scenario, 28 input data are uncertain. Seven are related to flight conditions and aspect angles of the aircraft, such as the altitude, Mach number, or engine power setting. Nine describe IR optical properties of the various aircraft surfaces. Twelve are related to atmospheric conditions, such as visibility or relative humidity.
We assume that interactions among two or three factors can be significant, but that interactions involving more than three factors are negligible. We want to properly estimate factor effects and interactions between two factors, thus we make use of a 2048 runs fractional factorial design of resolution VI for 28 factors [2]. Each factor is described by two levels, which are specified thanks to knowledge on operational conditions and meteorological databases. We compute the aircraft IRS associated to the design of experiments, and analyze them through a second-degree polynomial model, under the assumption that the residuals are Gaussian.
The analysis of variance shows that 80 % of the IRS variance is explained with only five factors. We do not want to leave off potentially important factors, so we keep the ten most significant variables before going on to the next stage. These variables explain 95 % of the IRS variance: six are atmosphere related factors, and four are flight conditions variables. The factors associated to aircraft characteristics are not significant in this scenario, because most of the aircraft properties have been supposed to be perfectly known, and thus do not appear in the sensitivity analysis. Other conclusion could be raised, if the aircraft was considered less known.

3. Quasi-Monte Carlo estimation of the IRS dispersion

The performance criterion associated to an optronic sensor, when the observed IRS is scalar, simply consists in the probability that the sensor irradiance produced by the aircraft is below some given threshold α, which represents the background clutter. A well-known tool to estimate such non-detection probabilities is the Monte Carlo stochastic sampling. The main drawback of this method is the slow convergence, scaling asymptotically with the inverse square root of the number of samples and starting from what is often a large initial error. We thus rely on an alternative approach, the Quasi-Monte Carlo method, which makes use of a slightly different kind of sampling: the pseudo-random numbers are replaced with uniformly distributed determinist sequences, the low discrepancy sequences, to improve the accuracy of approximations, for a fixed number N of simulation runs. The discrepancy is a measure of the uniformity of the points dispersion. The determinist nature of these sequences is a major drawback for confidence intervals estimation, but randomization methodologies have been developed: they preserve the low discrepancy and add randomness.
In this study, we use a scrambled Faure's sequence, with a Faure-Tezuka scrambling [3]. The N outputs $(y_1,y_2,...,y_N)$ computed enable to estimate:

- the cumulative distribution function of the IRS for our scenario,
- the non-detection probability P_α by:

$$P_{\alpha N} = \frac{1}{N}\sum_{i=1}^{N} I\left(\left|IRS\left(X_{1i},...,X_{10i}\right)\right| < \alpha\right),$$

where I stands for the indicator function and $X_1,...,X_{10}$ are the ten significant factors.

One single simulation run takes about five minutes, we thus limit N to 10000. The non significant input variables are fixed at a constant value. Among the ten most significant variables, only four can not be described by a uniform law. These factors are related to atmospheric conditions, and are dependent. We can find their values in meteorological databases, but we have not found enough data yet to estimate a joint probability density function. We thus perform random sampling with replacement from the database to obtain a combination of real values, instead of using scrambled Faure's sequences for these factors.

4. A neural network metamodel

In order to check whether some optronic sensor meets required specifications, we do not need accurate estimations of extreme IRS values. It is therefore of great interest to build a metamodel of the IRS simulation code, suited to a chosen scenario, and to save the use of the much more expensive simulation for IRS close to typical detection thresholds.
Our computer simulation of aircraft IRS is complex, we thus preferred nonlinear modeling. Neural network metamodels [4] give very satisfying IRS predictions. The input data are the ten most significant factors of § 2, they are reduced and centered. A single-layer perceptron with seven hidden neurons and 4000 training samples, chosen by random sampling among the 10000 of § 3, enables to estimate non-detection probabilities, for the 6000 remaining test samples, with errors in the order of 0.5 %.

Bibliography

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