Optimization of Radiation Model of Infrared Decoy with Neural Network

Guanwu Zhou

College of Computer Science, Xi'an Shiyou University, Xi'an, Shaanxi Province, 710065, P. R. China.
Email: Zhougw@xsyu.edu.cn

Abstract. In this paper, a numerical model is proposed to calculate the infrared radiation characteristics based on the solution of radioactive transport. However, due to the demand of the real-time, a method with back-propagation neural network (BPNN) is developed to optimize the proposed model. The results of simulation experiments show that BPNN possesses good prediction accuracy, and can make the numerical model achieve the real-time requirement.

1. Introduction
Optical countermeasures have played an increasingly important role in modern war. Since the emergence of heat-seeking missiles, a number of technical countermeasure projects have been initiated to defeat the infrared (IR) homing missile technology [1]. IR guided missiles are the most effective weapons to kill low flying aircraft and helicopters whose hot spot is in a certain spectral regions of mid-IR. So pyrotechnic infrared decoys which imitate the tail pipes radiation of aircraft were developed in the late 1950s and today they are still the most commonly used countermeasures to lure away the incoming heat seeking missiles [2]. However, poor trajectory of the infrared flare makes it possible for the missiles with imaging seeker to discriminate between the decoy flare and aircraft due to differences in their trajectory. The kinematic decoy flares, such as aerodynamic flares and propelled flares, have been proposed to overcome this problem, whose trajectory are stable and resemble closely to those of the aircraft to be protected [3].

However, the prior infrared decoy modelling formulas of radiation are unsuitable for kinematic decoy due to the differences of working mechanism and powder composition. In order to study their characteristics, in this paper, a numerical model was proposed to calculate the infrared radiation characteristics of Escort Free-Flight infrared decoy based on finite volume method (FVM) [4]. The detailed modelling processes of the numerical model was introduced in Section 2. Because of the real-time simulation requirement, a kind of neural networks was developed to optimize the numerical model in Section 3. Finally, experimental results were presented and discussed in Section 4.

2. Infrared Radiation Model
Compositions for escort free-flight infrared decoy mainly include magnesium and Teflon materials which provide propellant and infrared radiation. Its combustion flame shape is close to the rocket plume, so the FVM for solid rocket plume is used to calculate the radiation of flame. The calculation processes include: flow field calculation, radiation parameters calculation, discretization and solution of radiative transfer equation.
2.1. Flow Field Calculation
The ideal turbulent jet model is used to calculate the flow field. As shown in Figure 1, it is exhaust plume shape of Nozzle and the area with black slant lines is the core radiant area of exhaust plume [5].

![Exhaust plume shape of Nozzle](image)

Figure 1. Exhaust plume shape of Nozzle.

The equations about temperature distribution of exhaust plume can be written as follows:

\[
\begin{align*}
T &= T_0 \\
T_0 - T_n &= 1 - \frac{y_1 - y}{b} & (x \leq x_1, y \leq y_1) \\
T - T_n &= 1 - \left(\frac{y}{b}\right)^2 & (x > x_1) \\
T_n &= T_0 \left[1 + \left[p + \left(\frac{p}{\kappa} - \frac{1}{\kappa}\right)\right]\right] \\
p &= \frac{1 - (1/n)^2}{\left(y/y_n\right)^2} + 2/n & (n = T_0/T_a)
\end{align*}
\]

(1)

where, \(T\) is the temperature in different area, \(T_0\) is the temperature of plume in Nozzle section, \(T_a\) is atmospheric temperature.

2.2. Radiation Parameters Calculation
The radiation parameters of exhaust plume include spectral absorption coefficient of gas composition \(k_a\), scattering coefficient \(Q_{\text{sca}}\) and absorption coefficient \(Q_{\text{abs}}\) of carbon Particle. The spectral absorption coefficient of gas composition is given by:

\[k_a = C \times P \times 273 \times 1 \times 10^3 \times T_{\text{STP}}\]

(2)

where, \(C\) is mole percent of gas composition, \(P\) is actual pressure, \(T\) is actual temperature, \(K_{\text{STP}}\) is spectral absorption coefficient of gas composition.

Particle radiation parameters \(Q_{\text{sca}}\) and \(Q_{\text{abs}}\) are calculated by Mie theory widely.

2.3. Finite Volume Method for Radiation
The spectral radiation intensity at any position \(r\), along a path \(s\) through an absorbing, emitting and scattering medium described by radioactive transport equation can be given as [6]:

\[
\frac{dI_\lambda(r,s)}{ds} = -\kappa_{ek} I_\lambda(r,s) + \kappa_{a\lambda} I_{b\lambda}(r,s) + \frac{\kappa_{s\lambda}}{4\pi} \int I_\lambda(r,s') \phi(s,s')d\omega'
\]

(3)
where, \( I_\lambda (r,s) \) is the radiation intensity at the position \( r \) in the direction \( s \), and \( I_{b\lambda}(r,s) \) is the radiation intensity of blackbody. \( \phi(s,s') \) is the scattering phase function of energy transferring from the incoming direction \( s' \) to the scattered direction \( s \). \( \kappa_{e\lambda} \) is the spectral attenuation coefficient, \( \kappa_{a\lambda} \) is the spectral absorption coefficient, \( \kappa_{s\lambda} \) is the spectral scattering coefficient. The FVM was used to discretize the governing equation (3). In FVM, space within the domain of interest is divided into discrete non-overlapping volumes, and a single node is located centrally within each volume [7]. Gases and particles are assumed to be homogeneous in each volume. Since the direction is also an independent variable, it is subdivided into \( N_{\theta} \times N_{\phi} \) discrete, which sum to \( 4\pi \). Typical control volume and control angle are shown in Figure 2.

![Figure 2](image_url)

**Figure 2.** Typical control volume and control angle for FVM.

The FVM assumes that the magnitude of the intensity is constant in a given control volume and a control angle. After discretization, the following finite volume formulation can be obtained [8]:

\[
\sum_{i=1}^{NA} I_{i\lambda} \Delta A \int_{\Delta \omega} (s \times n_i) d\omega' = \left\{ -\kappa_{e\lambda} I_{\lambda} + S'_{i \lambda} \right\} \Delta V \Delta \omega'
\]  

(4)

where

\[
S'_{i \lambda} = \kappa_{a\lambda} I_{b\lambda} (r,s) + \frac{\kappa_{s\lambda}}{4\pi} \int I_{\lambda} (r,s') \phi(s,s') d\omega'
\]

(5)

where, \( A_i \) is surface area of the control volume, \( n_i \) is the outward unit normal vector at the control volume face. The step scheme is chosen here to relate control volume face intensity to the nodal intensity, in which the downstream face intensity is set to be equal to the upstream nodal intensity. The final discretization equations for a general control volume and control angle can be written as:

\[
a'_{iP} I'_{iP} = a'_{i} I'_{i} + b
\]

(6)

\[
a'_{i} = \sum_{i=1}^{NA} \max(A_i D'_i, 0) + (\kappa_{a\lambda} + \kappa_{s\lambda}) \Delta V \Delta \omega'
\]

(7)

\[
a'_{i} = \max(-A_i D'_i, 0)
\]

(8)

\[
D'_i = \int_{\Delta \omega} (s \times n_i) d\omega
\]

(9)

\[
b = S'_{i \lambda} \Delta V \Delta \omega
\]

(10)

In equation (10), the subscript \( I \) represents \( E, W, N, S, R \) and \( F \). BI-CGSTAB algorithm with precondition matrix is employed to solve the discretization equations.
3. Optimization with Neural Network

Figure 3 shows a group of simulation results of radiation characteristics of decoy base on the above numerical model. Every group of simulation took an average of 9.623279 minutes in 10 groups of simulations running in Windows XP with a AMD Athlon II X2 240 CPU (2.81 GHZ) and 2G memory. Though the time of every group of simulation took far less than computational time in reference [7], the numerical models still cannot reach the requirement of real-time for any time point.

**Figure 3.** Simulation for radiation characteristics of decoy.

3.1. **BP Neural Network**

The main problem of numerical models was that the numerical model of radiation took long computing time. The BPNN was built up to short the computing time of infrared radiation model. The typical structure of BPNN contains three layers and adjusts the input weight matrix W and β with Levenberg-Marquardt algorithm [9] in this paper. The optimized structure of decoy simulation includes BPNN and motion model of decoy, as shown in Figure 4.

**Figure 4.** Optimized structure of decoy simulation.

In the following, the specific steps of the regression method using BPNN were given.

1. Generate the raw data of decoy simulation including inputs and outputs through the model;
2. Normalize the raw data into the range (0-1);
3. Divide the input/output data pairs into training set and predicting set randomly;
4. Set related parameters of BPNN;
5. Input training set, run the learning algorithm to get weights W and β and performance of network;
6. Based on the configured parameters and weights obtained by Step 4 and 5, calculate the outputs of predicting set and the corresponding performance.

4. Simulation Analysis

In order to verify the validity and performance of the proposed neural network, in this section, many experimental results were presented based on the raw data generated by numerical model. All
experiments have been carried out in MATLAB 7.0 running on a personal computer which was the same as the platform of numerical models. The root mean square error (RMSE), computational time and the number of hidden neurons in the training and predicting period were used for evaluating the reasonableness of network structure and the performance of networks. The RMSE between the outputs of neural network and actual outputs is defined as:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (T_i - Y_i)^2}, \quad i = 1, 2, ..., N
\]

Where \( N \) is the number of data pairs, \( T_i \) and \( Y_i \) are the \( i \) th calculated output and the actual output respectively.

4.1. Experiments of BPNN

According to the step (1) in Section 3.1, raw data with 10000 radiation peaks of 10000 groups of simulations were generated by running radiation model of which inputs were set randomly within the range of values allowed. There were 3 inputs and 1 output of radiation model were selected to be the inputs and output of BPNN. In order to improve the predicting accuracy, 90% of raw data were extracted as training set, and the rest 10% of raw data were used as predicting set.

The performance of BPNN with different number of hidden layer were showed in Figure 5 (a), (b) for training set and predicting set, and the better structural parameters of BPNN were determined in accordance with RMSE, as given in Table 1.

![Figure 5](image-url)  
(a) RMSE of BPNN in training and predicting sets  
(b) Runtime of BPNN in training and predicting sets  

**Figure 5.** The performances of different algorithms in training and predicting phases.

**Table 1.** The selected structural parameters for BPNN.

| Nodes | Activation function | Output function | RMSE Training | RMSE Predicting | Runtime(s) Training | Runtime(s) Predicting |
|-------|---------------------|-----------------|---------------|-----------------|---------------------|---------------------|
| 25    | tansig              | purelin         | 0.00099999644 | 0.001043441     | 412.609375          | 0                   |

Figure 6 shows predicting errors, predicting outputs and actual outputs using BPNN with selected structural parameters. the predicting outputs were almost equal to the actual outputs, and the error curve between predicting outputs and actual outputs can be accepted completely, and the range of absolute error was 6.7439e-007 to 0.005. All the above experiments proved that BPNN as an optimization method of radiation model was reliable, and had good generalization capability and
predicting accuracy. The BPNN just only made adjustments partly for the radiation model, not only solved the problem of real-time requirement but also kept higher accuracy for the simulation data.

![Figure 6](image_url)

**Figure 6.** The simulation results for radiation intensity peak with BPNN.

5. **Conclusions**

In this paper, firstly radiation model is proposed, but existing the lack of real-time. Then from existed problems of the numerical model, an optimization methods using neural network is proposed for the numerical model. The BPNN was used to predict the radiation peak intensity base on a large amount of raw data, then gave the radiation intensity of each time point according to the radiation formula. The experimental results showed that BPNN not only had good generalization capability and predicting accuracy, but also made the simulation achieve the real-time for different inputs. In summary, the BPNN was able to optimize the numerical model of decoy based on requirement.

6. **References**

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