Fuzzy Matching Approach to Target Identification

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Abstract

The method of identifing radar target in frequency domain in terms of fuzzy neartude is presented. The process of backscatter data fitting is described firstly, and then the matching method based on fuzzy neartude is given. The experiments are done by the use of scattering data provided by Dr. D. L. Moffatt. The results obtained show that the identifier in this paper has good performance of target identifications.

Key words— Fuzzy neartude, Fuzzy match, Radar target, Target identification, Backscatter data.

1. Introduction

This paper is based on the impulse response concept advanced by Kennaugh and Cosgriff in 1958 and formalized by Kennaugh and Moffatt in 1965 and also the fuzzy neartude concept which will be defined later. It has been demonstrated that discrete spectral scattering data spanning the Rayleigh and low resonance ranges of the scatter define the gross physical properties(size,shape,and composition) of the target, and that the transient response waveform defined by Rayleigh and low resonance range data can be approximated by finite exponential sum . Thus rantional function approximations were postulated for the scattering transfer function in the Rayleigh and low resonance ranges of the scatter. This suggested that characterization of the scatter by a few complex natural resonant frequencies modeled as simple poles in the transfer function.

Once the poles are known, they may be used to classify or identify an object from its complex resonances. The problem in any case is to determine how we might use pole sets to classify and identify objects, since its pole set underlies all of an object's electromagnetic behavior. Because the poles appear in both the time- and frequency-domain response of an object,it might be anticipated classification and identification could be performed in either domain. That is indeed the case. One approach for doing this using transient data has been developed by Mains and Moffatt in 1975.

In this paper we are interested in using spectral or frequency-domain information. Firstly, the fitting process of scatering data is described. Then an algorithm for measuring the match degree between the backscatter data and fitting data is derived using fuzzy neartude. Finally,experiments are made in assessing the performance of the identifications.

2. Frequency-Domain Data Fitting And Fuzzy Decision

Suppose a linear polarized plane wave, with x-directed electric field

$$\vec{E}_i=\hat{x}E_0\cdot\exp(j(wt-kz)) \tag{1}$$

is incident upon an object at the origin. Here,w is radian frequency,k=w/c is the wave number and z is the direction of propagation. The x-polarized backscattered field, $\vec{E}_s$,at a large distance r along the negative z axis is given as

$$\vec{E}_s=\hat{x}\exp(j(wt-kf))G(jw)E_0/2\pi r. \tag{2}$$

This defines G(jw),the object's frequency response for backscattering at a specified aspect angle. With this definition,the power cross-section of the scatter,denoted as σ_s,is given by the equation

$$\sigma_s=4\pi r^2|\vec{E}_s|^2/|E_0|^2=|G(jw)|^2. \tag{3}$$

On another hand, we have:

$$|G(jw)|^2=G(jw)G^*(jw)=G(s)G(-s)\Big|_{s=jw}=B(-w^2)A(-w^2)^{-1},$$

where A(.)and B(.) are polynomials. So,letting $x=-s^2$,we have

$$\sigma_s=|G(jw)|^2=B(x)/A(x)=\sum_{i=0}^{N-2}b_i x^i/(1+\sum_{i=1}^{N}a_i x^i). \qquad (4)$$

Here, $\{b_i\}_{i=0}^{N-2}$ are called zero coeiffficents,and $\{a_i\}_{i=1}^{N}$ pole coeifficents.

Suppose that scattering data $\{\sigma_l\}_{l=1}^{L}$ at L (even number) frequencies are observed and the pole coeifficents $\{a_{ij}\}_{j=1}^{L}$ (i=1,2,...,m) of m interested targets are obtained, let:

$$(1+\sum_{j=1}^{N}a_{ij}x_l^j)\cdot\sigma_l=\sigma'_{il} \quad (l=1,2,\ldots,L,i=1,2,\ldots,m),$$

we obtain:

$$(\&) \qquad \sum_{j=0}^{N-2}b_{ij}x_l^{\,j}=\sigma'_{il} \qquad (l=1,3,\ldots,L-1,i=1,2,\ldots,m).$$

For given i, the overdetermined equation system (&) can be solved by the use of least-square methods. Assuming the least-square solution is $(b'_{i0},b'_{i1},\ldots,b'_{iN-2})^T$ (i=1, 2,...,m),the fitting data are calculated as follows:

$$\sigma_{il}=\sum_{j=0}^{N-2}b'_{ij}x_l^j/(1+\sum_{j=1}^{N}a_{ij}x_l^j). \qquad (i=1,2,\ldots,m,l=2,4,\ldots L)$$

It is necessary to measure the similarity between fitting data and scattering data for performing target identification. We first define m fuzzy subsets $\underset{\sim}{R}_i$ of $E_L=\{(\sigma_2,\sigma_4,\ldots,\sigma_L)\,|\,\sigma_l>0,l=2,4,\ldots,L\}$ (i=1,2,...,m).The elements of $\underset{\sim}{R}_i$ are scattering data from the ith target "possibly". Once the membership functions $u_{\underset{\sim}{R}_i}(\cdot)$ of $\underset{\sim}{R}_i$ (i=1,2,...,m) which describe the matching degree of $\{\sigma_{il}\}$ and $\{\sigma_l\}$ have been obtained, we make a decision as follows:

$$H_i\,\Big|\; u_{\underset{\sim}{R}_i}(\{\sigma_i\})=\max_{j=1}^{m} u_{\underset{\sim}{R}_j}(\{\sigma_i\}), \qquad (5)$$

where H_i means the scatter is the ith intersted target.

3. Fuzzy Matching Algorithm

It follows from eq.(5) that the matching algorithm is a key part of target identifications. The study here is based on the fuzzy neartude concept.

Definition 1: Let E_L be a universe, $\mathcal{F}(E_L)$ the family of all fuzzy subsets of E_L. The neartudr on $\mathcal{F}(E_L)$ is a map from $\mathcal{F}(E_L)\times\mathcal{F}(E_L)$ to $[0,1]$:

$$\rho : \mathcal{F}(E_L)\times\mathcal{F}(E_L) \longrightarrow [0,1],$$

which is satisfied with (i)$\forall \underset{\sim}{A},\underset{\sim}{B}\in\mathcal{F}(E_L)$,$\rho(\underset{\sim}{A},\underset{\sim}{B})$ takes maximum value when $\underset{\sim}{A}=\underset{\sim}{B}$ and minimum when $\underset{\sim}{A}=\underset{\sim}{0}$ and $\underset{\sim}{B}=\underset{\sim}{1}$; (ii)$\forall \underset{\sim}{A}, \underset{\sim}{B}\in\mathcal{F}(E_L)$,$\rho(\underset{\sim}{A},\underset{\sim}{B})=\rho(\underset{\sim}{B},\underset{\sim}{A})$; (iii)$\forall \underset{\sim}{A},\underset{\sim}{B},\underset{\sim}{C}\in\mathcal{F}(E_L)$,if $\underset{\sim}{A}\le\underset{\sim}{B}\le\underset{\sim}{C}$ or $\underset{\sim}{A}\ge\underset{\sim}{B}\ge\underset{\sim}{C}$, then $\rho(\underset{\sim}{A},\underset{\sim}{B})\geq\rho(\underset{\sim}{A},\underset{\sim}{C})$.

It can be seen from definition 1 that the neartude $\rho(\cdot,\cdot)$ is actually a binary fuzzy relation in $\mathcal{F}(E_L)$ satisfied with (i),(ii),(iii).It reflects the matching degree between fuzzy subsets of E_L.

$\forall \underset{\sim}{A},\underset{\sim}{B}\in\mathcal{F}(E_L)$,let $\underset{\sim}{A}\circ\underset{\sim}{B}=\sup\limits_{x\in E_L}(u_{\underset{\sim}{A}}(x)\wedge u_{\underset{\sim}{B}}(x))$ and $\underset{\sim}{A}\oplus\underset{\sim}{B}=\inf\limits_{x\in E_L}(u_{\underset{\sim}{A}}(x)\vee u_{\underset{\sim}{B}}(x))$,we have:

Lemma 1: $\forall \underset{\sim}{A}\in\mathcal{F}(E_L)$, $\underset{\sim}{A}\circ\underset{\sim}{A}=\sup\limits_{\underset{\sim}{B}\in\mathcal{F}(E_L)}\underset{\sim}{A}\circ\underset{\sim}{B}$, $\underset{\sim}{A}\oplus\underset{\sim}{A}=\inf\limits_{\underset{\sim}{B}\in\mathcal{F}(E_L)}\underset{\sim}{A}\oplus\underset{\sim}{B}$.

Lemma 2: If $\underset{\sim}{B}\supseteq\underset{\sim}{A}$ then $\underset{\sim}{A}\circ\underset{\sim}{B}=\bar{\underset{\sim}{A}}$; if $\underset{\sim}{B}\subseteq\underset{\sim}{A}$ then $\underset{\sim}{A}\oplus\underset{\sim}{B}=\underline{\underset{\sim}{A}}$, where $\bar{\underset{\sim}{A}}=\sup\limits_{x\in E_L}u_{\underset{\sim}{A}}(x)$ and $\underline{\underset{\sim}{A}}=\inf\limits_{x\in E_L}u_{\underset{\sim}{A}}(x)$.

From lemma 1 and 2 we have:

Theorem 1: Let E_L be a universe, ρ a map from $\mathcal{F}(E_L)\times\mathcal{F}(E_L)$ to $[0,1]$, $\forall \underset{\sim}{A},\underset{\sim}{B}\in\mathcal{F}(E_L)$,

$$\rho(\underset{\sim}{A},\underset{\sim}{B})=(\underset{\sim}{A}\circ\underset{\sim}{B})\vee(1-(\underset{\sim}{A}\oplus\underset{\sim}{B})). \tag{6}$$

Then, ρ is a neartude on $\mathcal{F}(E_L)$.

Apparently, if E_L has only one element,then

$$\rho(\underset{\sim}{A},\underset{\sim}{B})=(u_{\underset{\sim}{A}}(x)\wedge u_{\underset{\sim}{B}}(x))\vee(\overline{u_{\underset{\sim}{A}}(x)}\wedge\overline{u_{\underset{\sim}{B}}(x)}). \tag{7}$$

The first thing is to normalize the scattering data and fitting data:

$$\sigma'_{ij}=(\sigma_{ij}-\sigma_i^{min})/(\sigma_i^{max}-\sigma_i^{min}),\ \sigma'_j=(\sigma_j-\sigma^{min})/(\sigma^{max}-\sigma^{min}),$$

where $\sigma_i^{min}=\min\limits_j\sigma_{ij}$, $\sigma^{max}=\max\limits_j\sigma_j$ and so on($i=1,\ldots,m, j=2,4,\ldots,L$).

From eq.(7) we define: $\rho_{ij}=(\sigma'_{ij}\wedge\sigma'_j)\vee(\overline{\sigma'_{ij}}\wedge\overline{\sigma'_j})$($i=1,2,\ldots,m, j=2,4,\ldots,L$).Finally the match may be written by

$$Nei=\sum_{j=1}^{L/2}\rho_{i,2j},\quad i=1,2,\ldots,m. \tag{8}$$

The membership functions of $\underset{\sim}{R}_i$ are:

$$u_{\underset{\sim}{R}_i}(\{\sigma_j\})=Nei/\sum_{i=1}^{m}Nei,\quad i=1,2,\ldots,m. \tag{9}$$

4. Experiments And Conclusions

In assessing the performance of identifier presented in this paper, experiments are made for three diferent kind of targets. They are medium sphere(d=1.59m,ϵ_r=2.208), pro -late spheriod(major axis=1.59,minor axis=0.795m)and cube (edge length=0.682m).Ten times are assumed in the process of identifications for each target.Fig.1,Fig.2 and Fig.3 show the fitting data of prolate spheriod when three di-fferent pole coeifficents are applied.The experiments re-sults are tabulated in table1 which shows the performance of the identifier is good.This procedure allows an identi -fication to be made without the necessity of finding the poles from scattering data.Because of using fuzzy neartu-de as a measure of matching degrees between fitting data and scattering data,the matching process of the identifi-er is similar to brain's one.Thus the activity of the identifier is increased largely.

5. References

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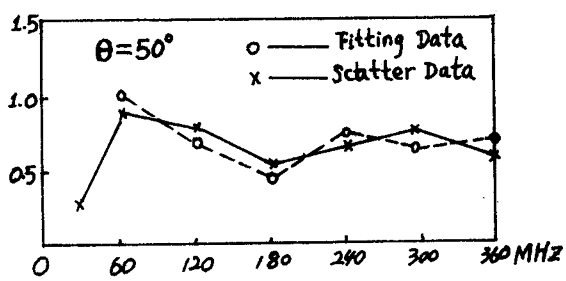

Fig.1 The Same pole Set

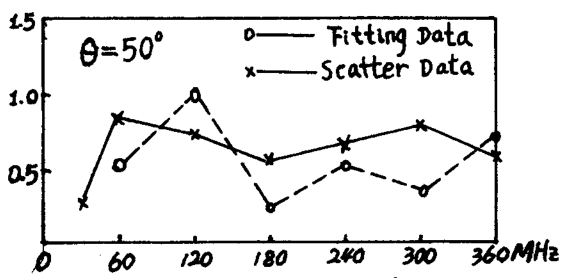

Fig.2 The different pole set

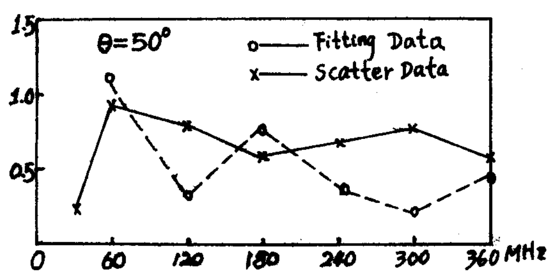

Fig.3 The different pole set

ident. \ resul.	med. sphe.	prola. spher.	Cube	Correct rate
medium sphere	10	0	0	1
prolate spheriod	0	9	1	0.9
Cube	0	1	9	0.9

Table 1 Results of identification