Data-Driven Method of Reverse Modelling for Multi-Function Radar

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***Abstract*—The common researches for radar system modelling are mostly based on deductive methods, which forward simulate the radar working process according to the information of radar parameters and expert system. However, the radar prior information obtained is limited under battlefield background. So it is difficult to model the radar operating modes and schedule schemes accurately, especially for the multi-function radars (MFRs) which are able to employ multiple modes flexibly. A novel method of reverse modelling for MFR is proposed. The information of the waveform is translated into grammar according to the theory of formal language, and the corresponding Finite-state Automaton (FSA) is composed as initialization. Then, according to the thought of data-driven, the transition relations and probabilities between MFR modes are yielded by analysing the intercepted signals. Finally, the stochastic finite automaton (SFA) is composed, achieving the MFR model by reverse modelling. Simulation with hypothetical MFR signal data is presented, showing that the proposed method is able to compose its SFA effectively, which can be used in MFR state recognition to support the adaptive radar countermeasures.**

Keywords—Multi-function radar; reverse modelling; syntactic pattern recognition; data-driven;

I. INTRODUCTION

Radar system modelling is the basic work for electronic warfare and intelligent jamming decision. While multi-function radars (MFRs) [1] present challenges in modelling, due to their abilities of executing multiple tasks in parallel and characteristics of switching operation modes flexibly. Especially under the battlefield background, the knowledge about hostile radars, such as parameters and scheduling strategies, is limited considering the dynamic game between both sides of the EW [2]. Therefore, it is of great practical significance for the research on the modelling of MFR with limited prior information.

Many literatures concentrate on the topic of radar system modelling [3-6], involving the model complexity, granularity, reusability, expandability, etc. Reference [3] systematically elaborates the mathematical modelling methods for phased array radars, dividing the models into functional level and signal level, which are addressed in detail in [4] and [5] respectively. Visnevski proposed the MFR syntactic model, composing the corresponding automaton to recognise the MFR states [6]. The methods above are all deductive approaches, modelling according to the forward working process based on the radar mechanism analysis. These methods need an overall understanding of the object radar. However, this requirement is generally not satisfied in EW, resulting in the roughness or inaccuracy of the model. The mechanism-based modelling is concluded by Astrom as “white box” problem, and the opposite “black box” problems are the data-based modelling methods [7]. Instead of reproducing the whole working process, the data-based methods focus on constructing the generalized mapping relations between input and output of the modelling object by analysing the data samples. The correlational studies include statistical modelling [8], data mining [9], meta-modelling [10], etc., which have performed well in the application of electromagnetic environment modelling [11,12], but seldom used in radar system area. Considering that the MFR signals intercepted by electronic intelligence (ELINT) systems can be used as training data, it should be a proper alternative that discovering the mapping relations between radar inner behaviours and outer waveforms, which can be viewed as a reverse modelling process for MFR.

As mentioned above, radar system modelling is the basis in a series of research work. However, the insufficient of radar prior information in battlefield limits the application of the common mechanism-based modelling methods. By utilizing the intercepted radar signals, a data-driven method of reverse modelling for MFRs is proposed in this paper. Firstly, via the theory of formal language, the information of the waveform is translated into grammar and the corresponding initial Finite-state Automaton (FSA) is composed. Then, according to the thought of data-driven, the transition relations and probabilities between MFR modes are yielded by analysing the intercepted signals to compose the MFR stochastic finite automaton (SFA), achieving the MFR model by reverse modelling. Finally, simulation with hypothetical MFR signal data is presented to attest to the validity of the proposed method.

II. SYNTACTIC MODEL OF MFR

A. Hierarchical Structure of MFR Signals

Signals of MFR are various, complex and flexible, making it difficult for the traditional ELINT system to analyse and decipher MFR signals. Visnevski deconstructed the MFR signals by multiple layers, and put forward a hierarchical signal structure [6], whose building block is the radar “*word*”, namely the static or dynamically varying groups of pulses that MFRs

ISBN 978-0-9928626-7-1 © EURASIP 2017

emit in different states. Take an example for the "Mercury" MFR given in [13], whose radar word structure is shown in Figure 1(a). Its words are all of equal length of 7.14ms and made up of 5 sections (A - E). Sections A, C and E are dead time of known duration. Section B is pulse-Doppler sequence with fixed pulse repetition frequency (PRF), and D is a scheduled PRI synchronization burst with 12 pulses. A radar "*phrase*" is made up of a finite number of words in a fixed order, such as the phrase "$w_1w_2w_1w_1$" in Figure 1(b). Each phrase as a whole is associated with a single task such as search or track.

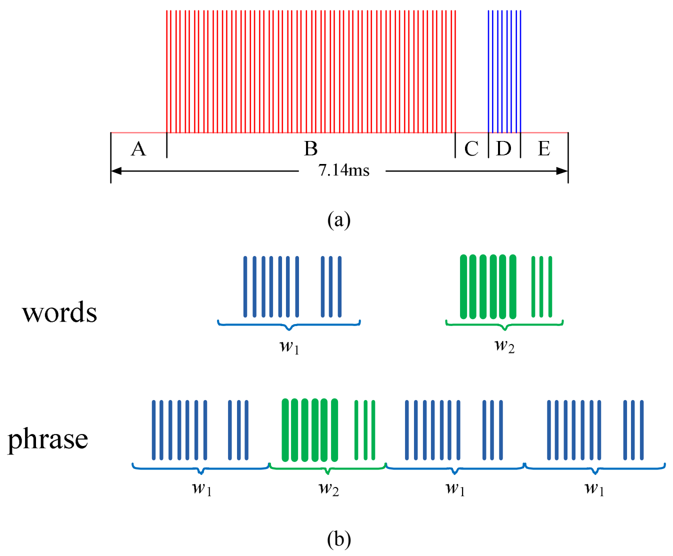

Fig. 1. An example of the hierarchical structure of "Mercury" radar signals

The radar word sequence transformed from the intercepted MFR pulse sequence via radar word extraction is a discrete stochastic process [14]. Thus, the MFR signals can be processed using the theories of discrete event dynamic system (DEDS) and formal language. It is with this signal structure that Visnenski proposed the method for MFR modelling based on syntactic pattern recognition. In this paper, we also studied the basis of the hierarchical structure and focused on the radar word sequence after signal sorting and word extracting for a single radar.

B. Fundamental of Syntactic Pattern Recognition

Syntactic pattern recognition is a method to describe the syntagmatic relations in the pattern class via the theories of formal language and automaton [15]. And formal language is put forward by Chomsky in the 1950s, which was used for the description of natural language in computers. The grammar in formal language is the finite set of rules for string production, represented as a four-tuple [13]:

$$G = \langle V, N, P, S_0 \rangle \tag{1}$$

where V is the set of terminal symbols of the grammar; N is the set of non-terminal symbols of the grammar; P is the finite set of grammatical production rules; S_0 is the starting non-terminal. There are four kinds of grammars in the Chomsky hierarchy of formal language, which are regular grammars (RGs), context-free grammars (CFGs), context-sensitive grammars (CSGs) and unrestricted grammars (UGs). Each kind corresponds to a kind of automaton, which is generally used as a language recogniser to classify the languages from input strings.

The fundamental of syntactic pattern recognition is deconstructing the pattern into symbols and strings and recognising them with grammar. The similarities of between the formal language model and the MFR signal model are used for MFR modelling and state recognition by Visnevski. He constructed the formal language alphabet for MFR signals and translated the operating regularities into grammars, achieving MFR state recognition via automaton. According to the characteristic of MFR, its signals are generally associated with the RG or CFG, corresponding to the finite-state automaton (FSA) and pushdown automaton (PDA), respectively. Visnevski has proved that the non-self-embedding CFGs can also correspond to FSAs [13]. Thus, we take FSA as example below.

FSA can be expressed as a five-tuple [15]:

$$\Lambda = \langle \Sigma, Q, \delta, q_0, F \rangle \tag{2}$$

where Σ is the finite set of input symbols; Q is the finite set of states; δ is the transition function; q_0 is the initial state; F is the finite set of final states. If the automaton state transfers from q to q' when input the symbol a, it can be denoted as $\delta(q, a)= q'$, where $q, q' \in Q$, $a \in \Sigma$. Considering the probability distribution of the grammar productions, a transition probability set $\mathbf{D}$ can be added into Λ, obtaining the stochastic finite automaton (SFA):

$$\Lambda_{sf} = \langle \Sigma, Q, \delta, q_0, F, \mathbf{D} \rangle \tag{3}$$

Instead of viewing all the patterns as equiprobable events, the probability distribution of patterns is used in recognition in SFAs, which helps to achieve better performance [16]. The final model yielded via the method in this paper is in form of the SFA for MFR.

III. DATA-DRIVEN REVERSE MODELLING FOR MFR

The forward modelling methods such as the syntactic model above are based on the sufficient prior information of radars. While in EW, the knowledge about the hostile radar that ELINT systems have is limited, except abundant of signal data. Therefore, this section concentrates on how to extract the key information from the radar data.

Firstly, the radar phrases of the object radar are translated into grammar according to the definitions in formal language [15]. On the basis of that, the process of MFR modelling can be decomposed into two steps: One is the FSA initialization, which means the composition of FSA from the components; the other one is the generation of SFA for MFR yielded by the data-driven algorithm, where the key are mapping the new state transitions and obtaining the transition probability set.

A. Step 1: Creating the Initial FSA

This step is based on the "breadth-first" algorithm [13], whose main idea is creating a FSA Λ with only the initial state and final state, traversing the input symbols and inserting the component Λ_i into Λ. The algorithm is shown in Table I.

TABLE I. PSEUDO-CODE OF FSA GENERATOR BASED ON "BREADTH-FIRST" ALGORITHM

Algorithm 1: Procedure of FSA initialization

Input: W←finite set of radar words; Q←finite set of states; $\Lambda_1, \Lambda_2, \ldots, \Lambda_k$←automaton components;
Output: $\Lambda \leftarrow (\Sigma, Q, \delta, q_0, F)$, finite-state automaton;
Nomenclature: Σ←alphabet W, finite set of input symbols; δ←mapping of transitions; q_0←initial state; F←finite set of final states

```
function FSA_Generator(W, Λ1, Λ2, …, Λk)
    Λ←Λ1
    for all Λi do
        for all α∈Σ do
            if α∈Qi then
                qfrom←argq(δ(qα, α))
                qto← δ({qfrom}, α)
                Σ←Σ \ α∪Σi
                Q←Q∪Qi
                δ←δ∪δi
                for all δ(qj, β) do
                    if δ(qj, β)=qfrom then
                        δ(qj, β)←α
                    end if
                    if δ(qj, β)∈Fi then
                        δ(qj, β)←qto
                    end if
                end for
                Q←Q \ Fi \ qfrom
            end if
        end for
    end for
    return Λ
end function
```

After utilizing the algorithm above, the FSA components corresponding to all the MFR operating modes are inserted into Λ, which can be used to recognise the MFR states by inputting MFR words sequence. It is not hard to see that the radar signal data is not used in the algorithm, so this step is still belonging to the forward modelling. Since it is impossible to infer the radar scheduling schemes only from the radar word set, the FSA composed here contains no transition mappings and probabilities between different operating modes. The main purpose is to initialize the FSA for the next step.

B. Step 2: Data-Driven SFA Generation

In this step, new state transition functions will be created with a data-driven method, and the transition probabilities will be yielded also. The main idea is inputting the radar words in order, recognising and counting the states using the FSA obtained in Step 1. If it points to the final state, a new transition mapping is constructed and counted that from the current state to the state with the next input symbol. Finally, the set of transition probabilities **D** is calculated as all the transition frequencies, yielding the SFA. The algorithm is shown in Table II.

TABLE II. PSEUDO-CODE OF SFA GENERATION BASED ON DATA-DRIVEN ALGORITHM

Algorithm 2: Data-driven method for SFA generation

Input: S←radar word sequence; $\Lambda \leftarrow (\Sigma, Q, \delta, q_0, F)$, FSA yielded in Step 1;
Output: $\Lambda_{sf} \leftarrow (\Sigma, Q_{sf}, \delta_{sf}, q_0, F, \mathbf{D})$, stochastic finite automaton;
Nomenclature: Q←finite set of states; Σ←alphabet W, finite set of input symbols; δ←state transition mapping; q_0←initial state; F←finite set of final state, $F \subset Q$; **D**←set of probabilities of mapping δ; $prob(\delta)$←probability of mapping δ; $c(q)$←number of state q; $c(q_i, q_j)$←number of the transition from state q_i to q_j; $Flag\_H$←mark for the occurrence of final state

```
function DataDriven_SFSA_Generator(S, Λ)
    Σ←W, Qsf←Q, δsf←δ, D←∅
    for all w∈S do
        if w∈Σ then
            qfrom←argq(δsf(q, w))
            qto←δsf(qfrom, w)
            c(qto) = c(qto) +1
            if qto∈F then
                qH←qfrom
                wH←w
                Flag_H←1
            else then
                if Flag_H=1 then
                    δsf(qH, wH) ← qto
                    δsf←δsf∪δsf(qH, wH)
                    c(qH, qto) = c(qH, qto)+1
                    Flag_H←0
                else then
                    c(qfrom, qto) = c(qfrom, qto)+1
                end if
            end if
        end if
    end for
    for all (δsf(qi, w)=qj)∈δsf do
        prob(δsf(qi, w)=qj) = c(qi, qj) / c(qi)
        D←D∪prob(δsf(qi, w)=qj)
    end for
    Λsf←(Σ, Qsf, δsf, q0, F, D)
    return Λsf
end function
```

The information of state transitions in the radar data can be extracted by the algorithm in Table II. According to the number of state transitions, the probabilities distribution can be calculated, yielding the SFA. It can be seen that, the data with higher quantity and quality used by the algorithm, the more state transitions may be covered in the data. Thus the frequencies will be more close to the true probability, and the model will be more close to the mechanism-based model with sufficient radar prior information. The missing or corrupted data only affects the probabilities, which can be ignored when most data is correct, showing the robustness of the proposed method. The advantages of the data-driven modelling method above are of reference significance in application.

IV. SIMULATIONS

A. Simulation Settings

The "Mercury" radar is used as examples in most relevant literatures, which demonstrates that it is of representativeness. Its real template of radar words has been presented in Figure 1(a), and the mode transitions of the equipment are shown in Figure 2.

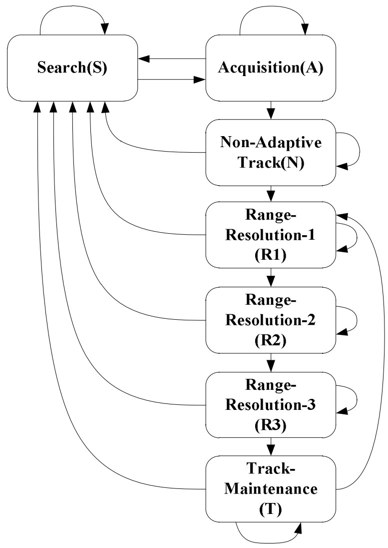

Fig. 2. Operating mode transitions of "Mercury" radar

Figure 2 indicates that this MFR has 5 operating modes. Before the target is detected, the radar employs the Search (S) mode; the target will be shot for several times in a row following the first time of detection for confirmation, and this mode is denoted as Acquisition (A); when the detected target is far from the radar, it is of low threat level, and radar will use the mode of Non-Adaptive Track (N), remaining a low data rate without special tracking beam; with the target getting close, the MFR will transfer to the mode of Track Maintenance (T); because the high-PRF or middle-PRF signals will cause range ambiguity, multiple PRFs will be used alternately at set intervals, namely the Range Resolution (R) mode. The arrows in the figure represent the transitions between different operating modes. It should be noted that the transitions in Figure 2 are only used to generate the hypothetical MFR signal data, but not included in the radar prior information.

TABLE III. PHRASE CONTENTS FOR "MERCURY" RADAR

Mode		Phrases	Mode		Phrases
Search (S)	4-Word Search (FS)	$[w_1w_2w_4w_5]$	Track-Maintenance (T)	3-Word Track (TT)	$[w_1w_7w_7w_7]$
		$[w_2w_4w_5w_1]$			$[w_2w_7w_7w_7]$
		$[w_4w_5w_1w_2]$			$[w_3w_7w_7w_7]$
		$[w_5w_1w_2w_4]$			$[w_4w_7w_7w_7]$
	3-Word Search (TS)	$[w_1w_3w_5w_1]$			$[w_5w_7w_7w_7]$
		$[w_3w_5w_1w_3]$			$[w_6w_7w_7w_7]$
		$[w_5w_1w_3w_5]$			$[w_1w_8w_8w_8]$
Acquisition (A)		$[w_1w_1w_1w_1]$			$[w_2w_8w_8w_8]$
		$[w_2w_2w_2w_2]$			$[w_3w_8w_8w_8]$
		$[w_3w_3w_3w_3]$			$[w_4w_8w_8w_8]$
		$[w_4w_4w_4w_4]$			$[w_5w_8w_8w_8]$
		$[w_5w_5w_5w_5]$			$[w_6w_8w_8w_8]$
Non-Adaptive Track (N) or 3-Word Track (TT)		$[w_1w_6w_6w_6]$			$[w_1w_9w_9w_9]$
		$[w_2w_6w_6w_6]$			$[w_2w_9w_9w_9]$
		$[w_3w_6w_6w_6]$			$[w_3w_9w_9w_9]$
		$[w_4w_6w_6w_6]$			$[w_4w_9w_9w_9]$
		$[w_5w_6w_6w_6]$			$[w_5w_9w_9w_9]$
Range-Resolution (R)	R1	$[w_7w_6w_6w_6]$			$[w_6w_9w_9w_9]$
	R2	$[w_8w_6w_6w_6]$		4-Word Track (FT)	$[w_7w_7w_7w_7]$
	R3	$[w_9w_6w_6w_6]$			$[w_8w_8w_8w_8]$
A or N or FT		$[w_6w_6w_6w_6]$			$[w_9w_9w_9w_9]$

The "Mercury" radar has 9 kinds of radar words (w_1, w_2, …, w_9). And the phrase contents for different modes are listed in Table III. For the parameters are identical with the real equipment, the generated data is able to simulate the real intercepted signals to some extent.

According to the formal language [15], the information in Table III can be translated into grammars as introduced in subsection II-B,

$$
G=\left\{\begin{array}{l}
\Sigma=\{w_1,w_2,w_3,w_4,w_5,w_6,w_7,w_8,w_9\}\\
N=\left\{\begin{array}{l}<State>,<S>,<FS>,<TS>,<A>,<N>,\\ <R>,<R_1>,<R_2>,<R_3>,<T>,<FT>,<TT>,\\ T_6,T_7,T_8,T_9,Q_1,Q_2,Q_3,Q_4,Q_5,Q_6,Q_7,Q_8,Q_9,S_1,S_2\end{array}\right\}\\
P=\left\{\begin{array}{l}
<State>\longrightarrow\ <S>|<A>|<N>|<R>|<T>\\
<S>\longrightarrow <FS>|<TS>\\
<FS>\longrightarrow w_1w_2w_4w_5\ |\ w_2w_4w_5w_1\ |\ w_4w_5w_1w_2\ |\ w_5w_1w_2w_4\\
<TS>\longrightarrow w_1w_3w_5w_1\ |\ w_3w_5w_1w_3\ |\ w_5w_1w_3w_5\\
<A>\longrightarrow Q_1\ |\ Q_2\ |\ Q_3\ |\ Q_4\ |\ Q_5\ |\ Q_6\\
<N>\longrightarrow S_1T_1\ |\ Q_6\\
<R>\longrightarrow <R_1>|<R_2>|<R_3>\\
<R_1>\longrightarrow w_7T_6\\
<R_2>\longrightarrow w_8T_6\\
<R_3>\longrightarrow w_9T_6\\
<T>\longrightarrow <FT>|<TT>\\
<FT>\longrightarrow Q_6\ |\ Q_7\ |\ Q_8\ |\ Q_9\\
<TT>\longrightarrow S_1T_6\ |\ S_2T_7\ |\ S_2T_8\ |\ S_2T_9\\
T_i\longrightarrow w_iw_iw_i\\
Q_i\longrightarrow w_iw_iw_iw_i\\
S_1\longrightarrow w_1\ |\ w_2\ |\ w_3\ |\ w_4\ |\ w_5\\
S_2\longrightarrow S_1\ |\ w_6
\end{array}\right\}\\
S_0=<State>
\end{array}\right.
$$

Below, the corresponding automaton will be composed base on this grammar.

B. Results

According to the formal language, the grammar G corresponds to a FSA: $\Lambda = <V, Q, \delta, q_0, F>$, where the input alphabet $\Sigma = \{w_1, w_2, \ldots, w_9\}$; final state $F=\{H\}$; set of state $Q=N\cup F$; state transition mappings $\delta=P$; initial state $q_0=<State>$. This Λ can also be presented by a production graph, as shown in Figure 3.

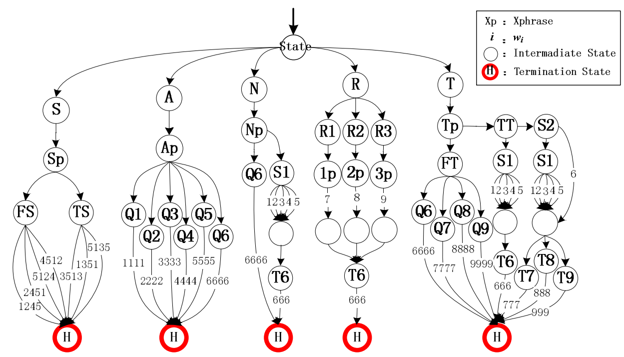

Fig. 3. Production graph for the initial FSA of "Mercury" radar

It can be seen in Figure 3 that the transitions between different modes are not included in the automaton. Based on the FSA above, the SFA $\Lambda_{sf} = <\Sigma, Q, \delta, q_0, F, \mathbf{D}>$ of MFR can be yielded via the data-driven algorithm in Table II. The production graph is presented in Figure 4.

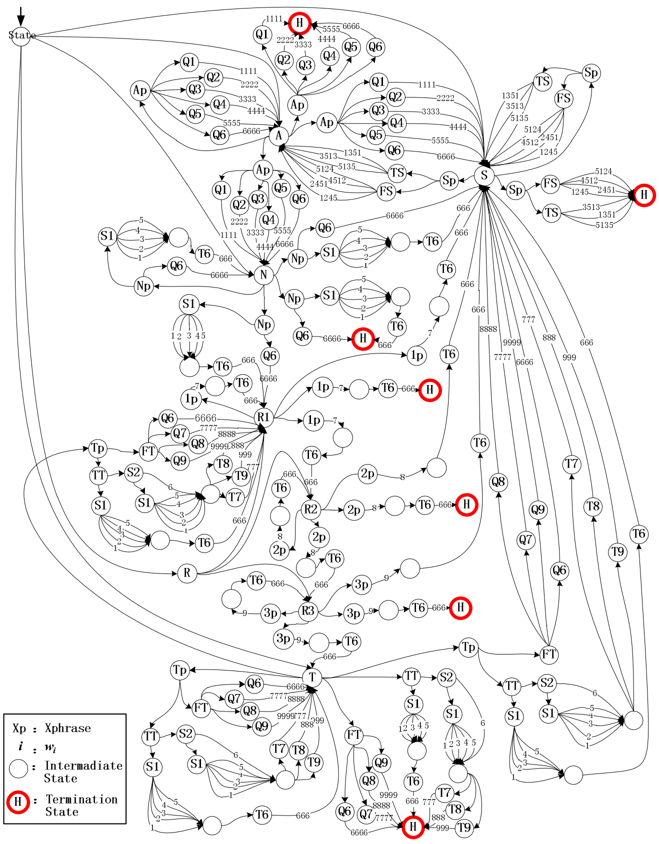

Fig. 4. Production graph for SFA of "Mercury" radar

All the arrows in Figure 4 represent the state transitions with specific probabilities. The result shows that, with the proposed method, the mappings and probabilities of state transitions can be yielded by analysing the intercepted MFR signals, composing the SFA and achieving the reverse modelling of MFR. The generated SFA contains more information, not only the state transitions, but also the transition probabilities. The time required in the recognition process does not increase significantly, because it only depends on the distance between the initial state and termination state. The MFR model can be used for radar state recognition, scheduling scheme inference and making jamming decisions, which are helpful for taking more effective radar countermeasures.

V. Conclusions

This paper concentrates on the problem of radar modelling under battlefield background with limited prior information, and a data-driven method for MFR reverse modelling is proposed. Firstly, based on the theory of formal language, an initial FSA is created; then, with the thought of statistic induction, the radar state transitions in the intercepted signals are recognised and counted, yielding the probability set and the SFA. The finally modelled MFR SFA can be used for recognising radar states, inferring behaviour regularities and supporting intelligent jamming decision, whose results are of practical significance in achieving cognitive electronic warfare.

The proposed method presents the modelling process in the ideal situation. However, further analysis should be added for inaccurate prior information and poor quality signal data, which is to be explored in future work.

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