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A novel fuzzy based approach for multiple target detection in MIMO radar

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Abstract

This paper deals with the problem of multiple target detection in MIMO Radar systems. We propose a novel fuzzy-based approach for detecting multiple targets when conventional Compressive Sensing algorithms fall short. Ease of interpretability, modeling, limited training data requirement and implementation are some of the benefits of the Fuzzy-Logic based approach. The variation of the probability of detection, the probability of false alarm and the Mean Squared Error with the Signal-to-Noise ratio are studied. Also, the time complexity of the proposed Fuzzy-based approach is measured

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Keywords: Sparsity ;Restricted Isometric Property (RIP) ;Fuzzification ;Membership Function; Mean Squared Error (MSE)

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1. Introduction

MIMO Radar has been achieving a considerable amount of attention in recent times. Unlike phased array radar, it does not require a correlation between the signals. Instead, all the signals in MIMO are independent. In conventional radar, target scintillation is considered to be a problem but in MIMO radar it is considered as a benefit. A MIMO radar can freely choose the probing signal transmitted via its antennas to increase the power around the location of the target to detect and approximate its location or beam pattern from the signal reflected back. In Multiple Input and Multiple Output Radar, many probing signals can be transmitted at the same time and reflection can be processed with the multiple receivers. This processing is done by relying on orthogonality of the signal that is probed.

MIMO radar can be used to improve spatial resolution and spatial multiplexing. MIMO radar is of two types: colocated and distributed MIMO systems. In colocated, all the antennas are closely situated such that their RCS is identical[1]. However, in distributed antenna system each target is spaced such that they meet the targets at different angles. In distributed system, each antenna has an individual cross-section. Every target in the radar system is identified with the RCS. A target RCS represents the amount of energy reflected from the target towards the receiver as a function of target aspect with respect to the transmitter/receiver pair. In MIMO radar the receiver enjoys the fact that the average of the Signal to Noise ratio is almost constant. But, in the case of phased array radar where it has only single path, the received SNR varies considerably. A major problem in localization systems is the location of the target, whether the target is stationary or moving. If they are moving Doppler effect has to be considered. Another problem is if they are closely spaced then it will be difficult to identify the targets. The maximum number of targets that the MIMO radar can find than the phased array radar is M_t, where M_t is the number of transmitting antennas. The advantage of using MIMO radar are as follows: Superior parameter identifiability, direct applicability of adaptive radars and large degrees of freedom.

The recent works have been mainly focused on detection and localization of target in the region of interest[11][12]. Similarly, in this paper, the problem of detection and the probability of false alarm is analyzed and verified. For the purpose of detection, various algorithms have been studied and utilized in the signal models constructed in the recent years[2][4][6]. Compressive Sensing algorithms like Orthogonal Matching Pursuit, Subspace Pursuit, CoSaMP, Iterative Hard Thresholding Pursuit and Fuzzy logic have been implemented and verified in this paper. The algorithms have been utilized for a various number of targets. A sparse localization framework is proposed for MIMO array. This framework is able to detect the number of targets with sub-sampled received signals.

The paper is organized as follows. In Section 2, we give basic insight on the concept of Compressive Sensing and Fuzzy Logic, in Section 3 we discuss the signal model for antennas with fixed positions. In Section 4, the proposed fuzzy-based approach is explained in detail. In Section 5, we discuss the simulation results. Finally, we make some concluding remarks in Section 6.

2. Background

2.1. Compressive Sensing

In practical scenarios, the received signals can be modeled as an underdetermined system of linear equations predominantly. An underdetermined system has an infinite number of solutions. Extraction of specific solutions to such systems urges the need to impose certain constraints. Sparsity is one such constraint that is exploited for solution estimation. A *M*N* matrix is said to be *K*-sparse if exactly *K* elements of the matrix are non-zero and all *(MN-K)* elements are zero. Sparse solutions do not exist for all system of equations. But in case, if the equations are found to have a sparse solution, the compressive sensing helps in recovery of such solutions[3][7]. The support of a vector *x*, also denoted by *supp(x)* is the l0-norm of the vector given by

$$\|x\|_0 = \{i \ , \ \forall\, x_i \neq 0 \tag{1}$$

If the vector is $\boldsymbol{K}$-sparse, then $\boldsymbol{supp(x) \leq K}$.

The other important criterion to be satisfied, to obtain bounded outputs is the Restricted Isometric Property (RIP). RIP helps to recover signals with high probability.

The K^{th} restricted isometric constraint of a matrix $\boldsymbol{\psi}$ is defined by δ_K , which satisfies

$$(1-\delta_K)\|x\|_2^2 \;\leq\; \|\psi x\|_2^2 \;\leq\; (1+\delta_K)\|x\|_2^2 \;\;, when\; \|x\|_0 \leq K \tag{2}$$

In most cases, the constraint $\boldsymbol{\delta_K \leq 0.1}$ from $\mathbf{n = O(\boldsymbol{K}\log \boldsymbol{N^{\beta}})}$ measurements, where $\boldsymbol{\beta}$ denotes a small integer.

There exist numerous Compressive Sensing techniques, from which we consider Orthogonal Matching Pursuit, CoSaMP and Iterative Thresholding Pursuit for analysis. The computational simplicity of the Orthogonal matching pursuit is its major advantage over other algorithms[8].

2.2. Fuzzy Logic

Classical logic yields solutions that are binary, '0' implying 'false' and a '1' implying 'true'. In cases where the solutions might be partially true or partially false, classical logic approaches may not find relevance. In such scenarios, a 'fuzzy logic' based approach is required, whose outputs lie in the range of 0 to 1 and not exactly 0 or 1. Fuzzy Logic, in other words, may also be termed as the 'many valued logic'. A 'true' value in classical approach, lies in a range of values in a fuzzy-based approach characterization. In other words, a fuzzy truth is an inexact description of a real true value. Fuzzy Logic finds its application in imprecise modes of interpretation. In general, a fuzzy logic system consists of three stages: an input stage, a processing stage, an output stage. The inputs to the system, known as 'crisp' inputs are nothing but the received vectors. The transformation of crisp inputs to fuzzy inputs is essential, and is termed as 'fuzzification'. Membership functions convert the crisp input to fuzzy inputs by mapping data from any domain ranges to the grade of membership between 0 and 1. The fuzzified inputs are then subjected to a rule base, for the decision making process. The decisions made are termed as the 'Inferences'. The output of the process, also known as the fuzzy output is then transformed to crisp outputs. By and all, the entire logic is a three stage progression including fuzzification, computation with a rule base and defuzzification[9],[10].

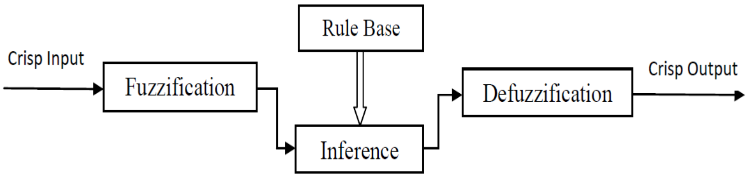

Fig. 1. Block diagram of fuzzy logic.

3. Signal Model

The model under consideration includes M_t transmitting nodes and M_r receiving nodes[5]. The position of the transmitting and receiving antennas are denoted by (t_m^x , t_m^y) and (r_m^x , r_m^y) respectively. Each transmitting antenna transmits electromagnetic waves that are reflected by the targets and are received by the receiving antennas with changes in wave properties and with a time delay. The carrier frequency modulating the transmitting waveform is f_c. There are K stationary point targets present in a clutter-free environment. Spatial sparsity is achieved by discretizing the region of interest into N grids. The grid coordinates are represented by $\{ (x_g,y_g) ,\;\; g \in [1,N] \}$, The baseband signal measured after reflection from the target is expressed as,

$$z_{mn}(t) = \sum_{g=1}^{N} s_{mn}^{g}\, x_m\big(t - \tau_{mn}^{g}\big) + q_{mn}(t) \tag{3}$$

where $q_{mn}(t)$ denotes the Additive White Gaussian channel Noise

τ_{mn} denotes the signal propagation time

s_{mn} represents the reflection coefficient allied to the g^{th} grid point

The propagation delay is obtained from transmitter-target and the target-receiver bi-static Euclidian distances. The presence of a target in the g^{th} grid point, forces the value of s_{mn}^{g} to be non-zero and the rest being zeros due to fading and attenuation. The received signal is measured by sampling at a rate f_s and L samples are obtained. Model (1) is given in vector form as,

$$z_{mn} = \psi_{mn} s_{mn} + q_{mn} \tag{4}$$

where

$$z_{mn} = [z_{mn}(t_0 + 0T_s) \quad z_{mn}(t_0 + 1T_s) \cdots z_{mn}(t_0 + (L-2)T_s) \quad z_{mn}(t_0 + (L-1)T_s)]^T ,$$

$$q_{mn} = [q_{mn}(t_0 + 0T_s) \quad q_{mn}(t_0 + 1T_s) \cdots q_{mn}(t_0 + (L-2)T_s) \quad q_{mn}(t_0 + (L-1)T_s)]^T ,$$

$$s_{mn} = [s_{mn}^{1} \quad s_{mn}^{2} \dots \dots s_{mn}^{N-1} \quad s_{mn}^{N}]^T \quad \text{and}$$

$$\psi_{mn} = \begin{bmatrix} x_m(t_0 + 0T_s - \tau_{mn}^{1}) & \cdots & x_m(t_0 + 0T_s - \tau_{mn}^{N}) \\ \vdots & \ddots & \vdots \\ x_m(t_0 + (L-1)T_s - \tau_{mn}^{1}) & \cdots & x_m(t_0 + (L-1)T_s - \tau_{mn}^{N}) \end{bmatrix}_{LXN}$$

with t_0 being the starting time of sampling and $T_s = 1/f_s$ denotes the sampling time.

We define $\psi = diag\left(\psi_{11}, \psi_{22}, \dots \dots, \psi_{M_tM_r}\right)$. The set of all received signals from different transmitter and receiver pairs , after sampling are stacked in the vector z given by,

$$z = \left[(z_{11})^T \dots \dots \dots \left(z_{M_tM_r}\right)^T \right]^T = \psi s + q \tag{5}$$

where,

$$s = \left[(s_{11})^T \dots \dots \dots \left(s_{M_tM_r}\right)^T \right]^T \text{ and } \quad q = \left[(q_{11})^T \dots \dots \dots \left(q_{M_tM_r}\right)^T \right]^T$$

The dimensions of s being $LM_tM_r X 1$ and contains M_tM_r sub-blocks with each block having K non-zero elements .

4. Fuzzy logic based approach

From the current signal model, the crisp input is the demodulated vector which is obtained by projecting the measured vector onto the modeled basis function. The demodulated vector consists of elements with wide-ranging magnitudes. So, transformation of the above mentioned crisp input to a fuzzy input is carried out by means of a membership function given by,

$$y = \begin{cases} (x-\alpha)/(m-\alpha), \ \alpha \le x \le m \\ (\beta - x)/(\beta - m), \ m \le x \le \beta \end{cases} \tag{6}$$

where $\boldsymbol{\beta}$ denotes the coefficient of the grid which reflects the maximum and

$\boldsymbol{\alpha}$ denotes the grid coefficient with minimum reflection

m denotes the mean value of the grid reflection coefficients

The fuzzified input is then fed to the system for computation of the fuzzy output by applying a set of rules defined in the rule base and the fuzzy output obtained is as follows,

$$y_i = \begin{cases} 1, \ |y_i| \ge (1-\varepsilon)\sigma \\ 0, \ otherwise \end{cases} \tag{7}$$

where $\boldsymbol{\varepsilon}$ denotes a constant such that $\mathbf{0} < \boldsymbol{\varepsilon} < \mathbf{1}$

σ denotes the maximum value of given by $\boldsymbol{y_i} \le \boldsymbol{\sigma}$, $\forall \ \boldsymbol{i} \ \boldsymbol{\epsilon} \ [\mathbf{1}, \boldsymbol{NM_tM_r}]$

The fuzzy output is then de-fuzzified by mapping the outputs to the membership function given by Equation(6) and the crisp output is obtained. The pseudo-code for the proposed approach is as follows,

- *Input: y=(x-xmin)/(xmax-xmin) is given to the membership function*
- *Initialize constant alpha { alpha = σ }*
- *The rule base takes decision on the input based on alpha value*
- *The indices of the values are utilized for extraction of grid identity*
- *If (Range<alpha)*
- *ind = 0 { ind = vector holding the Index values}*
- *The matrix is again rearranged to original indices*
- *The inference holds the result from the rule base*
- *The values are de-fuzzified from the inferences*
- *The crisp output obtained can be used for the probability of detection and false alarm.*

The presence of 1's in the crisp output vector at the grid indices where the targets are present, implies that the target is detected. Whereas, the presence of 1's at locations other than those specified above, contribute to the false alarm. The overall performance of the proposed approach is evaluated by computing the Probability of Detection and Probability of false alarm.

5. Results and discussions

In this section, we evaluate the performance of the proposed approach in section-IV. We consider MIMO radar with 4 M_t, 4 M_r nodes. Each antenna transmits waveforms with pulse repetition interval 0.125 ms modulated by a carrier frequency of 5 GHz. We assume that K targets are present in the space of interest. The maximum number of non-zero entries in target vector is $K*M_t*M_r$. The target space is discretized into N grids, where N=25. The dimension of the target vector is $((N*M_t*M_r) \times 1)$. Each receiving antenna operates with the sampling frequency of 5MHz. Here L is the number of samples and L is 625. The compressive sensing algorithms were iterated 1000 times. In this paper, three simulations have been performed. The first simulation is performed for analysis of the Compressive Sensing algorithms inclusive of OMP, CoSaMP, SP and IHTP. Then the second simulation is performed for the reconstruction of the original signal using fuzzy logic. In this simulation a threshold is fixed for the reflection coefficients and the probability of detection and false alarm are simulated. Here the value of σ is fixed to be 0.6. In the third simulation, the fuzzy logic results are compared with Compressive Sensing algorithms which are shown in the MSE vs SNR graph. Finally, the time complexity comparison is shown in Table 1. The number of realizations for the entire set of simulations was 500.

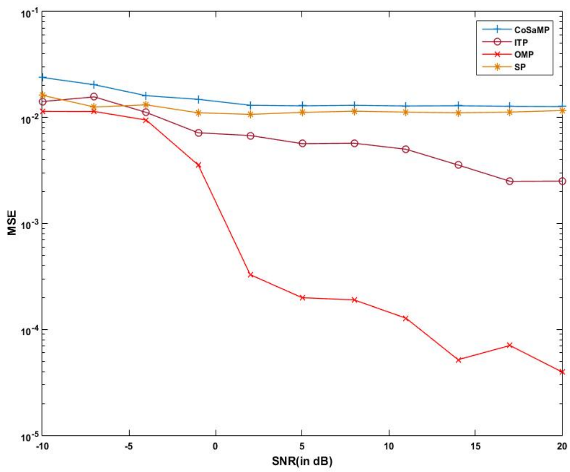

Fig. 2 MSE vs SNR for CS Algorithms

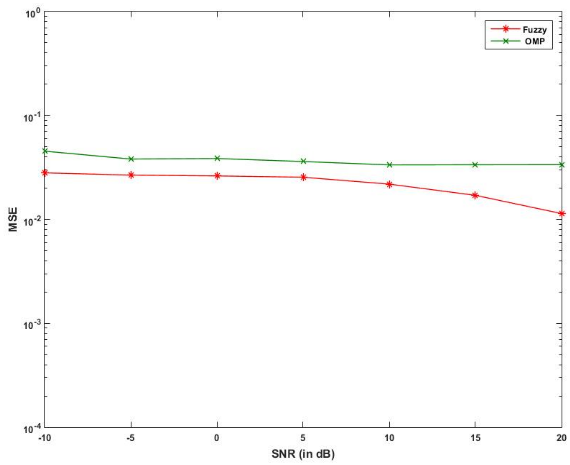

Fig. 3 Comparison of MSE of OMP and Fuzzy Logic for K=4

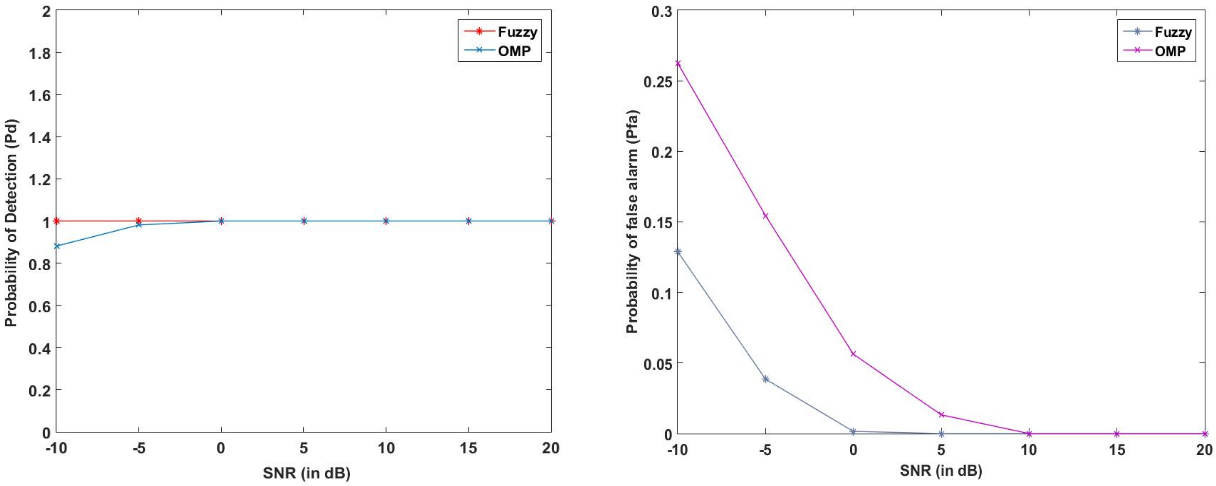

Fig. 4a Fig. 4b

Fig. 4 Comparison of Probability of detection and false alarm for OMP and Fuzzy-based approach for K=4

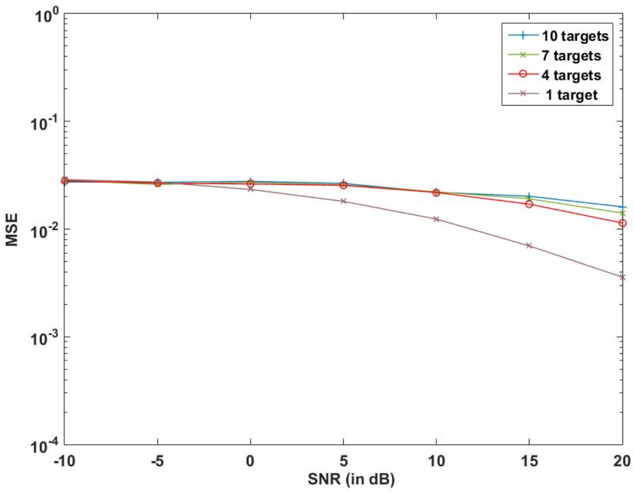

Fig. 5 MSE vs SNR for multiple target detection using Fuzzy Based approach

Fig. 2 shows the performance of traditional compressive sensing algorithms for single target detection in the current scenario under varying SNR conditions. The fact that Orthogonal Matching Pursuit performs better than the other algorithms is well elucidated from the plot. The reason being that in the OMP algorithm an atom picked once, never gets picked up again and the residues obtained on successive iterations are orthogonal to each other. Hence, the obtained results from the OMP algorithm are taken to be the benchmarks for further performance analysis of the proposed approach. Although the OMP algorithm has a better performance for single target detection, the algorithm fails on an extension to the multiple target scenario. The reason being that on increase in the number of targets the demodulated vector becomes denser, leading to the failure of sparsity-based approaches. This urges the need for a more efficient approach for detection of multiple targets. The comparison of the OMP algorithm and the proposed approach is shown in Fig.3 (K=4). For instance, the MSE at an SNR of -5 dB from the OMP algorithm is 3.81*(10^-2), whereas the error obtained from the fuzzy-based approach is 2.67*(10^-2). The error analysis is supported by the computation of the probability of detection and false alarm, as depicted in Fig. 4. From Fig. 4a, we observe that the probability of detection increases with increase in SNR and saturates at an SNR of 0 dB. Whereas, the probability of false alarm decreases with increase in SNR, as depicted in Fig. 4b. At sub-zero SNR conditions, say -10 dB the variation obtained from both the approaches is around 10-15%. This contributes to a minimum error and greater efficiency of the fuzzy-based approach when compared to the OMP algorithm. Fig. 5 shows the performance of Fuzzy-based approach for a different number of targets. It is explicit that, with an increase in the number of targets, the MSE increases. But the difference in error is very small, implying that the method can be extended to more number of targets notably 10 targets, as shown in the figure. The MSE in each case is found to decrease, with an increase in SNR for values greater than -5 dB. In the fuzzy logic based approach, appropriate selection of constant σ, influences the fuzzy output. The probability of detection and false alarm vary based on the constant σ. Therefore, an idle case would be to assign a value ranging between 0.5 and 0.7 to the constant σ. The time complexity for simulating the OMP algorithm and Fuzzy logic-based approach are 1.13 seconds and 4.88 seconds respectively.

6. Conclusion and future scope

We have proposed a MIMO radar system that detects multiple targets in the region of interest. We show that within the proposed framework, it is possible to detect K targets using about M_t ,M_r antennas, which are verified with simulation results. Moreover, the proposed fuzzy logic-based approach is suitable for multiple targets than traditional Compressive Sensing algorithms. The estimation of the probability of detection and false alarm show the advantage of using Fuzzy logic over Compressive Sensing. There is a trade off between fuzzy logic and Compressive Sensing algorithms for time complexity and accuracy. We also notice that, in MSE vs SNR graph, the estimation error is found to be in the order of 0.001 which shows that as the SNR increases, the algorithm becomes more regressive. The idea presented in the paper can be extended to using OMP in Fuzzy logic, where the probability of error might be reduced further.

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