Differentiation Between Manned Aircraft and Missile RADAR Signatures Using Fourier Analysis and Singular Value Decomposition

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Abstract

In defense scenarios the differentiation between unmanned missiles and manned aircraft is an important aspect of our country's ability to defend itself. The presented project shows how, based on synthetic data gathered from an electromagnetics simulation, singular value decomposition of the frequency response of different aircraft's shape is able to be used to differentiate between the different kinds of aircraft. The system remains reasonably accurate when the aircraft is imaged at different positions throughout the vision area of the radar system, suggesting that such a method could be reliably used, in real time, to quickly and efficiently determine the type of object detected by the RADAR.

I. The Need for RADAR Fingerprinting

RADAR (radio detection and ranging) is an invaluable tool for the early detection and warning of incoming hostile aircraft into a country's airspace. Different kinds of threats command different responses and countermeasures. Traditional simple RADAR systems cannot differentiate between metallic objects of similar sizes. RADAR relies on transmitting some known amount of electromagnetic radiation and analyzing how much of the radiation is reflected back toward the transceiver. Traditionally, radar systems rely on a human operator to analyze the received signal (the RADAR signature) of an object and report it. Unfortunately, this human-driven approach is slow, expensive and inaccurate. This project explores how singular value decomposition can be used with Fourier analysis of the signals to match known RADAR signatures to that of an incoming object.

II. RADAR Simulation Technique

It is neither economical nor practical in this case to configure a real RADAR system to generate the data needed for this exploration. Instead, a finite element analysis (FEA) method was used to simulate a RADAR system. The finite-difference time-domain technique was chosen for the electromagnetics simulation. The code implements a simplified two dimensional solution to Maxwell's equations in order to emulate the signal propagation of a rudimentary pulse RADAR system. A linear gaussian pulse was chosen because such a pulse is relatively simple to practically generate and it contains a wide span of frequency components, useful for determining the resonant points of a given body, in this case, an aircraft. The linear pulse, emulating the radiation pattern of a large patch antenna or a rudimentary forward firing phased array, was created using the total-field scattered-field technique. Three point receivers, emulating practical dipole antennas, were used to capture the "RADAR signature" of the object. These receivers are placed equidistant from each other and centered on the transmission pulse. Fig 1-3 are the diagrams of the situation with the transmitter shown in red, the receiver shown in blue and the object shown in green. The system was validated by visually inspecting the simulation and ensuring it conformed to a reasonable behavior.

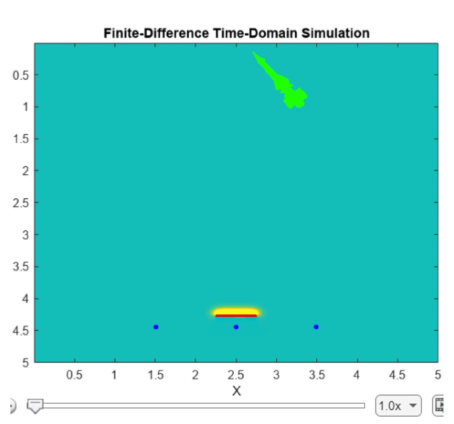

Fig 1: The initial linear wave as "transmitted" at the "antenna"

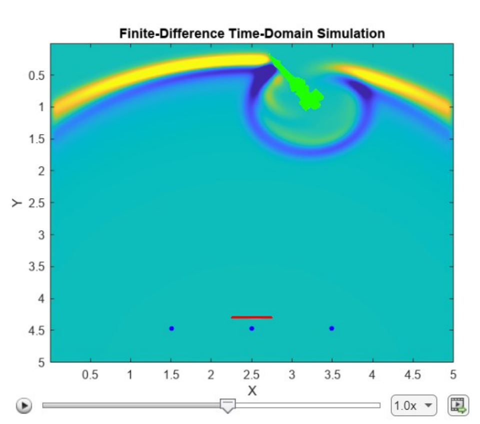

Fig 2: The wave expanding forward as it hits the metallic "missile."

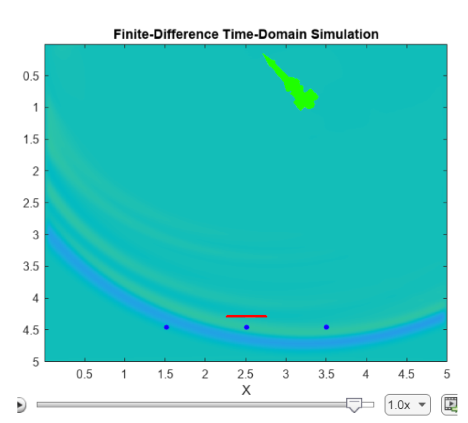

Fig 3: The wave reflecting back toward the "transceiver."

III. Need for Frequency Decomposition

The received RADAR signature of the aircraft is captured in the time-domain. Through testing, it was determined that alone, the time-domain response of the detected object is of little value for differentiating between aircraft. Instead, the frequency domain components of the signal were far more valuable. When decomposed, certain responses are representative of certain shapes of aircraft. To perform the frequency decomposition the Fast Fourier Transform (FFT) algorithm implemented in MATLAB was used. Determining the specific frequency components of the signal was unimportant because the algorithm used for pattern matching only compares the frequencies relatively. The first 30 taps of the FFT were analyzed, as these contained the most data. For example, the difference between the frequency response of the manned aircraft and missile is clear when comparing Fig 4 to Fig 5. The difference is seen due to the different shape of each aircraft.

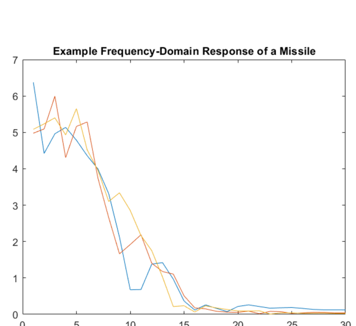

Fig 4: The frequency response of the missile in a certain position.

The frequency domain components shift less than time domain components.

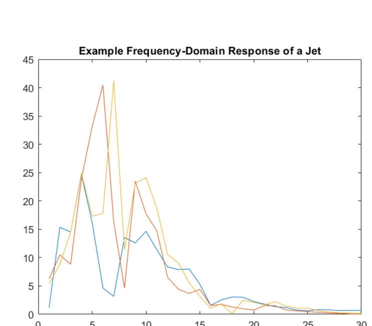

Fig 5: The frequency response of the manned aircraft in a certain position.

IV. RADAR Signature Matching Technique

Singular value decomposition is used to match the frequency response of a given aircraft to the shape of that aircraft. The method used is analogous to the Eigenfaces method described in the paper by Turk at el. however, singular value decomposition is used for pattern matching instead of eigenvalue decomposition. The implementation of the algorithm is as follows:

1. Gather a set of training data containing the frequency response of the desired objects are recorded.
2. Rearrange the data from each receiver such that they are linear, giving in a single column for each transmitted signal. This will create a single matrix, holding all received data.
3. Subtract the mean of the data from each data point to mean-center the matrix data.
4. Calculate the singular vales and singular vectors of the matrix to obtain the "singular frequencies" of each signal
5. Compare the "singular frequencies" of a given test to those of the training set and compute the closest match. This yields a prediction of the type of aircraft being seen.

This algorithm matches patterns in the frequency response of a given aircraft to the training data.

V. Simulation Parameters and Results

In the FEA simulation the relative magnetic permeability and permittivity values for stainless steel were used to represent the body of the missiles and manned aircraft. Values of one (free space) were used for the empty space. The 2D models used for the simulations can be seen in Fig 12. The data in the six figures below was collected for each simulation. As visible in the data, the time-domain response of the objects shifted back and forth depending on a variety of factors. This is evidenced by the time-domain means being erratic and spanning a wide area. The frequency domain mean peaks on a certain location and varies little based on the position of the object being imaged. This makes frequency response a good indicator.

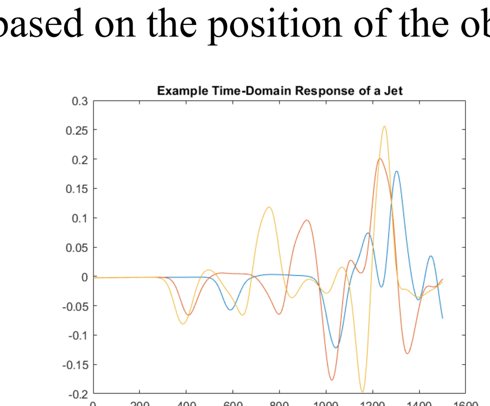

Fig 6: The time-domain response of the manned aircraft.

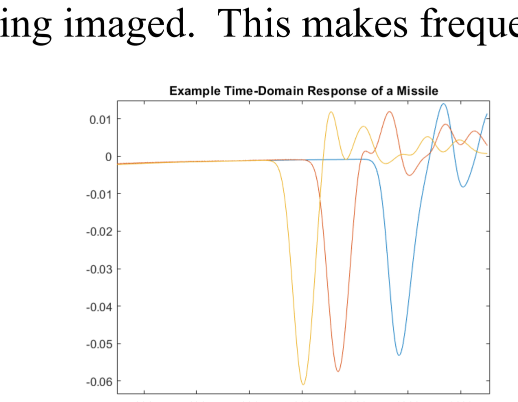

Fig 7: The time-domain response of the missile.

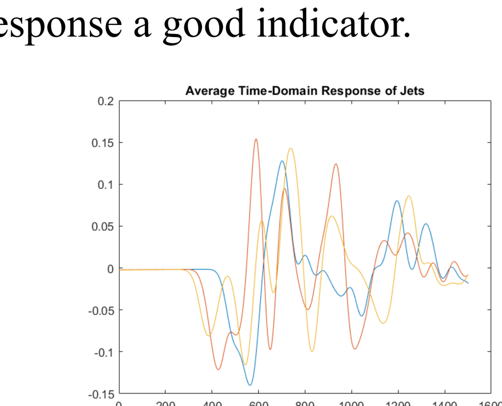

Fig 8: Mean time-domain response of the manned aircraft.

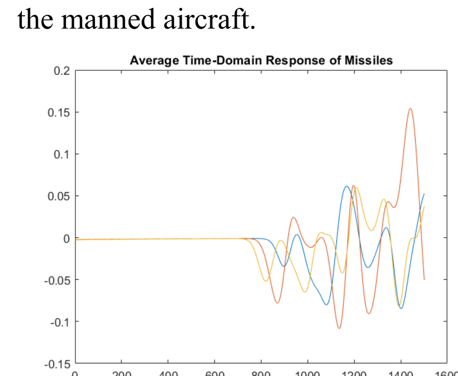

Fig 9: Mean time-domain response of the missiles.

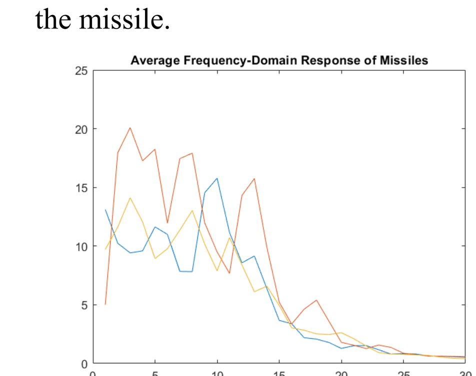

Fig 10: Mean frequency-domain response of the manned aircrafts.

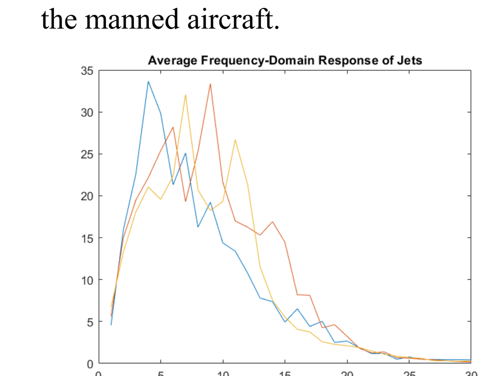

Fig 11: Mean-frequency-domain response of the manned aircraft.

VI. Validating the Predictions

The training data set for the model is made up of forty simulations. Twenty missiles and twenty jet aircraft, each with the imaged object in a random location in the top

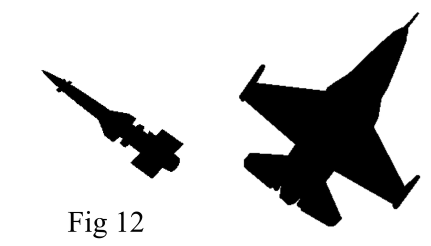

Fig 12

third of the simulation. In a real application, a database orders of magnitude larger would be desirable. Time constraints on this project and simulation performance limited the number ran. Generating large amounts of training data quickly compounds into a great computational task. For testing, ten of each aircraft, placed at random in the same way as before, were sampled, the success rate for missile prediction was 70% and for manned jet aircraft was 80%. The results are presented in Fig 13. The accuracy was impressive given the lackluster amount of training data.

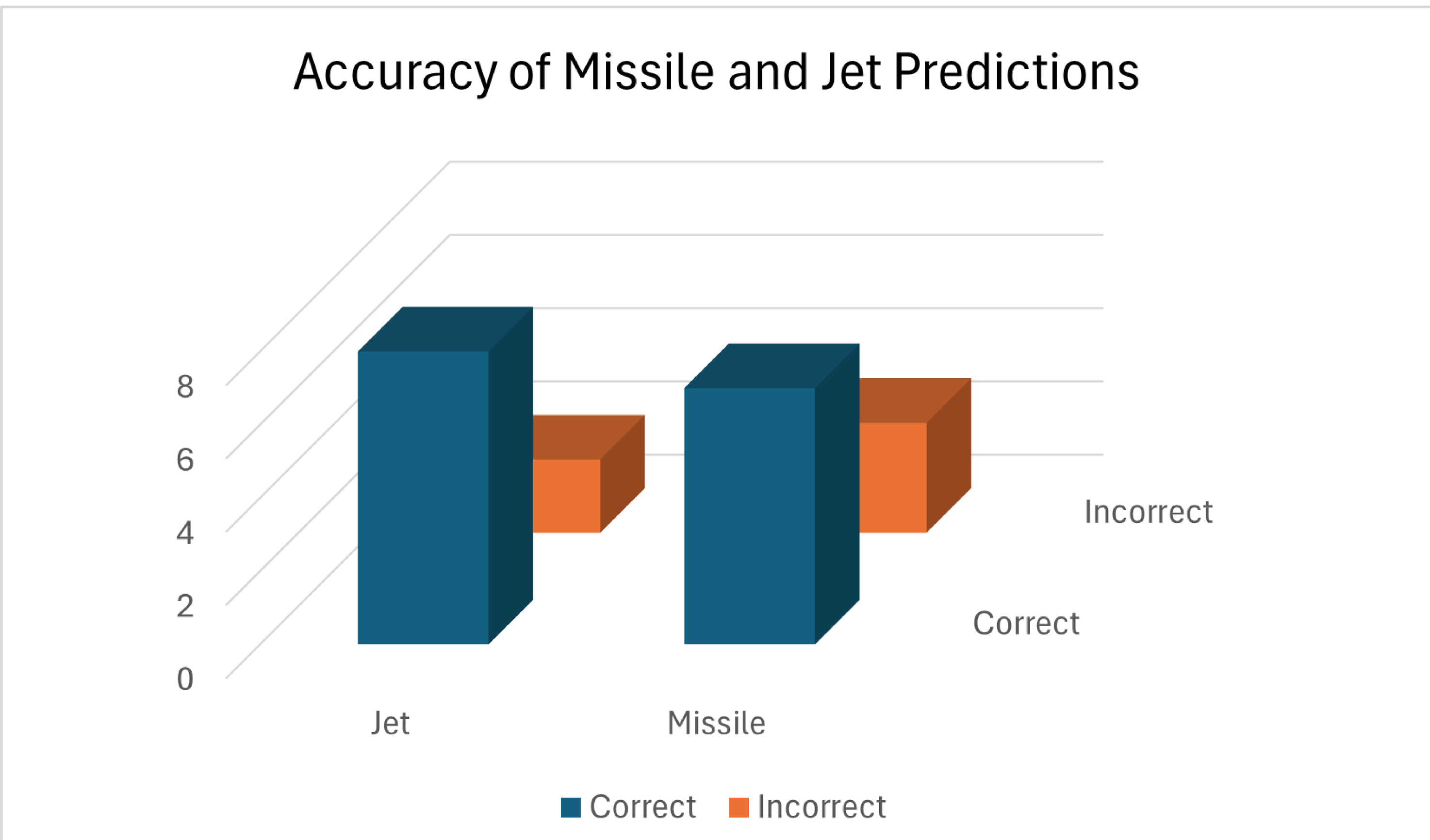

Fig 13: Results of preliminary testing of the proposed prediction engine.

VII. Further Testing and Research

None of the testing presented was statistically significant. In order to go beyond the proof of concept phase, the first step of improving the model would be to run enough FEA simulations to have a statistically significant amount of test data and validation data. Once this is achieved, a rational next step would be to implement a more descriptive FEA algorithm. The addition of a third spatial dimension as well as other elements such as a practical antenna simulation and simulated noise figures. Alternatively, after validating the 2D simulation, testing could be performed on a practical radar system. A variety of readings recorded from physical testing of real scenarios. This data could be used to train and validate the model, allowing it to be used in practical circumstances. If tested and improved upon, this technology could prove useful for defense and industrial use cases, such as private civilian air travel and self-driving vehicles. Overall, the ability to differentiate between different objects with a limited amounts of radar data in a computationally inexpensive way is significant in a variety of applications.

Works Cited

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