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Real-Time Moving Target Detection Using Deep Learning

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ABSTRACT

Moving Target Detection (MTD) is a vital discipline crucial for identifying and tracking objects across sectors like national security, surveillance, law enforcement, and more. Particularly crucial in radar and surveillance technologies, MTD faces challenges in detecting moving targets within synthetic aperture radar (SAR) signals, complicated by signal clutter from stationary objects. Our research introduces an innovative approach named Bayesian Fusion for Moving Target Detection (BF-MTD) within SAR signal processing. Leveraging Bayesian modeling, this technique efficiently pinpoints target positions. Initial steps involve using Short-Time Fourier Transform (STFT) and matching filters to identify potential target areas. Bayesian fusion refines the results, accurately determining real target locations with the guidance of a Naive Bayes classifier.

Keywords: Moving Target Detection, synthetic aperture radar, Short-Time Fourier Transform, Bayesian fusion

1.INTRODUCTION

Advancements in radar technology have propelled Synthetic Aperture Radar (SAR) systems into multifaceted applications, notably target detection and tracking. However, detecting moving targets in SAR signals is intricate due to SAR's inherent intricacies, such as high resolution and sensitivity to subtle shifts in target motion.

SAR's evolution encompasses ground-moving target detection, broadening its scope from imaging static objects [1, 2]. SAR's distinctive sensor technology empowers this capability, unaffected by factors such as fluctuations in light and shifts in weather conditions. This inherent resilience makes SAR an invaluable asset across diverse tracking scenarios [3]. Its versatility spans military realms like expansive battlefield surveillance, reconnaissance, and civilian domains like environmental monitoring and disaster assessment [4, 5].

SAR's distinctive feature lies in its high-resolution imaging of the Earth's surface. Achieved by leveraging platform motion, SAR synthesizes a virtual aperture, surpassing physical antenna limitations. On the other hand, radar, employing radio waves, detects and pinpoints objects by analyzing signal reflections. Radar's applications are widespread, from weather forecasting and air traffic control to maritime navigation and military surveillance [5].

In principle, SAR and radar technologies, with their unique attributes, contribute to an array of applications, from detailed imaging to precise target location and tracking.

2. RADAR TECHNOLOGY

Radar (Radio Detection and Ranging) is a versatile technology that employs radio waves to detect and locate objects in its vicinity. Through the emission of radio signals and analysis of their reflections, radar can determine an object's distance, speed, direction, and even shape or size in some instances. This technology finds diverse applications in weather forecasting, air traffic control, maritime navigation, and military surveillance [6].

Radar's operation involves emitting microwave pulses to illuminate an area and capturing reflections with a receiver. Precise measurement of the time delay between transmission and reception enables the calculation of object distances, referred to as range or slant range. Fundamental to radar's functionality is range resolution, enabling the differentiation of objects at varying distances and identifying separate objects within resolution cells.

Enhancing range resolution leads to increased pulse bandwidth and data rate. A typical radar system's layout is shown in Figure 1.1, includes components such as a transmitter emitting electromagnetic waves, an antenna for signal propagation, and a sensitive receiver for capturing and processing reflected signals. Signal processing extracts valuable information from received echoes, including range and relative speed measurements using the Doppler Effect [1].

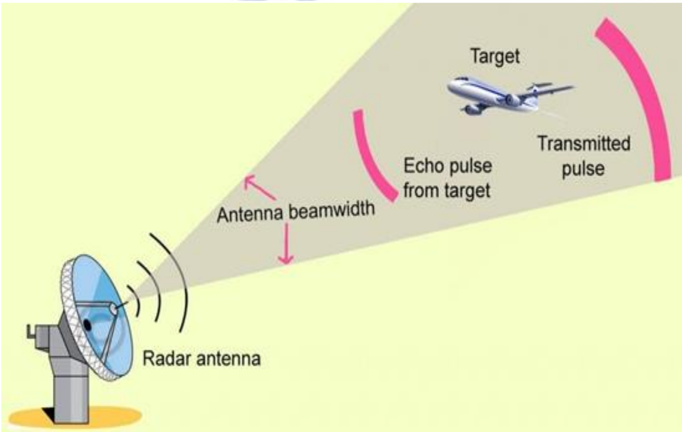

Figure 1.1: Typical Radar system layout.

The processed data is presented on a radar display, showing detected object locations relative to the radar's position. This display may convey additional details like target velocities and angles. The strength of radar technology lies in its ability to operate under diverse weather conditions, day or night, and detect objects over significant distances, contingent upon the system's capabilities [7, 8].

3. SYNTHETIC APERTURE RADAR

SAR satellites play a crucial role in capturing swaths of side-looking echoes, a process that leads to the generation of high-resolution imagery [9]. The effectiveness of SAR technology hinges on a combination of factors, including range resolution and the incidence angle. The range resolution, which essentially dictates the radar's ability to distinguish between objects at different distances, is influenced by the pulse length and the bandwidth.

In the context of real aperture radar, the along-track or azimuth resolution of the microwave pulse is subject to limitations imposed by diffraction effects. This limitation is directly linked to the radar's wavelength and the length of its aperture. Essentially, this means that when the radar's beam pattern is projected onto the Earth's surface from a certain range, the resulting raw radar data can be prone to azimuthal blurring. This blurring can render the data less focused and detailed, particularly in terms of the horizontal direction. Notably, Figure 1.3 illustrates the SAR radar configuration for imaging.

The outcome of employing the synthetic aperture method is an image that not only provides information about the amplitude or backscatter of the signals but also incorporates valuable phase information, which relates to the range of the objects being observed. This amalgamation of amplitude and phase data for each pixel of the image contributes to a more comprehensive and detailed understanding of the observed scene, making SAR an invaluable tool in various applications, from environmental monitoring to disaster assessment and more.

SAR capitalizes on the Doppler history inherent in radar echoes, engendered by the spacecraft's forward movement, to synthesize an expansive antenna [1]. This innovative approach achieves remarkable azimuth resolution in the resultant image, despite the antenna's physical compactness. During the radar's trajectory, individual positions prompt pulse transmission, with the returning echoes routed through the receiver and archived in an echo repository.

The implementation of SAR mandates an intricate amalgamation of onboard navigation and control systems, bolstered by the precision of Doppler and inertial navigation equipment.

4. MOVING TARGET DETECTION

Moving Target Detection (MTD) is a pivotal facet of radar and sensor technology that revolves around the identification and tracking of objects in motion within a specified area. Its significance spans diverse domains, including military surveillance, weather monitoring, traffic management, search and rescue, and more [11]. The precise detection and tracking of moving targets contribute to heightened situational awareness, better decision-making, and support for a wide array of operational endeavors.

MTD is a term primarily associated with Doppler processing systems in surveillance radars. It shares a similarity with the concept of Moving Target Indicators (MTI), which discerns moving targets from clutter based on amplitude differences using a delay line canceller mechanism. While MTI involves simpler filtering, MTD employs a more intricate composite algorithm [11]. MTD integrates various filters, such as Doppler filters, CFAR (Constant False Alarm Rate), zero velocity filters, clutter map subtraction, and post-processing as shown in Figure 1.2.

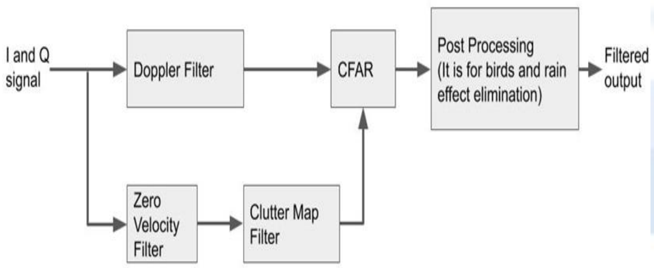

Figure 1.2: Illustration of moving target detection Process.

In SAR systems, MTD algorithms operate by analyzing the phase history and Doppler characteristics of returned radar signals. By evaluating the phase and frequency shifts between successive radar returns, the system can distinguish moving targets from stationary clutter and terrain features.

MTD in conjunction with SAR finds extensive applications, spanning both military and civilian domains such as traffic monitoring, maritime surveillance, and disaster response [5]. By augmenting situational awareness and bolstering intelligence gathering capabilities, this technology emerges as a prized asset for diverse industries and organizations.

5. PROPOSED METHODOLOGY FOR MOVING TARGET DETECTION SYSTEM

The methodology begins with a comprehensive problem analysis and the application of Bayesian Fusion (BF) techniques to identify target detection requirements. This involves considering diverse aspects such as target types, operational conditions, and desired performance levels. Subsequently, the process entails data acquisition from various sources, including sensors, cameras, or radar systems. This combination of data sets the stage for distinct signal processing stages, as depicted in Figure 1.3, meticulously designed to extract relevant signals associated with moving targets. An essential aspect of this process involves discerning between different target types and characterizing background clutter.

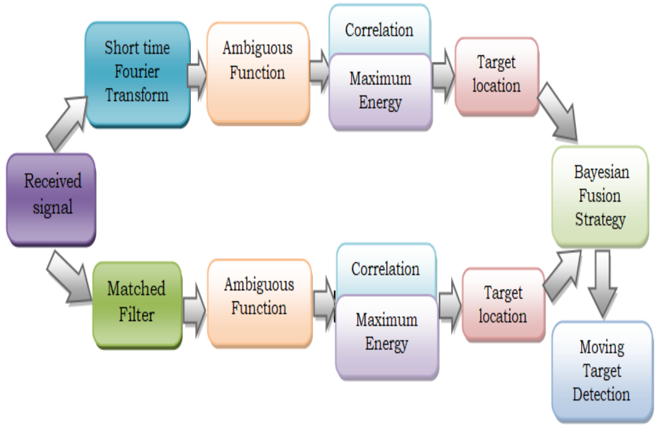

Figure 1.3: Proposed methodology for MTD system.

The pivotal Matched Filter (MF) plays a crucial role by enhancing the Signal-to-Noise Ratio (SNR) through frequency response optimization [12]. Furthermore, the utilization of Ambiguity Functions (AF) plays a key role in correlating Fractional Fourier Transform (FrFT) signals with the original ones. This correlation is essential for detecting pulse distortion caused by propagation delay and Doppler Frequency (DF). The AF correlation of the MF output enhances the identification of signals. The fusion of FrFT and MF outputs is of paramount importance for precise object localization in MTD scenarios.

The methodology also employs the power of Fuzzy inference, particularly emphasizing the Fuzzy-Bayesian Fusion for Moving Target Detection (FBF-MTD) and related work. This approach proves to be advantageous over the adaptive neuro fuzzy decisive technique. Moreover, the integration of Bayesian Fusion, Fuzzy Bayesian fusion, deep Recurrent Neural Networks (RNN), and deep Convolutional Neural Network (CNN) methods holds the promise of significantly enhancing the accuracy and reliability of the moving target detection system.

6. BAYESIAN FUSION

Bayesian Fusion (BF) is a probabilistic technique that merges measurements, observations, and predictions from various sensors to estimate the present state of moving targets and predict their future trajectories [13]. It employs probability distributions to represent uncertainties, integrates information, and adapts beliefs based on new data.

Bayes' rule, named after Thomas Bayes, assesses confidence in a quantity X using information about another Y. In this context, A represents a target state hypothesis, with its initial probability (a priori probability) denoted as $P(X)$. When a target emerges, sensors provide sequential evidence, Y, about its movement. The likelihood $P(Y|X)$ gauges the chance of observing Y given X. Bayes' rule updates (a posteriori probability) in X based on Y.

$$P(X|Y) = \frac{P(Y).P(X)}{P(Y)} \qquad (1.1)$$

where X' indicates X being false. $P(Y)$ is the likelihood of Y across all scenarios, incorporating prior information. As new evidence arrives at each step, Bayes' rule iteratively strengthens belief in target state hypothesis X, known as sequential Bayesian estimation.

7. DEEP LEARNING MODELS

The integration of Deep Learning (DL) techniques has ushered in a new era of significance and innovation in the field of moving target detection. By combining neural networks and advanced algorithms, DL offers a range of crucial benefits that are revolutionizing the way we approach this critical domain [15]. One of its primary advantages lies in its capacity to autonomously learn intricate patterns and features from complex sensor data, eliminating the need for manual feature engineering. This capability enhances the accuracy and robustness of target detection, enabling the system to discern moving objects from background clutter with exceptional precision.

Moreover, DL models excel in adapting to diverse and dynamic scenarios, making them well-suited for the ever-changing conditions inherent in moving target detection. Another compelling aspect is DL's ability to process data in real-time, enabling swift and informed decision-making, which is crucial in applications like surveillance and autonomous systems. The multi-modal fusion capabilities of deep learning further amplify its impact by seamlessly integrating data from various sensors, enhancing detection accuracy by leveraging complementary information [16].

Furthermore, the continuous learning and adaptability of deep learning models ensure that detection systems remain effective over time, adjusting to evolving target characteristics and environmental factors. As we delve deeper into the potential of DL, its scalability becomes apparent, enabling the analysis of extensive datasets and deployment across large geographical areas. The technology's capacity to uncover complex relationships and nonlinear patterns opens doors to uncovering subtle nuances that might escape traditional methods.

Looking forward, ongoing research and advancements in DL are poised to yield even more sophisticated architectures and techniques, propelling the field of MTD into a future characterized by unprecedented accuracy, adaptability, and efficiency. In essence, deep learning's transformative influence promises to reshape the landscape of moving target detection and its applications across diverse sectors.

DL models have gained significant attention in the field of MTD due to their ability to automatically learn and extract complex patterns from data [15]. The term "deep" refers to the multiple layers of interconnected neurons that make up these networks, allowing them to capture intricate features and hierarchies within the input data. In the context of MTD using SAR, both Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) play important roles in enhancing the accuracy and effectiveness of MTD systems. These models can be effectively employed to enhance the accuracy and efficiency of MTD within SAR systems.

8. RESULTS AND DISCUSSION

Within this section, a detailed comparison was undertaken using simulations, directly contrasting the BF-MTD method with the traditional MF technique. Following this, a comprehensive assessment was carried out to gauge the precision and reliability of the approach. The subsequent paragraphs delve into the results obtained from practical experiments, providing a robust validation of the viability and effectiveness of the method.

The effectiveness of the BF-MTD model [78] is confirmed through a thorough examination of simulation results conducted within a RADAR simulation framework. To validate the BF-MTD method, a radar simulation is performed using the MATLAB R2018a software tool.

The Simulation results encompass specific hardware and software components. A PC configuration: Intel I3 processor, 4 GB of RAM, Windows 10 operating system. The BF-MTD model undergoes robust evaluation through simulations mirroring real-world scenarios, thoroughly assessing its performance for MTD. Thorough testing validates the approach, making it suitable for real-world use.

9. SIMULATION RESULTS OF THE BF-MTD MODEL

To demonstrate the robustness and effectiveness of the method, simulations were conducted under different SNR conditions. In such cases, SNR starts from -10 dB and ends at 10 dB. The observed signal contains three components: target echo, Gaussian white noise at each sensor, and reverberation based on the cell-scattering model. Through these systematically designed simulations, the aim is to highlight the method's resilience and prowess in handling complex real-world conditions characterized by diverse levels of reverberation and noise.

The simulation outcomes are derived from the BF-MTD model, facilitated within a RADAR simulation environment. Figure 1.4 illustrates the efficacy of BF-MTD in detecting targets across multiple rounds. Within this visual representation, the target locations are denoted by blue dots, offering a contrast against the triangular markers that signify the positions of mountains within the geographical area. Particularly, the BF-MTD is adept at identifying the target's location by optimally positioning the RADAR at the center. As the simulation progresses through each round, the BF-MTD consistently excels in detecting numerous moving targets dispersed across the region under scrutiny.

Figure 1.4 demonstrates the transmission and reception of SAR signals, where emitted radar signals are captured by the receiver. Calculating the time taken for the radar signal to travel to and from the center provides the distance to the object. The detected objects are visualized for various rounds: initial round (0), 50 rounds, 100 rounds, and 200 rounds, as shown in Table 1.1.

Table 1.1: Comparing the BF-MTD with existing methods.

Variations	Metrics	FrFT	MatchedFilter	Multi-frameFrFT	Li *etal.*	BF-MTD
Varying number of targets-20	DT (sec)	11.422	10.497	13.945	10.808	7.009
	MSE	43713.44	41556.43	67291.44	38357.6	5626.9
	MT	0.516	0.427	0.659	0.407	0.205
Varying number of targets-20000	DT (sec)	11.694	11.408	14.402	11.144	6.852
	MSE	54728.75	44536.71	77417.07	42101.48	17102
	MT	0.412	0.259	0.634	0.261	0.152
Varying pulse repetition Level- 0.004	DT (sec)	10.709	8.312	11.238	8.103	5.904
	MSE	51536.82	45626.25	107643.6	39061.96	13087.99
	MT	0.449	0.346	0.182	0.229	0.176
Varying antenna turn velocity-3.1416	DT (sec)	11.341	9.158	13.803	9.305	6.484
	MSE	44447.43	35594.19	83140.02	36376.04	8209.485
	MT	0.497	0.390	0.414	0.395	0.200

10. CONCLUSIONS

This section outlines an approach for detecting moving targets within the range of a RADAR system, enabling users to track the positions of these objects. The BF-MTD method influences a Bayesian fusion strategy, specifically designed for SAR-based models. The BF-MTD method integrates STFT and matched filter outputs through a decision fusion model. Utilizing the NB classifier, the optimal parameter for target localization is determined. Target locations are identified based on the highest energy from STFT and MF responses. The NB classifier then probabilistically communicates the final target position to the SAR model.

The effectiveness of the BF-MTD approach is evaluated through simulation studies under various SAR scenarios. The assessment involves key metrics such as DT, MTR, and MSE, with comparisons against contemporary techniques.

In conclusion, the simulation results underscore the notable performance of BF-MTD across multiple metrics, including DT (5.904 sec), MSE (5626.9), and MTR (0.152). This highlights the superiority of the method compared to state-of-the-art techniques.

The innovative BF-MTD approach outlined in this study holds significant potential for real-time applications within the realm of SAR technology. By effectively integrating Bayesian fusion strategies and advanced signal processing techniques, the method offers a robust solution for detecting and tracking moving targets in SAR systems.

In real-time scenarios, such as surveillance, disaster response, and environmental monitoring, the BF-MTD approach can deliver accurate and timely results. Its ability to effectively fuse information from multiple sensing channels enhances target detection precision and reduces false positives, ensuring reliable performance even in dynamic and challenging environments.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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