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# IMPROVE THE SAFETY OF AIR TRANSPORT, ESPECIALLY IN MILITARIZED TERRAIN, BY USE OF SIDE LOOKING AIRBORNE RADAR AND SPACE TIME ADAPTIVE PROCESSING

**Summary.** The paper explores the potential to enhance aviation safety, particularly in militarized regions, by outfitting aircraft with Side Looking Airborne Radar (SLAR) and employing space-time adaptive processing (STAP) algorithms. The research objective revolves around implementing a model of side-looking airborne radar and the corresponding STAP algorithms. This technology enables the detection of slow-moving targets amidst strong interference, encompassing both passive (clutter) and active (jammer) elements. Slow-moving targets relative to the aircraft's speed include tanks, combat vehicles, command vehicles, artillery, and logistical assets of enemy forces. The theoretical framework of space-time adaptive processing is presented, elucidating the sequential steps of the classical Sample Matrix Inversion Space-Time Adaptive Processing (SMI STAP) algorithm. The paper underscores the significance of characteristic parameters delineating a linear STAP processor. The proposed solution facilitates the detection of enemy combat measures and enhances aviation safety. It outlines a radar model installed beneath

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the aircraft's fuselage and elucidates algorithms for space-time adaptive processing of radar signals. The simulations conducted within the article were executed using the MATLAB environment. The simulation results indeed suggest that the proposed solution holds promise for deployment in equipping aircraft of one's own military and those engaged in operations within conflict zones. This paper stands as one of the few contributions in the literature addressing the augmentation of aircraft safety through radar and space-time adaptive processing.

**Keywords:** radar, safety, space-time adaptive processing, signal processing, airborne radar, air transport

## 1. INTRODUCTION

Today, radars can be categorized based on their function, operational mode, range, probing signal type, or signal processing methodology. Nevertheless, this merely provides an overview of the wide range of radar systems customized for diverse applications. Additionally, radars can be classified based on the platform on which they are deployed.

Deploying radar on an aircraft surface inevitably introduces several technical challenges. Firstly, the high velocity of the aircraft leads to moving received echoes, necessitating specialized algorithms for their mitigation. Secondly, achieving effective target detection amidst significant clutter poses another substantial challenge. Consequently, this study explores the implementation of Side Looking Airborne Radar (SLAR) installed beneath the aircraft fuselage, coupled with Space-Time Adaptive Processing (STAP) algorithms to counteract interfering signals.

STAP represents a contemporary signal processing approach applied in radar systems. This technique is instrumental in detecting ground-based moving targets via radar systems mounted on airborne platforms. In the literature, radar interference is categorized into passive interference (referred to as “clutter”) and active interference (known as “jammer”). Passive interference encompasses echoes from signals reflected off buildings, vegetation, and other terrain obstacles, while active interference includes radio interference transmitters hindering the operation of one's own radar systems [1].

Aircraft equipped with active radar sensors and state-of-the-art signal processing capabilities possess real-time control and surveillance capabilities over their operational airspace. Enhanced operational awareness for pilots mitigates risks and threats posed by enemy combat assets. Therefore, the proposed solution holds potential for deployment in outfitting aircraft for military forces and those engaged in operations within conflict zones.

## 2. A LITERATURE REVIEW

The history of the beginning of STAP technology dates back to the early 1970s [2]. As a result of the work done by researchers, several monographs were published summarizing the current state of knowledge on STAP [3]. The publications of the aforementioned authors laid the foundation for future STAP research [4]. Until the late 1990s, STAP algorithms were based on statistical methods for estimating the disturbance covariance matrix. A very popular method, which later often served as a reference for new methods, was the Sample Matrix Inversion (SMI) method [3].

The publication [5] marked a significant advancement in scientific inquiry regarding the evolution of methods for estimating interference covariance matrices. It introduced a novel form of non-statistical interference covariance matrix estimation termed the Direct Data Domain method, commonly abbreviated as D3, making its debut appearance in the literature.

Subsequently, research on statistical methods for estimating clutter covariance matrices was discontinued, which seems appropriate, given the drawbacks with which they were characterized. The main ones include the need to access a huge amount of training data contained in distance bins, which was not infrequently difficult to fulfil. In the following years, efforts were made to introduce improvements to D3 methods by eliminating the disadvantages that occurred, which caused phenomena such as difficulties in detecting a target against a background of inhomogeneous interference or confusing target detection [6].

Another approach to estimate the clutter covariance matrix was through the Knowledge-Aided STAP (KA-STAP) method [7]. The concept behind this technique was to derive the clutter covariance matrix using information about the radar-scanned area or the present targets [8]. It is important to highlight that during the early 21st century, one of the primary research objectives of the US Defence Advanced Research Projects Agency (DARPA) was the development of the KA-STAP method [9]. Consequently, it is noteworthy that, based on the existing literature, it can be inferred that assessing the accuracy of prior knowledge about the scanned terrain compared to the actual radar data received. This constituted the primary focus of scientific research on KA-STAP algorithms.

In recent years, a fresh avenue of research has emerged in the advancement of non-statistical techniques for clutter covariance matrix estimation [10]. These approaches rely on sparse recovery algorithms within STAP [11]. Consequently, according to reports from the literature, there has been a surge in research publications over the past few years focusing on the refinement of methods for clutter covariance matrix estimation in STAP, particularly emphasizing the utilization of sparse recovery algorithms [12].

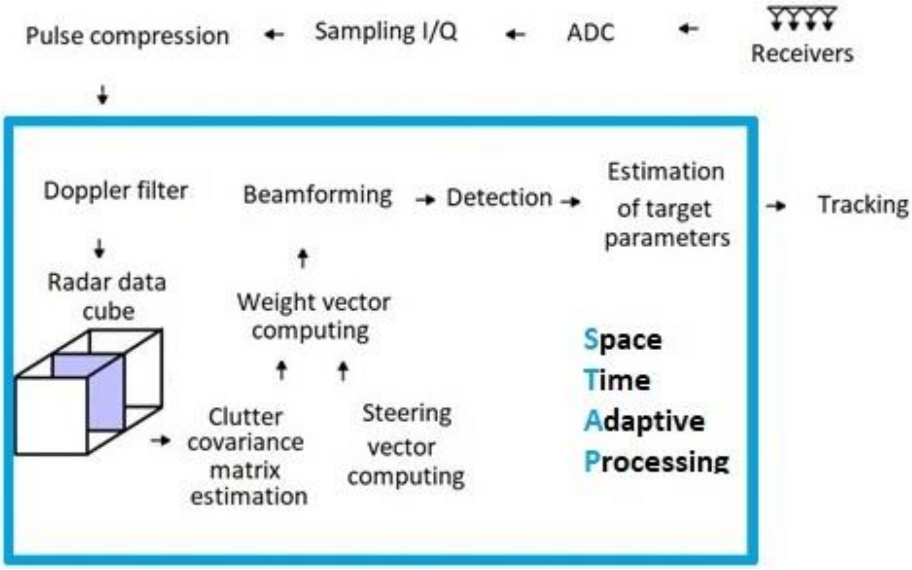

Fig. 2. STAP signal processing [3]

In order to realize the essence of the issues discussed in the publication, it seems very helpful to present a diagram of STAP processing, on which the process of estimating the clutter covariance matrix can be clearly located [3]. Hence, the above figure highlights the most important steps in the processing of the radar signal in STAP technology.

## 3. RESEARCH PROBLEM

The problem of this research is the implementation of a model of side looking airborne radar and the corresponding algorithms for space-time adaptive signal processing.

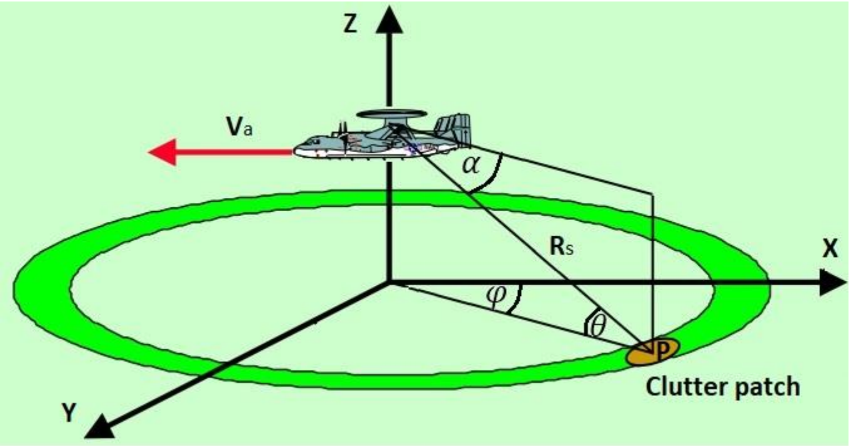

Fig. 2. Geometry of radar [4]

The paper adopts a model of the localization of the radar and the target according to the diagram in Figure 2. The letter *P* was used to denote the target, the distance of the radar to the target was denoted $R_s$, the elevation angle between the radar and the target was denoted $\theta$, and the azimuth angle between the radar and the target was denoted $\varphi$. The flight altitude of the aircraft is denoted *H*. The aircraft is moving in a straight line at a constant speed $V_a$. Located under the fuselage, the radar has a uniform linear antenna (ULA) radiating the target *P* at an angle $\alpha$. The radar emits electromagnetic waves at a wavelength $\lambda$, the radar signal is emitted as a sequence of *M* coherent pulses with a pulse repetition rate $f_r$. The pulses are emitted by *N* antennas spaced at a fixed distance *d* from each other. Accordingly, the received echo forms a radar data cube. The radar data cube consists of composite signal samples collected for *M* pulses by *N* antenna array elements for distance intervals from 1 to *K*.

Every STAP algorithm analyses the unprocessed data, utilizing a particular snapshot of the radar cube at a predetermined distance bin *k* [3]. Following this, assessments regarding the presence or absence of the target within the specified distance bin are commonly conducted. To accomplish this, a filter is devised, distinguished by its strong amplification of the pertinent signal from the target, alongside substantial suppression of all other signals (including interference from stationary objects and jammers). STAP is engineered to eliminate echoes originating from interference sources while preserving the signal originating from the target of interest [1].

## 4. RESEARCH METHOD

The data contained for the *k*-th snapshot of the raw data cube is a matrix [1]:

$$\boldsymbol{X_k} = \begin{bmatrix} x_{k,1,1} & x_{k,1,2} & \cdots & x_{k,1,N} \\ x_{k,2,1} & x_{k,2,2} & \cdots & x_{k,2,N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{k,M,1} & x_{k,M,2} & \cdots & x_{k,M,N} \end{bmatrix}. \tag{1}$$

For further processing, the matrix should be regrouped into a vector:

$$\boldsymbol{X_k} = [x_{k,1,1} \quad x_{k,2,1} \quad \cdots \quad x_{k,M,1} \quad x_{k,1,2} \quad \cdots \quad x_{k,1,N} \quad \cdots \quad x_{k,M,N}]. \tag{2}$$

$\boldsymbol{X_k}$ denotes the received echo. $\boldsymbol{X_k}$ consists of the sum of signals from the object $\boldsymbol{S_k}$, clutter $\boldsymbol{C_k}$, jammer $\boldsymbol{J_k}$ and noise $\boldsymbol{N_k}$ [1]:

$$\boldsymbol{X_k} = \boldsymbol{S_k} + \boldsymbol{C_k} + \boldsymbol{J_k} + \boldsymbol{N_k}. \tag{3}$$

According to the literature, the first step in STAP processing is to determine the control vector $\boldsymbol{S}(f_{sp}, f_d)$ for each target. This vector is the Kronecker product of the temporal steering vector $\boldsymbol{S_t}(f_d)$ and the spatial steering vector $\boldsymbol{S_{sp}}(f_{sp})$. The steering vector in the time domain is shown as [1]:

$$\boldsymbol{S_t}(f_d) = e^{j2\pi(M-1)f_d} \tag{4}$$

where $f_d$ is the Doppler frequency shift:

$$f_d = \frac{2 \cdot V_r}{\lambda} \tag{5}$$

where $V_r$ is the radial velocity between the target and the radar. The temporal steering vector is given as [1]:

$$\boldsymbol{S_{sp}}(f_{sp}) = e^{j2\pi(N-1)f_{sp}} \tag{6}$$

where $f_{sp}$ is the spatial frequency, which is expressed as:

$$f_{sp} = \frac{d}{\lambda}\cos(\alpha). \tag{7}$$

Finally, the steering vector takes the form [1]:

$$\boldsymbol{S}\left(f_{sp}, f_d\right) = \boldsymbol{S_t}(f_d) \otimes \boldsymbol{S_{sp}}\left(f_{sp}\right) = \begin{bmatrix} 1 \cdot 1 \\ e^{j2\pi f_{sp}} \cdot 1 \\ e^{j2\pi 2 f_{sp}} \cdot 1 \\ \vdots \\ e^{j2\pi(M-1)f_{sp}} \cdot 1 \\ 1 \cdot e^{j2\pi f_d} \\ e^{j2\pi f_{sp}} \cdot e^{j2\pi f_d} \\ \vdots \\ \vdots \\ e^{j2\pi(M-1)f_{sp}} \cdot e^{j2\pi(N-1)f_d} \end{bmatrix} \tag{8}$$

where the symbol $\otimes$ denotes Kronecker product.

Subsequently, the following stage involves the calculation of the clutter covariance matrix. To achieve this, the distance bin under examination, denoted as $k$, is partitioned into $N_c$ bins of clutter. It is postulated that the clutter component within a specific distance bin results from the amalgamation of signals emanating from each clutter patch. Consequently, the covariance matrix encompassing noise, clutter, and jammer for a particular snapshot of the radar data cube is delineated as [1], respectively [13]:

$$\boldsymbol{R}_n = E\{\boldsymbol{N}_k \boldsymbol{N}_k^H\} = \sigma^2 I_{MN} \tag{9}$$

$$\boldsymbol{R}_c = E\{\boldsymbol{C}_k \boldsymbol{C}_k^H\} = \sigma^2 \sum_{i=1}^{N_c} CNR \boldsymbol{S}_i\left(f_{sp}, f_d\right) \boldsymbol{S}_i^H\left(f_{sp}, f_d\right) \tag{10}$$

$$\boldsymbol{R}_j = E\{\boldsymbol{J}_k \boldsymbol{J}_k^H\} = I_M \otimes \sigma^2 JNR \boldsymbol{S}_j\left(f_{sp}, f_d\right) \boldsymbol{S}_j^H\left(f_{sp}, f_d\right) \tag{11}$$

where $\sigma$ is the power of the clutter source, $\boldsymbol{I}_M$ and $\boldsymbol{I}_{MN}$ denote the unit matrix of dimension $M \times M$ and $M \times N$, $\boldsymbol{S}_i\left(f_{sp}, f_d\right)$ is the steering vector of an individual clutter bin, $\boldsymbol{S}_j\left(f_{sp}, f_d\right)$ is the control vector of a given active interference source, CNR is the clutter to noise ratio measured in decibels and JNR denotes the jammer to noise ratio measured in decibels, respectively. Thus, the covariance matrix representing the combined effects of clutter, jammer, and noise can be expressed by the equation:

$$\boldsymbol{R_k} = \boldsymbol{R_c} + \boldsymbol{R_j} + \boldsymbol{R_n}. \tag{12}$$

By establishing both the steering vector and the covariance matrix encompassing clutter, jammer, and noise, ascertain the weight vector [14]:

$$\boldsymbol{w_k} = \varepsilon \cdot \boldsymbol{R_k^{-1}} \cdot \boldsymbol{S}\left(f_{sp}, f_d\right) \tag{13}$$

where $\varepsilon$ is a scalar, $\boldsymbol{R_k^{-1}}$ is the inverse covariance matrix of the sum of clutter, jammer and noise. $\boldsymbol{S}\left(f_{sp}, f_d\right)$ is the steering vector for one target to be detected. In practice, both $\boldsymbol{R_k^{-1}}$ and $\mathbf{S}\left(f_{sp}, f_d\right)$ are unknown [15].

As previously noted, the STAP processor functions as a linear filter, with its primary objective being the elimination of clutter, jammer, and noise to facilitate target detection. The relationship governing these processes is detailed in [16]:

$$Y_k = \boldsymbol{w}_{\boldsymbol{k}}^H \cdot \boldsymbol{X}_{\boldsymbol{k}} \tag{14}$$

where $Y_k$ is the resulting scalar. The symbol $H$ denotes the Hermitian transpose of the given matrix.

At this point it is worth quoting a very important parameter describing the degree of clutter in the received echo signal. This parameter is the clutter ridge slope $\beta$. In general, the higher its value, the more difficult it is to detect the target. Its relationship is given by the formula [17]:

$$\beta = \frac{2V_a}{df_r}. \tag{15}$$

This equation defines the position of the clutter in the space-time plane. It is worth noting that the distance between antennas $d$ takes a constant value at the stage of radar antenna design. Hence, when operating the radar at a specific pulse repetition frequency $f_r$, the value of the $\beta$ parameter can be directly influenced by selecting the value of the flight speed of the platform $V_a$ [3].

Another crucial measure indicating the clutter level in the received signal is the rank of the clutter covariance matrix. The rank of a matrix signifies the highest count of linearly independent vectors that form its rows (or columns). The rank of a matrix is expounded upon by Brennan's equation in the referenced paper [3]. The authors in question approximated the rank of the clutter covariance matrix as expressed by [18]:

$$r_c = \lfloor N + (M-1)\beta \rfloor. \tag{16}$$

The parentheses $\lfloor\ \rfloor$ denote rounding to the nearest integer.

## 5. RESEARCH RESULTS

The simulations conducted in this paper were executed using the MATLAB platform. Initially, simulation analyses were undertaken to assess the scope of application and practical viability of the proposed solution. In this context, the impact of the platform's velocity on radar performance under fixed parameters, as commonly referenced in literature [19], was investigated. Furthermore, the investigations were enhanced by examining the eigendecomposition of the clutter covariance matrix across various radar and platform configurations.

The last section presents the results of a complex simulation of a heterogeneous environment in which a target was randomly placed. The task of the radar and the STAP processing used was to eliminate clutter and correctly detect the target.

The radar and platform models as specified in paragraphs 3 and 4 were adopted for the simulation, with the parameters included in the corresponding tables.

Tab. 1

Parameters adopted to simulation.

| Parameter | Value |
|---|---|
| Antennas | 10 |
| Pulses | 10 |
| Radar operating frequency | 8 GHz |
| Wavelength | 0.0375 m |
| Distance between antennas | 0.01875 m |
| Platform flight altitude | 2000 m |
| Clutter ridge $\beta$ | 0.4…2.0 |
| Pulse repetition frequency | 12 000 Hz |
| Clutter to noise ratio | 30 dB |
| Signal-to-noise ratio | 10 dB |

### 5.1. Scope of applicability and operational use of the developed solution

Figure 3 depicts a graph illustrating the clutter's location in the received signal for various velocities of the platform's flight. As previously established, the velocity of the platform's flight directly influences the $\beta$ parameter. The $\beta$ parameter values are presented within the range of 0.4 to 2.0. For the parameters outlined in Table 1 and a $\beta$ parameter value of 1, a velocity of 90 m/s was determined, representing the optimal scenario in terms of target detection precision. Figure 3 illustrates that with an increase in the $\beta$ parameter, clutter (represented by more and more lines) emerges across a wider range of azimuth angles observed by the radar.

### 5.2. Analysis of the eigendecomposition of the clutter covariance matrix for individual radar and platform parameters

Additionally, the computational complexity, which directly impacts the processing time and target detection efficiency, was calculated for the parameters listed in Table 1. The figure below uses vertical lines to represent the rows of the clutter covariance matrix determined directly from Brennan's equation for various values of the parameter $\beta$. For the given simulation data, the row of the clutter covariance matrix is $r_c = 19$, as shown by the red vertical line in Figure 4. It is also evident that an increase in the parameter $\beta$ leads to a higher order of the clutter covariance matrix, thereby increasing the computational complexity of STAP processing and making target detection more challenging.

### 5.5. Correct target detection

To verify the accuracy of the proposed STAP method using the SMI algorithm, an additional simulation was conducted. A radar system consisting of 10 antennas operating at 10 GHz was assumed. The distance between the antennas was set to half the wavelength, which in this case is 0.015 m. The radar was mounted on an airborne platform moving along the axis of the antennas at a constant speed of 225 m/s at an altitude of 2000 m. For the given speed and pulse repetition frequency, the parameter $\beta$ is equal to 1. The radar-cross section (RCS) of the target was set to 1 m$^2$.

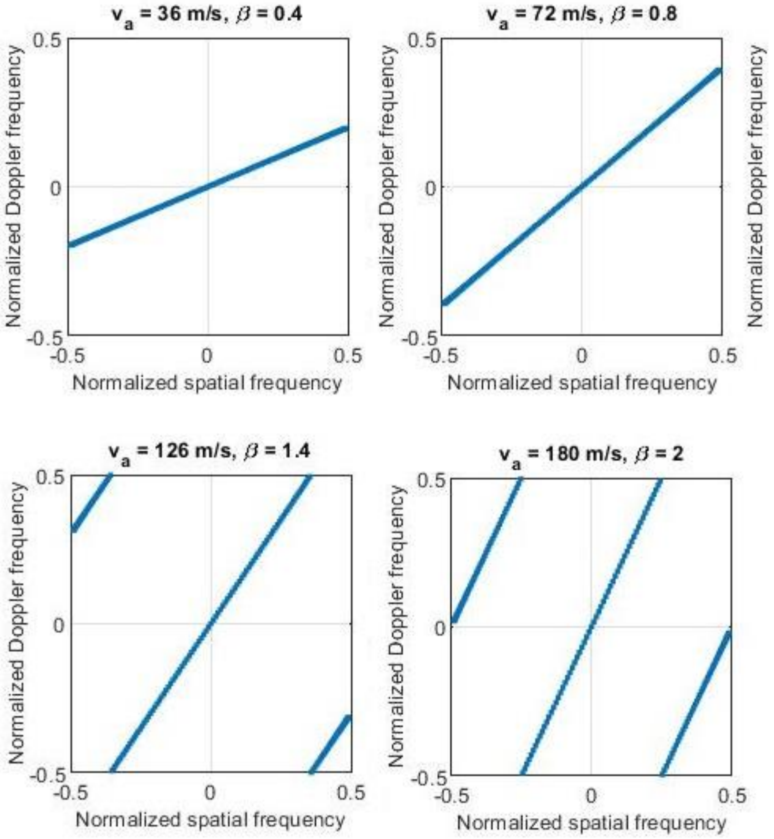

Fig. 3. Graphs of the location of clutter in the received signal for different values of the platform's flight velocity

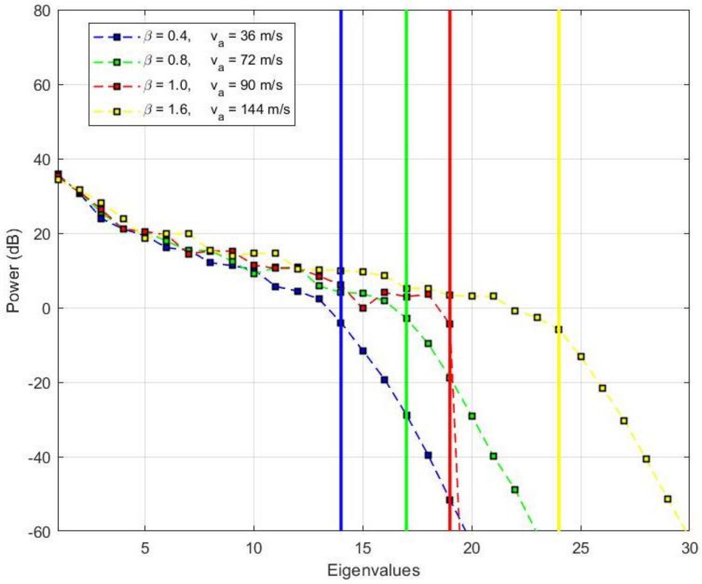

Fig. 4. Plot of the eigendecomposition of the clutter covariance matrix against the value of the parameter β

A commonly utilized model of heterogeneous forest-covered terrain, known in the MATLAB environment as the gamma model, was employed as clutter. Additionally, a jammer was positioned in the field. The parameters used for the simulation are presented in the following tables.

Tab. 2

Parameters adopted to simulation

| **Parameter** | **Value** |
|---|---|
| Velocity of target [ x, y, z] | [40 m/s, 40 m/s, 0 m/s,] |
| Location of target | x = 1500; y = 1500; z = 0; |
| Power of jammer | 100 W |
| Location of jammer [x, y, z] | x = 1100; y = 1200; z = 0; |
| Noise | Gauss noise |

As a result of the simulation, a string of 10 pulses was transmitted through the antenna array, with a pulse repetition frequency of 30 kHz and a pulse duration of 33 μs. Then the signal reflected from the target but also the clutter from the ground surface, the interference signal from the transmitter and the noise on the receiving side were received.

Figure 5a illustrates the values of signals received by the radar's antenna array as a function of range, following the transmission of the first pulse. At this point, due to the presence of significant clutter, the radar is unable to accurately determine the target's position. It is evident that the radar incorrectly suggests the target is located 1000 meters away.

Figure 5b depicts the values of signals received by the radar's antenna array as a function of range, after the first pulse transmission. This time, however, the raw data has undergone STAP processing using the proposed SMI-STAP algorithm implemented in the MATLAB environment. It is clear that the radar correctly identifies the target as being approximately 2200 meters away in a straight line.

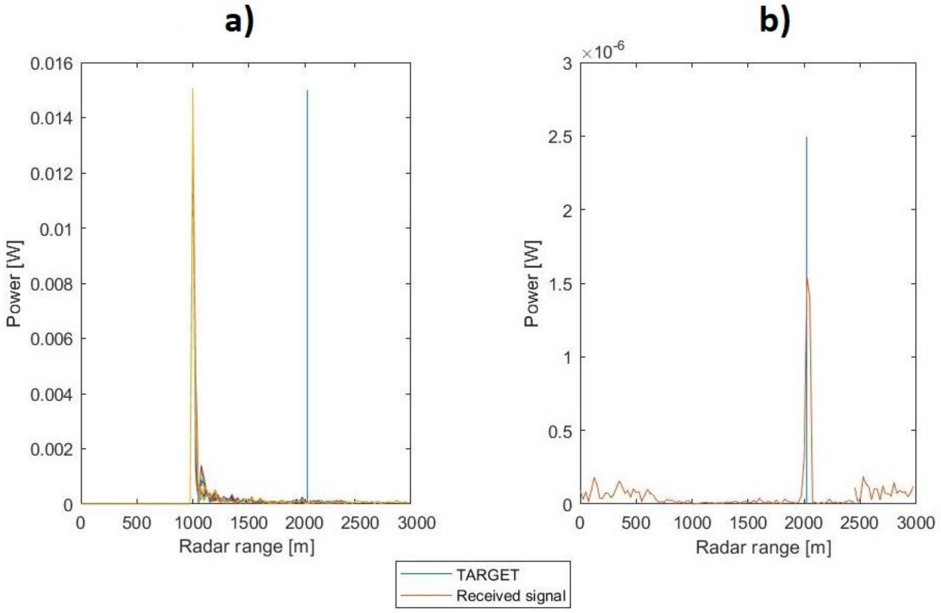

Fig. 6. Space time spectrum of interference before (a) and after (b) SMI-STAP processing

## 6. SUMMARY AND CONCLUSION

The article explores the potential for improving the safety of air transport, particularly in militarized areas, by outfitting aircraft with SLAR and the STAP algorithm. It outlines the theoretical foundations of STAP processing and describes the specific steps of the classical SMI STAP processing algorithm. The theoretical analyses, calculations, and simulation results conducted during the study lead to the following conclusions:

- in STAP processing, several approaches to estimating the clutter covariance matrix are suitable, with a shift away from statistical methods. At present, the most advanced techniques for estimating the clutter covariance matrix are non-statistical methods;
- the influence of the flight parameters of the flying platform on which the radar is mounted, such as speed and the angle of deviation from the axis of the antennas through the parameter $\beta$, which uniquely determines the degree of clutter and the frequency of its occurrence, is emphasized;
- the paper is one of the few items in the literature on enhancing aircraft safety with radar and STAP processing. It represents an original contribution to the development of knowledge and radar technology, and at the same time, this item, through the publication of some of the results in world journals, represents an important point on the map of the development of the field of STAP;
- the theoretical analyses presented in the article, the calculations performed, and the simulation results obtained are of great practical importance. The use of the STAP technique in radar systems contributes to increasing their usability and reducing computational complexity requirements.

In summary, this paper demonstrates that it is feasible to detect slow-moving objects (such as tanks, artillery, and drones) and enhance pilots' situational awareness during flight missions, especially in air transport operations.

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