PROCESSING ECHO SIGNALS REFLECTED FROM UNMANNED AERIAL VEHICLES AND RECEIVED BY RADAR

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In the modern world, with the surge of usage of the unmanned aerial vehicles many tasks related to detection of aerial objects have arisen and also the determination of their type within the cities and the countryside. Such tasks are the recognition and classification of aerial objects using radar stations. Aerial objects that need to be detected usually are unmanned aircraft and birds. Processing the signal received by radar from the aerial object to obtain a proper spectral signature is needed to solve such tasks. The most informative detail for determining the type of the aerial object is the presence or absence of the micro-Doppler effect in the spectral signatures. The perpose of this paper is to carry out and compare two strategies for filtering echo signals from interference and obtaining their spectral signatures. The first strategy involves application of several methods for filtering the echo signal, followed by a standard spectral analysis. The second strategy adds to the previous one the use of an autocorrelation and calculating spectral density. Comparison of the of the applied strategies for processing echo signals from aerial objects showed that the use of the autocorrelation results in a more pronounced, regular and refined spectral signature relative to the first approach with only filtering and spectral analysis . The application of these strategies for processing signals reflected from aerial objects will be used in a future research to design a system with deep integration of the physical and computational components.

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Introduction

In the modern world aerial traffic has arisen within urban development in addition to dense but regulated ground traffic. Aerial traffic is a mixture of unmanned aerial vehicle (UAV) and natural aerial objects, the identification of which requires new analytical approaches with the available hardware. This creates a new field of problems requiring modern solutions.

Various tasks of tracking signals from air objects received by radars while monitoring aerial traffic require to determine their type. Whether monitored object is artificial or natural needs to be determined in the most cases. In addition, some of the tasks require to understand the state of the aerial object and its possible behaviors in the near future. The tasks of analyzing and predicting the behavior of aerial objects are the most urgent at the moment and require careful research at all stages of implementation.

Determination of types of aerial objects is divided into two main classes of tasks:

1) Recognition.

2) Classification.

The main goal of the first class of problems for recognition is to distinguish in general artificial technological flying aerial objects from moving objects in midair of natural kind, such as ornithological ones. For this class of tasks, no deep processing of the initial data is required, which are usually presented in the form of echo signals. Echo signals are the signals which often received when the aerial object is observed by coherent Doppler radars [1]. For recognition a rather superficial filtering of the signal is required without application of more sophisticated methods and algorithms. The result of the recognition is the output answer of the system about whether the aerial object monitored by the radar is artificial or natural. Based on this answer the operator or a decision support subsystem can proceed to any actions related to the analysis or making predictions about object's behavior in the meantime. Then the operator or the decision support subsystem draws conclusions on the basis of the analysis and makes a decision appropriate to the situation, which corresponds to the more general tasks of the entire system.

The goal of the subtype of classification tasks mainly revolves around distinguishing between differentiateent types of aerial objects and automatically and autonomously drawing conclusions for determining the state and behavior of these objects. For this type of tasks more complete filtering is required for the subsequent identification of all possible features that may be contained in a burst of echo signal from aerial object received by radar. Often, developers of the systems for recognizing or classifying aerial natural or artificial objects do not pay enough attention to filtering and getting rid of the stochastic part in the spectral signatures despite the fact that obtaining a proper signal without superimposed noise and interference is very important for analysis and prediction [2].

During filtering echo signals reflected from air objects from the background noise and performing spectral analysis task of detecting Doppler and micro-Doppler frequencies appears often. The micro-Doppler contribution occurs in the spectral patterns of echo signals reflected from unmanned aircraft being monitored by radar in various conditions [3]. This means that, besides occurrence of the main Doppler contribution which is typical for any detected moving aerial object, unmanned aircraft also generates additional frequencies in spectral characteristic due to their rotating blades. Occurence of the additional frequencies is usually called micro-Doppler contribution or effect. Due to the fact that the spectra of various aerial objects vastly differentiate and also due to often strong interference, it is necessary to perform thorough filtering of the signal. This should ensure minimal loss of the useful information that will be required for further classification of differentiateent states and behaviors of aerial objects monitored by the radar.

The main purposes of this paper are the research of the methods for proper and accurate filtering and identification of the parameters of the echo signals received by radar from aerial objects such as UAVs.

As previously mentioned, most monitored moving aerial objects are man-made, such as UAVs of various types, and natural, mainly ornithological ones, or, in other words, birds. UAVs and birds do not differentiate much in speed characteristics, size. Even a flight behavior of UAV and birds often do not differentiate very much. Both birds and modern UAVs can, for example, hover in the air, which makes it difficult to determine the type of aerial object without analyzing the presence or absence of the micro-Doppler effect.

Due to the tasks described above, this paper proposes to study the impact of different methods of obtaining useful information from a radar echo signal.

The initial data are the components of a complex packages of the signals reflected from aerial objects such as the Mavic and Phantom quadrocopters. These packages are a mixture of signal and noise. The authors of this paper propose to carry out and compare two strategies of processing the echo signals:

1) Elimination of the noise from the mixture using filtering methods.

2) Getting rid of stochastic component of the signal by calculating the autocorrelation.

Having completed both tasks, it is possible to analyze the effectiveness of applied concepts, which are schematically presented in Figure 1.

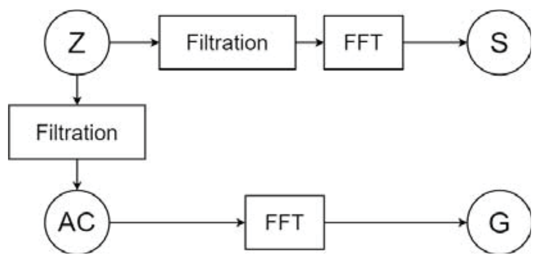

Figure 1. Two strategies for processing echo signal received by radar

The first way is to filter the signal, and then calculate the Fast Fourier Transform (FFT), which will result in the output of a range-spectral characteristic of the echo signal (S) with elimination of the white noise. The range-spectral characteristic is a number of spectra that are distributed over the distance from the radar. The spectra themselves represent the distribution of frequencies that are present in the echo signal reflected from an aerial object.

The second concept also involves the use of filtering, but then an autocorrelation is calculated, which is often used for signals as time functions, and which will remove the stochastic component of the signal.

Stochastics in a complex signal package are random signals that do not have a definite correlation with each other, therefore, after applying calculation of the autocorrelation of the signal, they should not retain their amplitude, while the periodical nature of the useful signal, which is needed to obtain the result, will, on the contrary, appear. Next, an FFT is performed for autocorrelation and the spectral density of the echo signal (G) is therefore calculated. Moreover, the spectral density is also range-spectral, because during conversion the dependence of the signal reflected from an aerial object from the distance will remain. Unlike spectrum, which is a frequency distribution, spectral density is a distribution of power of the frequencies.

1. Application of the filtering methods.

As mentioned above, the experimental data are in the form of the complex packages of echo signal, distributed by the distance from the radar observing the aerial object.

The signal is fed for processing in a digital form, since it has passed through an analog-to-digital conversion. The radar has a built-in analog-to-digital converter (ADC), which has approximately 1024 strobes. Each of the 1024 strobes is divided into a number of the discretes or range counts.

A radar device may have a different number of range counts, which does not significantly affect further calculations. Range counts or discretes and ADC strobes are interchangeable in their dependence to each other in further calculations. An example of the amplitude (real part) and phase (imaginary part) of a complex mixture of the white noise and useful part of the echo signal reflected from a man-made aerial object, distributed over the distance and separated by ADC strobes is shown on Figure 2.

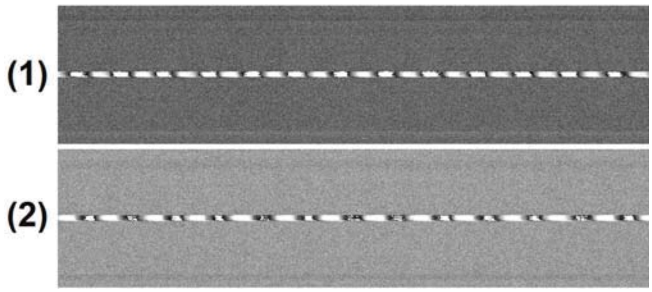

Figure 2. Real (1) and imaginary (2) parts of the complex mixture of the noise and echo signal from the UAV

In Figure 2, the number of strobes is represented as the length of the complex package, while the number of range counts each ADC strobe is divided into is represented as the height. The package of the signal reflected from the aerial object is numerically represented as a matrix, where the strobes are the elements of each row, and the discretes are the elements of the columns. The number of discretes or counts in the initial data is D = 240.

Figure 2 clearly demonstrates why due to the high level of white noise from the complex signal mixture it is impossible to determine to what type the object currently observed by the radar belongs to. Therefore, it is necessary to apply various filtering methods to the mixture of signal and noise, which neutralizes the effect of the transmission medium and the influence of external signals on the propagated package. After that it will be possible to properly carry out a spectral analysis of the signal, which will be more efficient without the presence of noise.

Each strobe of the digital signal in one discrete can be written as

$$\dot{Z}_n = \sum_{i=1}^{K} \dot{z}[i] = \sum_{i=1}^{K} (z_c[i] + jz_s[i]) \quad , \qquad (1)$$

where Z_n – mixture of signal and interference, K – number of the strobes, n – the current discrete, z[i] – complex number related to the current strobe in the series, $z_c[i]$ – real part of the complex number, $z_s[i]$ – imaginary part.

In order to remove noise and obtain only useful information it is necessary to carry out proper filtering. Applied filtration methods are given below as follows.

1) Matched filtering.

The digital complex package that the ADC of the radar outputs after analog-to-digital conversion is rectangular. Therefore calculation for a new element, which is obtained during the compression of the echo signal by range can be written as

$$\dot{z}_k[h] = \frac{1}{f}\sum_{i=h}^{f} \dot{z}[i] = \frac{1}{f}\sum_{i=1}^{f} (z_c[i] + jz_s[i]) \quad , \qquad (2)$$

where $z_k[i]$ – element of new filtered matrix, z[i] – element of the old matrix, *h* – current row, *f* – offset which equals 25.

Formula (2) is performed for each element of the old matrix of the echo signal reflected from the observed aerial object, except for those elements that do not fit into the size of the new matrix. The size of the matrix of the complex package is changed so that in each column the last elements in the number of *f* range counts are excluded from the rectangular pulse.

As a result, the complex signal package is compressed by distance, therefore the length of the matrix rows remains the same and the matrix height decreases by 25 and now is N = 215.

Result of the matched filtration is presented in Figure 3.

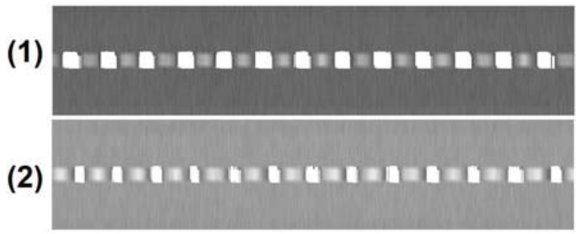

Figure 3. Real (1) and imaginary (2) parts of the signal after matched filtration

Figure 3 shows that despite of the performed matched filtration, the level of white noise did not decrease significantly. But at the same time, matched filtration ensured a clearer view of the useful periodic part of the complex signal.

2) Average filtering.

Average filtering consists of calculating the average value for each discrete and then subtracting it from each element of matrix. Average filtering can be written as

$$\dot{z}_k[n] = \dot{z}[n] - \frac{1}{N}\sum_{i=1}^{N} \dot{z}[i] = z_c[n] + jz_s[n] - \frac{1}{N}\sum_{i=1}^{N} (z_c[i] + jz_s[i]) \quad , \qquad (3)$$

where $z_k[n]$ – element of new filtered matrix, z[i] and z[n] – elements of the complex package, n – current row.

Result of the Average filtering is presented in Figure 4.

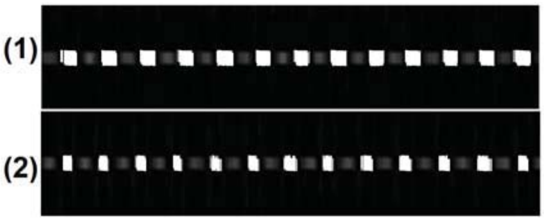

Figure 4. Real (1) and imaginary (2) parts of the signal from the UAV after average filtering

Average filtering method ensured suppression of the scale of interference in a complex package of the echo signal from aerial object, but at the same time the useful part of the signal also faded. This situation requires further refinement in order to add another layer of filtering and get a clearer picture of the periodic signal.

3) Application of the Butterworth filter.

The Butterworth filter has certain characteristics that are not found in many other filters. One of a such characteristic is that this type of filter has the of the flatest frequency response in a passband. The most interesting characteristic is that Butterworth filter can be transformed into a linear digital IIR filter [4].

The use of the Butterworth filter is necessary in order to reduce the effect of noise on the useful signal, despite the fact that useful information has been already identified and mostly vividly presented in the complex package of the echo signal.

In the course of the research it was decided to apply the third order Butterworth filter, because it has the most suitable frequency response for the filtration task for the situation founded. In addition, Butterworth filter is easy to implement, but at the same time has sufficient attenuation. To design the Butterworth filter, it was decided to use the Scipy library, which allows you to construct a relatively simple characteristic function of a linear filter based on given parameters [5].

It was decided to apply a digital linear IIR filter to remove the remaining noise. It's characteristic function can be written as

$$H(x)=\frac{b_0+b_1x^{-1}+b_2x^{-2}+b_3x^{-3}}{a_0+a_1x^{-1}+a_2x^{-2}+a_3x^{-}}, \quad (4)$$

where parameters b_0 = 0.00289819, b_1 = 0.00869458, b_2 = 0.00869458, b_3 = 0.00289819, a_0 = 1, a_1 = -2.37409474, a_2 = 1.92935567, a_3 = -0.53207537 are automatically generated by Scipy software.

Result of this additional filtration is presented in Figure 5.

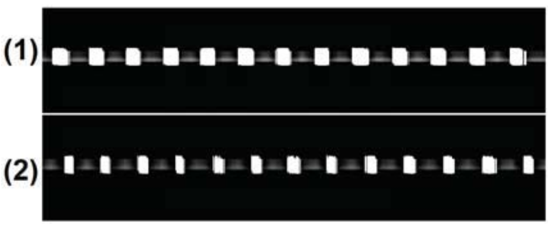

Figure 5. Real (1) and imaginary (2) parts of the echo signal from the UAV after additional filtration

As a result, after using all the filtering methods a complex package of signal reflected from the observed aerial object such as UAV was obtained. Complex matrix at this point has the most pronounced and clear useful periodic part of the signal.

4) Spectral a lysis.

After filtering a noise-free rectangular matrix of echo signal was obtained. Therefore, it is possible to carry out spectral analysis and obtain a range-spectral characteristic. Thereafter, an FFT is performed for each discrete or row in the matrix. The range-spectral characteristic of the signal is obtained for each realization S [n], where n = 1 … N.

The FFT calculation formula can be written as

$$\dot{S}[n]=\sum_{p=0}^{P/2-1}\dot{z}_n[2p]e^{-\frac{2\pi}{P/2}pt}+e^{-\frac{2\pi}{P/2}p}\sum_{p=0}^{P/2-1}\dot{z}_n[2p+1]e^{\frac{2}{P/2}}, \quad (5)$$

where S[n] – spectrum of each discrete in the matrix, z_n[2p] and z_n[2p+1] – even and odd elements in the row of the matrix, *P* – length of the row, *t* – digital transformation for sum of even and odd indexes.

To represent the result of the FFT it is needed to calculate an absolute value of spectra. After that the visualization of the range-spectral characteristic of the complex signal is obtained, which was reflected from the observed aerial object.

The result of using different filtration methods and subsequent spectral analysis is shown on Figure 6.

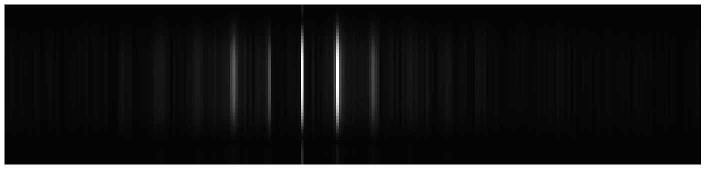

Figure 6. An example of the range-spectral characteristic of the echo signal from the UAV

2. Application of autocorrelation.

The second strategy implies calculation of the autocorrelation that will clear the original data from stochastic component instead of applying additional filtering. For each strobe of the rectangular matrix a new sequence of values is calculated, which reveals whether there is a dependence between different range counts of a digital impulse. Absence of this dependance between random external signals makes it possible to get rid of the stochastic component.

The algorithm for calculating the autocorrelation consists of iterating each element of the new matrix to equate it to averaged sum of the multiplications of the values of the vertical elements of the complex echo signal filtered from the noise. The initial data for calculations are the columns of the rectangular matrix and this elements are iterated for calculations in an amount from 0 to N [6].

The first step is to calculate the values of the signal matrix. The value of one element of the new spectral matrix calculated on the base of the complex package of the filtrated signal can be written as

$$\dot{R}_k[h]=\frac{1}{N-h}\sum_{i=h}^{N-h}\dot{z}_k[i]\dot{z}_k[i+h], \quad (6)$$

where R_k[h] – element of the new matrix, z_k[i] – elements of the complex package, h – current offset in amount from 0 to N.

To calculate result of the autocorrelation itself it is needed to take absolute value of each element of the new matrix after using formula (6). The matter of fact is that when calculating the autocorrelation the phase of the signal disappears, because all of its complex readings were basically squared at the first stage of computation. Counting autocorrelation implies multiplying the signal by the signal itself with different offset. As a result, it turns out that at the signal after computing its autocorrelation loses imaginary part of complex element.

Result of calculating the autocorrelation is presented in Figure 7.

Figure 7. Autocorrelation of the filtered signal

After calculating the autocorrelation the FFT is performed for each discrete or row in the new matrix. The result of the FFT is now the range-spectral density of the echo signal for each reading G [n], where n = 1 … N.

The range-spectral density is calculated similarly to (5) and can be written as

$$G[n] = \sum_{p=0}^{P/2-1} R_n[2p] e^{-\frac{2\pi}{P/2}pt} + e^{-\frac{2\pi}{P/2}p} \sum_{p=0}^{P/2-1} R_n[2p+1] e^{-\frac{2\pi}{P/2}pt}, \quad (7)$$

where G[n] – spectral density of each discrete in the matrix, $R_n[2p]$ and $R_n[2p+1]$ – even and odd elements in the row of the autocorrelation matrix, P – length of the row, t – digital transformation for sum of even and odd indexes.

Result of calculating the range-spectral density is presented in Figure 8.

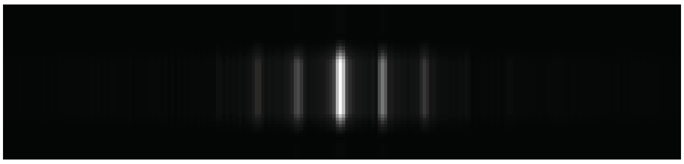

Figure 8. Range-spectral density of the signal

Figure 8 shows that with the application of the autocorrelation it is possible to achieve full clarity and symmetry of the spectral characteristic.

3. omparison of the applied strategies

To compare the applied strategies it is necessary to process numerous examples of the signals reflected from flying aerial objects monitored by radar. For filtering and spectral analysis programs were written using Python Shell with application of such scientific computing and mathematical libraries as Scipy and Numpy [5]. The Struct software was also used to input signals from the source files with .dat extensions. The specialized library for working with images Pillow was used to graphically represent the results.

The examples of the results of applying both strategies demonstrate that using autocorrelation gives more flat and pronounced micro-Doppler contributions in the spectral signatures of the signals. This happens due to the ability of the autocorrelation to remove the phase component from the spectral data. The image of spectral density is often completely symmetric compared to the spectral characteristic of the first strategy. However, in general there are not so many differences regarding the symmetry of spectral signatures between the results of the first and second strategies. Due to the flattening after computing autocorrelation of the signal much less number of informative peaks of the micro-Doppler contributions appear in spectral density characteristic compared to the resulting spectra of the first strategy.

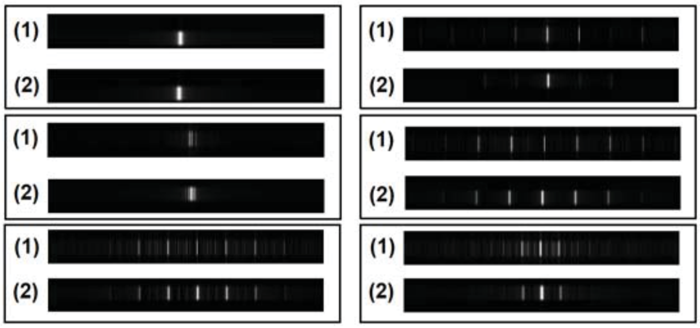

Figure 9. Examples of the results of applying filtering strategy and calculating the FFT (1) and computing the autocorrelation and FFT (2)

On the other hand, many of the iterative peaks in the range spectral characteristics as a result of the first strategy could be a result of the stochastic component that has not been removed from the mixture of signal and noise properly. This leads to the fact that the spectral signatures obtained using the first strategy signals could contain information that is not related to the monitored aerial object. In addition, the range-spectral characteristics have no regularity of spectral signatures, which could potentially damage accuracy of determination of the type of aerial object, since the resulting dataset will not retain the visual resemblance for different UAV samples.

Conclusion

This paper's goal of eliminating interference from mixture of signal and noise using both strategies has been reached. Comparison of the first strategy, that utilizes solely multiple filtering methods and FFT, and the second strategy, which implies ridding of the stochastics of the mixture of the signal and noise using computing the autocorrelation, has been performed.

The calculations has showed the relative efficiency of both approaches, but the most preferable for further research in this area is the use of the autocorrelation, since it gives a more accurate, flat and pronounced spectral signature of the signal from aerial object received by radar. Present research has provided a proof of concept of using autocorrelation for obtaining proper spectral signatures, which contain informative micro-Doppler contributions.

In the future authors plan to create a system with deep integration of physical and computational components with basis in this paper's research [7]. This system should be able not only to recognize the type of an aerial object, but also to classify it. Such system should be able to analyze behavior of the aerial object, as well as to draw conclusions based on the analysis and. Then, on the basis of the made conclusions made it should be able to make predictions about the future state of the object monitored by the radar station. The interaction of computational elements with physical ones in this system will manifest itself in the processing of the mixtures of signal and noise to obtain spectral signatures more convenient for further analysis.

In this system the close interaction of physical elements with computational ones will require a thorough study of the methodology of the theory of cyber-physical systems for a more specific and accurate understanding of issues related to deep integration.

References

1. A. A. Sentsov, S. A. Ivanov, S. A. Nenashev and E. L. Turnetskaya (2020), "Classification and Recognition of Objects on Radar Portraits Formed by the Equipment of Mobile Small-Size Radar Systems," *2020 Wave Electronics and its Application in Information and Telecommunication Systems (WECONF)*, 2020, pp. 1-4, doi: 10.1109/WECONF48837.2020.9131475.

2. B. Torvik, K. E. Olsen and H. Griffiths (2016), "Classification of Birds and UAVs Based on Radar Polarimetry," in *IEEE Geoscience and Remote Sensing Letters*, vol. 13, no. 9, pp. 1305-1309, Sept. 2016, doi: 10.1109/LGRS.2016.2582538.

3. P. Molchanov, K. Egiazarian, J. Astola, A. Totsky, S. Leshchenko and M. P. Jarabo-Amores (2014), "Classification of aircraft using micro-Doppler bicoherence-based features," in *IEEE Transactions on Aerospace and Electronic Systems*, vol. 50, no. 2, pp. 1455-1467, April 2014, doi: 10.1109/TAES.2014.120266.

4. I. Selesnick, C. Burrus, Generalized Digital Butterworth Filter Design. *IEEE Transactions on Signal Processing*. 46. 10.1109/78.678493.

5. P. Virtanen, R. Gommers, T. Oliphant, M. Haberland, T. Reddy, D. Cournapeau, E. Burovski, P. Peterson, W. Weckesser, J. Bright, S. Walt, M. Brett, J. Wilson, K. Millman, N. Mayorov, A. Nelson, E. Jones, R. Kern, E. Larson, SciPy 1.0: fundamental algorithms for scientific computing in Python. Nature Methods. 17. 1-12. 10.1038/s41592-019-0686-2.

6. T. Shimamura, N. Nguyen (2010), "Autocorrelation and double autocorrelation based spectral representations for a noisy word recognition system," in *Proceedings of the 11th Annual Conference of the International Speech Communication Association, INTERSPEECH 2010*. 1712-1715.

7. V. P. Shkodyrev (2020), Cyber-physical systems as a technological plat#form for synergetic integration of promising breakthrough technologies, SAEC. 2020. №1. L: https://cyberleninka.ru/article/n/kiberfizicheskie-sistemy-kak-tehnologicheskaya-platforma-sinergeticheskoy-integratsii-perspektivnyh-proryvnyh-tehnologiy (дата обращения: 02.06.2021).

ОБРАБОТКА ЭХО-СИГНАЛОВ ПРИ РАДИОЛОКАЦИОННОМ НАБЛЮДЕНИИ БЕСПИЛОТНЫХ ЛЕТАТЕЛЬНЫХ АППАРАТОВ

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Аннотация

В современном мире с ростом использования беспилотных летательных аппаратов возникло множество задач связанных с обнаружением летающих воздушных объектов и определением их типа как в черте города так и сельской местности. Одними из таких задач являются распознавание и классификация воздушных объектов с использованием радиолокационных станций. Летающие воздушные объекты, которых нужно обнаружить и определить их тип, обычно представляют собой искусственные в виде беспилотных летательных аппаратов и естественные, которыми могут быть, например, птицы. Чтобы эффективно решать данные задачи необходимо произвести обработку сигнала отраженного от воздушного объекта и получить такую спектральную сигнатуру, которая будет достаточно репрезентативной чтобы точно определить тип объекта. Наиболее информативной деталью в определении типа летающего воздушного объекта является наличие или отсутствие на спектральных сигнатурах микродоплеровского эффекта. Целью данной работы является осуществление и сравнение двух стратегий получения спектральных сигнатур эхо-сигналов, очищенных от помех или стохастической составляющей. Первая стратегия действий подразумевает использование нескольких методов фильтрации эхо-сигнала после чего производится спектральный анализ. Вторая стратегия включает применение автокорреляционной функции для удаления стохастической составляющей смеси сигнала и шума, что позволяет получить в результате спектральную плотность мощности. Сравнение результатов применения двух стратегий обработки сигналов, отраженных от воздушных объектов, наблюдаемых при помощи РЛС, показали, что использование автокорреляционной функции дает более выраженную, регулярную и очищенную спектральную сигнатуру относительно первого подхода с одной только фильрацией. Применение данных стратегий для обработки сигналов, отраженных от воздушных объектов, является основой для проектирования системы глубокой интеграции физической и вычислительной компонент.

Ключевые слова: *микродоплеровский эффект, беспилотный летательный аппарат, автокорреляционная функция, фильтрация, спектральный анализ.*

Литература

1. *A. A. Sentsov, S. A. Ivanov, S. A. Nenashev and E. L. Turnetskaya*. Classification and Recognition of Objects on Radar Portraits Formed by the Equipment of Mobile Small-Size Radar Systems // 2020 Wave Electronics and its Application in Information and Telecommunication Systems (WECONF), pp. 1-4, doi: 10.1109/WECONF48837.2020.9131475.
2. *B. Torvik, K. E. Olsen and H. Griffiths* (2016). Classification of Birds and UAVs Based on Radar Polarimetry // in IEEE Geoscience and Remote Sensing Letters, vol. 13, no. 9, pp. 1305-1309, Sept. doi: 10.1109/LGRS.2016.2582538.
3. *P. Molchanov, K. Egiazarian, J. Astola, A. Totsky, S. Leshchenko and M. P. Jarabo-Amores*. Classification of aircraft using micro-Doppler bicoherence-based features // in IEEE Transactions on Aerospace and Electronic Systems, vol. 50, no. 2, 2014, pp. 1455-1467, April 2014, doi: 10.1109/TAES.2014.120266.
4. *I. Selesnick, C. Burrus*, Generalized Digital Butterworth Filter Design. IEEE Transactions on Signal Processing. 46. 10.1109/78.678493.
5. *P. Virtanen, R. Gommers, T. Oliphant, M. Haberland, T. Reddy, D. Cournapeau, E. Burovski, P. Peterson, W. Weckesser, J. Bright, S. Walt, M. Brett, J. Wilson, K. Millman, N. Mayorov, A. Nelson, E. Jones, R. Kern, E. Larson,* SciPy 1.0: fundamental algorithms for scientific computing in Python. Nature Methods. 17. 1-12. 10.1038/s41592-019-0686-2.
6. *T. Shimamura, N. Nguyen*. Autocorrelation and double autocorrelation based spectral representations for a noisy word recognition system // in Proceedings of the 11th Annual Conference of the International Speech Communication Association, INTERSPEECH 2010, pp. 1712-1715.
7. *Шкодырев В. П.* Киберфизические системы как технологическая платформа синергетической интеграции перспективных прорывных технологий // SAEC. 2020. №1. URL: https://cyberleninka.ru/article/n/kiberfizicheskie-sistemy-kak-tehnologicheskaya-platforma-sinergeticheskoy-integratsii-perspektivnyh-proryvnyh-tehnologiy (дата обращения: 02.06.2021).

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