ISSN 2075-1087, Gyroscopy and Navigation, 2024, Vol. 15, No.1, pp. 61-68

Application of Sparse Representation of Complex Data in Railway Positioning and Collision Alert Systems Using Millimeter-Wave Radar

N.V. Panokin, I. A. Kostin, A. V. Averin, A. V. Karlovskii*, D. I. Orelkina, and A. Yu. Nalivaiko

Moscow Polytechnic University, Moscow, Russia

**e-mail: a.v.karlovskij@mospolytech.ru*

Received: January 15, 2024; reviewed: March 24, 2024; accepted: April 10, 2024

Abstract: The paper presents the results from the experimental study of a modified artificial neural network MFNN (minimum fuel neural network). Sparse representation of complex data with overcomplete basis and L0/L1 norm optimization are used instead of the classical fast Fourier transform (FFT) algorithm. The results showed a significant enhancement in the ability of obstacle recognition and autonomous railway control systems to distinguish between close objects such as trains on adjacent tracks at marshalling yards.

Keywords: railway transport, obstacle recognition, radar, angular resolution, artificial neural network, MFNN, overcomplete basis, L0 norm, L1 norm.

1. INTRODUCTION

In view of the continuous development of technologies for sensitive elements, neural networks and computer vision, autonomous control of transport happens to be in demand. Railway transport constitutes no exception, so the solutions aimed at the traffic safety improvement become increasingly relevant.

Radar-based methods have been used successfully to support the monitoring and control systems operation in various sectors of the national economy due to the advantages of radars, such as independence of weather conditions, ability to work in the darkness, relatively low cost, potential for automation, and autonomy.

The radar applications and modern methods of radar signals processing open up a number of prospects for safety enhancement and automation of processes in railway transport. Possible applications include the detection of technological obstacles on the way of snowplowing equipment, as well as detection of vehicles in the railway crossing areas to control crossing bars.

One of the solutions for the above tasks is to use millimeter–wave radars which can determine the direction of arrival (DOA) of signals reflected from obstacles. However, along with all advantages, the radars have a low angular resolution, due to which they are not able to reliably distinguish between closely spaced trains located on neighboring tracks. The situation is even more complicated at marshalling yards with a large number of trains on the tracks. Increasing the angular resolution of radars would allow them to be used for positioning on the tracks, since the SLAM technology is applicable to high-resolution radar images.

Reflected signals are processed using classical methods such as Fourier transform, cosine transform and wavelet transform with different bases for data representation by means of decomposition into orthogonal functions. The main disadvantage of these methods is low angular resolution. This can be improved using the algorithms such as multiple signal classification (MUSIC), estimation of signal parameters via rotational invariant techniques (ESPRIT), or minimum variance distortionless response (MVDR) [1–3]. At the same time, overcomplete basis methods based on sparse representation are best suited for reflected signals which are usually highly correlated. These methods use a basis with a large number of components, which are generally non-orthogonal and allow one to determine the direction of signals arrival more accurately [4–7]. In this case, the data are represented as a combination of a small number of basic functions of so-called sparse representation (SR). Optimization methods such as matching pursuit (MP), method of frame (MOF),basis pursuit (BP), complex-valued split Bregman method (CV-SBM), and some other methods [8–16] are used to find the optimal basic components of SR from an overcomplete basis dictionary:

$$\left\{max_{y\in\Omega}\, y^T x\right\} \to min, \text{ on condition that } Ax = b, \quad (1)$$

where

$\Omega = \left\{\omega \in \mathbb{C}^N \| \omega_i| \le 1, i-1,2,\ldots,N\right\} \subset \mathbb{C}^N, b \in \mathbb{C}^M$ are the input data;

$x = \left[\alpha_{\gamma_1}, \alpha_{\gamma_2}, \ldots, \alpha_{\gamma_N}\right]^T \in \mathbb{C}^N$ are the coefficients of the basis;

$A = \left[\phi_{\gamma_1}, \phi_{\gamma_2}, \ldots, \phi_{\gamma_N}\right] \in \mathbb{C}^{M\times N}$ is the matrix of overcomplete basis dictionary.

$D = (\phi_\gamma)$ is a basis dictionary, where $\phi_\gamma \in \mathbb{C}^M$ are the components of the basis with index $\gamma \in \Gamma$ and $\Gamma \subset L^2(\mathbb{R})$.

To determine the optimality of such a representation, the norms L_0 are used:

$$L_0 = \left(\sum_{i=1}^{I} |x_i|^0\right), \; |x_i|^0 = \begin{cases} 0 & \text{if } x_i = 0 \\ 1 & \text{otherwise} \end{cases}; \quad (2)$$

thus, L_0 is the number of non-zero elements in x, or L_1:

$$L_1 = \left(\sum_{i=1}^{I} |x_i|^1\right). \quad (3)$$

It has been shown in [15] that in this case the norms L_0 and L_1 are equivalent.

The results of theoretical studies of DOA methods can be found in many works including those mentioned above.

This paper presents the results of an experiment to assess the DOA method applicability and its efficiency for determining the presence of objects (train cars, locomotives) on adjacent railway tracks, using a millimeter-wave radar.

The method under study is based on the use of the MFNN neural network [15], a modified version of which [16] makes it possible to work with complex values and represents complex signals in the form of overcomplete basis coefficients with a minimum norm L_1.

Computer vision methods including radar-aided ones are in demand in the railway transport (see [17–19]); however, the main challenge for the wide use of radars is their insufficient angular resolution. During the experiment, it was checked whether it was possible to achieve high resolution of experimental radar when processing the received signals by the MFNN method.

The paper considers some options for implementing the MFNN neural network, describes its modification, presents the conditions and results of experiments, draws the conclusions about the applicability of the proposed method, and outlines the prospects for its use for the development of transport autonomous control systems. The test results can be applied in the areas where high resolution and accuracy of radar signal processing are required.

2. MODIFIED NEURAL NETWORK

A modified version of the MFNN neural network is shown in Fig. 1. It is described by a set of differential equations with complex variables:

$$\begin{cases} \dfrac{dx}{dt} = -A^T\left[Ax - y - b\right] - P_\Omega\left(x + A^T y\right), \\ \dfrac{dy}{dt} = -A\left[x + A^T y - P_\Omega\left(x + A^T y\right)\right] + b, \end{cases} \quad (1)$$

$$x \in C^N, y \in C^M, z = x + A^T y, z \in C^N,$$

where $P_\Omega(z) = \left[P_\Omega(z_1), P_\Omega(z_2), \ldots, P_\Omega(z_n)\right]^T$ is a modified function of activation

$$P_\Omega(z_i) = \begin{cases} \dfrac{z_i}{|z_i|}, \; if\, |z_i| > 1, \\ z_i, \; if\, |z_i| \le 1, \end{cases} \quad (2)$$

in which $|z_i| = \sqrt{\mathrm{Re}(z_i)^2 + \mathrm{Im}(z_i)^2}$, $i = 1,2,\ldots,N$, $x = \left[\alpha_{\gamma_1}, \alpha_{\gamma_2}, \ldots, \alpha_{\gamma_N}\right]^T \in C^N$ are the basis components, $A = \left[\phi_{\gamma_1}, \phi_{\gamma_2}, \ldots, \phi_{\gamma_N}\right] \in C^{M\times N}$ is the matrix of the overcomplete basis dictionary.

The neural network generates a vector of values of complex coefficients of x basis components. The modules of these coefficients are an estimate of the levels of reflected signals arriving in the directions that correspond to those used to form the overcomplete basis dictionary:

$$A_{m,i} = b_k e^{j2\pi d(m-1)\sin(\theta_i)}, \quad (4)$$

where $\theta_i = \dfrac{180°\cdot i}{N} - 90°$, i = 1, 2, …, N is the dimension of angular directions grid of the overcomplete basis dictionary, m = 1,2, …, M (M is the number of antennas in the radar's regular-space array).

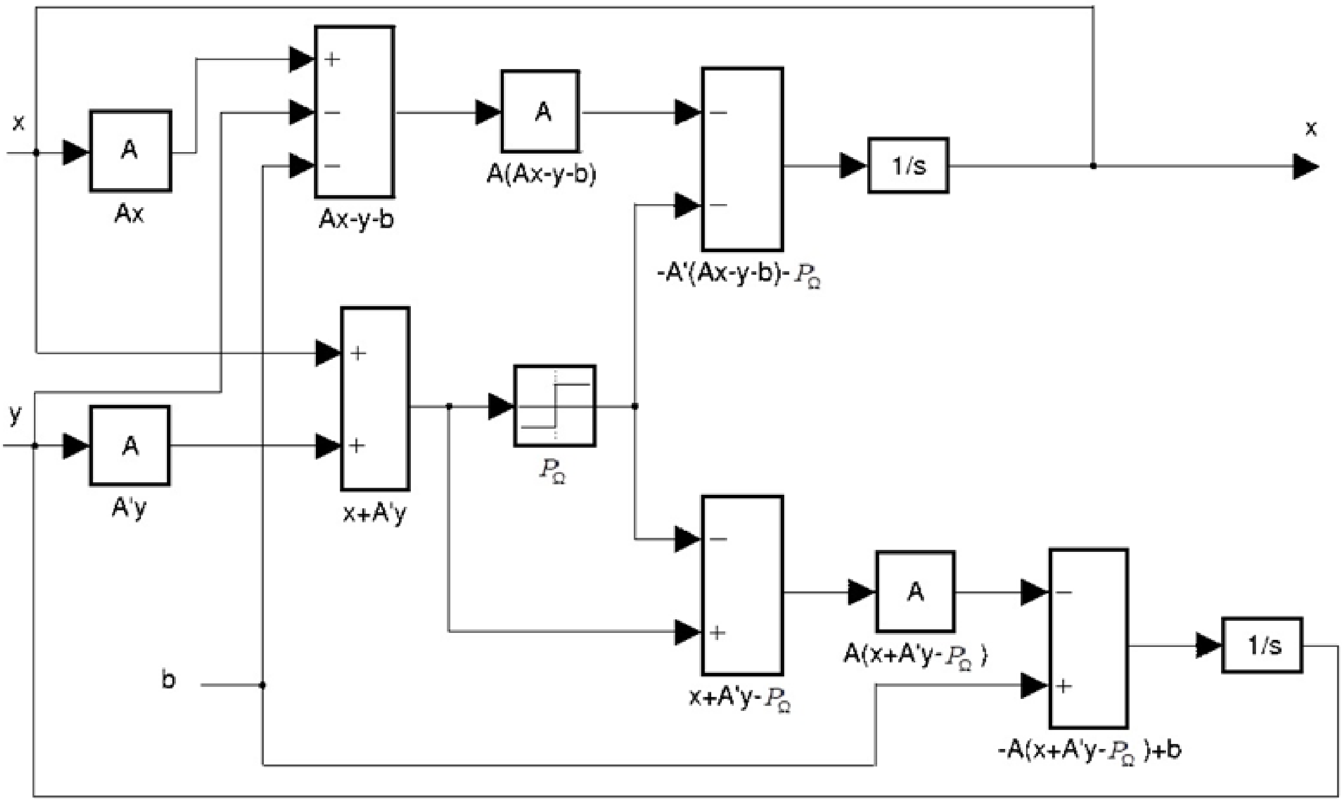

Fig. 1. MFNN neural network.

3. EXPERIMENTAL RESULTS

Experiments were conducted for a scene in which there are from one to three 0.6 × 0.3 m test reflectors spaced to 0.6 m and located at the distances of 10 and 5 m, simulating the angular dimensions (in the azimuthal plane) of train cars on adjacent tracks, located at the distances of 110 and 55 m. The flat reflectors were covered with foil reproducing random scattering on the structural elements of the cars (Figs. 2, 4, 6). The data were generated by a frequency-modulated continuous-wave (FMCW) radar with an operating frequency of 24 GHz, with a 16-channel antenna array. The results are shown in Figs. 3, 5, 7, where on top are the position and horizontal dimensions of the reflectors, marked with black line segments, on the left there are the results of the algorithm based on a 64-point FFT (Figs. 3, 5, 7*a*), and on the right there are the results when using an overcomplete basis 512 × 16 (Figs. 3, 5, 7*b*). For easier comparison with the results obtained at the railway station, the *X* axis is the horizontal displacement in meters, recalculated to a distance of 100 m, and the *Y* axis is the relative magnitude of response after the FFT, or the values of the weighting coefficient moduli for the method under consideration at the distance of the reflectors. Increasing the FFT dimension above 16 for the 16-channel linear array does not improve the angular resolution. The 64-point FFT was chosen in order to more clearly represent the pattern of the response to reflected signals due to a smaller azimuth angle step. The decision about the presence or absence of an object was made in accordance with the results of threshold processing by the Forward Automatic Order Selection Ordered Statistics Detector (FAOSOSD) algorithm [20]. The threshold level in Figures 3, 5, 7 and 9–11 is marked red.

It can be concluded that where conventional FFT-based processing gives one mark from three closely spaced objects (Fig. 5*a*), the proposed method provides significant increase in the resolution, and each object can be clearly distinguished (Fig. 5*b*).

Correlation of the reflected signals strongly affects the result obtained when using the FFT. In Fig. 7*a*, only two peaks can be seen for three reflectors at the distance of 5 m, so it is easy to draw a false conclusion about the absence of the central reflector. At the same time, thanks to the proposed method, the weighting coefficients with a level above the threshold are distinguished in the regions of all three reflectors, which can be clearly seen in Fig. 7*b*.

Fig. 2. Two test reflectors at a distance of 10 m.

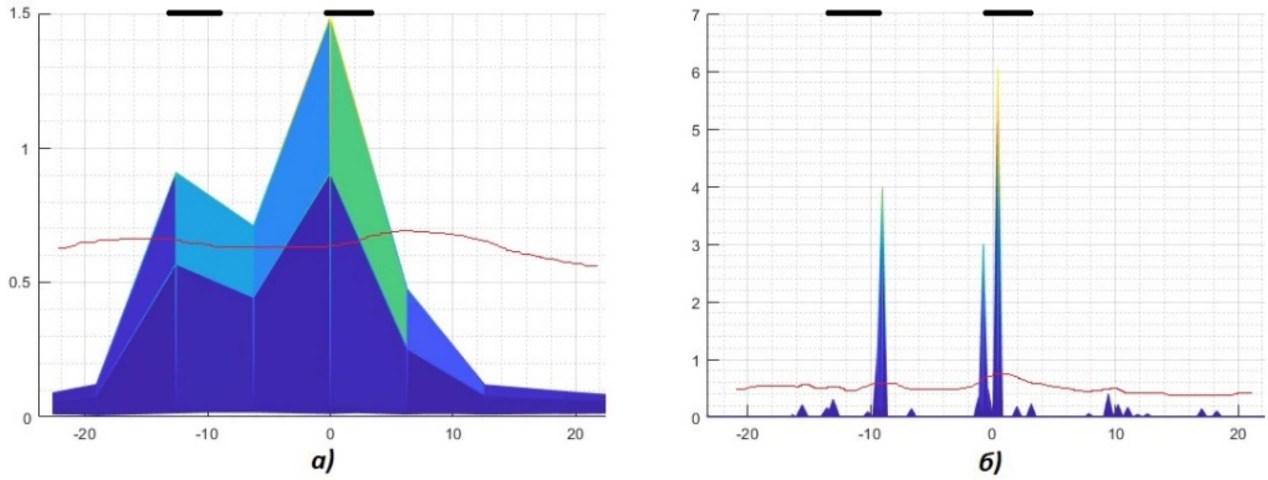

Fig. 3. Two test reflectors at a distance of 10 m. The results of reflected signals processing: *a*) based on 64-point FFT; *b*) when using an overcomplete basis.

Fig. 4. Three test reflectors at a distance of 10 m.

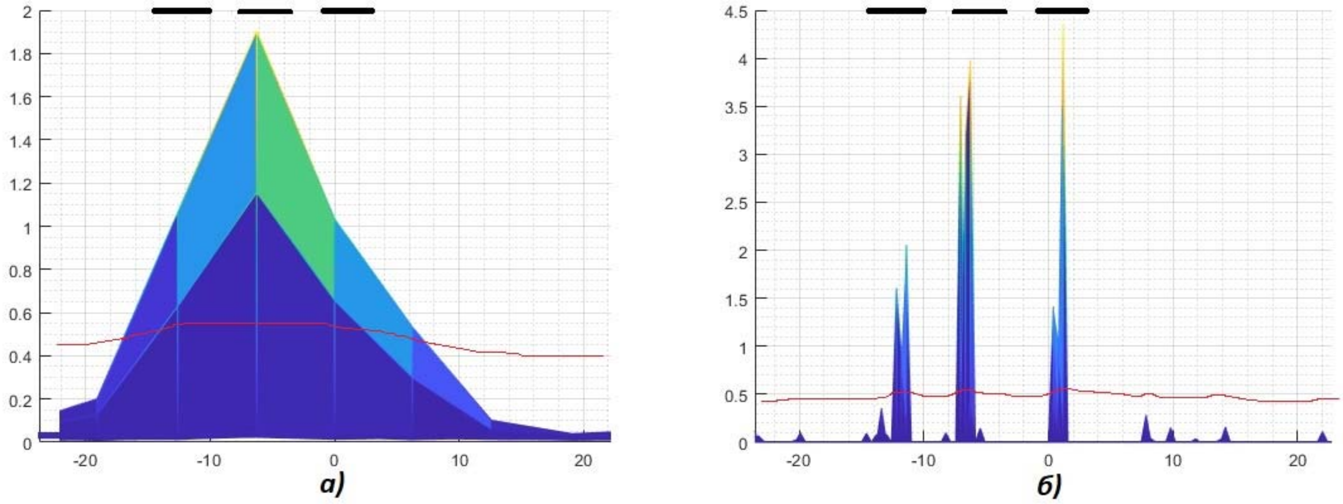

Fig. 5. Three test reflectors at a distance of 10 m. The results of reflected signals processing: *a*) based on 64-point FFT; *b*) when using an overcomplete basis.

Fig. 6. Three test reflectors at a distance of 5 m.

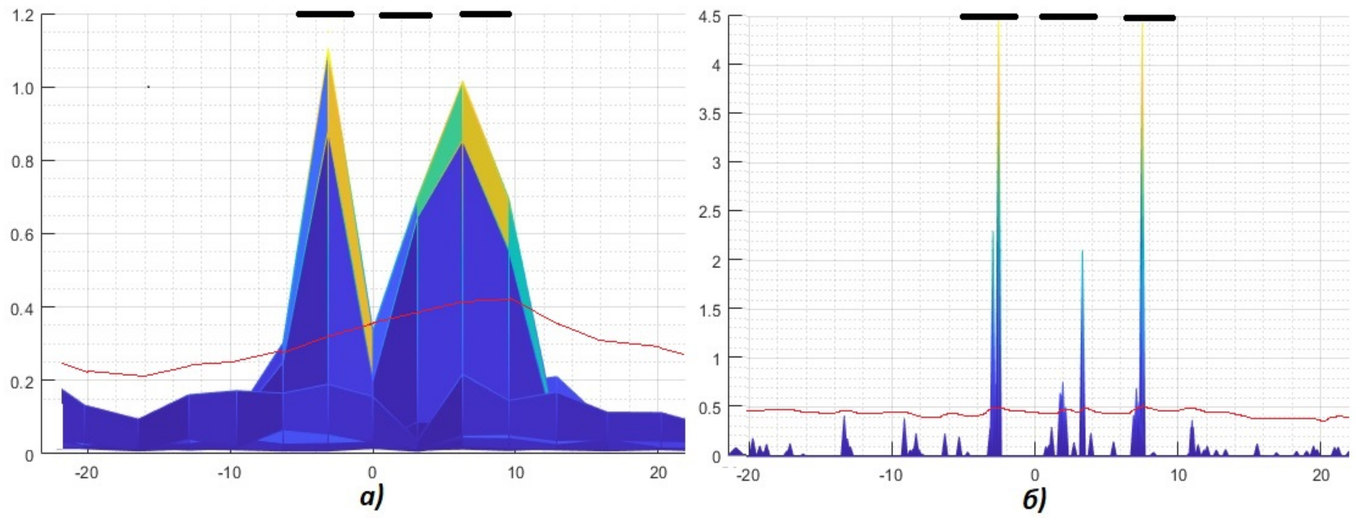

Fig. 7. Three test reflectors at a distance of 5 m. The results of reflected signals processing: *a*) based on 64-point FFT; *b*) when using an overcomplete basis

The results shown in Figs. 9–11 were obtained using a radar installed on one of the tracks (the main one) at the marshalling yard. The measurements were taken when there were one, two or three trains on the main and adjacent tracks. The distance to the nearest cars of the trains was the same (100 m). An example of railway trains location at the marshalling yard is shown in Fig. 8.

Fig. 8. Railway trains at the marshalling yard.

In the figures below, the black rectangles indicate the position and horizontal dimensions of the cars; on the left there are the results of the algorithm based on 64-point FFT (Figs. 9–11, *a*), and on the right there are the results of the method under consideration, using an overcomplete basis (Fig. 9–11, *b*). The *X*-axis is the horizontal displacement in meters, and the *Y*-axis is the relative magnitude of response after the FFT, or the values of the weighting coefficient moduli for the method under consideration at a distance of 100 m.

It can be seen from Fig. 9 that the weight coefficients found for the method under study make it possible to clearly determine the position of the car, including its edges. At the same time, at the level of –3dB, the FFT shows the region of possible position of the car more than 10 m in size.

If there are cars on adjacent tracks and no cars on the main one, it is impossible to know for sure with the help of the FFT that the main track is free: based on the response, an erroneous conclusion may be drawn that only the right track is occupied (Fig. 10). At the same time, the method under study makes it possible to determine the directions to both cars on adjacent tracks and decide that the main track is free.

The scenario when there are cars on all three adjacent tracks is shown in Fig. 11. It can be seen that the FFT does not make it possible to determine the number of occupied tracks, while the modified neural network gave a significant response in all three directions, which is equivalent to an angular resolution of better than 0.8 deg at some distance.

The use of neural networks instead of classical FFT also brings good results. This makes the neural networks a promising direction for the development of obstacle recognition and transport autonomous control systems.

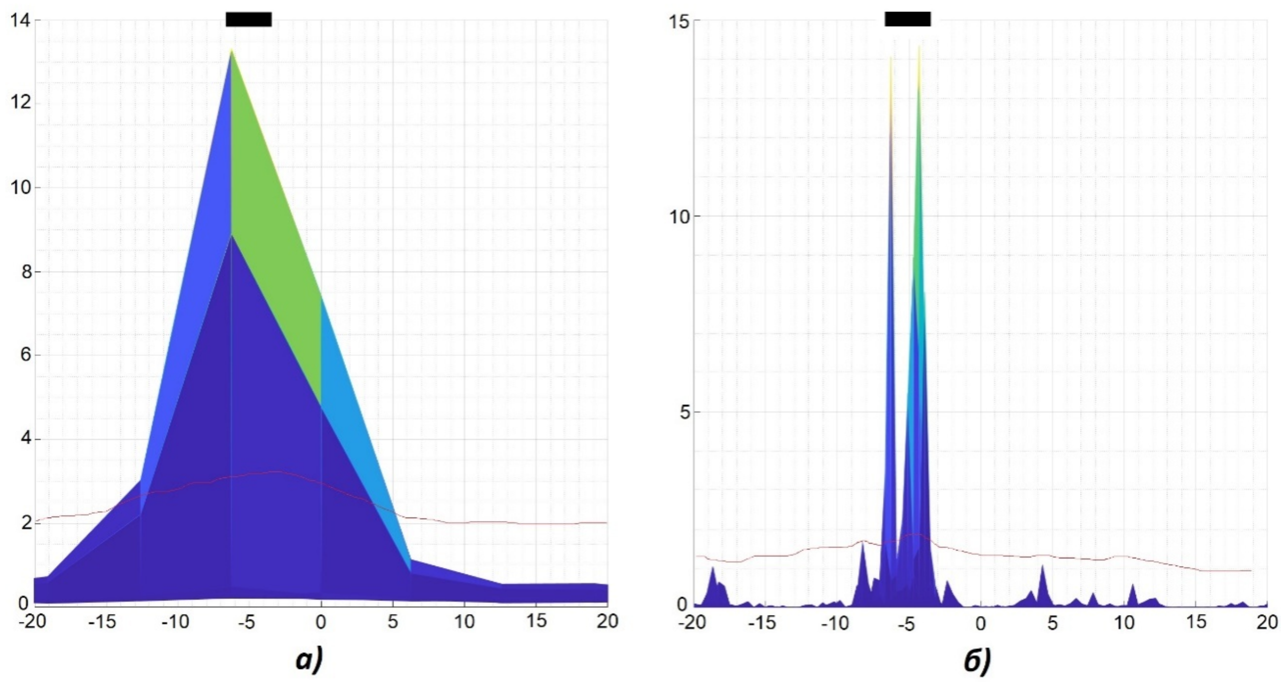

Fig. 9. One car on the main track at a distance of 100 m. The results of reflected signals processing: a) based on 64-point FFT; b) when using an overcomplete basis

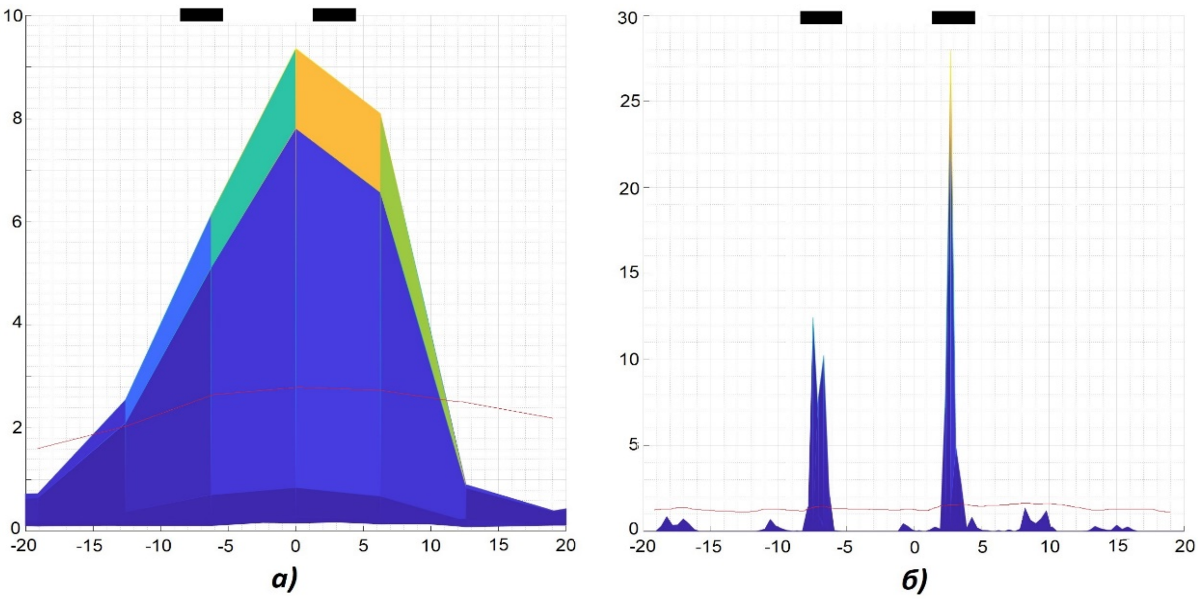

Fig. 10. Two cars on adjacent tracks at a distance of 100 m. Results of reflected signals processing.

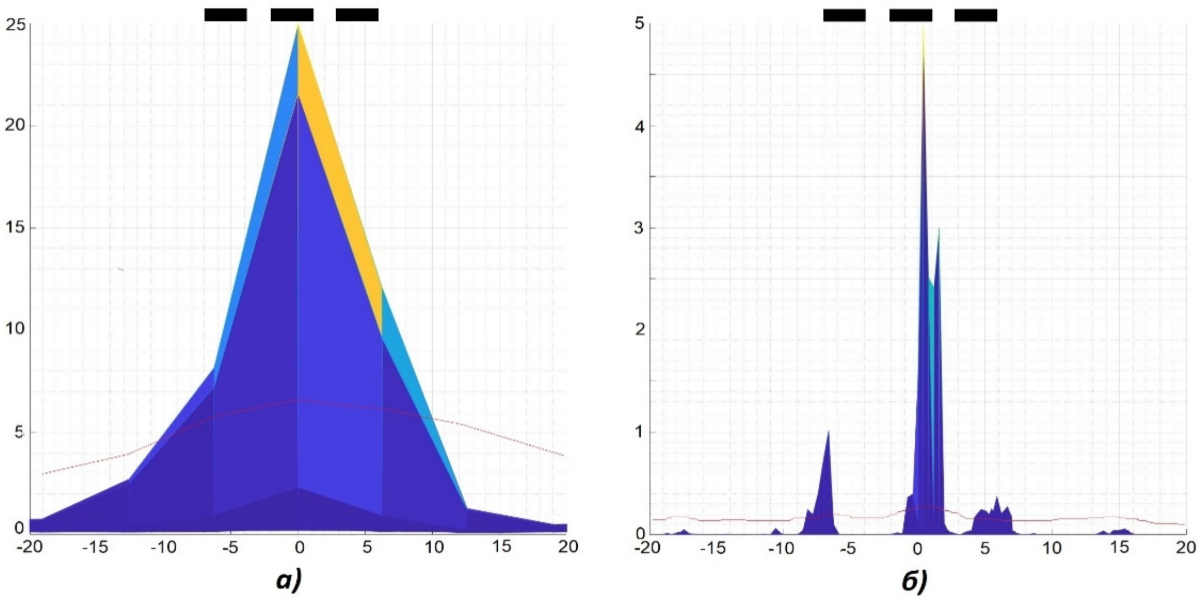

Fig. 11. Three cars on adjacent tracks at a distance of 100 m. Results of reflected signals processing

4. CONCLUSIONS

The experiments have demonstrated that the method of sparse representation of data, based on a modified neural network, overcomplete basis and L_0 norm (in [11] it was shown that in this case the L_0 and L_1 norms are equivalent) improves the ability of a millimeter-wave radar-based system to distinguish objects located close to each other. This makes the neural networks a promising direction for the development of systems for both obstacle recognition and SLAM positioning by the reference points of radar image. Using the neural networks, modern sensitive elements and image recognition technologies, it is possible to find innovative solutions for railway systems control and further develop the transport autonomous control systems.

FUNDING

The study was supported by the Ministry of Science and Higher Education of the Russian Federation, grant FZRR-2023-0008.

CONFLICT OF INTEREST

The authors of this work declare that they have no conflicts of interest.

REFERENCES

1. Cheng, P., Wang, X., Zhao,J., and Cheng, J., A fast and accurate compressed sensing reconstruction algorithm for ISAR imaging, *IEEE Access*, 2019, vol. 7, pp. 157019–157026, doi: 10.1109/ACCESS.2019.2949756.
2. Roy, R., Kailath, T., ESPRIT-estimation of signal parameters via rotational invariance techniques, *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 1989, vol. 37, no. 7, pp. 984–995,doi: 10.1109/29.32276.
3. Souden, M., Benesty, J., and Affes, S., On optimal frequency domain multichannel linear filtering for noise reduction, *IEEE Transactions on Audio, Speech, and Language Processing*, 2010, vol. 18, no. 2, pp. 260–276, doi: 10.1109/TASL.2009.2025790.
4. Cichocki, A., Unbehauen, R., Neural networks for solving systems of linear equations, Part II: Minimax and least absolute value problems, *IEEE Trans. Circuits Syst.*, 1992, vol. 39, pp. 619–633, doi:10.1109/82.193316.
5. Cichocki, A., Unbehauen, R., *Neural Networks for Optimization and S ignal Processing*, Stuttgart, Germany: Teubner-Wiley, 1993.
6. Xiong, K., Zhao, G., Shi, G., and Wang, Y., A convex optimization algorithm for compressed sensing in a complex domain: The complex-valued split Bregman method, *Sensors (Basel)*, 2019, vol. 19(20), p. 4540, doi:10.3390/s19204540.
7. Stanković, L., Sejdić, E., Stanković, S., Daković, M., and Orović, I., A tutorial on sparse signal reconstruction and its applications in signal processing, *Circuits Systems and Signal Processing*, 2019, vol. 38(11), pp. 1206–1263, doi: 10.1007/s00034-018.9-0909-2.
8. Yi, C., Zhou. C., and Takahashi, J., Quantum phase estimation by compressed sensing, *arXiv.org*, 2023, abs/2306.07008, doi: 10.48550/arXiv.2306.07008.
9. Bandler, J.W., Kellerman, W., and Madsen, K., A nonlinear L1 optimization algorithm for design, modeling, and diagnosis of networks, *IEEE Transactions on Circuits and Systems*, 1987, vol. 34, no. 2, pp. 174–181, doi: 10.1109/TCS.1987.1086100.
10. Zhang, Y., Xiao, S., Huang, D., Sun, D., Liu, L., and Cui, H., L0-norm penalised shrinkage linear and widely linear LMS algorithms for sparse system identification, *IET Signal Processing*, 2017, vol. 11(1), pp. 86–94, doi: 10.1049/iet-spr.2015.0218.
11. Ishii, Y., Koide, S., and Hayakawa, K., L0-norm constrained autoencoders for unsupervised outlier detection, in *Advances in on Knowledge Discovery and Data Mining*, Lauw, H., Wong, R.W., Ntoulas, A., Lim, E.P., Ng, S.K., and Pan, S. (eds), PAKDD 2020, Lecture Notes in Computer Science, vol. 12085, Springer Cham, 2020, doi: 10.1007/978-3-030-47436-2_51.
12. Rajko, R., Studies on the adaptability of different Borgen norms applied in selfmodeling curve resolution (SMCR) method, *Journal of Chemometrics*, 2009, vol. 23(6), pp. 265–274, doi: 10.1002/cem.1221.
13. Jahan, K., Niemeijer, J., Kornfeld, N., and Roth, M., Deep neural networks for railway switch detection and classification using onboard camera, *IEEE Symposium Series on Computational Intelligence*, 2021, doi:10.1109/SSCI50451.2021.9659983.
14. Malioutov, D.M., Cetin, M., and Willsky, A.S., Optimal sparse representations in general overcomplete bases, *Proceedings of the 2004 IEEE International Conference on Acoustics, Speech, and S ignal Processing*, Montreal, QC, Canada, 2004, pp. ii-793, doi: 10.1109/ICASSP.2004.1326377.
15. Wang, Z.S., Cheung, J.Y., Xia, Y.S., and Chen, J.D., Minimum fuel neural networks and their applications to overcomplete signal representations, *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, 2000, vol. 47, no. 8, pp. 1146–1159, doi: 10.1109/81.873870.
16. Panokin, N.V., Averin, A.V., Kostin, I.A., Karlovskiy, A.V., Orelkina, D.I., and Nalivaiko, A.Y, Method for sparse representation of complex data based on overcomplete basis, L1 norm, and neural MFNN-like network, *Applied Sciences*, 2024, vol. 14(5), p. 1959, https://doi.org/10.3390/app14051959.
17. Okhotnikov, A.L., Algorithm for selecting the equipment for machine vision systems in railway transport, *Nauka i tekhnologii zheleznykh dorog*, 2021, vol. 5, no. 1(17), pp. 65–74.
18. Khatlamajiyan, A.E., Orlov, V.V., and Nikolaev, I.S., Improving the traffic safety of trains using an onboard computer vision system, Proc. of VII All-Russian Conference with International Participation “Robustness of Locomotive Pool and Improving the Train Haulage Efficiency”, Omsk, OmGUPS, 2022, pp. 328–334.
19. Mashchenko, P.E., Shutilov, K.V., Analysis of sensors of computer vision systems for industrial railway transport, *Vestnik Inst. problem estestvennykh monopolii: Tekhnika zheleznykh dorog*, 2021, no. 1(53), pp. 40–45.
20. Magaz, B., Belouchrani, A., and Hamadouche, M., Automatic threshold selection in Os-Cfar radar detection using information theoretic criteria, *Progress in Electromagnetics Research B,* 2011, vol. 30, pp. 157–175, doi:10.2528/PIERB10122502.