High performance radar images modelling and recognition of real objects

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Abstract. In the work there is a modernization of the parallel algorithm for the radar images formation of 3D models with the synthesis of the antenna aperture. In the formation of the scene description, the various structures are used in which it is possible to use more efficient and derived calculations. In addition, it is the topical task to recognize objects on radar images. Thus, on the basis of the implemented parallel program for modelling, the high performance required for simulating multiple radar images can be achieved.

1. Introduction
This research is a continuation of ideas and methods used in [1], where high-performance radar images modeling approach was considered. The goal of this work is to obtain a greater acceleration of the parallel program for synthetic aperture radar modeling by building a kd tree describing a three-dimensional scene [2-4]. We used CUDA to perform a high-performance computing on a graphic card and achieve this goal. It is the main difficulty to form a trajectory signal along with the radar travel and then compute a radar image. In this study, an algorithm for obtaining radar characteristics was implemented with the construction of the kd tree structure, that allow to describe any three-dimensional scene.

2. Modelling and recognition
The main computationally expensive part of the radar images modelling algorithm is in the processing of radiated and reflected radar signals. In this work, a modification of the CUDA algorithm was implemented, which difference at the stage of the trajectory signal constructing is in a previously calculated kd-tree for any three-dimensional scene. The subsequent execution of the synthesis of the radar aperture was performed the same way as discussed in [1]. This approach of computable operations reducing allowed us to achieve a three-fold acceleration compared with the previous algorithm implementation.

In addition, during the research, we carried out the experiments of object recognition in radar images. There are many methods and approaches of object recognition, among which the popular methods are convolutional neural networks [5], support vectors, nearest neighbours, etc. [6]. In this work, the object recognition was performed using the method of support subspaces [7]. We used three-

dimensional models of the tank, BMP, BTR to construct the radar images. All sizes of the models were matched to the corresponding sizes of their real prototypes at the three-dimensional coordinate system. We used the modelling parameters presented in Table 1 when generated the training set. The bearing angle was 17°, which corresponds to the conditions of the real obtained SAR images training dataset. We modelled 100 images for each object. The step of rotation was equal the 3.6° in the observation plane. Figure 3 shows the real and modeled SAR images of BTR.

There are the results of research shown below which related to the construction of a training model sample and the subsequent recognition of real images using model images at the training stage. Figure 1, a), b) shows the real radar images of a tank from the widely known MSTAR database, and figure 2, a), b) shows radar images obtained by modelling using the synthetic aperture radar method, with angles the bearing angle of 17° and 15° and the aspect angles are 17 ° and 100 °, respectively.

Table 1. Modelling parameters.

#	Parameter	Value
1	Radar start point (x,y,z), m	(-4335.5,1325.5,-50)
2	Radar observation mode	spotlight
3	Synthesis lenght, m	100
4	Wave length (chirp), m	0.029 – 0.033
5	Azimuth resolution, m	0.3
6	Range resolution, m	0.3
7	Impulse duration, mcs	0.5
8	Min range, m	4510
9	Max range, m	4630
10	Azimuth step, m	0.25
11	Range step, ns	0.5

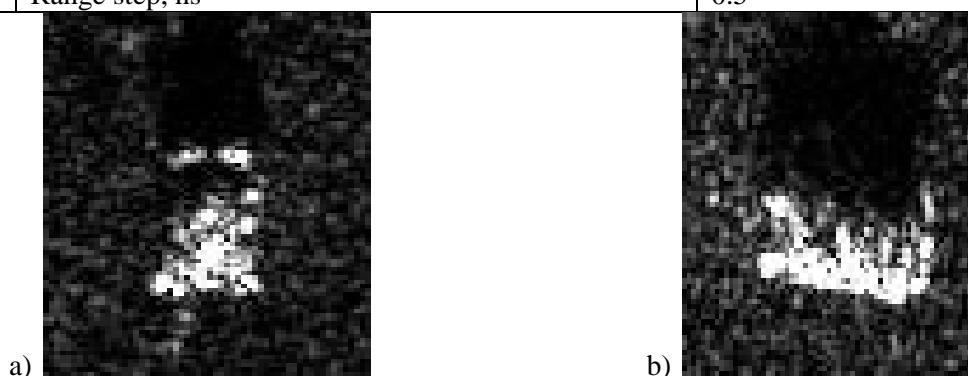a)   b)

Figure 1. MSTAR dataset SAR images: a) bearing angle 17°, elevation angle 15°; b) bearing angle 17°, elevation angle 100°.
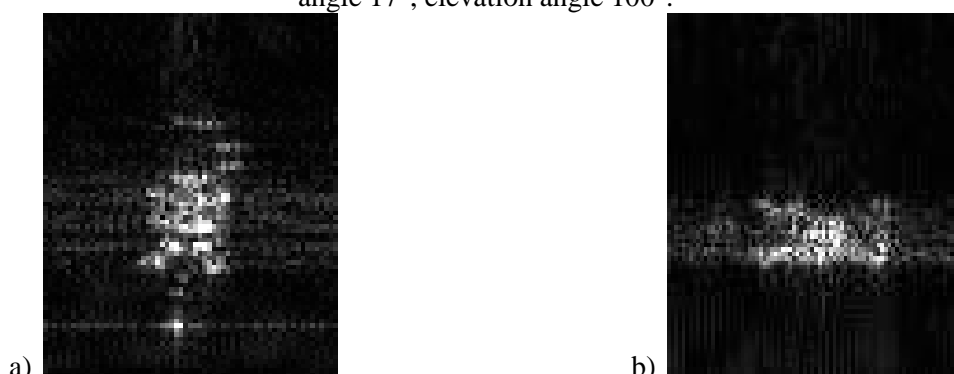

a)   b)

Figure 2. Modelled SAR images: a) bearing angle 17°, elevation angle 15°; b) bearing angle 17°, elevation angle 100°.

The recognition results for three classes obtained using the recognition contingency index based algorithm [7] (without subclassing) are listed in Table 2. Note that the result of 62.78% correct recognition of the three classes was obtained on a relatively small training set (300 images). The MSTAR training sample contains 587 of image samples.
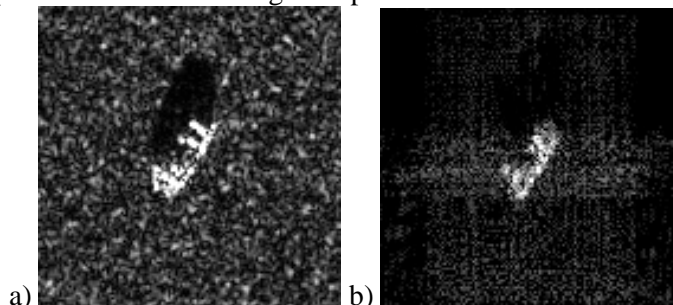

Figure 3. SAR images: a) model and b) real BTR target.

Table 2. Recognition results with modelled dataset training.

	Evaluated class			
	BMP2	BTR70	T72	
BMP2	402	124	61	68.48%
BTR70	134	43	19	21.93%
T72	119	51	412	70.79%

At the binary classification: the BMP and tank using the same algorithm, the result of 80.24% was achieved. The recognition results of the two classes without division into subclasses are shown in Table 3.

Table 3. Results of two objects recognition.

	Evaluated class		
	BMP2	T72	
BMP2	496	91	84.50%
T72	140	442	75.94%

In addition, we carried out the experiment of the real images recognition by training on model images, which obtained using the ray tracing approach [8]. Table 4 shows the recognition results. The total percentage of correct recognition was 27.6%. These results show that images modelled via raytracing is not quite suitable for recognition real images. Perhaps they can be used to create a simplified model of a three-dimensional scene.

Table 3. Results of objects recognition (dataset modelled via raytracing).

	Evaluated class			
	BMP2	BTR70	T72	
BMP2	207	270	221	29.66%
BTR70	78	67	51	34.18%
T72	331	146	105	18.04%

It should be noted that in the MSTAR database, the training sample has 587 images. In contrast to presented model images dataset, the rotation of an object in the MSTAR images was performed with an irregular step and with rather large positioning errors.

3. Conclusion
The paper shows that the results of objects recognition using real images has the ability of the effective usage at the developed software. The images were obtained by modeling can form the training dataset at the proposed algorithm. In addition, the parallel algorithm acceleration is obtained

by kd-tree construction let us help to perform high-computing and effective scattering calculation on the various object surfaces.

4. References

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