# Recognition Method of Dim and Small Targets in SAR Images based on Machine Vision

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***Abstract*—Aiming at the problems of long recognition time and low recognition accuracy of traditional SAR image dim target recognition methods, a method of SAR image dim target recognition based on machine vision was proposed. SAR images are collected and preprocessed by machine vision, and the image information is processed by PCA dimension reduction considering the linear characteristics of the data to extract image features. Then, the SAR image target feature key frame frequency band is divided by the segmentation results, and the recognition model is established based on the image trajectory tracking and target analysis. The proposed algorithm is applied and analyzed. The simulation results show that the proposed algorithm has good recognition rate, average recognition rate and false detection rate are 99% and 0.9%, and can effectively ensure the data processing performance.**

***Keywords*—Machine vision; SAR image; Weak target; PCA linear dimensionality reduction method; key frame frequency band**

## I. Introduction

Synthetic Aperture Radar (SAR) is an active microwave imaging radar. SAR has high range and azimuth resolution, and can obtain two-dimensional high-resolution images. Since the electromagnetic waves emitted by SAR have a longer wavelength and can penetrate clouds, fog, rain, smoke, haze, etc., SAR has a certain penetration ability and can work all day and all day long. Based on the above advantages, SAR is widely used in the military field, mainly used for: military intelligence reconnaissance and tracking, military terrain mapping, navigation and guidance, damage evaluation, etc. [1]. In addition, with the further maturity of SAR technology, SAR is also widely used in many civilian fields, such as resource monitoring, environmental monitoring, forest vegetation cover detection, disaster monitoring, and ecology, hydrology, archaeology, and deep space exploration. With the continuous development of SAR technology, the resolution of radars is getting higher and higher, the quality of SAR images is getting better and better, and new SAR images are constantly being produced [2]. What does not match it is that the interpretation of SAR images has developed slowly. The initial manual interpretation is completely performed by personnel based on the shape, size, shadow, position, and hue of the target in the image to extract the information in the SAR image. This method is not only extensive, the knowledge and the deep background of SAR, and the efficiency is very low, it is greatly affected by the subjective experience of the observer, and it is far from satisfying the current situation of massive SAR images that need to be analyzed. Target recognition in SAR images does not require manual intervention, and relies on computers to run related algorithms to automatically classify SAR image targets. The general target recognition step is: first extract the characteristics of the image target, and then recognize it through the corresponding recognition method [3].

Dim and small target recognition in SAR image is one of the core technologies in the automatic target detection system. When the distance is far, the imaging area of these targets on the focal plane is very small, generally not exceeding the size of the detector pixel. The target appears as dots in the image, and the signal-to-noise ratio is extremely low. The target is submerged by noise, which brings great difficulties to target detection. For more than ten years, the identification of small and dim targets in SAR images has been a research hotspot in the field of optics and infrared images [4]. The International Optical Engineering Society organizes an annual “Signal and Data Processing of Small Targets” conference to exchange new technologies for the recognition of small and small targets in SAR images. The International Optical Engineering Society defines the weak target as: the image size is less than 80 pixels, that is, less than 0.15% of 256×256. The research on the recognition of small and dim targets in SAR images originated from long-distance search and surveillance. For example, use wide-field telescopes to search for or track meteors, satellites or other moving targets in the sky, and use airborne or ground infrared (TV) search and tracking systems to search for long-distance targets. It uses image processing algorithms to automatically recognize targets in a cluttered background and strong noise environment. The performance of the algorithm is critical to the range and intelligence of the automatic target recognition system. Recognition of small and dim targets in SAR images is a difficult subject with important strategic application value [5].

At the same time, for the research of SAR target recognition algorithm, most scholars try to improve the algorithm from different angles to improve its target recognition accuracy, thereby reducing background clutter and noise interference factors in image recognition. Literature [6] proposed that the one-dimensional feature extraction of principal component analysis is used as the input data of the encoder, and then the SAR target image is used as the input of the neural network to realize the target recognition of two-dimensional data, and research has proved that the depth learning algorithm of fusion decision layer and feature layer has good adaptability and robustness. In reference [7], SAR image classification method based on target decomposition and support vector machine is used to decompose and combine features in polarization and establish polarization classification model. The experimental results show that the improved polarization image classification method has better classification performance and application effectiveness. Literature [8] proposed a view tensor sparse representation model based on target recognition, and used JT-OMP algorithm to calculate the sparse representation error of SAR tensor image data and multi view SAR image after the construction of recognition dictionary. Subsequently, the effectiveness of the algorithm was verified in the target recognition database. In reference [9], considering the decline in accuracy of ship target image due to the motion of the target, it proposed to combine clustering algorithm with SAR image recognition, and proposed HCA ship target aggregation algorithm in airborne SAR image. The distance algorithm is used as the basis for the generation of a single image. The experimental results show that this method can have good application performance in simulation experiments. Reference [10] proposed a SAR target recognition method based on adaptive kernel dictionary learning, that is, extracting nonlinear feature information through data space mapping, information dynamic updating, and minimizing error reconstruction. Simulation results show that this method has good recognition performance. In reference [11], zero phase component analysis is used to achieve feature extraction, and sparse technology is used to optimize the convolutional neural network SAR target recognition algorithm. The results show that the algorithm has high target recognition ability and good noise robustness.

Literature [12] designed a multi-azimuth SAR image for target recognition convolutional neural network (Convolutional Neural Network, CNN), three SAR images of the same target are input into the network as a pseudo-color image, making full use of the characteristics of SAR image data acquisition are improved, and the flattening operation is replaced by a pooling layer, which reduces the number of network parameters. The experimental results show that even on a small-scale SAR data set, the convolutional network has the characteristics of high recognition accuracy. Targets of different models in the same category also have excellent recognition performance. Literature [13] proposed a two-dimensional principal component analysis (2DPCA) and L2 regularization constrained stochastic configuration network (SCN) for integrated learning SAR image target recognition method, 2DPCA not only It can effectively extract the feature information of the target and reduce the amount of data through sparse representation. The SCN regularization algorithm has fewer parameters and can effectively avoid the network overfitting problem and improve the recognition rate of the network. Although the above two methods realize the recognition of small and weak targets in SAR images, they take a long time to recognize and the recognition efficiency is low. Literature [14] proposes a synthetic aperture radar (SAR) image target recognition method based on random weighted fusion of single-level signal decision-making layers, and uses sparse representation classification (SRC) to implement the multi-level and multi-component single-level signal representation obtained from SAR image decomposition. For decision-making, the error vector is fused by a random weight matrix, which contains a large number of random weights. According to the fusion results, different types of error statistics can be obtained. The decision variables are defined to reflect the correlation of different types. Finally, according to the minimum error is used to make category decision. Extensive experiments are carried out on the MSTAR data set and compared with many types of existing methods. The results show that the proposed method can effectively improve the overall performance of SAR target recognition. Literature [15] proposed a Capsule-based SAR image target recognition method, which uses multiple convolutional layers to achieve hierarchical processing, while using fewer convolution kernels, but the number of convolution kernels used in each layer gradually increases as the level deepens, which makes the extracted features more abstract. In the Primary Caps layer, the Capsule vector is composed of all the feature maps output by the last layer of the convolutional layer, so that the Capsule unit contains all the features of the target part or the whole to complete the complete instance of the target to achieve SAR image target recognition. However, the accuracy of the above two methods for small and weak target recognition in SAR images is low, resulting in poor recognition effect.

When the above methods are used for SAR target image recognition, they only focus on improving the accuracy of image recognition, but are difficult to analyze the characteristics of weak targets in SAR images. There are many factors involved in target weakening, including sensor itself, target scattering characteristics, background environmental factors and the amount of information about the target's environment. Based on the research limitations of previous scholars, the research proposes to use machine vision to recognize small and weak targets in SAR images. The image recognition is achieved through visual image acquisition - data preprocessing - feature extraction under linear dimension reduction - key frame division of target features. This not only ensures the effective detection of weak targets, but also considers the linear nature of data features, which improves the accuracy of algorithm recognition to a certain extent. At the same time, experimental simulation is used to verify the effectiveness of the algorithm, in order to provide a new idea for weak target image recognition.

## II. METHOD FOR RECOGNIZING DIM AND SMALL TARGETS IN SAR IMAGE

### A. SAR Image Acquisition based on Machine Vision

High-quality SAR images can better reflects the characteristics of the recognition target. In order to facilitate subsequent recognition operations and reduce the computational burden of the recognition algorithm, the use of machine vision imaging technology to collect SAR images enables the recognition algorithm to have relatively high recognition efficiency and recognition accuracy [16].

In the SAR image acquisition, the camera CCD is mainly used to convert the SAR signal into an orderly SAR signal and collect the target information to be identified. Considering the size of the target to be measured, as well as the imaging area, depth of field, working distance and other project requirements, the XF-5MDT05X65 telecentric lens is selected to cooperate with the camera to collect the image of the target to be recognized. The use of cameras to capture images has very strict requirements on the light source. When collecting SAR images, according to specific needs, choose a lighting plan to obtain the best lighting effect and obtain high-quality images. Considering that the recognition target is a small and weak target in SAR image, the forward illumination method is selected, and the LTLNC100-W linear light source is used to light it [17]. For detection targets with complex structures and relatively large targets, it is easy to have uneven features during the acquisition process. In order to ensure that the characteristics of different regions in the collected SAR images are uniform, multiple light sources are used to illuminate different regions to improve the SAR image. The gray value is uniform level. Multiple light sources mainly illuminate the target in the form of superposition of light fields, as shown in Fig. 1.

The top light source shown in the upper part of Fig. 1 is mainly aimed at the center area of the target, and the imaging of the edge area is achieved through the bottom light source. When two light sources are used at the same time, the image gray value can be relatively uniform and improved. The quality of SAR images lays the foundation for the subsequent identification of small and dim targets in SAR images [18].

### B. SAR Image Preprocessing

Hu's invariant moments can solve the problem of image lens distortion in the image acquisition process, and improve the authenticity of image geometric moments. Then by inverting the radial distortion model of the image, the pixel coordinates of the image are restored, and the mapping relationship between the image pixel coordinates is grayed out [19].

Before determining the geometric shape characteristics of the SAR image, it is necessary to clarify the $\alpha+\beta$ -order geometric moments contained in the SAR image:

$$m_{\alpha\beta}=\sum_{x=1}^{M}\sum_{y=1}^{N}a^{\alpha}b^{\beta}f\left(a,b\right);\alpha,b=0,1,2... \tag{1}$$

According to the calculation result of the above formula, it is known that the SAR image is $M\times N$ , and $f\left(a,b\right)$ is described as the actual gray value of the image, where $a$ and $b$ respectively represent the coordinate axis of the pixel point [20].

Suppose that in the discrete state of rotation, the sixth-order moments of translation, scaling, and rotation of $\alpha+\beta$ , which contains geometric features, are derived from the ideal result of no distortion of geometric moments in the above-mentioned pattern. However, compared with the ideal result, the real SAR image must have a certain degree of distortion. This part of the error will make the pixel coordinate $(a,b)$ and the gray level $f\left(a,b\right)$ in the image unable to accurately correspond, resulting in geometric deformation of the SAR image after conversion [21].

To this end, this paper corrects the $\alpha+\beta$ -order geometric moment of the SAR image by reversing the resolution of the radial camera distortion model.

Generally, the radial distortion model is defined as:

$$\begin{cases} a=\overline{a}+\left(\overline{a}-a_0\right)\left(O_1r^2+O_2r^4+...\right) \\ b=\overline{b}+\left(\overline{b}-b_0\right)\left(O_1r^2+O_2r^4+...\right) \end{cases} \tag{2}$$

According to the calculation results of the above formula, $(a,b)$ is described as the actual pixel coordinate value due to the influence of distortion, $\left(\overline{a},\overline{b}\right)$ can describe the ideal pixel coordinate unit, and $(a_0,b_0)$ is described as the global center pixel coordinate [22]. Use $O_i$ to describe the distortion coefficient produced by the $2i$ -level of the image, and set the distortion influence range to be related to the distance $r$ from the target point to $(a_0,b_0)$, and then:

$$r^2=\left(a-a_0\right)^2+\left(b-b_0\right)^2 \tag{3}$$

It is concluded that the geometric deformation in the SAR image collected by machine vision can be described by the second-order radial distortion coefficient $K_i$ , without considering the influence of higher-order distortion terms [23]. Therefore, the ideal pixel coordinate $\left(\overline{a},\overline{b}\right)$ is inversely solved by the simplified distortion calculation model obtained:

$$\begin{cases} \overline{a}=\dfrac{a+a_0O_1r^2}{1+O_1r^2} \\ \overline{b}=\dfrac{b+b_0O_1r^2}{1+O_1r^2} \end{cases} \tag{4}$$

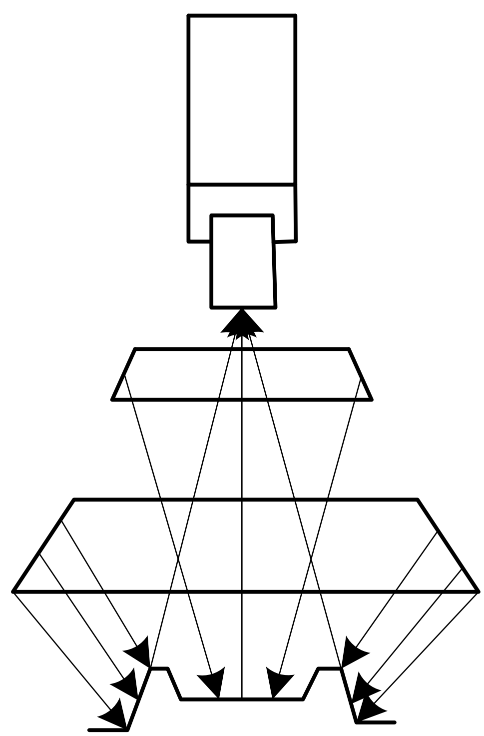


Fig. 1. SAR Image Imaging Scheme.

Bring the ideal pixel coordinates into equation (1) to obtain the corrected $\alpha+\beta$ -order geometric moment of the SAR image:

$$m_{\alpha\beta}=\sum_{a=1}^{M}\sum_{b=1}^{M}\left(\frac{a+a_0O_1r^2}{1+O_1r^2}\right)\left(\frac{b+b_0O_1r^2}{1+O_1r^2}\right) \tag{5}$$

The combination of formula (5) and formula (3) can obtain the Hu stock moment with translation, zoom and rotation functions, which can increase the influence factor of radial distortion during the acquisition process, and reduce the deformation caused by the acquisition of SAR images by the hardware device. The problem of reduced recognition accuracy is discussed in [24].

### C. SAR Image Feature Extraction

Feature extraction is an important research problem in SAR image target recognition. Choosing appropriate features can improve target recognition rate and timeliness. The definition of feature extraction can be divided into a narrow sense and a broad sense. Feature extraction in a broad sense refers to a transformation that uses various mathematical transformation methods to improve the distribution of original features in the feature space without changing the internal structure and parameters. It can compress feature dimensions, remove redundant features, and reduce calculations. Effect: Use the feature space transformation method commonly used in pattern recognition for feature extraction [25]. PCA is a commonly used linear dimensionality reduction method in pattern recognition. PCA takes the maximum change direction of the sample in a multi-dimensional space (that is, the direction of maximum variance) as the criterion for judging whether the vector is a principal vector according to the position distribution of the sample in the space. Realize sample compression and feature extraction. Suppose the projection of vector $x$ is $y$, $w$ is the projection matrix, and D can be represented by the inner product of $x$ and $w$, namely:

$$y=\left[w,x\right]=\sum_{i=1}^{n}w_ix_im_{\alpha\beta}=x^Txm_{\alpha\beta} \tag{6}$$

The purpose of PCA is to find an $w$ that maximizes the value of variance $E\left[y^2\right]$, $E\left[y^2\right]$ can be expressed as:

$$E\left[y^2\right]=E\left[(w^Tx)^2\right]=w^TE(xx^T)w=w^TC_xw \tag{7}$$

According to the theoretical knowledge of linear algebra, if the value of variance $E\left[y^2\right]$ is the largest, $E\left[y^2\right]$ can be expressed as:

$$E\left[y^2\right]=E\left[(w^Tx)^2\lambda_i\right]=w^TE(xx^T)\lambda_i=w^TC_x\lambda_i \tag{8}$$

$E\left[y^2\right]$, which maximizes the value of $w$ according to equation (8), is the eigenvector corresponding to the maximum eigenvalue of matrix $C_x$. for the component of eigenvalue $\lambda_i$, the variance of the principal component is also $\lambda_i$, which represents the dispersion degree of the sample in the direction of the principal component. Data dimensionality reduction is realized by controlling the contribution $n_i$ of principal component $\lambda_i$ to the data, and $n_i$ can be expressed by the following formula:

$$n_i=\frac{\lambda_i}{\lambda_1+\lambda_2+...+\lambda_p} \tag{9}$$

Generalized feature extraction methods basically have mature implementation algorithms, which have been widely used in SAR image target recognition. In a narrow sense, feature extraction is the process of extracting features that can reflect the essential attributes of SAR image targets [26].

### D. Key Frame Frequency Band Division of Target Feature in SAR Image

According to the above extracted SAR image features, the key frame frequency band of SAR image target features is divided. Firstly, the template matching method is used to construct the pixel feature point block matching structure model of SAR image target, as shown in Fig. 2.

In the block matching structure model shown in Fig. 2, the pixel frame is used to match the template of SAR image target. For the target image collected in the k-th subband, the key frame fusion method is used to construct the frequency band division model of SAR image target. According to the correlation between key frames, the mean square error function criterion (MSE) of SAR image target block fusion is obtained. The calculation formula is as follows:

$$MSE(e_1,e_2)=\sum_{x=1}^{N_1}\sum_{x=2}^{N_2}\frac{f_i(x,y)n_i}{f_{i-1}(x+e_1,y+e_2)(l_x,l_y)} \tag{10}$$

Where, $N_1\times N_2$ is the high-frequency band coding bandwidth distribution of SAR image target extracted by video codec framework, $(l_x,l_y)$ is the block fusion vector of SAR image template, and $f_i(x,y)$ and $f_{i-1}(x+e_1,y+e_2)$ represent the pixels of current frame and reference frame of SAR image target, respectively.

| | | | |
|---|---|---|---|
| 1 | 2 | 6 | 7 |
| 3 | 5 | 8 | 13 |
| 4 | 9 | 12 | 14 |
| 10 | 11 | 15 | 16 |

Fig. 2. Block Matching Structure Model of SAR Image Target.

The image pixel spatial fusion matching technology is used to realize the statistical analysis of weak and small target information in SAR image at each scale, and the statistical feature $G(c_1, c_2)$ is:

$$G(c_1,c_2)=\frac{z\cdot Length(C)MSE(e_1,e_2)}{h\cdot Area(inside(C))}+\theta_1\left|I-c_1\right|+\theta_2\left|I-c_2\right| \quad (11)$$

Where, $c_1$ and $c_2$ represent the gray coefficient and brightness coefficient of SAR image target respectively, and $z$、$h$、$\theta_1$ and $\theta_2$ represent the sparsity feature distribution function, both of which are constants greater than 0. The key frame detection method is used to analyze the key frames in the target statistical feature. The calculation formula of frequency band division $T$ of pixel key frames is as follows:

$$T=\frac{G(c_1,c_2)}{L_{low}\times L}\sum_{l\in Lowfreq.}\sum_{l=1}^{L}(E_k^{'}(l)-E_k(l))^2 \quad (12)$$

Where, $E_k^{'}$ is the low-frequency band part of the similarity information fusion feature component, $E_k$ is the low-frequency band part of the SAR image target pixel space, L is the number of DCT blocks of the SAR image target in each frame, and $L_{low}$ is the number of low-frequency bands.

### *E. Dim and Small Target Recognition in SAR Image based on Intra Coding Function*

According to the above obtained pixel key frame frequency band division results, track and analyze the weak and small targets in SAR image, mainly by constructing the intra coding function to realize tracking, and identify the weak and small targets in SAR image according to the tracking results. Firstly, the trajectory tracking function of each frame in the weak and small target area of SAR image is constructed, which is defined as follows:

$$v(g)=Tu^{-1}(u(1)-u(c(x))) \quad (13)$$

Where, $c(g)$ is the neighborhood gray function of SAR image target, and $u(\cdot)$ represents the trajectory tracking target function in key frame coding mode, which meets $u:[0,1]\rightarrow[0,1]$. Thus, the information feature quantity of weak and small targets in SAR image is extracted, and the expression of association rule coefficient $P(w)$ of targets in SAR image is obtained as follows:

$$F(w)=\frac{\exp\left\{-\delta\sum_{I\subset C}T_I(w)\right\}}{\sum_w\exp\left\{-\delta\sum_{I\subset C}T_I(w)\right\}}v(g) \quad (14)$$

Where, $\sum_{I\subset C}T_I(w)$ is the total number of boundary pixels of weak and small targets in SAR image, and $I$ is the spatial region neighborhood group of weak and small targets in SAR image. Then, the weak and small target recognition model of SAR image is constructed based on the intra coding function:

$$J=\sum_{k=1}^{n}\phi_r d(X_k,v_i)+F(w)\sum_{k=1}^{n}\phi_r d(\varepsilon,v_i) \quad (15)$$

Where, $\phi_r$ represents a neighborhood of the target image collected in the $r$ -th subband; $\varepsilon$ represents the low frequency band part of the average similarity information fusion feature component. According to the sparse prior representation results, the high-resolution prediction value at frame $m$ $(x,y)$ of the weak target $F_m(x,y)$ in the SAR image is obtained, and the weak target recognition results of the super-pixel SAR image are obtained to improve the detection and recognition ability of the weak target in the SAR image.

## III. Simulation Experiment Analysis

In order to verify the effectiveness of the weak and small target recognition method in SAR image based on machine vision in practical application, a simulation experiment is carried out by Vega software. Radar works is an important module in Vega software. It can produce real-time imaging radar simulation images based on physical mechanism. The operating environment of imaging radar is a comprehensive simulation environment composed of natural background, cultural characteristics and dynamic targets. One of the characteristics of radar works is that radar works runs in the same synthetic environment as Vega and sensor vision, and jointly provides fully correlated output windows and radar images. Before using the radar works module. It is necessary to set Vega basic modules (system configuration, window, channel, object, observer, motion mode, environmental effect, etc.), and then set the parameters of radar works module (radar type, resolution, frequency band, polarization mode, RCS range, surface side length, motion compensation mode, speckle noise level, carrier speed, image output mode, etc.) are set. The interface of radar works module in the visualization window Lyn X of Vega software is shown in Fig. 3.

The experimental parameter settings are shown in Table I.

Radar types in radar works module include real-time beam ground mapping, multi killer beam sharpening and synthetic aperture radar. The research in this chapter is only aimed at SAR. Radarworks supports six radar operating bands: K, Ku, x, C, s and l, and four polarization modes: VV, VH, HV and HH. The specific imaging parameter plan of SAR is shown in Fig. 4.

In this paper, a total of 8 SAR images are obtained through MSTAR database, including 26 ship targets, which are weak and small targets. They are used as the experimental samples for simulation test. The SAR image is shown in Fig. 5.

First, the algorithm proposed in the study is tested and applied for verification, that is, the loss value results of the algorithm with or without dimension reduction processing are counted. The results are shown in Fig. 6. The results of Fig. 6 show that before the algorithm is improved, the curve changes between the test loss value and the training loss value have a large difference, and when the epoch exceeds 200, the error trend of the two curves is large. However, the loss trend of the algorithm after dimension reduction is basically unchanged, and the difference affected by the value of epoch is small, indicating that the data loss has been improved.

Then, in order to further verify the effectiveness of this method, the SAR image dim target recognition method proposed in this paper, the multi azimuth SAR image target recognition method based on depth learning proposed in reference [12] and the SAR image target recognition method based on 2dpca scn regularization proposed in reference [13] are used to identify dim targets in SAR images, and the recognition accuracy of the three methods is verified, The result data is compared from two aspects of recognition rate and false detection rate, and the comparison results are shown in Fig. 7.

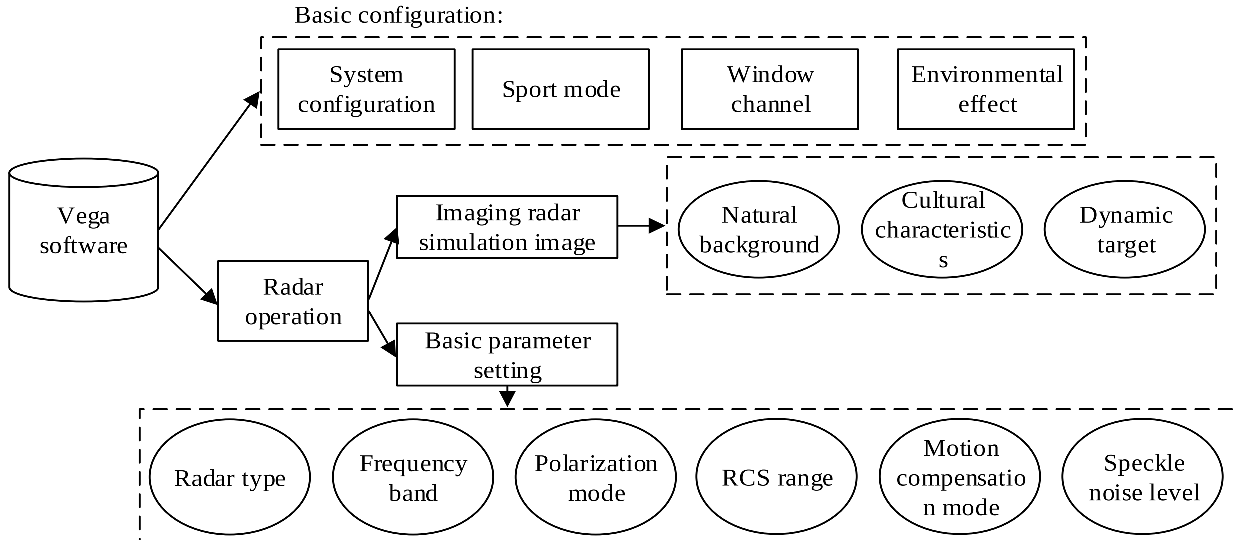



Fig. 3. Visual Operation Diagram of Vega Software.

TABLE I. EXPERIMENTAL PARAMETER SETTING

| | Parameter |
|---|---|
| Frame frequency of visual sampling | 12khz |
| Pixel set of image feature distribution | 120 |
| Identification interval | 1.5ms |
| Regional pixel distribution | 200*200 |
| Action characteristic decomposition coefficient | 0.46, 0.43 |

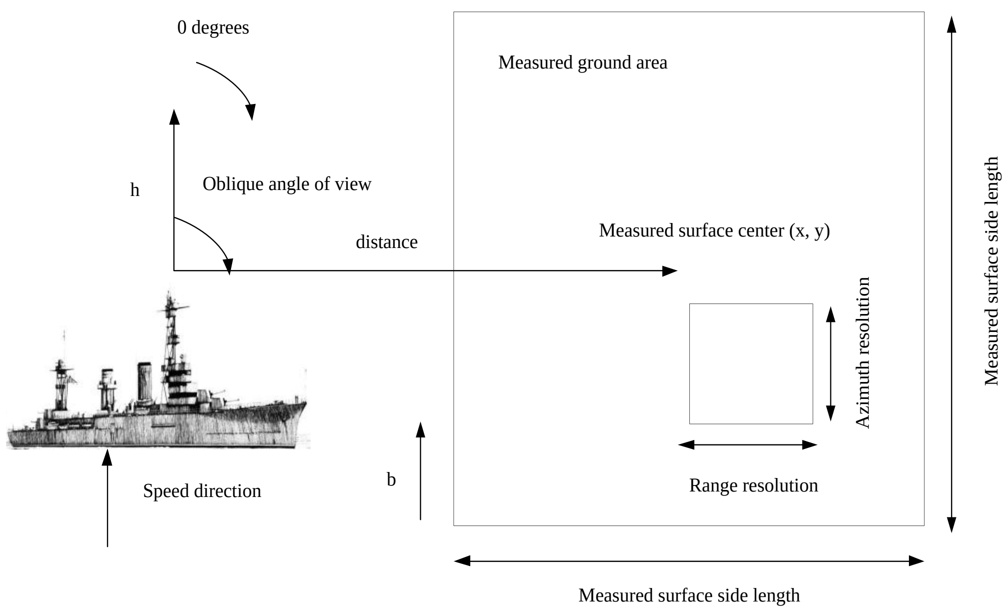



Fig. 4. Plan View of SAR Specific Imaging Parameters.

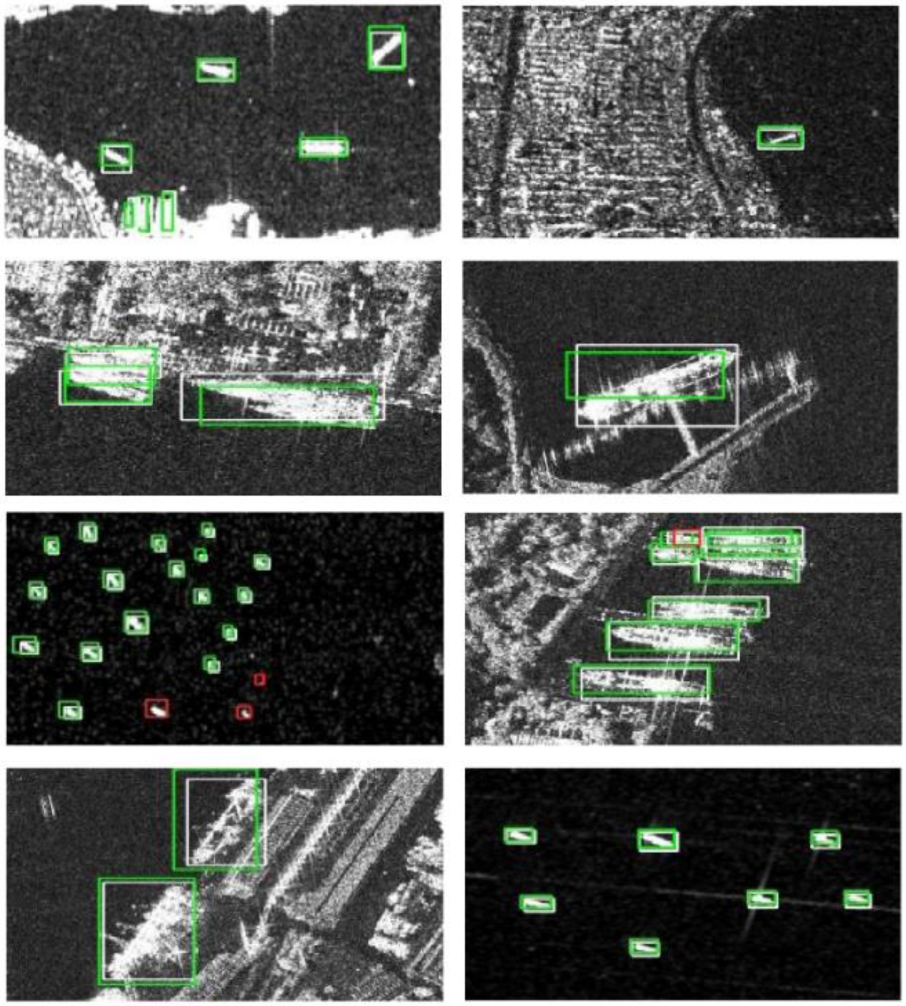
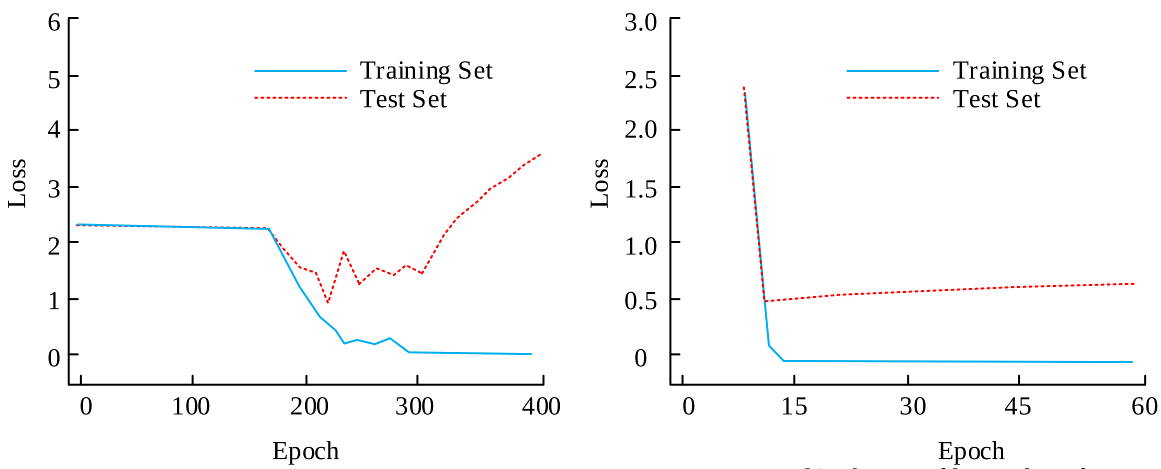


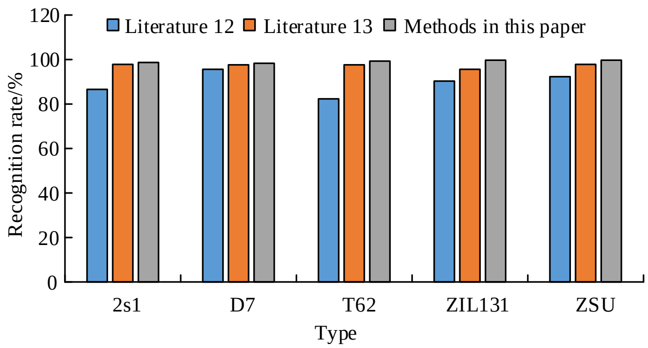
Fig. 5. SAR Image Samples.



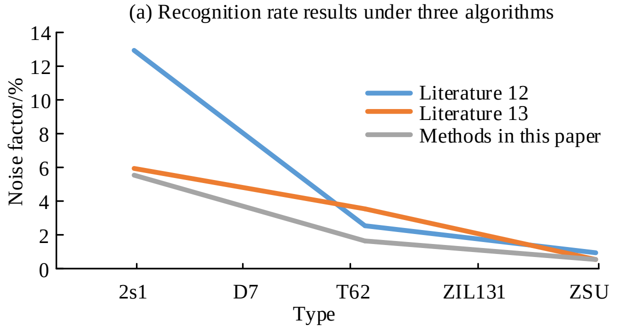

(a) Change of loss value of algorithm before improvement

(b) Change of loss value of improved algorithm

Fig. 6. Comparison Results of Weak and Small Target Recognition Accuracy in SAR Images of Three Methods.




(a) Recognition rate results under three algorithms




(b) Error detection rate results under three algorithms

Fig. 7. Comparison Results of Recognition Rate and False Detection Rate.

Fig. 7 compares the algorithms from the two aspects of target recognition rate and false detection rate. It can be seen from Fig. 7(a) that the algorithms proposed in the study show good recognition rates in different types of test sets, with the recognition rates basically above 98%, and the average accuracy reaching 99%, far higher than the recognition rates shown in [12] and [13]. It can be seen from Fig. 7(b) that the false detection rate of the proposed algorithm is lower than that of the other two algorithms, with an average of less than 0.9%, while the average false detection rate of literature [12] and literature [13] is 6.9% and 2.1%. The above results show that the SAR image recognition method based on machine vision has good recognition rate and false detection rate, and the overall performance is good.

The above experimental results show that the algorithm proposed in this paper has a good recognition rate in weak target recognition, and effectively realizes the processing of image data information. Compare the research results with literature [27]. Literature [27] proposed to improve the accuracy of target recognition in SAR images by improving CFAR algorithm and operation algorithm. Its expansion and research of target data proposed that the dimension reduction of data considered the limited factors in target recognition process. The algorithm proposed in literature [27] has good inspection accuracy, which is similar to the algorithm results proposed in the research, which shows that the machine vision algorithm can improve the application performance of the algorithm.

## IV. Conclusion

SAR is an active microwave imaging sensor. Its imaging principle is to install SAR on the radar platform, transmit electromagnetic waves regularly with the movement of the radar platform, and convert the received ground backscatter signal into SAR image information. SAR uses pulse compression technology to obtain high resolution, can work all day and all weather, has multi band and multi polarization working mode, has certain penetration ability to soil, vegetation, clouds, etc., and can continuously image the observation area, so as to identify obstacles hidden in trees and forests. SAR is widely used in military, geographical and national economic issues. Automatic target recognition (ATR) of SAR image is a key research direction of SAR image interpretation. SAR image target recognition is the combination of SAR image manual interpretation and computer automatic recognition processing. Its working process can be described as: finding out the region of interest in SAR image, and then classifying each region of interest to determine its category. Therefore, this paper proposes a weak and small target recognition method based on machine vision in SAR image, and the effectiveness of this method is verified by simulation experiments. The algorithm proposed in the study considers the impact of linear characteristics on data when extracting image data information, so it uses principal component analysis to reduce the dimensions of data. Different from the improvement of previous improved algorithms in large dimensions, the study pays more attention to multi-dimensional consideration of data information.

In view of the limited ability and short time, in addition to making some progress, there are still many technical problems to be solved and improved, and the practical feasibility of the design scheme needs to be tested and corrected in the project. In order to obtain ideal detection results, there are still many aspects of technology to be studied.

*1)* This paper mainly studies the weak and small target recognition in SAR image under static background. In fact, the background may be dynamic. Further research is needed to realize the weak and small target recognition in SAR image under dynamic background.

*2)* In this paper, the target is not tracked after the recognition of weak and small targets in SAR images. Tracking the target is essential to realize the real-time monitoring or attack of the target. Further research is needed in this regard.

*3)* The engineering implementation of the weak and small target recognition method in SAR image studied in this paper needs further research, especially the setting of recognition method parameters. At present, the setting of parameters is mostly based on experience. After further research, artificial intelligence method can be used to set parameters.

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