Journal of Physics: Conference Series

PAPER • **OPEN ACCESS**

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To cite this article: W Lu *et al* 2019 *J. Phys.: Conf. Ser.* **1267** 012002

IOP Conf. Series: Journal of Physics: Conf. Series **1267** (2019) 012002 doi:10.1088/1742-6596/1267/1/012002

Deep Learning for HRRP-based Satellite Recognition

W Lu[1,*], Y S Zhang[2], Y R Huo[3] and C Y Lin[4]

[1]Graduate School, Space Engineering University, No.1 Bayi Street, Huairou District, Beijing, China
[2]Space Engineering University, No.1 Bayi Street, Huairou District, Beijing, China
[3]Graduate School, Space Engineering University, No.1 Bayi Street, Huairou District, Beijing, China
[4]Space Engineering University, No.1 Bayi Street, Huairou District, Beijing, China

[*]wanglu199310@163.com

Abstract. An approach that employs deep learning technology is presented to recognize satellites based on radar high-resolution range profile (HRRP) data. We focus on extracting effective satellite recognition features in this paper. Thus, a deep learning model is constructed by gated recurrent unit (GRU) neural network and support vector machine (SVM) to extract more abstract and accurate features. Firstly, the radar HRRP data of four satellites is obtained by simulation. And data preprocessing has been done according to HRRP characteristic. Next, a GRU-SVM model is set up and some deep learning skills, such as dropout and cross validation, have been applied to improve recognition accuracy. The training results of GRU neural network show their effectiveness. In order to demonstrate the superiority of this approach, five other feature extraction methods have been used as a comparison based on clean satellite HRRP data and noisy data. The experiment results show that the presented GRU-SVM model could recognize satellites effectively and accurately, and has better recognition performance and noise robustness compared with five other methods.

1. Introduction

Space targets recognition is a primary function of space surveillance information system, and satellites recognition is of critical importance on this issue. However, few open research achievements have been reported. The difficulty of this problem is that satellites are simply too small or too far away for detailed information to be recognized, and few effective identification data can be obtained. With the development of wideband radar [1], wu could obtain lots of useful radar data, such as high-resolution range profile (HRRP), synthetic aperture radar (SAR) image, inverse synthetic aperture radar (ISAR) image, etc. HRRP is the amplitude of coherent summations of the complex time returns from target scatterers in each range cell [2], which represents the projection of the complex returned echoes from the target scattering centers onto the radar line-of-sight (LOS) [3]. It contains abundant target structure signatures, such as target size, scatterer distribution, etc. In addition, compared with SAR/ISAR image, HRRP has the advantages of easy acquisition and processing. That's why radar HRRP target recognition has received intensive attention from radar automatic target recognition (RATR) community [4-11]. So the work in this paper focuses on the satellites recognition based on the HRRP data.

Feature extraction and selection is a basic and crucial technology for radar HRRP target recognition research. It is important to adopt reasonable and effective features to improve recognition performance. For that reason, many researches have been done on feature extraction and selection methods by related scholars. In the early days, researchers often calculated the power spectrum, FFT-magnitude and various high-order spectrum of HRRP data, and used them as the features of classifier for target recognition [4-6]. Such engineered features are useful but rely on researchers' experience and skill. If we do not have sufficient prior knowledge for the applications, those features would be brittle and incomplete. In addition to features of artificial selection, machine learning algorithms have been widely utilized to represent features based on high-dimensional HRRP data by many researchers [7-11]: the principal component analysis (PCA) feature subspace is constructed to minimize reconstruction error for RATR [7]. Dictionary learning is adapted to extract the noise-robust and highly discriminative features of the HRRP [8-9]. Manifold learning is employed in target recognition of radar HRRP to reduce the feature dimensions [10-11]. These methods can work well on some occasions, but all of them are shallow architectures that cannot effectively characterize the radar HRRP. Therefore, how to automatically extract the deep abstract features, which are beneficial for target recognition, has become an important issue.

The deep learning theory [12] put forward by Hinton can effectively solve the above problem. The essence of deep learning is to construct a neural network containing multiple hidden layers to map the data in order to obtain the deep essential characteristics [13]. Some deep learning structures applied in several recent papers have been demonstrated to be useful for radar HRRP target recognition, such as autoencoder and its varieties [14-15], convolutional neural network (CNN) [16], recurrent neural network (RNN) [17-18]. Because of the unique structure of RNN, it has been widely applied to process sequential data such as action recognition [19], scene labelling [20], and language processing [21], and has achieved impressive results [22]. GRU neural network is a kind of RNNs and can learn long term reliance on information [23]. In this paper, the HRRP data of four satellites are obtained by simulation. For satellites recognition based on this sequential data, a recognition model has been designed in this paper, which contains GRU neural network as a deep features extractor and SVM as a classifier. Experiments have demonstrated that this GRU-SVM model performs well on the task of satellite recognition based on radar HRRP data and has relatively strong noise robustness.

2. Description and Preprocessing of HRRP

HRRP is the amplitude of the echo summation for target scattering centers in each range cell of wideband radar. Figure 1 shows the illustration of an HRRP sample from a satellite target. High resolution radar operates in microwave frequency band. Generally, the size of targets or their components is much larger than the wavelength of radar. For complex targets such as a satellite, the projection of an object on radar line of sight can be divided into many range cells by high resolution radar.

The radar signatures from scattering centers within the same range cell will be coherently summed into a single signature for that range cell. According to the literatures [2, 5], if the radar transmitted signal is $s(t)e^{j2\pi f_c t}$, the nth complex echo in the dth range cell ($d=1,2,\cdots D$) in the baseband can be approximated as

$$\tilde{x}_d(t,n) \approx s(t)\sum_{i=1}^{L_d}\sigma_{di}\, e^{-j\left\{(4\pi/\lambda)\left[R(n)+\Delta r_{di}(n)\right]\right\}} \tag{1}$$

where $s(t)$ is the complex envelop which approximates to be unvaried with the radial displacements for all scatterers in one range cell. f_c is the radar signal carrier frequency and λ denotes the wavelength of high resolution radar. L_d represents the number of target scatterers in the dth range cell. σ_{di} is the intensity of the ith scatterer in the dth range cell. $R(n)$ is the radial distance between target reference center in the nth echo and the radar. $\Delta r_{di}(n)$ is the radial displacement of the ith scatterer of the dth range cell in the nth echo. Usually, $s(t)$ is a rectangular pulse signal with unit intensity and could be omitted. After eliminating the initial phase of the nth echo $e^{-j(4\pi/\lambda)R(n)}$, the nth HRRP can be defined as

$$\begin{aligned}\mathbf{x}(n)&=\left[x_1(n),x_2(n),\cdots,x_D(n)\right]\\&=\left[\left|\sum_{i=1}^{L_1}\sigma_{1i}e^{j\phi_{1i}(n)}\right|,\left|\sum_{i=1}^{L_2}\sigma_{2i}e^{j\phi_{2i}(n)}\right|,\cdots,\left|\sum_{i=1}^{L_D}\sigma_{1i}e^{j\phi_{Di}(n)}\right|\right]\end{aligned} \tag{2}$$

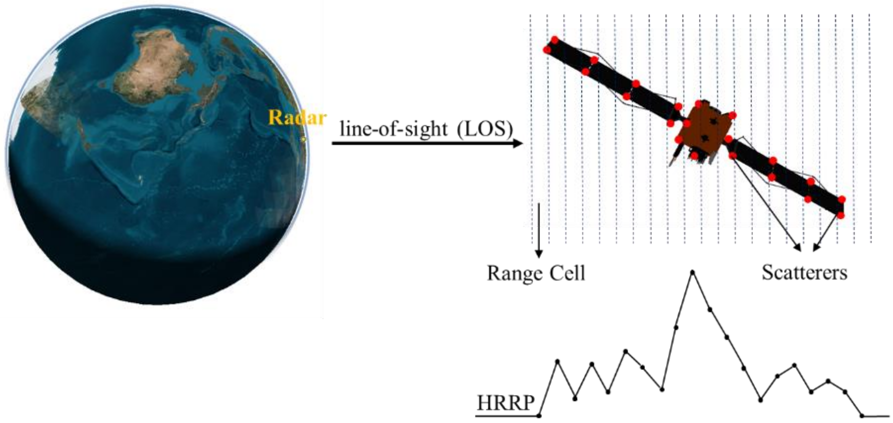
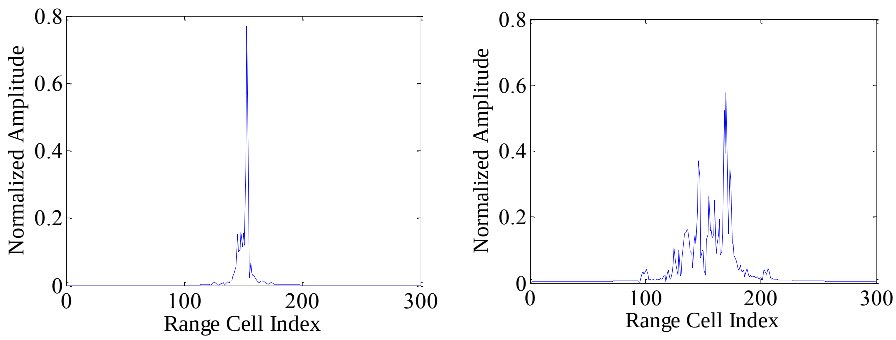


Figure 1. An HRRP sample from a satellite target.

Several issues should be considered when HRRP is applied to radar target recognition task. 1) The first one is time-shift sensitivity of HRRP. HRRP is only a part of received radar echo extracted by a range window, in which a target signal is included. So the position of target signal in HRRP may vary with the measurement. However, feature learning needs all the training samples to learn a uniform parameter model. So we adopt envelope alignment method [24] as time-shift compensation technique in this paper. 2) The second one is amplitude-scale sensitivity. It comes from the fact that the intensity of an HRRP is a function of radar transmitting power, target distance, radar antenna gain, radar receiver gain, radar system losses and so on. HRRPs measured by different radars or under different conditions will have different amplitude-scales. To deal with amplitude scale sensitivity, each HRRP is normalized by dividing maximum amplitude per frame. After the above preprocessing, the HRRP sample examples of four satellites are shown in Figure 2.

The last one is called target-attitude sensitivity. It means that the variation of target attitude will lead to different range shifts for different scattering centers on the target, even within the attitude region where the scattering center structure remains unchanged. Considering that the attitude of normal satellite is relative stable, it is expected to be solved by recognition methods.



(a) Sat1 (b) Sat2

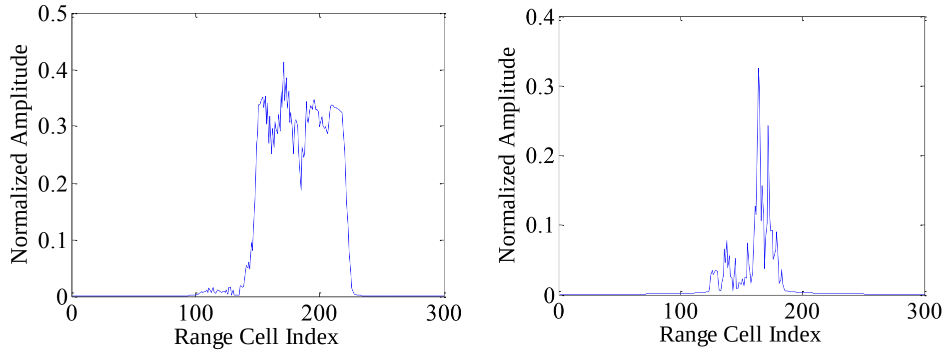


Figure 2. HRRP sample examples of four satellites.

3. GRU-SVM model

3.1. GRU

Compared with the feed-forward networks such as CNN, RNN has a recurrent connection where the last hidden state is an input to the next state [25-26]. RNN will remember the previous information and use the previous information to influence the output of following nodes, so it is better to solve problems related to time series data [27]. That is, RNN can obtain the output sequence from the input sequence at the current time step, and can also predict sequence in the next time step. However, RNN suffers from long-term dependencies problem, and gradient vanishing or exploding may occur during the training process, making it impossible to process long-term sequence data. In response to this problem, variants of RNNs such as long-short term memory (LSTM) [28-29] and GRU [30] have been proposed.

The GRU neural network is a variant of the LSTM network. There are only two gates in the GRU network unit, namely the update gate z and the reset gate r. The update gate is utilized to modulate the previous information inside the unit. The larger the value of the update gate, the more the status information of the previous moment insides. The reset door is used to control the previous state information which will be forgotten, the smaller the value of the reset gate, the more the previous state information is forgotten. Figure 3 shows a GRU model, where $\tilde{\boldsymbol{h}}$ denotes candidate activation. GRU model has been proved performing better than simple RNNs in the task of processing sequential data [31].

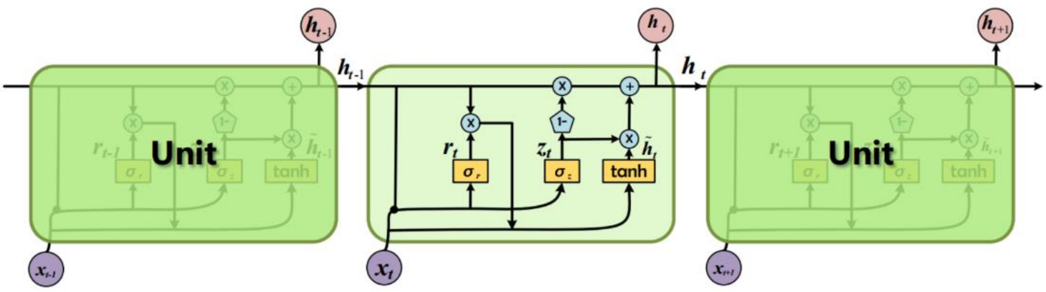


Figure 3. A Gated Recurrent Unit.

The update gate z_t is defined as

$$z_t = \sigma\left(\mathbf{W}_z \mathbf{x}_t + \mathbf{U}_z \mathbf{h}_{t-1}\right) \tag{3}$$

where $\mathbf{W}$ and $\mathbf{U}$ are weight matrix respectively. $\mathbf{x}$ denotes input data and $\mathbf{h}$ is known as hidden state. The reset gate r_t is defined as

$$r_t = \sigma\left(\mathbf{W}_r \mathbf{x}_t + \mathbf{U}_r \mathbf{h}_{t-1}\right) \tag{4}$$

The hidden state in a GRU is linearly modelled as

$$\mathbf{h}_t = (1 - z)\mathbf{h}_{t-1} + z_t \tilde{\mathbf{h}}_t \tag{5}$$

The candidate hidden state is

$$\tilde{\mathbf{h}}_t = \tanh\left(\mathbf{W}_h \mathbf{x}_t + \mathbf{U}_h \left(r_t * \mathbf{h}_{t-1}\right)\right) \tag{6}$$

where $*$ is element-wise product. The $\sigma(\cdot)$ and $\tanh(\cdot)$ are two different activation functions which can be defined as

$$\begin{aligned} \sigma(x) &= \frac{1}{1+e^{-x}} \\ \tanh(x) &= \frac{1-e^{2x}}{1+e^{2x}} \end{aligned} \tag{7}$$

In this paper, GRU is employed in the GRU-SVM model to extract effective features based on HRRP sequential data.

3.2. GRU-SVM model construction

In this paper, we build a GRU-SVM model. It consists of two parts： an encoder and a classifier. The encoder takes HRRP data of different satellites as input. Length-fixed feature vectors produced by the encoder contain sufficient information for target recognition. The classifier takes feature vectors as input for classifier and the corresponding satellites classes will be identified.

The encoder consists of an input layer, two GRU hidden layers of size 96 and a fully connected layer (activation function is ***linear*** and the number of units is 64). The output of this fully connected layer is feature vector. The classifier used here is SVM and takes feature vector as its input. The structure of GRU-SVM model is shown in Figure 4. In order to extract good features, the encoder is followed by two fully connected layers, whose activation function are ***relu*** and ***softmax*** respectively. This GRU neural network utilizes the ***Adam*** optimizer for optimization and use ***categorical crossentropy*** as a loss function to reduce the difference between the model classification value and the real value. At the same time, in order to make the training model more accurate, the bidirectional scheme as demonstrated in reference [32] is applied in GRU hidden layers.

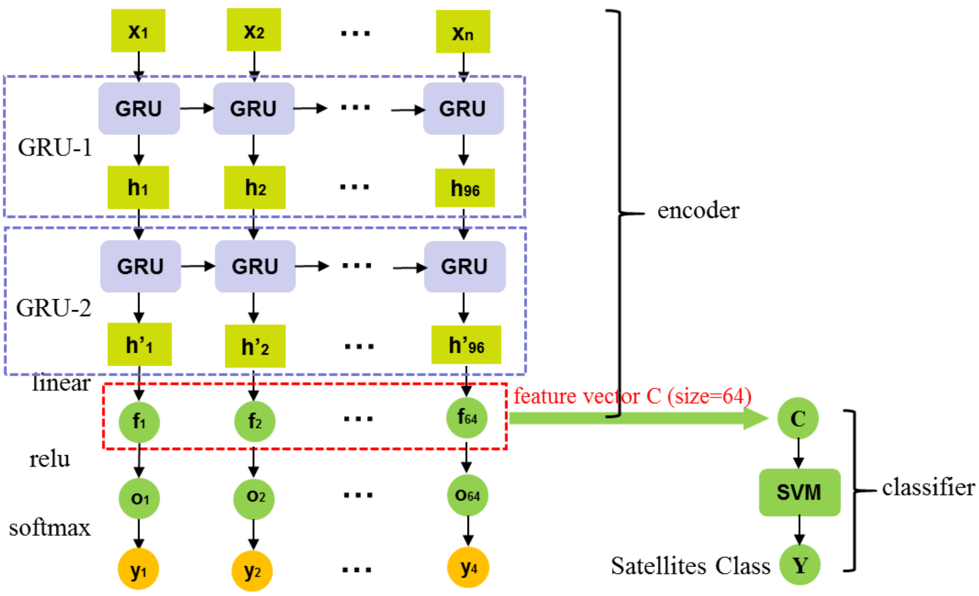


Figure 4. The structure of GRU-SVM model.

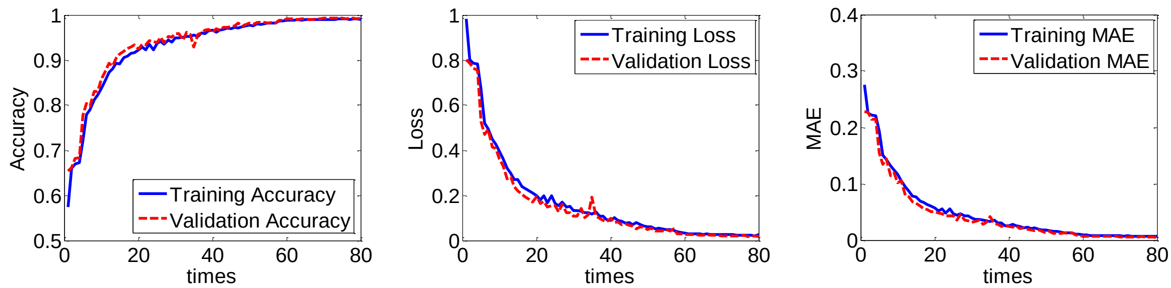
4. Experiments
In this section, testing experiments of GRU-SVM model have been carried out to obtain its recognition performance based on the HRRP data of four satellites, which all have 35000 HRRP of 300 dimensions. To better illustrate the advantages of this model, some frequently used feature extraction methods are utilized for comparison, including PCA, linear discriminant analysis (LDA), dictionary learning, autoencoder and simple RNN. In addition, noise is usually inevitable, which has great influence on the performance of radar target HRRP recognition. So recognition capability of these methods has also been tested when HRRP data with the noise of different signal-to-noise ratio (SNR) is utilized as input.

4.1. Training assessment
Most HRRP data of four satellites (about 70%~80%) will be applied as input to train the GRU neural networks and others are utilized as testing set. Meanwhile, 20% of training data is used as validation set to adjust the hyper-parameters. To avoid the problem of overfitting, ***Drop-out*** has been employed for the two GRU layers. In this paper, drop rate is set to 0.25. Activation function and loss function described in the section 3.2 are applied for GRU neural network. When the evaluation indicator is not improving, the learning rate will decrease in multiple. To accelerate the training, batch normalization inserted after each layer.

Recognition accuracy, loss and mean absolute error (MAE) are often applied to assess the training result. Recognition accuracy is the ratio of the number predicted correctly to the total testing number, and loss is defined the difference of prediction value and true value. Assuming $\hat{y}_i$ is the prediction value of ith sample, y_i is expected value, the MAE is defined as

$$MAE\left(y,\hat{y}\right)=\frac{1}{n_M}\sum_{i=1}^{M}\left|y_i-\hat{y}_i\right| \tag{8}$$

where M is the total number of samples. The training results of 80 times are shown in Figure 5. The recognition accuracy, loss and MAE all change as expected. The accuracy of training and validation set in the process of extracting feature reaches 99.1% and 99.3% and the loss and MAE continue to decline.



(a) Accuracy (b) Loss (c) MAE

Figure 5. Training records for 80 times.

4.2. Recognition preformation comparison
After training GRU neural network*s*, it is important to get the recognition results of GRU-SVM model. In order to demonstrate its effect and advantages, the recognition performance for testing data has been compared when different methods are applied to identify satellites. Two deep networks (GRU and simple RNN) and four shallow models (PCA, LDA, dictionary learning and autoencoder) serve as feature vector extractor, and linear SVM is used to classify the satellites (here linear SVM only serves as a simple baseline, thus it does not employ any feature extraction). The recognition accuracy of these six methods is shown in table 1 and their confusion matrices are shown in Figure 6. Compared with the latter five methods, GRU-SVM model has good recognition performance for the four satellites. Therefore, its total recognition accuracy rate is highest among this six methods.

Table 1. Accuracy of six recognition methods.

recognition methods	accuracy rate (%)
GRU-SVM	99.4
simple RNN-SVM	93.4
PCA-SVM	91.9
LDA-SVM	80.6
dictionary learning-SVM	86.4
autoencoder-SVM	91.5

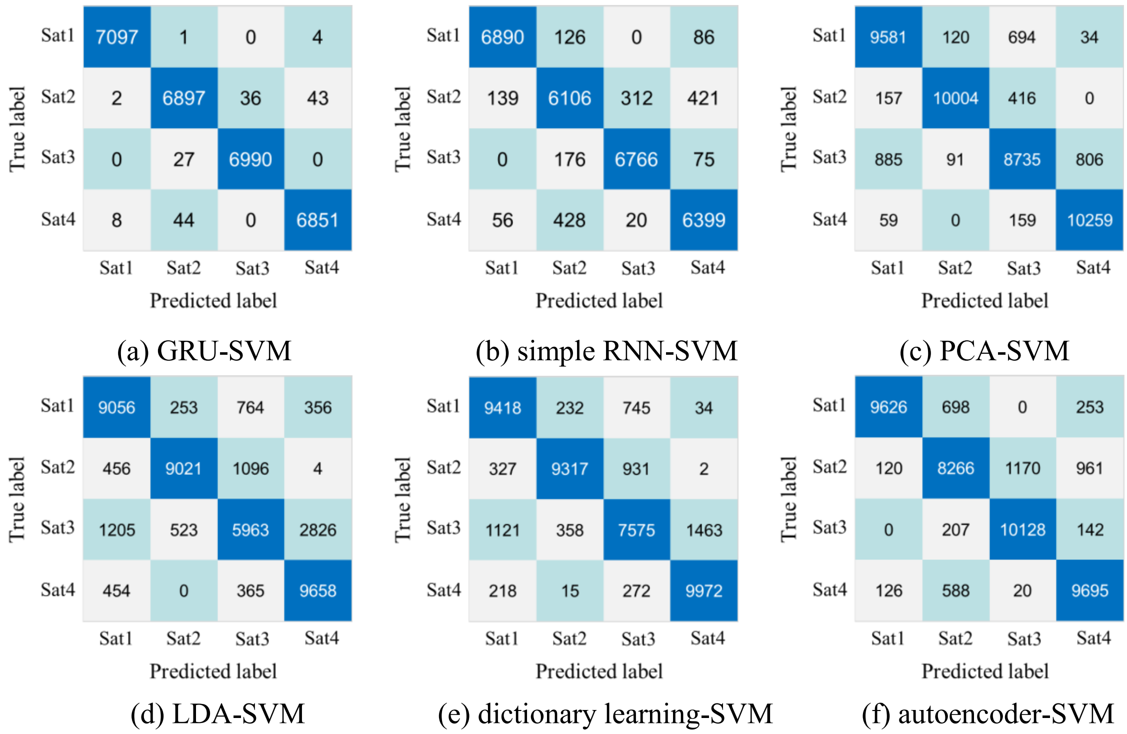


Figure 6. Confusion matrix of six recognition methods.

To further study the noise robustness of these six recognition methods, gaussian noise with different SNR (1dB, 10dB, 20dB and 30dB) is added to clean HRRP data. The recognition accuracy rate varies with SNR and the corresponding results are illustrated in the Figure 7. It shows that the GRU-SVM model has the greater capacity of robustness than five other methods. With the increase of HRRP data SNR, its recognition accuracy gets improved. It can be seen from this figure that when the SNR of satellites HRRP data is low, for example SNR=1dB, the recognition rate of these six methods is all less than 90%. However, the recognition accuracy of GRU-SVM model is still much higher than other methods. This demonstrates that the GRU-SVM model has greater noise robustness than other methods.

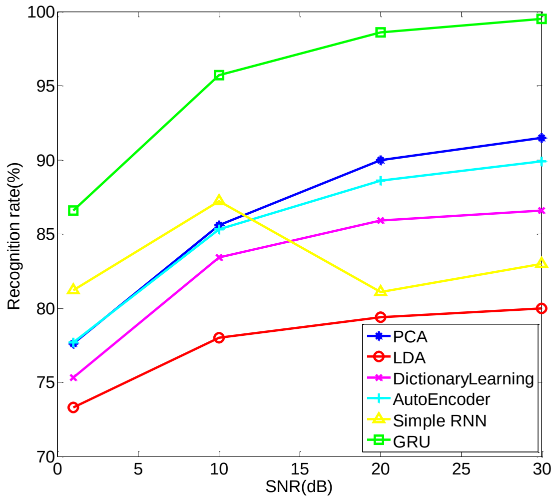


Figure 7. Recognition rate under different SNR noise.

5. Conclusion

In this paper, a GRU-SVM model has been designed for radar HRRP satellite recognition, and achieves better recognition performance than several traditional feature extraction methods in the experiments. According to the characteristic of HRRP data, we preprocess these data and establish the structure of GRU-SVM model. This model consists of two parts: GRU neural network as an encoder and SVM as a classifier. The effectiveness of GRU neural network has been validated in model training process. Performance comparison experiments are carried out to testing recognition accuracy of several shallow or deep models. The results demonstrate that the model presented in this paper achieves superior recognition performance than other models based on feature extraction, even for HRRP data with low SNR.

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