SAR Images Change Detection Based on Self-Adaptive Network Architecture

Jiao Shi, Xiaodong Liu, and Yu Lei

Abstract—**In the last few years, neural networks were introduced to change detection for a better understanding of remote sensing images. However, the designs of these neural networks were time-consuming processes of trial and error, which failed to account for their validity. Thus, a simple and efficient change detection method based on network architecture search in terms of the evolutionary algorithm is proposed to deal with SAR images change detection problems. In the proposed method, an efficient gene encoding is applied to represent the unpredictable optimal depth and the number of neurons in each hidden layer. Besides, a combinatorial evaluation strategy and a self-adaptive network solution selection are designed for effective and reasonable network architectures. What is more, a hidden layer random alignment crossover operator and a drawing lots mutation operator are designed for the enhancement of diversity of network architectures. Experimental results on a few SAR image data sets demonstrate that the proposed method can generate appropriate networks to solving SAR images change detection.**

Index Terms—**Change detection, evolutionary algorithm, network architecture search (NAS), neural network, SAR images.**

I. Introduction

SAR images change detection has been attracting increasingly interests along with the development of SAR systems. Benefit from its potential characteristics of all-weather and full-time working, SAR systems have been applied in many fields, such as disaster monitoring and resource exploration [1]–[3]. Wide applications of SAR systems provide rich SAR image resources for researches of change detection, which is leading to a bloom of SAR images change detection methods.

Change detection is a technique that distinguishes the changed and unchanged objects between a pair of multitemporal images derived in the same region. With respect to change detection on remote sensing images, it can be divide into three steps [4]: image preprocessing that mainly involves the coregistration of two remote sensing images; the generation of difference image; and the analysis of difference image. Especially, the third step is attracting major attention [5]–[8].

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There are also some change detection methods that perform well without difference images and play an important role in the advance of change detection [9], [10].

In recent years, neural networks are introduced to change detection because of its good performance in classification tasks [11]–[16]. Compared with traditional machine learning methods, neural networks are capable of mining deeper information on remote sensing images to prompt the overall accuracy of change detection. Zhang *et al.* [13] used stacked denoising autoencoders to learn the high-level representation of local features of remote sensing images and built a mapping network to explore the inner relationship between features come from different images. Gong *et al.* [14] proposed a method based on deep neural networks (DNNs) for solving SAR images change detection problems, which achieved a better performance than conventional change detection methods.

However, there are some problems hindering the practical implementation of these neural network-based change detection methods. These methods used architecture-fixed networks to perform change detection on different remote sensing data sets. However, different data sets usually have different complexities of analyses, which inclined to result in degraded performances. Besides, these methods need to be adjusted again and again when they were designed, which cost a lot of time. Furthermore, if a network is designed for each of remote sensing data set specifically, the overhead cannot be afforded.

Therefore, a simple and efficient change detection method based on network architecture search (NAS) is proposed for searching better architectures of a fully connected neural network to solve SAR images change detection problems in this letter. In the proposed method, there are three contributions highlighted. First, an efficient gene encoding is applied to represent the unpredictable optimal depth and the number of neurons in each hidden layer in fully connected neural networks. Second, a combinatorial evaluation strategy and a self-adaptive network solution selection are designed for urging networks to improve their performances. Third, a hidden layer random alignment crossover (HLRAC) operator and a drawing lots mutation (DLM) operator are designed for the enhancement of diversity of network architectures. The proposed method relieves from agnostic designs of network architecture and instead sets up an evaluation index to lead the generation of network, thereby causing an interpretable and reasonable network architecture.

The remainder of this letter is organized as follows. The proposed method will be detailed in Section II. The

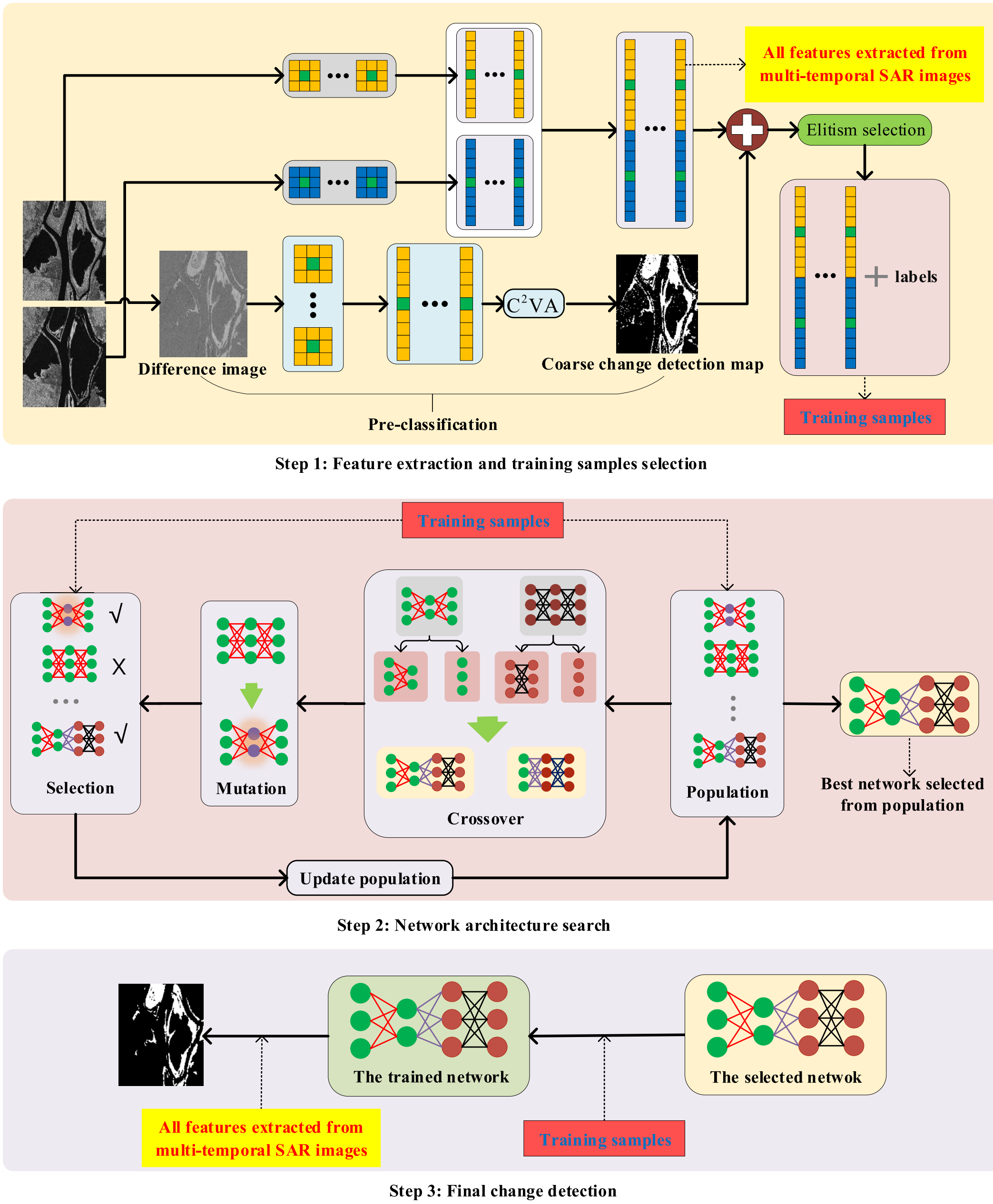

Fig. 1. Proposed SAR images change detection framework.

experiment design and experimental results are shown in Section III. Finally, the conclusion and further work are detailed in Section IV.

II. Methodology

In this section, the proposed evolving fully connected neural networks (EVONNs) for solving change detection problems will be detailed, in which a desired neural network is first obtained by EVONN and change detection is subsequently achieved. Fig. 1 illustrates the procedure of searching a promising architecture of neural networks for SAR images change detection.

A. Gene Encoding and Population Initialization

Gene encoding plays an important role in evolutionary algorithms. In EVONN, an efficient and easy-to-understand gene encoding is designed to represent unpredictable depth and number of neurons. Because the input size and output size of all neural networks have been customized according to the need of change detection problems, only the structures of hidden layers are encoded in the evolutionary algorithms. For example, an architecture of having three hidden layers where the number of neurons is 5, 9, and 12, respectively, can be encoded by a list [5 9 12].

When an individual is being initialized, the number of hidden layers is randomly generated in the first place, and the number of neurons of each hidden layer is randomly generated in the second place. Obviously, the initialization of a population of having N individuals is composed of N times of an individual initialization.

B. Combinatorial Evaluation Strategy

In order to give a quantitative measure of each individual in the population, a combinatorial evaluation strategy is designed in this letter. Theoretically, a test data set with true labels is used for evaluating the quality of the training process. However, absolutely accurate label information about SAR images could hardly be acquired when solving change detection problems, so researchers instead gave pseudo labels to each feature in SAR images for supervised training of a network [14], [15], exploring the inherent capacity of learning deep information of a network. Therefore, the training error is chosen to be an evaluation index to quantify the performance of candidate networks, in which a small training error is preferred.

Nevertheless, generalization cannot be promised without validation of test data set in the training process, instead easily resulting in overfitting. For this, an incomplete training strategy is applied on the candidate networks to avoid overfitting. Specifically, each candidate network is trained with a small number of epochs less than normal to relieve the overfitting problem, unexpectedly improving the efficiency of the evolutionary process. Besides, the complexity of the network is also taken into consideration to guarantee the generalization and improve the heuristic searching ability, in which simple network architecture is preferred. The combinatorial evaluation strategy composed of training error and the network's complexity forms a basis for the evolutionary direction of networks.

C. Self-Adaptive Network Selection

In this section, a self-adaptive network selection is designed based on change detection problems for selecting parent solution and ensuring the diversity of the new population, which is detailed in Algorithm 1. Note that the threshold α is formulated as follows:

$$\alpha = (T_{\max} - T_{\min})\frac{1}{N} \tag{1}$$

where $T_{\max}$ and $T_{\min}$ are the maximum training error and minimum training error of current population, respectively, and N is the population size.

Algorithm 1 Self-Adaptive Network Selection

Input: Two individuals, the self-adaptive threshold α.
Output: The selected individual.

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s1 ← The individual with larger training error.
s2 ← The other individual.
t1, t2 ← The training errors of s1 and s2;
c1, c2 ← The number of neurons of s1 and s2;
if t1 − t2 ≥ α then
    return s2.
else
    if c1 ≤ c2 then
        return s1.
    else
        return s2.
    end
end
```

D. Genetic Operation

In order to prompt the diversity of the architectures, genetic operations are designed based on the efficient gene encoding strategy. In general, a crossover operation occurs between two-parent solutions that are randomly selected from a mating pool, and the offspring solutions are subsequently modified by a mutation operator.

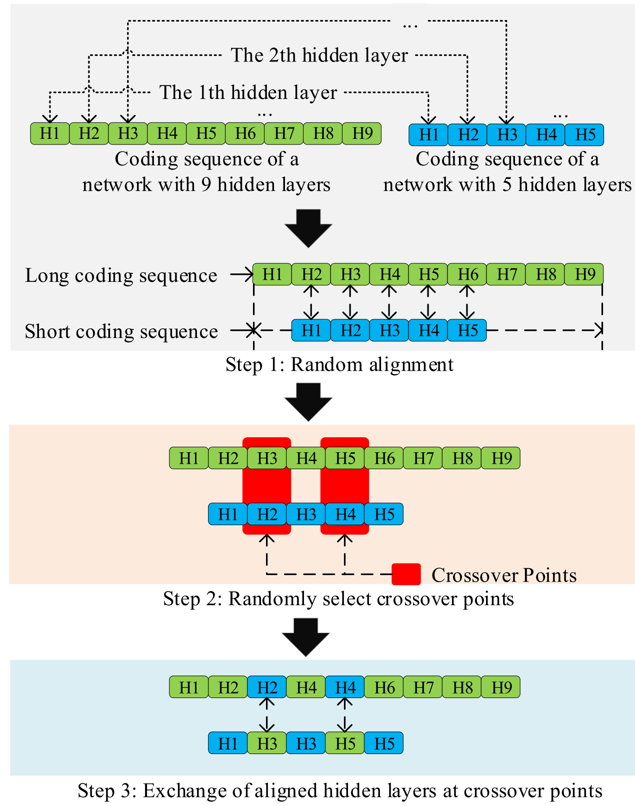


Fig. 2. Example to illustrate the crossover process.

1) Hidden Layers Random Alignment Crossover: A new crossover operator, i.e., HLRAC depicted in Fig. 2, is designed to recombine the chromosome fragments of parent solutions for generating offspring solutions. In order to fully explore the potential of chromosome in a pair of parent solutions, we try to pair chromosomes up as much as possible, which is the essence of the random alignment operation of crossover. The second step selects the crossover points, and the third step exchanges the chromosomes at crossover points.

2) Drawing Lots Mutation: A drawing lots strategy is designed to modify hidden layers, in which three types of modification that are involved, including adding a hidden layer, delete a hidden layer, and change the number of neurons. For satisfying the restriction when a mutation happens, a drawing lots pool that is formed by a limited number of different modifications that are used to determine which type of modification is performed on mutation points. Specifically, in the pool, the addition operators' size cannot exceed the number of the hidden layers that are allowed to be modified, while the sum of the addition operators' size and the length of the current individual cannot exceed the maximum hidden layer size. In addition, the number of deletion operations and change neuron number operations should be equal to the number of the remaining hidden layers that are allowed to be modified in the present moment. Fig. 3 shows a visual example for giving an intuitive insight.

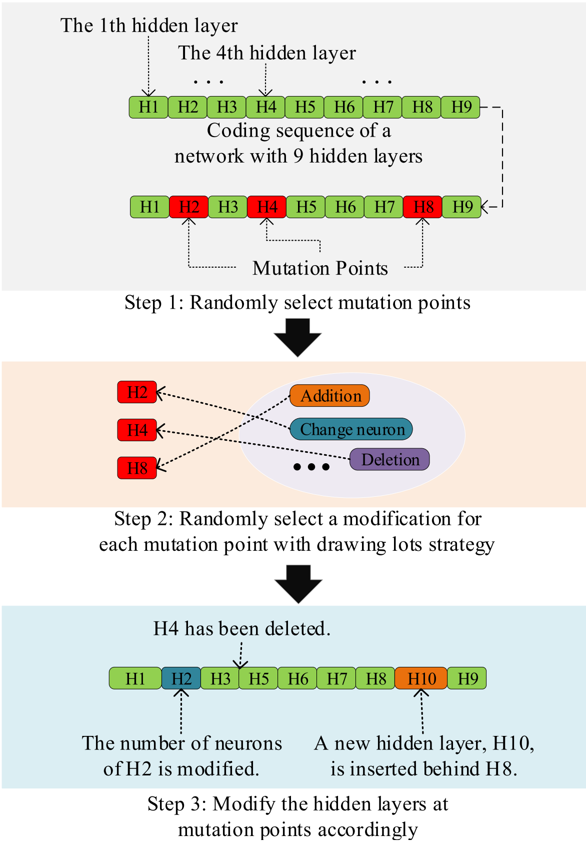


Fig. 3. Example to illustrate the mutation process.

E. Change Detection With the Best Neural Network

After the second stage of the proposed method, the best solution is selected to decode into a neural network that is viewed as performing better than any others. The network should be fine-tuned with training samples because it does not fully trained to be evaluated in the second stage. After fine-tuned, the network can be used to analyze the features extracted in the first stage and produce a final change detection map.

III. EXPERIMENT

In this section, the proposed method will be applied to real SAR image data sets to quantify its performances. Then, a comparison experiment with three change detection methods will be conducted to demonstrate its effectiveness. Finally, the conclusion will be derived.

A. SAR Image Data Sets and Evaluation Indexes

In the experiments, three real SAR image data sets are used to demonstrate the effectiveness of the proposed method, which are the Bern data set, the Ottawa data set, and the Yellow River data set, respectively. Besides, there are two multitemporal SAR images and one ground-truth image to shown real changed regions for a reference in each SAR image data set, which are displayed in Fig. 4(a)–(c).

In our experiments, except the intuitively visual way of showing change detection images, the percentage of correct classification (PCC) and kappa coefficient [14] are used to quantify the performance of the proposed method on the aforementioned data sets.

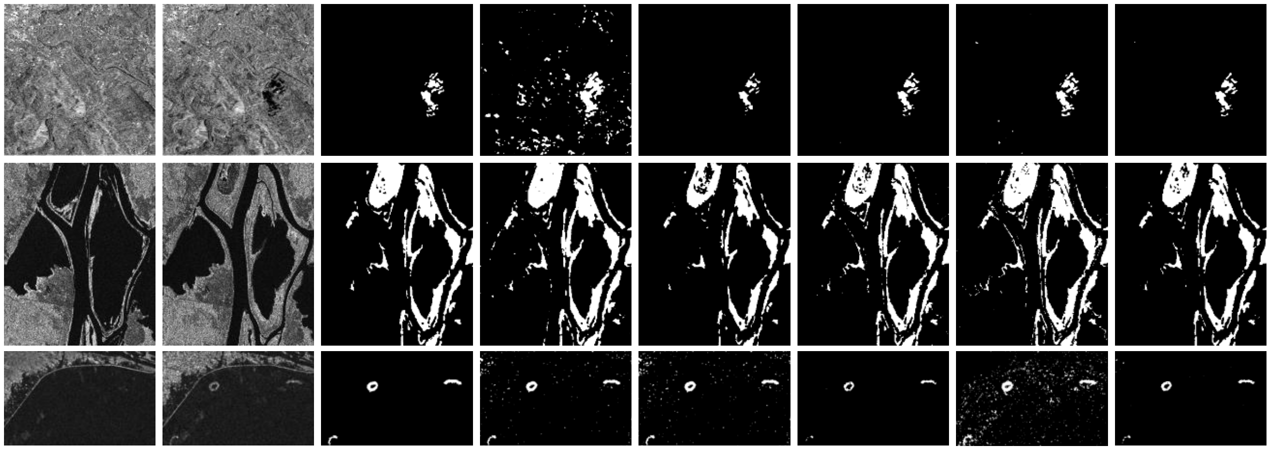
TABLE I
EVALUATION INDEXES OF CHANGE DETECTION RESULTS

Dataset	Method	PCC	Kappa	Hidden layers
Bern	GGKI	0.9608	0.3796	–
	RFLICM	0.9964	0.8377	–
	DNN	**0.9968**	**0.9968**	250-200-100
	MSSDNN	0.9960	0.8545	100-50-20
	EVONN	0.9965	0.8589	142
Ottawa	GGKI	0.9799	0.9276	–
	RFLICM	0.9733	0.8935	–
	DNN	0.9809	0.9278	250-200-100
	MSSDNN	0.9719	0.8981	100-50-20
	EVONN	**0.9845**	**0.9845**	150
Yellow River	GGKI	0.9915	0.6916	–
	RFLICM	0.9878	0.5998	–
	DNN	0.9958	0.7651	250-200-100
	MSSDNN	**0.9669**	0.3567	100-50-20
	EVONN	0.9963	**0.7999**	149

B. Performances on SAR Image Data Sets

Fig. 4(d)–(h) shows the change detection results achieved by generalized Gaussian Kittler & Illingworth method (GGKI), reformulated fuzzy local-information c-means algorithm (RFLICM) [17], DNN method, multiscale superpixel segmentation-based DNN method (MSSDNN) [18], and the proposed method, respectively. In the change results on the Bern data set, the DNN method and the proposed method have similarly good performances visually. However, the change detection results achieved by GGKI and MSSDNN suffer from speckle noise, and the former is particularly serious. Although the change detection result on the Bern data set achieved by RFLICM is not disturbed by noise, it does not detect all changed regions. In the change results on the Ottawa data set and the Yellow River data set, it is apparent that the change detection result achieved by the proposed method suffers less speckle noise and presents more completely changed regions than the others. Furthermore, the neural networks generated by the proposed method to achieve change detection against the aforementioned SAR image data sets have only one hidden layer, while the DNN and MSSDNN methods use three hidden layers [14], which is detailed in Table I. Although deep networks can generate more representative features to promote the performance of classification than shallow ones in general, the reasonable design is more meaningful than simply increasing the depth of the network in practice.

In order to conduct a direct comparison between these methods, PCC and kappa coefficient are used to quantify their performances. Table I indicates that the proposed method achieved the best performances on the Ottawa and Yellow River data sets and approximately best performance on the Bern data set. Besides, the proposed method uses simpler architecture than the DNN method, which means that the former uses less computational resources than the latter to achieve similarly good performances.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 4. SAR images of data sets and change detection results. (a) SAR image I_1. (b) SAR image I_2. (c) Reference map and change detection result achieved by (d) GGKI, (e) RFLICM, (f) DNN, (g) MSSDNN, and (h) EVONN.

IV. Conclusion

When dealing with SAR image change detection problems, networks are usually designed by virtue of the experience of researchers. However, an artificially designed network can hardly guarantee good performances on several different SAR images change detection problems. Thus, an SAR images change detection framework based on NAS in terms of an evolutionary algorithm is proposed in this letter. For a fast heuristic search, an efficient gene encoding is applied to represent the unpredictable optimal depth and the number of neurons in each hidden layer. Besides, an HLRAC and a DLM are designed for the diversity of solutions. Through the proposed framework, network architectures can be designed in terms of specific SAR images change detection problems. Experimental results on SAR image data sets demonstrate that the proposed method can generate appropriate networks targeted for different SAR images change detection problems to promise good performances.

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