Research on the Fusion Pattern Recognition System Based on the Concept of Production Education Integration and Application of Generative Countermeasure Network

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Abstract. In order to highlight the practical application value of network data and information fusion behavior under the background of industry-education integration, a fusion pattern recognition system that applies generative confrontation network under the concept of industry-education integration is designed. First, the cyclic neural network is used to generate independent text information packets. While establishing the generation of the confrontation network framework, various reinforcement learning parameters are adjusted to realize the construction of the hardware execution environment of the recognition system. On this basis, build an embedded network framework, with the help of EEPROM chip and LD3320 chip circuit, to supervise the fusion process of network data information identification and implementation behavior, and realize the construction of the system's software execution environment. Combined with the related hardware equipment structure, complete the research on the fusion pattern recognition system of the application generation confrontation network under the concept of integration of production and education. Comparative experiment results show that with the application of the above system, the mean value of network data information fusion time is reduced from 17.9 s to 11.2 s, while the maximum amount of information processed by a single fusion process reaches 9.3×1012T which can be used in the context of the integration of production and education Effectively highlight the practical application capabilities of network data information fusion behavior.

Keywords: Industry education integration · Confrontation network · Fusion pattern recognition · Network text · Learning parameters · Embedded framework · Chip circuit

1 Introduction

The integration of industry and education refers to that vocational schools actively set up professional industries according to their specialties, closely combine industry and teaching, support and promote each other, and turn the school into an industrial business entity integrating talent training, scientific research and scientific and technological services, thus forming a school running mode in which schools and enterprises complement

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each other. The integration of industry and education is the deep cooperation between industry and education, and the deep cooperation between colleges and enterprises to improve the quality of talent training. The school running mode of "combination of production and education, integration of school and enterprise" is a new development road for vocational schools. However, due to the actual situation of each school is different, the characteristics of each profession is different, so the specific approach is not the same.

The basis of the combination of production and education is "production", that is, it must be based on real product production. With such a foundation and atmosphere for professional practical teaching, students can learn the true skills and teachers can teach the true level. Such "production" cannot be simply factory production. It must be closely integrated with teaching. Its purpose is to "teaching". When the combination of production and education is relatively mature, it will gradually develop into "production, learning, and research". After realizing the integration of production and education, the school has truly formed the ability of "production, learning, and research". The vocational school has adapted to the needs of the market, and the formation of development capabilities has been implemented, and there is a foundation for strengthening and improving.

According to the existing conditions and management conditions, it is more possible to introduce enterprises with more advanced management and technology in the society, and are willing to join the school enterprise cooperation. Through the use of the school's equipment, product production, the introduction of teaching content in the production process, the school and enterprise jointly formulate the implementation teaching and production plan of the combination of production and teaching, so that teachers can learn technology and students can join in the production, so that production can produce benefits, school and enterprise win-win, symbiosis and common prosperity.

For to improve the effect of production and education integration, a fusion pattern recognition system based on generative countermeasure network is designed.

2 Convergence Mode of Generating Confrontation Network

2.1 Text Generation Based on Recurrent Neural Network

This research is based on the sequence model to achieve text generation. This process refers to modeling along the one-dimensional dimension of the text tag sequence to construct a language model and then generate text. Common forms of sequence models include recurrent neural networks, sequence-to-sequence models, attention sequence models, etc.

For many years, recurrent neural networks with long-term and long-term memory units have shown excellent performance from natural language generation to handwriting generation. Recurrent neural network belongs to the category of deep learning, and it is also a common sequential model. It has achieved good results in many tasks of natural language processing. As shown in Fig. 1, the basic recurrent neural network is a network model for output inference in the form of shared parameters in the sequence dimension. The recurrent neural network can be expanded on the time axis. Through this expansion, the model can be understood as a deep network with the number of layers as the sequence length, and the particularity lies in the weight sharing among the layers. The main idea behind the recurrent neural network is to apply the temporal information of linear data structure [1, 2]. In the original neural network, the default assumption is that each input data is completely unrelated, but in many tasks, this is an unreasonable assumption and important information is lost. The basic structure of the recurrent neural network is shown in Fig. 1.

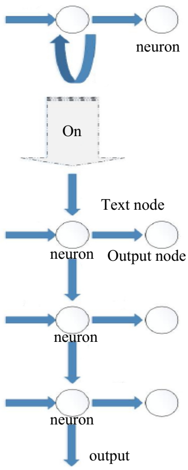

Fig. 1. The idea of cyclic neural network text generation

2.2 Generation of Countermeasure Network Framework

Generative confrontation network is not a complete model, but a network training framework. The structural design of the generative adversarial network is clever and simple. The original framework has only two components: the generator and the discriminator. Among them, the generative model used by the generator is not limited, but the training goal of the generator is always to fit the generated sample distribution as close as possible to the real sample distribution. When there is no discriminator, a loss function that measures the gap between the generated sample and the real sample needs to be defined in advance. The training of the generator needs to rely on multiple rounds of iteration to adjust the parameters and continuously minimize the loss function. But this method has a big problem, because the artificially defined loss function usually has limited characterization ability and can only one-sidedly describe the difference between the real sample distribution and the generated sample distribution [3]. There are two main problems in applying generative adversarial networks directly to sequence generation tasks including text generation. First of all, the generative confrontation network is designed to generate continuous-valued data, but it is difficult to directly generate discrete symbol sequences from continuous-valued data.

Facing the continuous value data task, the generator changes from random sampling to sampling controlled by generator parameters in the training process. The overall loss of the model is determined by both the discriminator parameters and the generator parameters. The loss gradient can be used to fine tune the parameters of the generator, so that the generator can produce more real data. However, if the data to be generated is composed of discrete tags, the small change of generator parameters will not sample new tags, that is, the sequence results sampled in the discrete space do not change, so the guidance signal given by the discriminator to the generator will lose its inherent directivity. The emergence of discriminator in Generative countermeasure network is to solve this problem. The training goal of discriminator is to maximize the probability of true sample judging as true and minimize the probability of generating sample judging as true, that is to find the best segmentation method between generated sample distribution and real sample distribution. Ideally, a fully trained discriminator is equivalent to a strong loss function [4]. At this time, the training goal of the generator is transformed from minimizing the difference between the generated sample and the real sample to weakening the discriminator's ability as much as possible. The overall structure of the framework for generating countermeasure network is shown in Fig. 2.

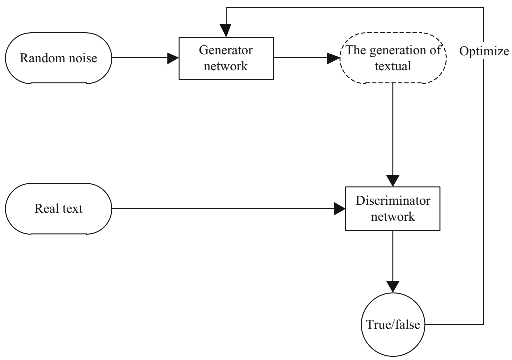

Fig. 2. Overall structure of the framework for generating countermeasure network

2.3 Reinforcement Learning Parameter Adjustment

There are some problems in the generation of discrete data such as text. The image data generation with good effect of the original generation countermeasure network belongs to the typical continuous data generation task, so the parameters in the model can be directly optimized, and finally the false image is generated. The image data are expressed in the form of real value tensor in computer. If it is a black-and-white image, it can be encoded as a two-dimensional matrix composed of gray values. If it is a multi-channel image such as a color image, it can be encoded as a three-dimensional tensor. In either case, the elements in the tensor are in the real number space, and their values have fixed meanings, which represent the properties of a certain dimension of the image. If the real values of tensors are directly aggregated together, they naturally represent an image. In short, the original image can be restored from tensor representation without "sampling" operation.

The principle of reinforcement learning parameter adjustment is shown in Fig. 3.

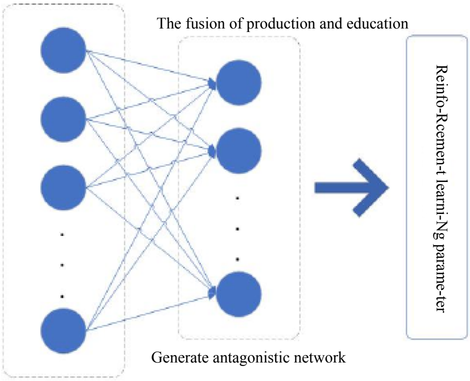

Fig. 3. Reinforcement learning parameter adjustment principle

Simulation and generation of sequential data is an important problem in unsupervised learning. Text generation can be classified into this problem. For a long time, recurrent neural network (CNN) has been regarded as an effective method to deal with sequence problems. Most of the deep learning text generation models are based on recurrent neural networks. Both feature matching and reinforcement learning face similar difficulties, that is, the reward signal is sparse [5, 6]. In order to alleviate the problem of signal sparsity, layered technology has become the most direct way of thinking. Some people think that text generation is naturally generated at the level of grammatical structure, because real text samples have such levels as semantic structure and part of speech. According to the characteristics of hierarchical structure, the whole character sequence generation problem is decomposed into a combination of several partial character sequence generation problems, which can build a more easy to learn model for complex problems.

3 Pattern Recognition System Based on the Concept of Integration of Production and Education

3.1 Embedded Network Framework

The traditional recognition framework of the embedded network is shown in Fig. 4. The whole system is mainly composed of several main modules such as MCU main control chip, dedicated network identification chip, identification list and counter network information collection.

(1) Core controller: the main control chip used to control the special network information identification chip, which can be programmed to achieve relevant functions. The system uses the way of serial port to USB to communicate with the upper computer. Its main types are 51 single-chip microcomputer, STM series, arm series, etc. this system uses 51 single-chip microcomputer as the core control unit.
(2) Data acquisition: a module used to collect data signals, and the collected data information analog signals are transformed into digital signals after preprocessing such as endpoint detection, denoising, etc. The purpose is to extract features of digital signals and match patterns to obtain the final recognition results.
(3) Recognition list: as the most characteristic module of offline information recognition. Because it is different from online recognition, it has a huge database of data recognition, which can be called through the network. While offline identification is to temporarily store the recognition command in the recognition list, and match the identification results of the identification chip, so as to get the recognition result with the highest matching degree and feed back to the user.

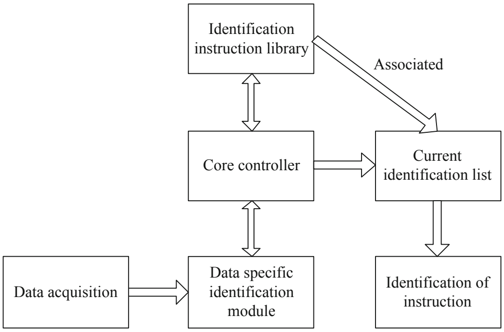

Fig. 4. Embedded network framework

There are differences between learning signals and reinforcement. The guidance signal in reinforcement learning is also called reinforcement signal. Reinforcement signal is provided by environment, which is a dynamic evaluation of action. Reinforcement signals in reinforcement learning are usually scalar. This training method does not directly tell the intelligent system what the correct action is or how to produce the correct action. Compared with supervised learning, the system obtains less information from the external environment each time, so it must rely on more rounds of attempts to learn. In this way, the intelligent system can continuously improve the action strategy to adapt to the environment [7, 8].

In the field of text generation, the traditional method is based on the recurrent neural network to complete the word-by-word generation of the text. Although this method of predicting the next word based on the generated sequence is reasonable in theory, it will be affected by gradient dispersion in actual engineering. Can't play the best role. At the same time, text generation models based solely on cyclic neural networks have the problem of not being able to judge complete sequence information, and prone to problems such as word repetition. Therefore, other technical means should be used to generate models on the basis of cyclic neural networks. Make improvements. If the word-by-word generation is changed from a classification problem at each time point to a decision problem that hopes to obtain the greatest expected return at the current time point, then the text generation problem can be solved using reinforcement learning techniques.

3.2 EEPROM Chip

Due to the disadvantages of off-line nonspecific countermeasure network fusion pattern recognition system, such as limited recognition instructions and limited storage space, users can only have limited command interaction when using it, and when changing instructions, they need to write the program code in ROM register of single chip microcomputer. The process is complex, which makes the interaction very troublesome, and it is also in the actual operation Problems that need to be avoided and improved in the process. Therefore, the EEPROM external register module is added, and the contents of the register can be directly rewritten by the upper computer, so that the recognition command can truly realize the function of dynamic free addition. It not only solves the problem of complex changing instructions, but also avoids the problem of limited recognition command. As long as the register is written into the register through PC according to certain protocol, it can be written in real time To identify. EEPROM chip structure is shown in Fig. 5.

AT24C02, as a two-wire serial EEPROM, is a low working voltage 2K-bit serial electrically erasable read-only memory [9]. The internal organization is 256 bytes, each with 8 bits. Considering that in the recognition process, the recognition instruction needs to cover the length of a sentence, this article has also improved this by changing the 8-bit byte to 16 bytes, and the internal organization has been reduced from 256 to 128. Bytes to lengthen the content of each identification. The main features of the chip are:

(1) Working voltage: 1.8 V–5.5 V;
(2) Input/output pins are compatible with 5 V;
(3) Application in internal structure: 128 * 16 (2k);
(4) Two wire serial interface;
(5) The input pin is filtered by Schmidt trigger to suppress noise;
(6) Two way data transmission protocol;
(7) Compatible with 400 kHz (2.5 V);
(8) Support hardware write protection;
(9) High reliability: read and write times: 1000000 times, data storage: 100 years.

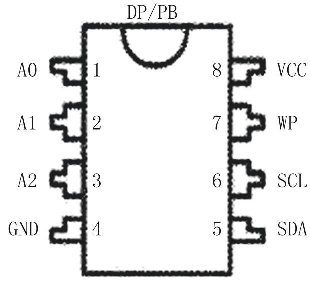

Fig. 5. EEPROM chip structure

3.3 LD3320 Chip Circuit

As one of the most important modules in the hardware platform, the process of reading and writing the function register is mainly between the speech recognition chip ld3320 and the main control chip. The register of ld3320 supports the serial spi read-write method of software and hardware, parallel read-write of software simulation and hardware parallel read-write. This design uses the parallel software simulation timing. The timing of parallel writing is shown in Fig. 6, and that of parallel reading is shown in Fig. 7.

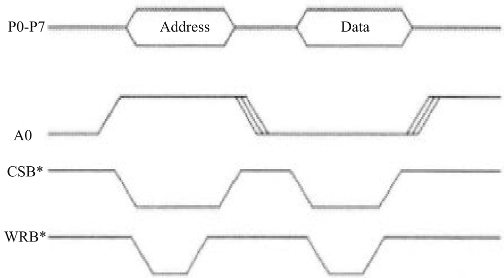

Fig. 6. Parallel write timing

When the read-write address is ready, in the parallel read-write sequence, make Ao equal to 1, pull CSB down and WRB up to write address respectively; when Ao is equal to 0, make CSB pull down and RD pull up to read in data. One of the main disadvantages of the existing text generation methods is that the binary feedback signal of the discriminator is sparse, because it can only be calculated when the whole text sample is completed.

In addition, the scalar guiding signal for the entire text is obviously insufficient in information, because it can no longer retain relevant information about the intermediate grammatical structure and semantics of the generated text, so the generator cannot be targeted for learning. All generative models based on generative adversarial networks face the problems of unstable training and mode collapse [10]. The two major issues in text generation tasks are also content to be considered. How to stably implement training and

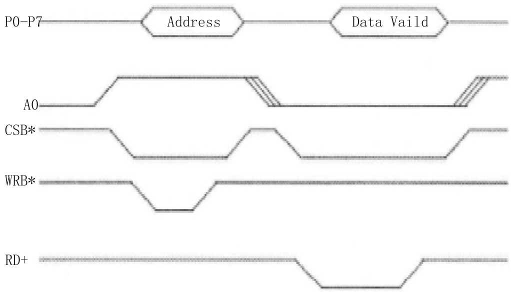

Fig. 7. Parallel read timing

how to obtain diverse texts. There is no perfect solution at the model level. Researchers still need to carefully adjust the hyperparameters to alleviate it. These questions.

It should be noted that in this read-write mode, the MD pin of MCU needs to be pulled down. At this time, the related components of ld3320 will have a long time delay, which will affect the operation of writing data to the 0 × 37 register, and the chip will also be interfered at this time, resulting in abnormal operation. In the process of identification, the register of 0 × 37 is the entrance of the control chip, which starts the operation of chip identification and the whole identification process. Ld3320 chip circuit is shown in Fig. 8.

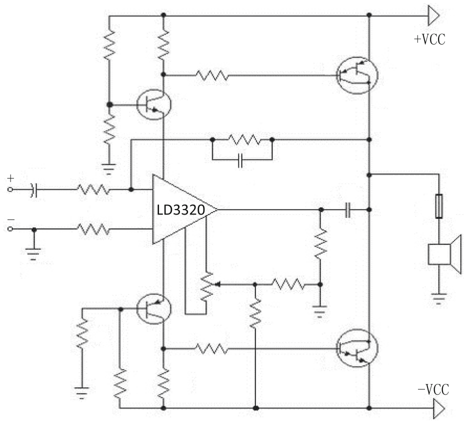

Fig. 8. LD3320 chip circuit

Layering is still one of the most promising techniques for signal sparsity. The typical method of hierarchical technology is to define several low-level subtasks. The learning content of each subtask is obtained by macro strategy, and then the subtasks learn micro strategies separately to complete the tasks assigned to them by macro strategies. The macro policy to solve the problem can be defined manually or acquired by learning. When domain knowledge for specific tasks is used in the construction of hierarchy, this method is very effective, but it can not flexibly adapt to other tasks.

The most direct way to build a text generation system is to use a recurrent neural network as a generator. Recurrent neural network is one of the most suitable models for sequence generation tasks in deep learning technology. It has the characteristics of simple structure and relatively fast inference speed. At the same time, in this task, the cyclic neural network has the characteristics of high randomness. As a new generative model training framework, the generative confrontation network uses the discriminator model to guide the generator model to optimize. Generative confrontation networks have achieved considerable success in real-valued data generation tasks. However, when the target task is to generate discrete tag sequences, generating adversarial networks has great limitations. An important reason is that the discrete output of the generator model makes it difficult to pass the gradient update of the discriminator model to the generator model. In addition, the discriminator model can only evaluate a completely generated tag sequence. For a partially generated sequence, it is very difficult for the original generation adversarial network framework to balance the current score and future scores when generating the entire sequence.

4 Comparative Experimental Analysis

In order to verify the practical application value of the pattern recognition system based on the concept of production education integration, the following comparative experiments are designed.

Debug the generated confrontation network to the application state as shown in Fig. 9. While ensuring that other experimental conditions remain unchanged, the experimental group host and the control group host are respectively connected to the network application environment. Among them, the experimental group host is equipped with a new recognition system, and the control group host is equipped with a traditional recognition system. In the same experimental environment, record the actual changes of various experimental indicators.

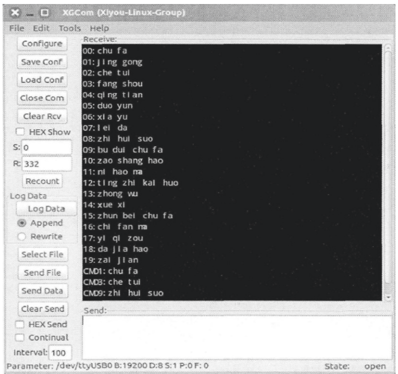

Fig. 9. Operation interface of generating countermeasure network

Make network information input equal to 1.0 × 10^9T, 2.0 × 10^9T, 3.0 × 10^9T, 4.0 × 10^9T, 5.0 × 10^9T, 6.0 × 10^9T, 7.0 × 10^9T, 8.0 × 10^9T, 9.0 × 10^9T, and record under different information input conditions, the specific changes of the actual mean fusion time are shown in Table 1.

Table 1. Comparison table of mean value of network data information fusion time

Network information input/($\times 10^9$T)	Actual fusion time/(S)	
	Test group	Control group
1.0	9.7	17.9
2.0	9.9	
3.0	10.4	
4.0	10.5	
5.0	10.6	
6.0	10.8	
7.0	11.0	
8.0	11.1	
9.0	11.2	

Analysis Table 1 shows that with the increase of network information input, the average fusion time of experimental group keeps increasing trend, and the global maximum value reaches 11.2 s, which is 1.5 s higher than the initial value of 9.7 s. The mean time of network data fusion in the control group remained stable throughout the experiment, which was 6.7 s higher than the maximum value of 11.2 s in the experimental group. To sum up, with the application of the pattern recognition system of application generation antagonism network fusion under the concept of industry education integration, the average time of network data information fusion has obviously decreased, which meets the practical needs of maintaining the application ability of information fusion behavior.

It is stipulated that every 15 min is regarded as a unit duration. Table 2 records the actual changes in the amount of information processed by the experimental group and the control group during a single fusion within 4 unit durations.

It can be seen from Table 2 that the amount of information processed by single fusion in the experimental group keeps a steady upward trend, and the global maximum value reaches 9.3×10^{12}t. In the control group, the amount of information processed by single fusion increased continuously, and gradually stabilized. The global maximum value reached 4.1×10^{12}t, which decreased by 4.7×10^{12}t compared with the extreme value of the experimental group. To sum up, with the application of pattern recognition system of application generation antagonism network fusion under the concept of industry education integration, the amount of information processed by single fusion has increased significantly, which can fundamentally improve the practical application value of network data information fusion behavior.

Table 2. Comparison of single fusion processing information

Experimental group	Experiment time/(min)	Information quantity of single fusion processing/($\times 10^{12}$T)	
		Test group	Control group
1	5	8.6	2.7
	10	8.6	2.8
	15	8.6	2.9
2	20	8.9	3.3
	25	8.9	3.4
	30	8.9	3.5
3	35	9.1	3.9
	40	9.1	4.0
	45	9.1	4.1
4	50	9.3	4.1
	55	9.3	4.1
	60	9.3	4.1

5 Conclusion

In order to highlight the practical application value of network data and information fusion behavior under the background of industry-education fusion, this research uses generative confrontation network to design a fusion pattern recognition system, and the effectiveness of this method is proved through experiments.

References

1. Du, Q., Liu, Q. Conditional generative adversarial network based on image semantic annotation of cloud model. Pattern Recognit. Artif. Intell. **31**(4), 379–388 (2018)
2. Liang, H., Hao, L., Song, J., et al.: The data visualization and pattern recognition method based on the fusion of incremental learning and Lasso. Chin. High Technol. Lett. **28**(1), 39–51 (2018)
3. Xie, C., Wang, Y., Lin, Z., et al.: Monte Carlo noise removal algorithm based on adversarial generative network. Pattern Recognit. Artif. Intell. **31**(11), 85–98 (2018)
4. Chen, Y., Li, Y., Yu, L., et al.: A system of convolutional neural networks based handwritten number recognition. Microelectron. Comput. **35**(2), 71–74 (2018)
5. Liu, S., Matt, G., Marco, Z., et al. (eds.): E-Learning, E-Education, and Online Training. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-93719-9. 15(01):1–15
6. Liu, S., Li, Z., Zhang, Y., et al.: Introduction of key problems in long-distance learning and training. Mob. Netw. Appl. **24**(1), 1–4 (2019)
7. Fu, W., Liu, S., Srivastava, G.: Optimization of big data scheduling in social networks. Entropy **21**(9), 902–918 (2019)

8. Xie, Z., Jiang, P., Yu, X., et al.: Hyperspectral face recognition system based on VGGNet and multi-band recurrent network. J. Comput. Appl. **39**(2), 388–391 (2019)
9. Liu, Y., Yao, L., Wu, Y., et al.: Target point tracks association and error correction with optical satellite in geostationary orbit and automatic identification system. J. Electron. Inf. Technol. **40**(7), 1546–1552 (2018)
10. Chen, T., Zeng, J., Xie, C., et al.: Intelligent identification system of disease and insect pests based on deep learning. China Plant Prot. **39**(4), 28–36 (2019)