Цель. С развитием технологии передачи больших объемов, интеллектуальный анализ временных рядов стал важной темой, которая привлекает к себе внимание общественности. На основании корреляции и общности временных рядов, рассмотрена быстрая модель интеллектуального анализа временных последовательностей.

Методика. Предложен метод определения корреляции, основанный на особенностях соответствующего коэффициента сдвинутой временной последовательности. В конечном счете, предложена быстрая модель интеллектуального анализа временных последовательностей, основанная на теории серых систем.

Результаты. Методология определения корреляции, предложенная в данной работе, является более эффективной, чем коэффициент линейной корреляции Пирсона, коэффициент ранговой корреляции Спирмена, коэффициент ранговой корреляции Кендалла и тест Гренджера на причинность.

Научная новизна. В работе предложено объединение быстрого метода определения корреляции последовательностей и метода выравнивания по кривой.

Практическая значимость. Результаты могут обеспечить теоретическую базу для определения корреляции регрессионного анализа и временного выравнивания.

Ключевые слова: *теория серых систем, временное выравнивание, корреляция, временная последовательность данных, интеллектуальный анализ данных, выравнивание по кривой, тест на причинность*

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IMAGE COMPRESSION AND ENCRYPTION SCHEME BASED ON DEEP LEARNING

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СХЕМА СТИСНЕННЯ ТА ШИФРУВАННЯ ЗОБРАЖЕНЬ НА ОСНОВІ ГЛИБИННОГО НАВЧАННЯ

Purpose. With the growing demands of image processing on the Internet, image compression and encryption have been playing an important role in image protection and transfering. In this paper we will investigate deep learning technology in image compression, and chaotic logistic map in image encryption, to obtain a scheme in image compression and encryption. We have evaluated this scheme with some performance measures and results show it is effective.

Methodology. We formulate the scheme using deep learning and chaos. With the deep learning technology, levels of features are extracted from an image and a certain level of features can be used as a compressed representation of the image. Chaos is used to encrypt the compressed image.

Findings. We first introduceda five-layer Stacked Auto-Encoder model, which is trained by the Back Propogration method, and then we obtained the compressed representation of an image. By using the logistic map method, a pseudo-stochastic sequence is generated to encrypt the compressed image.

Originality. We conducted a study of image compression and encryption. Image characteristics are extracted from an arbitrary level of our deep learning model, and they are used as the compressed representation of the image. The research on this aspect has not been found at present.

Practical value. We have evaluated this scheme on several randomly selected images. And results show it is robust and can be widely used for most images.

Keywords: *stacked auto-encode, deep learning, image protection, image feature, image compression, image encryption*

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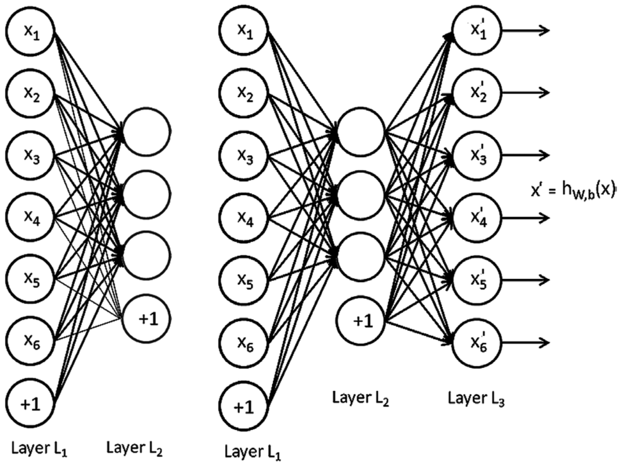
Introduction. With the development of multimedia technology and communication technology, multimedia entertainment has played an important role in people's daily lives. Pictures and videos take up the main part of multimedia entertainment. It brings austere challenge to store and transmit those data, and puts forward higher requirement on the limited-bandwidth Internet, especially for large and high-quality digital images. The limited bandwidth of the Internet greatly restricts the development of image communication, and thus the image compression technology has been attracting more and more people's attention [1]. The purpose of image compression is to represent and transmit the original large image with minimal bytes, and to restore the image with not-so-bad quality. Image compression reduced the burden of image storage and transmission on the network, and achieved rapid real-time processing on line. The information of an image is fixed, but the different representations of the image lead to different changes in the amount of data stored in the image. So in the representation with larger amount of data, some data is useless or represent the information that is represented by other data, they are irrelevant or redundant. The main purpose of image compression is to compress the image by removing redundant or irrelevant information, and to store and transmit digital compressed data on a low bandwidth network.

Image compression techniques can be traced back to the digital television signals proposed in the year of 1948. There is almost 70 years of history. During this period there have been a variety of image compression coding methods. Especially in the late 1980s, due to the wavelet transform theory, the fractal theory, the artificial neural network theory and the visual simulation method, image compression technology was well developed. Image compression methods can be classified into two kinds: one may lose information during compression, and the other one can keep full information, that is, lossless coding methods and limited-distortion coding methods. Lossless coding methods will not suffer loss of information after compressing images, yet without a good compression ratio. The basic principle of this kind of methods is as follows: an image consists of features, using the statistical features of the image, if a feature appears many times in the image, it will be encoded in shorter bits, and if a feature appears only once or limited times, it will be encoded in longer bits. And a complete image is always composed of a large number of repeated features. According to that, the image will be represented by many short-bits coding features and few long-bits coding features. On the basis of guaranteeing the image quality after compression, limited-distortion coding methods maximize the compression ratio. The original image and the compressed image look very similar though some information has changed. The normally used limited-distortion coding methods are: the predictive coding method, the transform coding method and the statistical coding method. The limited-distortion coding method is more frequently used than the lossless coding method because the former has a larger compression ratio. Its premises guarantee visual effects, which remove the information that the human eyes are not sensitive to.

The features of images can be learned automatically using deep learning models, rather than proposed manually. Suitable features can improve the performance of image recognition. Over the past years, features of images were always specified manually that depended on the designers' prior knowledge, and the number of features were very limited. Deep learning models can learn unlimited number of features automatically. A good feature-extraction method is a prerequisite for optimization of image processing. Using deep learning models, unpredictable features of images can be learned, and these unpredictable features can also be used for image protection. In this study, we proposed a model to compress and encrypt images. Based on SAE, a multi-layer model is constructed. An image is put into the first layer and the output data from a different level of layers reconstruct the original image at a different level of comprehension. If the size of the output data from an arbitrary layer is smaller than the size of the original image, the representation at this layer is a compression representation. Because the model has more than one hidden layer whose neurons are smaller than the input layer's, the model can achieve multiple levels of features, and each level of features represents a compressed image. So, multiple compression ratio can be obtained using this model. The compressed image is further encrypted using chaotic logistic map. This model can be used in tasks that have certain requirements for image transmission speed and security.

Analysis of the recent research and publications. ***Stacked Auto-Encoder.*** Auto-Encoder (AE) is a single hidden layer model, and is an unsupervised learning neural network, Fig. 1, *b*. It is actually generated by two identical Restricted Boltzmann Machine models (RBMs) [2], Fig. 1, *a*. A RBM and a reversed RBM generate an AE model. Stacked Auto-Encoder (SAE) is a multilayer AE, it is composed of several AEs. The previous AE's output is the later AE's input, i.e. several AEs' encoding sections are put together one by one and their decoding sections are put together in reverse order. This is a more complex AE model, having several hidden layers rather than one. Using greedy training methods, monolayer AE can be trained to learn weights directly, however, it is hard for SAE because several more hidden layers would consume too much computation time. In order to cut down the training time, the training process of SAE is divided into two steps: pre-training and fine-training. At first, each hidden layer is trained one by one, then the entire model is trained using the Contrastive Divergence (CD-k) [3].

In Fig. 2, the left three layers (X, h_1, h_2) constitute the encoding part of the SAE model. In the pre-training phase, the input data X is encoded and yield h_1, and then h_1 is decoded and yield X', the error $e = X' - X$, e is used to adjust the weights between the layer X and



a *b*

Fig. 1. RBM & Auto-encoder:

a — Restricted Boltzmann Machine (RBM); b — Auto-Encoder

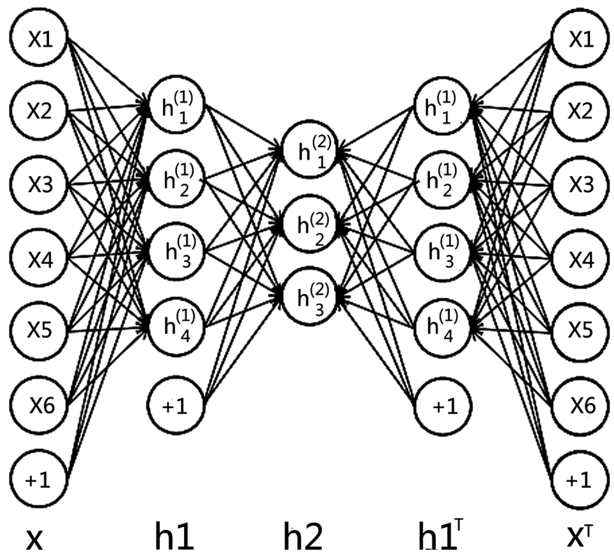


Fig. 2. Stacked Auto-encoder

the layer h_1; then the output value of previous AE is set as the input data of layer h_1, it is encoded and yield h_2, h_2 is decoded and yield h_1', the weights between the layer h_1 and the layer h_2 are adjusted using $e = h_1' - h_1$; after multiple encoding and decoding operations, pre-optimal parameters (W, b) are obtained, and they make the model easy to train in the fine-training phase.

The encoding part (X, h_1, h_2) of the SAE model is flipped to get a decoding part: (h_2, h_1^T, X^T). The two parts are combined to form a model that has the functions of encoding and decoding, Fig. 2. In the fine-training phase, the weights are finely adjusted so that the optimal solution is closer little by little. Using the CD-k algorithm and the gradient descent algorithm, the fine-tuning process gradually approximates the optimal solution of the model. The detailed fine-training process is described as the following steps [4]:

1. Feedforward processing is performed by computing the activation for each middle layer.

2. The grade error for the output layer is

$$\delta^{(ni)} = -(y - a^{(ni)})\cdot f'(z^{(ni)}). \qquad (1)$$

3. The grade error for every middle layer is

$$\delta^{(l)} = ((W^{(l)})^T \delta^{(l+1)})\cdot f'(z^{(l)}). \qquad (2)$$

4. The partial derivatives

$$\nabla_{W^{(l)}} J\left(W,b;x,y\right) = \delta^{(l+1)}\left(a^{(l)}\right)^T; \qquad (3)$$

$$\nabla_{b^{(l)}} J\left(W,b;x,y\right) = \delta^{(l+1)}. \qquad (4)$$

5. The overall cost function is set as the following

$$J\left(W,b\right) = \left[\frac{1}{m}\sum_{i=1}^{m} J\left(W,b;x^{(i)},y^{(i)}\right)\right]. \qquad (5)$$

SAE has strong representation expression ability and advantages of deep neural networks. AE can learn the characteristics of input data, then SAE can learn multi-level characteristics. In the first hidden layer, SAE can learn first-order features of the input data; in the second hidden layer, SAE can learn second-order features of the input data. E.g. the input data is a set of images, the first hidden layer may learn a collection of edges, and the second hidden layers may learn how to combine a number of edges together to form an outline, a higher hidden layer may learn much more vivid, special and meaningful features. Features of each level can help us better operate image processing, such as image classification, information retrieval of images, and so on. These features can also be used to compress images. For example, an image with 100 pixels is put into the input layer, the input layer has 100 neurons, each pixel is put into a corresponding neuron, then a hidden layer with only 10 neurons yields a 10-dimensional vector, which owns features of the input data and can be considered as a reconstruction of the input image, so this image is compressed and the compression ratio is 10.

Image encryption schema using chaotic logistic map. Chaos-based cryptographic algorithms have suggested efficient ways to develop secure image encryption. These algorithms are sensitive to their initial conditions. Any tiny change can cause greatly different responses that guarantees the efficiency of encryption schemas. The logistic map is one of them. It is an iterated logistic map that has proved great importance in many fields of information processing. Such fields include but are not limited in the following: population of biology, chemistry, encryption, communication and ecology. It also works in modelling the dynamics of a single species. The stability and bifurcation of the logistic map has been studied a lot, such as Cohen-Grossberg neural networks with delays [5] and the Neimark-Sacker bifurcation with delay [6].

The logistic map is of a non-linear recursive relation. It can suggest deterministic chaos. Its mathematical equation is written as

$$x_{n+1} = rx_n(1 - x_n), \qquad (6)$$

where x_0 is an initial condition which is a float number between 0 and 1 (exclude 0 or 1), r is a positive constant which is also a float number between 3.5699 and 4 (include 4, and 3.5699 is an approximation). After N iterations, a sequence will be obtained. The sequence is like the form of $\{x_1, x_2, x_3, ..., x_N\}$. It is a stochastic sequence which can further be used for encryption tasks. In this study, the initialized number x_0 is generated from the SAE model, and then is used for image encryption.

Image compression encryption model. The image is compressed using the SAE, and then the compressed image is encrypted using the sequence generated by the chaotic logistic map.

The diagram in Fig. 3 shows the algorithm of this model. See the following for detail:

1. Initialization. A five-layer SAE model is constructed (Fig. 2). In the model, the second layer has a smaller number of neurons than the input layer in order to realize the primary image compression, and the third layer has a smaller number of neurons than the second layer in order to realize the second-stage image compression. The rest fourth and fifth layers are separately the mirrors for the second and first layers. In the study of image processing using Convolutional Neural Networks (CNN), it was supposed and has been proved by a large number of experiments [7] that an image could be divided into a number of regions and the characteristics learned by CNN from different regions are similar or even the same. We use this supposition in our study. The image is divided into pieces which have the same size. Every piece is a sample. A training set consists of all pieces from one single image. For the convenience of handling images in SAE, values in this data set will be normalized as float numbers in the range of 0 to 1 before they are put into the model. Our model is trained using this normalized data set. Levels of learned features will be anti-normalized to get the final output, which are values of pixels for a compressed image. According to the dense representation, the image is compressed. The constant r is initialized.

2. Learning compression representation using the SAE model. The activation function f (·) is a nonlinear function, and the sigmoid function is used in the experiment. By training the SAE model, we get a compression representation from an arbitrary hidden layer. This representation then forms a compressed image. Because the sigmoid function output is a float number between 0 and 1, which meets the requirements for initializing x_0, a certain one from the output values is chosen as x_0. In the experiment, the first one is chosen.

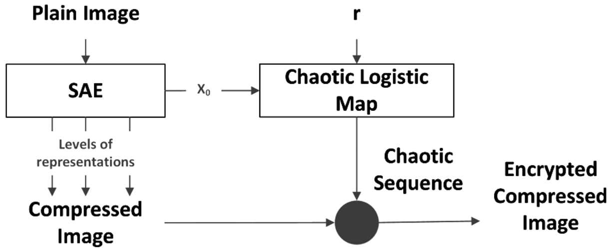


Fig. 3. The compression encryption model

3. Generating a chaotic sequence. Using chaotic logistic map with x_0 and r, a sequence S is generated, $S = \{x_1, x_2, x_3, ..., x_N\}$, where N is the size of the compressed image, e.g., a compressed image has 100 ∗ 100 pixels, N = 100 ∗ 100 = 10000.

4. Image encryption and image decryption. The encryption and decryption functions are described following, where E is the encrypted image, C is the plain image (the compressed image), S is the sequence generated in step 3), bitxor(–) is a bit XOR function

$$E = \text{bitxor}(C, S); \quad (7)$$

$$C = \text{bitxor}(E, S). \quad (8)$$

5. Image reconstruction. The compressed image is recovered through the SAE model. Fig. 2, if the compressed image came from the layer of h_2, a new model is reconstructed with only the layers of $\{X, h_1, h_2\}$ which shares the parameters learned in step 2). The compressed image is normalized and is put into the layer of h_2, then the output from the layer of X represent the recovered image.

The practicability of the algorithm will be verified in the next section.

Experiments. This new model was evaluated on several images taken from the standard set of images. They are house, airplane, lake and pepper. They have the same size as 512 by 512. Images split into pieces with the same size of 8 by 8. The number of neurons in the input layer was 64, and the number of neurons in the hidden layers was adjusted to achieve different compression ratios (CRs), that is, 4 : 1 and 16 : 1 for 16 and 4 neurons. In the back part of this section, the compressed images were encrypted. Correlation Analysis was performed to evaluate the effect of the encryption schema.

Compression effects are shown in Fig. 4. In order to quantitatively verify the effects, Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) are introduced. MSE [8] is the average of the square of the difference between the expected response and the actual output. It is also called squared error loss. PSNR [9] is the ratio of maximum power of the signal and the power of noise. It is commonly used to measure the quality of reconstruction in image compression. Their mathematical definitions are following equations

$$MSE = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I_0(i,j) - I_R(i,j)]^2; \quad (9)$$

$$PSNR = 10 \log_{10} \left(\frac{MAX_I^{\,2}}{MSE} \right), \quad (10)$$

where MAX_I is the maximum possible pixel value of the image, that is 255 in this experiment, $m * n$ is the image size, I_0 is the original image and I_R is the reconstructed image.

MSE and PSNR were computed for three primary colour channels (Red, Green and Blue, also called RGB), respectively. And the results at the CRs of 4 : 1

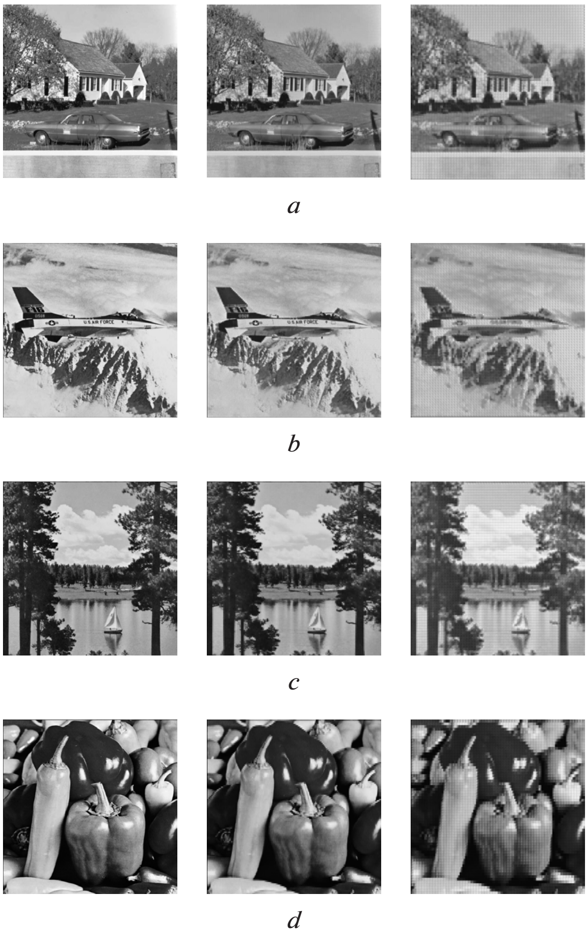


Fig. 4. Compression effects:

a – original image of house, image reconstructed at a CR of 4 : 1, image reconstructed at a CR of 16 : 1; b – original image of airplane, image reconstructed at a CR of 4 : 1, image reconstructed at a CR of 16 : 1; c – original image of lake, image reconstructed at a CR of 4 : 1, image reconstructed at a CR of 16 : 1; d – original image of pepper, image reconstructed at a CR of 4 : 1, image reconstructed at a CR of 16 : 1

Table 1

MSE and PSNR of the reconstructed images at a CR of 4 : 1

Images		R	G	B
House	MSE	37.7696	51.1280	37.0831
	PSNR	32.3594	31.0442	32.4390
Air-plane	MSE	21.4800	32.9829	15.8055
	PSNR	34.8105	32.9479	36.1427
Lake	MSE	32.2390	101.1015	56.4297
	PSNR	33.0470	28.0832	30.6157
Pepper	MSE	48.8470	60.6932	39.5987
	PSNR	31.2424	30.2994	32.1540

Table 2

MSE and PSNR of the reconstructed images at a CR of 16 : 1

Images		R	G	B
House	MSE	110.9180	136.8415	118.2971
	PSNR	27.6808	26.7686	27.4011
Air-plane	MSE	119.2817	114.3715	71.0135
	PSNR	27.3651	27.5476	29.6174
Lake	MSE	62.2023	174.2972	144.9320
	PSNR	30.1927	25.7179	26.5192
Pepper	MSE	71.5491	149.3480	74.9371
	PSNR	29.5848	26.3888	29.3838

and 16 : 1 are listed in Table 1 and Table 2, respectively.

The encrypted images of the compressed ones at CRs of 4 : 1 and 16 : 1 are shown in Fig. 5 and Fig. 6, respectively. Correlation Analysis was performed to quantitatively evaluate the effect of the encryption schema. The correlation coefficient is used to evaluate the correlation of a pair of adjacent pixels, and it is defined below [10]

$$r_{xy} = \left(E(xy) - E(x)E(y)\right) \Big/ \left(\sqrt{D(x)}\sqrt{D(y)}\right), \quad (11)$$

where r_{xy} is the correlation coefficient of the variables x and y, $E(\cdot)$ is the mean function, $D(\cdot)$ is the variance function, x and y are adjacent pixels.

To simplify the processing, colour images were converted to grayscale before use. Experiments were repeated ten times, correlation coefficients of each image were averaged. Results for reconstructed images and encrypted compression images at the CRs of 4 : 1 and 16 : 1 are listed in Table 3.

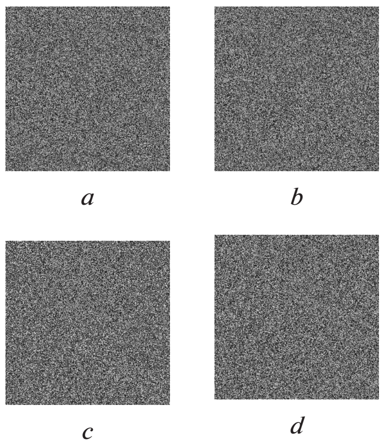


Fig. 5. Encrypted images of the compressed ones at a CR of 4 : 1:

a – encrypted house; b – encrypted airplane; c – encrypted lake; d – encrypted pepper

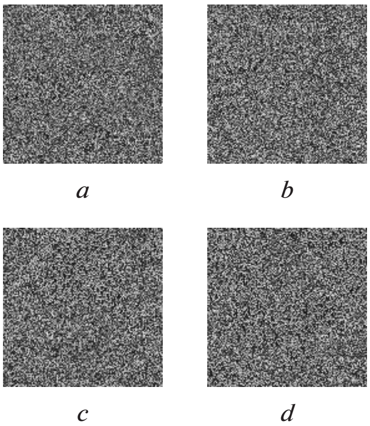


Fig. 6. Encrypted images of the compressed at a CR of 16 : 1:

a — encrypted house; b — encrypted airplane; c — encrypted lake; d — encrypted pepper

The experimental results show that this new model is effective and it can be used for image transmission and image protection on the Internet simultaneously.

Conclusions. A scheme of deep learning in image compression and encryption was proposed. Based on SAE neural networks, images are compressed. And then the compressed ones are encrypted using chaotic logistic map. This scheme can be used for image transmission and image protection on the Internet simultaneously.

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Table 3

Correlation Analysis for reconstructed images and encrypted compressed images at the CRs of 4 : 1

Images	CR of 4 : 1		CR of 16 : 1	
	Compressed	Encrypted	Compressed	Encrypted
House	0.9532	-0.0391	0.9369	0.0079
Airplane	0.9632	0.0038	0.9745	0.0361
Lake	0.9820	-0.0087	0.9855	0.0267
Pepper	0.9796	0.0488	0.9902	0.0261

References / Список літератури

1. Zhang, Chunhong, 2016. Application of Multi-Wavelet Analysis in Image Compression. *Revista Tecnica De La Facultad De Ingenieria Universidad Del Zulia*, No. 39(3), pp. 760–82.

2. Fischer, A., and Igel, C., 2014. Training restricted Boltzmann machines: An introduction. *Pattern Recognition*, No. 47(1), pp. 25–39.

3. Ma, X., and Wang, X., 2016. Average Contrastive Divergence for Training Restricted Boltzmann Machines. *Entropy*, No. 18(1), pp. 35–49.

4. Sarangi, P. P., Sahu, A., and Panda, M., 2013. A hybrid differential evolution and back-propagation algorithm for feedforward neural network training. *International Journal of Computer Applications*, No. 84(14), pp. 1–9.

5. Liu, Q., and Yang, S., 2014. Stability and bifurcation of a class of discrete-time Cohen–Grossberg neural networks with discrete delays. *Neural Processing Letters*, No. 40(3), pp. 289–300.

6. Sarmah, H. K. R., Das, M. C., and Baishya, T. K. R., 2014. Neimark-Sacker bifurcation in delayed logistic map. *International Journal of Applied Mathematics & Statistical Sciences*, No. 3(1), pp.19–34.

7. LeCun, Y., Bengio, Y., and Hinton, G., 2015. Deep learning. *Nature*, No. 521(7553), pp. 436–444.

8. Tiwari, M., and Gupta, B., 2015. Image Denoising Using Spatial Gradient Based Bilateral Filter and Minimum Mean Square Error Filtering. *Procedia Computer Science*, No. 54, pp. 638–645.

9. Karamchandani, S. H., Gandhi, K. J., Gosalia, S. R., Madan, V. K., Merchant, S. N., and Desai, U. B., 2015. PCA encrypted short acoustic data inculcated in Digital Color Images. *International Journal of Computers Communications & Control*, No. 10(5), pp. 678–685.

10. Zhang, Y. Q., and Wang, X. Y., 2015. A new image encryption algorithm based on non-adjacent coupled map lattices. *Applied Soft Computing*, No. 26, pp. 10–20.

Мета. З посиленням вимог до обробки зображень в Інтернеті, стиснення зображень та шифрування грають важливу роль у захисті зображень при передачі. Задля отримання нової схеми стиснення та шифрування зображень у цій роботі досліджується технологія глибинного навчання при стисненні зображень і хаотичне логістичне відображення в шифруванні зображень. Нами проведена оцінка цієї схеми за декількома критеріями ефективності, і результати підтвердили її ефективність.

Методика. Нами запропонована схема з використанням глибинного навчання та хаосу. За допомогою технології глибинного навчання із зображення вилучають рівні характеристик, і певний рівень характеристик далі може бути використаний в якості стиснутого представлення зображення. Хаос використовується для шифрування стиснутого зображення.

Результати. Спочатку нами введена п’ятирівнева (п’ятишарова) модель каскадного автокодувальника, що навчається за методом оберненого розповсюдження помилки, а потім ми отримали стиснене представлення зображення. За допомогою методу логістичного відображення генерується псевдостохастична послідовність для шифрування стиснутого образу.

Наукова новизна. Нами проведене дослідження стиснення та шифрування зображень. Із довільного рівня запропонованої моделі глибинного навчання вилучаються характеристики зображення, що використовуються в якості стиснутого представлення зображення. Дослідження за цим аспектом не були знайдені на сьогодні.

Практична значимість. Ми оцінили цю схему на декількох випадково обраних зображеннях. Результати показують, що схема стиснення та шифрування є робастною та може широко використовуватися для більшості зображень.

Ключові слова: *каскадний автокодувальник, глибинне навчання, захист зображення, ознака зображення, стиснення зображень, шифрування зображення*

Цель. С ростом требований к обработке изображений в Интернете, сжатие изображений и шифрование играют важную роль в защите изображения при передаче. Для получения новой схемы сжатия и шифрования изображений в этой работе исследуется технология глубинного обучения при сжатии изображений и хаотическое логистическое отображение в шифровании изображений. Нами проведена оценка этой схемы по нескольким критериям эффективности, и результаты подтвердили её эффективность.

Методика. Нами предложена схема с использованием глубинного обучения и хаоса. С помощью технологии глубинного обучения из изображения извлекаются уровни характеристик, и определенный уровень характеристик далее может быть использован в качестве сжатого представления изображения. Хаос используется для шифрования сжатого изображения.

Результаты. Сначала нами введена пятиуровневая (пятислойная) модель каскадного автокодировщика, которая обучается по методу обратного распространения ошибки, а затем мы получили сжатое представление изображения. С помощью метода логистического отображения генерируется псевдостохастическая последовательность для шифрования сжатого образа.

Научная новизна. Нами проведено исследование сжатия и шифрования изображений. Из произвольного уровня предложенной модели глубинного обучения извлекаются характеристики изображения, которые используются в качестве сжатого представления изображения. Исследования по этому аспекту не были найдены в настоящее время.

Практическая значимость. Мы оценили эту схему на нескольких случайно выбранных изображениях. Результаты показывают, что схема сжатия и шифрования является робастной и может широко использоваться для большинства изображений.

Ключевые слова: *каскадный автокодировщик, глубинное обучение, защита изображения, признак изображения, сжатие изображений, шифрование изображения*

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