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RESEARCH ARTICLE

Research on Face Intelligent Perception Technology Integrating Deep Learning under Different Illumination Intensities

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Abstract: Aiming at the problem of face recognition under different illumination intensities combined with deep learning algorithm, this research designs a new loss function, i-center loss function and integrates the structure of migration learning algorithm on the basis of LeNets++ deep learning network. The face image data set labled faces in the wild with different illumination intensities and the image data set of supermarket monitoring system are used to train and test the improved LeNets++ deep learning network based on softmax, center and i-center loss function, and a variety of common image recognition networks. The calculation results show that although the amount of data required for the training of LeNets++ deep learning network is much larger than other networks selected in the study, when the loss function is changed to i-center, the accuracy of face image recognition under different light intensities is significantly improved, reaching 99.65%. In the supermarket data set, the maximum face recognition rate of the algorithm using i-center loss function is 99.07%, which is 0.21% and 0.6% higher than that of using center softmax and softmax loss function, respectively. Therefore, experiments show that the improved deep learning neural network based on i-center loss function can improve the effect of face recognition under different illumination intensities.

Keywords: light intensity, deep learning, loss function, face recognition, LeNets++ algorithm

1. Introduction

At present, almost all the mainstream face recognition systems are constructed using deep learning algorithm. This face recognition system still has many shortcomings and immature places. The typical disadvantage is that it has poor face recognition effect in different light intensities, especially in dark environment (Chen et al., 2021).

Experts and scholars in the industry have conducted a lot of in-depth research on this problem. For example, Li and others used convolution network as the classifier at each level to design cascade convolutional neural networks (CNN), which solves the problems of character posture and image illumination in the image to a certain extent, but its disadvantage is that the algorithm is not good for the recognition of face with small size. Aiming at the poor effect of small-size face recognition, (Huang et al., 2015) carried out multiple upsampling and convolution operations on the images input to the neural network and spliced the convolution results for processing, which further improved the accuracy of face recognition of CNN algorithm. Yang et al. (2018) proposed the face net algorithm, which uses multiple deep convolutional neural networks networks as classifiers to score the face region in the image and further optimize the convolution results according to the scoring data. Most of these studies are implemented by replacing intelligent algorithms, and there are few studies on the improvement of loss function and size structure of the algorithm itself. Therefore, this research is of great research value by optimizing the loss function of deep learning face recognition algorithm to study its face recognition effect in the actual scene with changing light intensity (Alskeini et al., 2018; Ley, 2019; Liu et al., 2020; Shepley, 2019).

2. Optimization of LeNets++ Algorithm for Face Recognition Based on Deep Learning

2.1. Improvement of loss function of face recognition algorithm integrating deep learning

Face recognition is to let the system distinguish who the detected face is. Its essence is equivalent to the classification task in machine learning (Wang et al., 2020). At present, most of the face recognition algorithms used in the market belong to deep learning algorithms, which have many shortcomings. Especially, in the real recognition environment, because the illumination intensity of the environment is different, the face recognition rate is often low. Moreover, most of the current algorithm models with good face recognition effect are deep learning models (Li et al., 2021; Yang et al., 2018; Wang et al., 2020). This model needs a lot of data to train to ensure that

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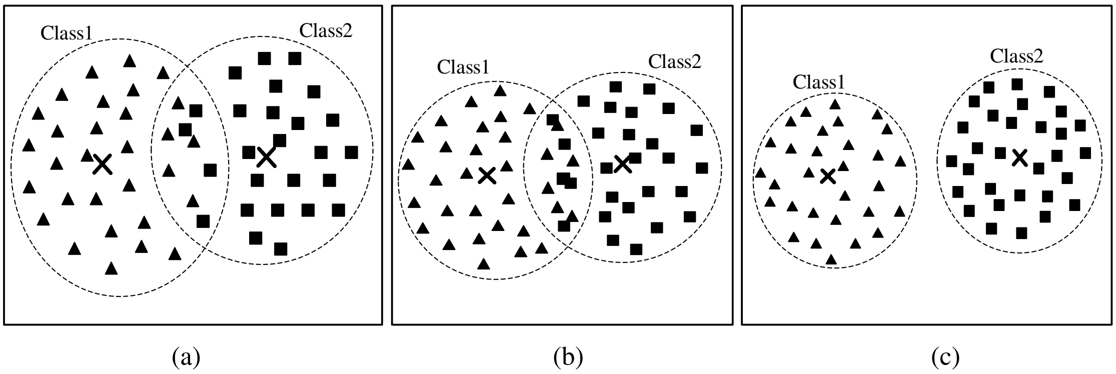
Figure 1
Visualization of classification results using different loss functions



the algorithm has sufficient robustness and recognition accuracy (Wang et al., 2021). However, in some application scenarios of face recognition, the amount of data often cannot meet the requirements. For the first problem, a new loss function is proposed below. The discussion and improvement of the second problem will be carried out in Section 1.2.

Study starts with the common image classification loss function softmax. The loss function softmax can separate multi-category features, but the distance that the samples are separated in the feature space is not large, that is, the compactness of each data in the feature space after classification and the separation between classes are not high (Li et al., 2018; Wu & Jiang, 2018; Xie et al., 2018). Besides, the data classification effect of small feature difference is poor, and it is more suitable for image classification tasks where the category of the test data exists in the training data set. These characteristics make the effect of the loss function for face recognition unsatisfactory.

Because no matter how large the amount of data collected, the number of samples in the training set is small compared to the total population of the world, and there will inevitably be a large number of categories of test data that do not exist in the training set. To solve these problems, the center loss function is generally used in the industry. However, the treatment effect of the loss function is still not ideal. Therefore, a new loss function i-center is proposed in this study, and its formula is as follows:

$$L = L_s + \lambda L_c + \gamma L_I \tag{1}$$

where L_s is the softmax loss function, L_c is the center loss function, L_I is the newly designed loss function term, the three formulas are shown in equations (2), (3), and (4), λ and γ are the coefficients used to balance each loss term, where equations (2) and (3) are the loss functions commonly used in the industry, and formula (4) is designed according to the data characteristics in this study:

$$L_s = -\sum\nolimits_{i=1}^{m} \log \frac{e^{w_{y_i}^T x_i + b_{y_i}}}{\sum\nolimits_{j=1}^{n} e^{w_j^T x_i + b_j}} \tag{2}$$

$$L_c = \frac{1}{2}\sum\nolimits_{i=1}^{m} \| x_i - c_{y_i} \|_2^2 \tag{3}$$

$$L_I = \left(\frac{S}{m} \sum_{k=1}^{m} \| c_k \|_2^2 - \| c_y \|_2^2 \right)^2 \tag{4}$$

In this formula, $w_{y_i}^T$ and b_{y_i} are the model coefficients, x_i is the feature i, y_i is the category i, c_{y_i} is the feature center of the y_ith category, and $\| c_k \|_2^2$ and $\| c_y \|_2^2$ represent the modulus of different category centers and different data labels. S is a coefficient, which is used to control the size of the radius. The L_I term is added to move the center of the category to a circle S times the radius.

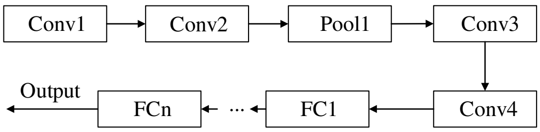
Use randomly selected face image samples with different illumination, posture, and occlusion in real scenes, and use softmax loss function, center-softmax joint loss function, and I-center loss function to train the deep learning network, and use PCA to reduce the output high-latitude vector of the final fully connected layer of the network to two dimensions, and the sample is processed by various algorithms and the output data are reduced and visualized, as shown in Figure 1.

As shown above, Figure 1(a) is the result of algorithm classification based on the softmax loss function. The overall distance between the data within the class is relatively large, and the distance between the classes is relatively close. Figure 1(b) is the classification result based on the center-softmax joint loss function algorithm. Although the data distance within the class is reduced, the distance between the classes is still relatively close. Figure 1(c) is the classification result based on the I-center loss function algorithm. The data distance within the class is further reduced, the distance between classes is also significantly increased, and the classification effect is greatly improved.

2.2. Training method improvement of LeNets++ algorithm for face recognition based on deep learning

For each face recognition algorithm, its recognition effect is limited by the amount of training data to a certain extent, especially the improved algorithm model based on neural network (Li et al., 2018; Liyew, 2017). If its recognition accuracy obviously exceeds that of manpower, it needs a large amount of real data for reasonable training. However, in many application scenarios of face recognition system, the amount of real training data that can be provided often cannot meet this requirement, and even if the amount of data can meet the requirements, the training model also needs a lot of time and computer resources. To solve this problem, this research proposes to introduce the transfer learning method into the LeNets++ algorithm of deep learning face recognition, which is introduced in detail below (Liyew, 2017).

Figure 2
Schematic diagram of classical hierarchy of CNN algorithm



Transfer learning is a method to transfer the model parameters trained in one task to the models of other tasks to improve the training effect of the new model. When the data are insufficient, we can use the transfer learning method to select the appropriate model from others' trained models and fine tune its parameters, so that the algorithm model developed by ourselves can take into account both better application effect and higher training efficiency. To introduce the application mode of transfer learning in this study, we need to start with the classical CNN hierarchy. The schematic diagram of CNN classical hierarchy model is shown in Figure 2.

As shown in Figure 2, generally, the function of the front convolution layer is to preliminarily extract face shape features and detect edge information, and the subsequent convolution layer is responsible for deeply extracting and integrating the preliminarily extracted face features to obtain more advanced and overall face feature information, which is then output to subsequent fully connected (FC) layers, and it is used to integrate advanced face features for the specified image classification task in the next step. After integrating the migration learning, it is generally necessary to delete the last FC layer (Gilani et al., 2017). In addition, the parameters and structure positions of other computing layers are not adjusted. In some cases, a new FC layer needs to be trained and added to the structure level. Specifically, for face recognition tasks, it is necessary to judge the feature similarity between new and old data sets. The main evaluation dimensions are the type, number and proportion of human races, the proportion of the number of male and female faces, the age distribution of face objects, and the quality level of the data set (mainly including expression, light intensity, occlusion position, and degree). First, look at the most common situation. If it is found that the feature difference between the two sets of data sets in these dimensions is small after comparison, it should be integrated into migration learning by removing the last FC layer and connecting a new FC layer to train the overall model and update parameters. After comparing the data sets, it is found that although the similarity is high, the data volume of the new data set is much larger than that of the old data set. Similarly, the last FC layer is removed and replaced with the new FC layer, but the difference is that only the parameters of the new FC layer need to be trained, and all parameters of other layers of the algorithm remain unchanged. This is because in the case of large amount of data, there is less possibility of over fitting problem after model training, so the weights of other layers can be used as the initial condition for training. The last migration learning combination method is quite different from the first two. It is used when the difference between the old and new data sets is obvious and the new data set is large. At this time, only the last FC layer needs to be deleted without adding other hierarchies, and then, all parameters of the whole model are initialized, and then, the new data set is used for training again. This is because when the similarity between the old and new data sets is poor, the model parameters trained based on the original data set do not have enough borrowing value. The direct use of the original model parameters will greatly reduce the training effect and application effect of the new model. On the other hand, because the new data set has enough data, it is not easy to over fit even if the parameters are retrained, so the operation of re-initializing the parameters is adopted.

3. Improved Face Recognition Algorithm Based on Different Illumination Intensities

To verify the effect of the improved deep learning algorithm after using the I-center loss function on face image recognition with different light intensities, the labled faces in the wild (LFW) face public data set is adapted to train the LeNets++ depth based on the three loss functions mentioned above and a variety of common image recognition algorithm models. The accuracy of their face recognition is tested and compared. In the experiment, the LeNets++ network uses the Prelu activation function, the learning rate $\gamma = 0.0001$, the parameter $s = 0.5$, and the network structure is shown in Table 1.

As shown in Table 1, "(5,64)/1,2 × 2" means that there are two cascaded, 64,5 × 5 Conv layers with a step length of 1, and other string meaning rules are consistent with it. In addition, it is worth explaining separately the LFW face public data set, which is the most used data set by academia for evaluating the effect of face recognition. It is composed of more than 13,000 collected photos of celebrities in natural scenes. The subject will not deliberately cooperate with the photo, and the light intensity of the scene is different, which is closer to the real application scene of the face recognition system. Therefore, it is particularly suitable for the simulation experiment of this research. Finally, after running each algorithm, the results of collating the data are shown in Figure 3.

Looking at Figure 3, it can be found that the amount of face image data required for the improved LeNets++ deep learning network under the network structure is 260m, which is much larger than other algorithm networks. This is mainly because the hierarchical structure of the improved LeNets++ deep learning network is more complex. To avoid over fitting of the model, more data training is required. When the loss function is not improved, the accuracy of human face recognition is 98.36%, which has no obvious advantage compared with other algorithms. When the loss function is changed to center softmax and i-center, the accuracy of face image recognition under different illumination intensities is significantly improved, reaching 99.44%

Table 1
Structure of LeNets++ deep learning network

	Stage			
Items	The first stage	The second stage	The third stage	The fourth stage
Layer	Conv + pool	Conv + pool	Conv + pool	FC
Structure of this floor	(5,64)/1,2 × 2 + 2/2,0	(5,128)/1,2 × 2 + 2/2,0	(5,256)/1,2 × 2 + 2/2,0	2

Figure 3
Test results of each algorithm on LFW data set

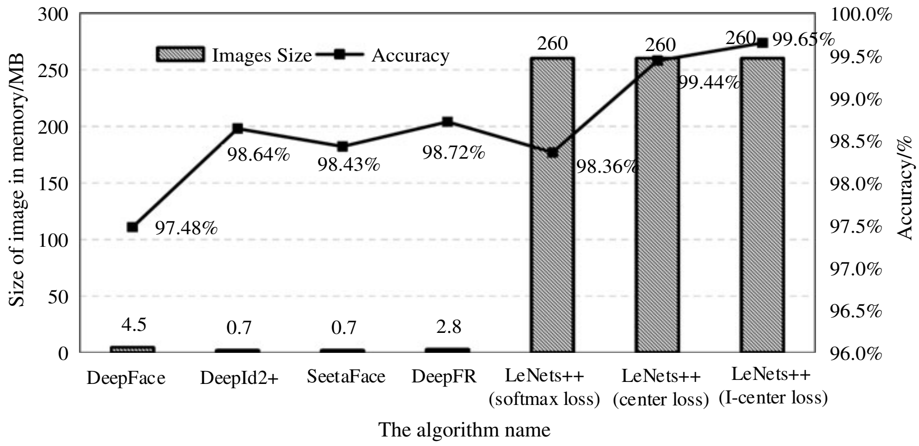
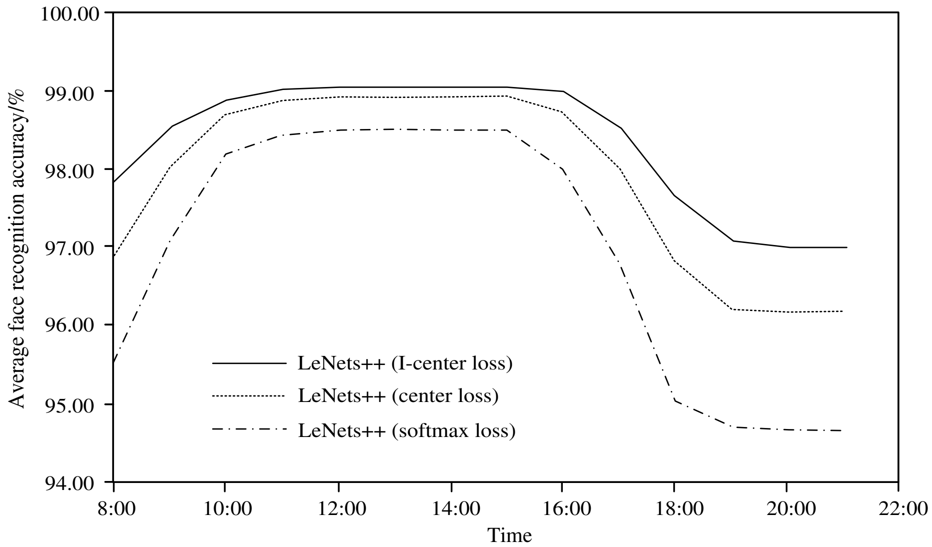


Figure 4
Image face recognition accuracy of daily monitoring system in supermarket stores



and 99.65%, respectively. This shows that after introducing L_c and L_I terms into the algorithm loss function, shortening the distance between various internal data, and increasing the center distance, the accuracy of face recognition can be significantly improved. To further verify the face recognition effect of the improved deep learning algorithm, 900 days of monitoring system image screenshot data of 30 stores from five large chain brand supermarkets in China are randomly selected to test the face recognition effect of each algorithm in practical application scenarios. The statistical results are shown in Figure 4. It should be noted that to give consideration to the complete expression of data change trend and the size of statistical workload, the image screenshot data of the store monitoring system are collected every half an hour from 8:00 to 22:00 at night.

As shown in Figure 4, LeNets++ algorithm with different loss functions is used to recognize the face of the image screenshots of the monitoring system at all times of the supermarket every day. The recognition rates of the three are poor in the morning. At 8:00, the accuracy of the improved lenets + + algorithm using i-center loss function, the improved lenets + + algorithm using center softmax loss function and the improved lenets + + algorithm using softmax loss function for face recognition of supermarket store images is only 97.83%, 96.91% and 95.54% respectively. With the enhancement of ambient light, the face recognition rate increases rapidly, but the improvement speed shows a rapid downward trend. Then, the recognition rate reaches the peak at about 11:00. The peak face accuracy of the three improved LeNets++ algorithms using i-center loss function, center softmax loss function, and softmax loss function is 99.07%, 98.86%, and 98.44%, respectively. Then, the face recognition rate of the three algorithms remains stable before 15:00. After 15:00, the recognition rate decreases again with the weakening of ambient light. In addition, because the ambient light at night is significantly weaker than that in the morning, the lowest value of supermarket image face recognition rate of the three algorithms appears at night. The lowest values of face recognition using the three improved LeNets++ algorithms of i-center loss function, center softmax loss function, and softmax loss function are 96.97%, 96.23%, and 94.68%, respectively. On the other hand, generally speaking, the face recognition rate of the algorithm using i-center loss function is significantly higher than that of other algorithms at all times, and the maximum recognition rate in one day is 99.07%, which is 0.21% and 0.6% higher than that of the algorithm using center softmax and softmax loss function, respectively. The data show that the improved deep learning neural network based on i-center loss function can improve the effect of face recognition under different illumination intensities.

4. Conclusion

Aiming at the problem of face recognition under different illumination intensities combined with deep learning algorithm, a new i-center loss function is designed, and the structure of migration learning algorithm is integrated on the basis of LeNets++ deep learning network. The improved LeNets++ deep learning network based on softmax, center, and i-center loss functions, and a variety of common image recognition networks is trained and tested using face image data sets under different illumination intensities, LFW face public data sets, and supermarket monitoring system image data sets. The results show that although the amount of face image data required by LeNets++ deep learning network is 260m, which is much larger than other networks selected in the study, when the loss function is changed to i-center, the accuracy of face image recognition under different light intensities is significantly improved, reaching 99.65%, while the maximum face recognition rate of the algorithm using i-center loss function in supermarket data set is 99.07%, and it is 0.21% and 0.6% higher than the algorithm using center softmax and softmax loss function, respectively. The data show that the improved deep learning neural network based on i-center loss function can improve the effect of face recognition under different illumination intensities.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

References

Alskeini, N. H., Thanh, K. N., Chandran, V., & Boles, W. (2018). Face recognition: Sparse representation vs. Deep learning. In *Proceedings of the 2nd International Conference on Graphics and Signal Processing*, 31–37. https://doi.org/10.1145/3282286.3282291

Chen, F., Zhai, J., Cheng, L., Dong, Y., & Xie, X. (2021). Research on vehicle apparent damage assessment technology based on intelligent regression calculation. *Procedia Computer Science*, *187*(1), 71–76. https://doi.org/10.1016/j.procs.2021.04.034

Gilani, S. Z., Mian, A., & Eastwood, P. (2017). Deep, dense and accurate 3D face correspondence for generating population specific deformable models. *Pattern Recognition*, *69*, 238–250. https://doi.org/10.1016/j.patcog.2017.04.013

Huang, L., Yang, Y., Deng, Y., & Yu, Y. (2015). Densebox: Unifying landmark localization with end to end object detection. *arXiv Preprint: 1509.04874*. https://arxiv.org/abs/1509.04874

Ley, T. (2019). Knowledge structures for integrating working and learning: A reflection on a decade of learning technology research for workplace learning. *British Journal of Educational Technology*, *51*(2), 331–346. https://doi.org/10.1111/bjet.12835

Li, J., Zhi, X., Wang, Y., & Cao, Q. (2021). Research on Intelligent recognition system of Cotton apical Bud based on Deep Learning. *Journal of Physics: Conference Series*, *1820*(1), 012134. https://doi.org/10.1088/1742-6596/1820/1/012134

Li, Y., Zheng, W., Cui, Z., & Zhang, T. (2018). Face recognition based on recurrent regression neural network. *Neurocomputing*, *297*, 50–58. https://doi.org/10.1016/j.neucom.2018.02.037

Li, Y. K., Wu, X. J., & Kittler, J. (2018). L1-(2D)2PCANet: A deep learning network for face recognition. *Journal of Electronic Imaging*, *28*(2), 1–16. https://doi.org/10.1117/1.JEI.28.2.023016

Liu, X., Wu, J. H., Man, Y. Y., Xu, X. B., Guo. J. F. (2020). Multi-objective recognition based on deep learning. *Aircraft Engineering and Aerospace Technology*, *92*(8), 1185–1193. https://doi.org/10.1108/AEAT-03-2020-0061

Liyew, M. B. T. (2017). Applying a deep learning Convolutional Neural Network (CNN) approach for building a face recognition system: A review. *International Journal of Emerging Technologies and Innovative Research*, *4*(12), 1104–1110. http://doi.one/10.1717/JETIR.17145

Shepley, A. J. (2019). Deep learning for face recognition: A critical analysis. *arXiv Preprint:1907.12739*. https://arxiv.org/abs/1907.12739

Wang, X., Lin, F., Zhou, L., Zhang, X., Hu, J., & Shen, D. (2021). Research on intelligent monitoring technology of grouting based on dielectric characteristics. In *IOP Conference Series: Earth and Environmental Science*, *861*(7), 072110. https://doi.org/10.1088/1755-1315/861/7/072110

Wang, X. P., Lin, F. Q., Zhou, L. N., Zhang, X., Hu, J., Shen, D. (2020). A real-time collision prediction mechanism with deep learning for intelligent transportation system. *IEEE Transactions on Vehicular Technology*, *69*(9), 9497–9508. https://doi.org/10.1109/TVT.2020.3003933

Wu, Y. L., & Jiang, M. L. (2018). Face recognition system based on CNN and LBP features for classifier optimization and fusion. *The Journal of China Universities of Posts and Telecommunications*, *25*(1), 37–47. https://doi.org/10.19682/j.cnki.1005-8885.2018.0004

Xie, H., Du, Y., Yu, H., Chang, Y., Xu, Z., & Tang, Y. (2018). Open set face recognition with deep transfer learning and extreme value statistics. *International Journal of Wavelets, Multiresolution and Information Processing*, *16*(4), 1850034. https://doi.org/10.1142/S0219691318500340

Yang, F., Han, C., Bai, B. X., & Zhang, C. (2018). Projected image correction technology research on autonomous-perception anisotropic surfaces. *Applied Optics*, *57*(2), 283–294. https://doi.org/10.1364/AO.57.000283

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