International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8, Issue-1, May 2019

Application of Hopfield Neural Network for Facial Image Recognition

Neha Soni, Enakshi Khular Sharma, Amita Kapoor

Abstract*: Hopfield model (HM) classified under the category of recurrent networks has been used for pattern retrieval and solving optimization problems. This network acts like a CAM (content addressable memory); it is capable of recalling a pattern from the stored memory even if it's noisy or partial form is given to the model. This paper presents a framework to use HM for machine recognition of human faces. The approach presented here uses Otsu's method to transform facial images (low and ultra-low-resolution) from grey scale to binary, and Hebb rule to store them in the W (weight matrix) of the network. HM is then tested with up to 45% distortion in facial images; the network is allowed to evolve asynchronously to a stable state. To check positive retrieval, we match (bit-by-bit) the stable state facial image with the original facial image. Our results show 100% retrieval for grey scale facial images (of 60×60 pixel size) for up to 30% distortion. This suggests that HM can be used for face-based security applications when the number of individuals allowed is a limited number like a high-security military area or a lab.

Index Terms*: Asynchronous Retrieval, Auto Associative Memory, Face Recognition, Hopfield Model.

I. INTRODUCTION

Human face plays a significant role in our societal connections; it is a person's unique identity. Using it as a means to security has received significant attention in the past few years [1, 2, 3]. A system capable of recognizing facial images can be used for a large number of applications like individual verification (in employee/national IDs, passports, drivers' licenses, banking etc.), surveillance (CCTVs (closed-circuit television) can be utilized to come across the proven criminals, thieves, etc.), and database exploration (investigating image banks of misplaced kids, refugee, certified drivers, assist recipients, etc.) [1], [5], [6], [7]. Machine recognition of facial images for biometrics has various benefits over other biometric techniques. The majority of the existing biometric techniques need voluntary engagement of the user. For instance, fingerprint/palm detection demands the user to stop and position his finger/thumb/palm on the finger/thumb/palm rest, for retina or iris recognition user needs to halt and procure a fixed position in front of the device for iris detection [8]. The above mentioned biometric methods entail numerous persons to utilize the same machinery to capture the above-mentioned traits.In contrast, machine recognition of facial images can be completed inertly without any involvement or explicit action of the individual; the camera installed at a place can be utilized to click the facial images remotely. Satisfactory high-precision facial images can be achieved using economical cameras. Also, it is entirely non-interfering and free from the risk of health hazards because of the transmission of microbes in the recognition equipments [9].

Investigators in last thirty years have inspected various distinctive techniques namely PCA (uses Eigen faces) [10], [11], [12], LDA (uses Fisher's faces) [12], ICA [13] etc. for facial image recognition. Various issue that make this task exigent are the deviations established due to wide-ranging expressions [12], [13], [14], [15], age [13], [14], [15], glasses [12], [15], rotation [15], size variations [11], [15], changing lighting conditions [11], [13] etc. The above mentioned factors deteriorate the precision of the majority of the facial image recognition systems [10], [11], [14].

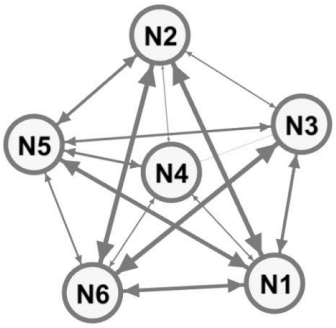


Fig 1 Hopfield model: Interconnections between six neurons [16]

This paper presents a framework to use Hopfield Model [17], [18], [19] for machine recognition of human facial images. The approach presented here uses Otsu's method [20], [21] for preprocessing i.e. transformation of images to binary images and Hebb rule [17], [18], [22], [23] for storage of binary images in *W*. We performed two experiments: studied the recall of two different sized image datasets using HM, one, low-resolution images (60×60 pixels), another ultra-low-resolution image (ULRI) (10×10 pixels). We studied the recall of these datasets in the presence of distortions for up to 45%; the network is allowed to evolve asynchronously to a stable state. To check convergence, we measured the similarity between the original fundamental memories and recalled stable image.

Revised Manuscript Received on 30 May 2019.
* Correspondence Author
Neha Soni*, Dept. of Electronic Science, University of Delhi, India.
Enakshi Khular Sharma, Dept.of Electronic Science, University of Delhi, India.
Amita Kapoor, Dept. of Electronics, SRCASW, University of Delhi, Delhi, India.

II. HOPFIELD MODEL

In 1980s [17], [18] Hopfield and Tank proposed the bio-inspired Hopfield model. Fig 1 demonstrates the interconnections between six neuron HM. The proposed recurrent model operates in two phases: the storage phase (calculation of weight matrix, W by means of Hebb's rule [17], [18], [22], [23] and the retrieval phase (recalling stored memories with the help of W). Fig 2 and Fig 3 illustrate the detailed algorithm for both the phases.

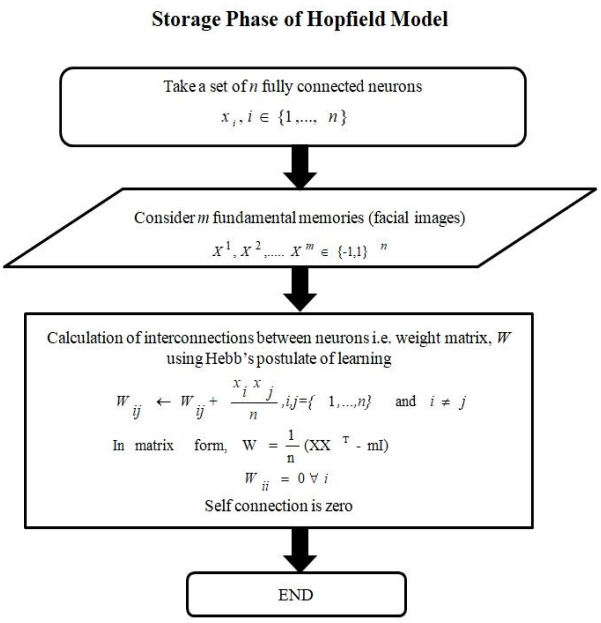


Fig 2 Storage Phase of the Hopfield Model

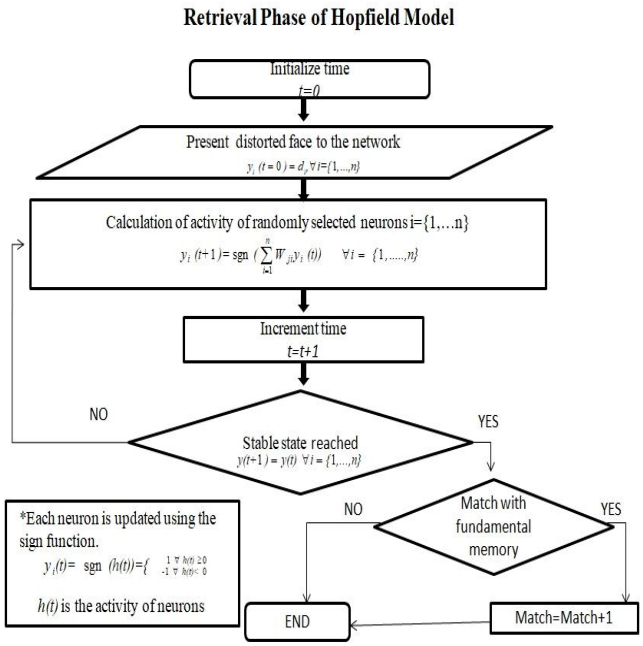


Fig 3 Retrieval Phase of the Hopfield Model

III. DATASET USED AND EXPERIMENT

We made use of facial images of different pixel size (202×249 to 60×60) for our experiment. Fig. 4 demonstrates the original dataset for our experiments. First, the pre-processing is done; the image size is reduced to 60×60 using row and column elimination. The converted images are then stored in weight matrix and retrieval of distorted images is done by implementing asynchronous Hopfield model. Fig. 5 represents the detailed framework used for our experiments.

Fig 4 Original dataset: (202×249 to 60×60) pixel size

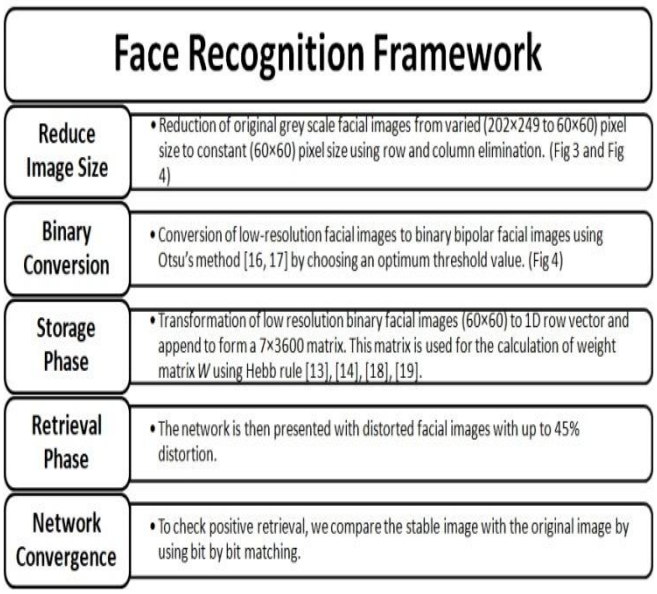


Fig 5 Framework for facial image recognition using Hopfield model

Asynchronous HM implemented updates one neuron at a time till a stable state is obtained. For every distortion percentage the network is fed with 500 distinct distorted images. Fig. 6 shows the training data with reduced size and their corresponding binary images (step 1 and step 2 of Fig. 5). Fig. 7 illustrates the test data and their corresponding recalled images ((I) 10%, (II) 25%, (III) 35% distortion).

In our second experiment, we choose five face images from above dataset and further reduced them to ultra low-resolution images (ULRI, 10×10 pixel size). These ULRI's are then transformed into binary images in a similar way as 60×60 face images, Fig 8. These binary images form the training data (matrix with 5×100 positions), which again requires the computation of weight matrix *W* (matrix with 100×100 positions) via Hebb rule. For an exploration of retrieval of distorted images, this is fed with distorted facial images with up to 17% distortion.

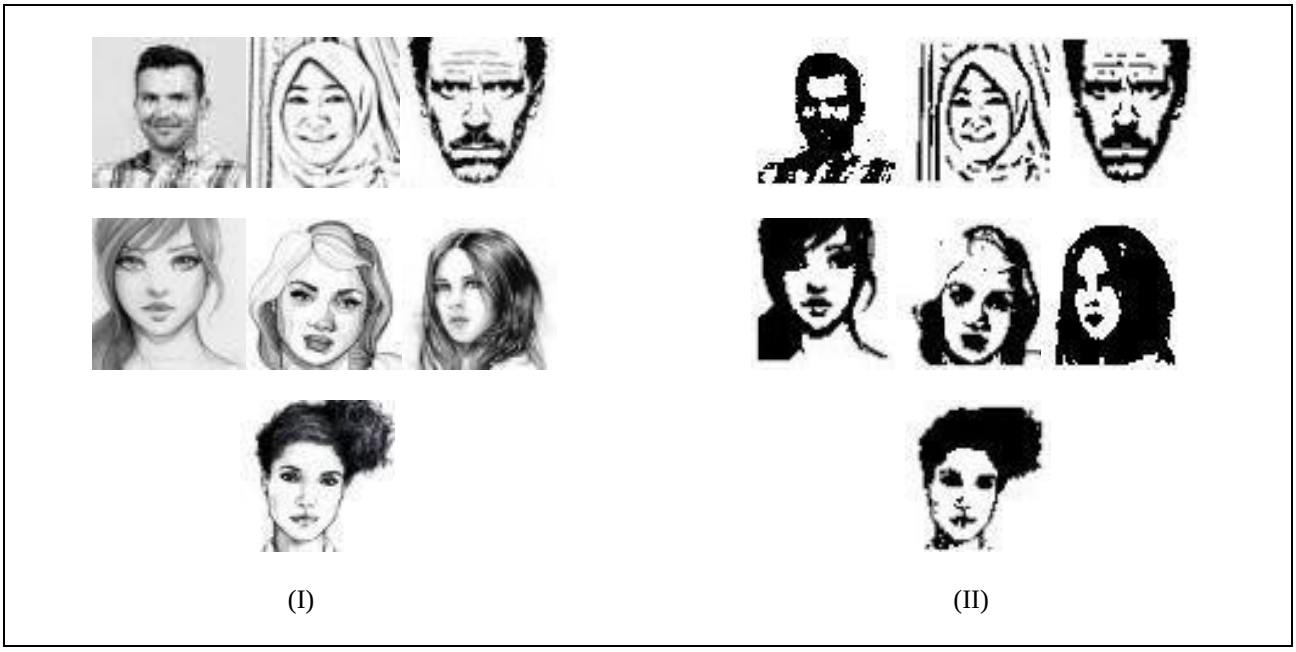


Fig 6 Training data with reduced size (60×60 pixel size), (II) Their corresponding binary images (60×60 pixel size)

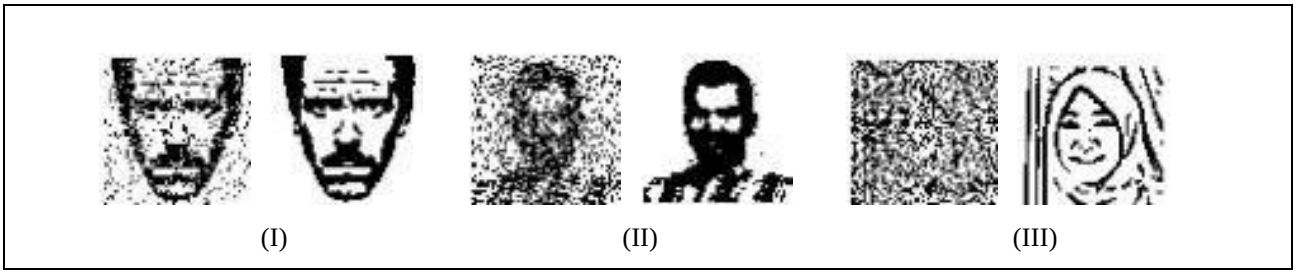
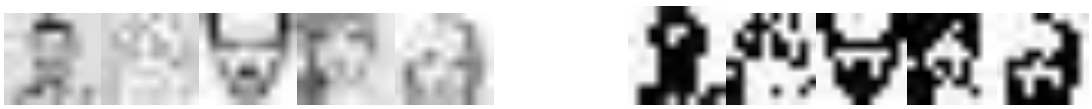


Fig 7 Test data and their corresponding recalled images ((I) 10%, (II) 25%, (III) 35% distortion).



(I) (II)

Fig 8 Training data with reduced size (10×10 pixel size), (II) Their corresponding binary images (10×10 pixel size)

Table 1 Results for HM for 7 facial images (60×60 pixel size).

Results for 60×60 (pixel size) facial images									
Facial images	**Distortion Percentage**								
	5%	**10%**	**15%**	**20%**	**25%**	**30%**	**35%**	**40%**	**45%**
1	100	100	100	100	100	100	99.8	94.4	72.2
2	100	100	100	100	100	100	100	99.8	88.8
3	100	100	100	100	100	100	100	99.4	86.2
4	100	100	100	100	100	100	100	100	85.2
5	100	100	100	100	100	100	100	96	69
6	100	100	100	100	100	100	97.6	91	63
7	100	100	100	100	100	100	99.4	96	78.2

Table 2 Results for HM for 5 ULRI's (10×10 pixel size)

Results for 10×10 (pixel size) facial images									
Facial images	**Distortion Percentage**								
	1%	**3%**	**5%**	**7%**	**9%**	**11%**	**13%**	**15%**	**17%**
1	100	100	100	100	100	100	100	100	100
2	100	100	100	100	100	100	100	100	99.8
3	100	100	100	100	100	100	100	99.4	99.8
4	100	100	100	100	100	100	100	99.8	99
5	100	100	100	100	100	100	99.8	100	99.6

IV. RESULTS AND CONCLUSIONS

Distortions introduced due to light variations, aging, accessories, and expressions lie within the range of 5 to 15%, by means of HM we have been able to attain successful recovery of at least 97% for up to 35% distortions for low-resolution images and for ULRI facial images 99% for up to 17% distortions, this is a significant improvement over previously reported results.

Table 1 encapsulates the result of our first experiment in which we used 7 facial images (60×60 pixel size). Our results demonstrate 100% retrieval for grey scale facial images (of 60×60 pixel size) for up to 30% distortion. This suggests that HM can be used for face-based security applications when the number of individuals allowed is a limited number like a high-security military area or a lab. Table 2 demonstrates the results for the 5 ULRI's. For the distortion of up to 11%, the model recalled all the distorted images correctly.

The diminished network size for ULRI (1/36 of the first experiment: the tiny 100 neuron model) can be simply embedded on a chip and used for a range of safety and recognition purposes for individual electronic devices. The results for the low-resolution images and ULRI show significant improvement and can aid in achieving size invariance for machine recognition and various other vision tasks.

ACKNOWLEDGMENT

One of the authors, Ms. Neha Soni, wants to thank Department of Science & Technology, Ministry of Science & Technology, New Delhi, India for sponsoring this work.

REFERENCES

1. Kusnadi, Adhi, and Daud Julio. "Security system with 3 dimensional face recognition using PCA method and neural networks algorithm." 2017 4th International Conference on New Media Studies (CONMEDIA). IEEE, 2017.
2. Lwin, Hteik Htar, Aung Soe Khaing, and Hla Myo Tun. "Automatic door access system using face recognition." International Journal of Scientific & Technology Research 4.6 (2016): 210-221.
3. Soni, Neha, et al. "Impact of Artificial Intelligence on Businesses: from Research, Innovation, Market Deployment to Future Shifts in Business Models." arXiv preprint arXiv:1905.02092 (2019).
4. Jafri, Rabia, and Hamid R. Arabnia. "A survey of face recognition techniques." Jips 5.2 (2009): 41-68.
5. Zhao, Wenyi, et al. "Face recognition: A literature survey." ACM computing surveys (CSUR) 35.4 (2003): 399-458.
6. Soni, Neha, et al. "Face recognition using cloud Hopfield neural network." 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET). IEEE, 2016.
7. Soni, Neha, et al. "Low-Resolution Image Recognition Using Cloud Hopfield Neural Network." Progress in Advanced Computing and Intelligent Engineering. Springer, Singapore, 2018. 39-46.
8. Sudhamani M.J., Venkatesha M K "Feature Level Fusion of Iris and Finger Vein Biometrics for Multimodal Biometric Authentication System". International Journal of Recent Technology and Engineering, Volume-7 Issue-5, 2019.
9. D. Zhang, editor. "Biometric solutions: For authentication in an e-world". (Springer Science & Business Media; 2012)
10. Mohammed, Abdul Adeel, et al. "Human face recognition based on multidimensional PCA and extreme learning machine." Pattern Recognition 44.10-11 (2011): 2588-2597.
11. Turk, Matthew A., and Alex P. Pentland. "Face recognition using eigenfaces." Proceedings. 1991 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE, 1991.
12. Martínez, Aleix M., and Avinash C. Kak. "Pca versus lda." IEEE transactions on pattern analysis and machine intelligence 23.2 (2001): 228-233.
13. Zhao, Haitao, and Pong Chi Yuen. "Incremental linear discriminant analysis for face recognition." IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 38.1 (2008): 210-221.
14. Bartlett, Marian Stewart, Javier R. Movellan, and Terrence J. Sejnowski. "Face recognition by independent component analysis." IEEE Transactions on neural networks 13.6 (2002): 1450-1464.
15. Dai, Ying, and Yasuaki Nakano. "Recognition of facial images with low resolution using a Hopfield memory model." Pattern Recognition 31.2 (1998): 159-167.
16. Kapoor, Amita, and Narotam Singh. "Effect of event sequence on intragroup dynamics: Simulation using modified Hopfield neural network." 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI). IEEE, 2016.
17. Hopfield, John J., and David W. Tank. "Computing with neural circuits: A model." Science 233.4764 (1986): 625-633.
18. Tank, David W., and John J. Hopfield. "Collective computation in neuronlike circuits." Scientific American 257.6 (1987): 104-115.
19. Singh, Narotam, and Amita Kapoor. "Cloud Hopfield neural network: Analysis and simulation." 2015 International Conference on Advances in Computing, Communications and Informatics (ICACCI). IEEE, 2015.
20. Sezgin, Mehmet, and Bülent Sankur. "Survey over image thresholding techniques and quantitative performance evaluation." Journal of Electronic imaging 13.1 (2004): 146-166.
21. Otsu, Nobuyuki. "A threshold selection method from gray-level histograms." IEEE transactions on systems, man, and cybernetics 9.1 (1979): 62-66.
22. Wasserman, P. D., and Neural Computing. "Van Nostrand Reinhold,"." Neural Computing Theory & Practice"-New York (1989).
23. Haykin, S. "Neural Networks-A Comprehensive Foundation Neural Networks-A Comprehensive Foundation, 1994." Neural Networks 8.4 (1995): 549-562.