Lecture Notes in Electrical Engineering 790

N. R. Shetty · L. M. Patnaik ·
H. C. Nagaraj · Prasad N. Hamsavath ·
N. Nalini *Editors*

Emerging Research in Computing, Information, Communication and Applications

ERCICA 2020, Volume 2

Springer

Lecture Notes in Electrical Engineering

Volume 790

The book series *Lecture Notes in Electrical Engineering* (LNEE) publishes the latest developments in Electrical Engineering - quickly, informally and in high quality. While original research reported in proceedings and monographs has traditionally formed the core of LNEE, we also encourage authors to submit books devoted to supporting student education and professional training in the various fields and applications areas of electrical engineering. The series cover classical and emerging topics concerning:

- Communication Engineering, Information Theory and Networks
- Electronics Engineering and Microelectronics
- Signal, Image and Speech Processing
- Wireless and Mobile Communication
- Circuits and Systems
- Energy Systems, Power Electronics and Electrical Machines
- Electro-optical Engineering
- Instrumentation Engineering
- Avionics Engineering
- Control Systems
- Internet-of-Things and Cybersecurity
- Biomedical Devices, MEMS and NEMS

For general information about this book series, comments or suggestions, please contact leontina.dicecco@springer.com.

To submit a proposal or request further information, please contact the Publishing Editor in your country:

China

Jasmine Dou, Editor (jasmine.dou@springer.com)

India, Japan, Rest of Asia

Swati Meherishi, Editorial Director (Swati.Meherishi@springer.com)

Southeast Asia, Australia, New Zealand

Ramesh Nath Premnath, Editor (ramesh.premnath@springernature.com)

USA, Canada:

Michael Luby, Senior Editor (michael.luby@springer.com)

All other Countries:

Leontina Di Cecco, Senior Editor (leontina.dicecco@springer.com)

**** This series is indexed by EI Compendex and Scopus databases. ****

More information about this series at https://link.springer.com/bookseries/7818

N. R. Shetty · L. M. Patnaik · H. C. Nagaraj ·
Prasad N. Hamsavath · N. Nalini
Editors

Emerging Research in Computing, Information, Communication and Applications

ERCICA 2020, Volume 2

Springer

Editors
N. R. Shetty
Nitte Meenakshi Institute of Technology
Bengaluru, Karnataka, India

H. C. Nagaraj
Nitte Meenakshi Institute of Technology
Bengaluru, Karnataka, India

N. Nalini
Nitte Meenakshi Institute of Technology
Bengaluru, Karnataka, India

L. M. Patnaik
National Institute of Advanced Studies
Bengaluru, Karnataka, India

Prasad N. Hamsavath
Nitte Meenakshi Institute of Technology
Bengaluru, Karnataka, India

ISSN 1876-1100 ISSN 1876-1119 (electronic)
Lecture Notes in Electrical Engineering
ISBN 978-981-16-1341-8 ISBN 978-981-16-1342-5 (eBook)
https://doi.org/10.1007/978-981-16-1342-5

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Contents

About the Editors

Prof. N. R. Shetty is Chancellor of Central University of Karnataka, Kalaburagi, and Chairman of the Review Commission for the State Private University Karnataka. He is currently serving as an advisor to the Nitte Meenakshi Institute of Technology (NMIT), Bengaluru. He is also Founder Vice-President of the International Federation of Engineering Education Societies (IFEES), Washington DC, USA. He served as Vice Chancellor of Bangalore University for two terms and President of the ISTE, New Delhi three terms. He was also Member of the Executive Committee of the AICTE and Chairman of its South West Region Committee.

Prof. L. M. Patnaik obtained his Ph.D. in 1978 in the area of Real-Time Systems and D.Sc. in 1989 in the areas of Computer Systems and Architectures, both from the Indian Institute of Science (IISc), Bengaluru. During March 2008 to August 2011, he was Vice Chancellor, Defence Institute of Advanced Technology, Deemed University, Pune. Currently, he is Honorary Professor with the Department of Electronic Systems Engineering, Indian Institute of Science, Bengaluru, and INSA Senior Scientist and Adjunct Professor with the National Institute of Advanced Studies, Bengaluru. During the last 50 years of his long service, his teaching, research, and development interests have been in the areas of parallel and distributed computing, computer architecture, CAD of VLSI systems, high-performance computing, mobile computing, theoretical computer science, real-time systems, soft computing and computational neuroscience including machine cognition. In these areas, he has 1286 publications in refereed international journals and refereed international conference proceedings including 30 technical reports, 43 books and 26 chapters in books.

Dr. H. C. Nagaraj was born on 4th April, 1959 in Bengaluru. He obtained his B.E. Degree in Electronics and Communication Engineering securing first class with distinction from the University of Mysore in 1981. He obtained his M.E. in Communication Systems from P. S. G. College of Technology, Coimbatore, Bharathiyar University in 1984 and secured first rank. He got his doctoral degree in the area of Biomedical Signal Processing and Instrumentation from Indian Institute of Technology Madras, Chennai in 2000. He assumed charge as Principal, Nitte Meenakshi

Institute of Technology, Bengaluru in September 2003 and till date he is serving as Principal. He has about 38 years of experience in teaching, research and administration. During his term as Principal in NMIT, Bengaluru, the institution has been conferred with Autonomous Status by the Visvesvaraya Technological University, Government of Karnataka and UGC, New Delhi; accredited by the National Assessment and Accreditation Council, National Board of Accreditation, AICTE, New Delhi for UG programmes, and a pico satellite weighing less than 1 kg was designed and fabricated and handed over to ISRO and was launched on 12th July 2010 from Sriharikota, Andhra Pradesh, India. Dr. H. C. Nagaraj has published a number of papers in National and International Journals, Conferences and delivered invited talks in the field of Biomedical Signal Processing, Image Processing, Mobile Communication etc. He got the Best Paper Award in the National Conference of Biomechanics held during February 22–24, 1996 at IIT Madras. He was awarded the Best Paper Award at State Level Seminar on “Introduction of Flexible System in Technical Education” held by the Government of Karnataka during February 1999 in Bengaluru. He has guided several students for their Ph.D. programmes and written a book titled *VLSI Circuits* published in 2006 for B.E. Students. He is a member of expert teams visiting various colleges for accreditation by NAAC and affiliation of UG, PG and Ph.D. programmes under Electronics and Communication, Biomedical Engineering Streams, on behalf Institution of Engineers, Visvesvaraya Technological University, Belgaum and Kuvempu University, Shimoga. He is a Fellow of the Institution of Electronics and Telecommunication Engineers (IETE), Life member of ISTE, Life Member of Biomedical Engineering Society of India and Member of Global Engineering Deans Council India Chapter (GEDCIC). Dr. Nagaraj has visited countries like USA, Canada, UK, Singapore, Malaysia, South Korea, Hungary etc. in connection with collaboration for academic activities. Presently, he is the Member of the Academic Senate at Visvesvaraya Technological University (VTU), Belagavi. He is also the Member of Court at Pondicherry University and Member of Expert Team for the evaluation of R&D projects funded by VTU.

Dr. Prasad N. Hamsavath is currently working as Professor and Head of the Department of Master of Computer Applications at Nitte Meenakshi Institute of Technology, Bengaluru. He completed his Ph.D. at Jawaharlal Nehru University, New Delhi, India. Dr. Prasad has more than 12 years of experience in different roles in both public and private sector enterprises, including the Ministry of Human Resource and Development, New Delhi, Government of India. He has received the prestigious “Dr. Abdul Kalam Life Time Achievement Award” and also received a “Young Faculty” award at the 2nd Academic Brilliance Awards.

Dr. N. Nalini is currently working as Professor at the Department of Computer Science and Engineering at Nitte Meenakshi Institute of Technology, Bengaluru. She received her M.S. from BITS, Pilani, in 1999, and her Ph.D. from Visvesvaraya Technological University in 2007. She has more than 17 years of teaching and 10 years of research experience. She has several international publications to her credit, and has received the “Bharath Jyothi Award” by Dr. Bhishma Narain Singh, Former

Governor of Tamil Nadu and Assam, given out by the India International Friendship Society. She is Lifetime Member of the ISTE, CSI, ACEEE and IIFS.

Enhancement of Low-Light Images Using CNN

Avvaru Greeshma Kavya, Uruguti Aparna, and Pallikonda Sarah Suhasini

1 Introduction

High-quality image plays a critical role in object detection and classification. Image enhancement has important contributions in object detection, classification, segmentation, recognition and speech detection and been used in many real applications like remote sensing, video processing, medical field, etc. To address the enhancement issues, there are many techniques of image enhancement, e.g., histogram equalization, log transformation, gamma correction, bilateral, CLAHE, etc. But, in recent research, it is found that deep learning contributes more than any other techniques of image enhancement. In this paper, the enhancement of low-light images using a deep learning platform, convolutional neural network (CNN), is implemented. With the popularity of smartphones and digital cameras, images play an important role in our daily life. Noise is present in any imaging system, but it makes imaging particularly challenging in low light. Since it is a low-light image, the photon number is low to build the actual image. The quality of an image is analyzed in subjective type, by eye vision, and objective type, by considering various parameters of noise like mean square error (MSE), structural similarity index measurement (SSIM), peak signal-to-noise ratio (PSNR), etc.

Low-light imaging is challenging due to low photon count [1] and low SNR. A variety of processes like denoising, deblurring in which, with the support of pipelining, image is enhanced by convolutional network. The limitation is that this is not applied to humans and dynamic objects. So, we take the low-light images with only object-level orientation [2], in which a simple illumination invariance method is proposed. But in real time, we need to take images in RGB illumination [3] in which an imposing structure can be illuminated and an illumination map is created. Furthermore, we need to take images as a set to propose a machine learning method

A. G. Kavya (✉) · U. Aparna · P. S. Suhasini
Velagapudi Ramakrishna Siddhartha Engineering College, Vijayawada, India

N. R. Shetty et al. (eds.), *Emerging Research in Computing, Information, Communication and Applications*, Lecture Notes in Electrical Engineering 790,
https://doi.org/10.1007/978-981-16-1342-5_1

on it. So, we take this into another level, by taking some simple unpaired training images [4], which are further made into a proper training set as MSR-net [5], and the trained set should go through many layers of the network we designed and the network layers with required functions to predict the performance [6]. Apart from all this, noise is the major problem in image enhancement, so a model with the joint framework of denoising and image enhancement [7] is proposed. A multi exposure framework [8], in which the input image and the synthetic image are fused according to their weights.

Apart from all this, in real time an image does not only contain a single noise, but come with a combination of noises. So, in this paper we analyzed with different combinations of noise and performance is evaluated with different parameters [9–11]. Different techniques are used to enhance the image added noises and are compared results [12].

2 Trained Model

In this paper, a model is defined using CNN, in which a dataset of images is trained. Noises like salt and pepper, Gauss, Poisson and speckle are defined in this model. An image captured contains more than a single noise in it. As the four different noises are defined in this model, a single noise and different combinations of noises are applied on each image in the dataset.

Figure 1 shows the model that is trained with the dataset such that the images go through different convolutional layers and add up so on, resulting in the enhanced image.

Since CNN consists of numerous layers, like convolutional layer, activation layer, pooling layer and fully connected layer, and several convolutional layers, i.e., a neural network, each convolutional layer in CNN performs convolution operation with the kernel. The size of the kernel is set through the term steps per epoch, and epoch is the term used to train the network number of times to understand the model defined. The Inception-ResNet-V2 architecture is used. Activation layer is the rectified linear unit, and its function is

$$\begin{aligned} F(x) &= 0, \quad \text{for } x < 0 \\ &= x, \quad \text{for } x = 0, x > 0 \end{aligned}$$

Pooling layer is a function that reduces the spatial size and performs max pooling; i.e., it subdivides the image pixels and places the maximum value of that subdivided image. The raw image will be with perfect illumination, and this image is gone through certain operations to result in a low-light image. This low-light image is used to enhance through the model enhancer.

Firstly, we applied a single noise to the dataset of 100 images resulting in the enhanced image as a low-light image. Due to the result that we have obtained, a

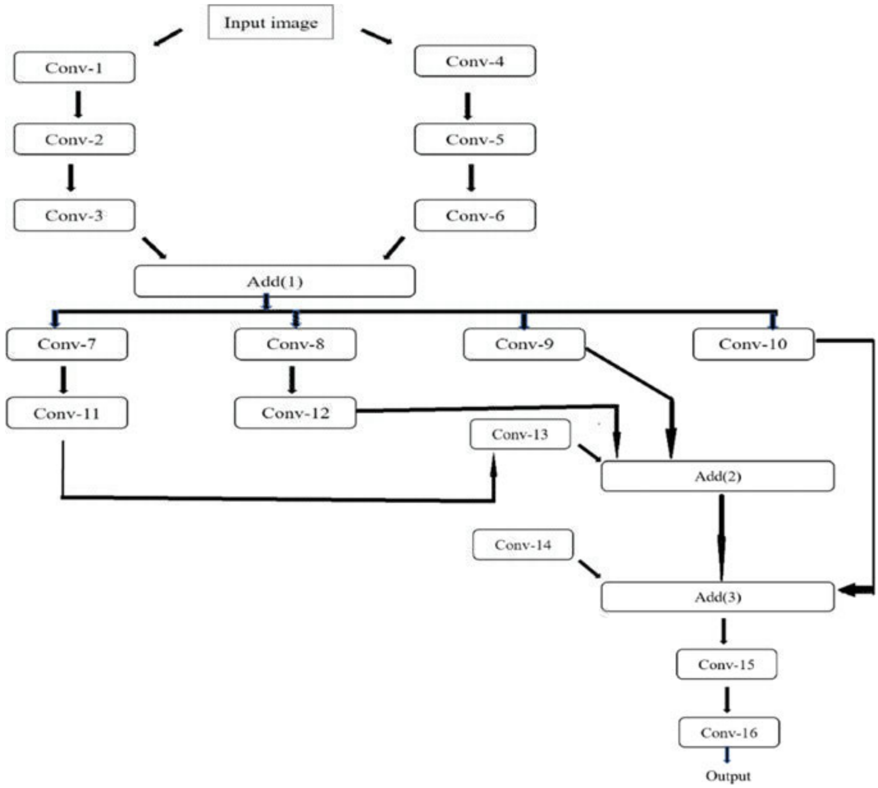

Fig. 1 Trained model

dataset of images of around 2000 (~2117) is trained with different noises with a number of epochs and steps per epochs. The enhanced image size is not similar to the original image size to compare. So, the enhanced image is reshaped to original image size. The results are evaluated, and comparison is made using the parameters like mean square error (MSE), peak signal-to-noise ratio (PSNR), and structure similarity index measurement (SSIM).

2.1 Evaluation Metrics

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}\left[I(x, y) - I'(x, y)\right]^2 \tag{1}$$

where $I(x, y)$ is the original image, $I'(x, y)$ is the enhanced image and $M \times N$ is the size of the image.

Peak signal-to-noise ratio (PSNR) is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation.

$$\mathrm{PSNR} = 20 \log \frac{\mathrm{MAX}}{\sqrt{\mathrm{MSE}}} \tag{2}$$

2.2 Algorithm

Figure 1 shows the architecture of trained model.

Algorithmic steps are as follows.

Step 1: Installing required software like TensorFlow and OpenCV.
Step 2: Uploading the images to form a dataset.
Step 3: Introducing virtual noise to every image in the dataset.
Step 4: Converting the RGB image to HSV image.
Step 5: Defining the dataset into an array with 2 elements X and Y. Element X is for input noisy images, and element Y is for predicted output images.
Step 6: Defining the convolution model.
Step 7: For the input sample defining the model enhancer, i.e., optimizer and loss function.
Step 8: Generating the X and Y elements by running the model for different time intervals, i.e., different combinations of epochs and steps.
Step 9: Predicting the output image for the given input image.
Step 10: Get the output for the given input.
Step 11: Reshaping of enhanced image to the size of original image.
Step 12: Comparing original image with the reshaped image to evaluate metrics.

2.3 Experimental Results and Observations

Single noises like salt and pepper, Poisson, Gauss and speckle are applied to the trained images as shown in Fig. 2. The enhanced outputs with CNN are compared, and it is found that, for Poisson noise, the results are better with less error as shown in Table 1.

The following experiments illustrate the performance of CNN when the images are added with different combinations of noise types. Further, the results with different numbers of epochs are also investigated.

With Single Noise:

Salt and pepper noise is applied with an increasing number of epochs, and steps per epoch is 3. The number of epochs used is 10, 35, 100, 500 with 3 steps per epoch and

Fig. 2 Original image with single noise [original (i), salt and pepper (ii), Gauss (iii), Poisson (iv), speckle (v)]

Table 1 Comparison of different parameters with single noise (S—salt and pepper, P—Poisson, G—Gauss, SP—speckle)

Noise	Epochs	Steps	Technique	MSE	PSNR	SSIM
Original image	–	–	–	0.0	100.00	1.00
S	10	2	CNN	2559.17	14.05	0.42
P	**10**	**2**	**CNN**	**826.97**	**18.96**	**0.76**
G	10	2	CNN	7560.74	9.35	0.31
SP	10	2	CNN	3402.86	12.81	0.43

other combinations as 53 number of epochs and 39 steps per epoch. As the number of epochs and steps per epoch are increasing, the time taken for training the model is also increasing. The enhanced images for corresponding number of epochs and steps per epochs are shown in Fig. 3. And the parameters are given in Table 2.

This analysis proves that while increasing the number of steps and epochs, the enhancement will be better.

With Double Noise:

Fig. 3 Enhanced images for different numbers of epochs

Table 2 Comparison of parameters for different numbers of epochs

Noise	Epochs	Steps	Technique	MSE	PSNR	SSIM
S	10	3	CNN	907.67	18.55	0.70
S	35	3	CNN	706.11	19.64	0.80
S	53	3	CNN	779.54	19.21	0.73
S	100	3	CNN	803.40	19.08	0.80
S	**500**	**3**	**CNN**	**443.45**	**21.66**	**0.83**

Two different types of noises are applied to images. Figure 4 shows the low-light image, and the input is given with double noise as salt and pepper along with Poisson and trained 469 images with 10 epochs and 2 steps. Table 3 is related to Fig. 5.

With Three Different Noises:

Here three noises as salt and pepper with gauss and poisson are added, trained 1071 images with 10 epochs and 2 steps per epoch, 35 epochs and 3 steps per epoch respectively. The parameters are given in Table 4.

Figure 6 shows the enhanced images after applying three noises, viz., salt and pepper with Gauss and speckle, trained 1071 images with 10 and 35 epochs and 3 steps per epoch, respectively. The parameters are given in Table 5.

With Four Different Noises:

The model is investigated with a combination of four different types of noises. The parameters with the number of trained images are observed. Finally, the results of CNN when trained with 929 images, epochs of 5 and 2 steps per epoch are

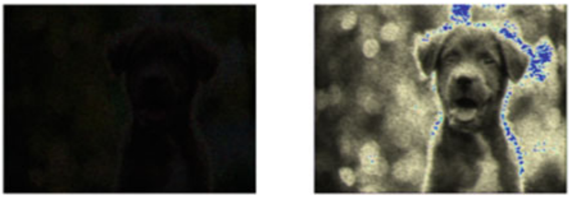

Fig. 4 Low-light image with two types of noises and enhanced image

Table 3 Comparison of parameters

Noise	No. of images trained	Epochs	Steps	Technique	MSE	PSNR	SSIM
S&G	1071	10	2	CNN	2978.39	13.39	0.44
S&G	**1071**	**35**	**2**	**CNN**	**1962.412**	**15.20**	**0.49**

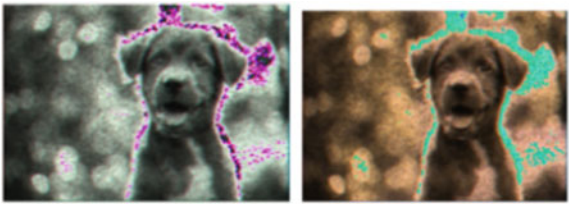

Fig. 5 Enhanced images for S&P and Gaussian noises

Table 4 Comparison of parameters

Noise	Epochs	Steps	Technique	MSE	PSNR	SSIM
S,G&P	10	2	CNN	2559.17	14.05	0.42
S,G&P	**35**	**3**	**CNN**	**1983.01**	**15.16**	**0.48**

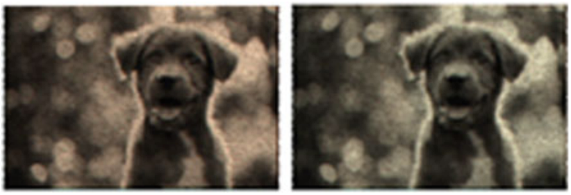

Fig. 6 Enhanced images for three types of noises (S&P, Gauss and speckle)

Table 5 Parameter comparison

Noise	Epochs	Steps	Technique	MSE	PSNR	SSIM
S,G&SP	10	3	CNN	3084.69	13.24	0.47
S,G&SP	**35**	**3**	**CNN**	**2605.52**	**13.97**	**0.49**

compared with other existing techniques like CLAHE, total variation, bilateral, log transformation, gamma correction and histogram equalization. Figure 7 shows the output images with different enhancement techniques, and Table 6 gives performance comparison.

The enhancement using CNN yields better results compared to other techniques.

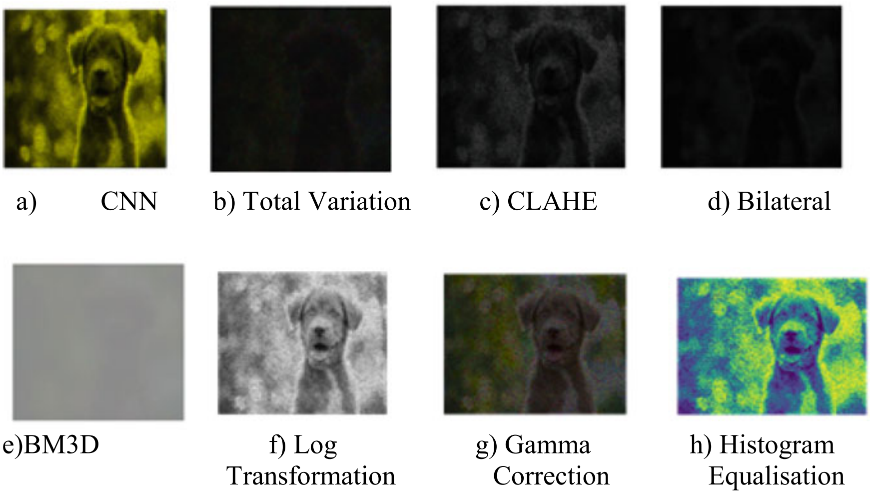

Fig. 7 Comparison of CNN with other techniques

Table 6 Comparison with other techniques

Technique	MSE	PSNR	SSIM
CNN	**706.11**	**19.64**	**0.80**
Total variation	11,371.71	7.57	0.14
CLAHE	11,321.80	7.59	0.15
Bilateral	14,195.65	6.61	0.05
Log transformation	5133.08	11.03	0.09
Gamma correction	7977.57	9.11	0.14
Histogram equalization	4652.49	11.45	0.11

3 Conclusion

Through parameters, it is observed that, by increasing the number of images in the dataset, by increasing the number of epochs and by increasing the steps per epoch, the performance of the enhanced image is improving correspondingly. This comparison with other techniques revealed that CNN technique is better than the earlier techniques of image enhancement. Google Colaboratory is used to execute the program; as we increase the images' number, epochs and steps, it takes much time to execute a particular cell of the program and the memory will be drained out. So, less number in images, epochs and steps are taken in these experiments. Further using GPUs, with large datasets the performance of CNN may be explored.

References

1. Chen C, Chen Q, Xu J, Kolthun V (2018) Learning to see in the Dark. In: IEEE/CVF conference on computer vision and pattern recognition, pp 3291–3300. https://doi.org/10.1109/CVPR.2018.00347
2. Loh YP, Chan CS (2018) Getting to know low-light images with the exclusively dark dataset. In: Computer vision and image understanding, vol 178, pp 30–42. https://doi.org/10.1016/j.cviu.2018.10.010
3. Guo X, Li Y, Ling H (2017) LIME: low-light image enhancement via illumination map estimation. IEEE Trans Image Process 26(2):982–993. https://doi.org/10.1109/TIP.2016.2639450
4. Jiang Y, Gong X, Ding Liu Y, Cheng CF, Shen X, Yang J, Zhou P, Wang Z (2019) EnlightenGAN: deep light enhancement without paired supervision. Comput Vis Image Underst 1:1–11
5. Shen L, Yue Z, Feng F, Chen Q, Liu S, Ma J (2017) MSR-net: low-light image enhancement using deep convolutional network. In: Computer vision and image understanding, pp 1–9
6. Jones Y (2017) Deep learning for image enhancement & visibility improvement, Article, pp 1–132
7. Tao L, Zhu C, Song J, Lu T, Jia H, Xie X (2017) Low-Light enhancement using CNN and Bright channel prior. In: International conference on image processing, pp 3215–3219. https://doi.org/10.1109/ICIP.2017.8296876
8. Ying Z, Li G, Gao W (2015) A bio inspired multi-exposure fusion framework for low-light image enhancement. J Latex Class Files 14(8):1–10

9. Arora S (2015) Performance evaluation of image enhancement techniques. Article 8(8):251–262. https://doi.org/10.14257/ijsip.2015.8.8.27
10. Jaya VL, Gopikakumari R (2013) IEM: a new image enhancement metric for contrast and sharpness measurements. Int J Comput Appl 79(9):19. https://doi.org/10.5120/13766-1620
11. Hanumantharaju MC, Ravishankar M, Rameshbabu DR, Manjunath Aradhya VN (2011) An efficient metric for evaluating the quality of color image enhancement. In: Proceedings of the 5th Indian international conference on artificial intelligence, pp 1016–1026
12. Lv F, Li Y, Lu F (2019) Attention-guided low-light image enhancement, pp 1–12

Identical Twin Face Recognition Using Gabor Filter, SVM Classifier and SURF Algorithm

A. K. Kavya Ashwini, R. Madhumitha, Mary Ann Sandra, S. Supriya, Ullal Akshatha Nayak, and K. Ranjitha

1 Introduction

Previously, manual experiments were done to identify the difference, and many more systems existed to show differences between twins. In the existing system, many processes are used for twins' identification like finger print, voice and iris recognition. A person can be identified uniquely using finger print identification process. The method proposed takes a scan image from the person and compares it with the database for identification. The iris recognition is also similar to finger prints identification. Every person has a unique iris, which helps us to identify the person through iris recognition method. The process of voice recognition works based on the voice to identify the twins. Finger print recognition has the drawbacks of slow processing and is easy to hack. Iris recognition also has drawbacks such as mismatching due to identification. In general, it is time consuming for identification, and if we have some faults in the eye, then iris recognition is not suitable for identification.

Similarly voice recognition also has demerits of easily being misused by another person. Hence, due to the above-stated drawbacks of fingerprint, iris and voice recognition, we use a more advanced system such as an identical twin face recognition system which extracts different features from the dataset and compares the two images precisely based on the similarities and dissimilarities using different algorithms such as multiSVM, Gabor features, Gabor filter bank and open surf. Upon completion of the above task, the two images are then combined to form a warp image from which we can identify whether the person is a twin, not a twin or is a different person by viewing the distortion level of the warped image.

A. K. Kavya Ashwini · R. Madhumitha · M. A. Sandra · S. Supriya · U. Akshatha Nayak (✉) · K. Ranjitha
Nitte Meenakshi Institute of Technology, Bangalore 560047, India
e-mail: akshatha.n@nmit.ac.in

N. R. Shetty et al. (eds.), *Emerging Research in Computing, Information, Communication and Applications*, Lecture Notes in Electrical Engineering 790,
https://doi.org/10.1007/978-981-16-1342-5_2

2 Proposed System

There has been a huge progress in facial recognition field of study and research, but there are still many challenges when it comes to differentiating between identical twins. Low accuracy has been the main drawback of face recognition, and this would be the one important objective to be accomplished. The main objective of this project is to create a face recognition system that can recognise similar faces and be able to differentiate between the identical twins. The purpose of the project is to develop an efficient algorithm in terms of low complexity, with maximum possible number of face detection factors, to reduce false identification of identical twins which in turn will provide a solution for differentiating between them. The sample images of identical twins are collected and are used in training the system in .pgm, .jpg and .bmp formats. Image processing is done using Gabor filter and speeded up robust features (SURF) algorithm. Machine learning dataset training and classification is done using multiSVM. Twins face recognition system will detect, extract and recognise frontal faces from the acquired images. The system should work and satisfy all the conditions of the proposed system and recognize the images of few twins at least.

This system can be designed using various other coding techniques, but MATLB can do the same with ease using its image processing applications, its functions and tool box (Fig. 1).

3 System Design and Implementation

System architecture has six stages. The first stage includes the input of the two images from the dataset. In the second stage of the system architecture, the system will detect the facial features of both the images. The third stage is the feature extraction; using algorithms such as Gabor filter and open surf, features of the input image are extracted. In the fourth stage, the identification of the face for the first image is done. In the fifth stage, features of the second input image are extracted using the same algorithms as specified above. The last stage is the classification, in which the images are classified using SVM (Fig. 2).

The above figure represents the system architecture and the overview of the system design. The steps involved are.

1. Training—in this process, the collected data is loaded, and it is used for training and feature extraction.
2. Classification—in this process, using the SVM, the given image is classified; this is done after training.

The system design mainly consists of.

- Image collection
- Image pre-processing
- Feature extraction

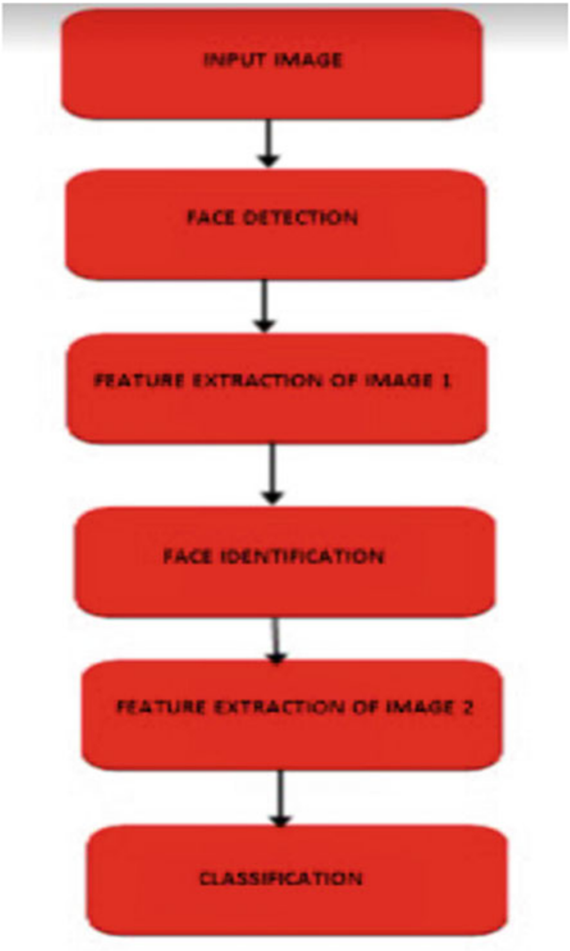

Fig. 1 Proposed system architecture

- Training
- Classification using multiclass SVM.

3.1 Image Collection

For training purpose, images of different identical twins are collected. The images will be stored in a standard format; in this system, we use the portable grey map (.pgm) images; while storing them, the sample images are taken from the internet or Kaggle dataset.

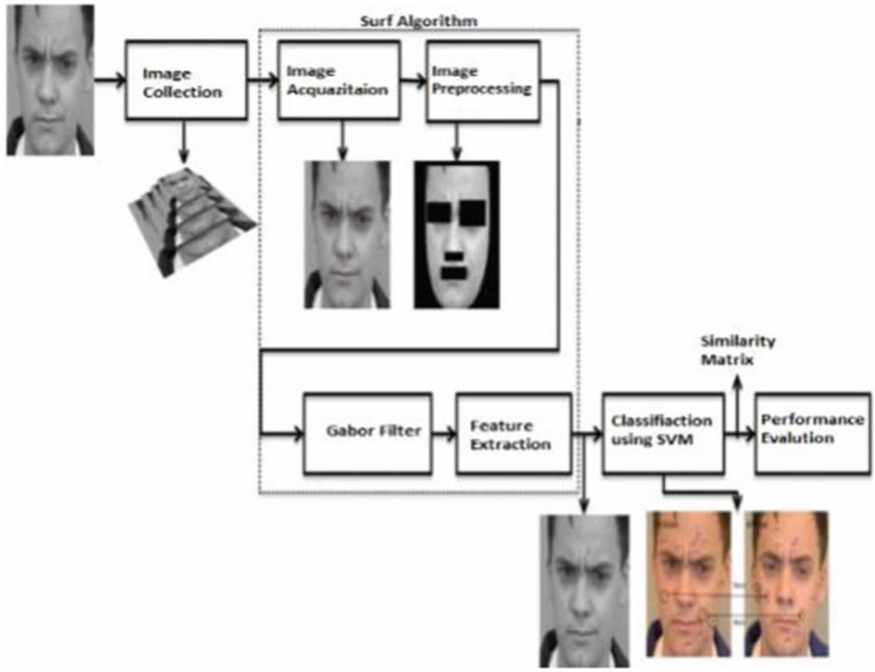

Fig. 2 System design

3.2 *Image Pre-processing*

For data that is uneven and noisy, image pre-processing plays a major role. In this process, the image is transformed to another image which has improved quality that is better for analysing. This transformation basically removes unwanted components of the image and enhances the image features. This step is important because it helps the image to be effective for subsequent task like feature extraction, data mining techniques that depend on image quality. The images and its statistical properties are observed in greyscale format as it makes boundaries and edges easy to analyse when in black and white. Also, the image is seen well in RGB when it comes to information related to colour formats. Here, the intensity image is converted into binary image by resizing the given image to 256×256, and as a result, the threshold is calculated. This also helps in converting the RGB image format to greyscale image. A histogram is used to compute the mean using this, it is scaled between 0 and 1 which is a normalized value.

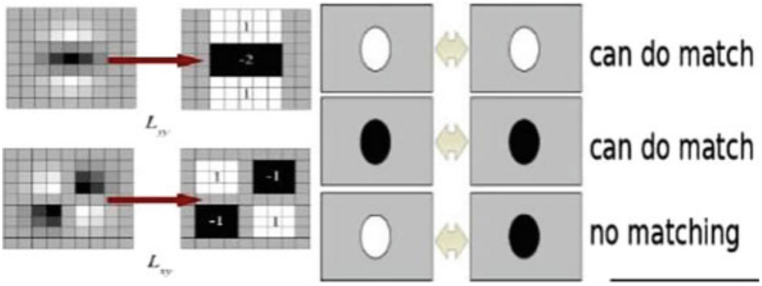

Fig. 3 SURF (Speeded up robust feature)

3.3 Feature Extraction

Feature extraction is done by using two different algorithms, speeded up robust features (SURF) and Gabor filter. These two methods will enable us to extract the features from the twin's images.

3.4 Feature Extraction in SURF

Key point detection can be done by feature extraction using SURF which in turn uses a very basic Hessian matrix approximation for storage of values. Hessian matrix exploits each column of the matrix which can be approximated by taking the difference between two instances which are evaluated at the two nearby points. The image is used in a quick and effective way for finding the sum of values of the pixels for the given image or for the grid of a given image. Faster matching occurs with very minimum information, and it also does not reduce the performance of the feature description of SURF algorithm (Fig. 3).

3.5 Feature Description in SURF

The descriptor is designed to be scale invariant and rotationally invariant and is partly inspired from scale invariant feature transform (SIFT) descriptors. These descriptors are used to locate and recognise objects, faces to reconstruct 3D scenes, to track object and to extract points of interest, and it uses Hessian matrix to find interest.

3.6 Gabor Filter

Gabor filter is used in image processing as a linear filter used for detection of edges. We use this filter to extract features at different angles. Optimization-based feature selection algorithm is used to find the features for the optimal feature subset. At each stage, an improvement is made. In image processing, this filter can also be used for texture analysis which means that it checks if there is frequency specifically for the image in particular direction of that region around the point.

3.7 Training

Training is done to assign the desired output of -0.9 to non-face feature vector and 0.9 to face feature vector; we will be able to obtain the network desired output based on these features. In this training process, first the datasets are trained, and then image acquisition is done, where in the image is resized and is pre-processed during which features are added.

3.8 Classification Using Multiclass SVM

The red and blue colours are two types of data in the below given image. Calculation of the distance to all the training samples is done, and the one with the minimum distance is taken for a test data in KNN. It is time and space consuming to measure all the distances to store all samples. But referring the below given image, much memory is not needed. Another idea is to find a line, which divides both the data into two regions. We get a new test data, and if it belongs to a blue group, we substitute it. This line is called as the decision boundary. This method is memory efficient and very simple. Such data which can be divided into two with a straight line is called linear separable (Fig. 4).

The above image shows that plenty of such lines are possible. The incoming data can be a noise because of which it is better if the lines pass as far as possible from all the points. The classification accuracy should not be affected by the noise. So therefore, the line with the greatest distance is chosen as it has lesser effect of the noise. So what SVM does is it finds hyperplane with largest minimum distance to the training samples. The bold line in the below image passing through the centre is the hyperplane (Fig. 5).

So to find the decision boundary, we need the proper training data. The data which are close to the opposite group are sufficient. In the above image, the blue-filled circle and two red-filled squares represent the support vectors and the lines passing through them are called support planes; these are used for finding our decision boundary. We may ignore other data as they are not needed for this purpose.