西南交通大学学报

第 55 卷 第 6 期
2020 年 12 月

JOURNAL OF SOUTHWEST JIAOTONG UNIVERSITY

Vol. 55 No. 6
Dec. 2020

ISSN: 0258-2724 DOI：10.35741/issn.0258-2724.55.6.18

Research article

Electrical and Electronic Engineering

FACE RECOGNITION SYSTEM FOR INDOOR APPLICATIONS BASED ON VIDEO WITH THE LNMF AND NMFSC METHODS

LNMF 和国家自然科学基金会方法的基于视频的室内应用人脸识别系统

Della Gressinda Wahana [a], Bambang Hidayat [a], Suci Aulia [b, *], Sugondo Hadiyoso [b]
[a] School of Electrical Engineering, Telkom University
Bandung, 40257, Indonesia
[b] School of Applied Science, Telkom University
Bandung, 40257, Indonesia, suciaulia@telkomuniversity.ac.id

Received: September 1, 2020 ▪ Review: November 2, 2020 ▪ Accepted: December 15, 2020

Abstract

Face detection and face recognition are among the most important research topics in computer vision, as many applications use faces as objects of biometric technology. One of the main issues in applying face recognition is recording the attendance of active participants in a room. The challenge is that recognition through video with multiple object conditions in one frame may be difficult to perform. The Principal Component Analysis method is commonly used in face detection. Principal Component Analysis still has shortcomings: the accuracy decreases when it is applied to large datasets and performs slowly in real-time applications. Therefore, this study simulates a face recognition system installed in a room based on video recordings using Non-negative Matrix Factorization suppressed carrier and Local Non-negative Matrix Factorization methods. Data acquisition is obtained by capturing video in classrooms with a resolution of 640 x 480 pixels in RGB, .avi format, video frame rate of 30 fps, and video duration of ±10 seconds. The proposed system can perform face recognition in which the average accuracy value of the Local Non-negative Matrix Factorization method is 71.61% with a computation time of 152,634 seconds. By contrast, the average accuracy value of the Non-negative Matrix Factorization suppressed carrier method is 86.76% with a computation time of 467,785 seconds. The proposed system is expected to be used for simultaneously finding and identifying faces in real time.

Keywords: Face Recognition, Non-Negative Matrix Factorization Suppressed Carrier, Local Non-Negative Matrix Factorization

摘要 面部检测和面部识别是计算机视觉中最重要的研究主题，因为许多应用程序都将面部作为生

物识别技术的对象。应用面部识别的主要问题之一是记录房间中活跃参与者的出勤情况。挑战在于，在一帧中通过具有多个对象条件的视频进行识别可能很难执行。主成分分析法通常用于人脸检测。主成分分析仍然存在缺点：将其应用于大型数据集时，准确性会降低，并且在实时应用程序中执行速度会很慢。因此，本研究基于视频记录，使用非负矩阵分解抑制载波和局部非负矩阵分解方法，模拟了安装在房间中的人脸识别系统。通过在教室中以 RGB 分辨率为 640 x 480 像素，.avi 格式，视频帧速率为 30 帧/秒和视频持续时间为±10 秒捕获视频来获取数据。所提出的系统可以执行面部识别，其中局部非负矩阵分解方法的平均准确度值为 71.61%，计算时间为 152,634 秒。相比之下，非负矩阵分解抑制载波方法的平均准确度值为 86.76%，计算时间为 467,785 秒。预期所提出的系统将用于实时同时发现和识别面部。

关键词: 人脸识别，非负矩阵分解抑制载波，局部非负矩阵分解

I. Introduction

The developing computer-based imaging technology is becoming increasingly difficult, including in the field of computer vision, in terms of research, and industrial needs. Computer vision allows computers to see and recognize an image as well as humans can. One of the image recognition methods referred to is for identification in the biometric system. The biometric system is a self-recognition technology using body parts or human behavior. The system searches and matches a person's identity in a reference database that has been previously prepared through the registration process [1]. Face recognition is a field of biometric research that is ubiquitous and easy to see being used in the real world. Its applications on the industrial side include security systems, attendance systems, driving safety [2], and even identification of criminals. Research on the human face has been carried out with certain advantages and difficulties because the human face presents a complex picture [3], [4].

In face recognition, there are two important phases, namely feature extraction and classification. The method commonly used is PCA (Principal Component Analysis). Although PCA is a well-known technique in image recognition, it still has problems in dealing with a very large face database, where the processing time is long and accuracy rapidly decreases as the amount of data grows [5], [6], [7]. In addition to PCA, there are reduction techniques such as Linear Discriminant Analysis (LDA) [8], Independent Component Analysis (ICA) [9], [10], Kernel Fisher Analysis (KFA) [11], and Non-negative Matrix Factorization (NMF). NMF uses space positioning to reduce the complexity of facial images, which is why it has been highlighted among other techniques [12], [13], [14]. A study of the eye region observed that Local NMF (LNMF) reaches 95.12% accuracy [15], [16]. [17] used NMF to reach 99% accuracy, but for FER (Facial Expression Recognition) it still needed improvement. NMF, which is better able to detect a facial part, will be suitable if implemented for face recognition video based in the classroom.

In this study, we developed automatic face recognition based on video recording using the NMF suppressed carrier (NMFsc) approach and compared it to LNMF to determine the best performance. The proposed system aims to facilitate locating students in the classroom using automatic face recognition. The face images used in this study are sourced from video recordings that were conducted in the classroom. From the videos, dataset images were captured and used as input in the face identification and recognition processes. The test parameters were based on the height and distance of the camera from the object. The parameters of the light intensity and feature extraction methods were also tested.

II. Materials and Methods

The system built in this study can perform facial recognition and display known faces if the facial image matches the database. The database was obtained from video recordings in a classroom. The video was taken with a resolution of 640 x 480 pixels in RGB, .avi format, frame rate of 30 fps, and duration of ±10 seconds. The recordings were conducted at a height of 2 meters and a distance of 1.5 meters between the object and the digital camera. The video recording process is divided into six conditions: 1-2) when the camera is centered with the lights respectively on and off; 3-4) when the camera is on the right with the lights on or off; and 5-6) when the camera is on the left with the lights on and off. In this system, odd numbers would indicate lights on and even numbers lights off.

Another condition in the acquisition process is either detecting a face that is looking directly at the camera or targeting the face object first. Face detection in this experiment uses the Haar Cascade Classifier from Open CV. Meanwhile, facial recognition feature extraction uses a comparison of the NMFsc and LNMF methods and KNN-Euclidean Distance as classifier.

A. Local Non-Negative Matrix Factorization (LNMF)

The LNMF method is a development of the NMF method. This method is intended to strengthen the local nature of the base image so that the resulting features are more suitable for use in cases that require local characteristics. This is done by adding a limitation to the cost function (Equation 1), to generate local properties of the formed factors [18], [19], [20].

$$D(A\|B) = \Sigma_{ij}(A_{ij} \log\frac{A_{ij}}{B_{ij}} - A_{ij} + B_{ij}) + \alpha \Sigma_{ij} u_{ij} - \beta \Sigma_{ij} v_{ij} \quad (1)$$

where $\alpha, \beta > 0, u_{ij} = W^T W \ dan \ v_{ij} = H^T H$. By using Equation 2, a change in the value of *H* will be obtained, while Equations 3 and 4 change the value for *W*.

$$H_{a\mu} = \sqrt{H_{a\mu} \Sigma_{i=1}^{n} W_{ia} \frac{v_{i\mu}}{(WH)_{i\mu}}} \quad (2)$$

$$W_{ia} = W_{ia} \Sigma_{\mu=1}^{m} \frac{v_{i\mu}}{(WH)_{i\mu}} H_{a\mu} \quad (3)$$

$$W_{ia} = \frac{W_{ia}}{\Sigma_{j=1}^{n} W_{ja}} \quad (4)$$

B. Non-Negative Matrix Factorization with Spareseness Constrain (NMFsc)

The NMFsc method is a method that has been developed after the NMF (Non Negative Matrix Factorization) method, because NMF is still lacking in terms of computation time. NMF requires more computation time to achieve convergence. To overcome this drawback, Hoyer proposed the NMFsc method, which showed that this method could achieve faster convergence. In general, this method finds sparsity in the face image which will later be made as a characteristic of the human face. Equation 5 is an expression of NMFsc, which is basically similar to the NMF or LNMF formula [21].

$$V \approx WH \quad (5)$$

To complete Equation 5, we must find the matrices W and H and the sizes of the matrices W (m x r) and H (r x n), with r value set arbitrarily. Then, we must initialize the sW and sH values, where these values are equivalent to the sparseness levels, and the range of sW and sH values is 0-1.

Thereafter we must determine the size of the spread of sparseness based on the relationship between the norm variables L_1 and L_2 using the predetermined values S_w and S_h. By using Equation 6, we will get the sparseness distribution limit.

$$sparseness\ (x) = \frac{(\sqrt{n} - (\Sigma|x_i|)/\sqrt{\Sigma x_i^2})}{\sqrt{n}-1} \quad (6)$$

where n is the dimension value of x.

For details, here is the algorithm for the NMFsc method:

1. Initialize random W and H matrices
2. Find the sparseness level of the matrix W and H
3. Find the difference between the V matrix and the WH matrix multiplication using equation 7.

$$D(V\|WH) = \Sigma|(V - WH)|^2 \quad (7)$$

If sW is used, Equation 8 is used to update the matrix value of W.

$$W = W - \mu_H (WH - V) H^T \quad (8)$$

If sH is used, Equation 9 is used to update the value of the matrix H.

$$H = H - \mu_W (WH - V) W^T \quad (9)$$

C. Cascade Classifier

Cascade classifier is a chain stage classifier, where each stage classifier is used to detect whether there is an object of interest in the image sub window. This process uses a multilevel classification. The filters at each level classify images that have been previously filtered. When the filter succeeds in passing the image region, the image region is then included in the next filter. Image region that has gone through all filters will be considered as “Face” and if the filter fails, then the area is considered as “Not Face.” This process is shown in Figure 1.

To determine whether the area is "Face" or "Not Face," Haar uses a training. This training process is known as the haar-training algorithm, which will produce a statistical model parameter when complete.

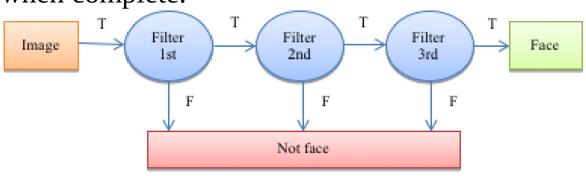


Figure 1. Cascade classifier

III. Design and Implementation

A. Pre-Processing and Feature Extraction

The face recognition system algorithm is shown in Figure 2. The system input is in the form of video, which will later be converted into frames. Then, further processing is carried out. In general, this system consists of several stages, including video data retrieval, pre-processing, feature extraction, and classification. The proposed system will carry out a face recognition process and the output of this system is in the form of a known face display that displays the name (text).

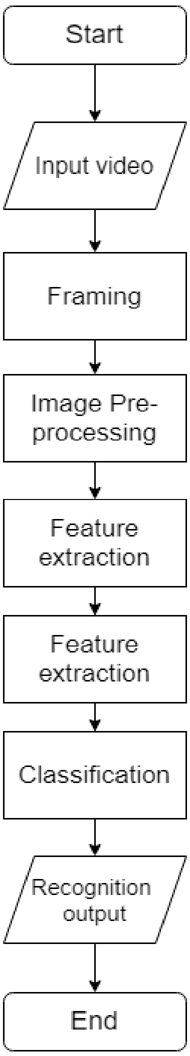


Figure 2. The workflow of proposed system

The preprocessing stage includes RGB-to-grayscale conversion, face detection, cropping, and resizing. Figures 3–5 show the results of each preprocessing stage.

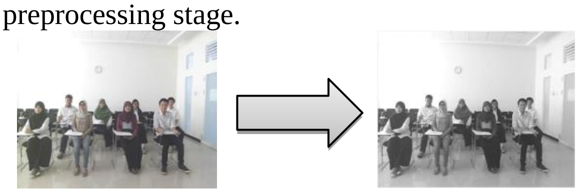


Figure 3. The example of the RGB to grayscale conversion process

Figure 4. The example of face detection results with red bounding boxes

Figure 5. Automatic cropping results

In this study, all face images will be resized to 30 × 30 pixels. Figure 6 shows that the face image, which is originally 35 × 35 pixels in size, is resized to 30 × 30 pixels for computational efficiency.

Figure 6. (a) Face image (35x35 pixel), (b) face image (30x30 pixel)

The next step is feature extraction using LNMF and NMFsc. In carrying out feature extraction using the LNMF method, there are several steps including normalizing the V matrix, initializing the W and H matrices, determining the difference between them, and updating them. In general, feature extraction using LNMF requires input in the form of a V matrix, which is a face image resulting from automatic preprocessing if for test data; for training data, the V matrix is obtained from manual preprocessing, which will later be reduced to two matrices, namely the W matrix (image base matrix) and the H matrix (coefficient matrix) as expressed in equation 5. After the V matrix, in the form of a face image matrix, is inputted, the normalization process will be carried out. This is done by dividing the V matrix with its maximum value (30 × 30 pixels).

Meanwhile, the feature extraction process with the NMFsc method has several stages that are similar to the LNMF method, including normalizing the V matrix, initializing the W and H matrices, determining the sH and sW values, determining the sparseness level of the W and H matrices, determining the difference between the W and H matrices, and updating the W and H matrices. In general, feature extraction using the NMFsc method also requires input in the form of a V matrix, which is an automatic pre-processing face image for test data; for training data, the V matrix is obtained from pre-processing results. Manual processing will later be reduced to 2 matrices, namely the W matrix (image base matrix) and the H matrix (coefficient matrix), as shown in equation 5. Unlike the LNMF method, the NMFsc method must determine the sH and sW values first, because this method emphasizes the level of sparseness in a face image.

B. Classification

After the characteristics of each training face image and the characteristics of each test face image are obtained from the feature extraction process, these characteristics are classified by the KNN-Euclidean Distance method. First, the targeting process is carried out, wherein the results of the targeting process will be matched with the results from the KNN. The targeting process can be seen in Figure 7, and the classification process can be seen in Figure 8.

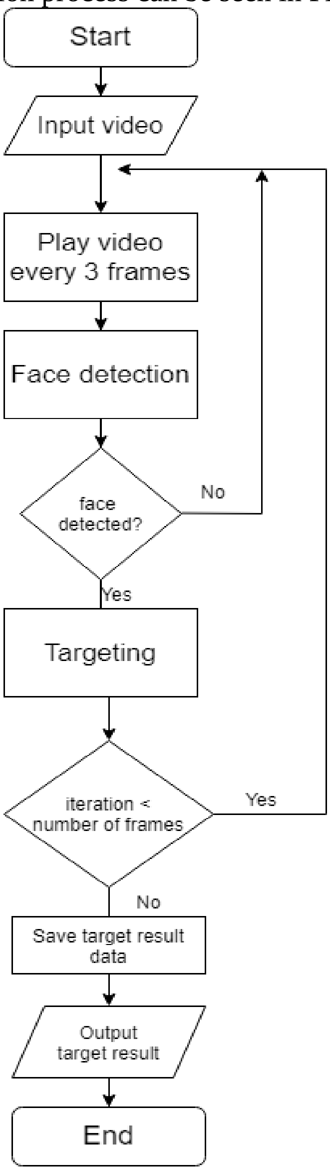


Figure 7. Targeting flowchart

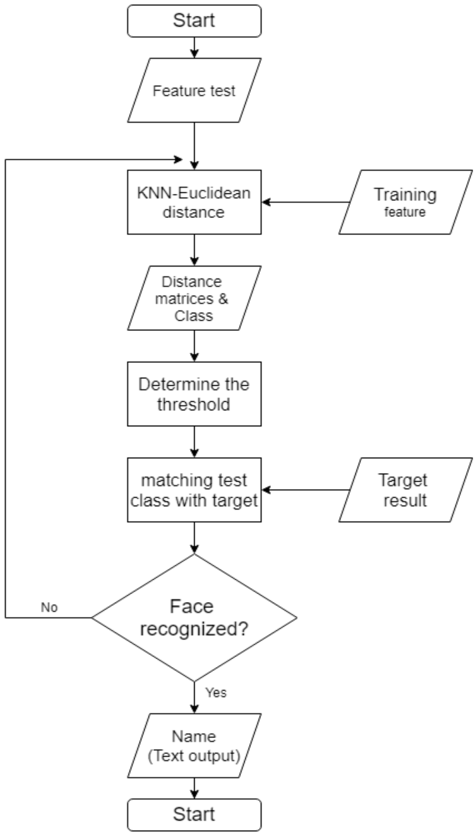


Figure 8. Flowchart of the classification process

C. Targeting

In this stage, class targeting is carried out against the faces that have been detected. The video is converted into a collection of frames, and each frame is processed at intervals of 3. Then, the face detection process is carried out on the frame. When a face is detected, it is targeted according to the detected face class name, but when no face is detected, the next frame can be immediately processed. This process is carried out as many as the number of frames, if it exceeds the number of frames, the target result data is stored, and then the results of this target class are matched with the results of the KNN-Euclidean Distance calcification process class.

IV. RESULTS AND DISCUSSION

Tests were carried out using a Casio Exilim digital camera as a video recorder. This digital camera is installed at a height of approximately 2 meters from the floor surface and a distance of approximately 1.5 meters in front of the object. In this test, 60 test videos will be taken where each video is tested 6 times. The recorded video has the following specifications:

a. 640 x 480 pixels resolution

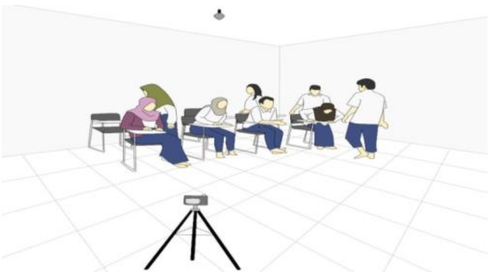
b. 10-second video duration at 30 FPS (Frame Per Second)

c. AVI (Audio Video Interleave) video format

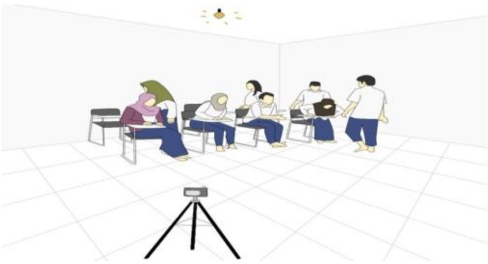
The system is tested using different camera positions and exposures, as shown in Figure 9. For each scenario, 10 video recordings are carried out.

(a)

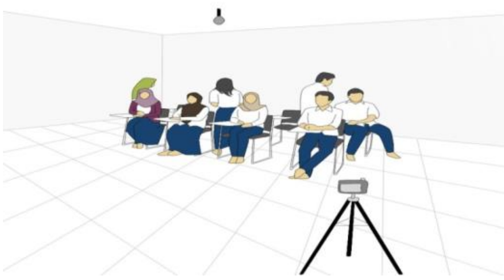
(b)



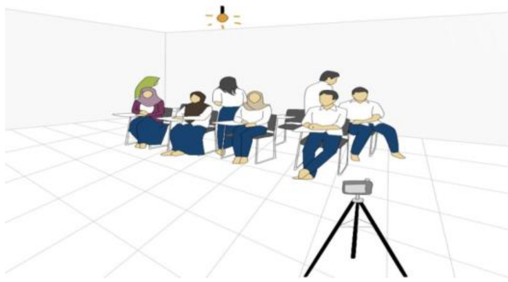
(c)



(d)



(e)



(f)

Figure 9. Testing scenario

The performance test parameters for the two proposed methods in this system include accuracy and processing times. Each method is analyzed based on an initialized scenario to show the effect of camera position and room lighting levels on the system's performance. The accuracy results of each method based on the designed scenario can be seen in Tables 1 and 2 and are illustrated in Figures 10 and 11.

Table 1.
The performance test of accuracy based on camera position and lighting level

Video	Accuracy of scenario- (%)					
	a	b	c	d	e	f
1	78,57	87,50	85,42	64,58	75,00	56,67
2	69,44	78,57	81,25	83,33	66,67	20,83
3	76,19	62,50	93,75	100,00	63,89	66,67
4	66,67	61,11	93,75	93,75	50,00	70,83
5	64,58	64,29	88,10	100,00	71,43	77,78
6	69,44	63,33	78,57	81,25	70,00	61,91
7	83,33	52,38	75,00	83,33	70,00	66,67
8	72,22	63,89	85,71	81,25	60,00	42,84
9	83,33	69,44	57,14	92,86	36,67	71,43
10	70,83	73,33	92,86	75,00	52,78	46,67

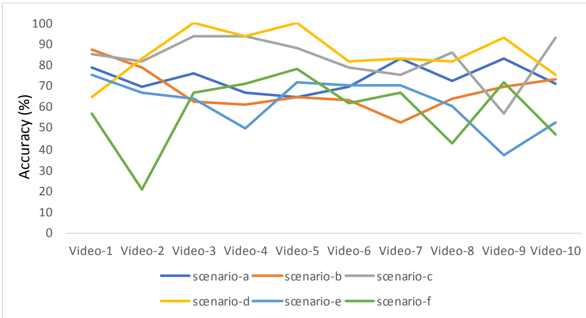


Figure 10. Accuracy in the LNMF method (a) - (f) scenario-1 - scenario-6 respectively

Table 2.
The performance test of time processing based on camera position and lighting level

Vid.	Time process of scenario- (s)					
	a	b	c	d	e	f
1	399,54	679,48	549,71	425,84	230,90	193,56
2	392,89	441,99	635,69	663,88	250,18	126,52

3	417,62	525,35	657,44	1007,07	259,39	371,95
4	414,14	437,45	623,85	521,49	210,00	401,18
5	525,60	477,78	599,23	972,24	354,17	400,93
6	617,97	267,55	258,08	520,00	614,84	590,72
7	620,64	244,01	387,25	622,03	353,19	494,35
8	794,58	248,67	443,36	713,13	357,01	574,06
9	598,32	404,66	453,67	440,39	233,05	756,01
10	502,68	385,91	336,59	395,82	311,41	369,19

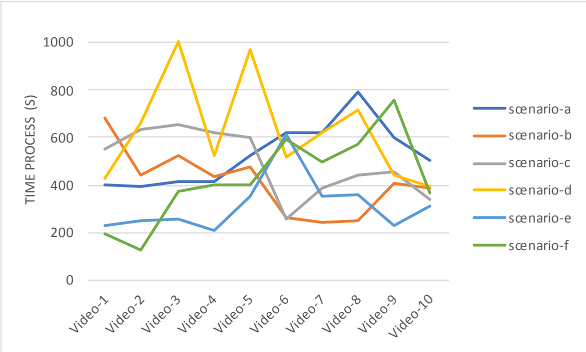


Figure 11. Accuracy in the NMFsc method (a) - (f) scenario-1 - scenario-6 respectively

Meanwhile, the computation time of each method is presented in Table 3.

Table 3.
Comparison of LMNF and NMFsc based on average time processing

Scenario	Processing time (s)	
	LNMF	NMFsc
1	174.113	528.395
2	143.702	411.283
3	141.347	494.48
4	198.474	627.289
5	131.1	317.414
6	127.07	427.846
Avearage	152.634	467.785

After the performance tests, a comparison is obtained based on the average accuracy value, shown in Figure 12, and based on the average computation time, shown in Figure 13.

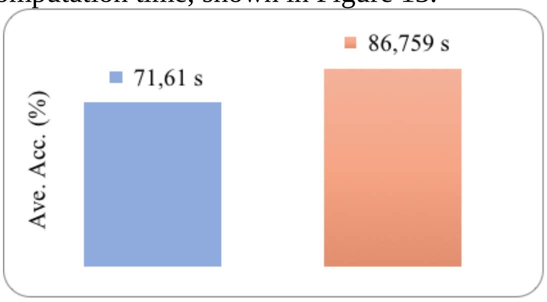


Figure 12. Performance comparison of LNMF and NMFsc methods based on accuracy

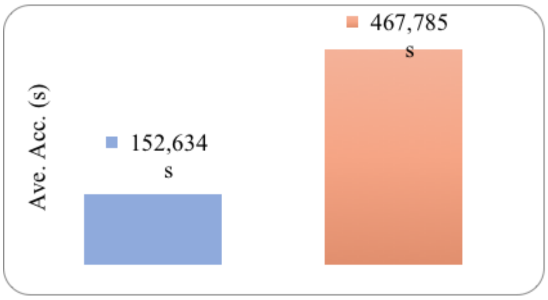


Figure 13. Performance comparison of LNMF and NMFsc methods based on computation time

By observing the comparison of the performances between the LNMF and NMFsc methods, it can be concluded that the NMFsc method has a higher average accuracy value than the LNMF method. Meanwhile, based on the average computation time, the LNMF method has a better average computation time than the NMFsc method. Light intensity and camera location affect system performance; if the camera is placed in front of the object, it will achieve a higher level of performance. In the LNMF method, the best accuracy is in condition four, namely 85.536% with a computation time of 198.474 seconds. This is achieved when the camera is placed to the right of the object with the lights on. In the NMFsc method, the best accuracy is in condition five with 98% and a computation time of 317,414 seconds, when the camera is placed to the left of the object and the lights are off.

V. Conclusion

In this study, the system of face-detection and face-recognition used in a video in the classroom was implemented. This aimed to create automatic presence detection. The video was taken with a resolution of 640 x 480 pixels in an RGB AVI format with a video frame rate of 30 FPS, and a video duration of approximately 10 seconds. The video recording process was carried out at a height of 2 meters and a distance of 1.5 meters between the object and the digital camera. The video recording process was divided into six conditions to determine the effect of light intensity. Face detection in this experiment used the Haar Cascade Classifier in Open Source Computer Vision Library (OpenCV). For facial recognition feature extraction, a comparison of the NMFsc and LNMF methods and KNN-Euclidean distance was used as a classifier. Based on the test results, the NMFsc method had an average value of 86.76%, which is better than the LNMF method, which only reached 71.61%. Based on the average computation time, the LNMF method has a better average computation time than the NMFsc method with a ratio of 1:3. However, the limitations in video acquisition process was carried either detecting a face that is looking directly at the camera or targeting the face object first. Therefore, it needs further development in the research methods for when facial conditions do not face the camera.

REFERENCES

[1] BUDI, A., SUMA'INNA, S., and MAULANA, H. (2018) Pengenalan Citra Wajah Sebagai Identifier Menggunakan Metode Principal Component Analysis (PCA). *Jurnal Teknik Informatika*, 9 (2), pp. 166-175.

[2] GAO, H., YUCE, A., and THIRAN, J.-P. (2014) Detecting emotional stress from facial expressions for driving safety. In: *Proceedings of the IEEE International Conference on Image Processing, Paris, October 2014*. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, pp. 5961-5965.

[3] ZAFEIRIOU, S., ZHANG, C., and ZHANG, Z. (2015) A survey on face detection in the wild: Past, present and future. *Computer Vision and Image Understanding*, 138, pp. 1-24.

[4] MIN, R., HADID, A., and DUGELAY, J.-L. (2014) Efficient Detection of Occlusion prior to Robust Face Recognition. *The Scientific World Journal*, 2014, pp. 1-10.

[5] DHOKE, P. and PARSAI, M.P. (2014) A MATLAB based Face Recognition using PCA with Back Propagation Neural network. *International Journal of Innovative Research in Computer and Communication Engineering*, 2 (8), pp. 5291-5297.

[6] AHMAD, R.A.R., AHMAD, M.I., ISA, M.N.M., and ANWAR, S.A. (2019) Face recognition using assemble of low frequency of DCT features. *Bulletin of Electrical Engineering and Informatics*, 8 (2), pp. 541-550.

[7] PRATIWI, D. and HARJOKO, A. (2013) Implementasi Pengenalan Wajah Menggunakan PCA (Principal Component Analysis). *Indonesian Journal of Electronics and Instrumentation Systems*, 3 (2), pp. 175-184.

[8] THARWAT, A., GABER, T., IBRAHIM, A., and HASSANIEN, A.E. (2017) Linear discriminant analysis: A detailed tutorial. *AI Communications*, 30 (2), pp. 169-190.

[9] PERDANANTI, P.F., HIDAYAT, B., and AULIA, S. (2017) HOG and ICA Based Face Recognition System on a Surveillance Video. *Far East Journal of Electronics and Communications*, 17 (5), pp. 995-1009.

[10] MANTRI, S. and BAPAT, K. (2011) Neural Network Based Face Recognition Using Matlab. *International Journal of Computer Science Engineering and Technology*, 1 (1), pp. 6-9.

[11] MANIMOZHI, M., SANGEETHA, S., MALARVIZHI, M., and NIZAR, S.M. (2014) Kernel Fisher Analysis Based Feature Extraction for Face Recognition Using Euclidean Classifier. *International Journal of Innovative Research in Computer and Communication Engineering*, 2 (11), pp. 6727-6731.

[12] RAJAPAKSE, M., TAN, J., and RAJAPAKSE, J. (2004) Color channel encoding with NMF for face recognition. In: *Proceedings of the International Conference on Image Processing, Singapore, October 2004*. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, pp. 2007-2010.

[13] DUONG, V.-H., BUI, M.-Q., and WANG, J.-C. (2019) Matrix Factorization on Complex Domain for Face Recognition. In: MAZZEO, P.L., RAMAKRISHNAN, S., and SPAGNOLO, P. (eds.) *Visual Object Tracking with Deep Neural Networks*. IntechOpen. Available from https://www.intechopen.com/books/visual-object-tracking-with-deep-neural-networks/matrix-factorization-on-complex-domain-for-face-recognition.

[14] CORSETTI, M.A. and FOKOUÉ, E. (2015) Nonnegative Matrix Factorization with Zellner Penalty. *Open Journal of Statistics*, 5 (7), pp. 777-786.

[15] RAI, A., AGARWAL, V., and USHASUKHANYA, S. (2019) Partial face recognition. *International Journal of Recent Technology and Engineering*, 8 (2S8), pp. 1581-1584.

[16] BARTKOWIAK, A.M. and ZIMROZ, R. (2015) NMF and PCA as Applied to Gearbox Fault Data. In: JACKOWSKI, K., BURDUK, R., WALKOWIAK, K., WOZNIAK, M., and YIN, H. (eds.) *Intelligent Data Engineering and Automated Learning – IDEAL 2015. IDEAL 2015. Lecture Notes in Computer Science,* Vol. 9375. Cham: Springer, pp. 199-206.

[17] ALI, H.B., POWERS, D.M.W., JIA, X., and ZHANG, Y. (2015) Extended Non-negative Matrix Factorization for Face and Facial Expression Recognition. *International Journal of Machine Learning and Computing*, 5 (2), pp. 142-147.

[18] YANG, C., LI, T., YE, M., LIU, Z., and BAO, J. (2014) A Constrained Algorithm Based NMF_{α} for Image Representation. *Discrete Dynamics in Nature and Society*, 2014, 179129.

[19] CANADAS-QUESADA, F.J., VERA-CANDEAS, P., RUIZ-REYES, N., CARABIAS-ORTI, J., and CABANAS-MOLERO, P. (2014) Percussive/harmonic sound separation by non-negative matrix factorization with smoothness/sparseness constraints. *EURASIP Journal on Audio, Speech, and Music Processing*, 2014 (26), pp. 1-17.

[20] YANEZ, F. and BACH, F. (2017) Primal-dual algorithms for non-negative matrix factorization with the Kullback-Leibler divergence. In: *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, March 2017.* Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, pp. 2257-2261.

[21] ALAM, N., SARIM, M., SHAIKH, A.B., RAFFAT, S.K., NADEEM, A., and AHSAN, K. (2015) Face Recognition Using Non-negative Matrix Factorization (NMF) An Analysis of Order of Decomposition on Recognition Rate. *Research Journal of Recent Sciences*, 4 (4), pp. 77-82.

参考文:

[1] BUDI，A.，SUMA’INNA，S.，和 MAULANA，H.（2018）脸部图像识别为标识符孟古坎线法主成分分析（PCA）。期刊技术信息，9（2），第 166-175 页。

[2] GAO，H.，YUCE，A.，和 THIRAN，J.-P.（2014）从面部表情中检测情绪压力，以确保行车安全。在：电气工程师学会图像处理国际会议论文集，巴黎，2014 年 10 月。新泽西州皮斯卡塔维：电气与电子工程师协会，第 5961-5965 页。

[3] ZAFEIRIOU，S.，ZHANG，C.，和 ZHANG，Z.（2015）野外面部检测调查：过去，现在和将来。计算机视觉与图像理解，138，第 1-24 页。

[4] MIN，R.，HADID，A。和 DUGELAY，J.-L。（2014）鲁棒的面部识别之前对遮挡的有效检测。科学世界杂志，2014，第 1-10 页。

[5] P. DHOKE 和 M.P. PARSAI。（2014）使用 PCA 和反向传播神经网络的基于 MATLAB 的人脸识别。国际计算机和通信工程创新研究杂志，2（8），第 5291-5297 页。

[6] AHMAD，R.A.R.，AHMAD，M.I.，ISA，M.N.M.，和 ANWAR，S.A.（2019）使用低频 DCT 功能的组合进行人脸识别。电气工程与信息学通报，8（2），第 541-550 页。

[7] PRATIWI，D. 和 HARJOKO，A.（2013）使用 PCA 实现人脸识别（主成分分析）。印尼电子与仪器系统杂志，3（2），第 175-184 页。

[8] THARWAT，A.，GABER，T.，IBRAHIM，A. 和 HASSANIEN，A.E.（2017）线性判别分析：详细教程。人工智能通讯，30（2），第 169-190 页。

[9] PERDANANTI，P.F.，HIDAYAT，B.，和 AULIA，S.（2017）基于猪和 ICA 的监控视频人脸识别系统。远东电子与通讯杂志, 17（5），第 995-1009 页。

[10] MANTRI，S. 和 BAPAT，K.（2011）使用 Matlab 的基于神经网络的人

脸识别。国际计算机科学工程与技术学报，1（1），第 6-9 页。

[11] MANIMOZHI，M.，SANGEETHA，S.，MALARVIZHI，M.，和 NIZAR，S.M.（2014）使用基于欧氏分类器的人脸识别的基于核费舍尔分析的特征提取。国际计算机创新研究杂志与通信工程，2（11），第 6727-6731 页。

[12] RAJAPAKSE，M.，TAN，J.，和 RAJAPAKSE，J.（2004）使用 NMF 进行人脸识别的彩色通道编码。于：2004 年 10 月在新加坡举行的国际图像处理会议论文集。新泽西州皮斯卡塔维：电气与电子工程师协会，第 2007-2010 年。

[13] DUONG，V.-H.，BUI，M.-Q。和 WANG，J.-C.（2019）复杂领域的人脸识别矩阵分解。在：MAZZEO，P.L.，RAMAKRISHNAN，S.，和 SPAGNOLO，P.（编辑.）使用深度神经网络进行视觉对象跟踪。英特网。可从 https://www.intechopen.com/books/visual-object-tracking-with-deep-neural-networks/matrix-factorization-on-complex-domain-for-face-recognition 获得。

[14] CORSETTI，M.A. 和 FOKOUÉ，E.（2015）泽尔纳点球的非负矩阵分解。打开统计杂志，5（7），第 777-786 页。

[15] RAI，A.，AGARWAL，V.，和 USHASUKHANYA，S.（2019）部分面部识别。国际最新技术与工程杂志，8（2S8），第 1581-1584 页。

[16] BARTKOWIAK，上午 和 ZIMROZ，R.（2015）NMF 和 PCA，应用于变速箱故障数据。在：JACKOWSKI，K.，BURDUK，R.，WALKOWIAK，K.，WOZNIAK，M.，和 YIN，H.（编辑。）智能数据工程和自动学习–理想 2015。理想 2015。计算机科学讲义，卷 9375. 湛：施普林格，第 199-206 页。

[17] ALI，H.B.，POWERS，D.M.W.，JIA，X。和 ZHANG，Y.（2015）扩展的非负矩阵因式分解，用于面部和面部表情识别。国际机器学习与计算杂志，5（2），第 142-147 页。

[18] YANG，C.，LI，T.，YE，M.，LIU，Z.，和 BAO，J.（2014）基于约束的 NMFα 图像表示算法。自然与社会的离散动力学，2014，179129。

[19] CANADAS-QUESADA，FJ，VERA-CANDEAS，P.，RUIZ-REYES，N.，CARABIAS-ORTI，J。和 CABANAS-MOLERO，P。（2014）非负矩阵的打击/谐音分离具有平滑/稀疏约束的分解。EURASIP 音频，语音和音乐处理期刊，2014（26），第 1-17 页。

[20] YANEZ，F. 和 BACH，F.（2017）用库尔巴克-莱布尔散度进行非负矩阵分解的原始对偶算法。于：2017 年 3 月召开的电气工程师学会国际声，语音和信号处理国际会议论文集。新泽西州皮斯卡塔维：电气与电子工程师协会，第 2257-2261 页。

[21] ALAM，N.，SARIM，M.，SHAIKH，AB，RAFFAT，SK，NADEEM，A.，和 AHSAN，K.（2015）使用非负矩阵因子分解（NMF）的人脸识别识别率分解。最近科学研究杂志，4（4），第 77-82 页。