

Date of Submission	27/10/2019
Date of Acceptance	10/12/2019
Date of Publication	31/12/2019
Page numbers	3501-3506 (6 Pages)

**Cite This Paper:** Ayman M.A., Asma H. Al-Sanhani, Abdelftah A.T., Face recognition from a partial face view by partitioning and rotating facial images, 8(12), COMPUSOFT, An International Journal of Advanced Computer Technology. PP. 3501-3506.

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An International Journal of Advanced Computer Technology

ISSN:2320-0790

## FACE RECOGNITION FROM A PARTIAL FACE VIEW BY PARTITIONING AND ROTATING FACIAL IMAGES

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**Abstract:** This paper presents a novel technique for Face Recognition from a Partial Face View (FRPV), which consists of three phases. The first phase uses an existing algorithm to detect faces in input images. The second phase includes splitting the input images undetected by the first phase into two, four, six, or eight parts. Then, every part is rotated by a new split and rotate face detection (SRFD) algorithm until it detects a face in one of these partial images. The third phase uses the Eigenfaces method with train and test databases to perform recognition. This phase compares the selected test image with images in the train database until it recognizes the person and updates the train database. The FRPV system was implemented using a head-pose image database where every person has multiple images with several poses having different Pitch and Yaw Angles ranging from  $-90^\circ$  to  $+90^\circ$ . The results showed that the FRPV system outperformed previous methods. Its accuracy rate was equal to 96% for faces that had different poses. In addition, the SRFD method achieved a detection success rate of 67%, which is better than other similar methods.

**Keywords:** Face detection, Face recognition, Viola-Jones algorithm, Eigen-faces, Face Splitting

### I. INTRODUCTION

Face recognition is a biometric pattern recognition technique often used for personal identification purposes. Other biometric recognition techniques use physiological characteristics such as fingerprint, iris, retina, hand, hand-veins, palm, voice, and ear or behavioral traits such as keystrokes, gait, and signature [1]. Face detection can be regarded as the first step in a face recognition system and it is a critical step to facial analysis algorithms such as face identification, face alignment, head tracking, and face verification. Many factors, including speed and accuracy, must be considered to develop a useful face recognition system and increase the number of recognized subjects. A face recognition system employs different modules such as

Face localization, face normalization, face feature extraction, and face matching [2,3].

Face recognition techniques may use Holistic Matching, Feature-based, or Hybrid methods. In the Holistic Matching method, the whole face region is considered as input data to the system. The approach of using Eigenfaces is commonly used in face recognition. Other face recognition methods include Principal Component Analysis, Linear Discriminant Analysis, and Independent Component Analysis. The Feature-based method extracts the local features (eyes, nose, and mouth), their locations, and local statistics. They are fed into a structural classifier. Common extraction methods include generic methods that depend on edges, lines, and curves, feature-template-based methods, and Structural Matching methods that take into consideration geometrical constraints on the features. The Hybrid Method uses both

Holistic matching methods and Feature-extraction methods and it can be applied to 3D images. It allows the system to note the curves of eye sockets and the shapes of the chin or forehead [3].

Face identification is a classification problem to determine the person who was depicted in a given image. However, the face is a dynamically varying object because facial features change over time and parameters of acquisition may affect facial imagery collected under real-world scenarios. Furthermore, facial feature points change with the orientation angle. Multiple facial images for the same person from different view angles may be obtained to solve this problem, but this process is inconvenient, time-consuming, and requires larger storage space and longer response time.

Consequently, this research proposes a system that uses and updates an existing face database, compares faces with rotated angles to the faces with front views and identifies them, finds the maximum rotation angle in any direction where the face can still be identified, and finally, recognizes faces with different rotation angles. The system will recognize head pose with varying pitch and yaw angles while other factors, such as roll angle, will not be considered in this paper. The rest of this paper is organized as follows: Section 2 discusses the related work briefly and Section 3 presents the methodology of the proposed system. Then, Section 4 discusses the experimental results followed by the analysis in Section 5. Finally, Section 6 will conclude this work.

## II. PREVIOUS WORK

Different techniques for face recognition were discussed by [3]. One challenging problem in face detection is the pose variation, where a few methods were proposed to solve this problem in arbitrary poses. Sometimes, distributed processing can provide viable solutions to speed-up face recognition [4].

[5] used face detection and recognition techniques to check students' attendance in a classroom using a camera. This system employed a neural network to store multiple-angle and different-illumination face images where angle variations ranged from  $-50^\circ$  to  $+50^\circ$  with 40 image sets and a different image feature set. Another approach [6] presented a face recognition system based on different neural network models and training algorithms and selected the method with the best performance. The drawback of these two approaches was not considering the change in angle orientation other than in the horizontal plane. Improved real-time group face-detection systems were later introduced to perform students' face detection in real-time [7,8]. The experimental results of the latter system [8] showed better real-time performance with a face detection ratio equal to 94.73%. Overall, these class-attendance systems [5,6,7,8] become less effective when implemented in an uncontrolled environment. A more robust method using neural networks for face recognition was recently developed [9]. It handles facial images taken from different

angles, but its performance is significantly lower when the Yaw and Pitch angles are large. Furthermore, neural networks often require a long training time to be effective, and usage with other domains of datasets normally requires further training.

A method was developed to improve face detection performance by rotating the facial images, but it was focused on the frontal view of the entire face [10]. A different method used a side-view input image to identify people even from their multi-angled or side-profile views [11]. Alternatively, a deep dense face detector method that depends on deep learning was presented to detect faces in a wide range of orientations using a single model [2]. It has minimal complexity because it does not require extra components for segmentation, bounding-box regression, or Support Vector Machine classifiers.

[12] applied a preprocessing step followed by the recognition steps that handle blur and illumination further. More recently, a patch-based method was proposed for face recognition using a single sample per person and a fusion strategy to perform the recognition was developed [13]. These two methods [12,13] exhibited good robustness against different types of facial variations and occlusions such as expression and illumination. However, they did not give specific attention to orientation angles.

A method based on multi-view constrained local models was proposed to solve the problem of facial feature-point detection and tracking with large head-angles [14]. The approach combined a one-shape model with response maps that were targeted at various head orientations, and it adjusted the Constrained Local Models search algorithm to allow for switching to suitable response maps.

The Viola-Jones face detection method [15] is a benchmark face-detection framework for real-time face-detection. It is based on integral images, machine learning, and cascade classifiers, and it requires full-view frontal upright-faces with up to  $30^\circ$  of yaw and  $15^\circ$  of pitch [16,17,18]. However, it was shown to be erroneous in some situations [19,20].

To reduce computational time and storage requirements, exploiting Principal Component Analysis was suggested to compress the multi-dimensional data space for face recognition using an average half-face [21]. This method used the Viola-Jones algorithm with intensity-based registration for real-time face detection and registration. The system split the face into two halves. Then, it saved the average half face to use it in the next phase and to compare the two halves with each other. Finally, the first half was the test image and the other half was the recognized image. This system only handles images in the frontal view.

This research paper aims to identify faces in head-pose images that have different Pitch and Yaw Angles. It will propose a system focused on producing good results

without adding many complex time-consuming computations.

III. PROPOSED SYSTEM METHODOLOGY

The input to the Partial Face View (FRPV) system is a head-pose image database suitable for face detection and face recognition. FRPV employs the Viola-Jones method to identify faces with different face rotation angles. The system will create a database, use it with front views, and compare rotated faces to the faces with frontal views to identify them. After that, it will find the maximum rotation angle in each direction where the face can be recognized by the system.

A. Head-Pose Image Database

The head-pose image database is a benchmark of 2790 monocular JPEG facial images of 15 persons with variations of Yaw and Pitch Angles ranging from  $-90^\circ$  to  $+90^\circ$ , courtesy of [22]. For each person, a series of 93 images are available with different poses, where the background is neutral and uncluttered. The front directory consists of 30 frontal images of persons from the database with Yaw and Pitch Angles equal to 0. When the person is looking at the bottom or at the top, the Pitch Angle is  $-90^\circ$  or  $+90^\circ$ , respectively, and the Yaw Angle is 0. Positive and negative Pitch Angles correspond to the top and bottom directions, respectively. For Yaw Angles, positive and negative values correspond to the left and right directions, respectively.

The face recognition algorithm compares the input image to the images in the database. If a match is found, the person is identified. In the FRPV system, face recognition extracts the characteristic features of the faces and represents the face as a linear combination using the Eigenfaces approach [23].

B. The Phases of the FRPV System

FRPV consists of three phases: Initial Face Detection, Split and Rotate Face Detection, and Face Identification, as described below.

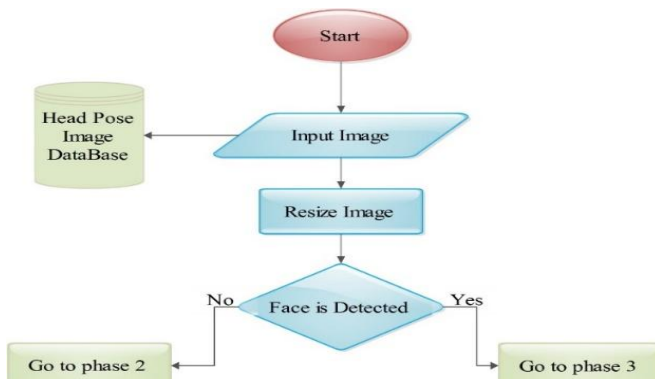


FIGURE 1. The first phase of the FRPV System

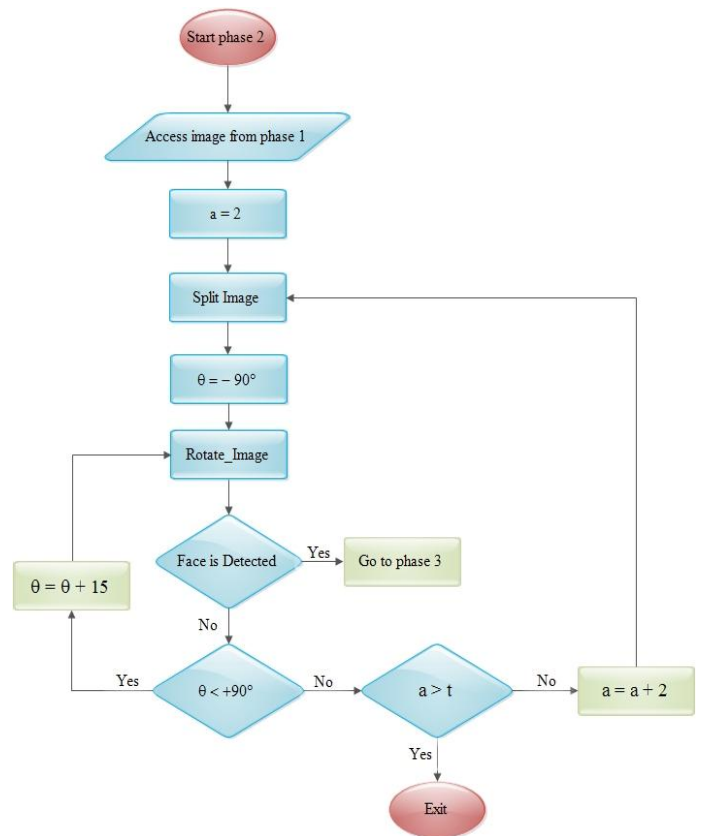


FIGURE 2. The second phase of the FRPV System: The SRFD algorithm

The first phase of FRPV, illustrated in Figure 1, employs the Viola-Jones algorithm to detect faces in images that were taken from multi-view angles where each image has non-zero Yaw and Pitch Angles. The Viola-Jones algorithm is a classical face detection method that uses signs based on Haar wavelet features, which are black and white rectangles. It generates the sum of pixel intensities in many rectangles in an image based on threshold values [24,25]. If no face is detected in this phase, the algorithm continues to the second phase; otherwise, it jumps to the third phase.

The second phase of FRPV, called Split and Rotate Face Detection (SRFD), takes each image where no faces were detected by the first phase, partitions it into parts, and then rotates each part with angles ranging from  $-90^\circ$  to  $+90^\circ$ . Figure 2 shows a flowchart of SRFD where  $a$  is the number of parts in the partition,  $t$  is the maximum number of partitions, and  $\theta$  is the rotation angle. Initially, SRFD starts with two parts and a rotation angle of  $-90^\circ$ . If no face is detected, the angle is increased until a face is recognized or the rotation angle reaches the maximum ( $+90^\circ$ ). If no face is detected yet, the original image is partitioned into more parts and the rotation steps are repeated for each part.

In the Face Identification phase, illustrated in Figure 3, the input image is compared to the images in the Train Database to determine the identity of the person with the

recognized face. If the person is identified, the Train and Test Databases are updated.

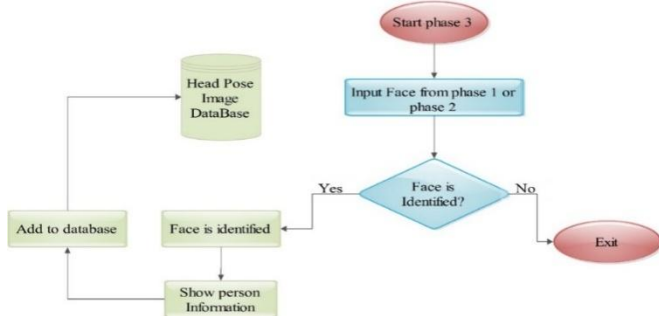
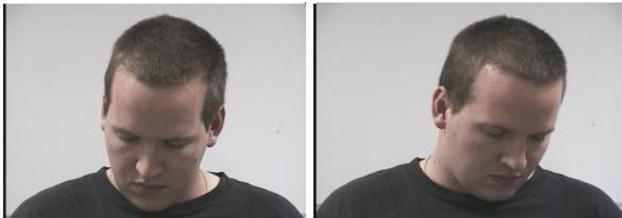


FIGURE 3. The third phase of the FRPV System

IV. IMPLEMENTATION AND DISCUSSION

The first step of FRPV attempts to detect a face in the images by using the Viola-Jones algorithm using an existing database [22] where each person has many 2D-images taken from multi-view angles. The eyes in these images are in straight lines, and each image has Pitch and Yaw Angles ranging from  $-90^{\circ}$  to  $+90^{\circ}$ . The FRPV system created a Train Database that has 480 images for many different people where each person has many images with different poses. This Train Database is used in the learning phase of face recognition, where a Test Database is used for images to be identified. The Train Database is updated by adding new images as they are identified.



(a) Detected face with Pitch  $-60^{\circ}$  and Yaw  $+30^{\circ}$   
 (b) Undetected face with Pitch  $-60^{\circ}$  and Yaw  $-15^{\circ}$

FIGURE 4. Example of the Face Detection phase



(a) Splitting an image into two parts



(b) Left half rotated by  $-15^{\circ}$  (c) Right half rotated by  $-15^{\circ}$

FIGURE 5. Example of splitting an image and rotating its parts

In the implementation of FRPV, the first phase detected 46 images with different Pitch and Yaw Angles. Figure 4 shows two sample input images used by FRPV. The image in Figure 4 (a) has Pitch and Yaw Angles of  $-60^{\circ}$  and  $+30^{\circ}$ , respectively, where the Viola-Jones algorithm detected a face in this image. However, the image in Figure 4 (b) has Pitch and Yaw Angles of  $-60^{\circ}$  and  $-15^{\circ}$ , respectively, and the Viola-Jones Algorithm failed to detect a face in it. Generally, the Viola-Jones algorithm performed well as a part of the FRPV system. Table 1 lists the Pitch and Yaw Angles of the test images where faces were detected in this phase. The overall Pitch angles for the detected faces ranged from  $-60^{\circ}$  to  $+60^{\circ}$ , whereas the Yaw Angles for the detected faces ranged from  $-45^{\circ}$  to  $+75^{\circ}$ .



(a) Sample image (b) Identified image

FIGURE 6. A selected sample image and the corresponding identified image

In the second stage (SRFD), each image undetected in the first stage was divided into two parts (left and right halves) and the parts were rotated with angles ranging from  $-90^{\circ}$  to  $+90^{\circ}$ , as shown in the example in Figure 5. The overall test results showed that splitting the image into more than two parts did not increase the number of recognized images. Therefore, only the results for splitting each image into two parts will be reported. Table 2 lists the image numbers of some images with faces detected in the second phase. The implementation results for all test images after the second phase of FRPV showed that faces with larger Pitch and Yaw Angles have been recognized. The Pitch Angles for recognized images ranged from  $-60^{\circ}$  to  $+90^{\circ}$  and Yaw Angles ranged from  $-90^{\circ}$  to  $+90^{\circ}$ . An example test image is shown in Figure 6 (a), where it was selected as one of the images used in the previous phases and it was not in the Train Database at that time.

To recognize a test image, the FRPV system uses the Eigenfaces method to compare this image to images in the Train Database, as shown in the example of Figure 6. If the image is identified, the system shows the personal information of the identified image. Test results showed that the FRPV system performed considerably better than other systems in terms of identification. Table 3 compares the recognition rate achieved by the FRPV system to those of the Face-Splitting system.

TABLE: I. Pitch and Yaw Angles for Some Test Images with Detected Faces

No.	1	2	3	4	5	6	7	8	9
Pitch	-60	-60	-30	-30	-30	-30	-30	-30	-30
Yaw	30	45	-15	0	15	30	45	60	75
No.	10	11	12	13	14	15	16	17	18
Pitch	-15	-15	-15	-15	-15	-15	-15	0	0
Yaw	-30	-15	0	15	30	45	60	-30	-15

TABLE: II. Pitch and Yaw Angles for Some Test Images with Faces Detected in Rotated Parts

No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Pitch	-60	-60	-15	15	15	15	30	30	30	60	60	60	60	60	60
Yaw	-15	0	75	-60	-45	75	-90	-75	-60	-90	-75	-60	-45	75	90

TABLE: III. Comparison Between the FRPV and Face-Splitting Systems

Systems	Full-Face	Half-Face	Face from Multi-View Angles
FRPV	98%	98%	96%
Face-Splitting [21]	92%	96%	< 20%

TABLE: IV. Comparison of FRPV/SRFD with Other Methods

Method	Faces Detected	Faces Undetected	Pitch & Yaw Range	Recog. Rate
FRPV/SRFD	62	31	-90°, +90°	67%
Viola-Jones [15]	46	47	+75°, -60°	49%
Face Part Detection [10]	42	51	+75°, -30°	45%
Real-Time Group Face-Detection [8]	25	68	+60°, -30°	27%

The SRFD method (i.e., the second phase of FRPV) was tested with 93 images that were not recognized by the first phase. The performance results of the proposed SRFD method, compared to other systems, are given in Table 4. As seen in the table, SRFD outperformed the other methods in terms of recognition rate and in the ranges of Pitch and Yaw Angles.

V. ANALYSIS

The FRPV system consists of three phases used for identifying a person from a partial face view. The first phase detects a face in the image using the Viola-Jones algorithm and if there are any images with no detected faces, they are sent to the second phase. The second phase, namely SRFD, splits each undetected image into two parts and rotates each part by angles ranging from -90° to +90°. The images with faces detected in the first and second phases are used by the FRPV system to identify the person in the third phase by comparing them with images in the database. If the FRPV system identifies the person, it inserts the recognized image into the database of identification images.

The FRPV system was implemented and compared to other systems to demonstrate its advantages. The FRPV system identification ratio was 98% for half-face, 98% for full-face and 96% for the face from multi-view angles. Finally, the implementation of the proposed SRFD method demonstrated that it out-performed other techniques especially with wider ranges of Yaw and Pitch Angles. The overall detection success rate of FRPV with SRFD was 67% while the other success rates were 49% for Viola-

Jones Face Detection [15], 47% for Face-Part Detection [10], and 27% for Real-Time Group Face Detection [8].

VI. CONCLUSIONS AND FUTURE WORK

This paper presented a new face recognition system. First, it applies an existing technique to detect faces. Then, it splits each undetected image into two halves and rotates them until detection is achieved. Finally, recognition of the detected face is performed and the face database is updated. Implementation results demonstrated the efficacy of this system and showed that it outperformed existing systems.

For future work, the FRPV system could be improved by increasing the identification rate for facial images obtained from multi-view angles, applying FRPV to video sequences, and working with three-dimensional images. For more advanced work, the system may be enhanced to detect face morphing and blending. However, this challenging topic may require more innovative solutions since it is still in its early stages [26].

VII. REFERENCES

- [1] Ibrahim, D.R., Tamimi A.A. and Abdalla, A.M.2017.“Performance analysis of biometric recognition modalities,” *In the 8<sup>th</sup> International Conference on Information Technology, Amman, Jordan.* DOI: 10.1109/ICITECH.2017.8079977
- [2] Farfade, S.S. and Saberian, M., Li, L.-J.2015.“Multi-View Face Detection Using Deep Convolutional Neural Networks,”*Proceedings of the 5<sup>th</sup> ACM on International Conference on Multimedia Retrieval*, pp.643-650.DOI: 10.1145/2671188.2749408
- [3] Naik,R. and Lad, K.2016.“A Review on Side-View Face Recognition Methods,”*International Journal of Innovative Research in Computer and Communication Engineering*, vol.4, no.3, pp.2943-2991. DOI: 10.15680/IJIRCC.2016.0403015

- [4] Hirayama, K. and Saiki, S., Nakamura, M. 2019. "Developing Real-Time Face Identification Device Composable with Distributed Applications." In: Duffy, V. (ed) *Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management. Human Body and Motion. HCII 2019. Lecture Notes in Computer Science*, vol.11581, pp.420-432. DOI: 10.1007/978-3-030-22216-1\_31
- [5] Kato, H., Chakraborty, G. and Chakraborty, B. 2012. "A Real-Time Angle- and Illumination-Aware Face Recognition System Based on Artificial Neural Network," *Applied Computational Intelligence and Soft Computing*, vol.2012, Article ID 274617, 9 pages. DOI: 10.1155/2012/274617
- [6] Al-Allaf, O.N., Tamimi, A.A. and Alia, M.A. 2013. "Face recognition system based on different artificial neural networks models and training algorithms," *International Journal of Advanced Computer Science and Applications*, vol.4, no.6, pp.40-47. DOI:10.14569/ijacsa.2013.040606
- [7] Alia, M.A., Tamimi, A.A. and Al-Allaf, O.N.A. Dec. 2013. "Integrated System for Monitoring and Recognizing Students During Class Session," *International Journal of Multimedia & Its Applications*, vol.5, no.6, pp.45-52. DOI: 10.5121/ijma.2013.5604
- [8] Tamimi, A.A., AL-Allaf, O.N.A. and Alia, M.A. 2015. "Real-Time Group Face-Detection for an Intelligent Class-Attendance System," *International Journal of Information Technology and Computer Science*, vol.6, pp.66-73. DOI: 10.5815/ijitcs.2015.06.09
- [9] Ranjan, R., Bansal, A., Zheng, J., Xu, H., Gleason, J., Lu, B., Nanduri, A., Chen, J.-C., Castillo, C.D. and Chellappa, R. April 2019. "A Fast and Accurate System for Face Detection, Identification and Verification," In *IEEE Transactions on Biometrics, Behavior, and Identity Science*, vol.1, no.2, pp.82-96. DOI: 10.1109/TBIOM.2019.2908436
- [10] Masayuki Tanaka (2019). Face Parts Detection (<https://www.mathworks.com/matlabcentral/fileexchange/36855-face-parts-detection>), MATLAB Central File Exchange. Retrieved October 12, 2019.
- [11] Naik, R.K. and Lad, K.B. 2017. "Human Recognition from Multi Angled Images," *International Conference on Research and Innovations in Science, Engineering & Technology*, ICRISSET2017 (Kalpa Publications in Computing), vol.2, pp.1-12. <https://easychair.org/publications/open/JtJQ>
- [12] Pearlina, S.A. and Hemalatha, M. 2016. "Face Recognition Under Varying Blur, Illumination and Expression in an Unconstrained Environment," *CIC 2016 Special Issue International Journal of Computer Science and Information Security*, vol.14, pp.48-54. <https://arxiv.org/ftp/arxiv/papers/1902/1902.10885.pdf>
- [13] Pang, M., Cheung Y., Wang, B. and Liu, R. 2019. "Robust heterogeneous discriminative analysis for face recognition with single sample per person," *Pattern Recognition*, vol.89, pp.91-107. DOI: 10.1016/j.patcog.2019.01.005
- [14] Rajamanoharan, G. and Cootes, T.F. Dec. 2015. "Multi-View Constrained Local Models for Large Head Angle Facial Tracking," *2015 IEEE International Conference on Computer Vision Workshop (ICCVW)*, Santiago, pp.971-978. DOI: 10.1109/ICCVW.2015.128
- [15] Viola, P. and Jones, J. 2001. "Robust Real-time Object Detection," *Technical Report CRL 2001/01*, Cambridge Research Laboratory. <https://www.hpl.hp.com/techreports/Compaq-DEC/CRL-2001-1.pdf>
- [16] Barnouti, N.H., Al-Dabbagh, Muhammed, S.S.M. and Al-Bamarni, H.J. Sept. 2016. "Real-Time Face Detection and Recognition Using Principal Component Analysis (PCA) – Back Propagation Neural Network (BPNN) and Radial Basis Function (RBF)," *Journal of Theoretical and Applied Information Technology*, vol.91, no.1. ISSN: 1817-3195.
- [17] Troitsky, A. 2016. "Two-Level Multiple Face Detection Algorithm Based on Local Feature Search and Structure Recognition Methods," *International Journal of Applied Eng. Research*, vol.11, no.6, pp.4640-4647.
- [18] Yang, S., Luo, P., Loy, C.C. and Tang, X. 2016. "Wider Face: A Face Detection Benchmark," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, pp.5525-5533. DOI: 10.1109/CVPR.2016.596
- [19] Islam, M., Naeem, A. and Hasan, N. May 2017. "Comparison between Viola-Jones and KLT Algorithms and Error Correction of Viola-Jones Algorithm," *International Journal of Computer Engineering and Applications*, vol.11, no.5. ISSN 2321-3469.
- [20] Orozco, J., Martinez, B. and Pantic, M. 2015. "Empirical analysis of cascade deformable models for multi-view face detection," *Image and Vision Computing*, vol.42, pp.47-61. DOI: 10.1016/j.imavis.2015.07.002
- [21] Shehzad, M.I., Awais, M., Amin, M. and Shah, Y.A. 2014. "Face Recognition Using Average Half Face Template," *International Journal of Technology*, vol.2, pp.159-168. DOI: 10.14716/ijtech.v5i2.408
- [22] Gourier, N., Hall, D. and Crowley, J.L. 2004. "Estimating Face Orientation from Robust Detection of Salient Facial Features," *Proceedings of Pointing 2004, ICPR, International Workshop on Visual Observation of Deictic Gestures*, Cambridge, UK.
- [23] Tamimi, A., AL-Allaf, O.N.A. and Alia, A. Feb. 2015. "Eigen Faces and Principle Component Analysis for Face Recognition Systems: A Comparative Study," *International Journal of Computers & Technology*, vol.14, no.4, pp.5650-5660. DOI:10.24297/ijct.v14i4.1967
- [24] Khryashchev, V.V., Lebedev, A.A. and Priorov, A.L. 2017. "Enhancement of Fast Face Detection Algorithm Based on A Cascade of Decision Trees," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol.42, no.2/W4, pp.237-241. DOI: 10.5194/isprs-archives-XLII-2-W4-237-2017
- [25] Soni, L.N., Datar, A. and Datar, S. Sept./Oct. 2017. "Implementation of Viola-Jones Algorithm Based Approach for Human Face Detection," *International Journal of Current Engineering and Technology*, vol.7, no.5, pp.1819-1823. E-ISSN 2277 – 4106.
- [26] Scherhag, U., Rathgeb, C., Merkle, J., Breithaupt, R. and Busch, C. 2019. "Face Recognition Systems Under Morphing Attacks: A Survey," *IEEE Access*, vol.7, pp.23012-23026. DOI: 10.1109/access.2019.2899367