Ain Shams Engineering Journal 9 (2018) 2917–2929

Contents lists available at ScienceDirect

Ain Shams Engineering Journal

journal homepage: www.sciencedirect.com

Multimodal student attendance management system (MSAMS)

Khaled Mohammed [a,*], A.S. Tolba [a], Mohammed Elmogy [b,c]

[a] Computer Science Department, Faculty of Computers and Information, Mansoura University, Egypt
[b] Information Technology Department, Faculty of Computers and Information, Mansoura University, Egypt
[c] Bioengineering Department, University of Louisville, Louisville, KY 40292, USA

ARTICLE INFO

Article history:
Received 10 January 2018
Revised 21 July 2018
Accepted 5 August 2018
Available online 7 November 2018

Keywords:
Student attendance management
Radio Frequency Identification (RFID)
Face detection and recognition
Near Field Control (NFC)
Multimodal person identification (MPI)
Multi-scale structure similarity index (MS-SSIM)

ABSTRACT

Effective student attendance management in higher educational institutions represents a big challenge for faculty members that need fast and accurate approaches. The traditional attendance manual approach is prone to spoofing and wasting a lot of faculty/students time and poor accuracy especially in the case of large student numbers. This paper presents an effective solution for the real-time student attendance management problem in large lecture halls. Fast response time and high accuracy imply using high-speed technologies and processes for student identification. In this paper, Radio Frequency Identification (RFID) and novel face recognition and identification approaches have been proposed and evaluated. A multimodal approach for student identification combined the power of both the traditional RFID approach and Multi-Scale Structural Similarity (MS-SSIM) index. Capturing the authentic face variability from a sequence of video frames has been considered for the recognition of faces and resulted in system robustness against the variability of facial features. Experimental results indicated an improvement in the performance of the proposed system compared to the state-of-the-art approaches at a rate between 2% and 5%. In addition, it decreased the time three times if compared with the state-of-the-art techniques, such as Extreme Learning Machine (ELM). Finally, it achieved an accuracy of 99%.

© 2018 Production and hosting by Elsevier B.V. on behalf of Ain Shams University. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

The emergence of the high-speed developing field – Internet of things (IoT) and its applications in all areas, especially in education, are a big challenge for Educational Institutions (EIs). Smart universities aim at improving both student satisfaction and business processes by focusing on Educational Business Intelligence (EBI). EBI is becoming crucial for the advancement of EIs. EBI is a data-driven approach to higher education provision. EBI is gaining increased attention with the evolution of data science and will help innovation, staying at the forefront of competition and enhances productivity. Educational Data Analytics (EDA) needs new methods for mining the massive amounts of data generated by educational institutions. EDA turns big EI data into actionable insights and intelligence. It will enhance the overall EIs performance by supporting organizational decision-making, management, and strategic planning by providing the basis for the following potential benefits [1–3]:

- Easy access to information and key performance indicators (KPIs).
- Data archiving, management and processing.
- Fast operations and evidence-based decision making.
- Seamless administration of all EI activities.
- Enhancing the educational and learning processes.
- Easy reporting.
- Trend analysis.
- Predictive modeling for forecasting and optimizing educational processes.
- Prescriptive analysis for setting a future vision.
- Management of Student Engagement (MSE).
- Benchmarking and predicting student performance against their engagement patterns.
- Early warning for at-risk students helps timely intervention before it becomes too late.
- Analysis and prediction of engagement patterns of different student groups (e.g., culture, ethnicity, age, etc.).
- Providing the senior management team with BI dashboard visualization.

* Corresponding author.
E-mail addresses: khaled.alburaihi@gmail.com (K. Mohammed), ast@astolba.com (A.S. Tolba), melmogy@mans.edu.eg (M. Elmogy).
Peer review under responsibility of Ain Shams University.

Production and hosting by Elsevier

https://doi.org/10.1016/j.asej.2018.08.002
2090-4479/© 2018 Production and hosting by Elsevier B.V. on behalf of Ain Shams University.
This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

- Improving student retention.
- Providing a comprehensive real-time reporting system.
- Improving teaching and learning effectiveness by streamlining operations.
- Maximizing operational effectiveness.
- Learning Analytics.
- Academic Analytics.
- Ensuring transparency for all stakeholders.
- Providing better feedback to students.
- Tracking organization performance against its mission.

This research is motivated by the need forEIs to design and implement robust systems for student identification and student attendance management. The major challenge is the design and implementation of a system, which can identify hundreds of student in real time using fast identification approaches, such as Radio Frequency Identification (RFID) and face recognition irrespective of the variability facing such a system. Tag identification usually happens in real time but faces the problems of multiple readings, reading unregistered tags (UTs), and reading outside the scope of regular reading "noise." Facial expression, pose variability, and variability of lighting conditions impose a big challenge for face recognition.

The RFID and face recognition modalities are found to be more suitable for educational settings due to many reasons:

1. The invasiveness and single purpose system of fingerprint render face biometrics better in addition to being used in proctoring in exam halls.
2. Possible use of face recognition in behavior analysis and monitoring during exams. Table 1 shows the comparison between the most common biometric identification technologies.

The major contributions of this paper are summarized as follows:

Multi-rate/modal identification of students.
Analysis of using multiple modalities (Face Recognition and RFID) and algorithms to quantitatively increase the recognition system performance in a way to avoid spoofing and harnessing the power of video image sequence liveness to capture more variability and hinder spoofing.
Improving system performance through a blend of recognition using HaarCascade+ PCA and verification using MS-SIM.
Solving the Tag collision problem in RFID.

2. Related work

2.1. Overview of educational business intelligence 3.0

The proliferation of IoT sensors and devices has gained huge interest in all fields. It led to a new emerging wave of higher education (Smart Education) or Education 3.0, which relies on business intelligence 3.0 and business analytics 3.0 to deliver smart outcomes. The number of smartphones and tablets surpassed the number of PCs and laptops in 2011 according to the Economist reports. The IoT capabilities enable mobile edge computing at large scale and add context and location awareness. They offer opportunities for action research, which will enhance the personalized advising, learning, and engagement. This section sheds light on the myriad of possibilities, which could improve educational business through mobile business intelligence (MBI).

Table 1
The comparison between the most common biometric identification technologies.

Technology/characteristic	Face recognition	Fingerprint
Ergonomic aspect	Non-invasive	Invasive
Cost	Medium cost and Multi-purpose	Medium costa Single purpose
Reliability	Very high	High
Social acceptability	High	Very High
Accuracy	High	Very high
Spoofing (Creating a fake biometric)	Very difficult	Very easy
Behavior analysis	Possible (dynamic)	Impossible

Akinduyite et al. [4] proposed a student attendance management system (SAMS) that is based on fingerprints. It is presented as a form of biometric identification that is unique and does not change in one's entire lifetime. The system consists of an enrollment phase and authentication phase. Minutiae points are extracted using ridge endings and bifurcations using the crossing number (CN) method. A Minutiae Score Matching (MSM) method was used for fingerprint recognition. The highest system accuracy is reporting 97.4% correct verification. The authentication phase required 4.29 s. The major advantage of fingerprint-based authentication is the impossible impersonation, but its invasiveness is not desirable.

Somasundaram et al. [5]designed and developed an android based mobile attendance management system. The system problem is that each student has to have a mobile phone. An SMSis sent to the parents for notification about absence cases.

Lodha et al. [6] proposed a SAMS that is based on using Bluetooth smart wireless technology using electronic tags to facilitate automatic wireless identification, with a Bluetooth smart enabled device. Each student has his Bluetooth low energy (BLE) tag, which is sensed by an android application via Bluetooth. Every student is given a particular tag, which can then be detected by the application. The students' tag IDs are registered in a student database. To avoid tags from outside the class, the application works within a limited range.

Bae and Cho [7] used the BLE 4.0 technology for designing and implementing a SAMS. Beacons are used to check students' attendance when they enter lecture halls. A beacon transmits its identifier information in the lecture hall, then the student's smart devices recognize this through an application and report their attendance to a local server.

Park and Moon [8] presented an RFID based SAMS. Students' tags are sensed by the RFID reader's antenna. RFID systems are subject to some problems, such as reader collision, tag collision, high cost, tag loaning, dishonesty, loss, and forgotten tags in addition to security challenges. Students can also leave the lecture hall without actually attending the lecture.

Ramakrishnan and Ramakrishnan [9] presented a fingerprint system for SAM that reconstructs the phase image of the minutiae. Lee [10] used a self-organizing map for attendance management based on face recognition.

Duncan [11] implemented the SAM using clickers, but the cost of clickers is a problem in addition to loaning problems. Quizzing and performing fast questionnaires through clickers is an advantage, but all these functions could be done using a smartphone. Table 2 gives a summarized comparison between the different SAMSs.

2.2. Overview of face detection and recognition

There are many approaches in the literature for face detection and recognition, such as Principal Component Analysis (PCA) [12–14], Support Vector Machines (SVM) [15,16], Local Binary Patterns (LBP) [17,18], Local Binary Pattern Histogram (LBPH) [19], Independent Component Analysis (ICA) [20,21], EigenFaces [22], and Linear Discriminant Analysis (LDA) [23,24]. Face detection and recognition is one of the most challenging problems until the moment. Unfortunately, there is no single technique, which is capable of face detection and recognition with 100% performance. This

Table 2
The comparison between different SAMSs.

System/Pros & Cons	Manual	RFID	Fingerprint	Bluetooth Smart	Beacons	NFC	Clickers	Multimodal
Efficiency	Low	Medium	High	High	High	High	High	Very High
Power consumption	NA	Low	Low	Low	Low	Low	High	Medium
Cost	N/A	Medium	Medium	Low	Low	Low	High	Medium
Spoofing/Impersonation	Possible	Possible	Impossible	Possible	Possible	Possible	High	Impossible
Data transfer rate	Low	Medium	Medium	High	Medium	Low	High	Medium
Time	High	Low	Medium	Low	-Time savings over paper registers -Cost savings over swipe card systems	Low	Low	Low
Internet or power connection	N/A	Needed	Needed	Needed	No need	Needed	Needed	Needed
Needed students Smartphone	No	No	No	Yes	Yes	Yes	No	__
Needed support from academic staff	Yes	No	No	No	No	No	Yes	No
Overall performance	Very Low	Medium	Medium	High	High	Medium	Medium	Very High

problem is due to many reasons, such as the distance between the face and the camera, poor lighting conditions, the difference of size captured images, and technical aspects, such as weakness of camera resolution. In this research, suitable techniques are presented and tested to improve detection and recognition results after the extraction of invariant features.

Chintalapati and Raghunath [25] evaluated and compared to five different approaches to holistic face recognition. It has been concluded that LBPH with Distance Classifier is the best algorithm that gives the best results. Performance evaluation conditions for the different approaches are summarized in Table 3 [15]:

2.3. Overview of RFID identification systems

Bai et al. [26–28] proposed a new method, which uses a sliding window for de-noising. This method has a low occurrence rate. It used the FIFO queue "win-buffer" to solve the problem and store the data. The method used a threshold of ID values to reduce noise. The performance of this method has been studied under different noise ratios. Each tag is repeated ten times, within 200 ms, the overall tag arrival rate is 1/sec. The differently tested noise ratios have been between 1 and 50%. The output readings are not in correct time order.

Bai et al. [26] proposed effective and efficient algorithms for RFID data filtering. These approaches included noise removal and duplicate elimination. They developed algorithms that are compared to baseline implementation and worked more efficiently. They require less buffer space for history storage to reduce noise and eliminate duplicates. The performance is dependent on the average rate of the tag. The highest rate of readings arrived is 1000 tags/sec, but the readings rate after 500 readings/sec got the large delays.

Mahdin et al. [29] proposed a de-noising algorithm that used the count-threshold and time-threshold parameters. It indicated the number of frequent reading and time set for the number of frequent reading that should be achieved in order. The proposed technique keeps the recent readings of the tags in the list and calculates the length of time by the difference between the initial time and the latest time of reading the tag. The performance of the proposed technique reduced the processing time from 0.308 s to 0.125 s, and the algorithm has performed well under the different arrival rates. Every tag has repeated the reading ten times. The applied noise ratio lied between 10% and 50%. Therefore, the noise ratio is very high. In addition, they proposed de-noising with duplicates elimination algorithm to improve performance and get rid of redundancy. The algorithm has studied output reading while checking the reading that has been outputted before. If the reading has not been outputted before then, state the output as true and no duplication. Otherwise, delete the reading. The performance of the algorithm is focused on small lists of distinct readings. The results showed increment in processing time whenever the arrival rate increased.

Roozbeh et al. [30] proposed a method that processed data to improve performance and get rid of the redundancy. The method keeps an initial timestamp for all existing items that were detected in the reader area. They compared between the initial timestamp for all RFID tags existing and the tags that are coming after each reading. If RFID reader got any difference with the existing one, the difference explains that the RFID reader has added the tag to the list of readings or removed the tag from the reader area. The method cannot work well with passive RFID tags because of the occurrence of false readings.

Kamaldin et al. [31] proposed a method for processing duplicate data. The method modified the Bloom approach for improving the performance. The approach used a single hash function. They compared their results with previous approaches, which are Bloom filter and d-left time bloom filter. The results have shown that filtering redundant data is better than other approaches in the different types of processing, such as true positive rate, false positive rate, and execution time. The Bloom approach is very complex and needs much processing time [32].

Peng et al. [33] proposed an approach, which uses multiple RFID tag readers that are used for cleaning the false negative and false positive readings. The idea of this approach is the RFID system

Table 3
A comparison of holistic face recognition algorithms [14].

Performance evaluation metrics	PCA + Distance classifier	LDA + Distance classifier	PCA + SVM	PCA + Bayes	LBPH + Distance classifier
False positive rate	55%	53%	51%	52%	25%
Distance of object for correct recognition	7 feet	7 feet	7 feet	7 feet	4 feet
Training time (ms)	1081	1234	24,570	29,798	563
Recognition rate (static images)	93%	91%	95%	94%	95%
Recognition rate (real time video)	61%	58%	68%	65%	67%
Recognition of occluded faces	2.5%	2%	2.8%	2%	2.3%

compares the current reading with the reading from the previous reader and the next reader if the reading is the same then the reading is correct. Otherwise, the reading is false, and the reader will be corrected when the current tag is read during both previous and next readings. Otherwise, the reading will be removed from the list. The approach did not work when using only one RFID reader.

3. The proposed sams modules

Fig. 1 shows the modules of SAMS. In Fig. 2, the enhanced detection and recognition approaches have been implemented to solve the problem of face recognition using both HaarCascade (HC) and PCA algorithms. The problems of the variability of face pose relative to the camera and facial expression variability are solved by processing a sequence of 16 successive video frames from the live video for more accurate face recognition.

3.1. Enhanced HaarCascade based face detection module

Haar-like features are extracted by convolving image blocks with Haar-like templates, which emphasize details in the image. The images are normalized to compensate for variation in lighting conditions. Low variance imagesare considered irrelevant as they do not include significant information.

The used templates are inspired by the way Haar basis functions were used for image transformation. A template-based feature is calculated as the difference between the sum of pixels in the black areas from the sum of pixels in the white areas, which emphasizes edges and regions of interest. Horizontal and vertical regionsare usually used in template design. To efficiently compute the sum of region pixels in area sub-images, the integral image *IM* at location $(i,j)$is calculated according to the following formula, as shown in Fig. 3 [34]:

$$IM(i,j) = \sum\nolimits_{m \le i, n \le j} I(m,n), \tag{1}$$

Eq. (1) represents the sum of the pixels above and to the left of i, j and I is the original image. To calculate the integral image IM at location(i, j)in one pass, the Eqs. (2) and (3) are used [35]:

$$ars(i,j) = ars(i,j-1) + I(i,j) \tag{2}$$

$$IM(i,j) = IM(i-1,j) + ars(i,j) \tag{3}$$

where $ars(i,j)$ is the accumulative raw sum.

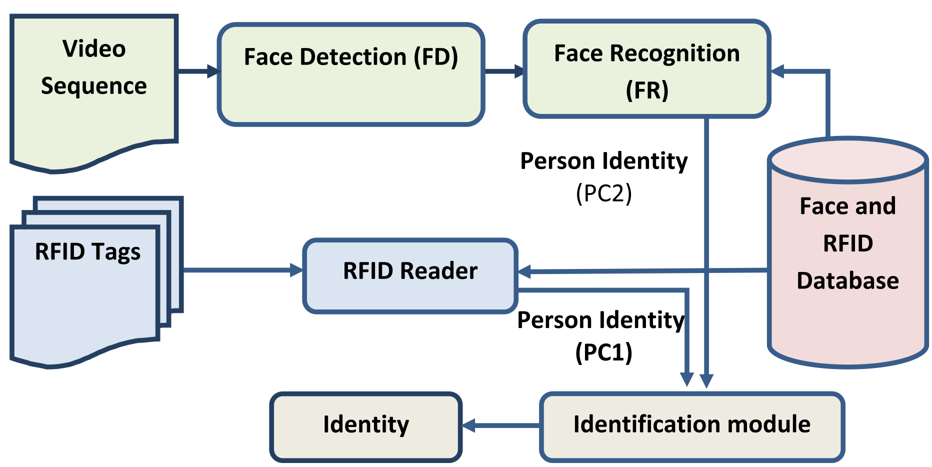


Fig. 1. The multimodal student identification system.

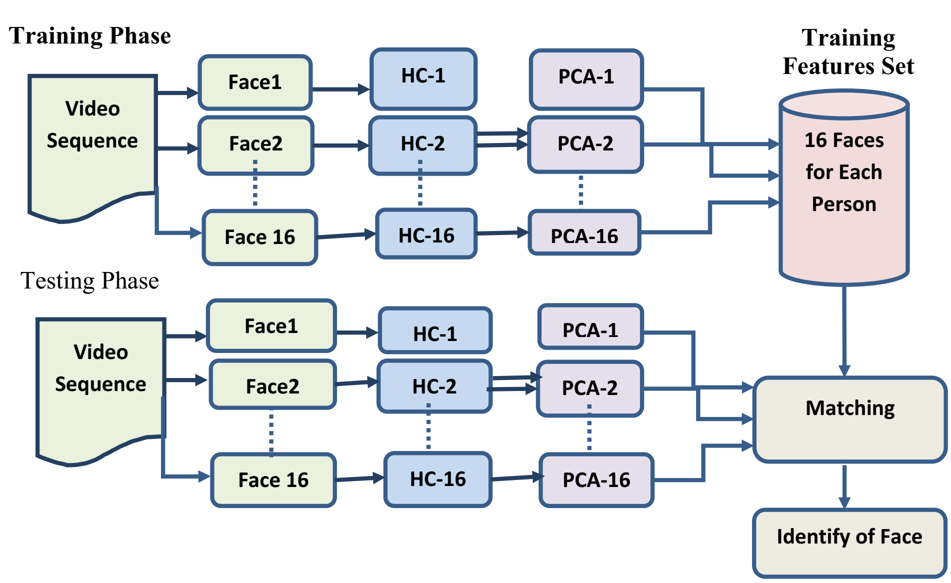


Fig. 2. The layout of enhanced face detection and recognition phases using both HaarCascade and PCA.

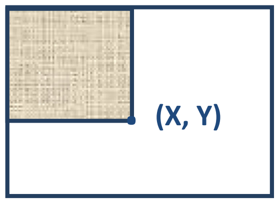


Fig. 3. The value of the integral image at point (i, j) is the sum of all the pixels above and to the left [34].

The sum of the pixels, which lie within the white rectangles, is subtracted from the sum of pixels in the gray rectangles. Figs. 4 and 5 show the possible template shapes for calculating rectangle features. Two-rectangle features are shown in (A) and (B). Figure (C) shows a three-rectangle feature, and (D) a four-rectangle feature.

Algorithm 1. Integral Image [35]

Input: an image Iof size N ×M.
Output: its integral image IM of the same size.
1. *Set IM(1, 1) =I (1, 1).*
2. *For i = 1 to N do*
3. *For j = 1 to M do*
4. $IM(i,j) = I(i,j) + IM(i,j-1)$ $-IM(i-1,j) + IM(i-1,j-1)$ *andIM is defined to be zero whenever its argument* (i,j) *ventures out ofI's domain.*
5. *End For;*
6. *End For;*

3.2. PCA based face recognition module

The training set R of 2D images is first converted into set one-dimensional vectors, which are constructed by row concatenation resulting in an image space:

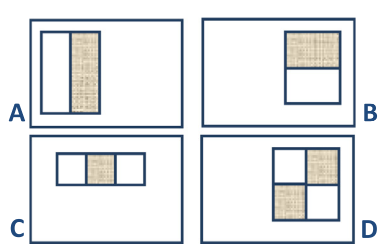


Fig. 4. An example rectangle features shown relative to the enclosing detection window [34].

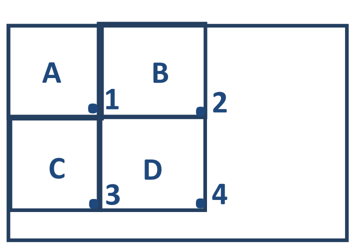


Fig. 5. The sum of the pixels within rectangle D can be computed with four array references A–D [34].

$$X = (X_1, X_{2,} \cdots, X_R) \in \Re^{D\times R} \quad (4)$$

where $X_i = (X_{i1}, X_{i2}, \cdots, X_{iD})$ are the concatenated rows of the i^{th} reference image. D = m × n is the pixels of a reference vector. R is the number of reference images in the training set. The covariance matrix C is then calculated for X according to the formula [36]:

$$C = \frac{1}{R}\sum_{i=1}^{R}(X_{i-}\bar{X})(X_{i-}\bar{X})^T = \phi\phi^T \quad (5)$$

where $\phi = (\phi_{1,}\phi_{2,}\cdots,\phi_R) \in \Re^{D\times R}$ and $\bar{X} = \frac{1}{R}\sum_{l=1}^{R}(X_i)$, which is the mean image of the training set. The eigenvalues and eigenvectors are then calculated from C. The r eigenvectors corresponding to the non-zero largest eigenvalues are then considered as the reference set of eigen faces given by $Q = (Q_{1,}Q_{2,}\cdots,Q_R) \in D \times R\Re$.

The Eigenface based features for an image of the training set is obtained by projecting that image on the eigenspace as follows [36]:

$$Z_i = Q^T Y_i, i = 1, 2, \cdots, R \quad (6)$$

where Y_i is the mean-subtracted image of X_i.

To classify a new test image, it should be first projected on the eigenspace constructed from the training set. Then, the resulted feature vector is fed into a pre-trained classifier for face recognition. Fig. 2 shows the multimodal person identification system based on enhanced HaarCascade, PCA, and RFID. Video sequence drove real-time variability, and virtual variability driven by the cascade strategy itself has been implemented to enhance system performance.

3.3. MS-SSIM based face detection and recognition

Wang et al. [37] proposed a multi-scale structural similarity (MS-SSIM) index for image quality assessment incorporating the variations of viewing conditions, such as luminance, contrast and structure in addition to the image sampling density, and distance from the observer. Multiple scales have been introduced to solve the problems imposed by the sampling resolution and distance from the observer. The MS-SSIM index between two images *x* and *y* is calculated according to the following formula [38]:

$$\boldsymbol{MS-SSIM}(\boldsymbol{x},\boldsymbol{y}) = [l_M(\boldsymbol{x},\boldsymbol{y})]^{\alpha_M}.\prod_{j=1}^{M}[c_j(\boldsymbol{x},\boldsymbol{y})]^{\beta_j}.[s_j(\boldsymbol{x},\boldsymbol{y})]^{\gamma_j} \quad (7)$$

whereα_M, β_j, and γ_j are the relative weights of the luminance l(x, y), contrast c(x, y) and structure s(x, y),respectively. For more details, please refer to [37]. To the authors' knowledge, this paper presents the first application of the MS-SSIM for face recognition in real-time, as shown in Fig. 6. The MS-SSIM index between stored face templates and the tested face is calculated. The most similar face according to the MS-SSIM identifies the person. To ensure that the face to be recognized by the system is a live face, motion detection has also been implemented using MS-SSIM.

3.4. MS-SSIM based motion detection

In [39], the authors presented the details of the Multi-Scale Structure Similarity Measurement System (MS-SSMS) and its application for motion detection in a smart home setting. For more information, please refer to [40]. Fig. 7 shows the layout of the combined module for face recognition using both Eigenfaces and MS-SSIM.

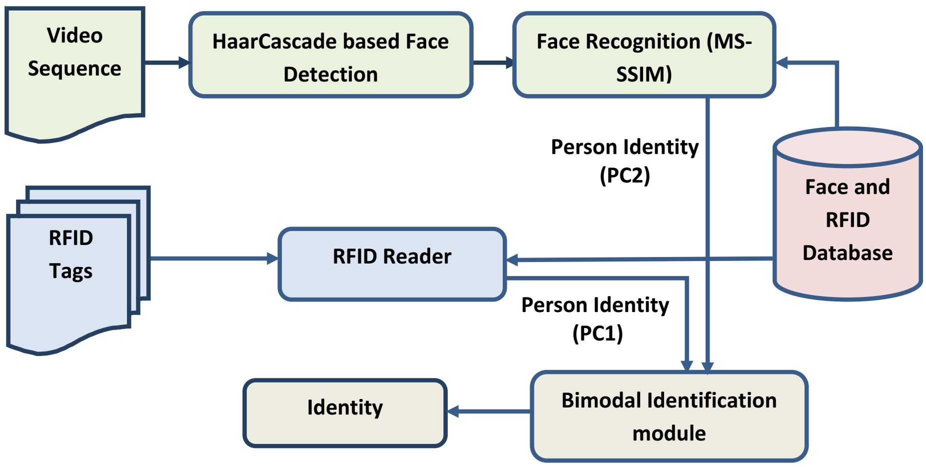


Fig. 6. The multi-mode person identification system based on HaarCascade, MS-SSIM, and RFID.

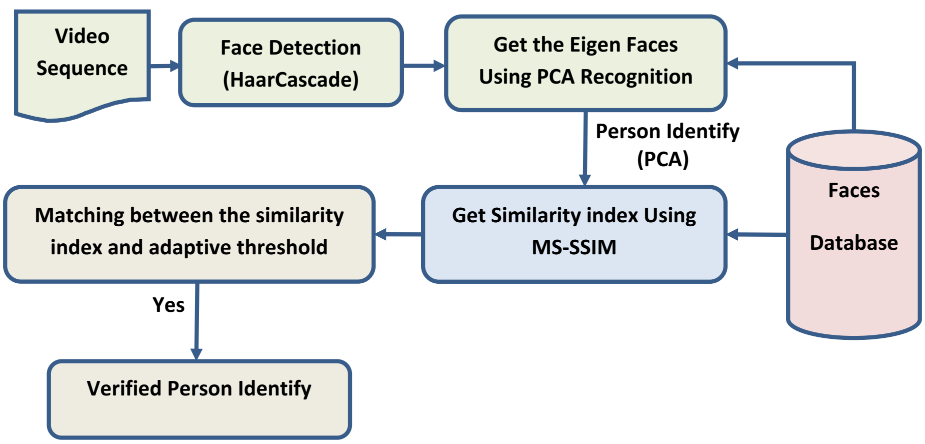


Fig. 7. The layout of the combined module for face recognition using both Eigenfaces and MS-SSIM.

Algorithm 2. MS-SSIM Based Motion Detection

Input: Two successive image frames f_t and f_{t+1}
Output: Motion or no-motion status
1. Start video capture
i. Calculate an adaptive similarity threshold to consider variabilities in lighting conditions and resolution.
ii Calculate the MS-SSIM for every two successive frames for 10 Times.
iii. Calculate both the mean and standard deviation of the 10 MS-SSIM values according to the following formulas to get the threshold limit for motion detection based on similarity [39]:

$$\theta = \mu - 3\sigma$$

$$\mu = \frac{\sum_{i=1}^{10} MSSSIM_i}{10}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{10} (MSSSIM_i - \mu)^2}{10-1}}$$

2. For i = 1 to N students Do
3. IF ID of the tag for student i is already detected and checked Capture two successive frames f_t and f_{t+1} and Calculate MS-SSIM
End IF;
IF MS-SSIM> θ then
Status = live student image
Else
Status = still student image
End IF;
4. End For;

3.5. RFID data filtering module

Algorithm 3. Tag-based Student identification

Input: Students' tags
Outputs: Students' identities
1. *Do*
2. *Capture tag ID and detect reading time.*
3. *IF the tag ID is not registered in students' RFID database then*
4. *Ignore it.*
5. *Else*
6. *IF within attendance period and not registered before in attendance table.*
7. *Register in the attendance table if his face was identifiedat that time period.*
8. *End IF;*
9. *End IF;*
10. *While time <= end of attendance registration time.*

Table 4 (Appendix A) shows the real-time test results of the system. The output attendance sheet for a group of students shows the EPC code for each attendant, his name and the date and time of lecture Hall entry.

3.6. Hybrid face recognition based on RFID, PCA, and MS-SSIM

Algorithm 4. Hybrid Student Identification Algorithm

Input: Tag ID, Face ID, Attendance Registration Period
Output: Attendance List

1. *For i = 1 to N students do*
2. *Capture Tag ID through RFID reader*
3. *Capturing face video*
4. *Detect the face Using HaarCascade*
5. *Use the Eigenfaces to match the face with the training faces of the previously identified tag ID in the face database to reduce the matching time and computations*
6. *IF a correctly identified student then*
7. *Double check his face recognition using the MS-SSIM.*
8. *End IF;*
9. *IF Identities of ID tag and face belong to a student registered in the course During the scheduled attendance period then*
10. *Add the student to the attendance list*
11. *End IF;*
12. *End For;*

3.7. Unfamiliar faces recognition sub-system (UFFRSS)

The faces, which are usually misclassified (Unfamiliar Faces – UF) by a trained system on a huge database, could be easily recognized once isolated based on training a specialized classifier and testing it on these faces. A sub-system is trained only on unfamiliar faces, and once a face of these is recognized by the main system, it should be passed to the UFFRSS to identify it and verify its correct identity. Fig. 8 shows the misclassified faces by the main system during both system training and testing. These difficult to recognize faces are called unfamiliar ones to the recognition system. A UFRSS specialized for identification of difficult faces will reduce their confusion with other faces and hence lead to better system performance.

4. System performance evaluation

The major challenges, which face a student identification system, have been tackled to a large extent using a multimodal approach that solves the face variability and RFID Tag collision problems. Tables 5–7 show the performance of the presented system in comparison with the state of the art approaches. The better performance of our approach resulted from capturing the real variability for different image frames in a video sequence. For example, the HaarCascade approach reported in [31] work on a single source image. Also, we assured that the face to be recognized belongs to a live video through motion detection based on adaptive face detection using MS-SSIM and time-bound of RFID tag detection. To the authors' best knowledge, this is the first time to apply an image quality measure for face recognition. The innovative idea for capturing authentic face variability (real-variability) through different frames in a video sequence is not like a HaarCascade, which tries to capture variability (virtual variability) from a single image. The results of Tables 5–7 indicate an increase in all performance measures and superiority over the

Fig. 8. The unfamiliar faces to the recognition system [41].

Table 5
The ORL Database: 40 Persons, 400 facial images.

Performance indicators	PCA	MS-SSIM	Eigen & MS-SSIM	Eigen & MS-SSIM with UFSS System
Accuracy	0.89	0.94	0.97	0.99
Sensitivity	0.88	0.89	0.98	0.99
Specificity	0.90	0.97	0.97	0.99
Precision	0.90	0.97	0.97	0.99
F-score	0.89	0.94	0.97	0.99
MCC	0.78	0.89	0.95	0.98

Table 6
The SDUMLA-HMT Database: 128 Persons, 768 facial images.

Performance Indicators	PCA	MS-SSIM	Eigen & MS-SSIM	Eigen & MS-SSIM with UFSS System
Accuracy	0.88	0.93	0.96	0.98
Sensitivity	0.83	0.88	0.93	0.99
Specificity	0.93	0.96	0.98	0.98
Precision	0.93	0.96	0.98	0.98
F-score	0.88	0.93	0.96	0.98
MCC	0.88	0.93	0.96	0.96

Table 7
The real-time video-based faces: 50 Persons, 250 facial images.

Performance indicators	PCA	MS-SSIM	Eigen & MS-SSIM	Eigen & MS-SSIM with UFSS System
Accuracy	0.89	0.94	0.96	0.98
Sensitivity	0.88	0.89	0.97	0.98
Specificity	0.90	0.97	0.96	0.98
Precision	0.90	0.97	0.96	0.98
Positive-prediction	0.90	0.97	0.96	0.98
Negative-prediction	0.88	0.89	0.97	0.98
False-negative-rate	0.12	0.11	0.03	0.02
False-positive-rate	0.10	0.06	0.04	0.02
F-score	0.89	0.94	0.96	0.98
MCC	0.78	0.89	0.94	0.97

Table 8
Time performance of the combined approach.

Approach	PCA	MS-SSIM	Eigenface with MS-SSIM
Recognition time	1.21 S/16 Frames	351.56 S/16 Frames	**2.88 S/16 Frames**

HaarCascade approach as tested on ORL, SDUMLA-HMT, and Real-time video-based face databases.

The student attendance accuracy is calculated as the percentage of correctly identified persons to the total number of persons who were introduced to the system for identification during testing a test set. The combined use of both RFID and Face Recognition implies that the accuracy is calculated as the percentage of correctly identified persons by both modalities during the testing phase. Table 8 explains the time performance of the combined approach.

Results show that PCA alone is not an efficient solution for the invariant face recognition compared with MS-SSIM. System performance has been enhanced using UFFRSS. Unfamiliar faces in this context mean those faces which are usually not correctly identified by the system during the testing phase. The misclassified faces during the original system training and testing are identified and used for training the UFFRSS. When the original system identifies a face, the result will be passed to the UFFRSS in case that the predicted face is a UF for verification purposes. Implementing the UFFRSS resulted in an overall system performance enhancement by about 2–3%.

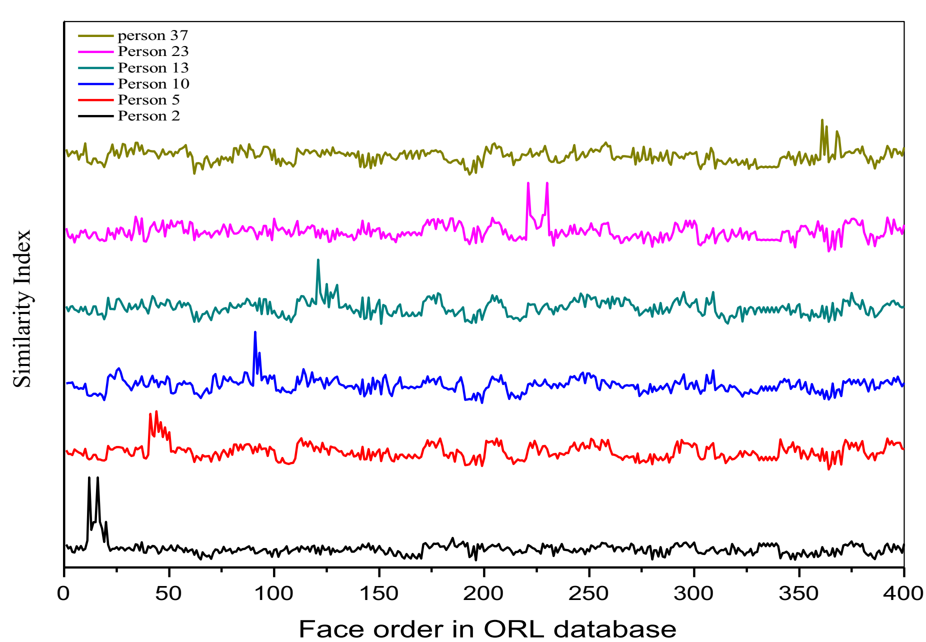


Fig. 9. The MS-SSIM index values for measuring the similarity between different faces in ORL.

Table 9
The comparison between our work and recently published works.

Databases	Authors/Year	Approaches	Accuracy (%)	Testing Time (s)
ORL	Jalled [42], 2017	PCA	92.50	–
		N-PCA	93.75	–
	Singh and Chhabra [43], 2014	PCETS	97.3	
	Iosifidis et, al. [44], 2016	Graph Embedded Extreme Learning Machine (GEELM)	99	–
	Shehab et al. [45], 2017	Graph Extreme Learning Machine	98.1	–
	Jia et al. [46], 2015	Two-Dimensional Extreme Learning Machine (2DELM)	93.8	0.0081
	Zhang et al. [47], 2017	Pre-trained Extreme Learning Machine (P-ELM)	74.50	0.0047
	Huang et al. [48], 2014	Unsupervised Extreme Learning Machines (US-ELM)	67.5	–
	Iosifidis et al. [49], 2015	ELM Enhancement	96	–
	Zong [50], 2011	ELM	97.11	6.38
	Wu et al.[51], 2013	LBP + ELM (3)	91.60	–
		LBP + ELM (5)	96.53	–
		LBP + ELM (7)	98.27	–
	Alom et al. [52], 2015	LBP + ELM	58.50	2.39
		LBP + RELM	76.63	1.85
		LBP + SPELM	79.47	1.79
	Proposed approaches	PCA Enhancement	89.00	1.21
		MS-SSIM	94.00	351.56
		Eigen & MS-SSIM	97.00	**2.88**
		Eigen & MS-SSIM with UFSS System	**99.00**	**2.88**

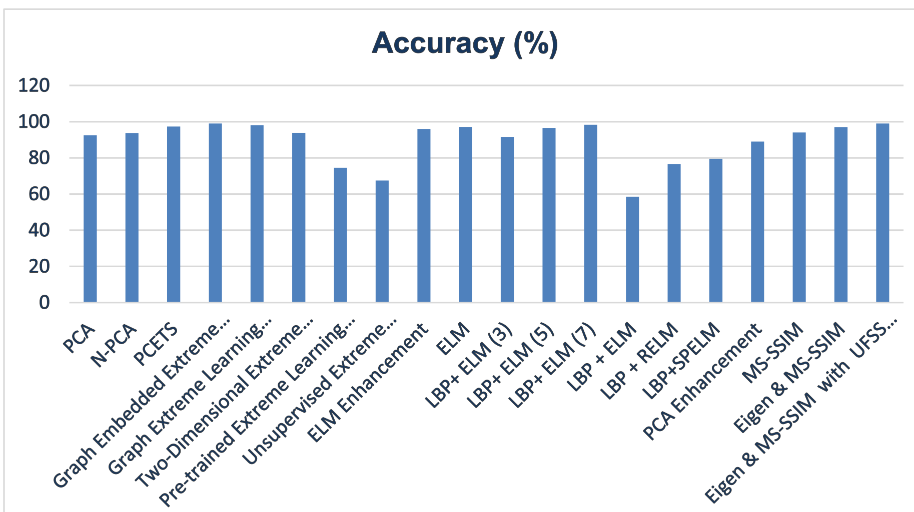


Fig. 10. The accuracy of face recognition approaches for the ORL database.

Table 10
The student at a time during attendancechecking [53].

FORTR	Accuracy	Time (Sec)
1	100%	0.026
2	100%	0.0272
3	100%	0.0418
4	100%	0.0456

The MS-SSIM index is also used to give clues about the UF faces as could be deduced from Fig. 9. Indices are plotted for the similarity between each image of a certain person in the ORL database and all the other 399 images which also include other 9 images for him. Multiple positive peaks point to the set of 10 images which belong to one person. We notice that within the set of similarity indices of a single person, there are gaps which indicate low self-similarity; such faces are pointed to as UF faces,

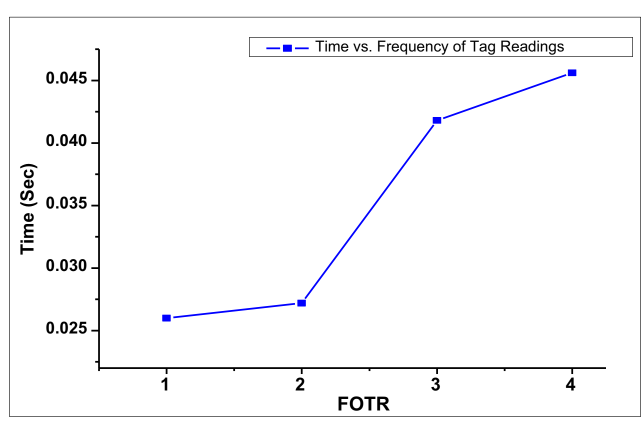


Fig. 11. Time vs. frequency of tag readings.

Table 11
Shows the results of traditional RFID and face recognition approaches.

RFID with proposed approaches	RFID		Face recognition		RFID with face recognition	
	Accuracy (%)	Time (Sec)	Accuracy (%)	Time (Sec)	Accuracy (%)	Time (Sec)
PCA Enhancement	100	0.027	89.00	1.21	89.00	**1.237**
MS-SSIM	100	0.027	94.00	351.56	94.00	**351.587**
Eigen & MS-SSIM	100	0.027	97.00	2.88	97.00	**2.907**
Eigen & MS-SSIM with UFSS System	100	0.027	99.00	2.88	**99.00**	**2.907**

which could be used in training the UFFRSS in addition to the misclassified faces during both training and testing phases of the original system. The black curve, for example, shows a clear gap indicating self-dissimilarity for the case of ten images from 11 to 20 which belong to person 2 in the ORL face database [41].

Table 9 shows the comparison between the proposed approaches and the recently published approaches such as those reported by Jalled [42], Singh & Chhabra [43], Iosifidis et al. [44], Shehab et al. [45], Jia et al. [46], Zhanget al. [47], Huang et al. [48], Iosifidis et al. [49], Zong [50], Wu et al. [51], and Alom et al. [52] which are using the same standard database "ORL" and strategies. Our results indicate better performance as could be seen in Table 9. For further clarification about the ORL standard database, please visit the website of ORL Database as [41].

Fig. 10 shows a chart histogram for comparison of the various face recognition approaches applied to the ORL standard face database. It indicates an enhanced performance relative to most of the approaches reported in the literature (Table 9).

4.1. The Frequency of tag reading (FOTR)

Table 10 and Fig. 11 show the relation between the change of the FOTR with the increase in attendance registration time. It has been choosing the case number 2 in group 1 because it is the less value and get reading matching two times, more detail about the results and solves the RFID tag anti-collision problem [53].

4.2. The results of combining the power of both the traditional RFID approach and face recognition (PCA with MS-SSIM)

Table 11 shows the results of traditional RFID and novel face recognition and identification approaches. The results indicate an enhanced performance relative to most of the approaches reported in the literature in the rate of accuracy between 2% and 5% and decrease the time three times if it compared with the best techniques such as ELM.

The complexity analysis if the MSAMS is found to be as given in Table 12.

Where, M = Boosting Rounds, N = Faces, K = features, n = Number of sliding windows, T = Search Time.

Based on previous results, the MSAMS has been achieved the following benefits as showing in Fig. 1 (Appendix A):

- Easy access to information and key performance indicators (KPIs).
- Academic Analytics.
- Fast student attendance

Table 12
Complexity of MSAMS.

Proposed approaches	PCA	MS-SSIM	Our System
Computational complexity	O (NMK)	O (n2)	O [N + MNK + n2 + T]

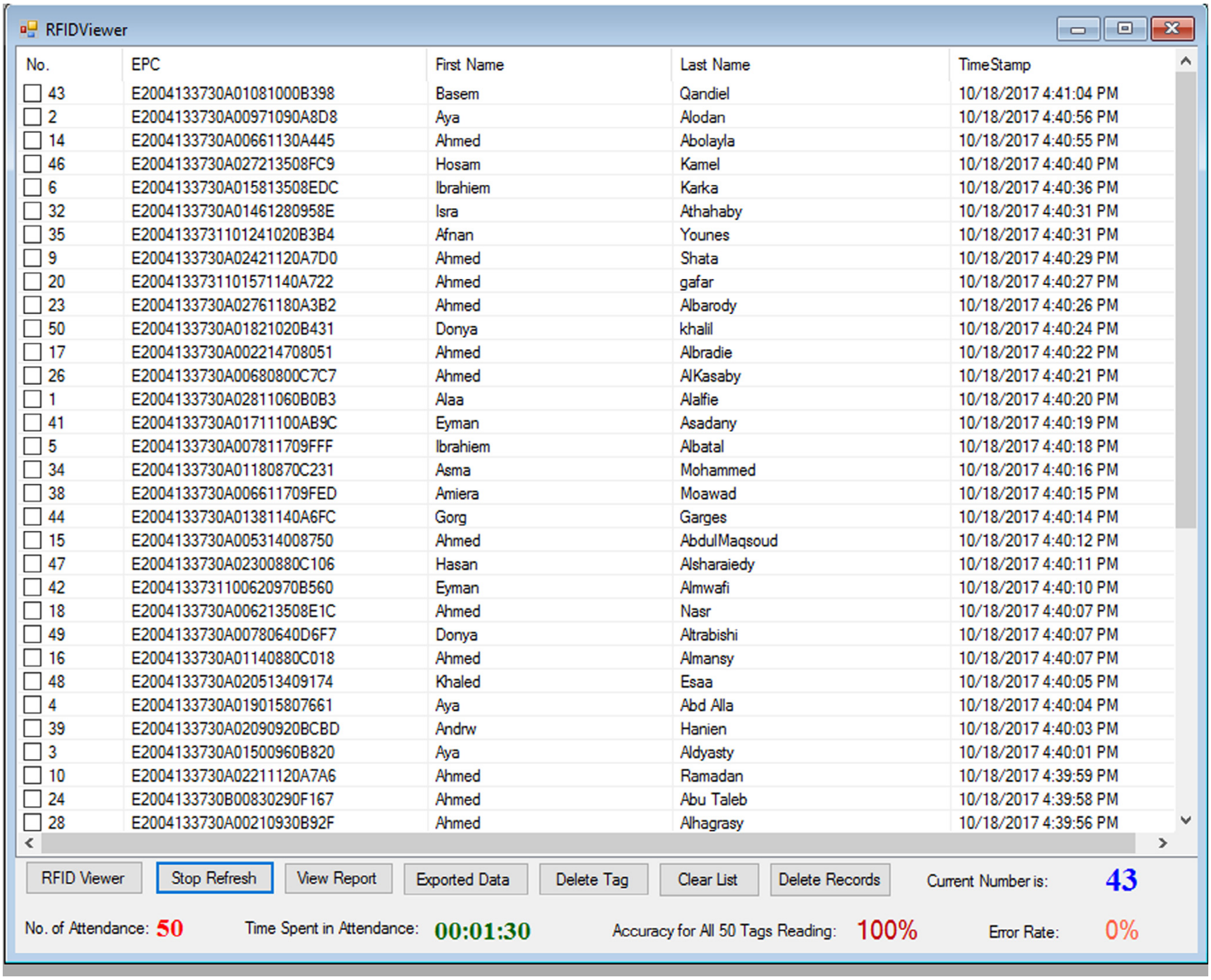
- Enhancing the educational and learning processes.
- Easy reporting.
- Prescriptive analysis for setting a future vision.
- Data archiving, management and processing (the system save the attendance sheet and can make processing for this data
- Fast operations and evidence-based decision making. (it can know the number of students absentin real time.
- Early warning for at-risk students helps timely intervention before it becomes too late.

5. Conclusion and future work

This paper presents a novel approach for multi-modal student identification and attendance management using both RFID and face recognition. The selection of the modality is driven by the need for a system for attendance management, which should be robust against spoofing and variability for facial features. To avoid giving tags to somebody other than the authorized person, a real-time face recognition system has been implemented using the multi-scale structural similarity index, which is traditionally used for image quality assessment. The proposed approach has been compared with the state of the art approaches and an enhanced version of it. Both the MS-SSIM approach and the enhanced Haar-cascade approach have shown promising results. The strength of the new approach lies in its innovative idea for capturing of authentic face variability (real-variability) through different frames in a video sequence in contrary to the Haar-cascade approach, which tries to capture virtual variability from a single image. Authentic variability has been acquired for face recognition and has shown excellent results. The introduction of the UFFRSS module helped to solve the problem of UFF recognition and enhanced the overall system performance. Future work will integrate the current system with the BLE 4 based Beacon System. The problem of RFID reader collision will also be solved in the future.

Appendix A

See Fig. A1 and Table 4.



No.	EPC	First Name	Last Name	TimeStamp
43	E2004133730A01081000B398	Basem	Qandiel	10/18/2017 4:41:04 PM
2	E2004133730A00971090A8D8	Aya	Alodan	10/18/2017 4:40:56 PM
14	E2004133730A00661130A445	Ahmed	Abolayla	10/18/2017 4:40:55 PM
46	E2004133730A027213508FC9	Hosam	Kamel	10/18/2017 4:40:40 PM
6	E2004133730A015813508EDC	Ibrahiem	Karka	10/18/2017 4:40:36 PM
32	E2004133730A01461280958E	Isra	Athahaby	10/18/2017 4:40:31 PM
35	E2004133731101241020B3B4	Afnan	Younes	10/18/2017 4:40:31 PM
9	E2004133730A02421120A7D0	Ahmed	Shata	10/18/2017 4:40:29 PM
20	E2004133731101571140A722	Ahmed	gafar	10/18/2017 4:40:27 PM
23	E2004133730A02761180A3B2	Ahmed	Albarody	10/18/2017 4:40:26 PM
50	E2004133730A01821020B431	Donya	khalil	10/18/2017 4:40:24 PM
17	E2004133730A002214708051	Ahmed	Albradie	10/18/2017 4:40:22 PM
26	E2004133730A00680800C7C7	Ahmed	AlKasaby	10/18/2017 4:40:21 PM
1	E2004133730A02811060B0B3	Alaa	Alalfie	10/18/2017 4:40:20 PM
41	E2004133730A01711100AB9C	Eyman	Asadany	10/18/2017 4:40:19 PM
5	E2004133730A007811709FFF	Ibrahiem	Albatal	10/18/2017 4:40:18 PM
34	E2004133730A01180870C231	Asma	Mohammed	10/18/2017 4:40:16 PM
38	E2004133730A006611709FED	Amiera	Moawad	10/18/2017 4:40:15 PM
44	E2004133730A01381140A6FC	Gorg	Garges	10/18/2017 4:40:14 PM
15	E2004133730A005314008750	Ahmed	AbdulMaqsoud	10/18/2017 4:40:12 PM
47	E2004133730A02300880C106	Hasan	Alsharaiedy	10/18/2017 4:40:11 PM
42	E2004133731100620970B560	Eyman	Almwafi	10/18/2017 4:40:10 PM
18	E2004133730A006213508E1C	Ahmed	Nasr	10/18/2017 4:40:07 PM
49	E2004133730A00780640D6F7	Donya	Altrabishi	10/18/2017 4:40:07 PM
16	E2004133730A01140880C018	Ahmed	Almansy	10/18/2017 4:40:07 PM
48	E2004133730A020513409174	Khaled	Esaa	10/18/2017 4:40:05 PM
4	E2004133730A019015807661	Aya	Abd Alla	10/18/2017 4:40:04 PM
39	E2004133730A02090920BCBD	Andrw	Hanien	10/18/2017 4:40:03 PM
3	E2004133730A01500960B820	Aya	Aldyasty	10/18/2017 4:40:01 PM
10	E2004133730A02211120A7A6	Ahmed	Ramadan	10/18/2017 4:39:59 PM
24	E2004133730B00830290F167	Ahmed	Abu Taleb	10/18/2017 4:39:58 PM
28	E2004133730A00210930B92F	Ahmed	Alhagrasy	10/18/2017 4:39:56 PM

Fig. A1. The student's attendance sheet in real time.

Table 4
The student's RFID based sample attendance sheet.

Student NO.	Student EPC	First name	Last name	Date time
1	E2004133730A02410690D2BE	Ala	Albashbishi	4/25/2017 2:59:14 AM
2	E2004133731102090940BCB9	Kholud	AboMosa	4/25/2017 2:59:14 AM
3	E2004133730A00780640D6F7	Esra	Alsaied	4/25/2017 2:59:14 AM
4	E2004133730A027213508FC9	Asma	Alsied	4/25/2017 2:59:14 AM
5	E2004133730A001613908942	Ahmed	Arnasah	4/25/2017 2:59:14 AM
6	E2004133730A015813508EDC	Amany	Abdoalal	4/25/2017 2:59:14 AM
7	E2004133730A02370930BADF	Amany	Salamh	4/25/2017 2:59:14 AM
8	E2004133731101241020B3B4	Doaa	Amer	4/25/2017 2:59:15 AM
9	E2004133730B00830290F167	Dalia	Saleh	4/25/2017 2:59:15 AM
10	E2004133730A01760990B649	Ahmed	Salam	4/25/2017 2:59:15 AM
11	E2004133730A02090920BCBD	Ahmed	Owaed	4/25/2017 2:59:15 AM
12	E2004133730A00980580DE22	Ahmed	AlBlat	4/25/2017 2:59:16 AM
13	E2004133730A019015807661	Amal	Aboeid	4/25/2017 2:59:16 AM
14	E2004133730A02180910BED4	Rehab	Mohammed	4/25/2017 2:59:16 AM
15	E2004133730A00210930B92F	Ahmed	Almoqadam	4/25/2017 2:59:16 AM
16	E2004133730A005314008750	Esra	Almarsawe	4/25/2017 2:59:16 AM
17	E2004133730A006611709FED	Basma	Shaeer	4/25/2017 2:59:17 AM
18	E2004133730A01461280958E	Hanan	Mohammed	4/25/2017 2:59:21 AM
19	E2004133730A007811709FFF	Asma	Albdrawe	4/25/2017 2:59:22 AM
20	E2004133730A020513409174	khaled	alburaihi	4/25/2017 2:59:22 AM

(continued on next page)

Table 4 (*continued*)

Student NO.	Student EPC	First name	Last name	Date time
21	E2004133730A01180870C231	Eslam	Shalal	4/25/2017 2:59:23 AM
22	E2004133730A006213508E1C	Rana	Albadwy	4/25/2017 2:59:24 AM
23	E2004133730A01821020B431	Hassan	Marof	4/25/2017 2:59:24 AM
24	E2004133730A013813608C77	Eman	Mohammed	4/25/2017 2:59:24 AM
25	E2004133730A012513608C60	Ahmed	Aladrowsy	4/25/2017 2:59:24 AM
26	E2004133730A00661130A445	Esra	Alshamile	4/25/2017 2:59:29 AM
27	E2004133730A01261310931C	Ahmed	Yousef	4/25/2017 2:59:29 AM
28	E2004133730A01140880C018	Esra	Mosa	4/25/2017 2:59:31 AM
29	E2004133730A01610860C47B	Aya	Mostafa	4/25/2017 2:59:32 AM
30	E2004133730A017512909385	Khaled	Zaher	4/25/2017 2:59:35 AM
31	E2004133730A02211120A7A6	Rowqieh	Alsaied	4/25/2017 2:59:36 AM
32	E200413373110062097 0B560	Asma	Alshami	4/25/2017 2:59:37 AM
33	E2004133730A01500960B820	Amany	Qasem	4/25/2017 2:59:39 AM
34	E2004133730A01381140A6FC	Ahmed	Esaa	4/25/2017 2:59:40 AM
35	E2004133730A00680870C1C4	Ahmed	Ibrahiem	4/25/2017 2:59:40 AM
36	E2004133730A02811060B0B3	Donia	Alatieq	4/25/2017 2:59:40 AM
37	E2004133730A00920970B59F	Ahmed	Awaly	4/25/2017 2:59:44 AM
38	E2004133730A01081000B398	Ahmed	Abo Alnajaa	4/25/2017 2:59:59 AM
39	E20041337311 02440930BAF6	Eslam	Alhadedy	4/25/2017 3:00:03 AM
40	E2004133730A00971090A8D8	Gehad	Alsaba	4/25/2017 3:00:07 AM
41	E2004133730A002214708051	Ahmed	Aldawmany	4/25/2017 3:00:28 AM
42	E2004133730A00680800C7C7	Hossen	Hassan	4/25/2017 3:00:31 AM
43	E2004133730A00691000B350	Asma	Ahmed	4/25/2017 3:00:33 AM
44	E20041337311 02360790CB12	Asma	Alsharqawe	4/25/2017 3:00:33 AM
45	E2004133730A01711100AB9C	Donia	Madkor	4/25/2017 3:00:39 AM
46	E20041337311 01571140A722	Ibrahiem	Mogahed	4/25/2017 3:01:03 AM
47	E2004133730A02761180A3B2	Ahmed	Algargawe	4/25/2017 3:01:17 AM
48	E2004133730A02421120A7D0	Esra	Alagmy	4/25/2017 3:01:20 AM
49	E2004133730A028313308FD7	Hosam	Hassan	4/25/2017 3:01:22 AM
50	E2004133730A02300880C106	Khaled	bakry	4/25/2017 3:01:24 AM

References

[1] Zulkefli NA, Miskon S, Hashim H, Alias RA, Abdullah NS, Ahmad N, et al. A business intelligence framework for higher education institutions; 2006.
[2] Kabakchieva D. Business intelligence systems for analyzing university students data. Cybernet Inform Technol 2015;15:104–15.
[3] Baepler P, Murdoch CJ. Academic analytics and data mining in higher education. Int J Scholarship Teach Learn 2010;4:17.
[4] Akinduyite CO, Adetunmbi A, Olabode O, Ibidunmoye E. Fingerprint-based attendance management system. J Comput Sci Appl 2013;1:100–5.
[5] Somasundaram V, Kannan M, Sriram V. Mobile-based attendance management system. Indian J Sci Technol. 2016;9.
[6] Lodha R, Gupta S, Jain H, Narula H. Bluetooth smart based attendance management system. Procedia Comput Sci 2015;45:524–7.
[7] Bae M-Y, Cho D-J. Design and implementation of automatic attendance check system using BLE beacon. Int J Multimedia Ubiquitous Eng 2015;10:177–86.
[8] Park S-H, Moon B-C. The development of attendance management system using the RFID. J Korean Inform Sci Soc 2007;vol 11.
[9] Ramakrishnan J, Ramakrishnan M. An efficient automatic attendance system using fingerprint reconstruction technique, arXiv preprint arXiv:1208.1672; 2012.
[10] Lee W-B. A attendance-absence checking system using the Self-organizing face recognition. J Korea Contents Assoc 2010;10:72–9.
[11] Duncan D. Clickers: a new teaching aid with exceptional promise. Astron Educat Rev 2006;5:70–88.
[12] Bhardwaj R, Gupta N. Face recognition using principal component analysis 2015.
[13] Swain C, Kumar SD. Face recognition using principal component analysis 2008.
[14] Patil SR, Pandey S, Chikaraddi V. Face recognition using principal component analysis. Global J Mech, Eng & Comp Sci 2011;1:110–3.
[15] Guo G, Li SZ, Chan K. Face recognition by support vector machines. In: Proceedings Fourth IEEE international conference on automatic face and gesture recognition, 2000; 2000, p. 196–201.
[16] MunirS, Gupta V, Nemade S, Alam MZ. Face recognition using support vector machines 2011.
[17] Zhao G, Pietikainen M. Dynamic texture recognition using local binary patterns with an application to facial expressions. IEEE Trans Pattern Anal Mach Intell 2007;29:915–28.
[18] Pietikäinen M. Local binary patterns. Scholarpedia 2010;5:9775.
[19] Zhao W, Chellappa R, Phillips PJ, Rosenfeld A. Face recognition: a literature survey. ACM computing surveys (CSUR) 2003;35:399–458.
[20] Hyvärinen A, Hurri J, Hoyer PO. Independent component analysis. In: Natural image statistics. Springer; 2009. p. 151–75.
[21] Rajgarhia A. Face detection using independent analysis. Technical report. Stanford, California, USA: Stanford University; 2007.
[22] Kshirsagar V, Baviskar M, Gaikwad M. Face recognition using Eigenfaces. In: 2011 3rd international conference on computer research and development (ICCRD); 2011, p. 302–06.
[23] Etemad K, Chellappa R. Discriminant analysis for recognition of human face images. JOSA A 1997;14:1724–33.
[24] Zhao W, Chellappa R, Phillips PJ. Subspace linear discriminant analysis for face recognition. Citeseer; 1999.
[25] Chintalapati S, Raghunadh M. Automated attendance management system based on face recognition algorithms. In:2013 IEEE international conference on computational intelligence and computing research (ICCIC); 2013, p. 1–5.
[26] Bai Y, Wang F, Liu P. Efficiently filtering RFID data streams. In: CleanDB; 2006.
[27] Tyagi S, Ansari A, Khan MA. Dynamic threshold based sliding-window filtering technique for RFID data. In: Advance Computing Conference (IACC), 2010 IEEE 2nd International; 2010, p. 115–20.
[28] Bashir AK, Park M-S, Lee S-I, Park J, Lee W, Shah SC. In-network RFID data filtering scheme in RFID-WSN for RFID applications. In: Intelligent Robotics and Applications. Springer; 2013. p. 454–65.
[29] Mahdin H, Abawajy J. An approach to filtering RFID data streams. In: 2009 10th international symposium on pervasive systems, algorithms, and networks (ISPAN); 2009, p. 742–46.
[30] Derakhshan R, Orlowska ME, Li X. RFID data management: challenges and opportunities. In: IEEE International Conference on RFID; 2007, p. 175–82.
[31] Kamaludin H, Mahdin H, Abawajy JH. Filtering redundant data from RFID data streams. J Sensors 2015;2016.
[32] Yongsheng H, Zhijun G. Redundancy removal approach for integrated RFID readers with counting bloom filter. J Comput Inform Syst 2013;9:1917–24.
[33] Ji Z, Luo Z, Wong E, Peng CTX. A P2P collaborative RFID data cleaning model. Hong Kong The 3rd International Conference on Grid and Pervasive Computing-Workshops 2008. IEEE; 2008.
[34] Viola P, Jones MJ. Robust real-time face detection. Int J Comput Vision 2004;57:137–54.
[35] Wang Y-Q. An analysis of the Viola-Jones face detection algorithm. Image Processing On Line 2014;4:128–48.
[36] Thakur S, Sing JK, Basu DK, Nasipuri M, Kundu M. Face recognition using principal component analysis and RBF neural networks. In: First international conference on emerging trends in engineering and technology, 2008. ICETET'08; 2008, p. 695–700.
[37] Wang ACBZ, Sheikh HR, Simoncelli EP. Image quality assessment: From error measurement to structural similarity. IEEE Trans Image Processing 2004;13:1G4.
[38] Chen M-J, Bovik AC. Fast structural similarity index algorithm. J Real-Time Image Proc 2011;6:281–7.
[39] Khalaf HA, Tolba AS, Rashad MZ. An optimal localization strategy for sensors in smart homes. Mansoura University; 2016.
[40] Khalaf HA, Tolba AS, Rashid MZ. Event triggered intelligent video recording system using MS-SSIM for smart home security. Ain Shams Eng J 2018;9(4):1527–33.

[41] ORLdatabase, <http://www.face-rec.org/databases/>. (Last visited: April 2017).
[42] Jalled F. Face recognition machine vision system using Eigenfaces. arXiv preprint arXiv:1705.02782, 2017.
[43] Singh G, Chhabra I. Human face recognition through moment descriptors. In: 2014 Recent advances in engineering and computational sciences (RAECS); 2014, p. 1–6.
[44] Iosifidis A, Tefas A, Pitas I. Graph embedded extreme learning machine. IEEE Trans Cybern 2016;46:311–24.
[45] Shehab MA, Kahraman N, Bilgin G. Face recognition using graph extreme learning machine with L21-norm regularization in ELECO, presented at the 10th International Conference on Electrical and Electronics Engineering, Turkey; 2017.
[46] Jia B, Li D, Pan Z, Hu G. Two-dimensional extreme learning machine. Math Probl Eng 2015;2015.
[47] Zhang Y, Wu J, Cai Z, Jiang S. Pre-trained Extreme Learning Machine. Springer International Publishing; 2017. p. 14–23. AG.
[48] Huang G, Song S, Gupta JN, Wu C. Semi-supervised and unsupervised extreme learning machines. IEEE Trans Cybern 2014;44:2405–17.
[49] Iosifidis A, Tefas A, Pitas I. Enhancing ELM-based facial image classification by exploiting multiple facial views. Procedia Comput Sci 2015;51:2814–21.
[50] Zong W, Huang G-B. Face recognition based on extreme learning machine. Neurocomputing 2011;74:2541–51.
[51] Wu JH, Han L, Li JT, Zhao YX, Tang LB, Zhao BJ. Face recognition based on LBP and extreme learning machine. Appl Mech Mater 2013:3526–9.
[52] Alom MZ, Sidike P, Asari VK, Taha TM. State preserving extreme learning machine for face recognition. In: 2015 International joint conference on neural networks (IJCNN); 2015, p. 1–7.
[53] Mohammed K, Tolba AS, Elmogy M. A multimodal wireless system for instant quizzing and feedback. Int J Comput Inform Syst 2018;8(1).