An Automatic Face Attendance Checking System using Deep Facial Recognition Technique

Thuy Nguyen-Chinh, Thien Do-Tieu, Sy Nguyen-Tan, Phuong Le-Van-Hoang, Qui Nguyen-Van, Phu Nguyen-Tan

***Abstract*—Nowadays, as computers are powerful enough for implementing complex algorithms, there are numerous applications that people utilize computers to run. In which, facial recognition is one of the most active fields of applications. In fact, computers can not only automatically identify who a person is, but also operate 24/7, which human beings cannot endure. This leads to the replacement of people by computers in some repetitive and real-time applications.**

In this work, we apply the facial recognition into an attendance checking system that uses faces of registered people to check their attendance. This system has a GUI which allows easy user-to-system interaction. The core of the system is a deep facial recognition technique, which has four stages (e.g., removing motion-blur frames, detecting faces, removing non-frontal-view faces, and recognizing). Particularly, in the recognition phase, we consider this stage as an open-set facial recognition problem, so the system is able to detect people who have not registered in the database before. Also, we boost the performance of the system by utilizing hardware resources of users' computers. Although the system is designed to run with a low-resolution webcam, its performance is reasonably accurate on our private dataset.

***Index Terms*—Face Attendance Checking, Facial Recognition, Deep Learning**

I. Introduction

Face recognition systems are being applied widely in real life such as tracking, managing employees, finding information about celebrities, and so forth. There are many approaches to design a face recognition system, but such these systems are frequently affected by light, non-frontal faces, resolution of cameras, etc. Thus, each method has specific challenges. Overall, a face recognition has two main stages which are face detection and face recognition, yet we want to create constraints on blur-clean and frontal-view faces of users that leads our system to have four stages: blur detection, face detection, landmark detection and face recognition.

A. Face detection

Face detection and alignment are essential to many face applications such as face recognition and facial expression analysis. However, the large visual variations of faces, such as occlusions, large pose variations and extreme lightings, impose great challenges for these tasks in real-world applications.

The cascade face detector proposed by Viola and Jones [1] utilizes Haar-Like features and AdaBoost to train cascaded classifiers, which achieve good performance with real-time efficiency. However, quite a few works [2][3][4] indicate that this detector may degrade significantly in real-world applications with larger visual variations of human faces even with more advanced features. Besides the cascade structure, [5][6][7] introduce deformable part models (DPM) for face detection and achieve remarkable performance. However, they need high computational expense and may usually require expensive annotation in the training stage. Recently, convolutional neural networks (CNNs) achieve remarkable progresses in a variety of computer vision tasks, especially face detection task. Li et al. [8] use cascaded CNNs for face detection, but it requires bounding box calibration from face detection with extra computational expense and ignores the inherent correlation between facial landmarks localization and bounding box regression. Face alignment also attracts extensive interests. Regression-based methods [9][10][11] and template fitting approaches [12][13][7] are two popular categories.

However, most of the available face detection and face alignment methods ignore the correlation between these two tasks. Though there exist several works attempt to jointly solve them, there are still limitations in these works. For example, Chen et al. [14] jointly show alignment and detection with random forest using features of pixel value difference. But, the handcraft features used limits its performance. From those previous experiments, we choose a new approach which integrates these two tasks using unified cascaded CNNs by multi-task learning called Multi-task Convolutional Network in section III-D.

B. Landmark detection

The locations of the fiducial facial landmark points around facial components and facial contour capture the rigid and non-rigid facial deformations due to head movements and facial expressions. They are hence important for various facial analysis tasks. Many facial landmark detection algorithms have been developed to automatically detect those key points over the years. In this paper, we use a dlib library which is a powerful source for face and facial landmark detection. We will discuss our implement in detail in section III-C.

C. Face recognition

After face detection and alignment, those regions of face are extracted to get feature vectors. Conventionally, one of the most popular features for face recognition is Gabor feature.

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Tudor Barbu [15] used Gabor transfrom to extract features, and then applied K-Nearest Neighbour (K-NN) based on clustering features to predict the identity of a face. This implementation achieved a quite impressed performance with an accuracy of 90% on the Yale Face Database B [22]. OpenCV [16], which is an open-source library focussing on Computer Vision algorithms, introduced a method called Local Binary Patterns (LBP) based on the Haar-Like feature. In term of speed, LBP has a really real-time efficiency, whereas it is not stable in term of accuracy. In particular, this method cannot face around noise which is a reason why LBP and Haar-Like feature are rarely applied in practical systems. Because of limitations of conventional features, approaches exploiting deep learning have gradually developed instead. Yi Sun, Xiaogang Wang, and Xiaoou Tang [17] built a deep model named Deep hidden IDentity (DeepID) which used Convolutional Neural Network (CNN) to extract face features. The advantage of this method was using a small dataset for training that was considerably relevant for applications which cannot collect a large dataset of users. Nevertheless, to reach a high accuracy, DeepID model became really complex with many neural network branches for each person. There were 10 patches of a face, which contain interesting information, chosen from each image, then they were scaled with three figures in RGB and gray channel. Totally, the model had 60 different networks to extract features for an image, then fed forward extracted features into a classifier using Joint Bayesian. DeepID achieved an excellent accuracy of 97.45% on Labeled Faces in the Wild (LFW) [23]. In 2014, the authors of DeepID introduced DeepID2 [18] which was an improved version of its predecessor. In the new version, interesting regions were built to eliminate useless patches which cannot provide high-level features. That work really helpfully affected the accuracy, specifically there was an increase in accuracy at 99.63%. In 2015, Google Inc. [19] exploited a deep CNN Inception [20] and a triplet loss function to form the FaceNet model, which was to extract features. Their outstanding point was using a hard triplet loss to separate features for each person, so FaceNet feature is robust in both face verification and face recognition. The accuracy of 99.63% on LFW and 95.12% on Youtube Faces DB [24] were high enough to represent the perfection of the model.

II. Proposed system

In this paper, we apply deep facial recognition techniques to the problem of face attendance checking. A system is built in order to manage appearances of students in a class, which is revealed in Fig. 1. As normally, a facial recognition system is organized as a pipeline of typical stages such as face detection, landmark detection, and face recognition. However, to ensure input frames for underlying algorithms are high quality, we append an early filter (the Blur detection stage) that are able to discard blur frames, which are caught by motions of people in front of a standard webcam. Then, clean frames are passed through the Face detection block to count the number of faces existing inside these frames. In our specific case, there is only one face per frame allowed to be processed, so frames that contain more than one faces are rejected by the block.

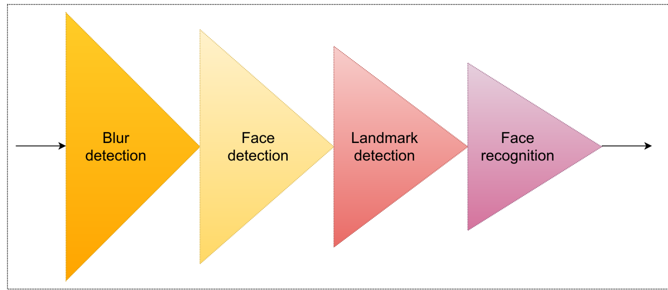


Fig. 1: The system pipeline. There are four stages, namely blur detection, face detection, landmark detection, and face recognition. These four blocks are in the descending order of size in the direction from input to output. This points out that our system is tougher to input frames from the camera when such frames passed through the system. Therefore, best frames are likely to be processed, which may improve the final recognition accuracy.

Afterward, the Landmark detection is to localize statistic-salient points in the face in order to verify whether the face is in the frontal view of the camera. This frontal-view check will help improve the accuracy of the face recognition algorithm. Finally, the Face recognition uses blur-clean, one-face, and frontal-view frames from previous stages to extract relevant features and then perform a classification task to indicate which category the input most likely belong to.

In addition, to leverage the ease in use, we design a friendly graphic user interface (GUI) so that people who want to use the system to manage (teachers) or check (students) attendance can interact with the application without any specific knowledge. To make the system more robust, we carefully analyze the distribution outlier of features representing for registered accounts. Therefore, the algorithm has the ability to detect people who have not registered in the application before, which is equivalent to the open-set problem in face recognition.

Our work is organized as follows. In section III, stages of the proposed system are described clearly, including motion-blur detection, face detection, frontal-view detection, and face recognition. Then, section IV is for reporting some experimental results.

III. Implementation

A. Motion-blur detection

The first stage of this system is detecting blurred images and rejecting them out of next stage. We know that the blurred image means each pixel in the source image gets spread out and mixed into surrounding neighbor pixels. For our attendance checking system, the motion blur happens when an object (namely face or webcam) moves during the exposure. So as to detect whether an image is blurred, we use the 2D-FFT (2D-Fast Fourier Transform) method.

We will review about Fourier Transform of Images. To compute the Fourier transform of an image, you need to:

- Compute DFT of each row, in place.
- Compute DFT of each column, in place.

When a signal is discrete and periodic, we use the discrete Fourier transform or DFT. Suppose our signal is a_n for $n =$

$0 \ldots N-1$, and $a_n = a_{n+jN}$ for all n and j. The spectrum of a is:

$$A_k = \sum_{n=0}^{N-1} W_N^{kn} a_n \tag{1}$$

where

$$W_N = e^{-i\frac{2\pi}{N}}$$

and W_N^k for $k = 0 \ldots N-1$ are called the *Nth roots of unity*. The sequence A_k is the discrete Fourier transform of the sequence a_n. Each is a sequence of N complex numbers.

The FFT is a fast algorithm for computing the DFT. If we take the 2-point DFT and 4-point DFT and generalize them to 8-point, 16-point, ..., 2^n-point (n is an integer), we get the FFT algorithm.

There are several ways to write an FFT. For instance, let m be an integer and let $N = 2^m$. Suppose that $x = [x_0, \ldots, x_{N-1}]$ is an N dimensional complex vector. Let $\omega = \exp(\frac{-2\pi i}{N})$. Then the DFT, $c = F_N(x)$ is given by

$$c_k = \frac{1}{N} \sum_{j=0}^{j=N-1} x_j \omega^{jk}. \tag{2}$$

Let $n = N/2$, let u and v be n dimensional vectors defined by

$$u_j = x_j + x_{j+n}, \ j = 0, \ldots, n-1 \tag{3}$$

$$v_j = (x_j - x_{j+n})\omega^j, \ j = 0, \ldots, n-1. \tag{4}$$

Then

$$c_{2j} = \frac{1}{2}(F_n(u))_j, \ j = 0, \ldots, n-1 \tag{5}$$

$$c_{2j+1} = \frac{1}{2}(F_n(v))_j, \ j = 0, \ldots, n-1. \tag{6}$$

To compute the DFT of an N-point sequence using equation (1) would take (N^2) multiplies and adds. The FFT algorithm computes the DFT using $(N \log N)$ multiplies and adds.

Practical issues: We translate the picture so that pixel (0,0), which now contains frequency $(\omega_x, \omega_y) = (0, 0)$, moves to the center of the image. Then, we display pixel values proportional to log(magnitude) of each complex number. For color images, do the above to each of the three channels (R, G, and B) independently.

Apply to our system, firstly, we calculate the FFT of the image. Secondly, we will compute the mean amplitude spectrum value of the entire pixels in image and. Finally, the result of this operation is compared to an optimal threshold which distinguishes blurred and non-blurred image as accurate as possible. The image is called non-blurred if and only if its average value greater than the threshold value, and vice versa. After that, non-blurred images are applied to face detection stage of the system.

B. Face detection

In this paper, we have used the Histogram of Oriented Gradients method for extracting features of the face and Linear Support Vector Machine (SVM) method for face detections.
The implementation of this method using the sliding window technique with the different sizes of the windows. Using the sliding window technique we could complete the calculation of HOG features, applied to detect and differentiate the face and the false face recognition using the SVM technique.
All of the pre-processing steps are automatically implemented before using Dlib library with the input of being given facial images and the output of localization the identified faces.

Fig. 2: Model structure. Our network consists of a batch input layer and a deep CNN followed by L2 normalization, which results in the face embedding. This is followed by the triplet loss during training.

C. Frontal-view detection

To check whether the shape of the faces has to be frontal, we implement these 3 following steps: Step 1.

1) Focusing on the center of the image. Only accept these faces that locate in the most central of the images. $((120-360), (90, 360))$
2) Identify the skew of the image: calculate the coordinate of these eyes and the angle deviation between two eyes in the horizontal direction. If the angle deviation is larger than 10 degree, the image will be ignored.
3) Identify the rotation of the image: choose the point which is the midpoint of the right and the left eye. If the nose which is deviated from the selected point is greater than 10 pixels in the horizontal direction, the image is ignored.

These steps are implemented based on 5-point facial landmark technique with Dlib library instead of a 68-point facial landmark in order to improve performance. If the image satisfies the condition, it will be accepted.

D. Face recognition

In this stage, faces in raw images are detected and aligned by Multi-task CNN, we use a convenient pre-trained FaceNet model to extract feature (in Figure 2) and then feedforward it to an SVM classifier for recognition.

1) Multi-task Convolution Network: The overall pipeline Multi-task CNN is shown in Figure 3. An image is initially resized to different scales to build an image pyramid, which is the input of the following three-stage cascaded framework with CNN architectures in Figure 4:

Stage 1: A fully convolutional network is exploited, called Proposal Network (P-Net), to obtain the candidate windows and their bounding box regression vectors. Then using the estimated bounding box regression vectors to calibrate the candidates. After that, employing non-maximum suppression (NMS) to merge highly overlapped candidates.

For each candidate window, P-CNN predicts the offset between it and the nearest ground truth (i.e., the bounding boxes' left top, height, and width). The learning objective is

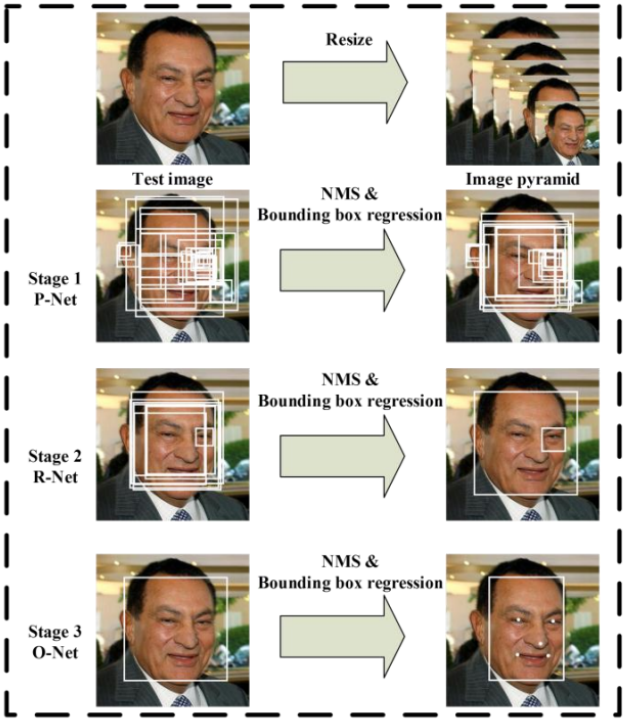


Fig. 3: Pipeline of our cascaded framework that includes three-stage multi-task deep convolutional networks. Firstly, candidate windows are produced through a fast Proposal Network (P-Net). After that, we refine these candidates in the next stage through a Refinement Network (R-Net). In the third stage, The Output Network (O-Net) produces final bounding box and facial landmarks position.

formulated as a regression problem, and the Euclidean loss is employed for each sample x_i:

$$L_i^{box} = \|y_i^{prediction} - y_i^{truth}\|_2^2 \tag{7}$$

Stage 2: All candidates are fed to another CNN, called Refine Network (R-Net), which further rejects a large number of false candidates, performs calibration with bounding box regression, and NMS candidate merge.

Stage 3: his stage is similar to the second stage, but in this stage, we aim to describe the face in more details. In particular, the network will output five facial landmarks' positions.

Similar to the bounding box regression task, facial landmark detection is formulated as a regression problem:

$$L_i^{landmark} = \|y_i^{prediction} - y_i^{truth}\|_2^2 \tag{8}$$

2) FaceNet model: This model use Inception-ResNet v1 architecture [20] and triplet loss to extract feature. Inception-ResNet v1 (in Figure 6) is a very deep convolutional network which combine ResNet network and Inception network with a complex structure. This deep network affords to extract high-level feature for object recognition, and combination with triplet loss gets better and better.

The embedding is represented by $f(x) \in R^d$. It embeds an image x into a d-dimensional Euclidean space. Here we want to ensure that an image x_i^a (anchor) of a specific person is closer to all other images x_i^p (positive) of the same person

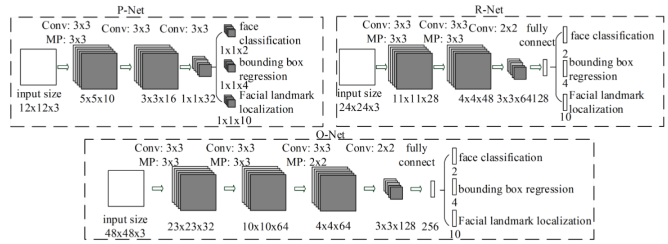


Fig. 4: The architectures of P-Net, R-Net, and O-Net, where "MP" means max pooling and "Conv" means convolution. The step size in convolution and pooling is 1 and 2, respectively

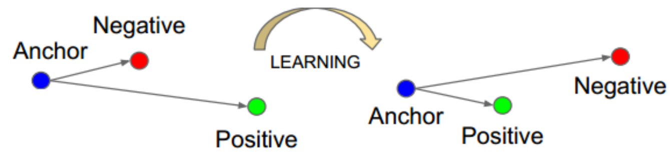


Fig. 5: The Triplet Loss minimizes the distance between an anchor and a positive, both of which have the same identity, and maximizes the distance between the anchor and a negative of a different identity.

than it is to any image x_i^n (negative) of any other person. This is visualized in Figure 5. Thus we want,

$$\|f(x_i^a) - f(x_i^p)\|_2^2 + \alpha < \|f(x_i^a) - f(x_i^n)\|_2^2 \tag{9}$$

where α is a margin that is enforced between positive and negative pairs. The loss that is being minimized is then:

$$L = \sum_i^N (\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha) \tag{10}$$

In this implement, FaceNet model has trained on the VGGFace2 dataset which over 9000 identities and over 3.3 million faces. VGGFace2 is a large-scale face recognition dataset from Google Image Search and have large variations in pose, age, illumination, ethnicity and profession. Therefore, embeddings are specifical for each person.

3) Training: To apply the Multi-task model and FaceNet model into Face Attendance system, we feedforward raw images of students into Multi-task CNN to get face patches, then extract the features of each patch with 512 dimension vector by pre-trained FaceNet model [21]. After that, we split the dataset of students into 3 subsets: training, validating and testing. Each person in training, validating, testing subset contains 30 images, 10 images and 30 images respectively. We decide to collect only 30 images for the training subset because we want to reduce the time for training and collecting images. Next, we use SVM classifier to train on training subset and validate on validating subset. The output of trained-classifier is a probability vector whose each element represents the ability of an identity anchor belong to. Thus, the anchor is determined by choose which identity has maximum probability, that suffers from mistakes when faces of strangers appear. To solve the open-set problem, we combine both two subsets: training and validating to the training threshold. This threshold helps us to eliminate unknown people, additionally ensure that the system achieves higher accuracy.

Fig. 6: Schema for Inception-ResNet-v1 and Inception-ResNet-v2 networks. This schema applies to both networks but the underlying components differ.

E. Graphic User Interface

The sections that follow describe how to create GUIs with PyQt5. This includes laying out the components, programming them to do specific things in response to user actions, and saving and launching the GUI; in other words, the mechanics of creating GUIs.

PyQt5 implements GUIs as figure windows containing various styles of uicontrol objects. You must program each object to perform the intended action when activated by the user of the GUI. In addition, you must be able to save graphical user interface development environment.

GUI Development Environment

The process of implementing a GUI involves two basic tasks:

- Laying out the GUI components
- Programming the GUI components

GUIDE primarily is a set of layout tools. However, you must create a PY-file that contains code to handle the initialization and launching of the GUI. This PY-file provides a framework for the implementation of the callbacks - the functions that execute and launch your GUI.

The Implementation of A GUI

Laying out the GUI components

While it is possible to write an PY-file that contains all the commands to lay out a GUI, it is easier to use GUIDE to lay out the components interactively and to generate one file that saves the GUI:

UI-file -contains a complete description of the GUI figure and all of its children (uicontrols and axes), as well as the values of all object properties.

Programming the GUI components

Once you have the UI-file, you will use PyQt5 to extract the UI-file to PY-file to execute the program. PY-files -contain the functions that launch and control the GUI and the callbacks, which are defined as sub-functions. This PY-file is referred to as the application PY-file in this documentation. Note that the application PY-file does not contain the code that lays out the uicontrols; this information is saved in the UI-file. The following diagram illustrates the parts of a GUI implementation.

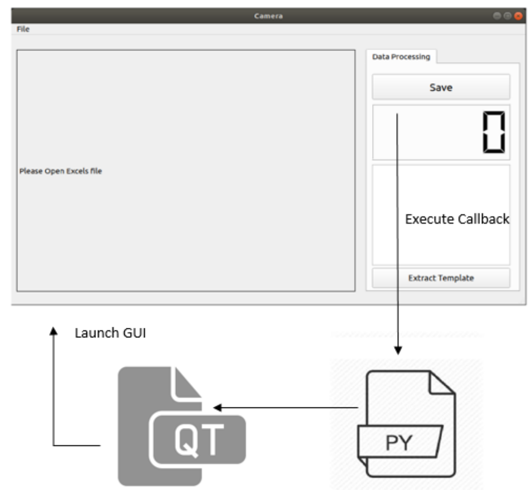


Fig. 7: Parts of GUI Implementation

The GUI is available from the QtDesigner shown in the figure below. The design is described briefly below. Subsequent sections show you how to use them.

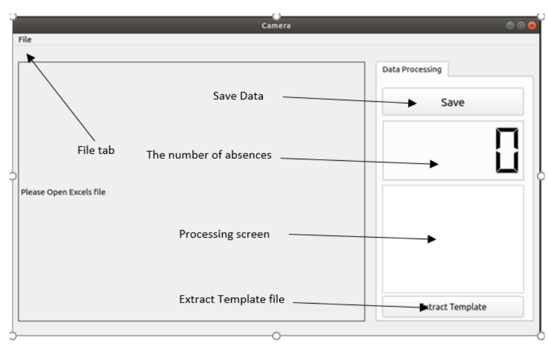


Fig. 8: GUI layout

F. Attendance management

This is the final phase of Face Attendance Checking System. It was designated to mark the presence of one resulted from our algorithm in a file of excel format, namely xlsx extension. To be used by the system, the excel file must meet a stringent format made up of essential contents and be generated by the GUI.

uicontrols	function
Open File Option	We use this option to open the existing file "Open" option appears and you can choose to open the file.
Start Camera	Open camera to start checking process
Stop Camera	Stop camera
Exit	We use this option to close the program. we can follow the steps: –Click on File tab >Exit, active file will be closed. When we close the file, we get the confirmation message to save the file or not or cancel the command.
Save	Store completely-checked student IDs on the document. Once program exits, this process will be automatically started so that you won't lose your work that has been completed if there is a power interruption or other system malfunction, the first time you Save, it will take you to the Save File dialog box.
Extract Template	We use this option to export the template in XLSX document. To Extract the file, we can follow the steps: – Click Extract Template . And then we can export it as per our requirement.

TABLE I. USER GUIDE

DANH SÁCH SINH VIÊN				
YOUR COURSE/SUBJECT/TITLE				
			1 = prensent	
			blank = absent	
ID	**Last Name**	**First Name**	**Group**	**Total**

Fig. 9: New standard excel form

Fig. 9 depicts a new standard empty excel table generated by our GUI. After obtaining a new file, we should fill in the table with the desired data (Fig. 10). The most special things in this table are column ID and Total. ID is considered a primary key because the algorithm will mark the presence of a specific person via his ID. To help the host in easy attendance management, we designed the column Total with a view to showing the number of absences in all.

Fig. 11 depicts an excel file's content after a checking progress finished. The GUI will automatically insert the only one new day column between Group and Total ones and in the tail of previous checked day. Letter 1 will be marked as presence in a cell of this column accordant to an ID. After attendance checking process is completed, the Total column will display the number of absences of previous days and the current one. Smartly can it display as we specially assigned a size-dynamic sum function to each cell of this column.

IV. Experimental result

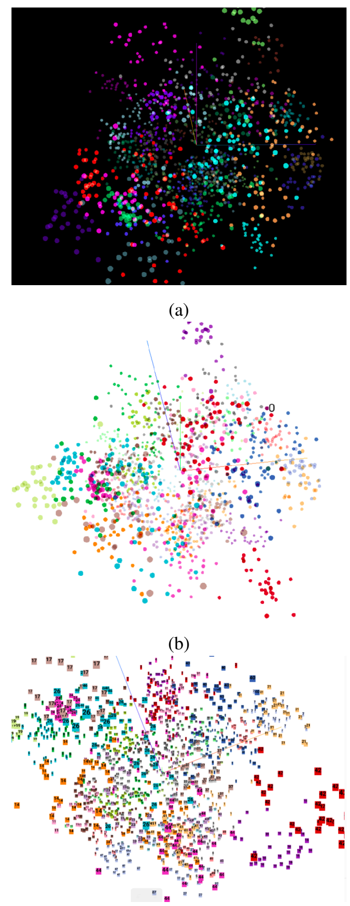
In this section, we first evaluate the effectiveness of the feature extracted from FaceNet. Then we will compare our system in different context such as: background, illumination, resolution of camera. Finally, we evaluate the computational efficiency of our system.

DANH SÁCH SINH VIÊN				
TRÍ TUỆ NHÂN TẠO TRONG ĐIỀU KHIỂN				
		1 = prensent		
		blank = absent		
ID	**Last Name**	**First Name**	**Group**	**Total**
1511844	Lương Hữu Phú	Lộc	1	
1512221	Phạm Ngọc Khôi	Nguyên	1	
1512396	Bùi Tấn	Phát	1	
1512534	Nguyễn Trọng	Phúc	1	

Fig. 10: Excel form contain pre-inputed data

DANH SÁCH SINH VIÊN					
TRÍ TUỆ NHÂN TẠO TRONG ĐIỀU KHIỂN					
			1 = present		
			blank = absent		
ID	**Last Name**	**First Name**	**Group**	**09/06/2018**	**Total**
1511844	Lương Hữu Phú	Lộc	1		1
1512221	Phạm Ngọc Khôi	Nguyên	1	1	0
1512396	Bùi Tấn	Phát	1		1
1512534	Nguyễn Trọng	Phúc	1	1	0

Fig. 11: Form is under checking



(a)

(b)

(c)

Fig. 12: Embeddings with PCA visualization

A. *Embedings*

Because we use pre-trained model FaceNet, we need to test specification of embeddings which is output of model. We use Principal Component Analysis (PCA) and t-SNE [25] to visualize embeddings in 3 dimension space in Figure 12 and Figure 13. In PCA visualization, embeddings of the same person close together, although they are not completely

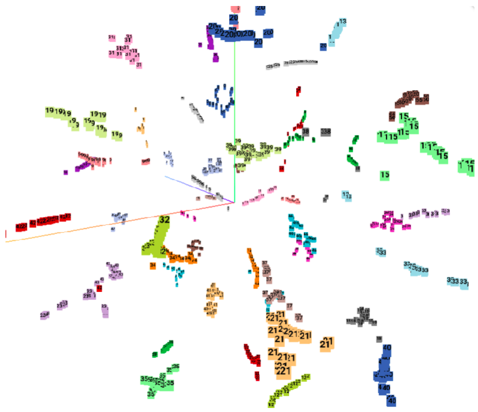


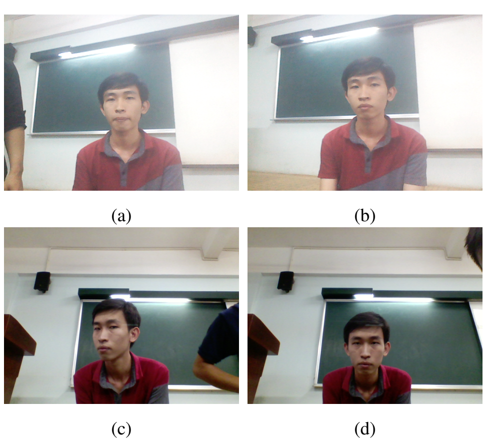
Fig. 13: Embeddings with t-SNE visualization

separable. In another of t-SNE, because t-SNE method include clustering stage, so embeddings totally belong to their classes. If embeddings of FaceNet model is not contain high-level of specification, reducing dimension algorithms cannot show or cluster embeddings properly.

B. Training

Training data is carefully collected with different views from $-70°$ to $70°$. This work can improve accuracy in pratical system ,because it is difficult for users to keep their faces in a correct position. In training data include 52 identities and 1560 images totally.

The accuracy of SVM classifier is 99.36%, after training classifier, we train to get the best threshold. We divide threshold in range $[0;1]$. As a result, threshold for 52 identities is 0.18825. Testing accuracy with threshold achieve 98.85% on testing subset. In practical environment, we test on 32 identities, three are 29 identites recognized easily and 3 identities who are not recognized continuously. In Figure 14, the (a),(b) are training images and (c),(b) are testing images, the effect of different ilumination lead the probabilities of testing anchor are lower than threshold, so training data have to cover many real-life cases to create the best classifier.



(a) (b) (c) (d)

Fig. 14: Unrecognized identity, (a),(b) are training images, and (c),(d) are testing images in pratical condition.

V. Conclusion

In this work, we applied the deep facial recognition techniques to solve the problem of face attendance checking. The system has a pipeline with four stages (e.g., motion-blur detection, face detection, landmark detection, and face recognition). Besides, the system is also integrated a friendly GUI, which allows users both teachers and students interact with it in an easy way. On our private dataset, the application perform accurately despite of the low-resolution webcam on typical laptops. This demonstrates that our underlying algorithm is effective to deal with this poor-quality input problem.

In the future, we will target to widen our dataset so that the dataset can be asymptotic to real applications. In addition, more algorithms will be considered to improve the ability of the algorithm to discriminate feature distributions of output classes.

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