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Face Recognition using CNN for Unconstrained Biometrics with Misalignment Covariate

Nilesh Pawar*[1] | D.T.Ingole [1, 2] | M.D.Ingole[2]

Abstract

Face Recognition is an important basic primitive for various applications and fields such as threat detection, immigration, educational institutions, video analysis & surveillance, sport and biometrics etc. In face recognition, face detection is first step to find out the region of face and this step suffers from variations while determining bounding box for face. This leads to the misalignment in face regions across the samples of intra-class and inter-class faces. In this paper, we have proposed to use convolutional neural network (CNN) to overcome this issue. CNN is a one of popular technique of deep learning. We compared proposed approach of generating training samples to be included in training of CNN such that it improves the recognition accuracy significantly as compared to the one when only original training samples are used in training.

1 | INTRODUCTION

Identifying a person based upon physical and behavioral attributes is the basic working principle of biometric recognition or biometrics. It is a field evolving briskly with wide range of applications involving computer access to bank transactions. Deploying such biometric systems in both government and private applications on large scale will definitely increase public awareness about biometric systems. The three commonly used modalities in the biometrics field are fingerprint, face, and iris. Few other modalities like hand geometry, ear, and gait are also in existence along with advanced topics such as multi-biometric systems and security of biometric systems.

Biometrics identity is used to identify and authenticate a person to grant accesses and controls. It is also used to isolate an individual from a crowd that is under surveillance. Biometric identifiers are the unique, computable features used to tag and designate people. Biometric identifiers basically have two categories, physiological and behavioral. Face recognition is a technique to identify an individual with the virtue his/her face. In this technique an image or video of a person is compared with the data present in the database and then the relative identification of that person is made. In order to make the comparison meaningful and infallible the projecting features of human face like the shape, structure and proportions, distance between the eyes, nose, mouth and jaw, the sides of the mouth, upper outlines of the eye sockets, the area surrounding the check bones and location of the nose and eyes are taken into consideration.

Among many biometric traits, fingerprint, face and iris, have been successfully applied to person verification and identification based applications such as person's verification in highly restricted or public areas, attendance system in office premises and forensics. There is huge demand for new applications where biometrics can play vital role as mentioned in [17]. Three factors are very important to consider for any of the biometrics system: scale, usability and accuracy [18]. Thus, ideal system would like to have extreme ends of axes of these three factors. There are two types of broad categories of biometric systems, controlled biometrics (traditional) and non-cooperative biometrics (unconstrained). In traditional biometrics systems, the user is made to cooperate with system and submit a biometric in a highly controlled manner by facing front and standing still [1]. On the contrary, in non-cooperative biometrics system, subject of interest is far from sensor and moving, allowing user not to get disturbed by identification process. In unconstrained biometrics, face can be good candidate to identify. In this paper, we have proposed to use convolutional neural network (CNN) to overcome this issue. CNN is a one of popular technique of deep learning. We compared proposed approach of generating training

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samples to be included in training of CNN such that it improves the recognition accuracy significantly as compared to the one when only original training samples are used in training. The remaining part of the paper is as follows. In next section 2, related work has been briefly presented. The proposed method is briefly explained in section 3. The experimental results and discussion are reported in section 4 and finally the paper is concluded with highlighting the inferences from experimental observation in section 5.

2 | RELATED WORK

This new alignment method led to most significant improvements, especially since in unconstrained biometrics gaze variations are more prone to happening. This work is very much useful to be considered in unconstraint biometrics since the pedestrian samples used in experiments are similar to those will appear in unconstraint biometrics.

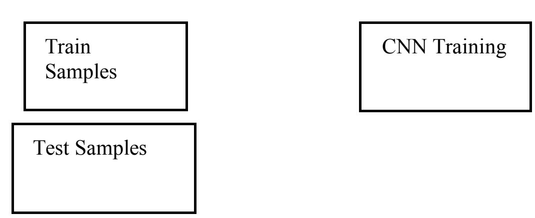
Until 2015, face recognition problem has been treated with two stages, namely, feature extraction and then, classification. Feature extracted could be global representation like PCA [1,7] and LDA [2,3,4], or could be local like SIFT [5,6], wavelet network [8,9] using each of the landmark localization [10,11] . Later, faces also represented as semi-local feature extraction using blocks of face images as in case of HOG, LBP based face or object recognition. These methods were later proved to be inefficient in large number of samples training.

In 2012, Alex Net was proposed by A. Krizhevsky [12], which got the first of the ILSVRC 2012 on classification task. .Deep ID series [13, 14, 15] and other algorithms have achieved excellent performance in face recognition. These models are trained on large-scale datasets, and the network architecture is complex. To overcome this issue, Xiang Wu proposed Light CNN [16] in 2015. Light CNN model has four convolution layers and it obtains 97.77% on LFW. Light CNN model B has five convolution layers which obtains 98.13% on LFW.

3 | METHODOLOGY

Face recognition is very complex problem assuming variety of subjects in different situations with various protocols of data acquisition. The main covariates such as non-uniform illumination, varied pose angles of subjects are dominant factors in unconstrained biometrics. Additionally, misalignment is also an intrinsic covariate because of which performance of face recognition degrades significantly. Misalignment happens due to the non-ideal performance in practical face detector. In most of situations of biometrics applications, there are limitations of training samples that can be captured at the time of enrollment from each of the subjects. The conventional techniques of classification such as k-NN, SVM along with feature representation, are suitable for less number of training samples. However, these techniques are not that robust where test samples include covariates of misalignment. To these kinds of problems, deep learning provides a very efficient way to handle misalignment, also they have capabilities to absorb large number of training samples and make training more meaningful. CNN architecture of deep learning is good for image classification problem. The CNN model for image recognition problem consist of many two operations, 1) Convolution and 2) Pooling.

The figure.1.a shows the baseline approach for face recognition using CNN. The original samples are used for training the CNN model. Further, we propose then approach where training samples and their augmented versions of samples are used in training as shown in figure 1.b.This approach requires same number of original samples as that in baseline approach. The augmented samples from original ones are generated using criteria of rotations, scaling. This ensures more covariates to include in gallery samples, so that trained model can handle samples with more variations in probe samples.



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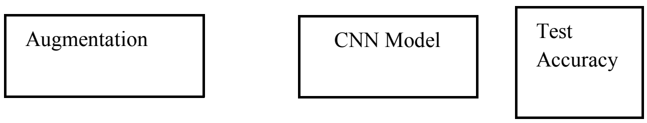

FIGURE 1a) Baseline Approach for training CNN model

The proposed approach uses 6 frontal samples from one of the session and their augmented version of images. This approach ensures there are enough samples for training the CNN model of face recognition.

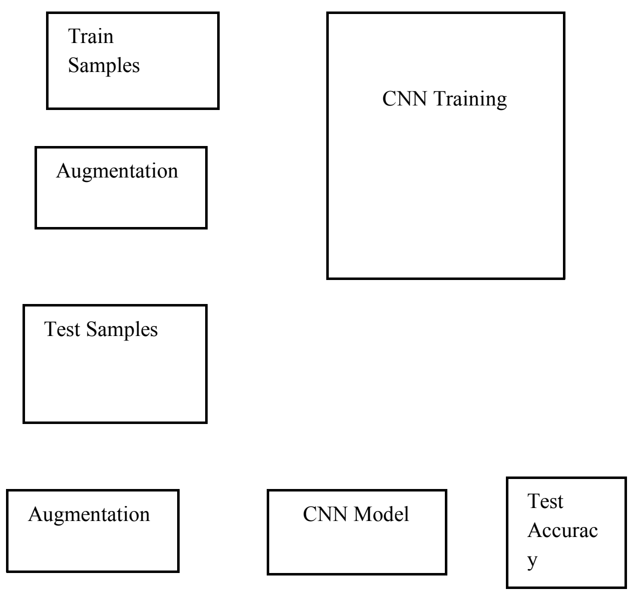

FIGURE 1 b) Proposed Approach using Augmented Samples in CNN

4 | EXPERIMENTAL RESULTS & DISCUSSION

We have analyzed the effectiveness of our proposed approach. The face dataset used in [19] has been employed in our experiments of face recognition. This dataset has varied pose angles structured across the 85 subjects. We have used few subjects for validating our hypothesis that training using augmented samples will boost the face recognition accuracy as compared to when only original samples are used for training. The methodologies are explained in detail in previous section. In the baseline approach, we used 6 frontal samples from one of the session. We tested on augmented samples of remaining frontal and posed angles samples. This ensures the testing is happening on the much-like unconstrained situation where face detection stage gives misaligned face boxes.

5 | CONCLUSION AND FUTURE WORK

Face recognition is an important basic primitive for various applications and fields such as threat detection, immigration, educational institutions, video analysis & surveillance, sport and biometrics etc. In face recognition, face detection is first step to find out the region of face and this step suffers from variations while determining bounding box for face. This leads to the misalignment in face regions across the samples of intra-class and inter-class faces. In this paper, we have proposed to use convolutional neural network (CNN) to overcome this issue. CNN is a one of popular technique of deep learning. We compared proposed approach of generating training samples to be included in training of CNN such that it improves the recognition accuracy significantly as compared to the one when only original training samples are used in training.

Table 1 shows the comparison of Baseline and Augmented approach for training and testing samples. We found recognition accuracy has a significant rise from 40 in baseline to 49 in augmented approach in training and testing samples

TABLE 1 Comparison for baseline and proposed approach with recognition accuracy.

Method	Training		Testing		Recognition Accuracy
	Types	# Samples	Types	# Samples	
Baseline	Train Original	30	Augmented of Test Samples	5924	40
Augmented Training	Train Original + Augmented	5612	Augmented Test Samples	5924	49

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Figure 2 shows the samples with all pose angles for one person

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FIGURE 2.Dataset Image samples for one person showing variation in illumination and pose angle

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