Face Recognition With Weight Variations

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Abstract-*In human Body weight variations are an integral part of a person's aging process. However, the lack of association between the age and the weight of an individual makes it challenging to model these variations for automatic face recognition system. In this paper, we propose a regularizer-based approach to learn weight invariant facial representations using different deep learning architectures, namely, sparse-stacked denoising autoencoders .We incorporate a body-weight aware regularization parameter in the loss function of these architectures to help learn weight-aware features. The experiments performed on theYALE database show that the introduction of weight aware regularization improves the identication accuracy of the architectures both with and without dropout.*

Keywords-Face recognition, biometrics, body-weight variations, facial aging.

I. INTRODUCTION

In computer technology image based on identical twin face recognition technology is challenging task. Traditional facial recognition system exhibit poor performance in differentiating identical twins and similar person under practical conditions. The following methods for differentiate identical twins.

Traditionally lot of manual experiments were performed to identify twins and also to recognize their features with difference, and many more systems were existed to show differences in twins by using finger prints, voice and iris as part of pattern recognition. In existing methods many techniques are used for twin's identification like finger print, voice and iris recognition. The process of finger print identification is used to identify unique person in industry or organizations . The method propose a deep learning based existing algorithms yield improved face recognition results, learning based rep-resentation algorithms require signicantly large amount of training data. It has been observed that representative train-ing data from the corresponding domain is important for learning robust representations. However, for face recognition with body weight variations, it is very challenging to obtain data with respect to various weight and age variations. Learning complex networks with fewer training data points leads to overtting and hence affects the

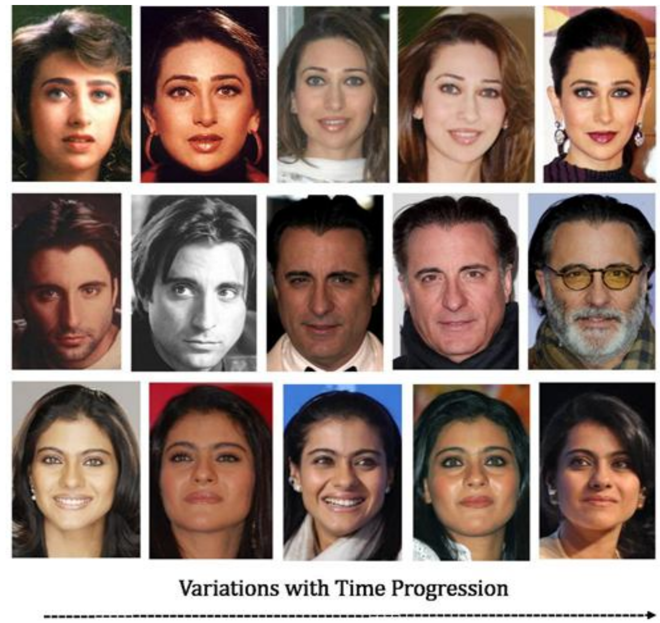

Figure 1. Face images of three subjects with different weight variations over time.

generalization ability on the testing data. Therefore, in this research, we propose a regularization based approach by modifying the existing loss functions of deep learning architectures and incorporating body-weight category parameter in the loss functions.

II. PROPOSED SYSTEM

Due to the lack of any xed pattern in body-weight variations, both within and between subjects, it becomes extremely challenging to model these variations (as shown in Figure 2). It is our assertion that learning body weight invariant representation can help to improve the face recognition performance. Thus, we propose a learning based algorithm for feature extraction and classication.

The proposed model comprises of a deep learning architecture for learning robust representations, followed by a Random Decision Forest (RDF) for classification . Since the proposed formulation is generic in nature, it is explained using two different deep learning architectures: Sparse-Stacked Denoising Autoencoders (SDAE) [11] and Deep Boltzmann Machines (DBM) [12]. The following subsection rst explains the basics of SDAE and DBM, followed by the proposed framework with multiple regularizers and dropout network [13].

A.SPARSE-STACKED DENOISING AUTOENCODERS

As the name suggests, Sparse-Stacked denoising autoen-ders are basically sequence of sparse denoising autoencoders stacked together. Since the complete architecture becomes too complex, greedy layer-by-layer training [14] is used to train the entire deep network. Stacking is performed such that the output layer of the rst autoencoder behaves as the input layer of the second autoencoder. The two primary compo-nents of an autoencoder are the encoder and the decoder. The encoder is responsible for transforming the input vector into a hidden representation while the decoder maps it back to the original input vector. For a given input vector, x, the hidden representation, y, is calculated as:

y D (Wx C b)

Denoising autoencoders can be stacked to form a deep network by feeding the latent representation (output code) of the denoising autoencoder found on the layer below as input to the current layer. The unsupervised pre-training of such an architecture is done one layer at a time. Each layer is trained as a denoising autoencoder by minimizing the error in reconstructing its input (which is the output code of the previous layer). Once the first k layers are trained, we can train the $k+1$-th layer because we can now compute the code or latent representation from the layer below.

Once all layers are pre-trained, the network goes through a second stage of training called fine-tuning. Here we consider supervised fine-tuning where we want to minimize prediction error on a supervised task. For this, we first add a logistic regression layer on top of the network (more precisely on the output code of the output layer). We then train the entire network as we would train a multilayer perceptron. At this point, we only consider the encoding parts of each auto-encoder. This stage is supervised, since now we use the target class during training.

This can be easily implemented in Theano, using the class defined previously for a denoising autoencoder. We can see the stacked denoising autoencoder as having two facades: a list of autoencoders, and an MLP. During pre-training we use the first facade, i.e., we treat our model as a list of autoencoders, and train each autoencoder seperately. In the second stage of training, we use the second facade. These two facades are linked because:

- the autoencoders and the sigmoid layers of the MLP share parameters, and
- the latent representations computed by intermediate layers of the MLP are fed as input to the autoencoders.

Algorithm 1: Denoising Sparse Autoencoder Training

Algorithm

Step 1. Use formula (1) to do corrupting operation on the original dataset X and get the result Xc.

Step 2. Use Xc as input to do forward propagation (i.e., coding phase) as shown in (2) and then get the output Y according to (3).

Step 3. Calculate loss value according to (9).

Step 4. Use back propagation to optimize the weights and biases.

Step 5. Repeat step 2 to 5 until the loss function converging. aining data sometimes leads

III. CONCLUSION

Body weight variations affect the performance of automatic face recognition system. Learning-based algorithms have been proposed to learn weight invariant features. However, they require significant amount of representative training data. Owing to the subjective characteristic of the problem, it is challenging to obtain large labeled training data for body weight variations and hence, it is not feasible to learn supervised weight models. In this research, we propose a regularization based deep learning approach to address this challenge. The effectiveness of the proposed approach is evaluated with multiple deep learning architectures and the results show that incorporating weight aware regularizers control over tting and improve the identication performance. This research can be further extended in multiple directions: extend the database to include more images with weight variations, and improve the algorithm with incorporating both age and weight variations.

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