Effective Implementation of Denoising and Age Estimation with the Help of Facial Features

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Abstract— Age estimation is a technology has applications in Human-Computer interaction. Age estimation has applications in various fields like internet security for minors, age specific shopping etc. Input image is taken through webcam and it is pre-processed to reduce the noise in the image. Then feature extraction is performed on this image using SIFT algorithm. The extracted features are compared with the trained images. Training is performed with the help of back propagation algorithm. Support vector regression is used to convert the resulting vector of feature extraction into a number reprsenting age.

Index Terms— Back propagation, feature extraction, noise reduction, non local means filter, SIFT, SVM

1 Introduction

Ageing has a number of dramatic effects on the face. The newborn's head appears wide and vertically short due to a large neurocranium that must house a brain that is more developed than the remainder of the face and a relatively small, pug-like nose and jaw bones that have yet to grow fully. The eyes of a young child appear large relative to the face. However, as the nasal and jaw regions grow the appearance of the eyes becomes proportionally smaller. Likewise, the forehead of a child appears large and high because the facial features below it have not fully grown. The forehead continues to grow but appears more proportionate as the rest of the face develops. Development is also characterized by the growth of the nose and nasal bridge into a more angular shape. The growth at approximately 20 years of age, the face continues to change. Nose and ear cartilage keep growing, progressively enlarging the size of those features. The skin also undergoes an array of changes in texture and appearance. During childhood, the skin is soft, firm and smoother than that of adults. By middle age, the connective tissue anchoring the skin to the bones of the face begins to change, leading to drooping that is exacerbated by a loss of adipose tissue. There is also a decrease in the amount of water-proteins in the skin which, among other factors, results in dehydration that encourages wrinkling. The onset of wrinkling is typically in the 30s or 40s and by advanced old age, a person's face can become an expansive carpet of noble ripples and lines. Along with wrinkling, hair becomes grey and of a lesser quantity, dentition may occur, eyebrows become thicker and the relative size of the eyes and shape of the lips changes [3]. Thus, given the myriad of changes that age brings to the face, age estimation may be sensitive to any of a number of cues that are indicative of age.

Age is one of the vital pieces of demographic information humans unconsciously use for profiling and making decisions in their social interaction. Despite the inexact relationship between an individual's face and the biological age, it is undeniable that the face conveys very informative hints on the underlying age. Gaining the ability to automate facial age estimation can facilitate human -computer interaction in commercial applications as diverse as targeted advertisement, services, robotics, entertainment and security and demographic data collection. However machine age estimation is not a simple task because the aging process is affected by numerous factors such as innate personal characteristics, diet, environment, culture, social factors and lifestyle, which are factors not easy to quantify. In this paper, we investigate the role of facial alignment in the context of automated age estimation, the first systematic investigation on this topic to our knowledge. Variations to face during aging can be shown in fig 1.

Fig 1. Variations of face during aging.

The rest of this paper is organized as follows. Section II gives a brief idea about automatic simulation of aging effects on face images and wrinkle feature based skin age estimation scheme. Section III gives the idea of the proposed system, estimating age. Section IV is conclusion.

2 Related Works

2.1 Toward Automatic Simulation of Aging effects on Face Images

The process of aging causes significant alterations in the facial appearance of individuals. When compared with other source of variation in face images, appearance variation due to aging displays some unique characteristics. In this paper we describe how the effects of aging on facial appearance can be explained using learned age transformations and present experimental results to show that reasonably accurate estimate of age can be made for unseen images. We also show that we can improve the result by taking into account the fact that different individual's age in different ways and only considering the effect of lifestyle. Proposed work can be used for simulating aging effects on new face images in order to predict how an individual might look like in the future or how he or she used for designing a face recognition system, robust to aging variation. Our work is motivated by following real life applications, which could be addressed by our method.

2.2 Wrinkle Feature Based Skin Age Estimation

With the rapid deployment of information technology and the availability of cheap yet high performance image capturing devices, new types of healthcare services such as self-diagnosis and treatment have become possible. Skin is the outer layer of the human body and has long attracted a great deal of attention, since its appearance conveys useful information on the health condition of the subject. In this paper, we propose a skin age estimation scheme based on its wrinkle features such as length, width and depth, which represents the physical condition of skin statistically and quantitatively. We collected wrinkle features and personal data from various subjects, including age and gender, and constructed the ground truth in consultation with dermatologists. For the estimation, we used a non-linear, multi-class SVM (Support Vector Machine). Via extensive experiments on our prototype system, we show that our scheme achieves a reasonable accuracy.

In this paper, we propose a skin age estimation scheme based on the wrinkle features including the length, width and depth. For the estimation, we use a non-liner, multiclass SVM. Hence, the estimation accuracy strongly depends on the validity of the feature data and the performance of the classifier used. We first revised our previous scheme to get a more accurate wrinkle length and width, and then we proposed a new method for estimating the wrinkle depth from gray scale images. For the purposes of classification and estimation, we used a non-linear, multiclass SVM.

Here proposed a wrinkle feature-based skin age estimation scheme that returns a statistical and quantitative value for a microscopic skin image depending on the physical skin condition. As for the wrinkle features, we used the length, width, and depth, which can be calculated automatically from skin images. We used SVM as the classifier, which was trained using feature data collected from microscopic skin images, personal data and the associated dermatologists' feedback. Experimental results showed that we achieved a maximum accuracy of 83% in the accuracy evaluation.

3 AGE ESTIMATION

Input image is taken through camera and the image may contain noises. It will affect the performance of the system. So for reducing the noise from the image we use a filter called NLM filter. Then features of the image are extracted and compared with the trained images. Training is performed with the help of back propagation algorithm. Use Support Vector Regression for getting age in number.

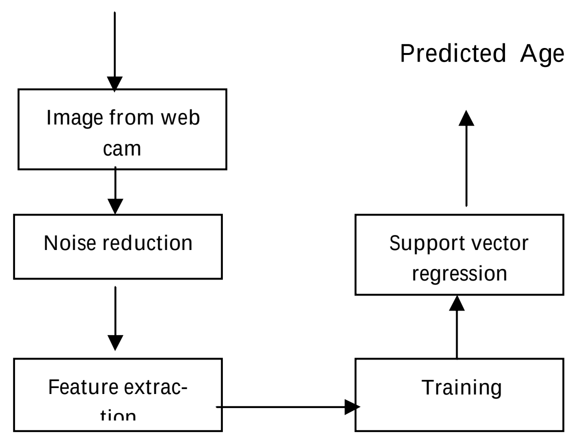

Fig 2. Block diagram of proposed system

3.1 Noise Reduction

We are using many methods for noise reduction. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. Image denoising is aimed at removing or reducing the noise so that a good-quality image can be obtained for various applications.

The NLM filter is an evolution of the Yaroslavsky filter (Yaroslavsky, 1985) which averages similar image pixels according to their intensity distance. Some filters, like the SUS AN (Smith and Brady, 1997) or the bilateral filters are based in the same principle. Non local-means denoising replaces the intensity of each pixel in the noisy image by a

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weighted average of all of the pixel intensities in the image. The main differences of the NLM with these methods is that the similarity between pixels is more robust in front of the noise level by using region comparison rather than pixel comparison and that pattern redundancy is not restricted to be local (therefore, non local). Pixels far from the pixel being filtered are not penalized due to its distance to the current pixel, as happens with the bilateral filter. First introduced by Buades et al. in, the Non Local (NL) means algorithm is based on the natural redundancy of information in images to remove noise [18][19]. This filter allows avoiding the well- known artifacts of the commonly used neighbourhood filters, and to replace the local comparison of pixels by the non local comparison of patches.

Algorithm For NLM Filter

a) Given an image Y, the filtered value at a point p using the NLM method is calculated

b) This is done by calculating as a weighted average of all the pixels in the image following this formula*:*

$$NLM(Y(p)) = \sum_{\forall q \varepsilon Y} w(p,q)\, Y(q)$$

$$0 \leq w(p,q) \leq 1 \quad \sum_{\forall q \varepsilon Y} w(p,q) = 1$$

(1) Where p is the point being filtered and q represents each one of the pixels in the image. The weights w (p,q) are based on the similarity between the neighbourhoods Np and N q of pixels p and q. Nj is defined as a square neighbourhood window centered around pixel i with a user-defined radius Rsim

The similarity w(p, q)is then calculated as

$$W(p,q) = \frac{1}{Z(p)} e^{\frac{-d(p,q)}{h^2}}$$

(2) Find the normalizing constant z(p)

$$Z(p) = \sum e^{\frac{-d(p,q)}{h2}}$$

(3) Z (p) is the normalizing constant; h is an exponential decay control parameter

Find the Gaussian weighted Euclidian distance of all the pixels of each neighbourhood:

$$d(p,q) = G_p \| Y(Np - Y(N_p)) \|^2_{Rsim}$$

(4) Where Gp is a normalized Gaussian weighting function with zero mean and p standard deviation (usually set to 1) that penalizes pixels far from the center of the neighbourhood window by giving more weight to pixels near the center. An adaptive non-local means filter is proposed which makes use of the new particle probability image and includes two Gaussian weighted Euclidean distance measurements: the first measures the similarity of pixel gray values between two neighbourhoods in the original gray scale image (as in non-local means filter), whereas the second quantifies the similarity in particle probability between the same neighbourhood. Since the latter measurement is capable of greatly enhancing the particles that are barely visible in the former, the proposed adaptive non-local means filter is intended to preserve weak particle-like objects when it is used to de noise images.

3.2 Feature Extraction

Scale-invariant feature transform (or SIFT) [1] is an algorithm in computer vision to detect and describe local features in images. The algorithm was published by David Lowe in 1999. For any object in an image, interesting points on the object can be extracted to provide a feature description of the object. This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image containing many other objects. To perform reliable recognition, it is important that the features extracted from the training image be detectable even under changes in image scale, rotation, noise and less affected to illumination.

SIFT consists of histogram representing gradient orientation and magnitude of corresponding image [1]. The features extracted are localized in spatial and frequency domains, and thereby reducing the probability of disruption by occlusion, clutters or noise.

6.3 Training and back Propagation network

Training is performed to get knowledge of images. Compare the input image features with the trained image. Once an image from the camera is stored for later use. When an input image is taken the first time it will not match with the stored image features and give an error message and store it. Training is performed with the help of back propagation algorithm [17].

Image recognition has been done in the past using image pixels to train a neural network via back-propagation. A typical ANN has N inputs and one or more output as shown in fig.3. The input layer is composed not of full neurons, but rather consists simply of the values in a data record, that constitutes inputs to the next layer of neurons. The next layer is called a hidden layer and there may be several hidden layers. The final layer is the output layer, where there is one node for each class. A single sweep forward through the network results in the assignment of a value to each output node, and the record is assigned to whichever class's node had the highest value. These actual pixels are fed into the network as the inputs. This approach works great when trying to recognize textures or objects with fixed orientation and scale. However, at different scale and orientation, it doesn't give encouraging results. Therefore tokens of an image are used for training the network.

During training, the network is trained to associate outputs with input patterns. When the network is trained, it identifies the input pattern and tries to output the associated output pattern. In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network to compute the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The back propagation algorithm is the most widely used method for determining the EW. The power of neural networks is realized when a pattern of tokens, during testing, is given as an input and it identifies the matching pattern it has already learned during training.

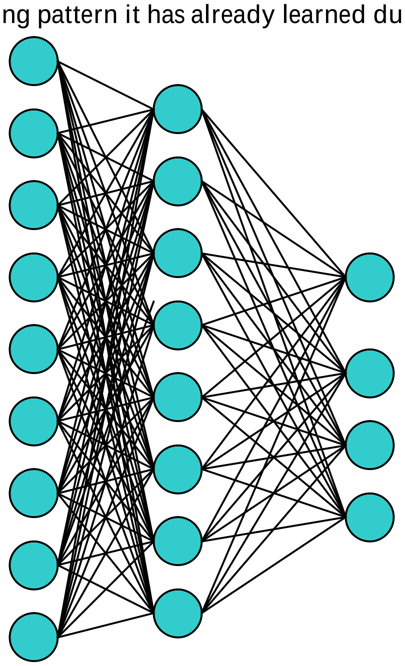

Fig 3: Example of simple Feed-Forward Neural Network

3.4 Age regression

Once an output is obtained from the training phase, a globally-learnt support vector regression using the radial basis kernel is used to regress the query onto a single continuous number representing the age.

7 CONCLUSION

The proposed method will give idea of calculating age from the input image. The advantages of this system are the reduction of noise with the help of Non Local Means Filter (NLM filter). This will improve the performance of the system. Then training the system for finding match between input image and database image. Support vector regression is used to predict the age. Age estimation has a number of applications in various fields. The system will expected to produce the accurate result.

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