3D FACE RECOGNITION USING HOG FEATURES BASED ON FINE-TUNING DEEP RESIDUAL NETWORKS

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By

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3D FACE RECOGNITION USING HOG FEATURES BASED ON FINE-TUNING DEEP RESIDUAL NETWORKS

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February 2020

Chair : Lili Nurliyana Binti Abdullah, PhD
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As the technology for 3D photography has developed rapidly in recent years, an enormous amount of 3D images has been produced, one of the researches for which is face recognition. Improving the accuracy of a number of data is crucial in the 3D face recognition problems. Traditional machine learning methods can be used to recognize 3D faces, but the face recognition rate has declined rapidly with the increasing number of 3D images. As a result, classifying large amounts of 3D image data is time-consuming, expensive, and inefficient. The deep learning methods have become the focus of attention in the 3D face recognition research. Current methods of assessing 3D face recognitions are limited and often subjective, complex or low accuracy. One of the most prominent methods for assessment showing great promise is residual neural network (ResNet), a shortcut connection way of training a very deep network by randomly dropping its layers during training and using the full network in testing time, which allows for a more quantitative evaluation. With the introduction of feature engineering of HOG method for extracting the discriminative information, and especially fine-tuning method for reconstructing the ResNet learning model, we are able to calculate a relative high accuracy for the extracted face region. This allows also researchers to effectively assess on a continuous accuracy with fine-tuned ResNet learning model of different depths. However, shadow learning technology is not available in many settings (e.g. curse of dimensionality, accuracy decline) yet so there still exists a need for this quantitative assessment from deep learning methods. How to extract the important and discrimative information from the raw data and efficiently recognize a large number of 3D face images with fine-tuned learning framework at high accuracy was the main task of this research. In our experiment, the end-to-end face recognition system based on 3D face texture is proposed, combining the geometric invariants, histogram of oriented gradients and the fine-tuned residual neural networks. The

research shows that when the performance is evaluated by the FRGC-v2 dataset, as the fine-tuned ResNet deep neural network layers are increased, the best Top-1 accuracy is up to 98.26% and the Top-2 accuracy is 99.40%. The framework proposed costs less iterations than traditional methods. The analysis suggests that a large number of 3D face data by the proposed recognition framework could significantly improve recognition decisions in realistic 3D face scenarios.

Keywords: 3D face recognition, image classification, feature engineering, histogram of oriented gradients, statistical deep learning, residual neural networks, fine-tuning, tensorboard.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Sarjana Sains

PENGECAMAN WAJAH 3D MENGGUNAKAN CIRI HOG BERDASARKAN RANGKAIAN SISA YANG MENDALAM

Oleh

SIMING ZHENG

Februari 2020

Pengerusi: Madya Dr. Lili Nurliyana Binti Abdullah, PhD
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Oleh kerana teknologi untuk fotografi 3D telah berkembang dengan pesat dalam beberapa tahun kebelakangan ini, sejumlah besar imej 3D telah dihasilkan, salah satu daripada penyelidikan yang merupakan pengiktirafan muka. Memperbaiki ketepatan beberapa data adalah penting dalam masalah pengenalan wajah 3D. Kaedah pembelajaran mesin tradisional boleh digunakan untuk mengenali wajah 3D, tetapi kadar pengiktirafan wajah telah menurun dengan cepat dengan peningkatan bilangan imej 3D. Kesimpulnya, mengklasifikasikan sejumlah besar data imej 3D adalah memakan masa, mahal, dan tidak cekap. Kaedah pembelajaran mendalam telah menjadi tumpuan perhatian dalam penyelidikan pengenalan wajah 3D. Kaedah semasa menilai pengiktirafan muka 3D adalah terhad dan seringkali subjektif, kompleks atau ketepatan yang rendah. Salah satu kaedah yang paling menonjol untuk penilaian yang menunjukkan janji besar ialah rangkaian saraf residual (ResNet), cara sambungan pintas latihan rangkaian yang sangat mendalam dengan secara rawak menjatuhkan lapisan semasa latihan dan menggunakan rangkaian penuh dalam masa ujian, yang membolehkan lebih banyak penilaian kuantitatif. Dengan pengenalan kejuruteraan ciri kaedah HOG untuk mengekstrak maklumat diskriminatif, dan terutama kaedah penalaan halus untuk membina semula model pembelajaran ResNet, kita dapat mengira ketepatan yang relatif tinggi untuk kawasan wajah yang diekstrak. Ini membolehkan para penyelidik untuk menilai secara berkesan dengan ketepatan yang berterusan dengan model pembelajaran ResNet yang diperhalusi dengan teliti yang berbeza. Walau bagaimanapun, teknologi pembelajaran bayangan tidak tersedia dalam banyak tetapan (mis. Laknat kepincangan, kemerosotan ketepatan) namun masih terdapat keperluan penilaian kuantitatif ini daripada kaedah pembelajaran mendalam. Bagaimana untuk mengekstrak maklumat penting dan diskriminatif dari data mentah dan mengiktiraf sejumlah besar imej wajah 3D dengan rangka kerja pembelajaran terperinci dengan ketepatan yang tinggi adalah tugas utama penyelidikan ini. Dalam eksperimen kami, sistem pengenalan wajah akhir-ke-

akhir berdasarkan tekstur muka 3D dicadangkan, menggabungkan invari geometrik, histogram kecerunan berorientasikan dan rangkaian saraf sisa yang sihat. Penyelidikan menunjukkan bahawa apabila prestasi dinilai oleh dataset FRGC-v2, apabila ResNet digunakan dalam rangkaian Rangkaian neural yang ditala dengan baik, peningkatan ketepatan Top-1 terbaik adalah 98.26% dan ketepatan Top-2 adalah 99.40%. Rangka kerja kos yang dicadangkan kurang daripada lelaran tradisional. Analisis menunjukkan bahawa sejumlah besar data wajah 3D oleh rangka kerja pengiktirafan yang dicadangkan dapat meningkatkan keputusan pengiktirafan secara nyata dalam senario wajah 3D yang realistik.

Kata kunci: Pengiktirafan wajah 3D, klasifikasi imej, ciri kejuruteraan, histogram kecerunan berorientasikan, pembelajaran mendalam statistik, rangkaian saraf residual, penalaan halus, tensorboard.

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My Mission in the future：

When I was a master student in Malaysia, sometimes I was confused about whether to pursue knowledge or my dream.

One day I visited a library in the University of Putra Malaysia, where is the core soul of this university. Each dissertation on the shelf, has a long title of student's research topic, with their name, date and creative technologies.

Their physical body was away, but their ideas and contributions last until the end of every student learning career.

There I discovered my mission in life!

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of science. The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

3D	Three-dimension
3DFED	Three-dimension Facial Expression Database
3D_RMA	Three-dimension Return Material Authorization
AI	Artificial Intelligence
ASM	Active Shape Models
B	Bias
BJUT	Beijing University of Technology
BU-3DFED	Binghamton University 3D Facial Expression Database
BN	Batch Normalization
CNNs	Convolutional Neural Networks
CASIA	Institute of Automation Chinese Academy of Sciences
CUDA	Compute Unified Device Architecture
CPU	Central Processing Unit
Dlib	C library (A general purpose cross-platform software library)
DCNN	Deep Convolutional Neural Network
FR	Face Recognition
FER	Facial Expression Recognition Challenge
FRGC 2.0	Face Recognition Grand Challenge version 2.0
FC	Fully connected
FP	Samples of False Positive
FN	Samples of False Negative
f	Function
GavabDB	Gavab.Database
G	Gradient

GAP	Global Average Pooling
GB	Gigabyte
GPU	Graphics Processing Unit
GHz	Gigahertz
HOG	Histogram of Oriented Gradients
H	The function of finding the histogram
ISO	International Organization for Standardization
kNN	The algorithm of k-Nearest Neighbour
LR	Linear Regression
LBP	local binary pattern
LNDP	local normal derivative pattern
ML	Machine Learning
max	The function of finding the maximum
NLP	Natural language processing
NIST	National Institute of Standards and Technology
PCA	The algorithm of Principal Components Analysis
ResNet	Residual Neural Network
ReLU	The activation function of Rectifier Linear Unit
S	Second
SVM	The algorithm of Support Vector Machine
SGD	The activation function of Stochastic Gradient Descent
SPMD	Single program multiple data
Tan	Tangent function
Top1	The one with highest probability
Top2	The first two with highest probability
TP	Samples of True Positive

TN	Samples of True Negative
VGGNet	The Visual Geometry Group Network
W	The weight of neural network
γ	The symbol of Gamma

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

3D face recognition is a classical research topic in the field of computer vision, and its essence is image classification. The recognition rate is the goal of human face recognition tasks. The traditional face recognition exists many problems, such as illumination change, head posture change, foreign body occlusion, and so on. At present, although there were many ways to solve these problems, the main challenges remain. To address these concerns, this research proposes an end-to-end fine-tuned deep learning model for face recognition based on 3D face textures images.

In recent years, the Convolutional Neural Network (CNN) has dramatically developed in various fields of computer vision, and the recognition algorithm based on convolutional neural network gradually applied in recognition tasks. The surveys (Karen Simonyan & Andrew Zisserman, 2015) found increasing of computing resources and the emergence of a large number of data sets, the deep learning method of the convolutional neural network provides many possibilities to improve the accuracy of 3D face recognition. With the gradual improvement of performance requirements for specific scene applications, designing a reasonable structure of the deep neural network has become a critical factor in determining network performance (Y. Sun et al., 2015).

With the rapid growth of the Internet, the smart computing equipment and social networking applications were increasingly used. There were hundreds of millions of 3D images uploaded every day to platforms such as Snapchat and Alipay, on which a large number of 3D face images were generated. Three main problems in creating 3D face recognition systems were that many researchers report were the 3D face pose, illumination changes, and variations in facial expression. Extracting better features were a key process for 3D face recognition (Parama Bagchi et al., 2015; Jian Zhang et al., 2016; Gawed M et al., 2013, Xueqiao Wang et al., 2015; Xiangyu Zhu et al., 2016). Furthermore, shallow learning (such as machine learning) including only one or no layer of hidden units leads to lack of ability to deal with large-scale data. These challenges have caused persistent problems for the robustness and reliability of such systems, which has driven many researchers to use deep learning for 3D face recognition tasks.

1.2 Problem Statement

In recent years, considerable attention has been directed to the application of Statistical methods of both machine learning and deep learning models in computer vision tasks. These methods have been used in 3D face recognition and prediction in numerous 3D face research works. However, predicting the probability of 3D face images for a large number setting remains a challenging task for many researchers.

With the development of imaging technology, the resolution of 3D face images was getting higher and higher, and the amount of information contained was also increasing, this put pressure on the work of the image recognition stages. However, different learning models have different generalization ability for extracting images features. When processing a large number of image data, the problems like curse of dimensionality increasing was caused because of a large number of non-discriminative data (Sima Soltanpour et al., 2017). The performance of 3D face recognition was sensitive to unimportant background information, the best way is to eliminate the influence of noisy on testing data. Besides, some factors such as posture, expression, and background information can still affect the result of 3D face recognition. As a result, the model training and testing becomes unstable due to the non-discriminative data generated in the pre-processing phases.

Quite a few researches have been conducted on the application of CNN structures in 3D face recognition tasks. When the deeper the layers of learning model are, the more problems like recognition accuracy decline, due to the network limitations of gradient vanishing and exploration. Nevertheless, no work has been done on reconstructing learning model by different fine-tuning strategies for modeling the extracted data. A literature review of some CNNs-based models applied for the field of 3D face recognition that shadow learning has been caused to these problems, some examples were given from the researches of Huiying Hu et al., (2017) and S Sharma et al., (2016).

These gaps encouraged this research to focus on the development of end-to-end fine-tuning based deep residual learning framework for 3d face recognition by using Hog Features. This thesis concentrates also on the feature engineering and computation with the aim of reducing the effects of curse of dimensionality on the computing performance and increasing the whole accuracy while solving the gradient vanishing and gradient explosion problems.

1.3 The Motivation and Significance of the Study

The primary objective of approach was proposed that it was to create an end-to-end face recognition system 3D textures-based with a high recognition accuracy, a satisfied performance and robustness while remaining practical. In this system, a custom residual neural network model was developed base on ResNet architecture for the 3D face recognition task. This model was fine-tuned with different depth using HOG features of 3D face images. The primary aim was to solve problems of gradient vanishing and gradient exploration. In this work, the fine-tuned ResNet models was trained with different depth using HOG based 3D texture images, maintaining faster calculations and the high accuracy of the growth of images.

When deep learning methods were applied in realistic 3D face scenarios, two challenges confronted were as follows: Firstly, the accuracy becomes unstable as 3D face images were added, this was because different deep learning networks have different generalization ability for extracting images features (Y. Sun et al., 2015). When processing a large number of image data, the deeper the layers of deep learning model were, the more problems such as gradient vanishing and gradient exploration will be caused (Christian Szegedy et al., 2015; Y. Sun et al., 2015); Secondly, as more and more complex deep learning models will be applied to the actual scenario, the recognition rate may be affected by the depth of a complex model. In this research, the research explored both issues. How to recognize a large number of 3D face graphics with high precision is the main task of this experiment.

1.4 The Objectives of the Study

The main purpose of this thesis is to investigate the effect of our 3D face recognition framework towards achieving the high recognition rate that outperform the accuracy in the state-of-the-art researches. The primary aim is to make contribution to the development of fine-tuned ResNet learning model for 3D face texture data in term of recognizing and predicting the outcome of individual face images. It is important to highlight that this study also intends to fill the gap in comparative studies by developing strategies that directly incorporate feature engineering in the process of constructing a 3D face recognition learning framework. More specifically, the foremost objectives of our research can be outlined systematically as follows:

1. To develop new robust face detection and alignment approaches in pre-processing stage to improve the framework efficiency, reduce the effects of curse of dimensionality and select the important data variables in each individual 3D image for the learning model.

2. To propose the HOG strategies for extracting the discriminate 3D face data in experimental learning models rather than simply inputting extracted data.

3. To propose a specifically designed fine-tuned ResNet learning models that are able to predict the probability of the extracted HOG-based face images, which is efficient in predicting the outcome at each epoch.

4. To analyze the experimental data using the fine-tuned ResNet models with different depth and using the Tensorboard to compare the probability results with standard evaluation metrics of accuracy.

1.5 The Research Scope

The focus of this thesis is on development deep learning-based framework for recognizing the 3D face texture images. More specifically, the aim is to develop fine-tuned CNNs architecture that are able to receive gray image as input data instead of the raw data from the FRGC 2.0 dataset. Face recognition can be viewed as a classification problem by establishing recognition framework according to the particular situation. Focus will be restricted to constructing fine-tuned Deep Residual Learning classification model that predict the precision and accuracy of events occurring during one or more fixed time intervals. In other words, 3D face recognition is considered as a classification problem in this research. The experiments also focus on the feature extraction process as a pre-processing technique for handling the computation workload and curse of dimensionality problems. By using image pre-processing, the fine-tuned model is able to process some information about the extracted raw data. The gathered information helps the framework to effectively learn and recognize the discriminate information for reducing actual computation and increasing the recognition rate. For this purpose, we use the custom HOG extraction method.

1.6 The Research Contributions

The following list demonstrates the contributions of the research:

- Proposed a 68 key points for detecting the exact face area, including eyebrows, eyes, nose, mouth, chin, etc. This method effectively improves detection precision rate for recognizes face images.

- Proposed a custom HOG algorithm for extracting the discriminate feature effectively reduce image dimensions and size.

- Proposed a new method of fine tuning based ResNet learning model which is useful for fixing the input data and recognizing the 3D face texture datasets.

- The result found a relationship between the comparison matrices and the proposed learning model with different depth layers. The relationship can help researchers better to evaluate the robustness of learning models and the effects of each epoch on the further experiments.

1.7 The Structure of the Dissertation

This thesis was mainly discussed in six large chapters, the remainder of this work is prepared as follows:

Chapter one: The introduction of 3D face recognition. The research background, research objectives and significance of the thesis were discussed. The development of deep learning was expounded.

Chapter two: Showing a comparison of shallow learning and deep learning and explains the content of deep network theory. This chapter summarizes the theoretical knowledge of deep learning, the convolution network and the principle of residual networks.

Chapter three: The robust 3D face detection and alignment modules were implemented and flexibly applied in 3D face raw data. In addition, the detailed steps of HOG feature extraction and the classification with the fine-tuned residual neural network were presented, an extraction pattern was proposed by combining the HOG features to the our fine-tuned of ResNet model. This chapter has carried out experiments on FRGC 2.0 database.

Chapter four: Using different test metrics to evaluate the performance of our proposed model and analyzed the performance values for each phase on the visualization tool of Tensorboard.

Chapter five: This section discusses the use of more specific performance indicators to evaluate proposed models, such as Top1 and Top2. Analyzing the performance of each stage on the model and finally compare it with related research.

Chapter six: A conclusion and outlook were made in our research. The research results in the postgraduate stage and the innovations of this thesis were comprehensively summarized. At the same time, this study analyzes the shortcomings of the research and the direction of future improvement.

1.6 Summary

Face recognition is the most typical pattern recognition. The feature information of the face can be extracted in different ways, and the collected information was compared or verified with the original information, thereby realizing the recognition of the human identity. The first chapter mainly introduces the research background and significance of 3D face recognition, then analyze various difficulties and challenges encountered in our research, and then propose the research object to the problems. The next chapter introduces the relevant research work, and gradually explains the application of contemporary machine learning methods and the basis of deep neural network algorithms in the 3D face recognition.

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