The Hong Kong Polytechnic University

Department of Electronic and Information Engineering

Final Year Project

Project Proposal

Machine Learning for Facial Image Super-resolution

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1. Objective

(1) Study different image super resolution algorithms and machine learning theories

(2) Implement image processing and recognition algorithms for facial image super resolution

(3) Evaluate the performance of different image super resolution algorithms

(4) Compare the traditional approach to deep learning approach for image super resolution

(5) Develop a GUI for facial image super resolution

(6) Make improvements on current image super resolution algorithms

2. Introduction

Single image super-resolution is to generate the high-resolution image given a single low-resolution one. This technique has many applications in the areas of image processing and computer vision, such as video surveillance and medical usage. In video surveillance, the face recognition rate drops significantly when the size of the facial image becomes smaller [1]. E. Bilgazyev et al. showed that the performance of face recognition of a low-resolution image could be increased by performing image super resolution [2].

Face Hallucination is a special case of image super resolution where the input is a facial image. The algorithms could be categorized in many ways, such as interpolation-based, reconstruction-based and example-based methods. However, the performance of interpolation-based and reconstruction-based methods is usually worse because they do not make use of the similarity and the structure of a human face [3]. In this project, majority of example-based methods of face hallucination will be investigated.

In 2014, the first deep learning method solving image super-resolution was invented using Convolutional Neutral Network (CNN) [4]. It showed the performance of image super resolution is comparable to the traditional methods. Afterwards, different deep learning methods are developed for solving single image super-resolution. In this project, different deep learning approaches will be compared to the traditional approaches.

3. Relevant Work

Principal Component Analysis (PCA)

PCA is a dimension reduction transformation to convert the sets of data into a lower dimensional orthogonal vector space that can best represent the data by minimizing the mean square errors. This method could be used for representing the facial image by analysing the major components of the human facial image from the training set. This could be useful for facial image super resolution because the high-resolution image could be generated by a linear combination of the major components from the high-resolution from the training set using the weights learnt from the low-resolution training set [5].

Locally Linear Embedding (LLE)

Locally linear embedding algorithm is one of the manifold learning methods that use the linear relation of the input data and the training data to generate the output data. [6] The idea of this algorithm is to find the k nearest neighbour in the training data that closed to the input data. Then, the input data could be represented by the linear combination of the training data. By using the weights in the low-resolution space, the high-resolution space could be generated, hence image super resolution is achieved.

Sparse Representation (SR)

In the past decade, sparse representation is found to be useful in many applications, especially for signal processing. The idea of sparse representation is that the signal is represented by a linear combination of the basic signals, and the number of the basic signals should be as small as possible. The idea of using it for image super resolution is to learn a sparse representation of the low-resolution image from the data set, then use the weights calculated to reconstruct the high-resolution image [7] [8].

Deep Learning

The first deep learning used for image super resolution is proposed using Convolution neutral network in 2014 [4]. Afterwards, there are a lot of variation of convolution neutral network proposed solving image super resolution problem. After that, other deep learning approaches are proposed for solving image super resolution such as Generative Adversarial Network [9] [10]. In this project, the convolution neutral network and the generative adversarial network will be considered.

4. Methodology

(i) Tools

- MATLAB R2016a with image processing toolbox
- Python with OPENCV and PyTorch

(ii) Dataset

- MIT Face Database
- Aberdeen face database

(iii) Mathematical Model

Two mathematical models will be considered in this project. They are linear model and probabilistic model [11]. Let X denotes the original high-resolution image, Y denotes the down low resolution. $\hat{X}$ denotes the estimated high-resolution image after super resolution.

Linear Model:

$$Y = HX$$

Where H is the kernel for down sampling.

Probabilistic Mode:

$$P(\hat{X}|\mathrm{Y}) = \frac{P(Y|\mathrm{X})P(X)}{P(Y)}$$

(iv) Procedure

In this project, majority of the example-based image super resolution will be implemented and compared. In this project, the Principal Component Analysis, Locally Linear Embedding and sparse representation will be investigated. Also, the latest deep learning will also be considered and compared to the traditional approaches. Most of the methods will be done using MATLAB except the deep learning methods. For the deep learning-based methods, python will be used and some existing libraries such as PyTorch and opencv will be required in this project.

This project also considers different image super resolution inputs. Some of the algorithms use the original size of the image as the input features. Some of them use a bicubic interpolation as the input feature before applying super-resolution. Some of them use first and second gradient as the input feature. This project will compare different input features.

Moreover, different noise conditions will also be considered. To conduct experiment with noisy image, the low-resolution image will be generated using down sampling and noise will be added in the input image. The original high-resolution image will be the ground truth image. Experiments will be done to compare the results for different super-resolution algorithms.

To compare and apply the algorithms, the same database will be used for fair measurement on different algorithms. The face alignment will be first done using the opencv library since some of the algorithms is scale, position and rotation dependent.

For the low-resolution and high-resolution training pairs, the high-resolution image will be down-sampling to different scales to make the pairs of low- and high-resolution images. For the experimental purposes, different noise will be added when the low-resolution image is produced, and further experiment will be done for testing. For the input testing image, some of the images from the dataset will be drawn as the testing image, and the remaining will be as the training samples.

A GUI using MATLAB may be done after all algorithms are implemented. The GUI can ask the user select different learning algorithms, training samples, input image. And then output the generated high-resolution image.

(v) Measurement

To measure the performance of the super-resolution algorithms, different parameters will be considered. The commonly used parameter is Peak Signal to Noise Ratio (PSNR). It can measure the mean square error of the generated high-resolution image to ground-truth image. However, it is not good measurement for image problems. Instead, Structural Similarity Index (SSID) will be considered in this project. Also, different scales of upscaling factors and different image sets will also be considered in the measurement.

Another way to measure the performance of different algorithms of facial image super resolution is the face recognition rate. As mentioned in the introduction, the face recognition rate might be increased if image super resolution is performed. In this project, the face recognition of the input low-resolution and generated high-resolution image will also be considered respectively for different algorithms.

5. Project Schedule

Time	Work
Sep 2018	Implementing the 1st algorithm: Principal Component Analysis (PCA)
Sep 2018	Implementing the 2nd algorithm: Locally Linear Embedding (LLE)
Oct 2018	Implementing the face alignment algorithm
Oct 2018	Implementing the 3rd algorithm: Sparse Representation (SR)
Nov 2018	Fine toning the three algorithms
Nov 2018	Implementing the measurement and face recognition system
Nov 2018 / Dec 2018	Implementing the Deep Learning Algorithm: Convolutional Neural Network (CNN)
Nov 2018 / Dec 2018	Implementing the Deep Learning Algorithm: Generative Adversarial Network (GAN)
Dec 2018 / Jan 2019	Measurement on different algorithms
Jan 2019	Developing a GUI
Feb 2019 - Apr 2019	Improvement on different algorithms / Report Writing

6. References

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