Image Processing Framework for Face Detection and Face Swapping in Group Photo Refinement

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Abstract. As the trend of big data and increasingly widespread social networking sites, people are enjoying sharing their daily lives by displaying selfies or group photos online, creating large amount of data, which indicates great effort that online servers or applications may have to spend to edit and process personal photographs. However, human face processing requires elaborate skill that is time-consuming if is operated manually. While image processing, as a crucial research area in fields of AI (Artificial Intelligence), plays its indispensable role of setting us free from these repetitive routines. In order to solve existing problems, this paper proposes a relatively reliable and complete framework to refine photos of human facial expressions of emotions among a set of group photos both partially and wholly based on existing techniques of face detection and face swapping. In addition, this framework also involves procedures of extraction of face features relied on Dlib library. Finally, a set of experimental results and relevant statics are displayed to indicate some future works that have to be carried out.

1. Introduction

1.1. Motivation

Nowadays, people are creating a bunch of data related to images, audio etc., which puts much more burden for online servers to perform a real time record and process, which is so-called big data time. In term of image data, people are increasingly addicted to taking selfies with novel postures in order to display on home pages of Facebook or Instagram to show personal characteristics. Apart from selfies, some other forms of staged photography like group photos are also popular among major social networking sites. In order to handle these big data, some applications functioned as photo refinement tools like BeautyPlus pervade in countries like Japan and China.

The thing is, different from selfies, group photos consist of several people may encounter some technical problems relate to facial expressions for every person when shooting each time. Imagine a case when 4 people named A, B, C, D respectively are taking group photos in front of a camera. Once a single photo is shot, though it would be a nice selfie for A in that he or she is smiling, yet for B, C, D who may be glancing at somewhere else, sleepy with eyes closed or turning away head to avoid flash lights from camera, this group photo is obviously terrible. The photographer may choose to take a few
more times to get a better result, which is practicable but time-consuming indeed. What if B wakes up from sleeping, while A loses patience and sneaks off, rolling his or her eyes next time? As we can see, for group of people, it is not easy to have every single one to achieve their best state to complete a delicate photo. Some people may say that camera tools like BeautyPlus would play its role in assisting people refining group photos later. However, the procedure to deal with refinement for such kind of mass data still depends on artificial labor to control every detailed aspect, which requires great effort. In order to handle problems like this, our group comes up with a complete framework to process several versions group photo that takes for same group of people, integrating them into a final satisfying image for everyone inside this photo. This framework, to a large scale, would do great help to people’s daily life in that it is meant to imitate and carry on procedures that human does to edit group photos for several people. That is, the framework would also include the process of repairing unsatisfied facial expressions of emotions into gentle looks. The only difference is that this framework automatically sorts out the most gentle-looking face from several versions of group photos for same bunch of people instead of doing what a professional photographer would do to artificially alter looks of human face.

1.2. Related works
It is worth noting that this framework is feasible and reliable based on existing achievements in this area. Some related works have been researched and formed complete system to offer help to our framework. Previous researches mainly lie in three fields: face detection and recognition, emotion recognition, and face swapping. For face detection, some accurate algorithm based on Convolutional Neural Network (CNN) at a faster rate provides ideal base to carry on the task [1] [2] [3] [4]. In addition, practical python library like Open Source Computer Vision (OpenCV) and Dlib has been developed fully to extract face features and matching [4]. Practical techniques for face ID verification are presented in noted companies like Apple and Facebook which is tested to have a recognition efficiency of 93% [2]. While in realm of emotion recognition, researchers propose specific emotion models for facial expression like anger, disgust, and fear etc. to evaluate whether sample faces can fit in designed models [5] [7]. In domain of face swapping that is another research hotpot, fast face-swap method based on CNN is suggested recently and is now available to take deeper researches [6] [7].

As we can see from related works, existing projects have managed to swap whole face for single person between photos. In our framework, however, we succeeded in swapping faces for group of people at the same time as well as swapping partially sense organs on faces at will for same person. Apart from these innovations, we adopted several methods mentioned above to construct the whole system and some detailed procedures and experimental results would be covered in the following parts.

2. Proposed Approach
The proposed photo combine system is going to analyze a series of pictures taken for a same group of people each of whom wears expressions of emotions that might not meet satisfactory on one particular photo. So, this system would focus mainly on eliminating unsatisfied facial expressions like closed eyes or corners of mouth pulling down to present a final result of all people equipped with suitable countenance. Since our system is targeted at mimicking the general step that human does when editing a group photo, it would be much easier to understand this process if we follow the common train of thought of human.

The architecture of this system is displayed in Fig 1, a set of photos acts as an original input which requires complex processing through the whole system including face detection, similarity comparison, sorting out most satisfied facial expression of emotions and then performing face swapping procedure for one same person. In order to make it clear, a more detailed discussion is going to be covered in following parts of this paper.
2.1. Face pre-processing

To begin with, original photos have to be pre-processed to detect the number of people existed. This framework involves refined Faster R-CNN to realize face detection procedure. The use of Faster R-CNN which reduces the burden of proposal generation to detect faces. Faster R-CNN contains two modules which is called Regional Proposal Network (RPN) and the Fast R-CNN detector. RPN and Fast R-CNN detection network share a set of conv layers to extract the features of the image. RPN are used to recommend candidate areas and ROI pooling convert input of different sizes to output of fixed length. It is tested that the refined version of faster R-CNN can perform at a precision rate at 100%, which is a little bit higher than its original version [1]. Finally, Classification and Regression are used to output the category of the candidate areas and the exact location of the candidate region in the image.

To be specific, with the help of existing face detection tool, we would get accurate coordinate positions, which does help to crop out single piece of image for one particular person according to obtained positions. Before this procedure operates, we have to choose one group photo from existing set to become the template which is selected according to calculation result from Formula (2) to receive adjustment and display as result finally. Step relates to choosing template group photo aims at limiting time cost via finding the picture that requires the least times of face swapping. Also, given that this system is targeted at every single person’s facial expression and a comparison of quality for facial expression is going to be required, so our primary practice to gather or classify sub-facial image for the same person among all photos in this same set. While during the classification procedure, a verification to identify human faces for same person in rest versions of group photo has to be carried out.

In term of similarity comparison to identify and pick out faces for same person, we would involve a particular step in dealing with 68 landmarks and 128-dimentional charctestic vectors, which would be a great amount of job to complete. Fortunately, Dlib library provides a relatively integrated wrapper class to assist us to extract features after face recognitions. The key point of similarity comparison is to calculate distances between landmarks that refers to Euclidean Distance formula (see in Formula (1)) and finally returns back a general similarity index between two existing human figures based on primate data information from landmarks and characteristic vectors. In addition, official guidance of Dlib library gives out a criteria of similarity threshold around 0.6 to judge whether two human figures could be identified as same person.

\[
Euclidean \ Distance = \sum_{i=1}^{n} \sqrt{(x_{1i} - x_{2i})^2 + (y_{1i} - y_{2i})^2} \quad (1)
\]

where \(x_{1i}\) denotes the \(i^{th}\) point’s coordinate position from certain set one (landmark points from template-image 1) and \(y_{1i}\) represents the \(i^{th}\) point’s coordinate position from random set of other images. The thing is, some existing research lies in this area also include similar practice of calculating
Euclidean distance for facial landmarks for single person at one time [5]. However, our framework refines this procedure by improve the number of people that can be recognized at the same time in order to better treat high quantities of big data.

2.2. Select most gentle facial expression of emotions
According to previous procedure, a concrete number of files have already been created to include sub-image of same human figure. This step is meant to complete the mission of winnowing a best sub-image that is most close to a gentle or smiling face which is definitely a best managed facial expression of emotions. In this step, our framework applies algorithm relates to Log-Gabor filter bank, which proposes a new methodology to recognize face emotion. The whole flow can be divided into three stages. firstly, a Log-Gabor filter bank of 5 scales and 8 orientations is used to detect the face and features. Secondly, images are divided into two purposes for training and testing. Euclidean distance is determined between these two kinds of images for classification of emotion. Finally, PCA are used to compress 8 orientations or 5 scales to reduce the dimensionality of the feature vectors. We improved these single steps and used more multimodal approach except facial expressions and the emotion detection rate are improved by 5%.

Also, we have to quantify this process and put forward an absolute criterium to evaluate emotion quality for every sub-image. Actually, there already exist a concise and received way to compute the ratio of landmark distance to face size, which indicates a proportion figure for height of eyes, width of eyebrows etc. to width of human faces. Previously, some researchers have done calculation procedures and proposed a probable range of these ratios for smiling face. However, consider that particular photo size and quality of photos would contribute slightly different results, our group manage to pick out some smiling faces as templates to compute a more suitable and narrower training set for our current trial. In general, we would apply a simplified model to sort out the smallest quadratic sum of distance between sample face and standard smiling image to ensure selected face can best fit in smiling face model, which is inspired by sum of squares of errors (see in Formula (2)) utilized in fields of machine learning.

\[
evaluation = \sum_{i=1}^{m} (h(x^i) - y^i)^2 \quad (2)
\]

where \(h(x^i)\) means the \(i\)th value of the prediction, \(y^i\)means the actual \(i\)th value to calculate the reliable parameters.

After obtaining the criteria to assess ideal face looking, we proceed in adapting squares of error formula into computing distances of heights and widths between ideal set and sub-image, forming a simple evaluation standard formula (see in Formula (3)). Theoretically, the smaller the distance is, the more likely that the particular person is close to smiling in sub-image. In this way, the sub-image with smallest amount in figure is chosen, waiting to be replaced to selected template that is decided at the very beginning. Theoretically, if we have 4 people in total to take a set of group photos, we are sure to determine one single and ideal sub-image for every people, that is 4 sub-images totally by this step.

\[
evaluation = (\text{brow slope of sample faces} - \text{standard brow slope})^2 + \cdots + (\text{mouth width of smaple faces} - \text{standard mouth width})^2 \quad (3)
\]

Note: there are four elements omitted in the ellipsis, including brow height, brow width, mouth height and eye height

2.3. Face swapping and final combination
Until this step, raw material that is waiting to be adjusted has already been prepared. Face swapping step can be divided into 3 small sections. The first section deals with obtaining a transmission matrix for transferring landmarks from ideal sub-image to selected templates. Noticeably, the number of matrix required equals to number of people existed in group photo. Since the whole data set contains accurate coordinate positions of landmarks is accessible via Dlib tools, it would be easy to compute the transmission matrix, which represents a mathematical relationship between two ‘T’ area consists of landmarks of eyebrows, eyes, nose and mouth. Then, the next section aims at erasing original ‘T’ area of templates and replace it with ideal sets, in which black masks are applied to cover this area. This section is much easier since we would get exact coordinate positions of ‘T’ area and get this area filled
with black pixels and then transplanted with landmarks from ideal sub-image. The final section involves color adjustment, which is necessary. Although images of same person for both template and ideal sub-image share similar optical environment and thus result in nearly same skin color, there still exist subtle differences between captured angle. In order to make the final combination more nature free of repairing trace, we have to obtain RGB color around ‘T’ area and apply them to newly replaced area.

So far, main jobs have been finished and the last step is merely pasting newly combined face back to its original position. In this way, a group photo with several people could be processed in similar procedures to get ideal emotions and repairing results. Although we followed the face swapping model in [8], the result turns out not all that perfect. Model mentioned in [8], however, still have flaws in adjusting the shades and tones of between faces, which results in an unnatural display of output. In order to handle this problem, our group made improvements on specific details and finally reached satisfying result (See in Fig 4 (b)).

3. Experiment Results

Several tests have been carried out in order to evaluate the accuracy of the proposed image processing framework for face detection and face replacement in group photo based on face-recognition. The performance has been tested on a group photo of 121 people, a group photo of 4 people and a group of 6 people to check the feasibility of the system. The system has been implemented in python, mainly using the Dlib library.

3.1. Training

The samples used in our tests are collected from different sources:

1) The group photo of 4 people and 6 people are captured by iphone7 plus with a 12 million pixels. The both two training sets include 5 images which all have different facial expressions. The photos have been taken at different hours and in different days in order to consider varied illumination conditions.

2) The group photo of 121 people is captured by SLR camera. This training set contains 9 images which differ in expressions and gestures. We cannot show this image later so these images are only used to show the accuracy rate in a large group photo. The faces are divided into a window size of 124 × 124 and 278 × 278 pixels for subsequent face replacement experiments. Although this does not match the typical aspect ratio of people’s face, it can achieve better results than rectangular windows in that it simplifies the detection of faces regardless their distorted faces inside the image. We calculate the accuracy of face-recognition in the group photo of 121 people using OpenCV library, CNN library, Face Recognition library and Dlib library and make a compare of these libraries. Based on the data which we get from the comparison, we finally chose Dlib library to conduct our experiment because it has a precision of 93.4% which shows a good accuracy.

3.2. Adopted metrics

Precision and Joint Degree have been used as quality metrics to evaluate the performance of the face detection and face replacement task, defined respectively as:

\[
\text{Precision} = \frac{\text{Number of Recognized Faces}}{\text{Number of Existing Faces} + \text{Number of False Recognized Objects}}
\]

This precision equation measures the accuracy of the algorithm, i.e. the percentage of the identified faces out of the total number of detected objects. Therefore, it is a measure of completeness.

3.3. Results Display

We choose the group photo of 6 people to illustrate our overall system process, while the group photo of 4 people we will only provide the effect picture to show our result.

3.3.1 Face detection. The tests on a desktop environment have been conducted on an Intel Core i5 processor at 1.6GHz and 8GB RAM with macOS operating system. Because of the portraiture rights, we can't show the photos of 119 people here. The pictures of 4 and 6 people we used later have won their approval. At the beginning of our project, we calculated the precision of different libraries to show
the practicability of face recognition algorithm in group photo of 121 people and dlib library shows a reliable performance of 100% recognition rate both on 4-people and 6-people group photo. Obviously, Dlib tools offer a more reliable and accurate performance. Hence, we are determined to use Dlib library to recognize faces in a group photo and prepare for our subsequent experiment.

To find the same person in different photos, we used the n-dimensional Euclidean distance that is defined in Part II (Formula (1)). This formula is of great worth in helping us to determine whether the particular person that is detected in images point to the same person from templates. We can extract 68 face landmark points, based on one photo, calculate the n-dimensional Euclidean space, the calculation results are shown in Table 1:

| People Sequence Number | Image 2 | Image 3 | Image 4 | Image 5 | Image 6 | Image 7 | Image 8 | Image 9 |
|------------------------|---------|---------|---------|---------|---------|---------|---------|---------|
| No. 1                  | 0.31265 | 0.30696 | 0.31326 | 0.30988 | 0.31771 | 0.29071 | 0.33738 | 0.30563 |
| No. 2                  | 0.21367 | 0.28162 | 0.22919 | 0.26581 | 0.22711 | 0.23329 | 0.21432 | 0.21264 |
| No. 3                  | 0.27244 | 0.25378 | 0.20339 | 0.24408 | 0.23752 | 0.19670 | 0.20953 | 0.25548 |
| No. 4                  | 0.28326 | 0.23787 | 0.29744 | 0.21232 | 0.25574 | 0.30450 | 0.26155 | 0.30877 |
| No. 5                  | 0.21260 | 0.19800 | 0.21320 | 0.21702 | 0.30061 | 0.28932 | 0.37325 | 0.29072 |
| No. 6                  | 0.21205 | 0.22777 | 0.24022 | 0.25043 | 0.19320 | 0.18393 | 0.14877 | 0.18951 |

Note: The sequence number of people and image is according to the stance of people’s position from left to right (people No. 1 ~ 9) respectively in Figure 3.

3.3.2. Obtain standard parameters and emotion evaluation model. We think that the eye height, mouth height, mouth width, brow height and brow width of a smiley face are all significantly different from the parameters of a normal face. So, we use these parameters to represent a smiley face. To achieve better results, we apply ratios to represent these parameters, for example, the eye height means the ratio of eye height (cm) and face width (cm). The advantage of using proportion instead of length is that different people have different face width and face height, and their facial features are different in size, but all in proportion to the whole, which will lead to more accurate results.

In this part, we firstly choose several smiley faces to calculate the parameters which we involved above, as shown in Fig 2. In addition, apart from exact data computed from 12 samples, we derived 6 approximate criterial standards for smiling faces, as shown in Table 2.
Table 2. 6 Criterial Standards for Smiling Faces derive from Practical computing

| Parameters | Brow Slope | Brow Height | Brow Width | Mouth Width | Mouth Height | Eye Height |
|------------|------------|-------------|------------|-------------|--------------|------------|
| Standards' Values | 0.2177 | 0.193 | 0.289 | 0.28111 | 0.0234 | 0.0301 |

Next, we need to evaluate a better face with satisfied facial expressions of emotions which can be used as generally reliable and accurate standard of smiling facial features. We know that the existing data are accurate, the prediction should be based on the existing data and try to fit the existing data to minimize the gap. We used Formula (2) that is covered in Part II. In our experiment, Formula (2) is adapted as Formula (3) to obtain a better face with satisfied facial expression of emotions and the computing data are included in Table 3.

### 3.3.3 Face swap

In this part, we used the group of 6 people to show the results, the original photos (nine versions of group photos for same bunch of people) are shown in Fig 3. Since we have got the reliable smiling parameters, we compare different parameters in our photos to find the best smiling face in different images. The comparison data is shown below in Table 3.

Table 3. The distance between the original face and the smiling face

| People Sequence Number | Image 1 | Image 2 | Image 3 | Image 4 | Image 5 | Image 6 | Image 7 | Image 8 | Image 9 |
|------------------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| No.1                   | 0.02542 | 0.11111 | 0.09    | 0.09    | 0.16    | 0.04    | 0.05444 | 0.09    | 0.09    |
| No. 2                  | 0.01579 | 0.18777 | 0.09    | 0.07111 | 0.08678 | 0.05099 | 0.18777 | 0.00790 | 0.18777 |
| No. 3                  | 0.05444 | 0.24730 | 0.18777 | 0.13444 | 0.16    | 0.16    | 0.11111 | 0.18777 | 0.18777 |
| No. 4                  | 0.00905 | 0.00059 | 0.11755 | 0.00020 | 0.14633 | 0.04671 | 0.05009 | 0.04671 | 0.08807 |
| No. 5                  | 0.08678 | 0.28444 | 0.09    | 0.24730 | 0.03734 | 0.10783 | 0.18777 | 0.05154 | 0.17827 |
| No. 6                  | 0.02777 | 0.15677 | 0.07111 | 0.13116 | 0.08807 | 0.11111 | 0.11111 | 0.16    | 0.07111 |
| Total Distance         | 0.21925 | 0.98798 | 0.64643 | 0.67421 | 0.67852 | 0.51574 | 0.75118 | 0.46726 | 0.80299 |

**Note:** the data closest to the smile training results are marked in red, that is, the photos selected as the replacement of facial features. Also, the sequence number of people and image is according to the stance of people’s position from left to right (people No. 1 ~ 9) respectively in Figure 3.

As we mentioned before, the original photo set is shown in Fig 3. It is worth noting in that we deliberately took group photos at different time of the day to create different hues for original photo set. As a result, these photos are at different exposure levels. During our framework, we take the exposure levels into consideration to choose the best template. Image1, which have two better smiling faces, are considered to be the best template in this original photo set. Based on the data shown in Table 3, we chose Image 1 as the template.
As for the step related to facial expression recognition, we only have to replace faces for people No.2 and No.4 to 5. In addition, people ranging from No.2 and No.4 to 5 receive faces from image 8, image 3, image 4, image 5 respectively. The result image after our system is shown in Fig 4 (b), which is partial image of framework output incudes people No.2 and No.4 to 5 in order to give out an obvious comparison, since we swap faces only for them. Also, it is worth to mention that the output group photo is adjusted based on image 1(Fig 4 (a)) as a comparison. Obviously, the final display of this framework presents a relative reliable and nature facial expressions of emotions. The thing is, our framework of face swapping is obviously superior to [8] in that our algorism displays a final result (Fig 4 (a) and Fig 4 (b)) without unnatural effects of inconsistency of hues in spite of the great variance in tones and shades of samples (Fig 3).
Recognize Facial Emotions

| Refined Log Gabor Filter Bank | Log Gabor Filter Bank [10] |
|-------------------------------|---------------------------|
| **Current Algorism**          | **Earlier Algorism**      |
| Refined Euclidean Distance Formula | CNN [5]                |
| **Recognition Mode**          | **Recognition Mode**      |
| multiple targets each time    | single target each time   |

| **Current Algorism**          | **Earlier Algorism**      |
| Refined CNN                   | Traditional CNN [8]       |
| **Swapping Quality**          | **Swapping Quality**      |
| swapping without obvious variance in tones or shades | swapping with apparent hue differences between original photos |

Note: All the parameters listed here is accorded with the steps described in flow chat in Fig 1.

According to this table, our framework did a relatively perfect job in improving the efficiency of precision rate both in face detection and facial emotion recognition respectively. Also, in term of face recognition, we innovatively adjusted the traditional algorism of Euclidean Distance Formula to realize a identity verification for multiple targets every time instead of single target each time in [5] and finally improved the efficiency of time.

4. Conclusion and Future Work

The work here presented focused on the detection and swap of faces in a group photo. This image processing system can be used to support users to automatically improve bad faces in group photo. The proposed approach achieves competitive results in terms of performance. In particular, good results have been obtained in terms of correctness. However, the precision of detection can be further improved. Now, it’s hard for our system to detect occluded face, future works will focus on the face detection and swap in several special cases for example illumination, occlusion and features. The accuracy of face swap still needs to be improved since today there is still some incongruity in the image and the expression does not fit perfectly. Also, a more complete model of the process of sorting out the best expressions still need to be proposed. Face detection and swap system has also been tested. Results proved the feasibility both in terms of performance and time consumption.

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