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Matching Sketches to Facial Photographs

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Abstract - The problem of matching a forensic sketch to a gallery of images is addressed in this paper. Previous research in sketch matching only offered solutions to matching highly accurate sketches that were drawn while looking at the subject (viewed sketches). Forensic sketches differ from viewed sketches in that they are drawn by a police sketch artist using the description of the subject provided by an eyewitness. We Individually represent both sketches and photos. It's a stepwise procedure so as to compare two images. There are various algorithms and approaches available for image comparison. The approach which we're going to use in our application is to compare images using Histogram Technique.

Keyword - *Forensic Sketch, Viewed Sketch, Sketch Brightness, Sketch Normalization, feature selection, Histogram Technique.*

1. Introduction

Progress in biometric technology has provided law enforcement agencies additional tools to help determine the identity of criminals. Due to budgetary reasons, many law enforcement agencies use many methods, which takes a lot of time and money to manually identify the criminal. In addition to DNA and circumstantial evidence, if a latent fingerprint is found at an investigative scene or a surveillance camera captures an image of a suspects face, then these cues may be used to help determine the culprit's identity using automated biometric identification. However, many crimes occur where none of this information is present, but instead an eyewitness account of the crime is available. In these circumstances, a forensic artist is often used to work with the witness in order to draw a sketch that depicts the facial appearance of the culprit according to the verbal description. Once the sketch image of the transgressor is complete, it is then disseminated to law enforcement officers and media outlets with the hopes of someone knowing the suspect. These sketches are known as forensic sketches and the sketch is of any form so with the help of Normalization we convert it into proper format .User can improve brightness if the input sketch is darker. This paper describes a robust method for matching forensic sketches to the photos in the database gallery maintained by law enforcement agencies. We stored all the information about the criminal in the database. Much like its counterparts in forensic sketch recognition, the paradigm for identification using computer generated matching tool can be greatly expanded through automated face. Recognition technology. However, despite several methods for matching hand drawn sketches to photographs appearing in the literature to our knowledge, there has been only limited research on matching sketches to facial photograph. This work attempts to develop a system that can successfully match sketches to gallery of photograph. This would aid in quickly and accurately identifying suspects involved in criminal activities.

The last point is significant since earlier studies on viewed sketches used PCA matcher as the baseline. It is now well known that the performance of PCA matcher can be easily surpassed by other face matchers.

The technique that is used in this paper is Histogram Technique which matches the sketches to facial photograph from the database and shows the result in the percentage.

2. Related Work

Most of the researches in photo-sketch recognition in the last ten years have been developed by Tang and Wang. The initial approaches developed by Tang and Wang (2002, 2003, 2004) [2], [3], [1] use global linear transformations, based on eigenface method [4], [5], in order to convert a photo into a sketch. In [6], the authors propose a new method for photo-sketch synthesis and recognition based on a multi scale Markov random fields (MRF). They use a multi-scale MRF model to learn face structures at different scales. Local patches in different regions Solution patches are stitched together and form a synthetic photograph. The transformation of a photo into sketch (or the reverse) significantly reduces the difference between them. After the synthetic image generation, in

principle, most of the algorithms for facial recognition may be applied directly. Klare and Jain [8] proposed a method of sketch matching that uses the same feature-based approach that has been successful in other heterogeneous face recognition scenarios (specifically, matching near-infrared face images to visible light). In using SIFT feature descriptors [9], the intrapersonal variations between the sketch and photo modality were diminished while still maintaining sufficient information for interclass discrimination. Such an approach is similar to other methods proposed in the literature [10], [11], [12] former of matching near-infrared images (NIR) to visible light images (VIS), where local binary pattern [13] feature descriptors are used to describe both NIR and VIS images.

In our paper we are using **Histogram Technique** for image comparison. Firstly, In that we perform preprocessing on input image that is normalization and improving image brightness.

The step for recognition of criminal face are mention below in this paper.

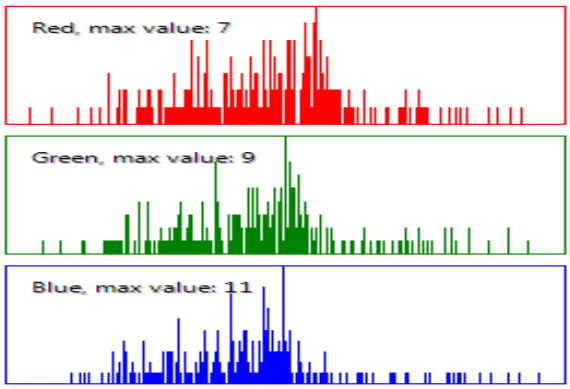
3. Normalization

In image processing, **normalization** is a process that changes the range of pixel intensity values. Applications include photographs with poor contrast due to glare, for example. Normalization is sometimes called contrast stretching or histogram stretching. In more general fields of data processing, such as digital signal processing, it is referred to as dynamic range expansion.
The purpose of dynamic range expansion in the various applications is usually to bring the image, or other type of signal, into a range that is more familiar or normal to the senses, hence the term normalization. Often, the motivation is to achieve consistency in dynamic range for set images to avoid mental distraction or fatigue. For example, a newspaper will strive to make all of the images in an issue share a similar range of grayscale.
Image Normalization can be divided into two steps. Step 1 is to improve the brightness or pixel intensity of an image by iterating through all the pixels in an image, i.e., from topmost left corner pixel (0, 0) to rightmost bottom pixel (x, y), where x is a width and y is a height or vice versa. Step 2 is to resize that image to a standard size which could be either reducing or increasing the picture size depending upon its actual size and the defined standard size for our system. Image resizing can be correlated with Normalized device co-ordinates picture adjust its size as per the screen resolution. Depending upon the resolution and image pixel intensity or brightness, the image may or may not get blurred. For e.g. an image of very low resolution and low brightness may get blur if its size is increased by a large ratio, whereas it may not blur if it already had a good resolution and pixel brightness, that's why step 1 is very important and step 2 is dependent on the step 1. This suffices the working of Image normalization.

Fig.1 Average face images of the neutral (left) and smiling (right) facial expressions before and after the normalization only

4. IMAGE COMPARISON TECHNIQUE

A histogram is a way of representing what kinds of colors are in a picture. You can create a histogram describing the light or red, green, or blue values in an image. A basic way of creating a histogram is to look at each pixel in a bitmap and for each of them find out what the value of the property you are looking at (RGB) is. For each possible value (typically 0-255), you have a variable which you increment. This way, when you are done with all the pixels, you can iterate over the variables and see how many pixels had low values, medium values, and high values of light, R, G, or B. We fiddled around a couple of days with this, but found out that in the end, this wasn't good enough for detecting differences in pictures, as two totally different pictures depicting almost the same (e.g. two corn fields) with the same composition of colors/light can be hard to differentiate using just a histogram. We tried comparing the two using average in colors, and variance but to no avail.



Simplifying

We're going to convert our normal image into Grayscale image and then that image into a histogram. After that we'll iterate through the pixels on both images and compare the two and then find out how many were different.

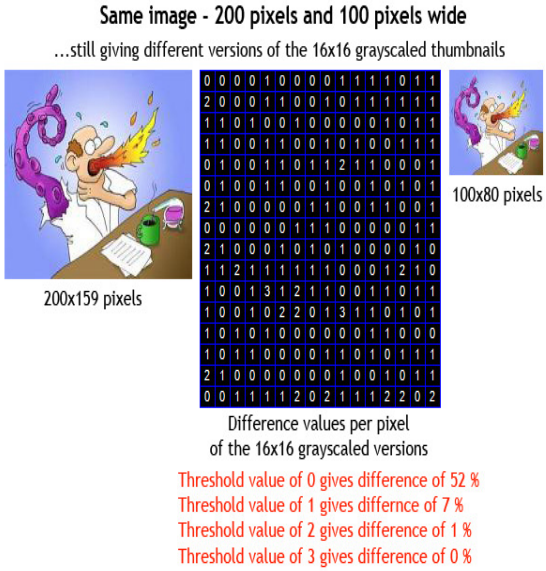
Here are the two images we used, with an XBOX controller, post-it with and without text and two different colored pens.

We thought we'd start out by using a grey scaled, 16x16 pixel version of each image, and see whether we needed higher resolution for practical use.

For each pixel We'd then get the difference of the brightness value compared to the other image's pixel in the same spot and save it in a double array of bytes (since R, G and B values in **`Bitmap`** can be between 0 and 255). We would then count all the values in the double array which weren't zero, divide this value by the amount of pixels in an image (256), and voilà –We would have a difference value in percentages.

4.1 Using a threshold

Here you can see the differences between a 200 pixels wide version of an image and a 100 pixels wide version of the same image:



The main objective behind using histogram is to find the distance between two different images, if output comes as zero then it's a perfect match else, it will result the percentage of match found, depending upon all the differences in its histogram distance.

5. Conclusion.

This paper investigated a challenging heterogeneous face recognition problem: matching composite sketches to facial photographs. The proposed method is tested by matching composite sketches against a large scale mug shot gallery set.

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