Literature Review on Scar Assessment System for Human Body

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Abstract— In case of a disease, a burn or an allergy, it is very important to have a regular check and a correct diagnosis by the doctor during the healing process of that scar or the patch effected. This will also help the doctor in deciding the perfect medicine for the patient's scars. Various Digital Image Processing techniques have been devised to solve this problem. Although use of soft computing based methods are very popular now in almost every area of work, lack of training data poses a big challenge. Thus developed method solve the problem of identifying the scar, wound or burn and it estimate the state of the scar , finding the number of clusters of scars in an image purely by using basic image processing ways. This method is effective and computationally fast in the decision making process for the doctors. Various techniques are discussed here.

Keywords: Scar Assessment System, SURF, SIFT Algorithm

I. Introduction

Skin injuries mainly include burn, wound and chronic wounds. Diagnosis based on medical images always had hurdles. The accurate comparison of the images which humans are unable to do with their eyes, make use of proper computer programs. A correct diagnosis by a medical professionals or doctor is important for treatment effectiveness which will save cost for the patient and time for the doctor and also medicines can be evaluated better eventually.

Various digital image processing techniques have been used to analyze the images and have had achieved lot of accuracy. This paper aims at establishing a scar assessment system which takes photographs from nonprofessional camera as input to: 1) automatically identify the location of scar from the photographs; 2) distinguish the scar whether wound, burn or tattoo and 3) assess the symptoms if there exists any abnormality in scars. It develops a method in which the first step in this paper is to have a database which contains the possible set of scars including wound, burn and tattoo. Second step is to identify the skin area from the image from the database. Third step will be identifying and segregating the scar area from the skin.

Superpixel segmentation phase is first applied to normalize photographs so that the size of photographs can be same. The photograph is then segmented into superpixels. In general, a superpixel refers to a set of pixels with same color and brightness. Based on the fact that the scar is on the skin, an ellipse is used to cover as many connected superpixels as possible automatically. These superpixels are called the skin-superpixels, which means they are skin-like superpixels. Wound area detection phase exploit the characteristics of scar to further detect whether or not a skin-superpixel is a part of the surgical wound.

First, this paper proposes to derive superpixels in training phase and detect scar in classification phase rather than using the absolute color values to locate scar.

Because it is sensitive to color bias due to nonprofessional cameras, this method could be more suitable in self-care scenario. Second, this paper proposes skin area detection and scar area detection to derive a scar area including ie wound, burn and tattoo (a set of superpixels). Even if the scar may be in different sizes and shapes, they could be composed of an arbitrary number of superpixels in arbitrary shape.

The contribution of this paper also includes a comprehensive performance evaluation. Experimental results show that the proposed system could achieve the goal in this paper efficiently and effectively.

II. Literature Review

A lot of work is being done in this field for better results. Detection of the scar is the first and the foremost step of the whole process.

Helfin et al. [1] suggests a new algorithm for detecting dermatological features on the face. The approach using the GrabCut segmentation algorithm coupled with quasi connected components is suggested for tattoo detection which can similarly be used for scar detection. It also suggests facial mark detection with refinement using the digital image processing with the facial modeling techniques The LoG filter has been used for pre-processing, SQI (Self Quotient Image) normalization is done and then histogram is computed over the filtered image to segment the skin pixel from the facial mark pixel. The conclusion of their experiment was that the automatic facial mark detection and tattoo segmentation that can flexibly filter candidate regions are essential for a good forensics solution.

Detection of scars can get complicated because of the difficulty in segregating them from the skin tone. One solution provided by Duang phasuk et al.[2] is the use of image negative method in preprocessing part for tattoo detection which similar technique can be used for segmenting tattoo from the skin patch. This paper tends to solve the problem in three steps. The first one is the skin detection where HSV model is used for skin color segmentation. The second step is being the clear detection of the clear graphic image of the tattoo segment. Third and the final step being to extract the tattoo segment from the skin area of the negative image and, as a result, the tattoo negative image is obtained and can be used for retrieval. Experimental result of this technique is that the number of false matches was decreased and the time spends in matching process reduced. Their better performance is due to the reduction of the number of key points in a query negative image

Ngan et al. [3] talks about segmenting the tattoo in a better way by determining skin pixels in a region near the tattoo. Graph-cut segmentation using a skin color model and a visual saliency map is used to find skin pixels. After segmentation, they determine which set of pixels are connected to each other that form a closed contour including a tattoo.

Sivaramakrishnan et al.[4] addresses acne-scar detection based on color image processing. The RGB model is being used for representing the data. Thousands of pixels were used as a database having scars from different complexion. Pixels from the background (skin) and from the lesions of interest (acne scars) were recorded from the images of various subjects, to build a knowledge base i.e., clusters associated with the skin and acne scars, respectively.

Zou and Kamata et al [5] proposed an algorithm for face detection in color images with complex backgrounds. It used skin color detection to improve the accuracy of detections. Using the skin color to recognize skin is very useful method. This paper, we want to find faces in images with complex undergrounds under various luminance. They proposed this algorithm for face detection in color images. It includes a modification for skin color detection and a proposal for those methods which can only used in gray-level before in face detection. This algorithm has utilized two effective tools to accomplish the detection: Gaussian mixture model (GMM) and Adaboost algorithm. It utilizes the methodology of GMM to construct several skin color models for different kinds of skin colors. Then it uses these skin color model in a parallel structure for skin detection, and try to find out face candidates. Then the face verification is implemented by a classifier trained by Adaboost algorithm with probability images as training samples is regarded as a body region. The last step performs shape matching by using Zernike moments.

Lin et al. [7] combined RGB, Normalized RGB, and HSV color spaces to detect skin pixels. This paper proposes a human face detection system based on skin color segmentation and neural networks. Experimental results show that the system results in better performance than some other methods, in terms of correct detection rate and capacity of coping with the problems of lighting, scaling, rotation, and multiple faces. Although the proposed method shows high detection rate, it still has some problems as stated in the following: I) since skin color information is used for face detection, if the illumination is too bright or too dark the system would fail in skin color detection. II) Since it determines a face candidate according to the location of two eyes, when eyes are not successfully detected, the system would fail in face detection.

Manoranjitham R et al. [8] compared many classical techniques, and according to its conclusion, the Harris corner detection has a good performance. The Interest point detection algorithm plays a vital role in computer vision applications. The most commonly used interest point detector is scale invariant feature transform (SIFT). The SIFT algorithm fails to match interest points on the edge due to Gaussian filter. In order to overcome this failure a bilateral-Harris corner detector has been proposed A combined approach of Harris corner with laplacian of bilateral filter is proposed to improve the detection of interest points. An experimental result shows that the proposed interest point detection algorithm achieves better performance. Proposed approach substantially improves the repeatability score of detected interest point, number of matched interest points between two images. The proposed approach is found to be more robust to various image transformations such as zoom+rotation, blur, viewpoint.

Esteva etal. [9] classified skin lesions by using deep convolution neural network. System requires no hand-crafted features; it is trained end-to-end directly from image labels and raw pixels, with a single network for both photographic and dermoscopic images. The existing body of work uses small datasets of typically less than a thousand images of skin lesions16, 18, and 19, which, as a result, do not generalize well to new images. Demonstrate generalizable classification with a new dermatologist-labelled dataset of 129,450 clinical images, including 3,374 dermoscopy images. In this paper it outlines the development of a CNN that matches the performance of Dermatologists at three key diagnostic tasks: melanoma classification, melanoma classification using dermoscopy and carcinoma classification. It restricts the comparisons to image-based classification. It utilizes a Google Net Inception v3 CNN architecture 9 that was pretrained on approximately 1.28 million images (1,000 object categories). It validate the effectiveness of the algorithm in two ways, using nine-fold cross-validation

Alamdari et al. [10] presented several image segmentation methods to detect acne lesions and machine learning methods that are used to distinguish different acne lesions from each other. The objective of this research is to find a proper computational imaging method for automatic detection of acne using images that are taken by cell phone and then the classification of the different type of acne lesions from each other. In this paper, present several image segmentation methods to detect acne lesions and machine learning methods used to distinguish different acne lesions from each other. Results illustrated that among texture analysis, k-means clustering, HSV model segmentation techniques, two level k-means clustering outperformed the others with an much accuracy. In addition, the accuracy of differentiating acne scarring from active inflammatory lesions is 80% and 66.6% for fuzzy-c-means and support vector machine method, respectively. Finally, the performance accuracy of classifying normal skins from detected acnes is 100% using fuzzy-c-means clustering

III. VARIOUS TECHNIQUES

1) Grab Cut: It is an interactive foreground extraction using iterated graph cuts.[1]
2) CLAHE: Histogram Equalization improves the contrast but something we lose details because of over brightness. To solve this problem, CLAHE (Contrast Limited Adaptive Histogram Equalization) is used. In this, image is divided into small blocks called "tiles". Then each of these blocks are histogram equalized as usual. So in a small area, histogram would confine to a small region (unless there is noise). If noise is there, it will be amplified. To avoid this, contrast limiting is applied.[1]
3) SURF: In computer vision, speeded up robust features (SURF) is a patented local feature detector and descriptor. It can be used for tasks such as object recognition, image registration, classification or 3D reconstruction. It is partly inspired by the scale invariant feature transform (SIFT) descriptor. The standard version of SURF is several times faster than SIFT and

claimed by its authors to be more robust against different image transformations than SIFT.SURF uses Wavelet responses in horizontal and vertical direction (again, use of integral images makes things easier). A neighborhood of size 20 X 20 is taken around the key point where s is the size. It is divided into 4x4 sub regions. For each sub region, horizontal and vertical wavelet responses are taken and a vector is formed.. Lower dimension, higher the speed of.[1]

4) Gaussian mixture model: It is based on the assumption that distribution of samples obeys the Gaussian distribution. Even though Gaussian model can describe the distribution of skin colors more colors more precisely than simple skin color model, the distribution itself is much more complex than Gaussian distribution, which means it is more sufficient to use mixture model to approximate the real distribution. A mixture model can be regarded as a type of unsupervised learning or clustering. The most used one in constructing a skin color model is Gaussian mixture model (GMM), which can be considered as a combination of different Gaussian models with different weights. In order to approximate the real distribution of skin colors, Gaussian mixture model was proposed to be applied. Gaussian mixture model usually [5]
5) Adaboost is a learning algorithm, which selects a small number of critical visual features from a larger set and yields extremely efficient classifiers. Adaboost was intended for intensity images, in which the information of chromaticity is not used. Therefore, this propose to convert the color image into a probability image.[5]

IV. CONCLUSION

This work looks at the problem of detection and assessment of scars for the medical community. This method proved to be near accurate for the majority images in the dataset. While very promising recent work has demonstrated that these dermatological features can be detected and assessed, there is much work yet to be done to accurately process scar images

Digital image processing techniques require relatively low computation time with near accurate results and are feasible. This methodology can be used to compare between the effectiveness of the various medicines available in the industry.

There are many existing approaches to segment a normalized image into several superpixels.

Proposed methods use SEED algorithm for segmentation.

The SIFT algorithm fails to match interest points on the edge due to Gaussian filter. In order to overcome this failure a bilateral-Harris corner detector has been proposed. Bilateral filter have a characteristics of edge-preserving, noise removing and causing smoothening of images.

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