Automatic Detection of Early-stage Malignant Melanoma from Skin Lesion Images

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ABSTRACT
The automatic detection of early stage malignant melanoma will give potential hope for diagnosis for melanoma skin cancer. This paper will also find a new method to analyse skin lesion images and this can enhance the dermatology department. Melanoma is the most dangerous form of skin cancer, accurate diagnosis is required to control the disease. So, the chances of false detection due to human error are high in a large population to be screened due to high workload on dermatologist and the objectivity in the interpretation of the screening which in turn can lead to fatal condition. The accurate and timely diagnosis of melanoma infection is essential to control and cure the disease. This study aims to explore the possibility of computerised diagnosis of early-stage malignant melanoma and to develop a novel image processing algorithm to reliably detect the presence melanoma from a sample skin image. Some image processing algorithms to automate the diagnosis of early stage melanoma on the skin are developed. This study curbs the human error while detecting the presence of early stage melanoma on the skin using image processing and automation. We achieved this goal using Image Segmentation and Morphological features descriptors. We also built the system in a robust manner so that it is unaffected by the exceptional conditions and achieved high percentage of sensitivity, specificity, positive prediction and negative prediction results.

Keywords:dermatoscopyautomatic image processing; biomedical image processing; dermatologist; segmentation; features descriptors.

I. INTRODUCTION
Melanoma is the most dangerous form of skin cancer, these cancerous growths develop when unrepaired DNA damage to skin cells (most often caused by ultraviolet radiation from sunshine or tanning beds) triggers mutations (genetic defects) that lead the skin cells to multiply rapidly and form malignant tumours. These tumours originate in the pigment-producing melanocytes in the basal layer of the epidermis. Melanomas often resemble moles; some develop from moles. The majority of melanomas are black or brown, but they can also be skin-coloured, pink, red, purple, blue or white. Melanoma is caused mainly by intense, occasional UV exposure (frequently leading to sunburn), especially in those who are genetically predisposed to the disease. Melanoma kills an estimated 10,130 people in the US annually.

If melanoma is recognized and treated early, it is almost always curable, but if it is not, the cancer can advance and spread to other parts of the body, where it becomes hard to treat and can be fatal. While it is not the most common of the skin cancers, it causes the most deaths. In 2016, an estimated 76,380 of these will be invasive melanomas, with about 46,870 in males and 29,510 in women

Figure 1 - Superficial spreading melanoma. Stanford Dermatology.

Statement of the problem
Melanoma is the most deadly variety of skin cancer. Although less common than other skin

cancers, it is responsible for the majority of skin cancer related deaths globally (Parkin, Bray, et al, 2005). Most cases are curable if detected early and several standardized screening techniques have been developed to improve the early detection rate (Stolz, Rieemann and Cognetta, 1994; Argenziano, Catricala et al, 2011). Such screening techniques have proven useful in clinical settings for screening individuals with a high risk for melanoma, but there is considerable debate on their utility among large populations due to the high workload on dermatologists(Parkin, Bray, et al, 2005).and the subjectivity in the interpretation of the screening (Pollitt, Geller et al, 2009).

This study derive a set of computer vision algorithms to automate popular skin self-examination techniques, that provides a pre-screening tool for individuals in the general population to help assess their risk. No computer application can provide a concrete diagnosis, but it can help inform the individual and raise the general awareness of this dangerous disease.

Motivation

The aim of the proposed system is the biggest detraction of dermatoscopy and other conventional methods, namely its dependence on the skills, experience and motivation of a human technician is removed. Used with images captured with an automated standard digital cameras equipped with macro lenses for viewing objects at close range, it would allow the system to make diagnosis with a high degree of certainty. It would also constitute a diagnostic aid for the increasing number of cases of large population to be screened and imported melanoma in traditionally melanoma-free areas, where practitioners lack experience of the disease.

Limitation of the study

While the result of this study is encouraging, a large sample of skin lesion images would be ideal to increase performance. Before a system application is ready for release the asymmetry, border, and colour metrics must be tested against a large dataset of melanoma images to derive both risk scoring thresholds and receiver operating characteristic curves. It is likely the border and colour metrics must be revised to compensate for the focus and colour space on descriptor validation. Perhaps the most fruitful future work involves the components of the ABCDE metric not considered in this study. In particular, the evolution of a lesion over time is an extremely powerful indicator of melanoma. Many dermatologists will also confirm that the ABCDE

method is not necessarily a comprehensive collection of all the features they consider when diagnosing a melanoma. In this case, features derived from computer vision schemes like Bag-of-Words (Csurka, Dance et al, 2004)modelling and machine learning classifiers would be able to surpass the performance the original ABCDE method.

Another limitation experienced was difficulty uncounted in the process of collecting secondary data, therefore, this study rely on dataset browsed online.

Background

Melanoma develops in the melanocyte skin cells responsible for producing the pigment melanin which gives the skin, hair, and eyes their colours. Early stages of the cancer present themselves as irregular skin lesions. An example of an irregular skin blemish is shown in Figure **1**.Detection techniques for early stage melanoma use the morphological characteristics of such irregular skin lesions to classify risk levels.

A. Skin-Self Evaluations using the ABCDE method

Studies have shown that self-performed skin examinations can greatly improve early detection and survivability rates of melanoma(Pollitt, Geller et al, 2009). The most established method for skin self-examinations to date is the "ABCDE" promoted by the

American Academy of Dermatology. A detailed tutorial for conducting skin self-exams including example images for each feature is available in (American Academy of Dermatology, June 6, 2011). The "ABCDE" test provides a widely accepted, standardized set of lesion features to examine. The features are designed for members of the general public, but variability in the interpretation of the features weakens the overall utility of the test (Pollitt, Geller et al, 2009).

B. Image Processing for Digital Dermatoscopy and Digital Macro Photography

Epiluminescence Microscopy (ELM), also known as dermatoscopy, is a noninvasive technique for improving the early detection of skin cancer (Di Leo, Paoliitto et al, 2010). In dermatoscopy, a set of polarized light filters or oil immersion render selected epidermal layers transparent and macro lenses magnify small features not visible to the naked eye. Most dermatoscopes also include features to control lighting and focal conditions.

Dermatoscopy is frequently combined with digital imaging technology and a large body of research is devoted to developing computerized processing techniques operating on the digital images produced. An adaptation of the "ABCDE" method for skin self-examinations to dermatoscopic images was first presented in (Stolz, Rieemann and Cognetta, 1994).

The digital images processed in this project differ from conventional digital dermatoscopyin that they do not employ optical filters. Instead, they operate on the visible light images produced by standard digital cameras equipped with macro lenses for viewing objects at close range. In this sense they are analogous to the conventional skin self-exam. In general, macro photography images of skin lesions are taken under loosely controlled lighting and focal conditions. Many of the images acquired using less expensive consumer-grade macro lenses also exhibit a certain degree of barrel distortion toward the edges of their field of view.

Methodology

The techniques used to compute relative risk scores follow an image-processing pattern similar to that of any feature extraction algorithm. Images are pre-processed, a region of interest (feature) is identified, and then individual feature descriptors are run on the region of interest. The results from aMATLAB implementation of the score computation were analysed by a group of trained dermatologists
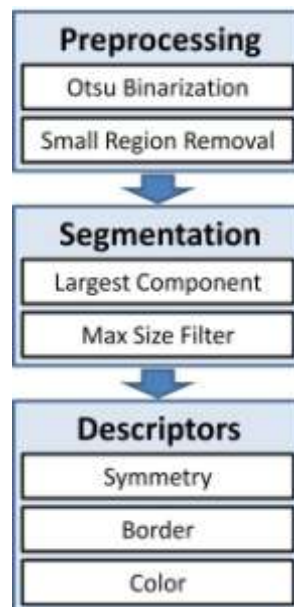

Figure 2 - Algorithm Flow

A. Pre-processing

Once a magnified image of a skin lesion is captured it is passed to a pre-processor. The pre-processor performs global image binarization via Otsu's method (Otsu N, 1979). Following binarization, a connected components analysis is performed and small region removal for both positive and negative regions removes most of the image noise. A sample output from the pre-processing stage is shown in Figure **3**.
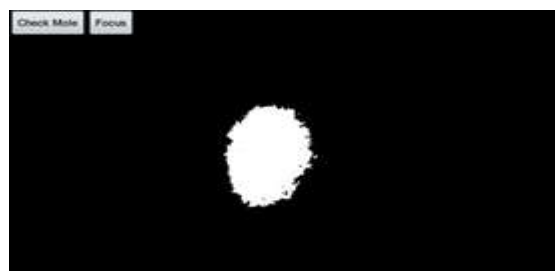

Figure 3 - Binarized image with small region removal

B. Image Segmentation

Following binarization and denoising in the pre-processor, the region representing the skin lesion is segmented from the rest of the image. There are many techniques in the technical literature for extracting lesion regions in digital images, including a difference-of-Gaussians (DoG) and support-vector machine (SVM) approach in (Cho, Freeman, Tsao, 2007). However, both the static images and the images acquired live by the mobile application were taken under controlled conditions by an expert user and did not require such complex segmentation techniques. Instead, the segmentation algorithm searches for the largest remaining connected component. Most medical imaging is designed to maximize the percentage of an image's field of view devoted to its subject, so the largest component in the pre-processed images is nearly always the lesion. Occasionally large shadows in the images were mistaken for a lesion so a maximum allowable lesion size restriction was imposed.

C. Morphological Feature Descriptors

After pre-processing and segmentation, the images are ready for analysis by the individual feature descriptors. Three feature descriptors inspired by the "ABCDE" skin self-examination form the core of the risk assessment. Those features are asymmetry, border, and colour.

1) Asymmetry

In(American Academy of Dermatology, June 6, 2011), a lesion is considered potentially cancerous if "one half is unlike the other half." This guidance is relatively vague, so techniques developed for dermatoscopy were used for inspiration. The asymmetry score calculation is based on the symmetry map technique presented in (Schmid-Saugeon, Guillod and Thiran, 2003). Symmetry maps encode a measure of a region's symmetry, known as symmetry metric, relative to a range of axes of symmetry defined by angle. Lesion colour and texture comparisons were used to encode symmetry in(Schmid-Saugeon, Guillod and Thiran, 2003).Commonly the symmetry metric is a function of distance R from a region's centre. In (Schmid-Saugeon, Guillod and Thiran, 2003), a symmetry map is created for the range of symmetry axes passing through a region's centre with angles ranging from 0 to 180 degrees. An example symmetry map taken from(Schmid-Saugeon, Guillod and Thiran, 2003), is shown below in Figure **4**. In this map both the texture and colour symmetry metrics are shown. To derive a scalar symmetry score from the symmetry map, the global maximum is used
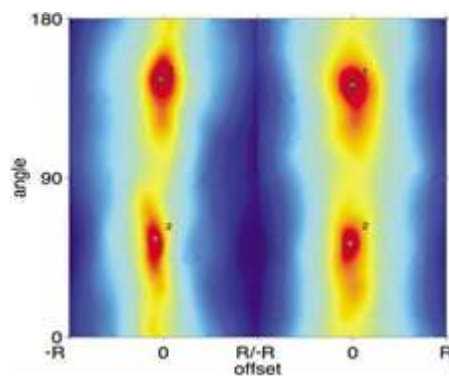

Figure 4 - Example symmetry maps from (Schmid-Saugeon, Guillod and Thiran, 2003). Texture symmetry is shown on the left and colour on the right. Note the high correlation between the maps and 90 degree periodicity.

The symmetry map technique is attractive because it is able to achieve a degree of rotational invariance via the max operator. However, calculating symmetry maps with such a high resolution in angles is computationally expensive and colour and texture can vary depending on the image's lighting and focus. Lighting and focus are not traditionally majorfactors in dermatoscopy but they have a large impact in macro photography. To streamline the symmetry scoring process a symmetry metric more suitable to the loosely controlled imaging conditions of this project was selected and a "sub-sampled" symmetry map approach was adopted.

Unlike colour or texture, borders exhibit a better invariance to imaging conditions. To exploit this property an inclusionmetric was devised. For each pixel belonging to a lesionregion, a counter was incremented if that pixel's mirror about a specified symmetry axis was also included within

the lesion region. After each pixel was examined the inclusion counter was normalized by the number of pixels in the lesion region. The inclusion metric is analogous to a probability score between 0 and 1 that a given pixel will have a mirror. It is also not a function of distance R from the region's centre. A diagram illustrating the inclusion calculation is shown in Figure **5**.
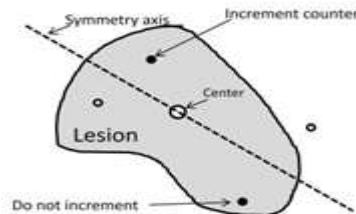

Figure 5 - Calculating the inclusion symmetry metric

The inclusion symmetry metric was computed for the axes passing through a region's centroid at angles of 0, 45, and 90 degrees as shown in to form a "subsampled" symmetry map. At these angles, the inclusion metric can be computed quickly using matrix index arithmetic and a binary mask of the region of interest. As with the conventional symmetry maps, the maximum symmetry score over all three angles was taken as the lesions symmetry. For convenience, the score was converted to units of asymmetry by subtracting it from 1. In general a lesion with a high asymmetry score is at a higher risk of being cancerous.
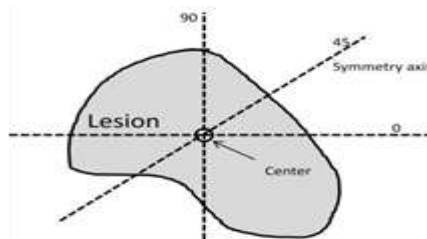

Figure 6 Symmetry axes used for symmetry computation

2) Border

In(American Academy of Dermatology, June 6, 2011) the shape and strength of a region's border are considered collectively when assessing risk but the automated algorithm examines only border strength. This is because the simple segmentation techniques used were a relatively noisy measure of a lesion's boundary and the segmentation noisequickly corrupts any border shape metric. However, border strength is relatively easy to compute. Using the gradient-of-Gaussian edge detection kernel developed by Canny in (Canny J, 1986), a smoothed map of an image's intensity gradient is computed via 2D convolution. The intensity gradient map can also be computed using a two-stage filter combination of Sobel and Gaussian kernels. An example image gradient map from the live feed of a mobile phone is shown in Figure **7**.
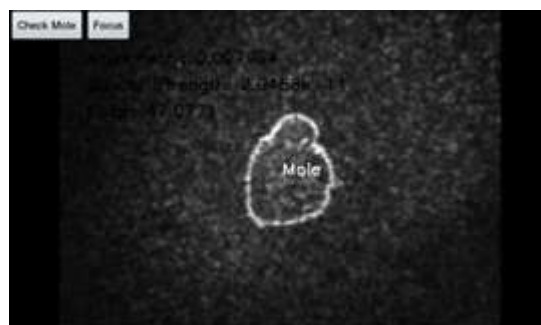

Figure 7 - Gradient magnitude with Gaussian blur

Once the image gradient map is computed, the gradient magnitude values at each pixel along the lesion's border are summed and normalized by the border's size to calculate the average gradient magnitude along the lesion's border. This average gradient metric forms the border strength risk value. In general lesions with poorly defined borders (ie: with low average gradient magnitude) are a higher cancer risk.

Proper choice of the Gaussian smoothing kernel is important given the relative inaccuracy of the lesion segmentation. If too small a kernel is used, the border pixels may not fall directly over pixels with a high gradient magnitude as in **Figure 8**. If a large kernel is used the effects of the local gradient will be diluted. For a 600x800 pixel image as in Figure **7** and **Figure8**, a Gaussian kernel size of 30x30 pixels provides adequatesmoothing.

Figure 8 - Gradient magnitude map with narrow Gaussian blur. Note the dark bars within edge boundaries.

3) Colour

InAmerican Academy of Dermatology, June 6, 2011), lesions are potentially cancerous if they exhibit variations in colour from one area to another. They may also be cancerous if they have shades of tan, black, or brown. In macro photography, colour values may be highly variable due to the many implementations of colour balancing algorithmsemployed by camera manufacturers. To reduce variability, all lesion images were converted to grayscale before scoring. The standard deviation of the grayscale intensity values of all the pixels belonging to lesion regions was calculated. This standard deviation value was taken as the colour variation risk. In general, lesions with a higher colour standard deviation are considered to be a higher cancer risk.

D. Descriptor Validation

An initial MATLAB implementation of the feature descriptors was run on a set of test images containing both cancerous and non-cancerous skin lesions. The results were presented to a group of trained dermatologists both to determine the individual value of each metric and to help quantify the potential risk scales for each feature. A detailed study involving many hundreds of samples of cancerous lesions would be required to assign an absolute scale to each metric. Lacking such a study, the lesions were simply ranked relative to each other based on the relative risk predicted by each of the three features. The dermatologists were asked to comment on the relative ranking for each feature.

The asymmetry metric was especially useful in sorting lesions relative to risk. A simple threshold applied to the symmetry metric accurately separated cancerous from non-cancerous regions. The border strength metric appeared to rank lesions correctly by border definition, but failed to separate cancerous from non-cancerous lesions. This may be a fundamental flaw in the border feature or perhaps a reflection of the fact that the border strength metric ignores the"scalloped" and "irregular" properties of borders suggested by(American Academy of Dermatology, June 6, 2011). Colour intensity proved least useful, failing to rank lesions in the test set correctly by colour variation. This is perhaps due to non-uniform lighting and could be corrected by proper gamma-space image normalization and scaling. The colour metric is also calculated on pixel intensity values alone, without placing higher weighting on tan or black regions as prescribed by(American Academy of Dermatology, June 6, 2011). A more effective approach may be to score colour in the 2-dimensional hue/chrominance space after compensating for colour balancing variations.

II. CONCLUSION

The detection of Melanoma is done by dermatologists manually using skin self-examinations to date is the "ABCDE" and Epiluminescence Microscopy (ELM). So, the

chances of false detection due to human error are high especially among large populations when the dermatologists have workload. This paper curbs the human error while detecting the presence of melanoma on the skin sample by using Image Segmentation and Features descriptors techniquesto detect melanoma on images of lesion skin samples. The system in a robust manner so that it is unaffected by the exceptional conditions and achieve high percentages of sensitivity, specificity, positive prediction and negative prediction values.

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