METHOD AND SYSTEM

Field of Invention

This invention relates to a novel mobile imaging system. In particular, it relates to a smartphone imaging system that may be suitable for the early detection of melanoma.

Background

Melanoma is the most aggressive form of skin cancer. It is responsible for the majority of skin cancer related deaths. Most cases are curable if they are detected early. However, in some countries, there is a trend towards more advanced disease staging at presentation, due to lack of patients' awareness and delayed or missed diagnosis by primary care physicians [12]. There is a pressing need for an accessible and accurate pre-screening solution to improve the general awareness.

Increasingly, smartphones are equipped with multi-core CPUs and high resolution image sensors. All this creates the opportunity to use a smartphone to analyze a captured image for disease diagnosis and self-screening.

Several automatic melanoma diagnosis systems have been proposed in the literature [14], [10], [2], [20]. However, they focus on dermoscopic images (including [22], which uses mobile phones for dermoscopic image analysis). Dermoscopic images are taken with the aid of liquid medium or non-polarised light source and magnifiers, under well-controlled clinical conditions. Dermoscopic images include features below the skin surface, which cannot be captured with normal cameras equipped in smartphones. There have been a few isolated work that investigated images captured from smartphone. In [19], a mobile-system working for images taken from mobile camera is presented. However, to detect lesion, they used a very basic thresholding method. To describe a lesion, only simple color features (mean/variance of some color channels, the difference of color through vertical axis) and border features (convexity, compactness) were extracted, and these features are subjected to a simple kNN classifier. It is unclear about the accuracy of their proposed system. [4] also focuses on images taken from mobile camera. The lesion detection and feature extraction are performed on mobile devices while the classification can be performed on the mobile device or in a cloud

environment. However, in that work, the emphasis is on system integration, and the authors did not clearly mention what algorithms / features were used for diagnosis.

Generally, an automatic melanoma detection system can be divided into three main stages of segmentation, feature extraction, and classification. Some algorithms have been investigated for dermoscopic images taken under well-controlled conditions, but there is little attention on smart-phone captured images taken under loosely-controlled lighting and focal conditions.

The segmentation stage aims to determine lesion region from captured images. There are several common methods to perform lesion segmentation [25], [2]: histogram thresholding, clustering, edge-based, region-based, and active contours. Among these methods, histogram thresholding and region-based are most often used. Histogram thresholding methods use image histogram to determine one or more intensity values for separating pixels into groups. The most popular thresholding method for lesion segmentation is Otsu's method [16]. Region-based methods form different regions by using region merge or region split methods.

The feature extraction stage aims to extract features that describe the lesion. There are many methods proposed such as pattern analysis, Menzies method, ELM 7-point checklist, etc. [24]. However, again, most of these methods are usually applied to images taken from a dermatoscope. For melanoma, the most important warning sign is a new or changing skin growth. It could be a new growth or a change in the color, size or shape of a spot on the skin. To help people to carry out self-examinations their skin, American Academy of Dermatology promoted a simple method called "ABCDE" [15] corresponding to Asymmetry of lesion, Border irregularity, Color variation, Diameter and Evolving. There are many methods used in the literature to capture color variation, border irregularity, asymmetry because computer-aided diagnosis systems usually perform diagnosis based on a single image. Evolving features are not used generally. The reviews can be found in [14], [10], [2].

Although there are many features used in previous work to describe color variation and border irregularity, most of these features are general features such as mean, variance of different color channels; compactness, convexity, solidity of shape. They are not specifically designed to capture color and border information of lesion.

As such, there is a need for an improved mobile system and method for the early diagnosis of melanoma that is quick, accurate, and less taxing on the power and memory capacity of the mobile device, robust to noise and distortion that arises in uncontrolled image-capturing environments, and tuned for visible light images captured using mobile systems.

Summary of Invention

In accordance with an aspect of the invention, there is provided a device for analysing an image of an object and evaluating the risk or likelihood of a disease or condition, the system comprising: (a) an image capturing device for capturing the image of an object; and (b) a processor for executing a set of instructions stored in the device for analysing the image, the set of instructions includes a library of algorithms stored in the device, and is configured to localize the object region, extract features of the object, and classify the object based on a set of pre-determined parameters, wherein the set of pre-determined parameters is any one selected from the group: color, border, asymmetry and texture of the object. Preferably, the set of instructions comprises quantifying the color variation and border irregularity of the object.

Preferably, the image of the object is taken using a smartphone mobile device. Such images are unlike previous work focused on ELM images (epiluminescence microscopic or dermoscopic images), XLM (cross-polarization ELM) or TLM (side-transillumination ELM) that are captured in clinical environments with specialized equipment and skills. Images taken using a smartphone mobile device are simply visual images of the object "as is", i.e. topical appearance of the object. Using such images to evaluate the risk or likelihood of a disease or condition simply on the topical appearance of the object poses its own set of challenges which this invention seeks to overcome. These will be described in detail below.

Preferably, the object is a lesion on a patient's body and the disease is melanoma.

Preferably, the device further comprising a graphical user interface for indicating to a user the results of the analysis.

In accordance with an aspect of the invention, there is provided a method for analysing an image of an object and evaluating the risk or likelihood of a disease or condition, the method comprising: (a) pre-processing the image; (b) localizing the object; (c) characterize and extract features of the object

based on a set of pre-determined parameters selected from the group: color, border, asymmetry and texture of the object; and (d) classifying each parameter to obtain a result. Preferably, localizing the object comprises a fusion of two segmentations; a minimal intra-class-variance thresholding algorithm to locate smoothly-changing object borders, and a minimal-spanning-tree based algorithm to locate abruptly-changing borders.

In accordance with an aspect of the invention, there is provided a computer-readable medium including executable instructions to carry out a method according to the an aspect of the invention. In particular, an embodiment of the present invention relates to a computer storage product with a computer-readable medium having computer code thereon for performing various computer-implemented operations. The media and computer code may be those specially designed and constructed for the purposes of the present invention, or they may be of the kind well known and available to those having skill in the computer software arts. Examples of computer-readable media include, but are not limited to: magnetic media such as hard disks, floppy disks, and magnetic tape; optical media such as CD-ROMs and holographic devices; magneto-optical media such as floptical disks; and hardware devices that are specially configured to store and execute program code, such as application-specific integrated circuits ("ASICs"), programmable logic devices ("PLDs") and ROM and RAM devices. Examples of computer code include machine code, such as produced by a compiler, and files containing higher-level code that are executed by a computer using an interpreter. For example, an embodiment of the invention may be implemented using Java, C++, or other object-oriented programming language and development tools. Another embodiment of the invention may be implemented in hardwired circuitry in place of, or in combination with, machine-executable software instructions.

In accordance with another aspect of the invention, there is provided a method and system that is designed for the early detection of skin cancer using mobile imaging and on-device processing. In particular, smartphone-captured skin mole images may be used together with a detection computation that resides on the smartphone. Smartphone-captured images taken under loosely-controlled conditions introduce new challenges for skin cancer detection, while on-device processing is subject to strict computation and memory constraints. To address these challenges and to achieve high detection accuracy, we propose a system design that includes the following novel elements:

- Automatic feature selection: under the well-known Normalize Mutual Information Feature Selection (NMIFS) framework, we propose a mechanism to include the coordinate of the variable values to improve the feature selection results.

- Skin mole localization using fast skin detection and fusion of two fast segmentation algorithms to localize the mole region: a minimal intra-class-variance thresholding algorithm to locate smoothly-changing mole borders and a minimal-spanning-tree based algorithm to locate abruptly-changing borders. This design leads to a localization scheme that is accurate and has small computation requirement.

- New features to mathematically quantify the color variation and border irregularity of the skin mole; these features are specific for skin cancer detection and are suitable for mobile imaging and on-device processing. In particular, in an embodiment of the present invention, the invention detects the malignancy of a skin mole by measuring its concentric partitions' color uniformity, and the algorithms used by the present system and method quantify this. The present invention also uses a new border irregularity descriptor that is robust to image noise suitable for our image modality and capturing environment.

- New feature selection mechanism that takes into account the coordinate of the feature values to identify more discriminative features

- A classifier array and a classification result fusion procedure to compute the detection results. The present invention uses an array of classifiers and results fusion that is more appropriate for this invention.

Previous systems and methods are based on epiluminescence microscopy (ELM) imaging used in the clinical environments. ELM images are taken with the aid of liquid medium or non-polarised light source and magnifiers, rendering the surface translucent and making subsurface structures visible. Thus, subsurface structures can be used to aid diagnosis. However, ELM images can only be captured by specially-trained medical professionals. On the contrary, the present system employs mobile imaging that captures visible light image and can be used by the general public. The present method addresses the limitations arisen in mobile imaging. In particular, the present invention performs the detection using on-device processing. This is in contrast to some systems that perform processing at

remote servers. Note that processing at remote servers has several issues: (i) Privacy is compromised; in particular, mole checking involves images of body parts; (ii) Resource planning and set-up of the server infrastructure is required; (iii) Network connectivity and transmission delay may affect the diagnosis. On-device processing solves these issues. The present system is designed to enable accurate on-device detection under strict computation and memory constraints.

Still more particular, the system and method of the present invention focuses on two new features which can efficiently describe the color variation and border irregularity of lesion.

As indicated earlier, there are many features can be extracted to describe color, border or texture of lesion. It likely has some noise features also redundancy between features which may reduce the classification rate. Hence, a feature selection that is done in offline mode to select only good features is necessary. Only selected features will be used to judge if a lesion is cancer/non-cancer. Furthermore, feature selection has a important role in mobile-based diagnosis system where there are strict computational and memory constraints. Advantageously, by using a small number of features, it will have some benefits such as reduce feature extraction time and storage requirements; reduce training and testing time; reduce the complexity of classifier, and increase in classification accuracy in some cases.

Feature selection algorithms can be divided into two categories according to their evaluation criteria: wrapper and filter [13]. Wrapper approach uses the performance of a predetermined classifier to evaluate the goodness of features. On the other hand, filter approach does not rely on any classifiers. The goodness of features is evaluated based on how much the relevance between them and class labels. In this work, we follow filter approach because it is very fast which allows us to compare different methods. Furthermore, it is more general than wrapper approach because it does not involve to any specific classifier.

In filter approach, the relevance is usually characterized in terms of mutual information. However, the drawback of mutual information is that it only uses the probability of variables while ignoring the coordinate of variables which can help the classification. To overcome this drawback of mutual information, we propose a new feature selection criterion taking into account the coordinate of variables when evaluating the goodness of features.

The final stage of automatic melanoma detection is to classify extracted features of lesions into either cancer or non-cancer. Many classification models can be used at this stage such as Support Vector Machine (SVM), nearest neighbor, discriminant analysis [14], [10], [2].

Brief Description of Figures

In order that the present invention may be fully understood and readily put into practical effect, there shall now be described by way of non-limitative examples only preferred embodiments of the present invention, the description being with reference to the accompanying illustrative figures.

In the Figures:

Figure 1 is a flowchart showing the segmentation procedure according to an embodiment of the present invention;

Figure 2 shows the results of legion segmentation according to an embodiment of the present invention;

Figure 3 shows the quantification of color variation and border irregularity as carried out by a method according to an embodiment of the present invention;

Figure 4 shows the classification accuracy with different number of selected color features carried out by a classification method according to an embodiment of the present invention;

Figure 5 shows an illustration of a screenshot of an application indicating results and diagnosis according to an embodiment of the invention; and

Figure 6 is a flow chart showing the system and method according to an embodiment of the present invention.

Detailed Description of The Preferred Embodiments

All publications and patent applications herein are incorporated by reference to the same extent as if each individual publication or patent application was specifically and individually indicated to be incorporated by reference.

The following description includes information that may be useful in understanding the present invention. It is not an admission that any of the information provided herein is prior art or relevant to the presently claimed inventions, or that any publication specifically or implicitly referenced is prior art.

Unless defined otherwise, all technical and scientific terms used herein have the same meaning as commonly understood by one of ordinary skill in the art to which this invention belongs. Although any methods and materials similar or equivalent to those described herein can be used in the practice or testing of the present invention, the preferred methods and materials are described.

Figure 6 is a flowchart setting the general steps taken by the present method according to an embodiment of the present invention. The general steps are set out below:

Given a smartphone-captured skin lesion image as input, the system of the present invention performs computation to determine the likelihood of skin cancer. Figure 6 depicts the system design with the following processing stages:

1. Pre-processing: Direct processing the smartphone-captured image is computation and memory expensive, and this exceeds the capability of mobile devices. Thus, in the preprocessing stage, the input image is down-sampled, an approximate mole location is determined using the down-sampled image, and a region enclosing the mole is determined and cropped from the high-resolution input image. The approximate mole location can be determined using a minimal intra-class-variance thresholding algorithm, and/or a minimal-spanning-tree based algorithm, on the down-sampled image. The cropped region will be processed in the subsequent stages.

2. Skin mole localization: It is challenging to achieve accurate segmentation of skin lesions from smartphone-captured images under loosely-controlled lighting and focal conditions. Instead of using sophisticated but computationally-expensive segmentation algorithms, we propose to localize the skin lesion with a combination of (i) fast skin detection and (ii) fusion of two

fast segmentation outputs. In particular, Otsu's method and Minimum Spanning Tree (MST) method are used to identify smoothly-changing and abruptly-changing mole borders, respectively. In the fusion processing, segments connected to boundary of skin region are removed, union of remaining segments is computed, the largest connected region is determined from the union results, and median filter is applied to the final segment.

3. Feature computation: After localizing the skin mole, we characterize it by features belonging to four feature categories: color, border, asymmetry and texture. In addition, we propose a new color feature and a new border feature:

    a. New color feature: For abnormal skin lesion, its color varies nonuniform from the center to the border. We propose a new feature to capture this characteristic. The lesion is first divided into N partitions (N sectors with equal degree) and each partition is further divided into M subparts. After that, each partition is described by a M -component vector where each component is the average of pixel values of a subpart. Finally, maximum distance between the vectors quantifies the color variation. This feature is called as color triangle feature. This proposed method is computed for gray scale, red and hue channel of the lesion. Values of N are chosen from {4, 8, 12, 16}. For each value of N, values of M are chosen from {2, 4, 8}. Feature selection is used to determine the optimal parameters.

    b. New border feature: We propose a new method called border fitting to quantify the irregularity of lesion border (irregular skin mole indicates abnormal condition). First, the lesion border is approximated by piecewise straight-lines. After that, the angles between every two adjacent straight-lines are computed. Mean and variance of the angles are used to characterize the border irregularity. Number of lines is chosen from {8, 12, 16, 20, 24, 28}. Feature selection is used to determine the optimal parameter.

4. Feature Selection: There are many features extracted to describe color, border or texture of a skin lesion. Likely, some are noise features. Also, redundancy between features may reduce the classification rate. Hence, a feature selection that is done in offline mode to select only good features is necessary. Only selected features will be used in the system to determine if a lesion is cancer/non-cancer. Furthermore, feature selection has an important

role in our mobile-based diagnosis system, where there are strict computational and memory constraints. By using a small number of features, it will have some advantages such as reduction of feature extraction time and storage requirements, reduction of training and testing time, and reduction of the complexity of classifier. Note that it has been recognized that the combinations of individually good features do not necessarily lead to good classification performance. Finding the best feature subset with at most m features from a set of M features necessitates examining W feature subsets:

$$W = \sum_{i=1}^{m} \binom{M}{i}$$

Thus, it is hard to search for the optimal feature subset exhaustively.

The invention will now be described in greater detail.

Segmentation

It is challenging to achieve accurate segmentation of skin lesions from smartphone-captured images under loosely controlled lighting and focal conditions. Instead of using sophisticated segmentation algorithms, which can be computationally-expensive, the present invention first start out by localizing the skin lesion with a combination of fast skin detection and fusion of fast segmentation results. The segmentation process consists of two main steps. As a first step, a mask of skin regions is generated using skin detection method. By doing skin detection, we discard pixels from non-skin regions to simplify the image for subsequent processing step. At second step, we extract the lesion by using a combination of different segmentation methods. Fig. 1 shows the flowchart of the segmentation procedure and is described in detail below.

1. Skin Detection

The reason of doing skin detection first is to simplify the image, so an exact classification of skin and non-skin region is not needed as long as we extract a simple foreground and keep the whole lesion region inside. Here we use an approach based on skin color model to detect skin pixels [5]. First we convert the image from *RGB* color space into YC_bC_r color space. We collect 100 skin images and 36 non-skin images from the internet to form our skin detection dataset. Skin images are selected with

different skin colors and various lighting conditions. The skin color distribution is close to an elliptical distribution [11], so we detect skin pixels using an elliptical skin model on C_bC_r space [5], [11]. As the skin mole we want to detect may not have skin color, we fill all the holes inside the skin region.

2. Lesion Segmentation

In developing a mobile-based diagnosis system, we need a segmentation method that can achieve high precision under the computation constraint. As different segmentation methods have distinct limitations, we want to apply several basic segmentation methods with low computation usage, and then use some criteria to merge the results.

After we get the skin region as the area to do our segmentation method, we perform two segmentation methods and use some rules to combine results from both methods. Here we select Otsu's method [16] and Minimum Spanning Tree (MST) method [8] to get initial segmentation results.

Otsu's method is a general histogram thresholding method that can classify image pixels based on color intensity, and it may not detect clear edges on image, for example, the lesion boundary. Otsu's method is simple and takes much less time compared to other lesion segmentation methods [10].

MST method is a fast region-based graph-cut method. It can run at nearly linear time complexity in the number of pixels. It is sensitive to clear edges but may not detect smooth changes of color intensity.

By combining the two different segmentation results, we expect to get a good segmentation on lesion with either clear border or blur border in a fast computation. Based on some rules to perform fusion of different segmentation in [10], we apply the following procedures to merge the two segmentation results. First, we remove all segments in either results that are connected to the boundary of skin region. Second, we take the union of the two results and then find the largest connected region in the union result. And last, we perform a post processing method of using median filter on the final segment to smooth the border. Fig. 2 shows results of single segmentation methods and their combination. Fig. 2(a-c) show an example where Otsu's method gives a better result than MST method. Because in this image, the lesion border is not clear, Otsu's method detects a more accurate border. Fig. 2(d-f) show an example where MST method gives a better result than Otsu's method. In this image, the lesion border is clear but the color is not

uniform inside the lesion region, so MST method finds the exact border of the lesion. After we take the union from two different methods, we can get more accurate segmentation results.

Feature Calculation

1. *Feature Extraction*

Given the lesion image segmented described above, we examine 80 features belonging to four categories (color, border, asymmetry and texture) to describe the lesion. These features are presented in follows.

(a) Color Feature

Given a color lesion, we calculate color features widely used in the literature such as mean, variance of pixel values on several color channels. The used color channels are gray scale; red, green, blue (from RBG image); hue and value (from HSV image). To capture more color variation, we also use information from histogram of pixel values [14], [10], [2]. A histogram having 16 bins of pixel values in lesion is computed and number of non-zero bins is used as feature. This method is also applied on 6 channels mentioned above. Features achieved from these channel are called as *num_gray, num_red, num_green, num_blue, num_hue* and *num_value.*

For normal skin lesion, color varies uniformly from the center to the border. We propose a new feature to capture this characteristic. The lesion is first divided into *N* partitions and each partition is further divided into *M* subparts. After that, each partition is described by a *M*-component vector where each component is the average of pixel values of a subpart. Finally, maximum distance between the vectors quantifies the color variation. This feature is called as color triangle feature. This proposed method is computed for gray scale, red and hue channel of lesion. Values of *N* are chosen as 4, 8, 12 and 16. For each value of *N,* values of *M* are chosen as 2, 4 and 8. An illustration for proposed method is presented in Fig. 5(a). Totally, we extract 54 color features to describe the color variation.

(b) Border Feature

To describe the irregularity of border, we compute shape features such as compactness, solidity, convexity, variance of distances from border points to centroid of lesion [14].

We also propose a new method called as border fitting to quantify the irregularity of border. First, the lesion border is approximated by mean-square-error method with lines. After that, the angles between every two adjacent lines are computed. Average and variance of the angles are used to describe border irregularity. Number of lines L are chosen as 8, 12, 16, 20, 24 and 28. An illustration for proposed method is presented in Fig. 5(b). Totally, 16 features are extracted to describe the border irregularity.

(c) Asymmetry Feature

To compute the asymmetry of lesion shape, we follow the method in [2]. The major and minor axes (first and second principal components) of lesion region are determined. The lesion is rotated such that the principal axes are coincided the image (x and y) axes. The object was hypothetically folded about the x-axis and the area difference (Ax) between the two parts was taken as the amount of asymmetry about the x-axis. The same procedure was performed for the y-axis (so, we get Ay). The asymmetric feature is computed as $\frac{Ax+Ay}{A}$ where A is lesion area.

(d) Texture Feature

To quantify texture feature of lesion, a set of features from the Gray Level Co-occurrence Matrix (GLCM) of gray scale channel is employed. The GLCM characterizes the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image. GLCM-based texture description is one of the most well-known and widely used methods in the literature [6]. In this work, GLCM is built by considering each two adjacent pixels in horizontal direction.

Four features extracted from GLCM to describe lesion. They are contrast, energy, correlation and homogeneity. As shown in [6], to achieve a confidence estimation for features, GLCM should be dense. Hence, before GLCM calculation, the pixel values are quantized to 32 and 64 levels. It means that we computed 8 texture features from two GLCM. To capture edge information in lesion, we also use Canny method to detect edges in lesion. Number of edge pixels are counted and normalized by lesion area. This number is used as feature. Totally, 9 features are extracted to describe the texture of lesion.

2. *Feature Selection*

Given set *F* of *n* features and class label *C*, the feature selection problem is to find a set *S* having *k* features ($k < n$) such that it maximizes the relevance between *C* and *S*. The relevance is usually characterized in terms of Mutual Information (MI) [17], [1], [7]. Because the consideration all possible subsets having *k* features requires C_n^k run, it is difficult for using exhausting search to find the best subset.

(a) Feature selection procedure

Because of above trouble, in this work, we used the well-known feature selection procedure called Normalize Mutual Information Feature Selection (NMIFS) [7] to select features. In NMIFS, at beginning, the feature that maximizes relevance with target class *C* is selected as first feature. Given set of selected feature S_{m-1}, the next feature f_m is chosen such that it maximizes the relevance of f_m to target class *C* and minimizes the redundancy between it and previous selected features in S_{m-1}. In other words, f_m is selected such that it maximizes *G* function

$$G(f_m) = I(C, f_m) - \frac{1}{|S_{m-1}|} \sum_{f_s \in S_{m-1}} NI(f_m, f_s) \quad (1)$$

where *I* is mutual information function measuring the relevance between two variables and is defined as

$$I(X,Y) = \sum_y \sum_x p(x,y) log \frac{p(x,y)}{p(x)p(y)} \quad (2)$$

NI is normalized mutual information function and is defined as

$$NI(X,Y) = \frac{I(X,Y)}{min\{H(X), H(Y)\}} \quad (3)$$

where H is entropy function 2. (From information theory, $I(X, Y) \geq 0$; $I(X, Y) < 1$ if X or Y is binary variable; $0 < NI(X, Y) < 1$)

(b) Disadvantage of MI-based criterion

MI usually is widely used in feature selection problem to measure the relevance between variables. However, from (2), we observed that MI is a measure based on the probability functions. It is independent to coordinate of variable values which may be useful in classification context. For examples, in two categories classification, suppose that number of samples in each category are equal and there are two features f_1, f_2 which perfectly separate two categories. By Vapnik-Chervonenkis theory [21], the feature has larger margin between two categories will give a better generalization error. Hence, it should be better than another feature. However, by using MI, it is easy to show that these features will have same MI value with class label *(C)* which equals to 1. A well-known criterion considering the coordinate of features is Fisher criterion (F-test). However, there are some disadvantages of Fisher criterion figured out in [9]. Fisher criterion may not be good incase (i) the distribution of the data in each class is not a Gaussian; (ii) mean values of classes are equal/approximate.

(c) New feature selection criterion

To overcome drawback MI-based criterion, we propose a new criterion taking into account the feature coordinate when evaluating the goodness of features. The general idea of our new criterion is inspired from the work of Wang et al. [23] in face recognition problem. In that work, authors defined a new transformation called "Average Neighborhood Margin (ANM) maximization" which pulls the neighboring images of the same person towards it as near as possible, while simultaneously pushing the neighboring images of different people away from it as far as possible. We adapt the general idea to the feature selection problem and propose a goodness of feature *f* defined as

$$M(f) = \sum_{i=1}^{N} \left\| \sum_{k \in N_i^e} \frac{\|f(i) - f(k)\|_1}{N_i^e} - \sum_{j \in N_i^o} \frac{\|f(i) - f(j)\|_1}{N_i^o} \right\|_1 \quad (4)$$

where N is number of data points (samples); for each sample i, N_i^o is the set of the most similar samples which are in the same class with i; N_i^e is the set of the most similar samples which are not the same class with i; $f(i)$ is feature value of ith sample. Eq. (4) means that a feature is good if each sample is far from samples belonging other classes while it is near to samples belonging same class. Because ANM criterion uses only local information and does not make any assumptions on the distributions of samples, ANM can overcome drawbacks of Fisher criterion.

Finally, to take advantages both MI and ANM, we propose a new feature criterion which replaces G function in eq. (1) by the following function

$$G(f_m) = \alpha * M(f_m) + (1-\alpha) * \left[I(C, f_m) - \frac{1}{|S_{m-1}|} \sum_{f_s \in S_{m-1}} NI(f_m, f_s) \right] \quad (5)$$

Margin ↓ $M(f_m)$; Relevance ↑ $I(C, f_m)$; Redundancy ↑ $NI(f_m, f_s)$

where $\alpha \in [0, 1]$ is weight that regulates to the importance of ANM. Note that M is normalized to [0, 1] before computing eq. (5).

EXAMPLE

Classification experiments

Experiment Setting

The database includes 81 color images provided by National Skin Center, Singapore. Number of cancer and non-cancer images are 29 and 52, respectively.

The segmentation process described above is applied on these images to extract lesion regions. After that, 80 features belonging four categories (54 color features, 16 border features, 1 asymmetric feature and 9 texture features) as described in earlier sections above are extracted to describe each lesion region. These features are normalized by z-score before subjecting to feature selection step. To compute mutual information between features, features should be first discretized. To discretize each feature, the interval $[\mu - 2\sigma, \mu + 2\sigma]$ is divided into k equal bins; where μ, σ are mean and standard deviation of feature. Points falling outside the interval were assigned to extreme left or right bin. From suggestion in [18], k should be $1 < k < 5$. We run feature selection with k = 2, 3, 4, 5. The best classification accuracy shown in next section is achieved at k = 5. Values of N_i^o and N_i^e in eq. (4) are set to 50% number of samples of class containing i^{th} sample. α in eq. (5) is set to 0.4.

Because all color, border, asymmetry and texture have important role in judging a lesion, we apply feature selection for each category of features. For each feature category, we select the subset of features giving highest classification accuracy. Feature selection is not necessary to apply asymmetric category because only one asymmetric feature is extracted. After achieving the feature subsets for each category, a SVM classifier [3] is trained for each subset. In testing stage, for each feature subset, the corresponding SVM is used to make a prediction. The output of SVM will be 1 (cancer) or 0 (non-cancer). Here, we use 5-folds cross validation for training and testing. To combine results of four classifiers, we sum their outputs (sum-rule). A lesion is judged as cancer if sum value is larger than 1.

As an example, Fig. 3 shows how the specific features of color variation and border irregularity is characterised and quantified. For abnormal skin lesion, its color varies non-uniformly from the center to the border. With this invention, we propose a new feature to capture this characteristic. With reference to Fig. 3(a), the lesion is first divided into N partitions (N sectors with equal degree) and each partition is further divided into M subparts. After that, each partition is described by a M - component vector where each component is the average of pixel values of a subpart. Finally, maximum distance between the vectors quantifies the color variation. This feature is called as color triangle feature. This proposed method is computed for gray scale, red and hue channel of the lesion. Values of N are chosen from {4, 8, 12, 16}. For each value of N, values of M are chosen from {2, 4, 8}. Feature selection is used to determine the optimal parameters.

In addition to the above, we also propose a new method called border fitting to quantify the irregularity of lesion border (irregular skin mole indicates abnormal condition). With reference to Fig. 3(b), the lesion border is first approximated by piecewise straight-lines. After that, the angles between every two adjacent straight-lines are computed. Mean and variance of the angles are used to characterize the border irregularity. Number of lines is chosen from {8, 12, 16, 20, 24, 28}. Feature selection is used to determine the optimal parameter.

Feature Selection Results

	MI-based criterion	Our criterion
color	num hue, color triangle (red channel, $N = 16$, $M = 8$), num red, num green	num hue, color triangle (red channel, $N = 16$, $M = 8$), num value
border	mean of border fitting ($L = 28$)	variances of border fitting ($L = 28$, $L = 8$)
asymmetry	$(Ax + Ay)/A$	
texture	correlation of GLCM (32 levels quantization), number of edge pixels, contrast of GLCM (64 levels quantization)	

Table I

Table I shows selected features in each category when MI-based criterion and our criterion are used in feature selection. The classification accuracy is given in Table II.

	MI-based criterion					Our criterion				
	color	border	asymmetric	texture	combine	color	border	asymmetric	texture	combine
non-cancer	94.00	82.55	92.36	84.55	90.18	94.18	79.27	92.36	84.55	90.55
cancer	86.00	66.00	33.33	76.67	90.00	90.00	76.00	33.33	76.67	96.67
average	90.00	74.27	62.85	80.61	90.09	92.09	77.64	62.85	80.61	93.61

Table II

For texture features, feature selection using MI-based criterion and our criterion give same best feature subset. The highest accuracy is 80.61% when 3 features are selected.

Fig. 4(a) shows the classification accuracy with different number of selected color features. The MI-based criterion achieves highest accuracy 90% when number of selected features equals 4. The highest accuracy of proposed criterion is 92.09% when number of selected features is only 3.

From Table I, we can see that color triangle features always appear in selected features for both MI-based criterion and our criterion. This confirms the efficiency of proposed color triangle features. We also see from this table that number of non-zero bins of histogram are a good feature to capture color variation.

Fig. 4(b) shows the classification accuracy with different number of selected border features. The MI-based criterion achieve highest accuracy 74.27% when only one feature is selected. By using MI-based criterion, we have no chance to get a higher accuracy even more features are added. The highest accuracy of proposed criterion is 77.64% when 2 features are selected. From Table I, we can see that border fitting features are selected features for both MI-based criterion and our criterion. This confirms the efficiency of proposed border fitting features.

Table II also shows the accuracy when four classifiers corresponding to 4 feature categories are combined by sum rule. When combined, our criterion outperforms MI-based criterion. The average accuracy of MI-based criterion and our criterion are 90.09% and 93.61%, respectively. Our criterion also achieves a high accuracy (96.67%) for cancer samples. It is important in practice where a high accuracy detection for cancer is required.

Mobile Implementation

Because the image taking from mobile may have a big size, the image will be resized to a lower resolution for reducing time processing and memory to store image. After lesion segmentation, 9 selected features (by our criterion, table I) including 3 color features, 2 border features, 1 asymmetric feature and 3 texture features will be extracted to describe that lesion. These features will be subjected to corresponding SVM classifiers. The results from 4 SVM classifiers will be combined by sum rule to give final score. The final score is in the interval [0,4]. A high score means

high cancer risk. The average processing time for each image on a Samsung Galaxy S4 Zoom (CPU: Dual-core 1.5GHz, RAM: 1.5GB, Camera: 16Mp) is less than 5 seconds. The screenshot mobile application is shown in Fig. 5.

Conclusions

In the present invention, we proposed (i) an efficient segmentation scheme by combining fast skin detection and fusion of two fast segmentation results; (ii) new features which efficiently capture the color variation and border irregularity of segmented lesion and (iii) an efficient mechanism for selecting features. Based on the features selected by the proposed criterion, an automatic melanoma diagnosis system using a mobile platform is proposed.

In summary, the present invention relates to a mobile imaging system for early diagnosis of melanoma. In particular, the invention relates to capturing images using a smartphone and having a detection system that runs entirely on the smartphone. Smartphone-captured images taken under loosely-controlled conditions introduce new challenges for melanoma detection, while processing performed on the smartphone is subject to strict computation and memory constraints. To address these challenges, we propose to localize the skin lesion by combining fast skin detection and fusion of two fast segmentation results. We propose new features to capture color variation and border irregularity which are useful for smartphone-captured images. We also propose a new feature selection scheme to select a small set of good features used in the final system. Our evaluation confirms the effectiveness of proposed algorithms and features. In addition, the invention includes a system that computes selected visual features from a user-captured skin lesion image, and analyzes them to estimate the likelihood of malignance, all on an off-the-shelf smartphone.

Features used in current system are hand-design features. By using automatic feature extraction methods e.g. sparse coding, it may help to find more efficient features.

Whilst there has been described in the foregoing description preferred embodiments of the present invention, it will be understood by those skilled in the technology concerned that many variations or modifications in details of design or construction may be made without departing from the present invention.

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CLAIMS

1. A device for analysing an image of an object and evaluating the risk or likelihood of a disease or condition, the system comprising:

   (a) an image capturing device for capturing the image of an object; and

   (b) a processor for executing a set of instructions stored in the device for analysing the image, the set of instructions includes a library of algorithms stored in the device, and is configured to localize the object region, extract features of the object, and classify the object based on a set of pre-determined parameters,

   wherein the set of pre-determined parameters is any one selected from the group: color, border, asymmetry and texture of the object.

2. The device according to claim 1, wherein the set of instructions comprises quantifying the color variation and border irregularity of the object.

3. The device according to any one of claims 1 or 2, wherein the object is a lesion on a patient's body.

4. The device according to any one of the preceding claims, wherein the disease is melanoma.

5. The device according to any one of the preceding claims, wherein the device further comprising a graphical user interface for indicating to a user the results of the analysis.

6. A method for analysing an image of an object and evaluating the risk or likelihood of a disease or condition, the method comprising:

   (a) pre-processing the image;

   (b) localizing the object;

   (c) characterizing and extracting features of the object based on a set of pre-determined parameters selected from the group: color, border, asymmetry and texture of the object; and

   (d) classifying each parameter to obtain a result.

7. The method according to claim 7, wherein localizing the object comprising a fusion of two segmentations; a minimal intra-class-variance thresholding algorithm to locate smoothly-changing object borders, and a minimal-spanning-tree based algorithm to locate abruptly-changing borders.

8. A computer-readable medium including executable instructions to carry out a method according to any one of claims 6 or 7.