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Gout Images Detection and Recognition by Neural Network

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ABSTRACT

Gout skin detection and tracking has been the topics of an extensive research for the several past decades. Many heuristic and pattern recognition based strategies have been proposed for achieving robust and accurate solution.This paper demonstrates how a Gout skin detection recognition system can be designed with artificial neural network. Note that the training process did not consist of a single call to a training function. Instead, the network was trained several times on various input ideal and noisy images, the images which contents Gout skin . The objective of this study was to develop a back propagation artificial neural network (ANN) model that could distinguish gout image by several parameters for testing are Energy , Entropy , Average andVariance. Although only the color indices associated with image pixels were used as inputs, it was assumed that the ANN model could develop the ability to use other information, such as shapes, implicit in these data. The 756x504 pixel images were taken in the field and were then cropped to 100x100-pixel images in testing phase. A total of 80 images of gout image and other images were used for training purposes. For ANNs, the success rate for classifying gout image was as high as 100%.

Introduction

There have been many applications of ANNs reported for the interpretation of images in the agri-food industry. Studies have been shown that for the interpretation of images ANNs can beas accurate as procedural models. Generally, ANNs can efficiently model various input /output relationships with the advantage of requiring less execution time than a procedural model. These features make the ANN approach very appealing for real-time image processing. Among feature-based detection methods, the ones using skin color as a detection cue, have gained strong popularity. Color allows fast processing and is highly robust to geometric variations of the face pattern[3,4]. The DSCT (Siemens Definition scanner) system is equipped with two X-ray tubes and two corresponding detectors. These tubes scan at 80 kbp and 140 kbp allowing for material-specific differences in the attenuation of the scanned tissue to be fused into data sets[2].

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Iris recognition is a method of biometric authentication that uses pattern-recognition techniques based on high resolution images of the irises of an individual's eyes. Not to be confused with another, less prevalent, ocular-based technology, retina scanning, and iris recognition uses camera technology, with subtle infrared illumination reducing specular reflection from the convex cornea, to create images of the detail-rich, intricate structures of the iris. Converted into digital templates, these images provide mathematical representations of the iris that yield unambiguous positive identification of an individual. Iris recognition efficacy is rarely impeded by glasses or contact lenses. Iris technology has the smallest outlier (those who cannot use/enroll) group of all biometric technologies[9].

A material decomposition algorithm (calcium, uric acid, soft tissue) of the data sets loaded in the dual energy viewer present on the Siemens MMWS. Doing so allows for accurate characterization of uric acid (colored in red) separately from soft tissue and calcium (colored in blue). The distribution of gout visualized showed deposition in tendons and ligaments as well as intra-particularly[1].

parameters used for skin modeling

The most reliable method of diagnosing gout is to aspirate the joint in order to obtain fluid to verify the presence of monosodium rate crystals (uric acid). Up to now, computed tomography (CT) has played only alimited role in the evaluation of gout, since conventional CT systems cannot reliably verify deposits of uric acid. However, a current study at the Vancouver General Hospital gives rise to speculation that dual-energy computed tomography (DECT) could radically change the management of this disease. DECT enables fast, noninvasive examinations and, based on initial evaluations, has the potential to surpass the clinical examination in terms of identifying sub clinical disease[5,6]. Investigations have confirmed the high sensitivity of the DECT method in detecting uric acid deposits.

The system is the only CT scanner worldwide that features two X-ray tubes capable of simultaneously producing different energies[4].

When building a system, that uses skin color as a feature foreface detection, the researcher usually faces three main problems. First, what color space to choose, second, how exactly the skin color distribution should be modeled, and finally, what will be the way of processing of color segmentation results for face detection. The most popular histogram-based non-parametric skin models require much storage space and their performance directly depends on the representative ness of the training images set. The need for more compact skin model representation for certain applications along with ability to generalize and interpolate the training data stimulates the development of parametric skin distribution models. This paper covers the some parameters shown in the table(1):

Table(1):image parameters which used in Random segmentation blocks algorithm with color space.

Parameter name	Parameter note
1-Average	Provide information about the contrast of the image high variance find high contrast
2-Variance	Provide information about the contrast of the image high variance find high contrast
3- Entropy	Measure of image information content, Provide information about the number of bit required to code the image
4- Energy	Provide Information about the data spread

Probability(p)=n(g) / m

g:color ; n:number of pixel with color(g); m:totol number of pixel in image

Average (g')=Σr Σc I(r,c) /m ....…..(1)

I(r,c): color at coordinate (r,c)

Variance(v)= $\sqrt{\sum_{n=0}^{l-1}(g-g')^2+p(g)}$ …...(2)

g':average ; l: number of colors in image

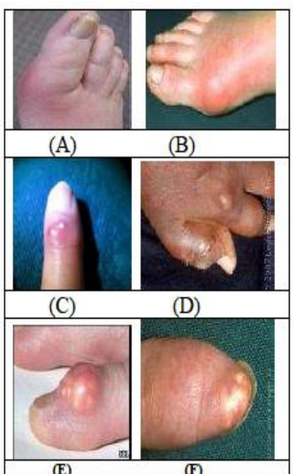
Entropy(E)= $-\sum_{g=0}^{l-1} p(g)\log_2[p(g)]$ ….(3)

Energy(En) = $\sum_{g=0}^{l-1}[p(g)]^2$ ……….…..(4)

The user has the opportunity both to supply a variance image of the input and to receive a variance image of the smoothed output. (A variance image is an image of the variances, that is the squares of the standard deviations, in the values of the input or output images.) Specifically, the possibility of using ANNs to distinguish between images of gout Image and another images, captured in real-time by a digital camera, was investigated. In this study, the use of ANNs was confined to the differentiation of gout and some species commonly encountered in the experimental fields. Classify each pixel as skin or non-skin individually, independently from its neighbors try to take the spatial arrangement of skin pixels into account during the detection stage to enhance the methods performance. Pixel-based skin detection has long history, but surprisingly few papers that provide surveys or comparisons of different techniques were published. Our goal, in this paper, is to describe and recognition gout and summarize characteristic features devoted to description of different color spaces used for skin detection[7]. The classical symptoms of gout are painful, visibly swollen joints. Gout is nevertheless difficult to diagnose, since quite a few diseases, for example various forms of arthritis, have similar symptoms. While imaging techniques can help to locate gout lesions, the specificity of X-ray, single-source computed tomography, magnetic resonance imaging and ultrasound is not sufficient to definitively confirm a diagnosis. This is done by aspirating the joint with a needle to remove the Diagnosing gout, a nasty disease involving swollen joints and often a good deal of pain, is difficult because the symptoms are often similar to various forms of arthritis.

Neural network design to Parametric skin distribution modeling

The size of the images was 756x504 pixels. These images were viewed and further cropped to a size of 100x100 pixels so that each included either gout image or a group another image . It would have been impractical to use the 756x504 pixel images, since the PC memory would have been inadequate. Images was taken not to include gout parameters(another image skin) in a given image, so as to simplify the ANN training process. The BMP images were converted to indexed images based on a red-green-blue (RGB) color system. Each pixel of an image was classified into one of 256 categories, represented by an integer in the range from 0 (black) to 255 (white).

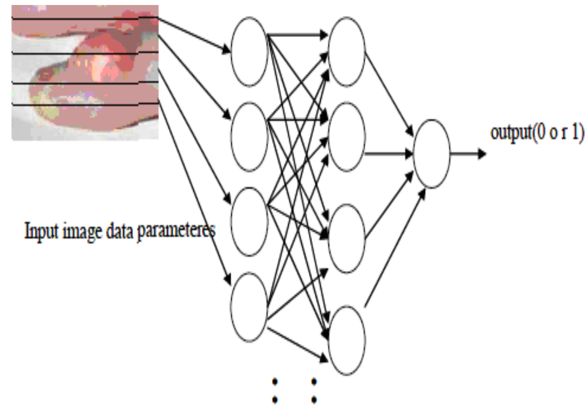


Figure(1):. (A) and (B) For(المنطقة فوق الابهام القدم) gout image; (C),(D) (المنطقة باصبع الابهام باليد) gout image; (E), (F) (منطقة اصبع الابهام بالقدم) gout image

Each assigned color index number served as an ANN input and, therefore, there were 10 000 (100x100) inputs for each image. Although the color indices were the only inputs used in this study, other features, such as shapes, were expected to be taken into account by the ANNs since information about them is implicit in the relationships between the pixel colors.

The algorithm for this paper is:

1- Start
2- Input image
3- Analyses the image
4- Find the Parameters for image
5- Appling ANN for image parameters
6- Compare neural results with Data base images
   a-if true then matching
   b-if false ask for insert image to images data base
7- Ask if there another image
   a-if true go to step(3)
   b-if false go to 8
8- End



Figure(2):The ANN structure for Type 1 output.

During training, the ANNs were presented with binary output data. Two classification schemes were tried to represent the output variable value of zero was assigned to not same image and a value of one to same image . Forty images of gout and another images of weeds were used to train the ANNs. Both output methods would ideally lead to the same results if the same classification thresholds were used and if there were enough images to ensure proper training of the ANNs. However, the slightly different ANN architectures that were used in each method could lead to differences in effectiveness, and, moreover, allows a more flexible interpretation of the results. Back-propagation networks were selected for this project because they have been successfully used in various image processing applications Each PE in the input layer received the color index value of one of the pixels in the input images. One hidden layer was used between the input and output layers.

The formulation of the rules for classification based on segmentation is carried out by the context information and the classes relationships. Generally in higher hierarchy spectral information could yield good results, such as Energy, Entropy and Variance. To distinguish different objects which are very close spectrally form parameters. The parameters inputs to neural network and then training and testing it to found results.

Figure(3): psoriasis (الصدفية) images

Recognition rate for ANNs=total succeeded identical fictions / total number of trials * 100%.

The results shown in Table (3) indicate that ANNs can, in general, classify and distinguish images of gout image from images with a success rate of 80 to 100%. number of PEs in the hidden layer, the highest success rate classification was obtained. To further improve ANN performance in image recognition and classification, other methods may be investigated in the future. Firstly, due to computer memory limitations, the number of PEs inthe hidden layer was limited to 300 in this study i.e., 3% of the number of input PEs. Although there is no method for determining the best number of PEs to include in the hidden layer based on the number of inputs, the number of PEs used in this work may have been insufficient for such a large amount of input data. More PEs in the hidden layer would result in better performance. However, more computer memory would be required to generate such ANNs, and a faster processor would also be needed to save time during training.

Conclusion

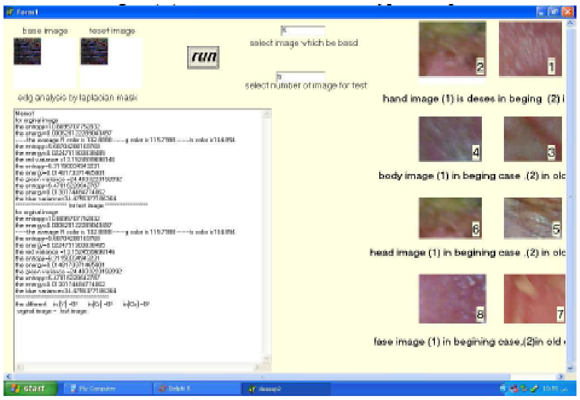
This study was undertaken to develop an ANN to classify images taken from the field and detect the gout . The images were taken from internet and Hospital . Colour index values were assigned to the pixels of the indexed image and used as ANN inputs[8]. There were 40 images, 100x100 pixels, for training, and 20 images for testing. Many back propagation ANN models were developed with different numbers of PEs in their hidden and various output layers. The performance of the ANNs was compared and the success rate for the identification of gout was observed to be as high as 80 to 100%.The results indicate the potential of ANNs for fast image recognition and classification. The maximum individual error for ANNs is 0.0037 called accepted error and the maximum overall error is 0.5 when the momentum is 0.5. Table(2) shown the results for image parameters.

Table(2):compare between two different images

Parameter name	Image(1)parameters	Image(2)parameters
entropy	9.88502155472831	10.0441885386596
energy	0.00147810826427482	0.00119119463100283
average R color	117.9236	152.0716
average G color	92.8496	109.4224
Average B color	81.946	111.6132
entropy	4.64209097460996	4.63773921605553
energy	0.0498367593261242	0.0468302375051628
red variance	6.27447267152303	6.15502100548075
entropy	5.43099133051117	5.30212487716184
energy	0.0293607706493251	0.0301934099720008
green variance	13.1198144806039	11.7581242486219
entropy	5.84579061572267	5.31609889716782
energy	0.0235562337711224	0.0301868182440296
blue variance	20.9089776801885	15.658529892524

Table (3) : ANNs effect and Recognition rate

PEs in hidden layers	Learning rate	Momentum rate	Recognition rate
70	0.2	0.5	80%
80	0.2	0.5	80%
90	0.2	0.5	80%
100	0.2	0.5	80%
110	0.2	0.5	80%
120	0.2	0.5	80%
130	0.2	0.5	80%
150	0.2	0.5	80%
160	0.2	0.5	80%
180	0.3	0.5	90%
200	0.3	0.5	90%
210	0.3	0.5	90%
230	0.4	0.5	100%
240	0.4	0.5	100%
260	0.4	0.5	100%
280	0.4	0.5	100%
300	0.4	0.5	100%

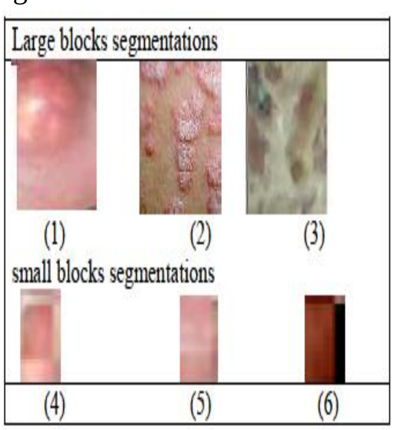

Figure(5):interface program

The most important conclusions we draw are listed below:

1- Parametric skin modeling methods are better suited for constructing classifiers in case of limited training and expected target data set. The generalization and interpolation ability of these methods makes it possible to construct a classifier with acceptable performance from incomplete training data.

2- The methods that are less dependent on the skin cluster shape and take into account skin and non-skin colors overlap automatically constructed colors pace and classification rules skin classifier for large target datasets.

3-Evaluation of color space goodness 'in general' by assessing skin/non skin overlap, skin cluster shape, etc. regardless to any specific skin modeling method cannot give the impression of how good is the color space suited for skin modeling, because different modeling methods react very differently on the color space change.

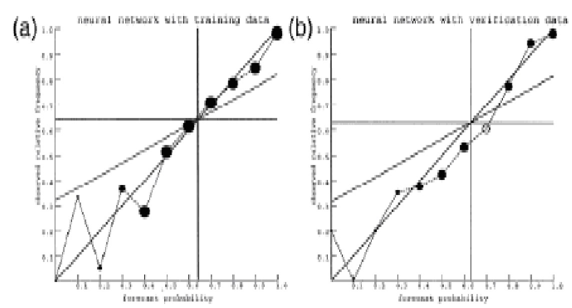


Figure(6): (1) gout skin blocks images size 100 * 100;(4),(5) ,(6) gout skin blocks images size 10*10 ; (2),(3) psoriasis skin block size 100*100

Gout Skin detection can also be used as an efficient preprocessing filter to find potential skin regions in color images prior to applying more computationally expensive gout

- ●Used 80 images to build a general color model.
- ●Density is concentrated around the color line and is more sharply peaked at red than blue.
- ●Most colors fall on or near the space color line.
- ●There is a marked skew in the distribution toward the red corner of the color image .

It is possible that color spaces other than RGB could result in improved detection performance. The skin colors form a separate cluster in the RGB color space. Hence skin color can be used as a cue for skin detection in images and videos. The performance of different color space may be dependent on the method used to model the color for skin pixel.



figure(7) . (a) ANNs with training data, (b) ANNs with verification data.

The recognition results by Random segmentation blocks algorithm shows superior efficacy for gout skin detection.

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تحديد وتمييز صور مرض النقرس باستخدام الشبكات العصبية

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الخلاصة:

تم الكشف عن مرض النقرس من عقود عدة من الماضي واقترحت العديد من الاستراتيجيات التي اعتمدت مبدا تمييز الانماط للتعرف على صور الخاصة بالمرض لتتمكن من وضع حلول قوية ودقيقة لذلك. اعتمدت الشبكة العصبية كطريقة للتعرف على صور النقرس لوحظ ان عملية التدريباستدعاء مفرد لداله التدريب بدلا من ذلك الشبكة العصبية تتدرب على نموذج الادخال لبعض الوقت حتى للصور التي تحتوي على ضوضاء .استخدمت شبكة الانبعاث الخلفي لتمير صور النقرس وتحديد الصور وبيان معاملاتها الاربعة التالية Average , Entropy , Energy و.Variance ، اعتبر اللون هو العامل الرئيسي لمدخلات الشبكة . 756x504 pixel حجم الصور المعتمدة كان يتم اختيار جزء من الصورة بحجم ١٠٠*١٠٠ لعملية الاختبار الخاصة بالشبكة العصبية تم تدريب واختبار ٨٠ صور واثبت النظام نجاحة ١٠٠ بالمئة.