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Identification of Malignant Melanoma by Wavelet Analysis

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This paper presents a different method for classifying benign and malignant melanoma skin lesions from digital images. The features used for classification were collected from coefficients created by Wavelet decompositions. Wavelet analysis, like Fourier transformation, is used for a number of operations in signal analysis. Images can also be treated as signals with their color values constituting the signal. The mean and variance of wavelet coefficients for a two level decomposition were calculated and used in a neural network to make a classification. The ability to correctly discriminate between benign and malignant lesions was about 83%.

Introduction

The incidence of malignant melanoma has increased dramatically over the past few decades. Although a potentially fatal disease, malignant melanoma has a near 100% cure rate if detected and excised early. Early diagnosis is obviously dependent upon patient attention but also accurate assessment by a medical practitioner. Dermatologist will see numerous melanoma patients, honing their capacity to make accurate diagnoses but general practitioners and other medical professional may not develop such an accurate eye. A computer aided diagnosis system is not meant to replace a trained Dermatologist but to assist less trained practitioners. Such a system would be useful for remote medical clinics that do not have the luxury of a trained dermatologist on hand.

This paper makes use of Matlabs Image Processing Toolbox and Wavelet toolbox for all image analysis and wavelet calculations.

Biology

Melanocytic (pigmented) lesions are formed by groups of specialized cells called melanocytes. Under normal conditions melanocytes live in isolation under the epidermis, the top layer of skin, producing a brown pigment called melanin. Melanin is passed on to keratinocytes that migrate to upper epidermal layers, playing an important role in protecting the skin by absorbing ultraviolet radiation, reducing the incidence of DNA damage. Increasing UV radiation results in an increase in melanin production, darkening the skin tone. When melanocytes group together, brown pigmented lesions may become visible on the skin. Such lesions may be benign or malignant [12] [Figure 1].

Benign pigmented lesions, known as benign nevi, are typically symmetrical with clean, abrupt edges and may or may not be raised from the surrounding skin [12]. Malignant melanoma is a cancerous condition where melanocytes grow unchecked, producing growths with variations in size, color, density and contour. To help medical practitioners recognize melanoma, the American Cancer Society developed the ABCD check list: A (asymmetry), B (border irregularity), C (color variation), and D (differential structure). Lesions exhibiting these characteristics are more likely to be malignant but an accurate diagnosis often requires a skin biopsy. Using these rules, clinicians have a correct diagnosis rate of 65-80% [2].

Wavelets

Wavelets are an extension Fourier analysis. The mathematics of Fourier analysis dates back to the nineteen century but it wasn't until the mid twentieth century, with the advent of fast algorithms and computers that Fourier analysis began to make an impact on the world. Widely used in signal analysis, hardly a scientific field hasn't been impacted by this technique.

The Fourier transform essentially converts a signal from the time domain to the frequency domain, giving a frequency representation of the signal [Figure 2]. Fourier transformation relies on the fact that a signal can be represented by a combination o sine and cosine functions. Coefficients are calculated which determine how to combine sinusoid to produce the signal. Since sinusoids are not of limited duration, they extend from minus to plus infinity, coefficients calculated from these base waves loose all time information. Windowing techniques are often used to focus the transformation on a specific section of time but the accuracy is limited.

Wavelet analysis uses a similar approach but instead of sinusoids, waves of limited duration, termed basis function or mother wavelets, are used [Figure 3]. Unlike Fourier transformation, a number of different mother wavelet families exist. While Fourier transformation breaks a signal up into sin and cosine functions of various frequencies, wavelet transformation breaks a signal up into shifted and scaled versions of the mother wavelet [Figure 4]. Since the wavelet is of limited duration, it can be shifted down the signal at known intervals. At each step a coefficient is calculated representing how closely the wavelet resembles this section of signal. By scaling the wavelet, stretching or compressing it, information about the overall signal trend to small details can be obtained.

Wavelet analysis uses the terms approximations and details. Approximations are the high scale low frequency components while details are the low scale high frequency components. Approximations are what give a signal its identity. The language content of a person's voice is mostly distinguished by its approximations. Details provide distinct characteristics, such as unique tonal qualities in each individual's voice.

Wavelet decomposition can be an iterative process occurring over several levels. The original signal is decomposed into approximations and details with the approximations feeding the next level of decomposition, creating a decomposition tree [Figure 5].

Current Techniques

Image classification is a four step process: image acquisition, segmentation, feature extraction and classification.

Imaging: Epiluminescence microscopy (ELM) has become the method of choice for imaging skin lesions [4]. ELM uses a bright, halogen light projected onto the skin, rendering surface structures translucent making subsurface structures visible. Although ELM produces high quality images, it requires special equipment.

Segmentation: Researchers have previously used a number of segmentation techniques such as fuzzy-c-means, SCT/center split, PCT/median cut, split and merge and multiresolution segmentation. Since Melanocytic lesions are typically noticeably darker than the surrounding tissue, simple thresholding techniques are usually very effective.

Feature Extraction: Melanoma is often defined primary by asymmetry and variations in color, texture and border regions so most researchers focus on features that best represent this variability. Some groups represent asymmetry by calculating the fragmentation index [1], circularity factor [3], or asymmetry index [12]. Border irregularities are sometimes represented by the sharpness of transition from the lesion to skin [3]. Color features can be represented by parameters such as mean and standard deviation of each color channel [1, 3].

Classification: Classification typically uses standard pattern recognition techniques such as neural networks, nearest neighbor and discriminate analysis.

A Neural Network Based Wavelet Approach

The ABCD system requires a lot subject judgment on the part of the practitioner. Since firm clinical inspection rules do not exist, it is not possible to make a good rule based classification system. If clearly defined description existed for what constitutes features such as border irregularity or color variability, it would be relatively easy to extract the necessary features and make an accurate diagnosis. Since such information does not exist we must rely on a classification system requiring less domain knowledge, such as a neural network. Neural networks are a kind of *black box* where data is entered and the network "figures out" the necessary juxtapositions required to draw a reasonably accurate conclusion.

Variability appears to be what most separates malignant melanoma from benign nevi therefore the best approach at image manipulation and feature extraction would retain as much of the data variability as possible. Previous classification systems have focused on collecting numerous data points hoping to best represent the lesion. Wavelet analysis by its very nature looks at variability within a signal, in this case color indexes in an image. Since images are only composed of color values, changes in texture, granularity, and color are all represented by the same value system. Wavelet analysis looks at these changes over different scales which should detect whole lesion changes such as texture and color, and local changes like granularity. Wavelet coefficients also become kind of a *black box* of data, they represent the image, and changes within the image, but you don't know exactly how.

Image Preparation

Digital images of melanoma and benign nevi were collected in JPEG format from different sources totaling 72, half melanoma and half benign. Matlab's Wavelet Toolbox only supports indexed images with linear monotonic color maps so the RGB images were converted to indexed images. The next step in the process was to segment the lesion from the surrounding skin. Since a clear color distinction existed between lesion and skin, thresholding was very suitable for this task. A black and white image was produced and its size increased by six pixels all around in order to include the entire border region in the segmented image. The black and white image was then AND'd with the original, producing a segmented image of the lesion on a white background. A minimum bounding box around the lesion was then drawn and the lesion cropped [Figure 6].

Wavelet Transformation and Feature Extraction

A two level stationary wavelet transformation was performed on the segmented image. The wavelet coefficients of interest reside within the lesion region alone, not the surrounding tissue. The black and white mask from the segmentation step was used to determine which coefficient to select from the transformed image. Typically, discrete two dimensional wavelet transforms produce a wavelet matrix half the size of the original image using a technique called down-sampling where only half the coefficients are preserved. In order to maintain the original image size, a stationary wavelet transformation was used which suppresses down-sampling, producing a wavelet matrix the same size as the input matrix. For both levels, the mean and variance of wavelet coefficients for approximations and details were calculated, resulting in a total of 8 features. Features were then normalized to range between 0 and 1.

Neural Network Classification

The feed forward back propagation neural network consisted of 8 input nodes, 3 hidden nodes and one output node with an output value of 0 representing benign and 1 representing malignant melanoma. Due to the small sample size, it was not possible to separate the images into training and testing sets so a 'leave one out' technique was used. One feature set was removed from the group and the network trained on the remained 71. The one left out was then used for testing and the networks accuracy determined. This process was repeated for all 72 feature sets. Average percent accuracy, false positives and false negatives were calculated from the 72 test networks. False positives are benign samples that were classified as malignant and false negatives are malignant samples classified as benign.

Results

Unlike Fourier transformation which only uses sinusoids as base functions, wavelet analysis allows for the use of many different mother wavelets. Wavelets from different families have features that may be more suitable for certain tasks. Three wavelets from four different families were tested to see if the wavelet family itself had any impact on the classification. The results showed regardless of wavelet family the overall classification accuracy was about 83% with false positives and false negatives being about equal at 16% [Table 1]. These numbers represent the best of twenty 'leave one out' runs through the data. Since the neural network used random starting values, network accuracy varied slightly with each run. The average accuracy for all twenty runs was about 73% (data not shown).

A number of different network topologies were tested. Hidden node numbers from two to five were tested with three performing best. Since wavelet transformation can be an iterative process, it was important to determine the optimal level of decompositions to best classify the subjects. Mean and variance for approximations and details for five levels were calculated. Different combinations of mean and variance from just one to all five levels were tested. Statistics for the first two levels provided marginally better accuracy. As more levels were added to the classifier, accuracy dropped nominally but variability between different training sets increased dramatically, even with different numbers of hidden nodes.

As a verification test, the wavelet coefficients were randomized within each feature set. The same leave one out process as above was performed and the accuracy, as expect, was about 50% [Table 2]. With randomized coefficients, the network was unable to make a classification.

Conclusion and Future Direction

Several published classification systems show accuracy rates ranging from 60%-92% which coincides with the estimated rates obtained by general practitioners. One commercial product, SolarScan by Polartechnics, has an accuracy rate of 92%. SolarScan is a complex system, taking high quality ELM images and using advanced image analysis techniques to extract a number of features for classification. This paper, using wavelet analysis alone, produces accuracy rates lower but comparable to their commercial system.

Wavelets allow us to look at images on different scales, focusing in on different features with each scale. Small scale coefficients may detect granularity within the image while large scale coefficients may represent the overall trend of the image; is it raised or flat. Wavelet coefficients hold a lot of information but the difficulty is how to best represent this information for classification. Mean and variance are fairly simple ways of representing this data so other statistical technique should be explored.

A number of different features were tried for this project; all were mean and variance of wavelet coefficients at different levels. The final system uses eight features but it is not known how many of these are important for making an accurate classification. The system may be improved by using only variance values from a five level decomposition, or any number of other combinations. In addition to improving the features selected from wavelet decompositions, the system may also be improved by adding additional non-wavelet based features used by other researchers such as fractal dimension of the border or asymmetry measurements.

As a first attempt at wavelet analysis for melanoma recognition, this paper demonstrates the approach holds promise. While not powerful enough on its own, wavelet analysis provides and additional mechanism for feature extraction.

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Malignant Melanoma Benign Nevus

Figure 1 Images from DermIS [5]

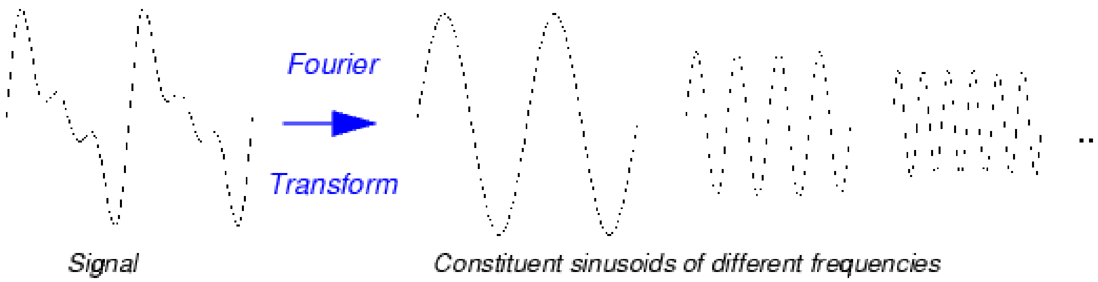


Figure 2 Fourier transformation converts signal into combinations of sinusoids of different frequencies.

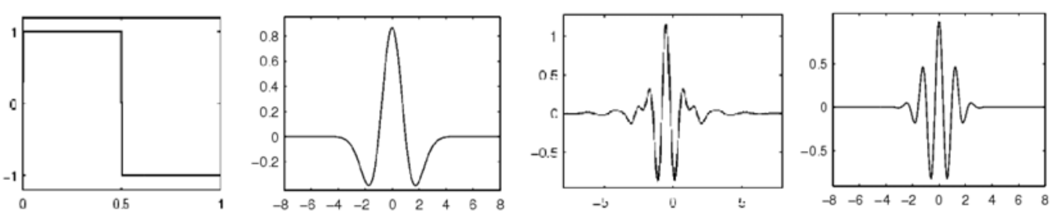


Figure 3 Wavelet family examples, from left to right: Haar, Mexican Hat, Daubechies and Morlet.

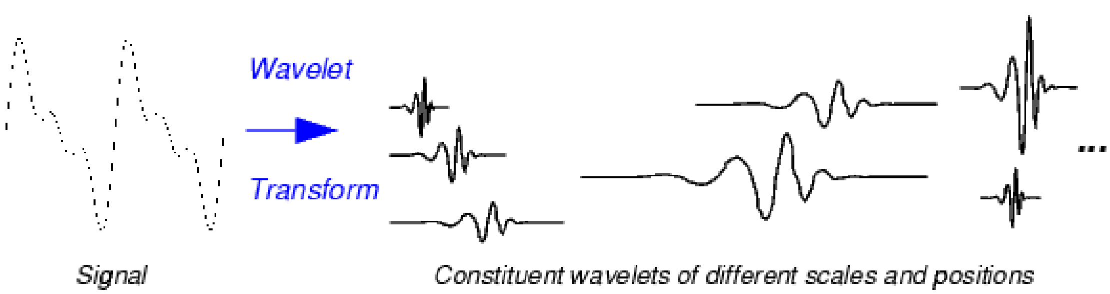


Figure 4 Wavelet analysis represents the signal as combinations of scaled and shifted mother wavelets.

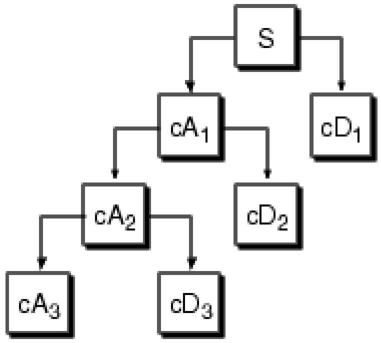
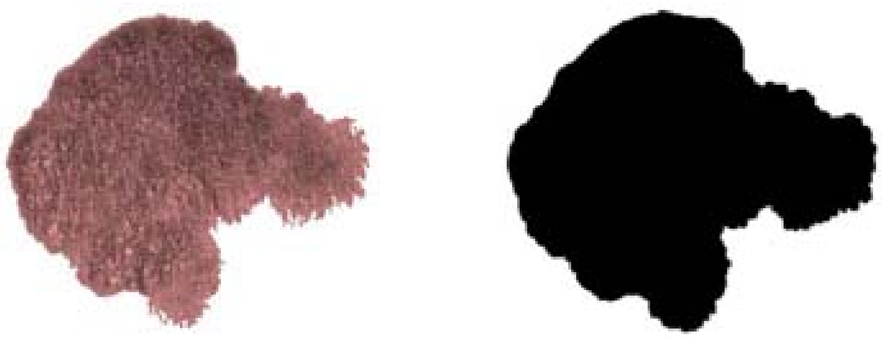


Figure 5 Wavelet decomposition tree. 'S' is the source image which is decomposed to cA_1 (associations) and cD_1 (details). cA_1 is then decomposed to make the level two decomposition.



Segmented Binary Mask

Figure 6 Segmented malignant melanoma image from figure 1 with binary mask used for wavelet calculations.

Wavelet	Total Accuracy (%)	Percent False Positives	Percent False Negatives
Daubechies 2	84.932	16.216	13.889
Daubechies 6	83.562	18.919	13.889
Daubechies 10	83.562	18.919	13.889
Coiflet 1	83.562	16.216	16.667
Coiflet 3	86.301	18.919	8.3333
Coiflet 5	83.562	18.919	13.889
BiorSplines 1.5	83.562	16.216	16.667
BiorSplines 3.1	84.932	16.216	13.889
BiorSplines 5.5	83.562	13.514	19.444
Symlet 2	84.932	10.811	19.444
Symlet 4	84.932	13.514	16.667
Symlet 6	83.562	18.919	13.889

Table 1: Classification accuracy of different mother wavelets. Numbers represent an average of 72 networks, one run through the data with a 'leave one out' approach. False positives are benign images classified as malignant while false negatives are malignant images scored positive.

Wavelet	Total Accuracy (%)	Percent False Positives	Percent False Negatives
Daubechies 2	45.2	51.4	58.3
Coiflet 1	47.9	59.5	44.4
BiorSplines 1.5	54.8	51.4	38.9
Symlet 2	52.1	43.2	52.8

Table 3: Percent accuracy with wavelet coefficients randomized within each feature.