Assessment of malaria in pregnancy using a novel Wavelet-based analysis of ultrasound images

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Abstract

The exact mechanisms leading to placental changes caused by malaria in pregnancy are not completely understood. However, the change in the appearance of the placenta with the acquisition of malaria could be detected using ultrasound image analysis. A method to classify healthy and malarial ultrasound scans of the placenta using image texture analysis is presented. The Discrete Wavelet Transform (DWT) is performed on a region of interest (ROI) of the placenta image. A significant difference is seen between healthy and infected placenta images in the DWT level two approximation coefficient. Features were extracted from this coefficient and were used as the input to two classification algorithms: Support Vector Machines and Neural Networks. Both classifiers were able to characterize the images as either 'healthy' or 'malaria infected' with accuracies as high as 87%.

1 Introduction

Over 45 million women [8] become pregnant in malaria endemic regions per year. Malaria in pregnancy can cause maternal anemia and impaired fetal growth leading to various complications including low birth weight, spontaneous abortion, premature birth and stillbirth. *Plasmodium falciparum* is the main cause of disease and death from malaria. This type of malaria modifies the surface of red blood cells (RBCs) so that asexual parasites can adhere to the placenta. The placental tissue changes with the accumulation of parasite. Here, we investigate whether automated image texture analysis can be used to detect an alteration in the ultrasound images.

The current diagnosis for malaria is a blood test, which can often give a false-negative result since the malaria parasite sequesters in the placenta and therefore may not be present in the blood. The use of ultrasound image texture analysis as a computer aided diagnosis tool could replace the use of blood tests as a means of diagnosis.

The use of wavelet decomposition for ultrasound image texture analysis has been applied to many tissues in the human body [3] [5] [7]. The Discrete Wavelet Transform is computed by successive low pass and high pass filtering of the signal. The signal is then decimated by halving the number of samples to form each scale. The choice of wavelet therefore defines the scaling function, and the filters.

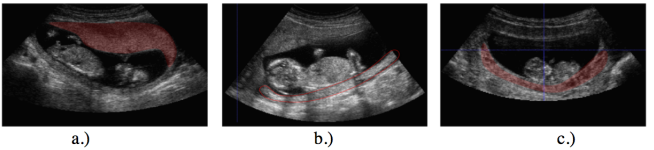

Figure 1: Ultrasound images of the placenta (highlighted/outlined in red) a.) a large placenta b.) a placenta effected by fetal shadowing c.) a small placenta

This process of wavelet decomposition can be applied to the 2D ultrasound images; a 1-D filter is applied to the rows of the image. The same transform is then applied to the columns of each channel of the result. This produces four sub-bands- LH1, HL1 and HH1- corresponding to the finest scale wavelet coefficients (the detail), and LL1 represents the coarse level coefficients (the approximation). To obtain the next decomposition, the sub-band LL1 alone is further decomposed and sampled. This process can be iterated: the approximation sub-band is successively decomposed and the image is represented as many resolution components. The coefficients from each level of decomposition can then be extracted. The features derived from these coefficients are used to uniquely characterize the texture [1].

Application of this method to this specific task presents difficulties due to the size of the placenta. The placenta can also suffer from shadowing from the fetus. In this application, unlike some in obstetrics, any method needs to work across a range of gestational ages (GAs). For placenta images of a very young GA, the size of the placenta is often too small for the application of texture analysis due to a insufficient ROI leading to difficulties in delineating the boundary of the placenta. The images in Fig 1 depict some of the cases outline above. The images also highlights the difference in the positioning of the placenta between scans.

2 Method

2.1 Selecting the Region of Interest (ROI)

Each slice in the X-Z orientation of the 3D ultrasound volume files was manually scanned to obtain the optimum 2D slice. This slice contained the least shadowing and the largest cross sectional area of the placenta. The slice number was then used in a MATLAB algorithm to extract the 2D slice from the 3D volume. This 2D slice was then cropped to obtain a rectangular ROI. This ROI was chosen to include an area of the placenta that is as large as possible without including any other tissue. During this process, some scans were discarded for further use due to poor quality of the image of the placenta. Examples of such images are shown in Fig 1 b.) and Fig 1 c.).

2.2 Discrete Wavelet Transform (DWT)

DWT was performed using the Daubechies 3 wavelet function and two levels of decomposition. This wavelet function was chosen due to the results of preliminary tests performed to determine the most suitable wavelet function. The Daubechies family of wavelets produced the 'best' set of coefficients. This is because the approximation and detail coefficients maintained details and texture patterns seen in the original image. The Daubechies wavelets are

often used in image texture analysis, as the wavelet functions are approximately fractal. It was also found that after two levels of decomposition, information was lost and the detail coefficients did not contain a significant amount of data.

Statistical features of the resulting coefficients were then calculated. These features included mean, standard deviation, normalized energy signature, maximum, minimum, and L2 norm. These features were then combined to form a feature vector for each image.

2.3 Classification

SVMs is a supervised machine learning method used for classification. They are created using two steps: Firstly, the sample data vectors are mapped to a high dimensional space. This is achieved by using a transformation $\Phi(x)$, which maps the data from the input space to the feature space. The kernel function, $K(x,y) = \Phi(x)\Phi(y)$ performs this transformation. There are many types of kernel functions that can be used including linear functions, quadratic functions and radial basis functions (RBFs). The algorithm then finds a hyper-plane in this feature space that has the largest margin separating classes of data [4]

The linear function, quadratic function and Gaussian radial basis function were all independently used to classify the features. 50% of observations were randomly selected to hold out as the test set using holdout cross-validation. The other 50% were used to train the SVM.

NN are non-linear machine learning methods that can be used as a supervised method to find patterns in data. The NN model simulates the functions of biological neurons. It consists of a number of interconnected artificial processing neurons called nodes, which are connected together to form a network.

A pattern recognition neural network was used in MATLAB to classify the data. The network is a feed-forward network with tan-sigmoid transfer functions in the hidden layer and the output layer. The inputs to this network were feature vectors for each image and the output of this network contained two output neurons corresponding to healthy or malarial.

The 'Scaled Conjugate Gradient Algorithm' was used to train the network. This algorithm randomly divides the input vectors and output vectors into three groups: 60% are used for training; 20% are used for validation (this is to ensure that the network is generalizing and also stops training before over-fitting); 20% are used as an independent set to test the network [6]. The data used in the testing stage provides an 'out-of-sample' dataset so that the network can be tested accurately.

3 Experimental Results

The method was tested on 52 3D ultrasound images (excluding those that were discarded). This included 26 healthy placenta images, 1 case of extreme malaria infection (i.e. very large parasite count) and 25 cases of varying parasite count. The images of the fetus were obtained from the Shoklo Malaria Research Unit (SMRU), Thailand, following the Intergrowth 21st protocol [7]. A GE Voluson I ultrasound machine; with a RAB2-5-RS; 2-5MHz /Real time 4D probe for the abdomen was used for all scans.

The DWT was performed on the ROI of each placenta to obtain the coefficients. Histograms were plotted to allow visualization of the statistics of the coefficients. It can be seen from Fig 2 that there is a considerable difference between the level two approximation coefficients for the cases of a healthy (red) and highly infected placenta (blue). The other histograms show an overlap between the coefficients of the separate images.

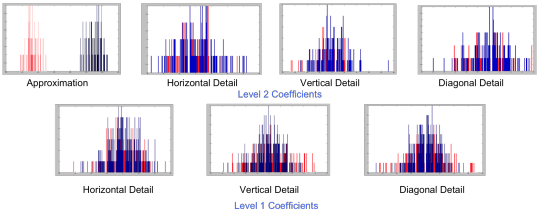

Figure 2: Histograms of DWT coefficients (Daubechies 3, Level 2)

Features used	Correct Classification Rate (%)		
	Linear Kernel	Quadratic Kernel	RBF Kernel
Mean and SD	75	72	76
Mean and Energy	77	80	83
Mean and Max	77	73	81
Mean and Min	81	72	80
Mean and L2 Norm	80	72	79
SD and Energy	81	68	80
SD and Max	72	75	79
SD and Min	73	68	77
SD and L2 Norm	51	56	60
Energy and Max	77	**85**	80
Energy and Min	81	80	84
Energy and L2 Norm	77	80	84
Max and Min	80	78	80
Max and L2 Norm	77	79	79
Min and L2 Norm	81	77	84
All Features	75	68	76

(a)

Features used	Correct Classification Rate (%)			
	Training	Validation	Testing	All
Mean and SD	92	83	70	86
Mean and Energy	78	83	83	80
Mean and Max	80	67	**87**	79
Mean and Min	89	70	83	84
Mean and L2 Norm	78	57	63	71
SD and Energy	92	73	73	85
SD and Max	82	57	73	76
SD and Min	88	73	83	84
SD and L2 Norm	78	67	63	73
Energy and Max	82	80	83	82
Energy and Min	83	67	70	78
Energy and L2 Norm	88	70	80	83
Max and Min	84	67	83	81
Max and L2 Norm	90	87	80	87
Min and L2 Norm	92	77	70	84
All Features	90	74	81	85

(b)

Table 1: (a) SVM Classification Results & (b) NN Classification Results

The aim was to use the Discrete Wavelet Transform to detect a difference between images of a healthy placenta and images of a malarial infected placenta. For this reason the detail coefficients were rejected for use in classification and the approximation coefficient was used alone.

Fig 2 represents a case of extremely high parasite count and a healthy placenta. Histograms for lower parasite counts were also plotted to see if there was still a sizeable distinction between the the infected and the healthy case to ensure that this method is robust for all severities of malaria. A substantial difference was still observed between the two cases.

The statistical features were extracted directly from the coefficients and then combined to construct a feature matrix containing all 6 features. This feature matrix was then input into the classifiers. To assess the accuracy of the individual features, each possible combination of pairs of features was analysed. Classification results may depend heavily on which data is used in the training set and which is used in the test set. For this reason three trials per test were performed and the average of these taken. The results are presented in Table 1 with the best results highlighted in **bold**.

4 Conclusions & Future work

This paper has presented a novel method of applying the DWT to images of the placenta to characterize the texture change seen in the presence of malaria. It has been shown that a substantial difference in the level two approximation coefficients is observed between a healthy and malaria infected placenta. Features were extracted based on the statistical measures of this coefficient only. The results of the classification experiments have shown that this technique can differentiate between a healthy and malarial placenta image. The best performance for the SVM classifier was seen using the quadratic kernel and a combination of the Energy Signature and Maximum; this achieved a classification accuracy of 85%. A higher correct classification rate of 87% was seen for NN using the Mean and the Maximum.

For the next stage, the inverse DWT of the approximation coefficient could be taken to observe the reconstructed coefficient in the image domain. This could lead to a better understanding of the change in physiology of the placenta with the accumulation of parasite.

The results from this study are very promising and provide sound preliminary work that can be extended to validate the clinical application of this method. An increased, more varied dataset is needed to undertake more experiments to evaluate the effects of GA, maternal age and the positioning of the placenta on the results. Importantly, with the availability of portable ultrasound systems, if our further studies are successful, this method could be readily employed as a clinical tool in practice in the developing world.

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