A Comparative Analysis of Wavelets for Vascular Similarity Measurement

Reza Derakhshani, Sriram Pavan Tankasala, Simona Crihalmeanu, Arun Ross, Rohit Krishna

Abstract— Vascular Similarly Measurement (VSM) is an important tool in many biomedical applications. However, designing a robust computational VSM remains a challenge. We investigate different wavelet families and their orders to find their efficacy as feature extractors for computational VSM. Using a 50-subject dataset of RGB ocular surface vasculature images, we show that a compact feature vector composed of wavelet packet energies derived from Db1 wavelets, in conjunction with Fisher linear discriminant analysis and judged by the ensuing ROCs, is best suited for this task. Coif1 and Rbio2.4 were found to be the next best two wavelets for this purpose. Repetition of the same experiments using neural networks confirmed the optimality of the above suite of features for VSM.

I. INTRODUCTION

Vasculature similarity measurement (VSM) plays an important role in prognosis of various diseases, including cardiovascular, cancer, and ocular diseases with vascular manifestations. In the US, approximately 20-30 million people are estimated to be at risk of various vascular diseases [1]. A robust quantitative measure of similarity between imaged vasculature can help identifying various pathologies at the early stage or provide an objective monitoring tool to observe the progression or regression of a disease in response to the variable(s) of interest.

Estimation of variations in abnormal vascular patterns in angiogenesis, arteriogenesis, lymphangiogenesis and especially vasculogenesis are among the main goals of VSM [2]. For instance, coronary vessel blockage can induce hypoxia and result in formation of collateral blood vessels from nearby epithelial cells. Another VSM application area is characterization of human ocular vasculature. For instance, there is a wealth of research for tracing and describing retinal vasculature [3-5]. Ocular vascular diseases include retinopathy and glaucoma. Around 4.1 million Americans aged between 24-74 years suffer from reduced vision due to various retinopathies [40]. It is estimated that by 2050, 16 million Americans aged over 40 will have diabetic retinopathy and another 6.3 million could be suffering from glaucoma [6-8]. A leading cause of irreversible blindness worldwide, glaucoma affects more than 2.7 million individuals aged 40 and older in the United States [8] and 60.5 million people globally [9]. Another important application of VSM is in drug delivery [10]. For instance, intraocular drug delivery through non-corneal (conjunctival to sclera) pathways can be analyzed using a measurement of similarity between conjunctival vascular patterns prior and post to the process [11, 12]. Various physiological factors (diabetes, hypertension, and sickle cell disease) may also change the normal appearance of the conjunctival vasculature. Besides conjunctivitis, inflammation of the cornea (keratitis) or that of the iris and ciliary body (iridocyclitis) causes dilation of the anterior ciliary arteries, resulting in a rose-pink band in that area. Hypertension and diabetes may also change ocular surface vasculature. Thus, we used a dataset of ocular surface vasculature images captured in visible light for this study. However, we note that our results can be extended to VSM for other similar vascular patterns garnered from different tissue or imaging modalities.
various biomedical applications \[13, 14\], we chose wavelet analysis approach for feature extraction. Discrete wavelet transform (DWT) and particularly its extension, the discrete wavelet packet transform (DWPT) are of especial interest here due to DWPT’s full decomposition, which may provide further information for VSM. In this paper, we use DWPT-based energy signatures to analyze the utility of different wavelet families for VSM. In conjunction with the aforesaid features, Fisher Linear Discriminant Analysis, neural networks, receiver operating curves (ROC) and their area under the curve (AUC) were used to gauge the utility of the respective wavelet types for linear and nonlinear data driven VSM.

In this study, we use a dataset of vasculature seen on the white of the eyes captured by color digital photography. As intimated earlier, this type of vasculature is important for prognosis of various ocular vascular diseases, while the results shall still be valid for study of other vascular tissues and modalities using the suggested computational VSM.

The white of the eye, or sclera, is generally avascular. Though it has some perforator vessels, they do not have a utility in this study as it stands. However, the outer surface of the sclera is covered by a fine elastic tissue called episclera that contains blood vessels nourishing the sclera. Its anterior part is covered by conjunctiva, also carrying vasculature. Conjunctiva is a thin membrane containing secretory epithelium that helps lubricate the eyes for eyelid closure. The part of the conjunctiva that covers the inner lining of the eyelids is called palpebral conjunctiva, and the part that covers the outer surface of the eye is called ocular (or the bulbar) conjunctiva. The blood vessels found in the episclera and the bulbar conjunctiva provide the vascular arcades of interest in this work. The episcleral and conjunctival vasculature can be easily seen and photographed in visible spectrum given vessel color and thinness and clarity of the bulbar conjunctiva. Henceforth, and in the interest of brevity, we shall simply refer to this vascular system as conjunctival vasculature. A close observation of conjunctival vasculature reveals layers of intricate surface microcirculation that manifest as rich and complex texture (Figure 1). The apparent density and details of these vascular patterns motivated us to use them for this wavelet-based VSM study, which can ultimately aid many related biomedical applications.

The rest of this paper is arranged as follows: section II describes the dataset and its collection protocol. Section III explains preprocessing, feature extraction, and classification algorithms used in this study. Section IV provides the detailed results, and finally sections V and VI present the concluding discussions and future work.

II. DATA ACQUISITION

There are four target regions of interest (ROI) available for imaging conjunctival vasculature: to the left and right of the iris in the left eye (L1, Lr), and similarly there are two target areas in the right eye (R1, Rr). For this study, we obtained digital RGB eye images of 50 volunteers under the auspices of Institutional Review Board protocol UMKC AHS IRB 06-22e. Volunteers were asked to avert their gaze to the left and right in order to expose more conjunctival vasculature in each of the L1, Lr, R1, and Rr target areas. Images were captured at 5 ft (152 cm). A second set of images was taken in a similar fashion about 20 minutes later. These two sets of captures were used for classifier training and testing, respectively. The imaging equipment consisted of a Canon\textsuperscript® 20D dSLR camera mounted on a tripod. Optics consisted of a Canon\textsuperscript® EF 70-200 mm f/4L USM telephoto lens. We conducted this indoors, with no flash photography in a typical office setting with florescent ceiling lights. Images were saved in JPEG format. Exposure times varied from 1/50 to 1/80 seconds at 400 ISO. MATLAB\textsuperscript® 2007b 64 bit (Mathworks, MA) and x86-based computers were used for all the computations.

III. METHODS

A. Preprocessing

First, we segmented the pixels covering white of the eye from those of the eyelids and the iris. Next, maximum-area rectangles were inscribed in each of the four target ROIs: L1, Lr, R1, and Rr. We performed four different image enhancement routines to improve segmented images of the conjunctival vasculature, namely extraction of the green-layer (G) from RGB color images, contrast-limited adaptive histogram equalization (CLAHE), specular reflection removal, and line enhancement. The proposed segmentation technique uses clustering in RGB pixel space followed by k-means clustering algorithm to partition these pixels into three clusters. Euclidean distances between the origin of the coordinate system and the centroid of each cluster are computed in order to label the regions as sclera, iris and background. The largest distance is associated to the sclera cluster and the smallest distance is associated to the iris cluster. Within the sclera cluster, the largest connected region represents the sclera. Two binary images, a mask for the sclera region and a mask for the iris region represent the output (Figure 2).

![Figure 2. Image segmentation. Through a two-phase iterative process, the pixels represented as RGB-tuples are partitioned into three clusters: sclera (C_s), iris (C_i), and background (C_b). With the sclera being typically whiter than the rest of the eye in RGB space, after clustering, a scleral mask is generated by computing the convex hull, H_s, of the pixels labeled as sclera (C_s), determining the convex hull, H_i, of the pixels within H_s that are labeled as iris (i.e., C_i \cap H_s). The iris mask is H_i - H_s. ROI is found as the largest inscribed rectangle within the scleral mask. Subsequently, ROI’s green channel is extracted, contrast-enhanced, and provided to the feature extraction module.](image-url)
Due to natural and uncontrolled illumination conditions during image acquisition, glare and specular reflection can be seen in the ROIs. As a result, pixels pertaining to scleral region may not be labeled as sclera pixels by the clustering algorithm. These pixels are included in the scleral region by the convex hull of the sclera cluster. However, the convex hull will also include pixels pertaining to the iris region represented. To address this, the overlap region between the convex hull of the sclera and the convex hull of the iris is removed from the convex hull of the sclera. The final scleral mask, when imposed on the original image will identify the region of interest corresponding to the sclera.

Color-filtering: It is known that using a green filter during imaging of conjunctival vasculature provides better “red-free” vascular images [15]. Given the three-channel recording format in digital cameras implemented via on-sensor RGB filtering known as Bayer patterns [16], one can easily retrieve the green-wavelength gray-scale image from a digital RGB image. Thus the green layer of the conjunctival ROIs was used for capturing conjunctival vasculature (Figure 1).

Specular Reflection Removal: Specular reflections on the sclera have different topologies, shapes, and sizes with no specific location in the image. Specular reflection is created through a complicated process that depends on the materials under consideration, the roughness of the surface, the angle of illumination, the angle of viewing, and the wavelength of incident light. The method used to detect the specular reflection uses the power law transformation [41] given by the equation:

\[ S = cR^\gamma \]  

where \( S \) is the output image, \( R \) is the input image, \( c \) is a constant usually set to 1, and \( \gamma \) is a real number. For \( \gamma > 1 \), the power law transformation maps a narrow range of brighter pixels values to a wider range of values. For \( \gamma < 1 \), the power law transformation maps a narrow range of darker pixels values into a wider range of values. Our algorithm uses integer values of \( \gamma \) in the range \([1, 10]\) through the following steps:

1. Convert the image from RGB (red, green, blue) color space to the HSI (hue, saturation, illumination) color space.
2. Consider the illumination component of the HSI color space as the input image \( R \) in equation (1) of the power law transformation.
3. Compute the output image \( S \) for different \( \gamma \) values using equation (1).
4. Compute the histogram for each image \( S \).
5. Compute the filtered histogram for each image \( S \) using the moving average \([1/3 1/3 1/3]\) filter.
6. Compute the slope \( \theta \) of the filtered histogram.
7. For the filtered histogram corresponding to each \( \gamma \), find the first negative \( \theta \) (denoted as \( \theta_{\gamma} \)) and its corresponding intensity value, \( I_{\gamma} \), as a potential threshold value for detecting specular reflection.
8. Examine the distribution of \( \theta_{\gamma} \) as a function of \( \gamma \) to select \( \gamma_{\text{opt}} = \arg\max (|\theta_{\gamma} - \theta_{\gamma-1}|) \).
9. The threshold to detect specular reflection is selected as the mean of all thresholds values found for \( 5 \leq \gamma \leq 10 \).
10. Use the threshold value to obtain the specular reflection mask as a binary image.

Contrast Enhancement: Contrast Limited Adaptive Histogram Enhancement, or CLAHE, is a neighborhood contrast enhancement operating on intensities of local pixels or tiles [17]. That resultant intensity histogram conforms to a new corrected distribution for each tile. Enhanced tiles are stitched together using interpolation to avoid tile boundary artifacts, and contrast enhancement is capped to a predefined limit to avoid noise amplification. The following CLAHE settings were experimentally determined and applied to all ROIs: tile size of 8×8 pixels, exponential distribution adjustment with distribution parameter 0.1, 256-bin histograms, and contrast enhancement limit of 0.005.

B. Feature extraction

One approach to generate templates for vascular identification is by way of structural features, where vascular primitives (characteristic landmarks) such as bifurcations and crossovers are used for spatial minutia matching. However, such assignments are neither trivial nor clear for the intricate conjunctival vasculatures of interest (e.g. please see Figure 1). Furthermore, given the mobility of different layers of the mucus membrane that carry conjunctival vasculature, minutia-based templates are not robust and stable; changing the number and location of perceived vessel crossovers across different gaze directions and thus compromising measurements needed for VSM. In lieu of precise but rigid and unstable structural minutia, one may consider the patterns of conjunctival vasculature as texture, gaining robustness against naturally occurring distortions and imaging artifacts, albeit at the expense of precision. One way to analyze texture is through wavelet transforms. Wavelets have been extensively used in many areas of image and signal processing in recent years [18]. Wavelet-based features are used as efficient and robust descriptors of texture in image processing [18, 19]. Given their reported success in image texture recognition, sub-band energies of wavelet packets were used in this study [20, 21].

Wavelet decomposition of a signal is obtained from its correlation with a set of scaled and shifted basis functions [22]. Alternatively, it can be shown that under certain constraints this process is equivalent to a cascade of low and high pass filters through a tree-like structure [23]. This phenomenon can be extended to two dimensions to measure spatial and frequency characteristics of an image into horizontal, vertical, and diagonal components using 2D basis functions. Also known as mother wavelets, various generative basis functions such as Daubechies, Coifman, biorthogonal, reverse biorthogonal, Symlet, and Meyer have been introduced [15, 28]. Since it has been shown that the choice of wavelets has an impact on the quality of the ensuing features, we conducted a thorough examination of the following wavelet families given their reported success in texture detection [19, 24]:

\[ \begin{align*} 
\theta_{\gamma} &= \arg\max (|\theta_{\gamma} - \theta_{\gamma-1}|) \\
\gamma_{\text{opt}} &= \frac{5 + 10}{2} \\
\gamma &\in [5, 10] \\
\theta_{\gamma} &\in [-1, 1] \\
\end{align*} \]
- Daubechies mother wavelets of order 1 to 21,
- Symlets of order 2, 4, 6, and 8,
- Coiflet family of order 1 to 5,
- Bi-orthogonal wavelets of order 1.1, 1.3, 1.5, 1.7, 2.2, 2.6 and 2.8, and
- Reverse bi-orthogonal wavelets of order 1.1, 1.3, 1.5, 1.7, 2.2, 2.6, and 2.8.

An extended form of wavelet decomposition is known as a wavelet packet analysis, where in addition to high frequency components of the decomposition tree, the low-pass half is also decomposed. Though of a higher footprint and redundant for reconstruction, wavelet packets might be better suited to feature extraction [25]. In this research, we chose wavelet packet sub-band energies as texture signatures of corresponding images given their reported utility in texture recognition. The rapid growth of feature length with decomposition level [26] detrimentally affects the ensuing classification stage [27, 28]. One way to avoid the resulting large volumes of wavelet data is through pruning the full wavelet packet decomposition tree by using only branches that satisfy a criterion of interest. One such sparse wavelet packet tree spanning method for wavelet energy signatures is through entropy, which is an estimate of irregularity and information density [29]. By applying Shannon entropy, sets of wavelet packet decomposition energies are obtained at each level. Subsequently, only nodes satisfying a certain level of entropy are spanned to eventually obtain a sparse, less redundant wavelet packet decomposition (Figure 3). The resulting energies of this sparse wavelet packet decomposition are then sorted in a descending order, and a certain percentage of the largest energies are retained as the feature set [30].

C. VSM as Classifiability of Fisher LDA

When using classifiers with continuous output, one may also obtain a plot of Genuine Accept Ratio, also known as sensitivity, versus False Accept Ratio (1-specificity); by varying the decision threshold. Such a plot is known as the Receiver Operating Characteristic (ROC) curve, which is an important tool in characterization of classifiers [31]. The area under the curve of ROC plots, ROC AUC, is an important scalar metric describing a system’s overall classification quality across all different thresholds, especially when dealing with imbalanced or multimodal class distributions [31, 32]. Thus, we used ROC AUC as measure of goodness after linear classification to estimate the utility of each wavelet family for VSM.

Our choice for linear classifier was Fisher’s Linear Discriminant Analysis or LDA [28], which has been successfully applied to related problems (e.g. [33]). LDA is a linear supervised classification and dimensionality reduction method, which casts multidimensional features into a single dimension using a linear mixture so that a ratio of inter vs. intra class distance [34] is optimized.

D. VSM as Classifiability of Neural Networks

Given the dependence of neural networks (NN) learning and generalization capabilities on their size and configuration, we tested a range of one hidden layer neural networks. We examined a range of 5 to 205 nodes with hyperbolic tangent activation function for the hidden layer. To mitigate over-parameterization and improve generalization, the neural networks were trained using Bayesian regularization. Using Bayesian regularization in lieu of validation based early-stopping further benefits cases such as the problem at hand, where setting aside portions of the already scarce training data for validation-based early stopping is a challenge. Given the convergence neural nets to a different local solution after each gradient descent, and to ensure more accurate depiction of the classification results, five randomly initialized NN were trained to provide an overall ROC for each test case.

IV. RESULTS

Given the 150×300 pixel size of conjunctival ROIs, we used a seven-level wavelet packet decomposition [35], providing up to 47 decompositions. As mentioned earlier, based on their reported pertinence [36, 37], a variety of Daubechies (DB1-D14), Coifman (COIF1-COIF5), biorthogonal (BIOR1.1-BIOR2.4), reverse Biorthogonal (RBIO1.1-RBIO2.4), and Symlet (SYM2-SYM8) wavelets were examined. To find the best wavelet method and feature vector dimensionality, various wavelet packet energies from sparse entropy-spanned trees were sorted ascendingly. Next, using the ROC AUCs of Fisher LDAs as quality measure, the following observations were made:

![Figure 3. Wavelet packet decomposition tree shown for level 2 deconstruction using bi-orthogonal 2.2 wavelet and Shannon entropy for adaptive sparse tree spanning. The magnitude-sorted decomposition energies were considered as feature vectors.](image-url)
Figure 4. Classifiability of feature vectors at three different lengths (2-4, color coded) in terms of average test ROC AUCs using Fisher LDA classifier. Overall, feature vectors comprised of the top-two DB1 energies emerged as the best, followed by feature vectors of the same length using COIF1 and RBIO2.4 wavelets.

Table 1: Fisher LDA Classification Results for Each Wavelet and Ocular Area (Feature Vector Length of 2, Green Channel CLAHE-Enhanced Images).

<table>
<thead>
<tr>
<th>ROI</th>
<th>Wavelet</th>
<th>LJ Test AUC</th>
<th>LR Test AUC</th>
<th>Rl Test AUC</th>
<th>Rr Test AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ll</td>
<td>DB1</td>
<td>0.6694</td>
<td>0.7509</td>
<td>0.6132</td>
<td>0.6239</td>
</tr>
<tr>
<td></td>
<td>COIF1</td>
<td>0.6674</td>
<td>0.6224</td>
<td>0.6309</td>
<td>0.6239</td>
</tr>
<tr>
<td></td>
<td>RBIO2.4</td>
<td>0.7210</td>
<td>0.6643</td>
<td>0.6333</td>
<td>0.6333</td>
</tr>
<tr>
<td>Lr</td>
<td>DB1</td>
<td>0.7210</td>
<td>0.6643</td>
<td>0.6333</td>
<td>0.6333</td>
</tr>
<tr>
<td></td>
<td>COIF1</td>
<td>0.6674</td>
<td>0.6224</td>
<td>0.6309</td>
<td>0.6239</td>
</tr>
<tr>
<td></td>
<td>RBIO2.4</td>
<td>0.7210</td>
<td>0.6643</td>
<td>0.6333</td>
<td>0.6333</td>
</tr>
</tbody>
</table>

- Examining feature vectors of lengths up to 30, the top 2 wavelet decomposition energies provided the best overall results (i.e. 2D vectors per each feature and ROI). Energies beyond this range were almost zero or not visited by the entropy-spanned wavelet tree, and thus larger feature dimensionalities were not considered.

- The top three wavelets types were found to be DB1, COIF1 and RBIO 2.4. Figure 4 depicts a subset of the results for feature vector dimensions 2-4 in the interest of brevity. BIOR1.1 and RBIO1.1 were not repeated since they are equivalent to the depicted DB1. In summary, 2D feature vectors were created from the top two DB1, COIF1 and RBIO 2.4 wavelet packet energies for each of the four LI, Lr, RI, and Rr ROIs, using CLAHE of green layer of images. As explained earlier, the first set of ocular captures from 50 volunteers were used for training the LDAs and the second set of captures (acquired 20 minutes later) were used as test data. Table 1 summarizes the performance of the aforementioned 2D feature vectors, where wavelet energy features from DB1, COIF1, and RBIO2.4 decompositions were assessed for each of the four conjunctival ROIs. As evident from the results, DB1 proved to be the best with overall test ROC AUCs as high as 0.733 (Lr), followed by COIF1 and RBIO2.4.

- For nonlinear NN classification, we chose the best feature sets found during the LDA studies, namely the highest two energies from decomposing preprocessed conjunctival ROI with DB1, COIF1, or RBIO2.4 wavelets. Again, DB1 provided better results with an average test ROC AUCs as high as 0.75 (Lr), followed by COIF1 and RBIO2.4. The results are obviously better than those of the Fisher LDA, but not by a wide margin. The leading performance of DB1 features with neural nets further suggests them as a better choice for both linear and nonlinear VSM.

V. DISCUSSIONS

The discussed wavelet based VSM achieves two goals: First, we identify the best wavelets within the confines of our choices for feature extraction and classification methodologies. Second, we show the robustness of the utilized compact feature set. In most of the biomedical applications, data acquisition is performed using high-grade image acquisition systems in a fully controlled environment. In this study, ocular imaging was performed in a regular office setting, which introduces artifacts such as specular reflection and glare due to reflective properties of the ocular surface. Thus, further artifact removal steps may improve ROC AUC values. Having said that, we conjecture that by keeping the two largest wavelet decomposition energies, the largest textural elements due to major conjunctival vasculature are taken into account, which are also visible despite unfavorable imaging artifacts. Previous methods for VSM include human involvement or semi-automated methodologies, but in this study we introduce a fully automated system for VSM feature extraction. The results highly correlate with image capturing range and optics providing a scope for betterment of AUC values with higher quality vascular images.

VI. CONCLUSIONS AND FUTURE WORK

The main motive of the study was to focus on feature extraction step of the VSM in general and to find the best set of wavelet basis functions for VSM in particular. We successfully implemented a classifiability-based method for
VSM using RGB images of conjunctival vasculature observed on the white of the eye using both linear (Fisher LDA) and nonlinear methods (neural networks). We observed that wavelet packet analysis using DB1, COIF1 and RBIO 2.4 wavelet basis functions can successfully yield texture information for VSM.

In the future, we would like to extend our study by utilizing over-complete and data driven wavelets for VSM. We wish to include no-reference image quality measures to rule out captures corrupted by motion blur, focus, and lighting artifacts. Other optical enhancements such as utilizing polarized lights, focus and exposure bracketing, and the addition of blue layer to the green may further enhance the quality of acquired conjunctival images and thus the VSM.

To further improve image registration and segmentation, one may use iris as an ocular landmark and scaling reference. We used an energy-ranked list of features, however a multivariate, classification-guided feature search and selection, such as sequential floating feature selection [38], or other similar wrapper methods [39] may further enhance VSM accuracy.

ACKNOWLEDGMENT
We are grateful for the assistance of Ashish Anand (former graduate research assistant, CSEE, UMKC) for acquiring the study images. This work was funded by a grant from Center for Identification Technology Research (CITeR), a National Science Foundation Industry-University Cooperative Research Center.

REFERENCES


[40] http://www.cdc.gov/visionhealth/basics/ced