

# Effects of Image Compression and Degradation on an Automatic Diabetic Retinopathy Screening Algorithm

C Agurto<sup>1,2</sup>, S Barriga<sup>1,2</sup>, V Murray<sup>1,2</sup>, M Pattichis<sup>2</sup>, B Davis<sup>1</sup>, and P Soliz<sup>1,3</sup>

<sup>1</sup>VisionQuest Biomedical, <sup>2</sup>University of New Mexico, Electrical and Computer Engineering Department, and  
<sup>3</sup>University of Iowa, Department of Ophthalmology and Visual Sciences

## Abstract

Diabetic retinopathy (DR) is one of the leading causes of blindness among adult Americans. Automatic methods for detection of the disease have been developed in recent years, most of them depending on segmentation of bright and red lesions. In this paper we present an automatic DR screening system that does not require segmentation of features and it is only based on textural features obtained using multiscale Amplitude Modulation-Frequency Modulation (AM-FM) decompositions. From the AM-FM decompositions we extract the instantaneous amplitude, instantaneous frequency magnitude, and relative angle for each of the combinations of scales. These features are the inputs of a classification algorithm that uses k-means and partial least squares (PLS). The algorithm achieves an accuracy of detection of 0.88 area under the ROC curve (AROC) for a set of 280 images from the Messidor database. Testing is done using the cross-validation methods, with 168 images being used for training and 112 for testing. The original algorithm is then used to analyze the effects of image compression and degradation, which are expected to be present in an eventual implementation of the system on a clinical setting. Results show that the algorithm is insensitive to illumination variations, but that high rate of compression and large blurring effects degrade its performance.

## Purpose

According to the National Eye Institute, diabetic retinopathy (DR) is one of the leading causes of blindness among working-age Americans. It has been shown that regular comprehensive eye exams and timely treatment can lead to improved outcomes and reduced loss of vision. However, to screen the tens of millions at risk for DR would tax the healthcare system beyond capacity. Furthermore, since only 10% of all the acquired retina images present with DR and require treatment, a means for automatic screening would allow ophthalmologists to concentrate on patients requiring treatment and intervention. Furthermore, automating the process would make broad access to a screening service feasible.

In practice, a DR screening system will be located in a clinic where images will not be checked for quality by a certified technician. Automatic systems to check for image quality have been reported, but these are not yet robust enough to filter out all possible image quality problems. An algorithm for DR screening should be robust enough that it can compensate for a certain level of image degradation. Furthermore, the limitations imposed by image quality of an automated DR screening algorithm should be understood to ensure proper interpretation of the automatic classification results.

Image compression is an important consideration in clinical and well as telemedicine settings. Larger images that are being produced by today's instruments and may tax the bandwidth required for transmission through the network and for storage of the medical data. It is common practice in ophthalmology to compress the retinal images. Our proposed screening system will require transmission of images through the internet to a central server that will be doing the processing and returning the screening result. One of the goals of our research is to study the effects of compression on the accuracy of an automated screening system.

In this paper we present an automatic algorithm for Diabetic Retinopathy (DR) screening and the effects that compression and degradation of the data have on the performance of the algorithm. We used 280 images from the MESSIDOR database. Of those images, 168 were used for training of the classification algorithm and 112 for testing using the cross-validation method. The algorithm achieved an accuracy of 88% AROC for the

original, unmodified. In order to simulate less than perfect conditions on a clinical setting, the images were degraded by using JPEG compression (50% and 30% quality), a Gaussian blurring filter (9x9 and 13x13 pixels wide), over exposure (histogram saturated), and under-exposure.

## Methods

### A. AM-FM Decompositions

An image can be represented as a sum of their amplitude and frequency components, as in:

$$I(x, y) \approx \sum_{n=1}^M a_n(x, y) \cos \varphi_n(x, y) \quad (1)$$

where  $M$  is the number of AM-FM components,  $a_n(x, y)$  denote instantaneous amplitude functions (IA) and  $\varphi_n(x, y)$  denote the instantaneous phase functions. For each AM-FM component, the instantaneous frequency (IF) is defined in terms of the gradient of the phase  $\varphi_n$ :

$$\nabla \varphi_n(x, y) = \left( \frac{\partial \varphi_n(x, y)}{\partial x}, \frac{\partial \varphi_n(x, y)}{\partial y} \right). \quad (2)$$

In terms of textural features, for each component, we are interested in using the instantaneous frequency (IF) and the instantaneous amplitude (IA).

### B. Frequency Scales and Filterbanks

AM-FM components are extracted from different image scales. Here, we consider the use of 25 bandpass channel filters associated with four frequency scales and nine possible Combinations of Scales (CoS). We estimate a single AM-FM component over each combination of scales using Dominant Component Analysis.

At lower frequency scales, the magnitude values of the |IF| are small and the extracted AM-FM features reflect slowly-varying image texture. For example, the most appropriate scale for blood vessels is the one that captures frequencies with a period that is proportional to their width. On the other hand, the fine details within individual lesions, such as the small vessels in neovascular structures, are captured by the higher-frequency scales. To capture the different scales, we use a multi-scale channel decomposition.

Table 1 relates the number of pixels and the frequencies ranges of each band-pass filter. The combinations of scales were grouped in such a way that contiguous frequency bands were covered. In this way, structures that only appear in a specific frequency range or appear between two or three contiguous bands are captured. For this reason, the nine combinations of scales (CoS), given in Table 1, were grouped to encode the features for different structures. An example of a retinal image one of its AM-FM components are shown in figure 1.

TABLE 1  
Combinations of Scales

Combination Number	Filters	Frequency Bands	Range in cycles/mm
1	8:25	M + L + VL	0.028 to 0.32
2	1	LPF	0.226 to $\infty$
3	20:25	VL	0.113 to 0.32
4	14:19	L	0.057 to 0.16
5	8:13	M	0.028 to 0.08
6	14:25	L + VL	0.057 to 0.32
7	8:19	M + L	0.028 to 0.16
8	2:7	H	0.014 to 0.04
9	2:13	H+M	0.014 to 0.08

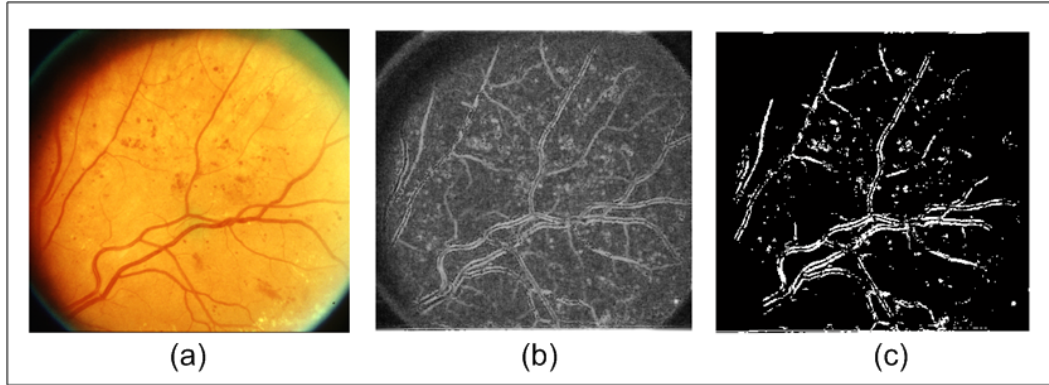


Fig 1. a) Original retinal image; b) Instantaneous Amplitude using CoS 1; and c) Thresholded Image of (b) showing large IA values.

### C. Classification Algorithm

To test the significance of the AM-FM processing as a methodology for diabetic retinopathy screening, 280 images of the MESSIDOR database were selected. These images are classified by ophthalmologists in 4 levels where Risk 0 correspond to non DR images, Risk 1 mild DR, Risk 2 moderate DR, and Risk 3 corresponds to an advance stage of DR. The retinal image was divided in regions of 40x40 pixels. We excluded the optic disc for our analysis. A total of 360 regions were obtained for each retinal image. The procedure to extract the features and reduce their dimensionality is the same than our first experiment. After the features are extracted, an unsupervised classification method, k-means, is applied. Finally a linear regression method, Partial Least Square (PLS), was applied to obtain the estimated classes. We use 168 images for training of our model and 112 images for testing using cross-validation. Fig. 3 shows the procedure to classify the retinal images.

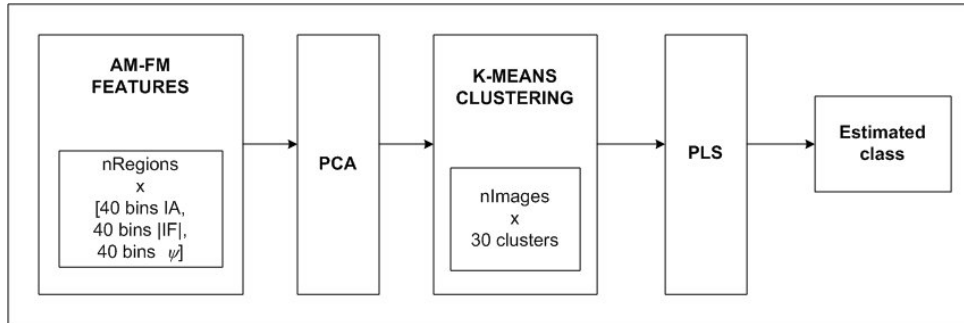


Fig. 2. Procedure to classify retinal images. First the features are extracted using AM-FM. Then a reduction of dimensionality method (PCA) is applied for each CoS. After that k-means is applied in order to reduce the dimensionality. Finally, PLS is applied to obtain the estimated class for each image.

#### D. Image Degradation and Compression

To test the robustness of our DR screening algorithm, the images from the test were degraded set using the following parameters:

- JPEG compression @ 50% quality
- Gaussian blurring filter 9x9 pixels wide
- Under exposure by 60%
- JPEG compression @ 30% quality
- Gaussian blurring filter 13x13 pixels wide
- Over exposure by 40%

#### Results and Discussion

Table 2 shows the results of applying the DR screening algorithm to the Messidor database. The original images are full quality, and achieved an AUC of 0.88, with best sensitivity and specificity of 98%/58%. Gaussian blurring affects the algorithms the most, reducing its performance to 0.53 and 0.46 AUC. High compression ratios also affect the performance of the algorithm, particularly at the 30% quality level. At this level the images show distortion in color and pixelation. Under and over exposure do not significantly affect the performance of the algorithm. These results validate the premise that AM-FM is not sensitive to uneven illumination.

We should also note that the model was trained in the original, high-quality images. Preliminary results show that if we add some of the degraded images to our training set the accuracy increases significantly.

Type of images	AUC	Best Sens/Spec	Type of images	AUC	Best Sens/Spec
Original Images	0.88	98%/58%	JPEG 50% quality	0.73	91%/53%
Gaussian Blur 9x9	0.52	75% /34%	JPEG 30% quality	0.62	84%/34%
Gaussian Blur 13x13	0.46	75%/32%	Under Exposure 60%	0.84	96%/56%
			Over Exposure 40%	0.88	98%/55%

Table 2. Performance of the DR screening algorithm

#### Conclusions

This paper presented results of an automatic DR screening algorithm and the effects of image degradation and compression on its performance. These results show the importance of controlling certain variables of the photographing process, such as movement of the patient that could potentially cause blurring of the images. Also, as image compression becomes more important to transmit these images to a central screening system, the effects of the artifacts caused by high levels of compression need to be compensated.

**Breakthrough:** AM-FM has been previously applied to areas of research such as fingerprint matching and texture analysis. In this paper we present a new application to diabetic retinopathy screening using frequency scales, k-means, and partial least squares. In addition, we analyze the effects of image degradation and compression on the performance of the algorithm.

**Previous Publications:** The theoretical basis for applying AM-FM for retinal images has been presented at the 2008 Asilomar Conference on Signals, Systems, and Computers. The results of the fully-implemented DR screening algorithm have not been presented previously.