

A Machine-learning Approach to Retrieving Diabetic Retinopathy Images

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ABSTRACT

Diabetic retinopathy (DR) is a vision-threatening complication that affects people suffering from diabetes. Diagnosis of DR during early stages can significantly reduce the risk of severe vision loss. The process of DR severity grading is prone to human error and it also depends on the expertise of the ophthalmologist. As a result, many researchers have started exploring automated detection and evaluation of diabetic retinal lesions. Unfortunately, to date there is no automated system that can perform DR lesion detection with the accuracy that is comparable to a human expert. In this poster, we present a novel way of employing content-based image retrieval for providing a clinician with instant reference to archival and standardized DR images that are used for assisting the ophthalmologist with the diagnosis of a given DR image. The focus of the poster is on retrieving DR images with two significant DR clinical findings, namely, microaneurysm (MA) and neovascularization (NV). We propose a multi-class multiple-instance DR image retrieval framework that makes use of a modified color correlogram (CC) and statistics of steerable Gaussian filter (SGF) responses. Experiments using real DR images with comparisons to other prior-art methods demonstrate the improved performance of the proposed approach.

Categories and Subject Descriptors

H.3.3 [Information Search and Retrieval]; I.5 [Pattern Recognition]

General Terms

Algorithms, Performance

Keywords

Diabetic retinopathy, image retrieval, multiple-instance learning, Color Correlogram, Steerable Gaussian Filters, Fast Radial Symmetric Transform

1. INTRODUCTION

Diabetic retinopathy (DR) is one of the leading causes of blindness among adults. Diabetes is a disease associated with the blood vessels. Glycosylation reaction occurs between sugar and

the proteins in the vessel walls, owing to a large amount of glucose coursing through the circulatory system. Organs like the eyes and the kidney have microvasculature that is more susceptible to damage because of glycosylation. Studies have shown that timely DR diagnosis and treatment can significantly reduce the risk of severe vision loss [1]. By improving the assessment qualities of DR severity levels, the quality of diagnosis of DR can be significantly improved.

Unfortunately, there is a dearth of computer-based systems that can match the level of performance achieved by ophthalmologists. Further, an even more difficult task is fast and accurate DR severity grading. This has not been properly addressed by existing systems. An ophthalmologist's painstaking visual examination of a digital retinal image and physical comparison with standard images are still the best methods for identifying and assessing DR.

In previously published works, there have been several attempts to develop content-based image retrieval (CBIR) systems. Structured Analysis of the Retina (STARE) project aimed at automatic diagnosis and comparison of images, including annotating image contents and searching for images similar in content [2]. Though the retrieved images appear to be largely similar in appearance, they are not clinically relevant. Thus the method is of limited clinical use.

The proposed research aims at filling this gap in both technical capability and clinical practice by developing a computer-based system with the innovative idea of content-based retrieval and classification of DR images with clinical relevance.

The remainder of this article is organized as follows: Section 2 presents the algorithm. Section 3 provides the results of the new algorithm and Section 4 provides concluding remarks.

2. PROPOSED APPROACH

Multi-Class Multiple Instance Learning (McMIL) for DR classification is already studied in [3]. It can be observed that McMIL performs best for DR image amongst the other methods compared against in that article. The authors therefore, propose McMIL for DR image retrieval also.

Image retrieval, unlike classification requires a distance or density estimation. It is imperative thereby that for the purposes of retrieval a McMIL based distance approach has to be developed. Work on this is already done in [4]. A Hausdorff distance is used in Citation-KNN. It is defined as the least distance between two bags. In certain MA and NV images, very few regions of the image are affected and the other instances resemble that of a Normal image. The minimal Hausdorff distance thus doesn't provide any information and it doesn't suffice. This calls for a new way of measuring the distance between two bags. The authors are currently developing a new distance framework and

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ACM-BCB'12, October 7-10, 2012, Orlando, FL, USA

ACM 978-1-4503-1670-5/12/10

ranking algorithm called the Rank-KNN. It considers distances between two bags at an instance level rather than at bag-level.

Suppose there are two bags A and B with m and n instances each. The minimum distance between the i^{th} instance of A and all instances of B is given by,

$$D_{(i)}(A, B) = \min_{b \in B} d(a_i, b_j) \quad \forall j \in \{1, 2, \dots, n\} \quad (1),$$

where, $d(\cdot, \cdot)$ represents the Euclidean distance between two instances.

Let Q be the bag of instances for a query image. Equation (1) is used to calculate the minimum distances between every instance in Q and instances of all the images in the database. Sorting individually a similarity list (SL) is obtained. The mean of ranks in the SL belonging to that particular bag is calculated. After repeating this procedure for each bag, a *bag-level aggregated similarity rank* (ASR) is obtained. The rank list thus formed is called the *m-Rank*. Since only few instances contribute towards label, retrieval using only on the nearest neighbors need not necessarily give optimum results. To overcome this, *citer-Rank* is incorporated into *M-Rank* to make it more robust. The procedure of calculating citers is explained in [4]. A final *meanRank* is obtained by averaging *m-Rank* and *citer-Rank* of Q .

The feature space operated upon for this approach is based on a CC approach described in [5]. This feature space is modified by spectral tuning described in [3]. These features are extracted for each instance and can be further augmented with Statistic of SGF [6] and Fast radial symmetric transform [7]. This provides for an accurate catching of the proper instance representations.

3. RESULTS

Table 1 presents the results of $\geq k$ hit-rate and also shows mean accuracy for the retrieval of top 5 images retrieved. The performance metrics have been adopted from [8]. These are also compared against some state of the art methods. The experiments are performed on a database containing 425 images assembled from well-known public databases. These contain an unbalanced ensemble of 160 normal images, 181 MA images and 84 NV images. The retrieved images are considered a hit as long as the retrieved images and the query images contain the same label.

Some of the state-of-art image retrieval systems used for comparison is Gabor features [9] and semantics of histogram of neighborhood moments [10]. Another well-studied feature for CBIR purposes related to general images is the color correlograms [11, 5]. CC describe the global correlation of local spatial correlation of colors. Gabor features is a strong representation of textures. HNM feature is especially preferred in medical image retrieval [10]. HNM is considered good color feature because it takes into account the spatial correlation and the global distribution of colors.

Table 1. Mean accuracies and $\geq k$ hit rates in percentages.

	Mean Accuracy	≥ 2 hit-rate	≥ 3 hit-rate	≥ 4 hit-rate	≥ 5 hit-rate
AutoCC	60.85	79.06	64.47	42.35	23.29
Gabor	68.61	83.76	75.76	59.52	31.76
HNM	68.04	84.47	74.58	55.76	32.00
Proposed	75.48	88.70	82.58	68.00	43.29

State-of-art methods like Gabor filters, original CC and HNM fail to produce satisfactory results as texture or color features, by themselves cannot be good feature descriptors. The proposed approach combines color and texture feature and this with McMIL produces good results.

From table 1, it can be noted that $\geq k$ hit-rate at each rank is much higher than the other methods. This implies that the retrieved images have more clinical relevance than the other methods.

4. CONCLUSION

Our preliminary study in this poster suggests that McMIL is a promising approach for DR classification. Specifically, in the preliminary results reported in this paper, the McMIL-based retrieval algorithm retrieves DR images that are of clinical relevance than otherwise. Further developments are under way, including more experiments with comparison with other leading approaches and analysis of the performance of our algorithm.

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