

# Intraretinal Fluid Pattern Characterization

Subjects: [Optics](#) | [Ophthalmology](#) | [Others](#)

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The accumulation of fluids in the retinal layers is one of the main causes of blindness in developed countries. The main strategy for its study and diagnosis is through the use of Optical Coherence Tomography (OCT) images. This allows experts to observe the layers of the retina in a cross-sectional view. Commonly, for the analysis of these accumulations by means of computer diagnostic support systems, precise segmentation strategies are employed.

Optical Coherence Tomography

computer-aided diagnosis

feature selection

texture descriptors

texture analysis

medical imaging

image analysis

intraretinal fluid

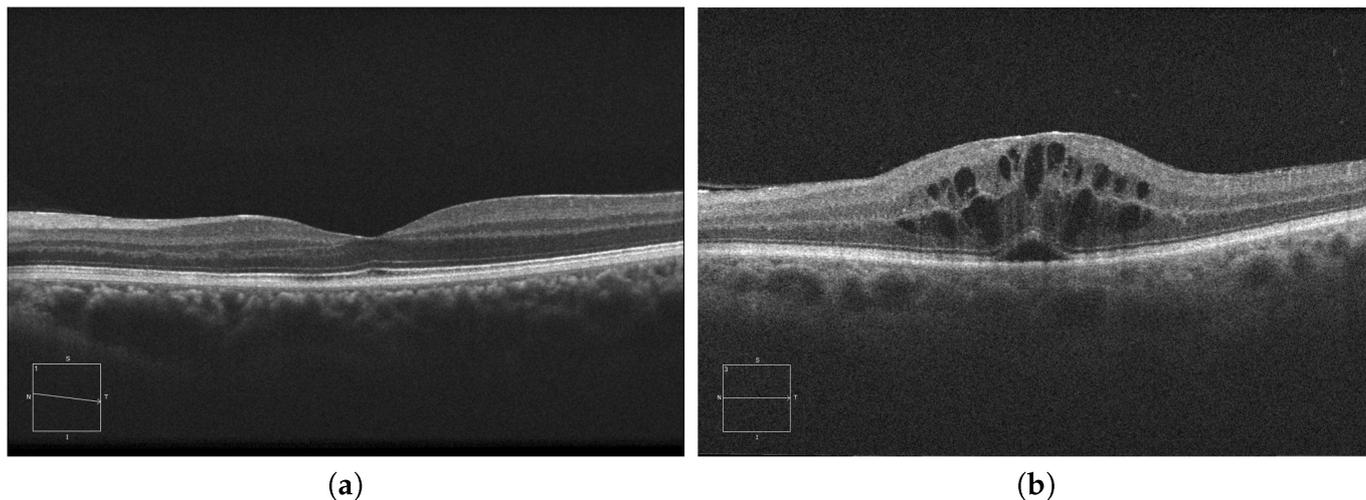
macular edema

## 1. Introduction

The retina represents the neurosensory layer of the eye. It is the area of the eye in which light is transformed into nerve impulses. Furthermore, it represents one of the most studied parts of the human body thanks to its ease of access and the fact that many pathologies leave their trace on it (such as Parkinson's disease [\[1\]\[2\]](#), multiple sclerosis [\[3\]](#), Alzheimer's disease [\[4\]\[5\]](#), hypertension [\[6\]\[7\]](#), etc.).

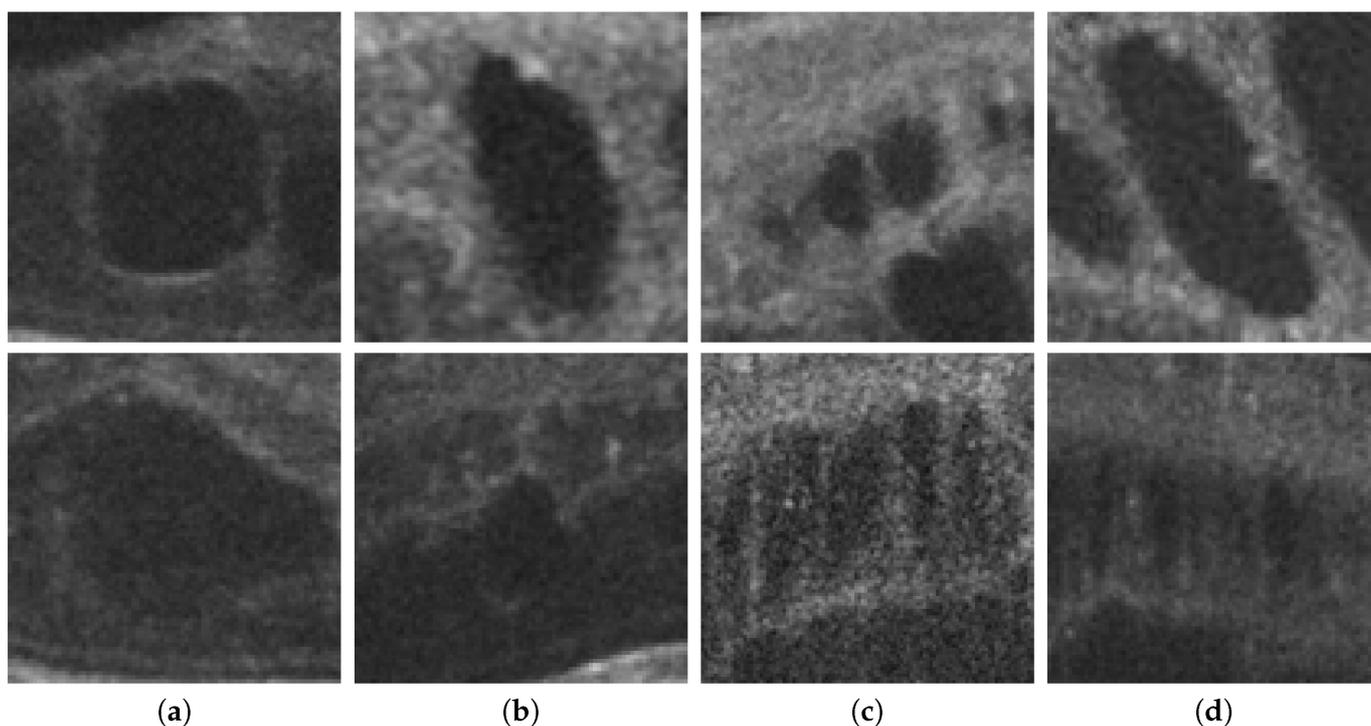
Among the most significant damages to the structures of the retina we can find those caused by pathologies such as Age-Related Macular Degeneration (AMD) and diabetes (which leads to Diabetic Retinopathy or DR). These pathologies affect the fragile capillaries that nourish the retina, and when this vascular system is damaged or altered, fluid loss is a common outcome. These progressive accumulations gradually alter the delicate morphology of the retinal layers. If these accumulations of fluid are not detected in time, they will lead to severe vision impairment. These fluid accumulations are so prevalent that they represent one of the main causes of blindness in developed countries [\[8\]\[9\]\[10\]\[11\]](#).

For the diagnosis of these accumulations, experts study the presence of abnormal artifacts in images extracted by Optical Coherence Tomography or OCT [\[12\]\[13\]\[14\]](#). This medical imaging modality is capable of generating cross-sectional images of the retina, allowing the morphology of its layers to be studied. To do this, the OCT device sends a beam of low coherence light to the retina, which is reflected, refracted and absorbed by the retinal tissues. The device subsequently compares a reference beam with the light received from the retina, studying the differences to generate the final image [\[15\]\[16\]](#). An example of both a healthy retina and a retina with severe fluid accumulations can be seen in **Figure 1**.



**Figure 1.** Macular Optical Coherence Tomography (OCT) images. **(a)** OCT without the presence of cystoid regions. **(b)** OCT with the presence of cystoid regions.

In the rise of computer aided diagnosis (CAD), several methodologies have been designed based on classical segmentation to extract a mask containing these fluid accumulations [17][18][19][20]. However, due to the nature of cysts (often mixed with healthy tissue, capture device artifacts, and other pathologies), this approach is not always appropriate. As shown in **Figure 2, 1<sup>st</sup> row**, some of the fluid accumulations may have high contrast, defined borders but, in the majority of fluid accumulations, what clinicians observe is what is shown in **Figure 2, 2<sup>nd</sup> row**: diffuse, low-contrast fluid accumulations. This is why the study for the characterization of intraretinal fluids appeared [21].



**Figure 2.** Examples with accumulations of intraretinal fluid with adequate definition for a segmentation (1<sup>st</sup> row) and counter-examples with blurred, merged, and obfuscated edges that are hard to segment precisely (2<sup>nd</sup> row). (a,b) Individual cystoid fluid bodies. (c,d) Groups of fluid accumulations.

## 2. Sample characterization

Instead of looking for a precise segmentation, this strategy analyzes a vector of different characteristics to determine whether a region (or independent sample) of the image corresponds to a region with or without intraretinal fluid. In this way, what we are learning are the main features that identify the regions with fluid: an intraretinal fluid characterization [\[21\]](#)[\[22\]](#).

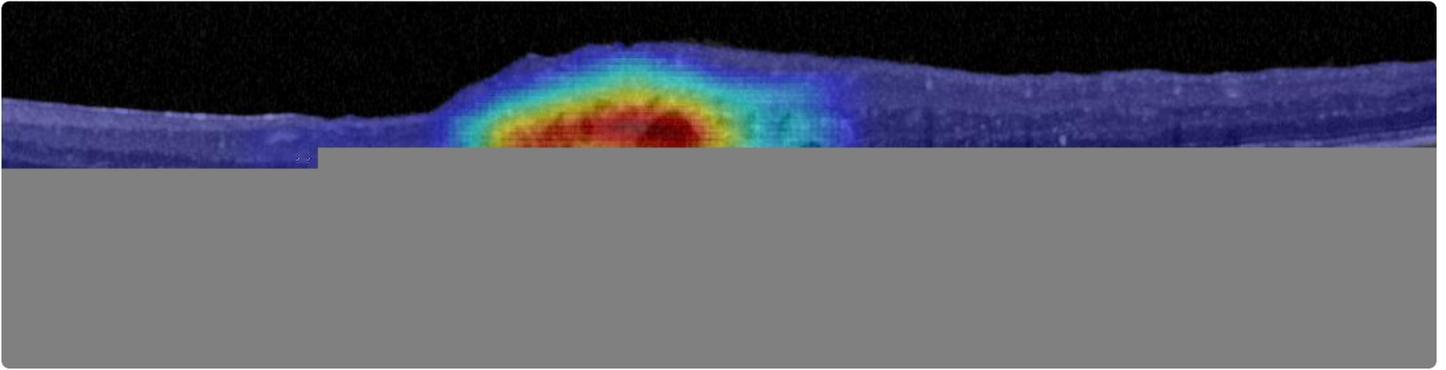
To characterize these regions, a complete library of characteristics is used to analyze different points of view from the same sample. These characteristics study different aspects of the statistical distribution of the gray levels of the image, the spatial patterns formed by them (texture) and the self-similarity or symmetry of the samples. Regarding statistical distribution, values like the minimum, mean, median, standard deviation, skewness, entropy and kurtosis of the gray level histogram are commonly used. On the other hand, when considering the texture analysis of the regions, the Gray-Level Co-Occurrence Matrix, Histogram of Oriented Gradients and the Gabor filters are among the most successful descriptors (mainly thanks to studying the gradient orientations, as fluid accumulations usually present a cystoid spherical shape while normal retinal structures present more horizontal patterns) [\[21\]](#)[\[22\]](#)[\[23\]](#).

Once we have defined the feature library, what we do is to create a dataset with defined size samples extracted from OCT images. These small-sized samples correspond to different regions of the OCT images (such as those seen in **Figure 2**), both from pathological samples and from healthy regions. These samples are labeled by experts and, from each one of them, the complete vector of characteristics defined in the library is extracted [\[21\]](#).

Finally, with this dataset of vectors describing the samples under different points of view and domains, a feature relevance study is performed with different feature selection strategies. Doing so, we obtain a reduced set of characteristics that tell us which aspects define a sample with intraretinal fluid accumulations from a normal retinal region.

## 3. Applications

With these characteristics, we can generate a vector from each sample that characterizes the most defining features of the fluid accumulations. Thanks to this, it is possible to train a classifier to be able to identify the different independent samples of the image into pathological or non-pathological.



**Figure 3.** Example of heat map generated using this fluid region characterization and a voting strategy.

If this trained model is combined with an exhaustive image sampling strategy (so that the retina is completely analyzed by the algorithm) we can obtain a representation of the fluid regions that is resilient to all the factors mentioned in the introduction, in addition to accurately representing the location and density of the intraretinal fluid accumulations [23]. **Figure 3** shows an example of a heat map generated using this strategy, representing with a cold-to-hot color scale the confidence of the system on the presence of fluid accumulations. Furthermore, this strategy can be extended to a more in-deep classification and characterization of the different types of fluid accumulations [24] or even with deep learning techniques that are able to generate their own feature library [25].

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