Segmentation Fusion Techniques with Application to Plenoptic Images: A Survey.

D. Evin[1,2], A. Hadad[1], A. Solano[1], B. Drozdowicz[1]
[1] Information System Laboratory, Engineering School, National University of Entre Ríos, Argentina
[2] Sensory Research Laboratory, INIGEM, UBA-CONICET

E-mail: {devin, ajhadad, asolano, bdrozdo}@bioingenieria.edu.ar

Abstract. The segmentation of anatomical and pathological structures plays a key role in the characterization of clinically relevant evidence from digital images. Recently, plenoptic imaging has emerged as a new promise to enrich the diagnostic potential of conventional photography. Since the plenoptic images comprises a set of slightly different versions of the target scene, we propose to make use of those images to improve the segmentation quality in relation to the scenario of a single image segmentation. The problem of finding a segmentation solution from multiple images of a single scene, is called segmentation fusion. This paper reviews the issue of segmentation fusion in order to find solutions that can be applied to plenoptic images, particularly images from the ophthalmological domain.

Introduction

The recent emergence of light field cameras in the consumer market [1, 2] has attracted the interest for developing applications which take advantage of the plenoptic images. Some of these applications include: face recognition [3], robotic navigation [4], 3-D microscopy [5], and computer graphics [6].

Conventional photographic cameras capture the intensity of light as it strikes their image sensing elements, while colour filters provide a second set of data, sorting the rays into different wavelengths. In addition, plenoptic cameras capture a third piece of information: angle. This allows cameras to go beyond, from focusing on a single plane to taking images at many different depths of a scene at once [7].

Combining multiple angle versions of a single scene to obtain information about the world is not a new idea. In fact nature has been doing this for thousands of years. The visual system of the mantis shrimp allows to these marine crustaceans to see 12 different colour channels, from ultraviolet to infrared, to distinguish linear and circular polarization, and to perceive depth using trinocular vision with each eye [8]. Another example is given by compound eyes of flying insects, which are composed by numerous simple-single aperture eyes. Although they have a lower spatial resolution compared to mammalian single-lens eyes, given the high flicker frequency fusion rate of compound eyes, their temporal resolving power is considerably higher than for a single aperture eye. Thus compound eyes are ideal for motion detection [9].

These combination of optics and computing processing to produce images that cannot be obtained with traditional cameras led to the appearance of new field: computational photography [10].

This paper outlines the state of the art of segmentation fusion techniques as a basis for a project aimed at integrating plenoptic images into ophthalmological diagnostic instruments, specifically using slit lamps. Its main purpose is to review the techniques already suggested in the literature to cope with the problem of using ***n*** images of a single scene to improve image segmentation in the context of ophthalmology. The rest of the paper is organized in the following order: the next section reviews the most referred algorithms and methods applied to solve the segmentation problem with a single image in ophthalmology. The third section describes the particularities of plenoptic imaging. The fourth section shows the strategies found to deal with the problem of segmentation fusion. Finally, the work presents the conclusions and future work.

Image Segmentation in Ophthalmology

Ophthalmological imaging is a subfield of medical imaging which makes use of specific methods and equipment to detail the state of different components of the human eye like the cornea, crystalline, iris, retina and optical nerve. **Figure 1** illustrates key functional and anatomical areas in human eye along with the most common diagnostic studies associated with their characterizations.

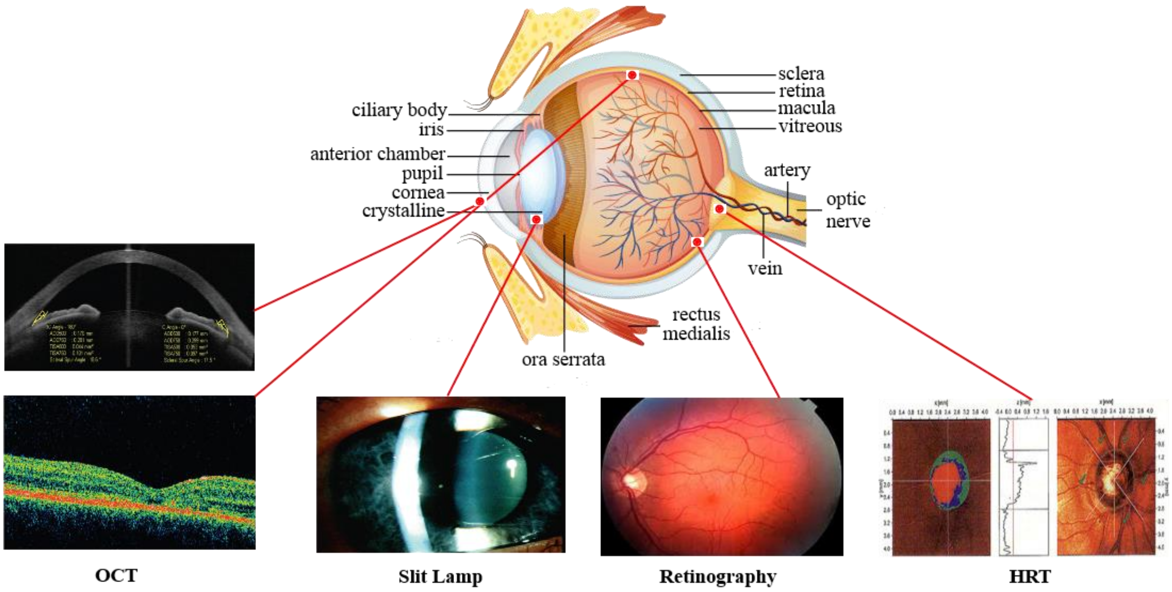

Figure 1. Human eye anatomy and main imaging methods

As can be seen in **Figure 1**, the human eyes have several structures and formations whose clinical characterization is fundamental to diagnose or to treat patients. The problem of segmenting those structures have its own body of research, and comprises the sub-tasks of pre-processing, feature extraction, and finally their localization and identification.
Hundreds of references related with the detection and segmentation of anatomic structures such as the optic disc, the fovea, and retinal blood vessels from digital colour fundus images can be found in the literature. But there are also other well studied cases related with the detection of abnormal elements such as exudates, microaneurysms, or haemorrhage.
In the following of this section, we present some work for each one of these tasks.

1.1. Optic Disc Segmentation

The optic disc or optic nerve head is the exit point for ganglion cell axons leaving the eye, which then form the optic nerve. **Figure 2** shows this landmark along with the macula, fovea and retinal blood tree. Authors of [11] propose a set of algorithms to recognise automatically main components of the fundus. The optic discs were located by identifying the area with the highest intensity variation of adjacent pixels, blood vessels were detected using a multilayer artificial neural network for which the inputs were derived from principal component analysis; and the fovea were identified using matching correlation and typical characteristics of this landmark such as the darkest area in the neighbourhood of the optic disc. They show that high sensibility and specificity can be achieved over a set of 112 cases.

In [12] authors use the active contour/snake model for the detection of optic disc. The high contrast of the optic disc is the key element in this approach, however this method may be sensitive to the initialization values for size and shapes. Later, these authors propose the detection of the optic disc using region growing and edge detection [13]. The results presented reveal high sensitivity and specificity for the delineation of fovea and the optic disc edges, but the method requires a precise selection of seed points for region growing.

In [14] a technique of unsupervised colour thresholding for detecting optic disc is used. Moreover, in this work authors try to find small yellowish structures, associated with the presence of exudates.

Several clustering strategies have also been proposed for the problem of optic disk detection. In [15] clustering techniques are applied for the initial localization, while the final definition of the optic disc is performed through circular Hugh transform and fuzzy approaches. The results in these tests are validated by ophthalmologists.

In [16] the optic disc detection is performed using k-nearest neighbour classifiers. This algorithm is a pixel level classification method, where intensity, edges and the outputs from Gaussian filters and Gabor wavelets are used as the set of attributes.

In [17] authors employs deformation techniques for the segmentation of the optic disc, which is subsequently used to distinguish between images from normal and glaucoma patients.

In [18] a technique for the segmentation of the optic disc based on histograms is presented. This technique includes the concept of fractal analysis, and authors found that their method is robust and computationally inexpensive.

In [19] a method for the automatic evaluation of the segmented optic disc is described.

The work of [20] integrates the local geometry of blood vessels with the image intensity for locating optic discs. A k-NN classifier is then applied to the optic disc segment. The results are relatively good for images with enough contrast but it is not so in case of low contrast

1.2. Fovea and Macula Segmentation

The macula is a pigmented oval area located in the central region of the retina, while the fovea is a small hole placed in the center of the macula, which contains the largest concentration of cone cells in the eye and is responsible for central, high-resolution vision. In [21] a method for macular segmentation using adaptive thresholds from optical coherence tomography is proposed. In this method various retinal layers are combined to detect the edges of the macula in images of normal and pathological retinas. The downside of this method is that it is not appropriate for low-quality images.

The work of [22] applies statistical methods for macular segmentation with the purpose of detecting macular structures with irregular sizes and shapes. These macular degenerations are typically associated with age.

1.3. Retinal Blood Vessels Segmentation

The work in [23] examines the relative importance of the red channel into the segmentation of blood vessels from retinal images. The segmentation of these vessels is obtained using red and green channels, and the results are compared against the output obtained using just the green channel. These results suggest that a differential treatment for colour channels is an approach worth considering for high precision segmentation.

The paper [24] proposes a vessel segmentation system based on the extraction of image ridges. These ridges, which coincide approximately with vessel center lines are used to compose primitives in the form of line elements. These elements are used to split the image into patches by assigning each pixel to the closest line element, and finally the feature vectors are computed making use of properties of the patches and the line elements. The feature vectors are classified using a k-NN classifier and sequential forward feature selection. Employing a set of 40 manually segmented images, authors find the performance of this system competitive with a couple of previously reported methods.

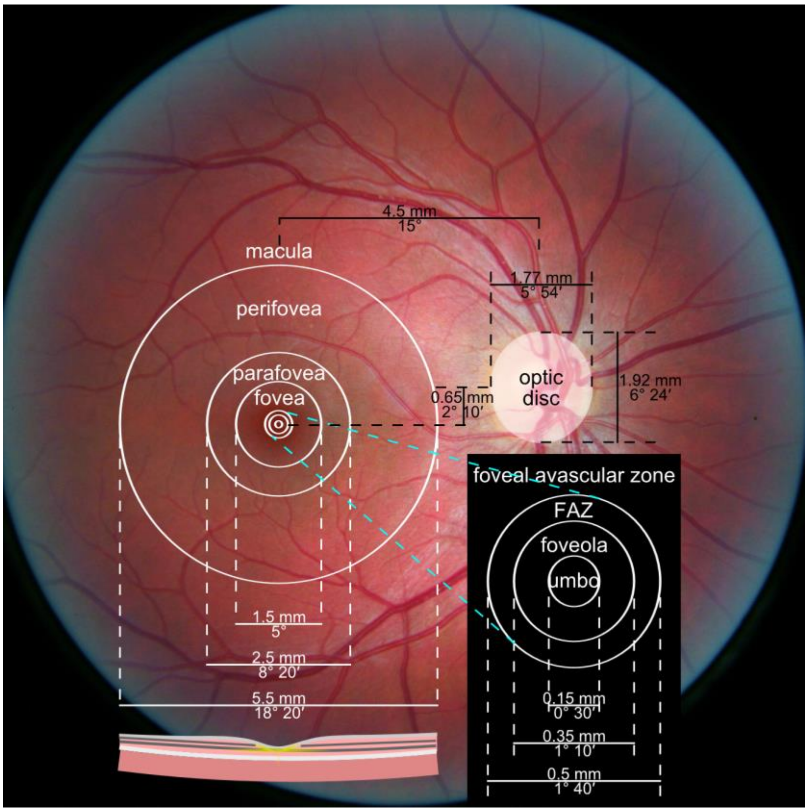

Figure 2. Macula, Optic Disc and Blood Tree in a Fundus Photography. Image by Photograph: Danny Hope from Brighton & Hove.

1.4. Microaneurysms, Exudates and Hemorrhage Segmentation

In [25] there is a proposal to detect retinal lesions from diabetic retinopathy patients. The pre-processing step eliminates background pixels and extracts the blood vessels and the optic disc from the original image. Then a filterbank extracts the set of candidate lesions. A feature set based on different descriptors, such as shape, intensity, and statistics, is formulated for each possible candidate region: this further helps in classifying that region. Finally an m-Mediods based modelling approach combined with a Gaussian Mixture Model is employed for the classification. It achieved a value of 0.981 as its area under the ROC curve, as against 0.977 for m-Mediods and 0.963 for GMM.

In [26] authors propose an exudate detection method which firstly perform normalization, denoising, and reflections/artifacts detection in the image; then selects between candidate segmentations based on mathematical morphology, and finally applies random forest to detect the exudates among the candidates. The method has been validated on three database, obtaining an AUC of 0.95.

In [27] the authors develop various fully automated systems for retinal haemorrhage measurement, but they ultimately found user interaction to be necessary to achieve satisfactory validity of segmentation.

In [28] authors compare the results of five different methods for microaneurysms detection, produced by five different teams of researchers on the same set of data. This set of data consisted of 50 training and 50 testing images, and beside the good results obtained for some types of aneurysms, the overall results shown that this is a challenging task for both the automatic methods as well as the human expert. The best performing system does not reach the performance of the human expert, indicating that there is room for improvement to solve this problem.

Plenoptic Imaging

Plenoptic imaging comprises a subset of computational photography approaches; specifically, those that aim at acquiring the dimensions of the plenoptic function with combined optical light modulation and computational reconstruction. Computational photography has grown tremendously in the last years in this interdisciplinary field, spanning optics, sensor technology and image processing. **Figure 3** shows a scheme of a plenoptic imaging system.

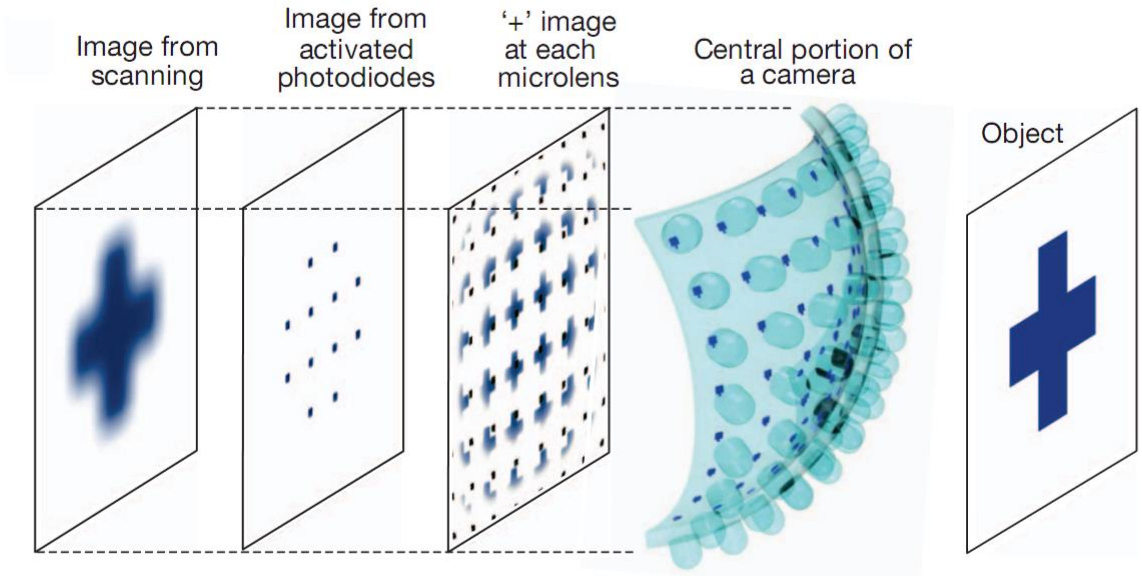

Figure 3. Conceptual View of Image formation in Light Field Cameras. Each microlens generates an image of the object ('+' pattern), with characteristics determined by the viewing angle. These images generates a proportional photo current at the corresponding photodiodes. The result is a sampled reproduction of the object. Image from [29]

The image formation involves two steps: measurement and processing. For the former, the camera has a sensor (CCD or CMOS) which provides with a directional sampling of the irradiance passing through each point in the sensor. Through the processing step, the captured light field can be used to recover a conventional image making focus on any depth of the original scene. The key rationale behind this processing comes from the projection-slice theorem, proposed by Bracewell in 1956 [30].

By the other hand, plenoptic photography also can be used to compose images from different perspectives. As under each microlens lays a set of pixels (as many as the microlens size or sensor resolution), they capture the rays coming from different directions of the same scene. Therefore, if the image is reconstructed employing the pixels from the same position under each microlens, it's possible to obtain the image in perspective, built upon the rays with the same angle from the scene. **Figure 4** depicts the same scene from two different perspectives.

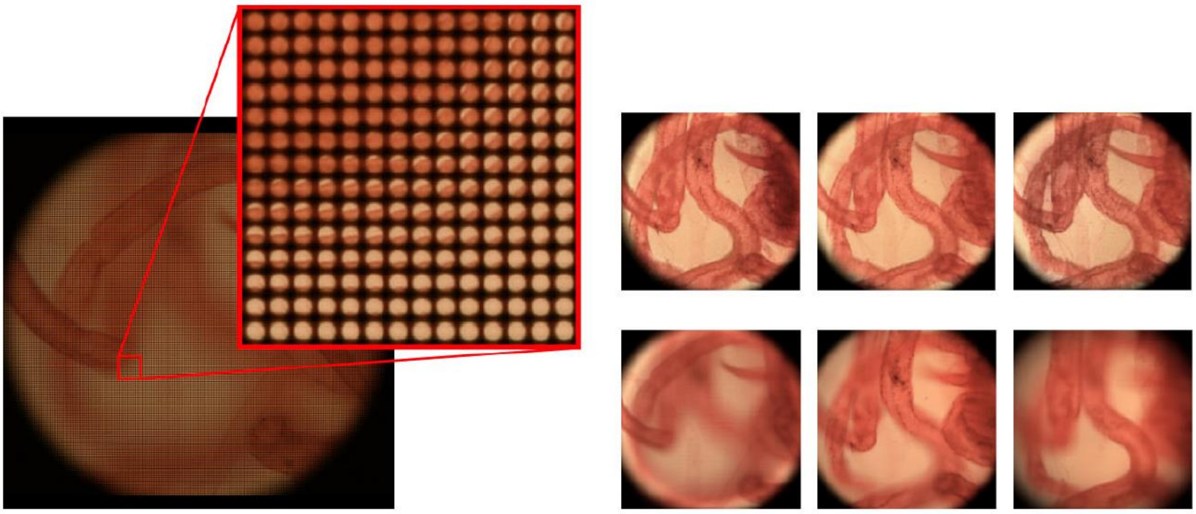

Figure 4. At left is a light field of several insect legs, captured in a single snapshot by a microscope into which a microlens array has been inserted. The objective was 25x/0.45NA. Magnifying a portion of this light field (inset), we see the circular subimages formed behind each microlens. Each is a view of the microscope's aperture. At right is a sequence of perspective views (top) and a focal stack (bottom), computed from this light field. (Extracted from [31])

Segmentation Fusion

Segmentation fusion is the common terminology used in the literature to refer to the task of finding a segmentation solution from multiple images of a single scene, or from a single image but using several algorithms, or various instances of the same algorithm. These scenarios are referred as *"n images, one algorithm"* and *"one image, n algorithms"* paradigms respectively.

Several strategies have been proposed to deal with the synthesis of a single solution from multiple segmentations. The most common strategy applied to solve the problem of segmentation fusion consist in obtaining *n* different segmentation hypotheses and applying a consensus strategy to gather and unify these *n* results into a single solution.

In [32] the authors propose an approach to the *"n images, one algorithm"* paradigm based on binary partition trees. This is an interesting work because instead of applying the segmentation fusion as a post-processing step, it attempts to handle the segmentation fusion applying the consensus decision during the construction of a hierarchical model representation which unifies the *n* images. The authors claim that solving the fusion decision during an early phase results in two benefits. First, it allows to define a hierarchical framework for the segmentation problem which is flexible and can be easily instantiated according to the field of application. Second, by operating the fusion on the internal data structures involved in the algorithmic construction of the hierarchy, instead of spatial regions of the segmentation maps, existing machine learning solutions for "non-spatial" data fusion can be used [33]. They use Binary Partition Trees (BPTs) [34], a technique widely applied in the field of remote sensing, for the hierarchical model. Authors illustrate and explain the benefits of their approach on two cases of remote sensing images: mono-date multi-imaging on urban areas, and multi-date imaging on agriculture areas. With the study cases they conclude that the experiments carried out on satellite multi-image datasets shown that the quality of the induced morphological hierarchies are sufficient to further perform improved segmentation, however, this preliminary work doesn't provide any quantitative comparisons with other segmentation schemes or with a gold standard.

In this sense, to count on apriori information as reference, several works [35-37] apply atlas-based segmentation methods. These methods have the property of segmenting the image with no well-defined relation between regions and pixels intensities. If the information about difference between these regions is incorporated in the spatial relationship between them, other regions, or within their morphometric characteristics, the atlas-based segmentation is expected to work well. In [35] the authors propose two approaches for combining multi-atlas segmentation and intensity modelling based on segmentation using expectation maximisation (EM) and optimisation via graph cuts. In [36] the authors present a framework to address the consequent problems of scale in multi-atlas segmentation. In this work a custom subset of atlases was selected for each query subject and provided more accurate subcortical segmentations than those given by non-selective combination of random atlas subsets. This approach was tested using a database of 275 atlases. An image based similarity criterion as well as a demographic criterion (age) in a leave-one-out cross-validation study were used. This work concludes that selecting atlases from large databases for atlas-based brain image segmentation improves the accuracy in the final segmentations. Additionally this work shows that the image similarity is a suitable selection criterion. Authors also give results based on selecting atlases by age which demonstrate the value of meta-information for such selection. Jia et al [37] present a multi-atlas-based framework for the segmentation of *n* target images. In this approach two strategies were described: a tree-based groupwise registration method for concurrent alignment of both the atlases and the target images, and an iterative groupwise segmentation method

Another typical approach for the segmentation task is the Markov Random Field (MRF) [38-40]. A MRF is similar to a Bayesian network in its representation of dependencies; the differences are that Bayesian networks are directed and acyclic, whereas Markov networks are undirected and may be cyclic. In [38] a multi-channel image segmentation method that uses a MRF region label model with adaptive neighbourhoods is described. Bayesian inference is applied to realize the combination of evidence from different knowledge sources. In such a way, the optimization of the shape of a neighbourhood set is achieved by following a criterion that makes use of hypothesis on the Markovian property by exploiting the local image content. The authors illustrates the results of this strategy through optical remote sensing data. Another segmentation algorithm based on MRF processing was proposed in [39]. The images are segmented initially by growing regions of similar colour values. Then, for refining initial clusters in a feature space they use a MRF processing. That processing works with the KNN classification rules among the neighbours of a pixel. It has been observed that, though using only chromatic information, good segmentation results are obtained. The luminance information improves the quality of segmentation in some cases. Results for different colour spaces such as the OHTA coordinate space, YIQ, CIELAB and UVW are also presented. On the average the performance in the OHTA space was better than the others. In [40] a simple MRF model for unsupervised image segmentation based on image features which has a new processing pipeline is proposed. The traditional two-component MRF model for that segmentation requires training data to estimate the necessary parameters for the model, and thus is unsuitable for unsupervised segmentation. The proposed pipeline solves this problem by introducing a function-based weighting parameter between the two components. Using this method, the simple MRF model is able to automatically estimate those model parameters, and to produce accurate unsupervised segmentation results. Experiments demonstrate that the proposed algorithm is able to segment various types of images (gray scale, color, texture) and it achieves an improvement over the traditional methods. In [41] authors propose a maximum-likelihood clustering for this task. The clustering registers all the images in a multisensor ensemble simultaneously. Experiments involving rigid-body and affine transformations show that the clustering method is more robust and accurate than competing pairwise registration methods. Moreover, the clustering results can be used to form a rudimentary segmentation of the image ensemble.

Another clustering approach was reported in [42]. The segmentation fusion procedure combine several segmentation maps associated to much simpler partition models in order to finally get a more reliable and accurate segmentation result. The label fields to be fused are obtained by K-means clustering on an input image, expressed in different colour spaces. The fusion strategy aims at combining these segmentation maps with a final clustering procedure using as input features the local histogram of the class labels, previously estimated and associated to each site and for all the initial partitions. This fusion framework has been successfully applied on the Berkeley image database. By the other hand [43] reports its results using the same database, but the authors address the parameter selection problem by applying a general ensemble clustering methods in order to produce a consensus segmentation. The main contribution consists of applying and comparing a broad variety of representative and widely used ensemble clustering methods for the segmentation combination problem.

The first step consist in obtaining *m* segmentations using 3 state-of-art segmentation models to generate 3 ensembles: TBES ensemble (Texture and Boundary Encoding-based Segmentation), UCM ensembles (Ultrametric Contour Map) and TBES & UCM ensembles. Each ensemble is composed by 10 segmentations obtained by varying the parameter values of the segmentation algorithms used to generate the ensemble. The ensemble clustering methods used were: BOK (Best of K), BOEM (Best One Element Moves), EAC SL/AL (Evidence Accumulation), RW (Random Walker), Hypergraph based methods, Information theory based methods, Kernel based methods and Clustering based on semidefinite programming. The results obtained were compared with the human segmentations of each image.

The results suggest that good segmentation results may be obtained by using general ensemble clustering methods without knowing ground truth. In this context it must be emphasized that in many application scenarios, supervised learning is not applicable because the ground truth information is not available. Thus, ensemble clustering methods are preferred in scenarios where parameters of segmentation algorithms are unknown.

Finally, in [44] authors propose a method which exploits the semantic information of images. They propose a novel method for weakly supervised semantic segmentation. The training images are labelled only by the classes they contain, not by their location in the image. On test images instead, the method predicts a class label for every pixel. The main innovation of this proposal is a multi-image model (MIM) a graphical model for recovering the pixel labels of the training images. The model connects superpixels from all training images in a data-driven approach, based on their appearance similarity. For generalizing to new test images they integrate them into MIM using a learned multiple kernel metric, instead of learning conventional classifiers on the recovered pixel labels.

Conclusions and Future Work

In this work we inquire about the feasibility of applying segmentation fusion techniques to plenoptic ophthalmological images. In the first part we reviewed the problem of image segmentation in ophthalmology. We outline some of the strategies proposed to segment anatomic structures such as the optic disc, the fovea, and retinal blood vessels, and abnormal elements such as exudates, microaneurysms, or haemorrhage from digital colour fundus images. Then we detailed the characteristics of plenoptic images, and finally we described the problem of segmentation fusion along with some proposals and applications of this problem to different environments.

The segmentation fusion approaches found in the literature can be broadly classified into atlas-based methods, statistical characterizations approaches, and machine learning based techniques. For the purpose applying segmentation fusion into plenoptic images, we consider that both statistical and machine learning techniques would be appropriate, but only with unsupervised methods due to the lack of a gold standard for ophthalmic plenoptic image. We also identify the atlas-based approach as the more difficult to adapt to our target scenario because with the available data in this field there would be difficult to build reliable ophthalmic atlases. However, many heuristics from that approach would be exploited, for example the a priori information related with the shape, localization and geometric relations of the fovea, macula and blood tree.

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