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An Approach Of Dictionary Generation For Diabetic Retinopathy Detection

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***Abstract*—A good eye is an important and a significant factor in retaining independence and quality of life of all living beings. Diabetic retinopathy is a retinopathy caused by complications of diabetes that damages the retina. It affects back part of the eye and also damages the blood vessels of the retina. This effects blurry vision, scarring, cloudiness and increased pressure, which leads to blindness. This work is helpful to detect the diabetic retinopathy (DR) related lesions from fundus image and it can capable to detect these lesions without using pre/post processing. The method based on the concept of marking the points of interest (POI) in lesion location to make a visual word dictionary. The POIs region helps to classify the fundus image neither the retina image is normal nor diabetes affected one. The approach extends by adding feature information with visual word dictionary and so it is applicable for different types of lesions in retina with specific projection space for each class of interest instead of common dictionary for all classes. The red and bright lesions are classified by visual words dictionary with cross validation and cross dataset validation to show the efficiency of this approach. Finally the Bayesian classifier is proposed for classification. The visual word dictionary does not depend on resolution of the image. The proposed work shows the ability to detect and classify the retina images in different conditions.**

***Index Terms*—Diabetic Retinopathy, Point of Interest (POI), Retina, Red and Bright lesion, Bayesian classifier, Visual word dictionary.**

I. INTRODUCTION

A good eye is an important and a significant factor in retaining independence and quality of life of all living beings. Diabetic retinopathy is the most common diabetic eye disease, which occur to changes in the blood vessels of the retina triggered by diabetes that can lead to a complete loss of sight if not treated in a timely manner. The longer a human being has diabetes, the larger the risk becomes of increasing diabetic retinopathy.

In [1], the latest reports have exposed that approximately 25 thousand people with diabetes go blind every year due to Diabetic Retinopathy. Early diagnosis of DR and treatment [2] can prevent loss of sight, and therefore, systematic screening of diabetic patients is a cost-effective health care practice [4]. On the other hand, due to the large amount of people that need program and annual reviews, an automated and precise screening tool is a useful adjunct in diabetes clinics. Currently, some greatly accurate programs exist for automated detection of exact DR associated lesions [5]–[7]. These algorithms necessitate different pre and post processing steps of the retinal images depending on the damage of interest with corrections for resolution and color normalization to account for images with different fields of sight [10].

Diabetic retinopathy causes several types of retinal lesion. The most common lesion and usually the first sign of retinopathy, is the micro aneurysm (red lesion) are small red spots. These are caused by a swelling of very small capillary vessels in the retina. Hemorrhages (red lesion) are the red blots varying in size and shape. These are small bleeds within the retina or near the surface. Hard exudates (bright lesion) are the shiny pale white or yellow sharp edged features. These are fatty deposits caused by leaking fluid. Some of the lesions due to Diabetic Retinopathy are as shown in Fig. 1.

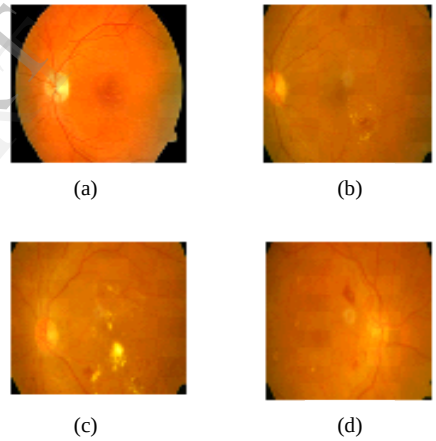


Fig. 1. Normal retina and DR-related lesions. (a) Normal retina, (b) Microaneurysm, (c) Exudates, (d) Hemorrhages

Automated bright lesion detection has resulted in very accurate categorization and has been discussed by [8], [9], [11]. In [9], the several different lesion specific detectors into a single automatic detection program and recommended that a single algorithm that is able to identify multiple DR related lesions [9]. In [13], the retinopathy online challenge published the results of five research groups using different algorithms for pre-and post processing and detection of microaneurysms. Computer-based feature detection has the advantage of being able to develop the lesion features such as colorization [11] or discontinuities in the image such as texture, color, or boundaries [12].

Most of the methods used for automatic DR lesion detection are based on precise segmentation techniques developed for identifying each specific lesion. These methods have been achieving increasing accuracy rates but normally a method developed for the detection of one kind of lesion cannot be directly used to detect another kind.

A number of studies can be developed for an automatic detection of diabetic related lesion like microaneurysm, haemorrhages [5]-[8], [15], [16], and exudates [10], [25]. Detection of microaneurysms requires pre processing of images and also requires removing blood vessel and optic disk. The detection and removal of these structures is a necessary when single-lesion detection is required [15].Detection of lesion using region of interest was developed in [16] and [15]. In [15] the regions were categorized using texture descriptors at multiple scales. Similar to [15] the method described in this paper also uses region categorization and perform the analysis of images.

In this paper, specific regions in an image are to classify lesion and creates a vocabulary to capture general properties between regions. The difference between [15] and this paper is how to categorize the regions and our approach does not specify a specific size for any of the region of interest. This paper investigates a process that does not need any laborious pre and post processing but nevertheless deals with image differences of retinal fundus photograph directly.

The approach is to indicate region of interests containing particular lesions and then identifies points of interest within these regions that become words within a visual dictionary. For final classification Bayesian Classifier is proposed for a supervised learning method as well as a statistical method. This approach extends earlier work as it is independent of the image resolution, color space representation, and to detect different lesions. The point of interest and visual dictionaries is used in image classification and image retrieval [17]-[21].

Section II presents the visual dictionaries for diabetic retinopathy detection. Section III introduces our method. Section IV presents the results and discussion. Finally, Section V presents the conclusion of this paper.

II. METHODOLOGY

This thesis proposed a solution to categorize DR-related lesions based on the idea of selecting features around nearby invariant points of interest and visual vocabulary of images. This new model in the computer vision literature uses a set of greatly extensible feature representations, and classifies diabetic retinopathy related lesions in fundus images without requiring pre or post processing in the analyzed images.

In this paper the diabetic retinopathy related lesion detection is done in two stages: training stage and testing stage. In training stage, the overall behavior of the lesions is learned and to define what makes the lesion image different to normal image. Using the learned information to test new image is done in testing stage.

A. Detection of Local Features

To represent the visual content of a given image, find a set of point of interest in such images and characterize their surrounding regions. It is desired to prefer scale invariant point of interests in order to accomplish a representation robust to some achievable image changes. In this approach each image in a group can be represented using a large number of POIs. It is then probable to compute a local descriptor in the region, and to store these local descriptors in an indexing data construction [25].The theory of this method is that POIs in an image express more information than other points. Therefore, POIs can be robustly estimated, even if the image suffers distortion as the major standard of quality for a POI algorithm is repeatability [25].

To detect diabetic retinopathy related lesions, initially mark ROIs within the retinal images. These ROIs are considered as good representatives of diabetic retinopathy related lesions. For normal images, the entire region in the retinal image can be considered a ROI. For each training image with a given diabetic retinopathy related lesion 2–5 ROIs are marked. Then in the training phase to locates POIs in all images. For finding good representative POIs the parameters are specified to a good exchange among categorization accuracy and calculation efficiency. POIs are establish at discontinuities in the image, being either textural or containing some other boundary situation. It is desirable to prefer scale invariant POIs in order to accomplish an illustration that is robust to achievable image changes for example rotations, degree, and partial occlusions. There are various methods for finding and characterizing POIs such as Speeded-Up Robust Features (SURF) [24] and Scale-Invariant Features Transform (SIFT) [26]. Both of these methods accomplish high repeatability and uniqueness. This paper uses the SIFT method to mark POIs. By means of SIFT, each training image creates a sequence of POIs. These POIs are filtered and only POIs within the ROIs marked are reserved for additional processing**.** Once the point of interest in an image can be found, then their neighborhoods are differentiating by means of a local descriptor.

SIFT algorithm is one of the most robust method under transformation, scale and rotation transformations**.** In brief, SIFT have two steps:

1. POI detection: In this stage, the algorithm searches for candidate points invariant to scale changes using a variation of Gaussian function. For this many feature points are produced. From these feature points the low contrast points are eliminated and the remaining points are called points of interest (POI).
2. POI characterization: In this stage one or more orientations are assigned to each feature point location based on neighbourhood image gradient direction. In order to achieve invariance to rotation, this stage selects a space around each point of interest and rotates such space towards the most recurrent direction of the gradient.

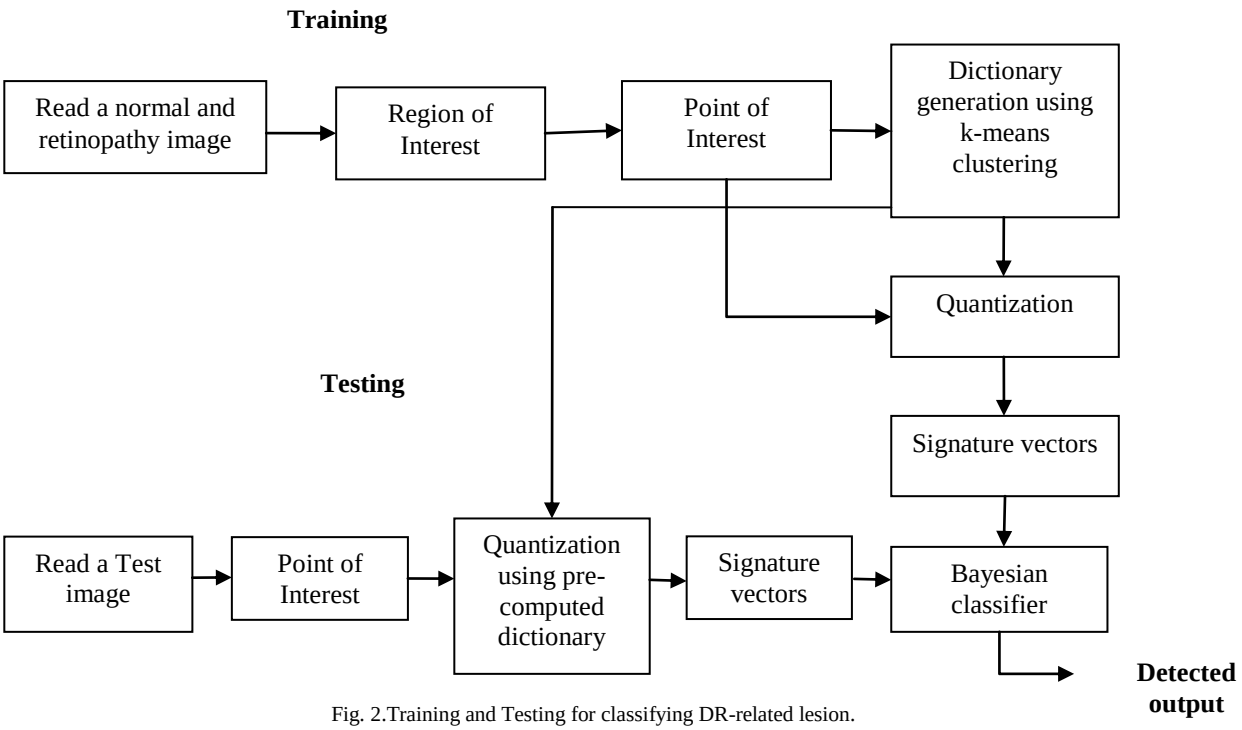


Fig. 2.Training and Testing for classifying DR-related lesion.

SIFT and SURF methods are good low-level representative feature detectors. Yet the distinctiveness power comes with a benefit and a disadvantage. When searching for a definite target, the distinctiveness power is very significant attribute. Despite, when searching for multipart categories as the capability to generalize becomes paramount. To conserve the discriminatory power of such descriptors found by SIFT and SURF while rising their generalization, the idea of visual dictionaries [22] can be established. The method of dictionaries considers the high-dimensional descriptor spaces and split into various regions and finds the one of the best set of POIs from the whole set of point of interest via clustering technique.

B. Visual Vocabularies

Visual vocabularies comprise a robust representation method as each image is treated as a group of regions. For each region the only information is the appearance of every region [17]. Dictionary words are not in the space of images but at the space of local feature description of the point of interest in the image. Every region of POIs becomes a visual word of a dictionary, for the construction of a visual vocabulary.

Once POIs are found, and then create a dictionary representing distinct features of diabetic retinopathy related lesion images of interest and normal images. From a training set of examples, the objective when creating a visual vocabulary is to learn the generative modal selects the representative regions for a given problem. The number of selected regions must be large enough to discriminate applicable changes in the images and disregard irrelevant features.

To create visual dictionary, initially choose its size k or number of words. A k too low group together too much POI into the same visual word looses the capability to differentiate significant information. A k too high memorizes the information of the POIs in the training set looses its capability to generalize. To accomplish this, the clustering task is performed by means of k-means algorithm [27] and then all the POIs in normal images are clustered into k/2 groups, as are the point of interests in the region of interest containing diabetic retinopathy related lesions. This results k words in a dictionary. The visual dictionary has the same number of normal and diabetic retinopathy related lesion words by applying the k-means clustering. Nevertheless, it is not a severe requirement to have the same number of words for normal and diabetic retinopathy related lesions. The dictionary sizes considering an exchange between categorization accuracy and computational effectiveness.

C. Training and Testing

The visual word dictionary is created from the training images, using the fine selection of candidates regions in normal and diabetic retinopathy related images. Once the visual word dictionary is created, then the point of interest within the ROIs from the training sets are assigned to the closest visual word of the dictionary. This process is called projection or quantization [18], [25]. At the end of this quantization process, a set of feature vector in each image is denoted by a signature or histogram consists of the selected visual words. Then this histogram is given to the input to a machine learning classifier in the last stage.

Formally, the quantization performs a rigid task that is each point of interest is recognized to the closest visual word in the dictionary and the accumulation function is the sum [25].Once a point of interest is coordinated to a visual word the matching entry in the histogram is increased by one. Finally the Bayesian Classifier is proposed for a supervised learning method as well as a statistical method for classification. The classifier was trained by adding the signature vectors calculated from the training images containing images with a given lesion and normal images are fed into the classifier. A Bayesian classifier is a simple probabilistic classifier based on applying Bayes theorem with strong independence assumptions. Bayesian classifier assumes that the presence or absence of a particular feature of a class is unrelated to the presence or absence of any other feature, given the class variable.

To analyze multiple lesions, create different dictionaries and train different classifiers. Then to test a new image, its point of interests are located and quantized onto the pre-computed dictionary to create its signature vector. Then it can be given to the input of the trained classifier. The training and testing for classifying DR lesions are as shown in Fig. 2.

3.2.1. Algorithm for training

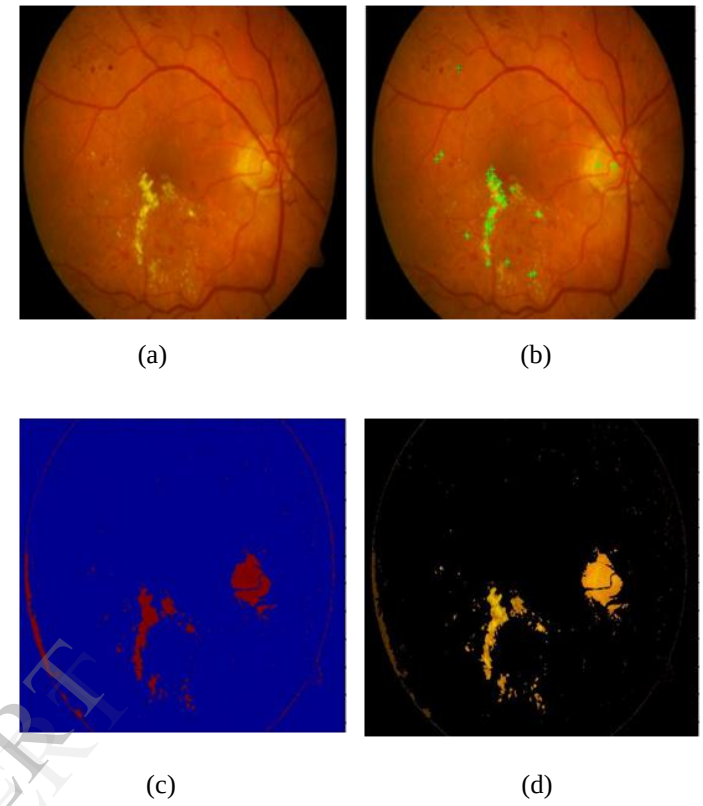
Input: a collection of images containing diabetic retinopathy related lesion, X_d;
Input: a collection of normal images, X_n;
Step 1: Mark region of interest in X_d images.
Step 2: Mark point of interest in $X_d \rightarrow P_d$;
Step 3: Mark point of interest in $X_n \rightarrow P_n$;
Step 4: Creating dictionary for the set of POI in P_n through k-means clustering, D_n;
Step 5: Creating dictionary for the set of POI in P_d through k-means clustering, D_d;
Step 6: $D_d \; U \; D_n \rightarrow D$;
Step 7: For each input image X_i in $X_d \; U \; X_n$, quantize its POI onto D and creating its signature vector S_{vi};
Step 8: Train the classifier using all signature vector and generating the classification modal M which is able to differentiate normal images from DR related lesion image.

3.2.2. Algorithm for testing

Input: test image X_j;
Input: the pre-computed dictionary D.
Input: the pre-computed training modal M.
Step 1: Mark point of interest in $X_j \rightarrow P_j$;
Step 2: Quantize the point of interest P_j on to a pre-computed dictionary D and creating its signature vector S_{vj};
Step 3: By using the learned modal M, classify this signature vector as normal or DR related lesion.

III. Result And Discussion

In this section the results for the classification method are presented. Here the diabetic retinopathy lesion detection is done in two stages: training stage and testing stage. In training stage two images will be trained that is one normal retinal image and one diabetic retinopathy lesion image. In this training stage initially mark the point of interest for identifying the local features of both normal image and lesion image. Identifying these features is done by using the SIFT method. After marking point of interest, create visual dictionary using k-means clustering. This dictionary contains features of both normal image and lesion image.



(a) (b)

(c) (d)

Fig. 3 Results for classifying DR lesions. (a) Original image, (b) SIFT features, (c) Segmented output, (d) Classifier output.

Once the visual word dictionary is created, then the point of interest from the training sets are assigned to the closest visual word of the dictionary called quantization. Then to create a training signature vector or training histogram and this will be given to the input of Bayesian classifier. After completes the training stage then begins the testing stage.

In testing stage, one new test image has been tested. Fig. 3(a) shows the test image for testing. Here initially the point of interest can be marked on the test image using SIFT method for identifying the local features. Fig. 3(b) shows the point of interest marked on the test image using SIFT technique. Then these features of the test image are projected with the pre computed dictionary and to create the signature vector or histogram of the test image. Fig. 3(c) shows the segmented result of test image. This testing feature vector can be given to the input of Bayesian classifier. This classifier can be used to classify and to detect the test image is normal image or diabetic retinopathy lesion image. Fig. 3(d) shows the classifier output of the test image.

IV. CONCLUSIONS

For identifying and detecting the diabetic retinopathy related lesions, automated screening algorithms can be used to get accurate result. But for detecting specific lesions require many pre and post processing steps of images. In this paper, the visual dictionary approach can be introduced for detecting diabetic retinopathy related lesions. The intention of this paper was to illustrate an explanation for detecting different lesions without requiring any pre- or post processing procedures. This approach is explained automatically calculates POIs that are representative and extremely distinguishing of such regions and, simultaneously, are scale-invariant and robust to some image conversions. The technique builds a powerful visual vocabulary upon the POIs. Then the point of interest on a image can be quantized. Finally the method uses a Bayesian classifier is to point out the classification of such an image. This approach is independent of the image resolution, color space representation, and does not assume any specific size of the lesion.

REFERENCES

[1] M. D. Abramoff, M. Niemeijer, R. Russell, and B. van Ginneken, "Evaluation of a system for automatic detection of diabetic retinopathy from color fundus photographs in a large population of patients with diabetes," *Diabetes Care*, 2008.

[2] Q. Mohamed, M. C. Gillies, and T. Y. Wong, "Management of diabetic retinopathy: A systematic review," *J. Amer. Med. Assoc.*, 2007.

[3] S. R. Salomao,and R. Belfort, Jr., "Visual impairment and blindness: An overview of prevalence and causes in Brazil," *Anals Braz. Acad. Sci.*, 2009.

[4] M. James, D. A. Turner, D. M. Broadbent, J. Vora, and S. P. Harding, "Cost effectiveness analysis of screening for sight threatening diabetic eye disease," *Br. Med. J.*, 2000

[5] A. D. Fleming, S. Philip, K. A. Goatman, J. A. Olson, and P. F. Sharp, "Automated microaneurysm detection using local contrast normalization and local vessel detection," *IEEE Trans. Med. Imag.*, 2006.

[6] L.Giancardo, T.Karnowski, Y.Li,K.Tobin, and E.Chaum, "Microaneurysm detection with radon transform-based classification on retina images," in Proc. Intl. Conf. IEEE Eng. Med. Biol. Soc., 2011.

[7] B. Antal, I. Lazar, A. Hajdu, Z. Torok, A. Csutak, and T. Peto, "Evaluation of the grading performance of an ensemble-based microaneurysm detector," in *Proc. Intl. Conf. IEEE Eng. Med. Biol. Soc.*, 2011.

[8] A. D. Fleming, S. Philip, K. A. Goatman, G. J. Williams, J. A. Olson, and P. F. Sharp, "Automated detection of exudates for diabetic retinopathy screening," *Phys. Med. Biol.*, 2007.

[9] A. D. Fleming, K. A. Goatman, S. Philip, and J. A. Olson, "The role of haemorrhage and exudate detection in automated grading of diabetic retinopathy," *Br. J. Ophthalmol.*, 2010.

[10] M. J. Cree, E. Gamble, and D. J. Cornforth, "Colour normalisation to reduce inter-patient and intra-patient variability in microaneurysm detection in colour retinal images," in *Proc. Workshop Digital Image Comput.*, 2005.

[11] M. Niemeijer, B. van Ginneken, S. R. Russell, and M. S. A. Suttorp-Schulten, M. D. Abr`amoff, "Automated detection and differentiation of drusen, exudates, and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis," *Invest. Ophthalmol. Vis. Sci.*, 2007.

[12] H. F. Jelinek, K. Al-Saedi, and L. Backlund, "Computer assisted topdown assessment of diabetic retinopathy," in *Proc.World Congr. Biophys. Biomed. Eng.*, 2009, pp. 127–130

[13] H. F. Jelinek, A. Rocha, T. Carvalho, S. Goldenstein, and J. Wainer, "Machine learning and pattern classification in identification of indigenous retinal pathology," in *Proc. Intl. Conf. IEEE Eng. Med. Biol. Soc.*, 2011, pp. 5951–5954.

[14] M. Niemeijer, B. van Ginneken, M. J. Cree, A. Mizutani, G. Quellec,H. Fujita, and M. D. Abr`amoff, "Retinopathy online challenge: Automatic detection of microaneurysms in digital color fundus photographs," *IEEE Trans. Med. Imag*, Jan. 2010.

[15] B. Zhang, K. Karray, L. Zhang, and J. You, "Microaneurism (MA) detection via sparse representation classifier with MA and non-MA dictionary learning," in *Proc. Intl. Conf. Pattern Recogn.*, 2010..

[16] C. Agurto, V. Murray, E. Barriga, S. Murillo, M. Pattichis, H. Davis, S. Russel, and M. Abr`amoff, P. Soliz, "Multiscale AM-FM methods for diabetic retinopathy lesion detection," *IEEE Trans. Med. Imag.*, Feb. 2010

[17] K. Mikolajczyk and C. Schmid, "Scale and affine invariant interest point detectors," *Intl. J. Comput. Vision*, Jan. 2004.

[18] E. N. Mortensen, H. Deng, and L. G. Shapiro, "A SIFT descriptor with global context," in *Proc. IEEE Intl. Conf. Comput. Vision Pattern Recogn*, 2005.

[19] J. Winn, A. Criminisi, and T. Minka, "Object categorization by learned universal visual dictionary," in *Proc. IEEE Intl. Conf. Comput. Vision*, 2005, pp. 1800–1807.

[20] J. Sivic and A. Zisserman, "Video Google: A Text Retrieval Approach to Object Matching in Videos," in *Proc. IEEE Intl. Conf. Comput. Vision*, 2003, pp. 1470–1477.

[21] P. Hough and B. Powell, "A method for faster analysis of bubble chamber photographs," *Il Nuovo Cimento*, 1960.

[22] G. Csurka, C. R. Dance, L. Fan, J. Willamowski, and C. Bray, "Visual categorization with bags of keypoints," in *Proc. Workshop Stat. Learn. Comput. Vision*, 2004.

[23] F.-F. Li and P. Perona, "A bayesian hierarchical model for learning natural scene categories," in *Proc. IEEE Intl. Conf. Comput. Vision Pattern Recogn.*, vol. 2, pp. 524–531, Jun. 2005

[24] E. Valle, "Local-descriptor matching for image identification systems," Ph.D. dissertation, Ecole Doctorale Sciences et Ing´enierie, University de Cergy-Pontoise, Cergy-Pontoise, France, 2008.

[25] D. Lowe, "Distinctive image features from scale-invariant key points," *Intl. J. Comput. Vision*, vol. 60, no. 2, pp. 91–110, Feb. 2004.