Extraction of Texture Based Features of Underwater Images Using RLBP Descriptor

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Abstract. In this paper, we present an approach for extraction of texture features of underwater images using Robust Local Binary Pattern (RLBP) descriptor. The literature survey reveals that the texture parameters that remain constant for the scene patch for the whole underwater image sequence. Therefore, we proposed technique to extract the texture features and these features can be used for object recognition and tracking. The underwater images suffer from image blurring and low contrast and performance of feature extractors is very less if we employ directly. Thus, we propose a novel image enhancement technique which is combination of different individual filters such as homomorphic filtering, curvelet denoising and LBP based Diffusion. We employ DoG based feature detector, for each detected interest point, the texture description is extracted using RLBP feature descriptor. The proposed feature extraction technique is compared and evaluated extensively with well known feature extractors using datasets acquired in underwater environment.

Keywords: Feature descriptor, Feature matching, DoG, RLBP, Underwater image pre-processing.

1 Introduction

Feature detection and matching of stable and discriminative features are fundamental problems of research in computer vision and machine learning. Feature detector and descriptor are playing an important role in applications like image matching, image stitching, and image registration. In underwater images, extracting the invariant features is a big challenging task because of optical properties of the water. The absorption and scattering processes of the light in the water influence the overall performance of underwater imaging systems. Even the same object in the pair of images which are captured from same viewpoint can be drastically different due to varying water conditions. Color and geometrical variations are very high between pair of underwater images due to the optical properties of the water. As a result, the description of the same point of an object may be completely different between underwater images taken under the same conditions. The current state-of-the art feature descriptors such as SIFT, SURF, KLT and DAISY, which extracts geometric features and cannot be employed directly because of geometric variations of underwater images. Therefore, it is required to extract the features which remain constant in the whole sequence.

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In general, the key points finding in a given image is very challenging problem due to variation in illumination, scale and orientation. The key points are selected based on the distinguishable property of the locations, such as corners, junctions and blobs. In past two decades, many researchers proposed techniques for detection of key points. The most widely used detectors can be classified into two categories such as Hessian-based and Harris-based detectors. Harris and Stephens in 1988 [1] presented a Harris feature detector; it is based on the auto-correlation matrix. This technique is not neither to scale nor to affine transformations [2] due to the fact that the Harris corner detector does not provide a good basis for matching images of different sizes because it is very sensitive to changes in image scale. Schmid et al. [3] showed, the Harris corner detector performs excellent in the evaluation of single-scale interest point detectors. Lindeberg [4] proposed a technique for automatic scale selection based on Hessian matrix as well as Laplacian. Mikolajczyk et al. [2] have further extended this technique to create robust and scale invariant feature detector based on the combination of Harris-Laplacian and Hessian-Laplacian. In this method Harris measure to select the location and Laplacian to select the scale. R. Garcia et al. [5] detected key points in underwater turbid images, using a combination of Hessian and Harris point detectors.

The literature survey reveals that the texture parameters that remain constant for the scene patch for the whole underwater image sequence. One of the most popular texture descriptors is Local Binary Pattern (LBP) [6], which is computationally simple, efficient, good texture discriminative property and has been highly successful for various computer vision problems like face image analysis, dynamic texture recognition, motion analysis, texture analysis [7] etc. LBP has a property that favors its usage in interest region description such as computationally simplicity and tolerance against illumination changes. LBP operator is structural and statistical texture descriptor in terms of the characteristics of the local structure, so that it is most powerful for texture analysis. LBP have some drawbacks, namely it is sensitive to noise and sometimes it produces same binary code for different structural patterns, which will reduce its discriminability. In order to overcome these demerits Y. Zhao et al. [8] proposed another variant of the LBP, called Completed Robust Local Binary Pattern, which is robust on flat image areas usually found in underwater environment. The Robust Local Binary Pattern (RLBP) descriptor outperforms the existing local descriptor for the most part of the test cases, particularly for images with severe illumination variations and noise.

In this paper, we propose feature extraction technique for underwater images based on detection and extraction of texture based features using RLBP descriptor. We detect the keypoints using DoG based feature detector and the texture information of the feature points are stored using RLBP descriptor. In order to extract reliable and robust features from underwater images, it is necessary to enhance the quality of underwater image prior to feature extraction. We propose a novel image enhancement technique which is combination of different individual filters such as homomorphic filtering, curvelet denoising and LBP-Diffusion which are employed sequentially on degraded underwater images. The rest of the paper is organized as follows: Section 2 describes proposed image enhancement technique. Section 3 provides theoretical background of proposed feature extraction technique. The experimental results are presented in Section 4. Finally, section 5 draws the conclusion.

2 Enhancement of Underwater Images

In this section, we present an underwater image enhancement technique, which is a combination of different individual filters and employed sequentially on degraded underwater images.

2.1 Homomorphic Filtering

Homomorphic filtering [9] is used to correct non-uniform illumination and to enhance contrasts in the image. It is a frequency filtering technique, preferred to others techniques because it corrects non-uniform lighting and sharpens the image features at the same time. The mathematical representation of filter function is given below:

$$H(w_x, w_y) = (r_H - r_L) \cdot \left(1 - \exp\left(-\left(\frac{w_x^2 - w_y^2}{2\delta_w^2}\right)\right)\right) + r_L, \quad (1)$$

where $r_H = 2.5$ and $r_L = 0.5$ are the maximum and minimum coefficients values and δ_w a factor which controls the cut-off frequency. Computations of the inverse Fourier transform to come back in the spatial domain and then taking the exponent to obtain the filtered image.

2.2 Curvelet Denoising

The Curvelet Transform introduced by Candes and Donoho in 1999 a multi-scale representation suited for objects which are smooth away from discontinuities across curves [10]. Curvelets via wrapping [11] is used for removing noise [12] from underwater image. Let signal be $\{f_{i,j}; i,j = 1 \dots N\}$, where N is some integer power of 2. It is corrupted by additive noise and signal $g_{i,j}$ can be mathematically expressed as

$$g_{i,j} = f_{i,j} + \varepsilon_{i,j}, \qquad i,j = 1 \dots N, \quad (2)$$

where $\{\varepsilon_{i,j}\}$ are independent and identically distributed as normal $N(0,\sigma^2)$ and independent of $\{f_{i,j}\}$. Underwater image denoising is done through soft thresholding techniques, operator with threshold T is defined as

$$D(g_{i,j}, T) = sgn(g_{i,j}) * \max(g_{i,j} - T, 0). \quad (3)$$

Soft thresholding is more efficient as it shrinks towards zero. BayesShrink approach is used for calculating threshold for soft thresholding. It achieves near minmax rate over a large number and yield visually more pleasing images.

2.3 LBP Based Diffusion

Mandava et al. [13] combined LBP and non linear diffusion [14], LBP is used to classify the textons of image around a pixel into flat, spot, corner and edge regions. Depending on different types of regions, a variable weight is assigned into the diffusion equation; it is adaptively encouraging the strong diffusion in flat or spot regions and less on the edge or corner regions. When diffusing more on flat regions, the diffusion preserves edges and local details. The diffusion process is mathematically described as

$$\frac{\partial}{\partial t} I(x, y, t) = \nabla \cdot (c(x, y, t) \nabla I), \tag{4}$$

where $I(x, y, t)$ is the image, t is the iteration steps and $c(x, y, t)$ is the so called diffusion function and is monotonically decreasing function of the image gradient magnitude. The discrete diffusion structure is

$$I_{i,j}^{n+1} = I_{i,j}^{n} + (\nabla t) \cdot \begin{bmatrix} c_N\left(\nabla_N I_{i,j}^n\right) \cdot \nabla_N I_{i,j}^n + c_S\left(\nabla_S I_{i,j}^n\right) \cdot \nabla_S I_{i,j}^n + \\ c_E\left(\nabla_E I_{i,j}^n\right) \cdot \nabla_E I_{i,j}^n + c_W\left(\nabla_W I_{i,j}^n\right) \cdot \nabla_W I_{i,j}^n \end{bmatrix}. \tag{5}$$

The *N, S, E* and *W* are referred to as north, south, east and west respectively, express the direction of the local gradient, and the local gradient is designed using nearest-neighbor differences

$$\nabla_N I_{i,j} = I_{i-1,j} - I_{i,j,}\ \nabla_S I_{i,j} = I_{i+1,j} - I_{i,j,}\ \nabla_E I_{i,j} = I_{i,j+1} - I_{i,j,}\ \nabla_W I_{i,j} = I_{i,j-1} - I_{i,j.} \tag{6}$$

3 Extraction of Texture Features

We detect interest points using Difference of Gaussian (DoG) based feature detection technique which is part of SIFT. For each interest point, a texture descriptor is built using RLBP technique to distinctively describe the local region around the interest point. Finally, the feature descriptors are matched using Nearest Neighbour Distance Ratio (NNDR) to measure the similarity.

3.1 Detection of Interest Points Using DoG

The scale invariant features are detected from a reference image using Difference of Gaussian technique [16].

Scale-space extrema detection: In this step Interest or key points are detected. Difference-of-Gaussian pyramid is computed from the differences between the adjacent levels in the Gaussian pyramid. Then, key points are obtained from the points at which the Difference-of-Gaussian values assume extrema with respect to both the spatial coordinates in the image domain and the scale level in the pyramid.
Keypoint Localization: Scale-space extrema detection produces too many keypoint candidates, some of which are unstable. A detailed fit to the nearby data for accurate scale, location and ratio of principal curvatures is done. This information allows points to be rejected that have low contrast or poorly localized along an edge.

3.2 RLBP Descriptor

In RLBP, the value of centre pixel in 3x3 local area is replaced by its average local gray value of the neighborhood pixel values, in which the RLBP is calculated. Compared to the centre gray value of LBP, the average local gray value of RLBP is more robust to noise and illumination variants. The Average Local Gray Level (ALG) is defined as

$$ALG = \frac{\sum_{i=1}^{8} g_i + g}{9}, \tag{7}$$

where g represents the gray value of the centre pixel and $g_i(i=0,...,8)$ denotes the gray value of the neighbour pixel. Then the LBP process is applied by using ALG as the threshold instead of the gray value, named Robust Local Binary Pattern (RLBP). This can be defining as follows:

$$RLBP_{P,R} = \sum_{P=0}^{P-1} s\left(g_p - ALG_c\right)2^P = \sum_{P=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + g_c}{9}\right)2^P, \tag{8}$$

where g_c represents the gray value of the centre pixel and $g_p(p = 0, \dots, P-1)$ denotes the gray value of the neighbour pixel on a circle of radius R, P is the total number of the neighbours and $g_{ci}(i = 0, \dots, 8)$ denotes the gray value of the neighbour pixel of g_c.

ALG ignores the specific value of an individual pixel. While sometimes the specific information of the central pixel is needed. To make a balance between anti-noise and information of individual pixel, we define a Weighted Local Gray Level (WLG) as follows:

$$WLG = \frac{\sum_{i=1}^{8} g_i + \alpha g}{8 + \alpha}, \tag{9}$$

where g and g_i are defined in Eq. (7), α is parameter set by user. It should be notice that WLG is equivalent to the conventional ALG if α is set as 1. Now the RLBP can be calculated as follows:

$$RLBP_{P,R} = \sum_{P=0}^{P-1} s\left(g_p - WLG_c\right)2^P = \sum_{P=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + \alpha g_c}{8 + \alpha}\right)2^P, \tag{10}$$

where g_p, g_c, g_{ci} are defined as in Eq. (8), α is the parameter of WLG.

In order to incorporate spatial information into the descriptor, the input region is divided into cells with Cartesian grid 4 x 4 (16 cells) is used. For each cell a RLBP histogram is built. The resulting descriptor is a 3D histogram of RLBP feature locations and values. The number of different feature values ($2^{N/2}$) depends on the neighborhood size N of the chosen RLBP. The final descriptor is built by concatenating the feature histograms computed for the cells to form M x N x $2^{N/2}$ dimensional vector, where M is the gird size and N is the RLBP neighborhood size.

We compute the similarity between the descriptors using NNDR based technique. The threshold T is set empirically. The ambiguity distance compares the distance between the closest and the second closest descriptor. The distance ratio is threshold to avoid matching when the nearest neighbors are very similar. Considering $d_{L,1}$ first closest descriptor and $d_{L,2}$ second closest descriptor, ambiguity distance can be defined as

$$NNDR = \frac{\sqrt{\sum_{i=1}^{128}(d_R(i) - d_{L,1}(i))^2}}{\sqrt{\sum_{i=1}^{128}(d_R(i) - d_{L,2}(i))^2}} < T \tag{11}$$

4 Experimental Results

We conducted several experiments in order to validate our method for underwater video sequence captured in small water body in which the object was kept at a depth of 5 feet from the surface level of the water. The underwater image capturing setup consists of a waterproof camera which is Canon-D10. The camera is moved around an object at a distance between from 1m to 2m, near the corner of the water body to capture the video sequence. We have captured three set of video sequences (dataset1, dataset2 and dataset3) in three different water conditions with various turbidity levels. From each video sequence, we select two test frames which are not consecutive (frame 1 and frame 20) for experimentation.

4.1 Evaluation of Image Enhancement Technique

To evaluate the performance of our proposed method, we compared both quantitatively and qualitatively with other techniques [15] and [9] by considering first frame of each dataset. The experimental results show that our approach based on curvelet transform yields improved PSNR (Peak Signal Noise Ratio) values compared to wavelet based image denoising techniques shown in Table 1.

Fig. 1. Result of Image enhancement method: First column: original images, Second column: after homomorphic filtering, Third column: after curvelet denoising, Last column: after LBP- Diffusion

We also employed image contrast measure to evaluate quantitatively and evaluation results are shown in Table 2. Generally, the higher the contrast value means that the clearer the image. We compute the contrast measurement for both original and enhanced images using the equation given below:

$$C(I) = \frac{\sqrt{\frac{1}{N}\sum_{v=1}^{N}\sum_{\chi=r,g,b}(I_v^{\chi}-\bar{I}^{\chi})^2}}{\sum_{\chi=r,g,b}\bar{I}^{\chi}}, \quad (12)$$

where I is the image with N pixels, $C(I)$ is the contrast, χ is the index of the chromatic band (red, green and blue channels) and $\bar{I}^{\chi}$ is mean value, which is calculated for each channel independently using Eq. 13.

$$\bar{I}^{\chi} = \frac{1}{N}\sum_{v=1}^{N} I_v^{\chi} \quad (13)$$

We compared the contrast measure of our approach with Bazielle approach [15] for original image and enhanced underwater image (Fig. 1). Our approach yields better contrast value for enhanced image.

Table 1. Comparison of curvelet with wavelet for denoising based on PSNR and MSE (*Mean Square Error*)

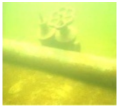
Dataset	Frames	Methods	PSNR(dB)	MSE
1		Haar Wavelet	45.780	1.7170
		Sym4 Wavelet	47.609	1.1277
		Db4 Wavelet	47.579	1.1355
		Curvelet	**52.782**	**0.3426**
2		Haar Wavelet	48.233	0.9765
		Sym4 Wavelet	50.238	0.6154
		Db4 Wavelet	50.212	0.6192
		Curvelet	**52.307**	**0.3822**
3		Haar Wavelet	49.982	0.6529
		Sym4 Wavelet	51.370	0.4743
		Db4 Wavelet	51.347	0.4767
		Curvelet	**52.218**	**0.3901**

Table 2. Comparison of our approach with Bazielle approach [15] based on contrast of the image

Data sample	Original Image	Bazielle et al. Approach	Our Approach
dataset1	2.58	2.34	**5.53**
dataset2	2.50	5.12	**5.15**
dataset3	2.46	1.79	**3.33**

4.2 Evaluation of Feature Extraction Technique

The proposed method is compared with standard feature extractors such as SIFT [16], SURF [17], KLT [18], [19] based on the repeatability measure. The repeatability measurement is computed as a ratio between the number of point-to-point correspondences that can be established for detected points and the mean number of points is detected between two images.

We used three set of frames namely dataset1, dataset2 and dataset3, which are enhanced using proposed image enhancement method. The descriptors are matched using NNDR approach and results of feature matching for three datasets are shown in Fig. 2. The descriptors having a value below a threshold is selected as the matched point, threshold value is 0.8 for all the datasets. Experimental results clearly show that, our proposed method yields good repeatability rate compared to KLT and Hessian method shown in Table 3. Hence, our proposed method is efficient technique for detecting feature points for underwater images.

Table 3. Comparison of repeatability measure of our approach for feature detection with other feature detectors

Approaches	Frame 1 keypoints	Frame 2 keypoints	Number of Matches	Repeatability	Processing Time (Sec)
KLT	86	71	39	0.4968	14.8
Hessian	92	84	52	0.5909	11.4
Our approach	99	88	67	**0.7165**	**10.2**

The comparison of results of proposed RLBP feature descriptor with other standard descriptors is presented using recall and 1-precision in the Table 4. The comparative results clearly show that the value of recall and 1-precision of proposed method is very high compared to SIFT and SURF method.

Table 4. Recall and Precision values for feature matching of dataset1, dataset 2 and dataset 3

Datasets	Methods	Recall	1-Precision
Dataset1	SIFT	0.62	0.58
	SURF	0.68	0.61
	Our Approach	**0.71**	**0.64**
Dataset2	SIFT	0.59	0.56
	SURF	0.67	0.60
	Our Approach	**0.73**	**0.65**
Dataset3	SIFT	0.62	0.58
	SURF	0.64	0.57
	Our Approach	**0.69**	**0.59**

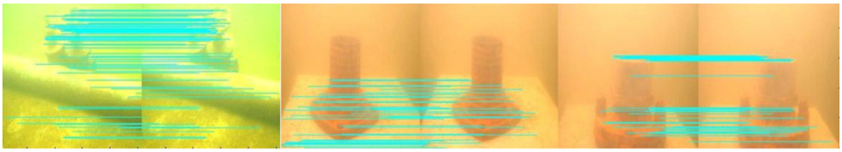


Fig. 2. The result of feature points matching using proposed method for enhanced images of dataset1, dataset2 and dataset3

5 Conclusion

In this paper, we proposed feature extraction technique for underwater images based RLBP descriptor. Since there is no benchmark database is available for underwater image sequence, we conducted experiments using our own captured image sequences. The proposed image enhancement technique comprises three filters such as homomorphic filter, curvelet denoising and LBP-diffusion, which are employed sequentially for enhancing the quality of degraded underwater images. Experimentally we showed that curvelet transform yields higher PSNR value compared to wavelet and it also observed that our approach yields very high contrast value for enhanced underwater images. For the enhanced underwater images, interest points are detected using DoG based feature detector and texture description is extracted using RLBP descriptor. The experimental results shows that, the combination DoG with RLBP descriptor yields high repeatability, recall and precision rate compared to other techniques. The processing time of our technique is low compared to other state-of-the-art techniques. The proposed technique can be employed to extract the texture features in order to match the objects or track the objects in video sequence of underwater environment.

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