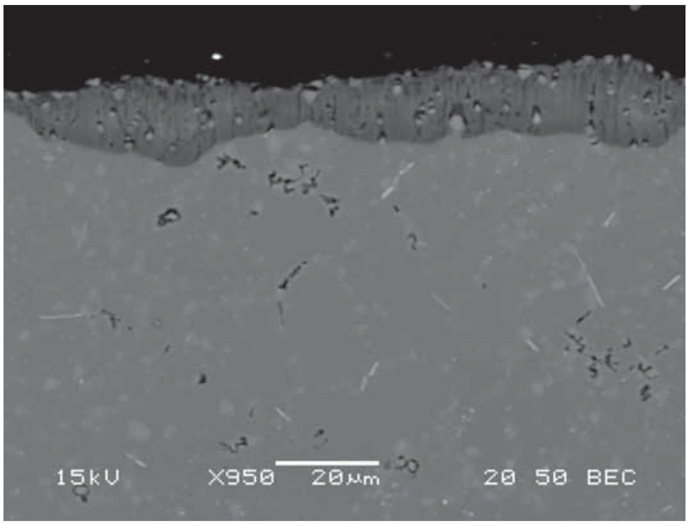

Figure 3. A356 T6 anodized.

4. Conclusions

• The A356 components obtained by SLC with T6 treatment can highly improve corrosion resistance by anodizing despite the non-uniform thickness.

The anodizing possibility of these components offers new perspectives to obtain components by SSM processes.

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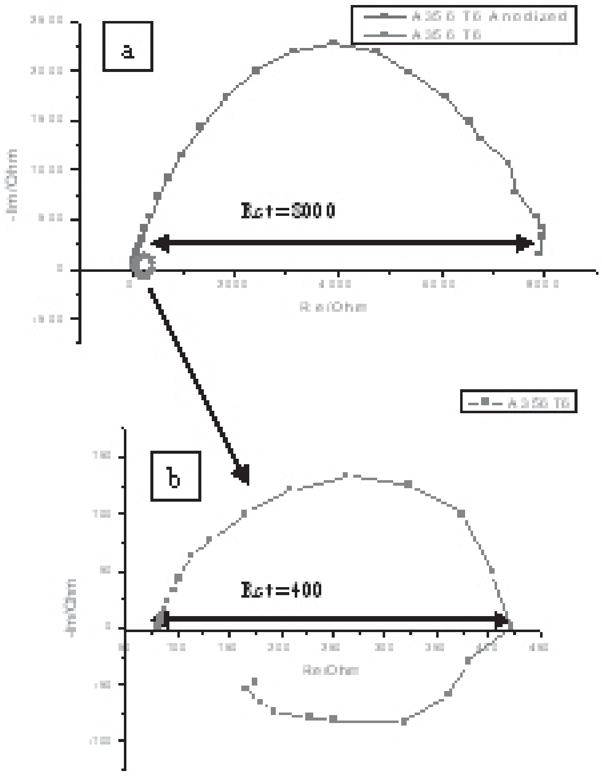

Figure 4. a) Nyquist plots for A356 T6 and A356 T6 anodized; B) Nyquist plot for A356 T6 .

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FEATURE-BASED MATCHING OF UNDERWATER IMAGES

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Keywords: underwater imaging, lighting artifacts, image matching.

This work investigates performance of recent feature-based matching techniques when ap¬plied to registration of underwater images. Matching methods are tested versus different contrast en¬hancing pre-processing of images. As a result of the performed experiments for various dominat¬ing in images underwater artifacts and present deformation, the outper¬forming preprocessing, detection and descrip¬tion methods are proposed.

1. Introduction

Underwater vehicles are usually equipped with video cameras to provide a visual feedback of the seafloor. In this scope matching of images acquired under water has several important applica¬tions, such as photo-mosaicing, depth estima¬tion, motion tracking, etc. Feature-based matching of two overlapping images consists in detecting salient features in each image, de¬scribing the detected features and actual matching of descriptors. Complexity of the matching task consists in overcoming the geo¬metric deformation and photometric differences between images. The water medium introduces even more difficulties for matching techniques comparing to overland. Underwater images suffer from effects such as diffusion, scatter and caustics. Moreover, there is a wider range of possible deformations due to less controllable camera movements. All these differences should be overcome by robustness and invariance of the detection and description methods applied to match the images.

In this work, several experiments have been carried out. Two descriptors, SIFT [1] and SURF [2], were tested in conjunction with five different detectors. Three classical detectors, Harris [3], Hessian [4] and Laplacian [5], were used in their straightforward form, which is not invariant to scale. The two other detectors, DoG and FastHessian, are the original detectors of SIFT and SURF, respectively. As opposed to the previous three detectors, they perform multi-scale detection. Several matching methods, represented by possible combinations of detec¬tor and descriptor, were tested on 80 image pairs from four underwater sequences. In all cases RANSAC [6] was used to estimate homo¬graphies. Initial matches following the esti¬mated homography were accepted as correct correspondences, or inliers, while the rest of the matches were rejected as outliers.

SIFT and SURF proved to be efficient for images of overland scenes, often failed to match images acquired under water without special preprocess¬ing of the latter. However, undesired underwater artifacts, such as diffusion, blur, scatter, noise, caustics and artificial lighting, displayed by Fig.1, which obstacle successful matching of underwater frames, can be sup¬pressed to a considerable extent by applying special pre-processing to the images. All matching techniques were tested versus differ¬ent conversion to grayscale, such as the blue chan¬nel from the RGB image, luma channel after con¬version to YIQ, or the first principal component after PCA of the image. Next, dif¬ferent contrast enhancement techniques were applied, including normalization, equalization and CLAHE [7].

Figure 1. Underwater effects: diffusion, non-uniform lighting, caustics.

For each configuration of **pre-processing**, **detection** and **description**, the number of successfully matched image pairs per sequence was counted, as well as the percentage of outliers, averaged through the evaluated matched pairs. The bigger this percentage is, the more difficult it is to estimate the motion.

2. Results and Discussion

Performed tests show that classical conversion to grayscale via luma component provides better results than selecting the dominant color channel or applying PCA. Among the contrast enhance¬ment methods CLAHE appeared to be in general the most effective when dealing with underwater effects. Table I summarizes the outperforming pre-preprocessing for each effect.

Underwater Artifacts	Conversion to Grayscale	Contrast Enhancement
Clutter, Blur, Low contrast	YIQ	CLAHE
Non-uniform Lightning	YIQ	Normalization CLAHE
Caustic Patterns	YIQ PCA	Normalization

Table I. Recommended preprocessing for different underwater artifacts.

When photometric effects can be partially suppressed by special pre-processing, geometric de¬formations should be overcome solely by the matching technique. SIFT and SURF descriptors are fully invariant to translation and rotation of images, and, when used with DoG and FastHessian, they are also invariant to scale. Fig.2 illus¬trates these types of deformations. Moreover, since each descriptor itself covers change of scale to some degree, both of them demonstrate good results when applied to keypoints detected by Harris, Hessian and Laplacian if scale change between images is not significant.

However, in our experiments camera motion is not constrained. Thus, image pairs are often warped by more complex deformations (affine or projective). SIFT occurs to be robust to wider range of these deformations. Only full SIFT was able to match all the tested image pairs, when full SURF failed for 5% of them. However, when SURF is able to match the image pair it outperforms SIFT in terms of percentage of inliers at least by 10%. Among single-scale detectors, Hessian outperforms Harris and Laplacian. On the other hand, DoG and FastHessian –being approximations to Laplacian and Hessian for multi-scale

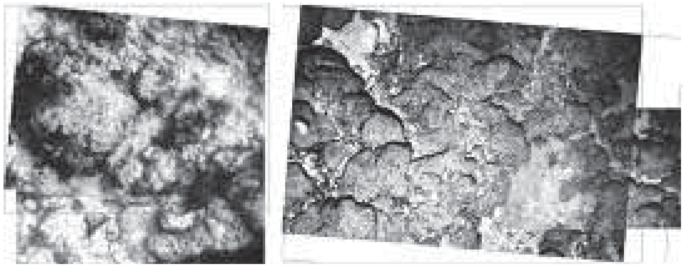

Figure 2. Geometric deformations: translation and rotation, scale.

detection and speed– show good localization accuracy. DoG appears to be robust against significant oscillations in image intensities. Table II summarizes the outperforming detection and description methods depending on complexity and amount ("S"=significant, "I"= insignificant) of deformation present between images.

Deformation	1	2	3	4
Translation & Rotation	S	S	S	S
Change in Scale	I	S	I	S
Affine Deformation	I	I	S	S
Projective Deformation	I	I	S	S
Detector	Hessian	FastHessian	Hessian	DoG
Descriptor	SURF	SURF	SIFT	SIFT

Table II. Recommended detector and descriptor depending on complexity of deformation.

3. Conclusions

Performed tests proved that recent feature-based image matching techniques provide a good basis to deal with underwater images. SIFT and SURF descriptors demonstrated good performance when used with non-scale-invariant detectors under restriction of slight scale deformation. Hessian detector outper¬formed Harris and Laplacian. SURF appeared to be more discriminative providing higher than SIFT percentage of inliers. However, SIFT outperforms SURF in terms of robustness to affine and projec¬tive deformations, thus being the best method for loop closing detection when constructing the mosaic.

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