Study and Performance Evaluation Binary Robust Invariant Scalable Keypoints (BRISK) for Underwater Image Stitching

D A Jatmiko\textsuperscript{1*}, S U Prini\textsuperscript{2}
\textsuperscript{1}Department of Informatics Engineering, Faculty of Engineering and Computer Science, Universitas Komputer Indonesia, Indonesia
\textsuperscript{2}Research Center for Electronics and Telecommunication (PPET), Indonesian Institute of Sciences, Jalan Sangkuriang Komplek LIPI Gedung 20 Dago, Bandung 40135, Indonesia

Email: *didit@email.unikom.ac.id

Abstract. In this paper, performance evaluation of Binary Robust Invariant Scalable Key points (BRISK) for underwater image stitching is presented. Underwater image stitching is quite challenging because usually images produced by underwater cameras have few features and noise such as motion blur and underexposure. In this paper, we proposed a robust algorithm for the underwater image stitching which consists of several stages: taking an image frame, getting a key point using BRISK, feature matching using Random Sample Consensus (RANSAC), homography estimation, and perspective warping. The experimental result shows that the proposed algorithm can be implemented for underwater image and achieve better matching results even the less detected keypoints.

1. Introduction
Underwater image mapping is quite challenging in both image processing and computer vision because it widely used for observation objects, autonomous underwater vehicle\[1\] for preventing anomaly object for underwater region, or monitoring such as earthquake prediction, and tsunami alarming\[2\]. However, unlike the mainland, the are many issues for underwater image mapping, such as backward scattering, light absorption and sea snow\[3\], low contrast, colour distortion, few features, as well as noise such as motion blur and underexposure.

Numerous methods for underwater image processing have been proposed to overcome these issues in previous studies, such as depth estimation based on blurrieness\[4\]. This paper proposes three steps: (a) Estimation of pixel blur by calculating the difference between the original and multi-scale Gaussian-filtered images, (b) Making rough depth maps by applying maximum filters to pixel blurriness maps by assuming uniformly local depth in small patch, (c) Refinement of depth maps using CMR and guided filters to refine the depth maps. Other related research is using dual channels prior dehazing model, weighted enhanced image mode filtering, and inpainting\[3\]. This paper proposes issue for underwater depth map considers the influence of mud sediments in water using Kinect, remove colour image, and then inpainting processing scattering from the depth maps. For other method with colour approach\[5,6\], a previous research which introduced a robust colour correction method underwater images by combines better colour mapping and colour transfer-based methods\[5\]. Another research is using hybrid techniques\[7\] with the initial aim is to compensate such type of distortions by compensate unwanted colour cast. The difficulty in extracting suitable feature lies on balancing two goals: high-quality description and low computational requirements. BRISK achieved comparable quality of matching at much less computation time. BRISK method\[8\] is used to improve image resistance to rotational and
scale changes as well as detection and extraction in the image merging process. This method has a scale making process that aims to detect features namely key point. Therefore, the BRISK method is resistant to scale changes. There is a process of estimating feature orientation and sample pattern rotation so that the BRISK method becomes resistant to rotation. Several previous studies have used a BRISK method related to low computational requirements\[9–13\]. In this system, there are other stages, namely matching features and merging images. This feature matching stage aims to look for features that are similar between image 1 and image 2.

In this paper, we proposed the underwater image stitching process, which consists of several stages: taking an image frame, getting a key point using BRISK, feature matching using RANSAC method, and then making homography estimation and perspective warping. The result shows that the proposed algorithm can be implemented at underwater image and achieve better matching results even the less detected key points.

2. Method

2.1. BRISK

The Binary Robust Invariant Scalable Key points (BRISK) algorithm is a feature point detection and description algorithm with scale invariance and rotation invariance. It constructs the feature descriptor of the local image through the greyscale relationship of random point pairs in the neighbourhood of the local image, and obtains the binary feature descriptor[14]. The BRISK algorithm includes three main stage: key point detection, key point description and descriptor matching[8].

![Figure 1. BRISK key point description – BRISK sample pattern[8]](image)

2.2. RANSAC

The Random Sample Consensus (RANSAC) is an algorithm introduced by Fischler and Bolles[15] has become widely used robust fitting of model estimation problems especially in image processing area due to its ability tolerating an instability of outliers. Two reasons this algorithm contributed to are wide adoption. It is simple and can potentially deal with outliers contamination rates greater than 50%[16]. RANSAC estimates a global relation that fits the data, while simultaneously classifying the data into inliers (points consistent with the relation), and outliers (points not consistent with the relation)[17]. RANSAC uses the smallest set possible and proceeds to enlarge this set with consistent data points[18]. This algorithm has been applied to a wide range of model parameters estimation problems in computer vision, such as feature matching, registration, or detection of geometric primitives[19].
RANSAC uses three variables to control the model estimation process\cite{19}. First, determines whether or not a data point agrees with a model. This stage has some error tolerance that determines a space within which all compatible points must fall in. Second variables are the number of model hypotheses that are generated. It depends on the probability to draw a sample including only in data points. As the proportion of outliers and the minimal sample set size increase the number of model hypotheses must be increased to obtain a good estimate of the model parameters. The proportion of outliers depends on the noise level and how many models are supported by the data set. Furthermore, one tolerance variable is needed to determine if a correct model has been found. An extracted model is at last chosen if there is sufficient support from the data points for this model. In case of multiple models in the data, more models are extracted until there is insufficient support for any more models. The basic algorithm is summarized as follows\cite{18}:

**RANSAC Algorithm**

- Select randomly the minimum number of points required to determine the model parameters.
- Solve for the parameters of the model.
- Determine how many points from the set of all points fit with a predefined tolerance $\varepsilon$.
- If the fraction of the number of inliers over the total number points in the set exceeds a predefined threshold $\tau$, re-estimate the model parameters using all the identified inliers and terminate.
- Otherwise, repeat steps 1 through 4 (maximum of $N$ times).

The number of iterations, $N$, is chosen high enough to ensure that the probability $\rho$ (usually set to 0.99) that at least one of the sets of random samples does not include an outlier. Figure 3 shows the performance of RANSAC algorithm for determine between outliers and inliers. The outliers are denoted by red dots; they did not have any influence on the results, which are represented in blue colour\cite{20}.

![Figure 2. Performance of RANSAC algorithm for determine between outliers and inliers][20]

3. Results and Discussion

3.1. BRISK Key point Result

At first step, all the test images detected using the BRISK algorithm. The results of the key points obtained from all test images that can be seen in Table 1.

| Object | Detected Key points |
|--------|---------------------|

[2]
The most important in the key point detection process using the BRISK algorithm is the corner of image. In Image 5, key point image detected only 12 key points. This is because Image 5 has a few corners. After all key point is obtained, RANSAC method is using for showing how many features are actually matching in each test image, and next step is making homography estimation and perspective warping. The results can be seen in Figure 3, Figure 4 and Figure 5 below.
Figure 3. Stitching process and result from large number of key point detected. (a) Image 1[21]. (b) Image 2[21]. (c) Key point detected. (d) Key point matching. (e) Stitching result.
Figure 4. Stitching process and result from medium number of key point detected. (a) Image 3[21]. (b) Image 4[21]. (c) Key point detected. (d) Key point matching. (e) Stitching result.
Figure 5. Stitching process and result from small number of key point detected. (a) Image 5[21]. (b) Image 6[21]. (c) Key point detected. (d) Key point matching. (e) Stitching result.

4. Conclusion
Based on the test results, the BRISK algorithm is able to detect key points in all test images, Figure 1 has 2800 key points and this detection number is the highest of all test images. Meanwhile, Figure 5 has the least key points, which is 12 key points. Experimental results show that the stitching process has been successfully carried out on the entire test image and the BRISK algorithm is robustly proven to be used for underwater image stitching. The algorithm can also achieve better matching results even the detected key points less than 40 key points. The future study about this work is able to implemented this algorithm for real time image stitching.

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