ICIC Express Letters
Volume **15**, Number **6**, June **2021**

ICIC International ©2021 ISSN 1881-803X
pp. **617–625**

COMPARATIVE STUDY OF SIFT AND SURF ALGORITHM FOR TRADITIONAL THAI PAINTING RECOGNITION

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Received October 2020; accepted January 2021

Abstract. *Rapid and robust image matching has been applied in computer vision and robotics for numerous applications including recognizing patterns, where collective pattern images are computed and compared with identical image features. Not only Thai traditional painting has been symbolized Thai identifiable legacy for a long time, but also distinguished as the nation's invaluable arts and culture, which have been reserved and inherited from generation to generation. This paper focused on a comparative study of Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) algorithms by proposing and comparing the algorithms in recognizing Thai traditional painting patterns using SIFT and SURF techniques for classification of five Thai painting patterns: Kanokplew, Poomkaobin, Prajamyam, Dokpudtan, and Teppanom. The methods were able to classify appropriately and the preliminary outcome yielded a matching rate up to 75%. The consequence of the study had shown that the SIFT algorithm presented its ability to match feature keypoints in most of the experimental conditions, which was better than the SURF method. Conversely, its performance was still slow compared to SURF which had been extremely faster than SIFT. Nevertheless, the experiment presented that both methods achieved good performances of matching rates on the set database which can be applied in learning and publishing to those who are interested in studying and preserving Thai arts and culture.*

Keywords: Pattern classification, Traditional Thai painting, SIFT, SURF

1. **Introduction.** The computing process of feature detection involves detracting image data and corresponding in an identical pattern of the image. It is attentively examined from every image point where the image features are detected by comparing it with the reserved patterns. These are critical issues in the field of machine vision, robotics and applications. Moghaddam et al. [1] proposed that the supreme feature detection would be the image transformation technique with the extremely distinctive matching of rotation, scale, illumination, noise, and affine transformations. Whereas Sykora et al. [2] advocated using the database of the studied image of the training set and the testing set that had been created from the selected feature extraction techniques. Gupta et al. [3] also suggested that feature extraction was an essential phase, as the important features were extracted using feature extraction techniques, SIFT and SURF. Tareen and Saleem [4] mentioned that feature matching would be implemented after feature-detection-description by searching and mapping for each descriptor from the training set with the testing set of the images. Lu et al. [5] had adapted a threshold and minimum distance

DOI: 10.24507/icicel.15.06.617

constraint mechanism to obtain more feature points in a research of multi-small target SIFT feature detection.

Thai traditional patterns and paintings have been considered as a distinct national identity of Thailand, which is an invaluable art and culture of the nation. It is honored and praised internationally for being an exquisite and beautiful art delicacy. It is unlike any nation in the world. A Thai traditional painting pattern was born from the wisdom, ideas, and skills of Thai artists that were invented and created from nature such as lotus flowers, leaves, and flames. It is beautiful and delicate which is worthy of preservation. The Thai painting pattern could be seen everywhere, such as Benjarong porcelain, decorative ornaments, temples, and ancient sites [6]. The researcher is aware of the preservation of this knowledge and wisdom with the intention of maintaining the national identity and disseminating knowledge about Thai painting pattern art to future generations. As the Thai painting patterns have unique features, it requires specialized experts to be able to identify the name of the Thai painting pattern.

At present, there are studies on the identity of Thai painting patterns in Benjarong porcelain and the evolution of Benjarong porcelain patterns in various eras. It could be concluded that Thai Benjarong porcelain patterns are divided into 3 groups [7] which are 1) Teppanom and Thai animal group such as Teppanom-Garuda and Teppanom-Singha, 2) Phanprueksa or botanical group such as Pudtan, and 3) The Payok group such as Poomkaobin and Kredtao.

After having studied the relevant documents and research, it was found that no studies have been conducted and applied SIFT and SURF techniques in matching and classification with Thai painting patterns. Therefore, the purpose of this research is a comparative study of SIFT and SURF algorithms for Thai painting pattern recognition where the images used in this study are classified into five classes. Additionally, the research information about Thai painting patterns can be applied in learning and publishing to those who are interested in studying and preserving Thai arts and culture.

2. **Related Works.** In recently published research, there are various description techniques using for feature detection. The SIFT and SURF algorithms are recognized as reliable solutions, and suitable for semantic annotation of images. The SIFT descriptor is invariant to image transformations based on the Difference of Gaussian detector [8]. The outcome of this method is extremely efficient but moderately slow in computing and matching features of the images that would considerably affect real-time applications [9]. The SURF descriptor is scale invariant and resilient to image rotation based on the Fast-Hessian detector, and makes efficient use of integral images [10]. This consequence has been addressed by developing descriptors as a faster technique in computing and matching. It also relies on local gradient histograms but uses integral images to speed up the computation.

A research of comparison between SURF and SIFT methods conducted under several conditions and objects [11] which revealed that SURF technique performed the matching features better than SIFT technique. Nevertheless, the SIFT presented better results in condition of changes in illumination and blurriness of the image. In addition, another research which compared feature extraction techniques with the dataset of noisy and original images [12] resulted that SIFT technique was better in performance of feature extraction but executed slower than SURF technique. Another research about feature matching for stereo visual odometry [13] using the dataset with a sequence of stereo images taken in urban environment examined the percentage of matching rate and the average execution time for matching features of SIFT and SURF methods. The result highlighted that the percentage of SIFT algorithm was lower than SURF algorithm. Both of the methods showed that the rate of matching points steadily increased at the middle and gradually decreased towards the end, and the run time for SURF was much faster than SIFT.

In addition, there were studies on Thai painting pattern recognition techniques on the walls of Temple of the Emerald Buddha or Wat Phra Kaew, which were images of Ramayana epic, using the SURF method to match the images in the database and search for videos with consistent content to those images [14]. The study found that each Thai painting pattern had a different identity. The researcher then proposed an algorithm for classifying Thai patterns using computer vision technology and image recognition techniques [15] applying with SIFT and SURF algorithms to comparing the distinctive features of each Thai painting pattern image in each group, and compared the efficiency of the algorithm for pattern grouping. Another similar research about patterns in the Songket Palembang [16], traditional weaving in Indonesia, presented that the matching scores of distance measure and number of keypoints of the SIFT had better performance than the SURF, but SURF technique was extremely faster than SIFT technique. Furthermore, another study of comparison between SURF and SIFT methods for signature recognition application [17] also presented that in this comparative study SIFT technique gave more accuracy than SURF.

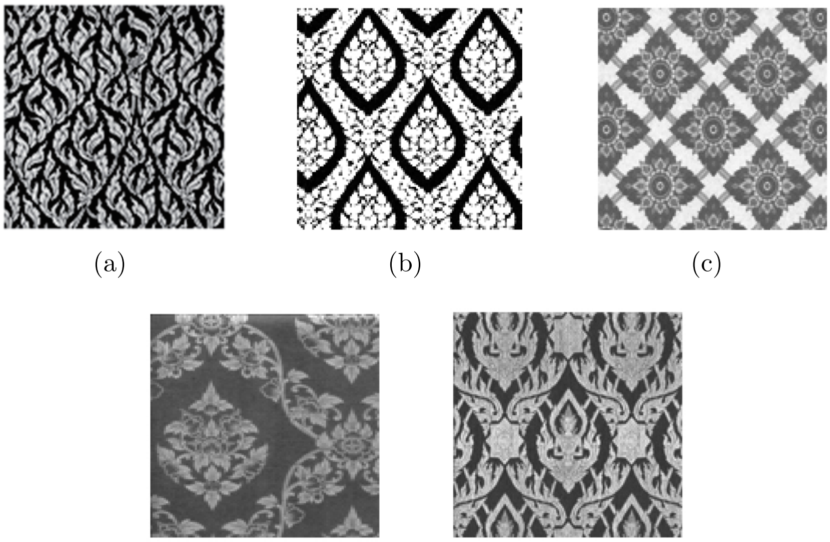
3. **Materials and Methods.** In this research, there are two algorithms used to distinguish and recognize the unique characteristics of Thai painting patterns, where the image of the selected Thai painting patterns will be computed and compared with SIFT and SURF to get the feature descriptor. The algorithms extract the features of the selected images for classification into five Thai painting patterns, which are Kanokplew, Poomkaobin, Prajamyam, Dokpudtan, and Teppanom.

3.1. **Thai painting patterns.** Thai painting is created from devotion to Buddhism. Therefore, the reason why craftsmen or artists created Thai painting patterns are based on ideas from garlands, lotus flowers, joss sticks' smoke, and candles' flame. The ideas have turned into various patterns such as Kanok, Plewplerng, Baitet, and Prueksachat. When studying the origin of those patterns, it is originated that each pattern had its own unique features and lines. It is considered as an invention of fine art and has been inherited as traditions since ancient times in Thailand. The images of the Thai painting patterns used in this research are Kanokplew, Poomkaobin, Prajamyam, Dokpudtan, and Teppanom. They are Thai painting patterns that appeared on ancient utensils, important historical sites, and decorated ornaments. The features of the prototype painting patterns used in this research are shown in Figure 1.

3.2. **Scale-Invariant Feature Transform (SIFT).** SIFT proposed by Lowe [9] explained about image rotation, affine transformations, intensity, and viewpoint change in the image matching features. The SIFT algorithm has four standard procedures. Firstly, scale-space extrema are estimated using the Difference of Gaussian (DoG) operator which is an approximation of Laplacian of Gaussian (LoG), and will be compared to find the difference of each image. Secondly, a keypoint localization has been acknowledged where the keypoint candidates are confined and refined by removing the low contrast points at various scales of the focus image using the DoG. Thirdly, a keypoint orientation assignment is based on the local image gradient using a 16×16 neighborhood around each detected feature. Lastly, a keypoint descriptor is generated to analyze the local image descriptor for each keypoint based on image gradient magnitude and orientation using a 4×4 spatial grid of eight gradient angle histograms [18]. A feature vector of 128 values is computed from the local image region around the keypoint. Equation (1) shows the convolution of the difference of two Gaussian, computed at different scales, with image "$I(x, y)$".

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \tag{1}$$

where G represents the Gaussian function, $k\sigma$ and σ are the difference of nearby scales and $I(x, y)$ represents the image.



(a) (b) (c) (d) (e)

FIGURE 1. The Thai painting patterns used in the experiment: (a) Kanok-plew, (b) Poomkaobin, (c) Prajamyam, (d) Dokpudtan, and (e) Teppanom

3.3. **Speeded Up Robust Features (SURF).** SURF algorithm is used in image similarity presentation and comparison. This technique is improved and processed approximately to DoG with box filters which is time-consuming. Square-shaped filters are used for approximation instead of Gaussian to analyze the image as the convolution with the square is much faster using the integral image. It also can be done parallelly for different scales. The Hessian matrix-based blob detector is used in SURF method to detect the keypoints. For orientation assignment, the algorithm applies wavelet responses in both directions horizontally and vertically, and applies appropriate Gaussian weights. For feature description, the SURF also applies the wavelet responses where a surrounding area around the keypoint is designated and separated into subscales. A feature vector of 64 values is computed from the oriented square local image region around the keypoint. At that point, the wavelet responses are computed and compared to get the SURF feature descriptor in each subscale. The sign of Laplacian, which is computed during the detection phase, can distinguish bright blobs on dark backgrounds from the reverse case. The features are sign-based compared in matching only if they have the identical type of contrast which allows faster matching [19-21]. Equation (2) represents the Hessian matrix in point $x = (x, y)$ at scale σ.

$$H(x, \sigma) = \begin{bmatrix} L_{xx}(x, \sigma) & L_{xy}(x, \sigma) \\ L_{xy}(x, \sigma) & L_{yy}(x, \sigma) \end{bmatrix} \tag{2}$$

where H is Hessian matrix, $L_{xx}(x, \sigma)$ is the convolution of Gaussian second-order derivative with the image I in point x, and similarly for $L_{xy}(x, \sigma)$ and $L_{yy}(x, \sigma)$.

3.4. **Feature descriptor.** This research studies and designs the algorithm for Thai painting pattern classification by beginning with extracting the distinctive features of the five prototype images and extracting the distinctive features of the images used in the experiment. Subsequently, the features of the images used in the experiment are compared with the features of the prototype images. Lastly, it could be classified using comparison results between the features of the tested images and the five prototype images. The algorithm workflow is as follows [22].

3.4.1. *Feature extraction.* The prototype images used in the experiment are Thai painting pattern images, which are Kanokplew, Poomkaobin, Prajamyam, Dokpudtan, and Teppanom as shown in Figure 1. The features of the prototype are extracted using the SIFT and SURF methods [23]. In order to obtain distinctive features that do not depend on the size and rotation of the image, the SIFT and SURF methods are a computer vision method for matching objects of two images with identical objects. The methods are popular in recognizing or classifying objects from images [24]. The SIFT operational principle is the calculation of the keypoint in areas where light intensity has changed around the feature. An example of keypoints in the prototype image is shown in Figure 2.

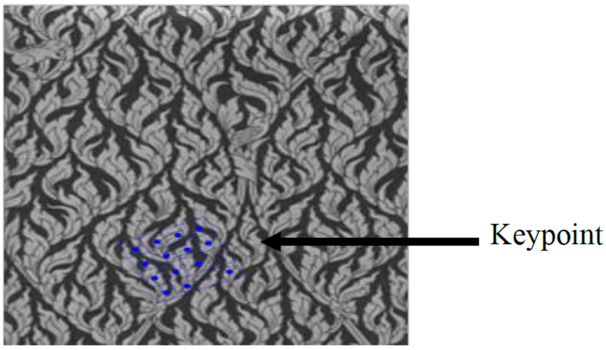


Figure 2. Example of keypoint in the prototype Kanokplew pattern image

Figure 2 presents an example feature of Kanokplew pattern for a keypoint. The prototype image of the Kanokplew pattern could be calculated 297 keypoints, the prototype image of the Poomkaobin pattern could be calculated 131 keypoints, the prototype image of the Prajamyam pattern could be calculated 1,203 keypoints, the prototype image of the Dokpudtan pattern could be calculated 233 keypoints, and the prototype image of the Teppanom pattern could be calculated 402 keypoints.

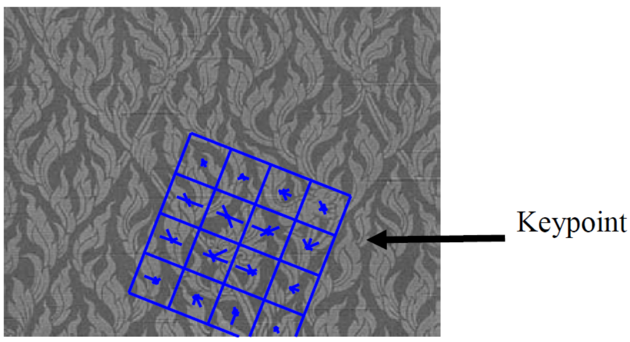


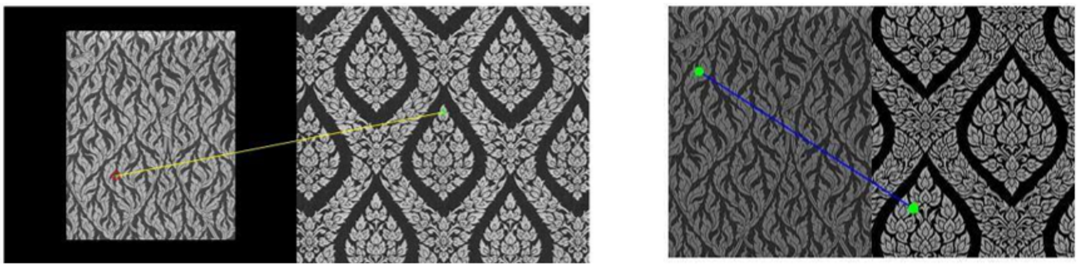
Figure 3. Example of keypoint in the tested Kanokplew pattern image

3.4.2. *Distinctive feature extraction of the tested images.* The tested images are extracted by the SIFT method along with the prototype images, in which the tested images do not need to be the same size as the prototype image, and the position of the pattern does not need to place at the same angle as the prototype image. An example of the feature matching is shown in Figure 4.

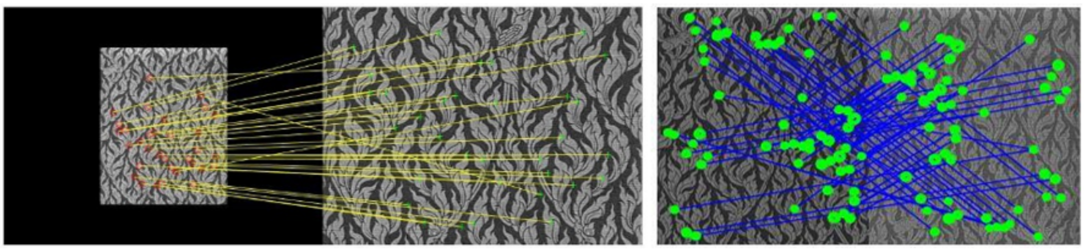
(a) Matching pairs between Kanokplew and Prajamyam

(b) Matching pairs between Kanokplew and Dokpudtan

(c) Matching pairs between Kanokplew and Teppanom



(d) Matching pairs between Kanokplew and Poomkaobin



(e) Matching pairs between Kanokplew and Kanokplew

FIGURE 4. Example of matching pairs of traditional Thai painting using SIFT and SURF techniques in comparison

In Figure 4, they are examples of the matching of the prototype Thai painting pattern, Kanokplew, with the five classes of Thai painting pattern images, showing a similar number of keypoints between the prototype image and each tested image by comparing the work between SIFT and SURF algorithms.

3.4.3. *Comparison between the features of tested and prototype images.* In the comparison process, the Euclidean distance is used between the features of tested and prototype images. The matching pair of keypoints with less displacement value than the threshold value is considered as a keypoint that has similar features to the prototype image. The tested images must be compared with the five prototype images and find the number of keypoints that have fewer displacement values than the threshold value, which is to find the number of keypoints similar to the prototype image.

At this stage, the tested images will be classified according to the similarity of the prototype image, divided into five classes according to the pattern of the prototype image as follows: Class I Kanokplew pattern, Class II Poomkaobin pattern, Class III Prajamyam pattern, Class IV Dokpudtan pattern, and Class V Teppanom pattern. The tested images that have the most similarity of keypoints to which prototype image will be classified in the same class as that prototype image: Kanokplew, Poomkaobin, Prajamyam, Dokpudtan, and Teppanom.

4. **Results and Discussion.** The accuracy experiment of Thai painting pattern classification using this proposed method with 50 images of Thai painting pattern consists of 10 images of each pattern: Kanokplew, Poomkaobin, Prajamyam, Dokpudtan, and Teppanom.

In feature extraction process, the similarity scores of the extracted keypoints of tested image and the keypoints of the prototype image are computed using Euclidean distance. If the keypoints have the similarity score greater than 0.9, the keypoints are considered as a matching feature. The keypoints of the prototype images consist of, 297 keypoints of the Kanokplew class, 131 keypoints of the Poomkaobin class, 1,203 keypoints of the Prajamyam class, 233 keypoints of the Dokpudtan class, and 402 keypoints of the Teppanom class. The five selected prototype images are the best optimal image of each class.

It is apparent from Table 1 that the summarized results of the comparative study of SIFT and SURF feature descriptors could clearly be seen that the SIFT used more feature keypoints than the SURF in every experiment class of all prototype pattern images. As in considering the time, the time taken by the proposed system for feature extraction and matching, the experiment has been implemented on a system of Intel Core i7-7500U (2.70 GHz) mobile workstation with 8 GB RAM.

Table 1. Comparative study of SIFT and SURF feature descriptors

	Classification results						
Detected feature keypoints	**Class I** *Kanokplew*	**Class II** *Poomkaobin*	**Class III** *Prajamyam*	**Class IV** *Dokpudtan*	**Class V** *Teppanom*	**Time taken for matching**	**Match rate (%)**
SIFT	674	523	458	437	460	0.17 sec.	74.78
SURF	479	352	285	271	255	0.05 sec.	75.12

The system runtime for feature extraction and matching was shown in Table 1, where SIFT and SURF features were analyzed on the entire database according to the total number of images. The experiment for feature matching with SIFT and SURF methods showed that there were numbers of the detected feature keypoints from each pattern in Classes I to V. The accuracy of the Thai painting pattern classification was shown in Table 1. There were 674 and 479 detected keypoints in Class I Kanokplew, 523 and 352 detected keypoints in Class II Poomkaobin, 458 and 285 detected keypoints in Class III Prajamyam, 437 and 271 detected keypoints in Class IV Dokpudtan, and 460 and 255 detected keypoints in Class V Teppanom for SIFT and SURF algorithms respectively. The result revealed that the system takes 2.48 seconds and 0.78 seconds for extracting SIFT and SURF features respectively. For the matching step, all possible matches for the prototype and test cases were considered. The system takes an average of 0.17 seconds and 0.05 seconds for matching SIFT and SURF feature vectors respectively.

The graph from Figure 5 indicated the number of feature keypoints that could be found in the five classes of Thai painting patterns. Especially in Class I Kanokplew and Class II Poomkaobin, there were numerous pattern details, as shown in Figures 1(a) and 1(b), resulting in a greater number of keypoints. In Class III Prajamyam, Class IV Dokpudtan, and Class V Teppanom, there were a similar number of keypoints. When comparing the searching methods, SIFT was able to find more pattern feature keypoints than SURF in all classes.

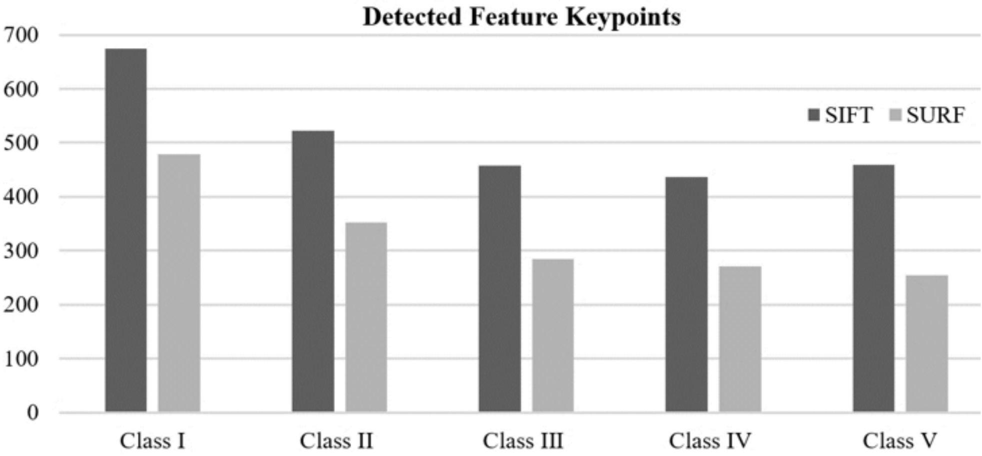


FIGURE 5. Comparison number of feature keypoints detected between SIFT and SURF

5. **Conclusion.** This research had investigated two feature detection methods using Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) for Thai painting pattern classification, which were two powerful tools for the feature detection component on the images in the computer vision and primarily used in pattern recognition, image retrieval, and many other applications in computer vision. Based on the experimental outcomes, it could be seen that the SIFT algorithm could detect more pattern feature keypoints and overall were more accurate in the feature-detector-descriptor for scale and affine variations, as compared to the SURF algorithm. SURF followed SIFT in the number of feature keypoints detected but the difference was considerably between both for the majority of the images. On the other hand, SIFT had suffered from speed. Not only SURF had feature-matching times less than SIFT, but also had a matching rate almost the same as SIFT. The overall performance of the SURF detector could be described as better than SIFT for most of the images. An implication of these findings was that the number of matches detected was not a decent indication of the performance evaluation of the algorithm, as the data yielded by this study disclosed that SIFT found more matching keypoints than SURF but the percentage of matching rate was less effective slightly. Further research should be done to construct these algorithms work for real-time matching, verifying other feature extraction algorithms, and finding the best feature extraction method.

REFERENCES

[1] B. Moghaddam, C. Nastar and A. Pentland, A Bayesian similarity measure for deformable image matching, *Image and Vision Computing*, vol.19, no.5, pp.235-244, 2001.

[2] P. Sykora, P. Kamencay and R. Hudec, Comparison of SIFT and SURF methods for use on hand gesture recognition based on depth map, *Proc. of AASRI Conference on Circuits and Signal Processing*, London, UK, pp.19-24, 2014.

[3] S. Gupta, K. Thakur and M. Kumar, 2D-human face recognition using SIFT and SURF descriptors of face's feature regions, *The Visual Computer*, pp.1-10, 2020.
[4] S. A. K. Tareen and Z. Saleem, A comparative analysis of SIFT, SURF, KAZE, AKAZE, ORB, and BRISK, *Proc. of International Conference on Computing, Mathematics and Engineering Technologies*, Sukkur, Pakistan, pp.1-10, 2018.
[5] P. Lu, Y. Ding and C. Wang, Multi-small target detection and tracking based on improved YOLO and SIFT for drones, *International Journal of Innovative Computing, Information and Control*, vol.17, no.1, pp.205-224, 2021.
[6] F. Virunhaphol, The development of Lai Kanok from the past to the present through multimedia, *Research and Development Journal Suan Sunandha Rajabhat University*, vol.5, no.1, pp.160-169, 2013.
[7] R. Niyomrath, *Benjarong Porcelains Wares and Nyonya Wares*, Suan Sunandha Rajabhat University, Bangkok, 2005.
[8] G. Lowe, Object recognition from local scale invariant features, *Proc. of International Conference on Computer Vision*, Corfu, Greece, vol.2, pp.1150-1157, 1999.
[9] D. G. Lowe, Distinctive image features from scale-invariant keypoints, *International Journal of Computer Vision*, vol.60, no.2, pp.91-110, 2004.
[10] H. Bay, A. Ess, T. Tuytelaars and L. V. Gool, SURF: Speeded Up Robust Features, *Computer Vision and Image Understanding*, vol.10, no.3, pp.346-359, 2008.
[11] A. Agarwal, D. Samaiya and K. K. Gupta, A comparative study of SIFT and SURF algorithms under different object and background conditions, *Proc. of the 18th IEEE International Conference on Industrial Technology*, Toronto, Canada, pp.42-45, 2017.
[12] S. Routray, A. K. Ray and C. Mishra, Analysis of various image feature extraction methods against noisy image: SIFT, SURF and HOG, *Proc. of the 2nd IEEE International Conference on Electrical, Computer and Communication Technologies*, Tamil Nadu, India, vol.1, no.1, pp.1-5, 2017.
[13] N. M. Suaib, M. H. Marhaban, M. I. Saripan and S. A. Ahmad, Performance evaluation of feature detection and feature matching for stereo visual odometry using SIFT and SURF, *IEEE Region 10 Symposium*, pp.200-203, 2014.
[14] G. Pangsomboon, W. Laonawatthana, P. Oungcharoon, S. Chanyachatchawan, R. Ranokphanuwat and N. Tuaycharoen, Mobile device augmented reality tour application for Ramayana story on Wat Prakaew wall, *Proc. of the 10th National Conference on Computing and Information Technology*, Phuket, pp.316-321, 2014.
[15] K. S. Fu, *Applications of Pattern Recognition*, CRC Press, Florida, 2019.
[16] D. Willy, A. Noviyanto and A. M. Arymurthy, Evaluation of SIFT and SURF features in the Songket recognition, *Proc. of International Conference on Advanced Computer Science and Information Systems*, Bali, Indonesia, pp.393-396, 2013.
[17] A. T. Nasser and N. Dogru, Signature recognition by using SIFT and SURF with SVM basic on RBF for voting online, *Proc. of International Conference on Engineering and Technology*, Antalya, Turkey, pp.1-5, 2017.
[18] Y. Li, Q. Li, Y. Liu and W. Xie, A spatial-spectral SIFT for hyperspectral image matching and classification, *Pattern Recognition Letters*, vol.127, pp.18-26, 2019.
[19] Y. Ke and R. Sukthankar, PCA-SIFT: A more distinctive representation for local image descriptors, *Proc. of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Washington, D.C., USA, DOI: 10.1109/CVPR.2004.1315206, 2004.
[20] J. Ma, J. Jiang, H. Zhou, J. Zhao and X. Guo, Guided locality preserving feature matching for remote sensing image registration, *IEEE Trans. Geoscience and Remote Sensing*, vol.56, no.8, pp.4435-4447, 2018.
[21] N. U. R. Malik, A. G. Airij, S. A. Memon, Y. N. Panhwar, S. A. Abu-Bakar and M. A. El-Khoreby, Performance comparison between SURF and SIFT for content-based image retrieval, *Proc. of IEEE International Conference on Signal and Image Processing Applications*, Kuala Lumpur, Malaysia, pp.214-218, 2019.
[22] A. Sedaghat and H. Ebadi, Remote sensing image matching based on adaptive binning SIFT descriptor, *IEEE Trans. Geoscience and Remote Sensing*, vol.53, no.10, pp.5283-5293, 2015.
[23] R. J. Alitappeh, K. J. Saravi and F. Mahmoudi, Key point reduction in SIFT descriptor used by subtractive clustering, *Proc. of the 11th International Conference on Information Science, Signal Processing and Their Applications*, Montreal, QC, Canada, pp.906-911, 2012.
[24] X. Zhang, Y. H. Yang, Z. Han, H. Wang and C. Gao, Object class detection: A survey, *ACM Computing Surveys*, vol.46, no.1, pp.1-53, 2013.