

A Novel CMF Detection using Particle Swarm Optimization Technique

Prof: Kanchi K Sen, Lekshmi A C (Student: Mtech CSE)
Kerala Technical University
Department of Computer Science Engineering,
Younus College of Engineering and Technology,
Vadakkevila, Kollam- 691010

Abstract—CMF(Copy Move Forgery) is a simple and effective operation for the creation of forged digital images by copying and pasting a continuous portion of pixels in an image after possible geometrical and illumination adjustment to a different location in the same image. To identify these forged digital images are one of the principle problem in image forensic. The several existing methods to detect region duplication based on searching the exact copies of pixel blocks cannot detect if those copied regions that had undergone transformations such as scaling or rotation. The SIFT(Scaled Invariant Feature Transform) technique had overcome this problem. Various approaches under the SIFT framework are most acceptable ways for CMF detection (CMFD) due to their robust performance. But for certain images such as images having very few matched keypoints these approaches can-not produce satisfactory results and sometimes these approaches produces error results. According to the observations, one of the reasons for this drawback of SIFT is that detection result produced by the SIFT based frame work highly depend on experimentally determined parameters. These EPV (Experimental Parameter Values)s are only applicable to few images, which limit their application. To solve this problem a novel approach of integrating particle swarm optimization(PSO) technique into the SIFT framework is proposed in this paper. It utilizes the PSO Algorithm to generate customized parameters values for images, which are used for CMF detection under SIFT based framework. This paper is also integrating a new module of image denoising in preprocessing step for better detection result.

Index Terms—CMFD, SIFT, EPV-CMFD, PSO, CPV-CMFD, Adaptive Median Filter

I. INTRODUCTION

The increasing availability and sophistication of digital imaging technology (digital cameras, computers, and photo editing software) and the popularity of the Internet, digital images have become our main information source. According to Merriam Webster, forgery is defined as the crime of falsely and fraudulently making or altering a document. Therefore digital image forgery involves falsely altering digital images. It is easy to expect that a forged image will cause troubling consequences. Forged images could be used to mislead the public opinion or for distorting the truth in news reports. They can also be used to destroy someone's reputation and privacy by changing his face in a photo with someone else. Academic papers could also contain some forged images that are used to exhibit better experimental results. Moreover, image

forgery can be used for miscarrying justice by wiping off an important object or person from an evidence image. As a result, the authenticities of images cannot be taken for granted any more.

CMF(Copy Move Forgery)[3][1] is a simple and effective operation for the creation of forged digital images by copying and pasting a continuous portion of pixels in an image after possible geometrical and illumination adjustment to a different location in the same image. To identify these forged digital images are one of the principle problem in image forensic.

All the CMF detection approach under the SIFT based framework have one common drawback, ie their detection result are extremely dependent on the selection of parameter values. In various literature, different parameter values may be seen. Normally the values are set according to experi-ence or some experiments on a number of forgery images. However these experience parameter value are applicable to a few images. Some time duplicated regions identified by the experience parameter value(EPV) based SIFT are incor-rect while true duplicated regions in the forged image are missed. Sometime the true matched keypoints indicated by EPV-SIFT[12] is too less to indicate the duplicated regions accurately. To solve the issue coming in EPV-SIFT, in this work we are trying to increase the efficiency of existng SIFT based CMF(Copy Move Forgery) Detection approaches by with Particle Swarm Optimization(PSO) Technology.

The aim of this work is to automatically generate suitable parameter values for each test image. It include two components one is elemental detection and the other is parameter estimation. Elemental detection[12] is derived from SIFT based framework. Its task is to detect CMF images. Parameter estimation[12] is a new component, which can generate suitable parameter values for each image. Using these values to determine the corresponding image may produce a satisfactory result. The Particle Swarm Optimization(PSO) algorithm is used to estimate parameter values. It is also integrating an adaptive median filtering method for image denoising in the preprocessing step.

II. EXISTING SYSTEM

A common manipulation in tampering with digital images is known as region duplication, where a continuous portion of pixels are copied and pasted to a different location in the same image. To make convincing forgeries, the duplicated regions are often created with geometrical or illumination adjustments. Fig. 2.1 exemplifies two main usages of duplicated regions in creating forgery images. For the example shown in the left panel, a rotated duplicated region is used to conceal undesirable contents in the original image. In the other case, two duplicated regions that are scaled, rotated, and mirrored are used to create contents that are not in the original image. These duplicated regions are well blended into the surroundings at the target locations, and become very difficult to detect visually.

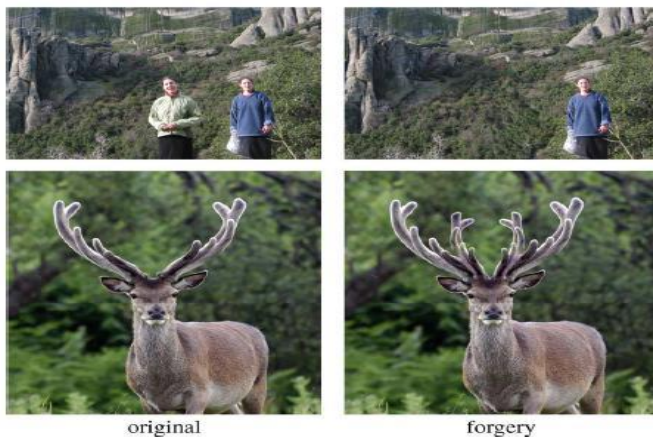


Fig. 1. Two original digital images and forgery images created based on them using duplicated and distorted regions.

In the recent years, approaches under SIFT based framework are widely applied to detect CMF, because they have robust performance in detecting duplicated regions with geometrical or illumination adjustments. Huang et al. proposed a preliminary SIFT based framework in 2008. They detected keypoints and build SIFT descriptors by using SIFT algorithm and then matched these keypoints to find general duplicated regions. They noticed that a parameter setting is important for detection results, so they made many experiments to find the best parameter values. Amerini et al, Pan and Lyu all of them paid highly attention to estimate duplicated regions. Although noticing the influence of parameter, they only set specific parameters for their image database. Jing-Ming Guo et al. used a DAISY descriptor instead of SIFT descriptor to detect uniform texture images. There are many efforts similar to Jing Ming Guo, which changed some algorithms of SIFT based framework to meet some detection purposes. However, they set parameters with their experience, which is only applicable to a few images. There are some counter forensics of SIFT based CMF detection, the essence of which is to process some key points and make those keypoints to be ignored by dissatisfying condition. However, the detection condition is determined basing on some parameters. Thus parameter

setting is important for forensic and counter-forensic. With the development of digital images, there are many mature tools that can detect images directly such as detect image keypoints, bulid descriptors and match keypoints, etc. They are helpful in coding, but may cause researchers to ignore the importance of detection parameters. Jian Li et al. segmented a test image into independent patches, and then used SIFT based detection approach to detect those patches. In their approach the used the vlFeat software to detect SIFT keypoints and build descriptors, with default values being used for detection parameters.

A. SIFT Based CMF Detection

Scale-invariant feature transform (SIFT) is an algorithm in computer vision to detect and describe local features in images. The algorithm was published by David Lowe[6] in 1999. In SIFT image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters. In preprocessing we prepare

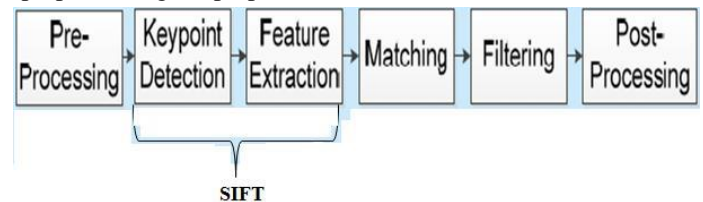


Fig. 2. SIFT Based Feature Extraction.

the original image for detection. First the image is scaled or resized the image to a suitable size. Here the original image is resized to a 256 256 image. Then convert the resized RGB image to a grayscale image. The Keypoint detection and feature extraction are done by SIFT algorithm[10][11][9]. Matching is to determine matched keypoints based on the feature vector. The regions around the matched key points are probably duplicated regions. Filtering is to eliminate mis matched keypoints which are identified as matched keypoints during matching but actually they are not. Post processing is to delete duplicated regions or estimate geometric transformation parameters and so on when necessary.[10] It depend on the different detection purpose.

B. SIFT Based CMF Detection using Particle Swarm Optimization Algorithm

The goal of this approach is to automatically generate suitable parameter values for each test image. The SIFT-PSO[12] includes two component, one is elemental detection and the other is parameter estimation. Elemental detection is derived from SIFT based framework. Its task is to detect CMF images. Parameter estimation is a new component, which values for each image. Using these values to detect the corre-sponding image may produce a satisfactory result. The PSO algorithm[4][7][12] is applied to estimate parameter values. The CMF detection approach using PSO generates suitable parameter values automatically for each image according to the features of the image.

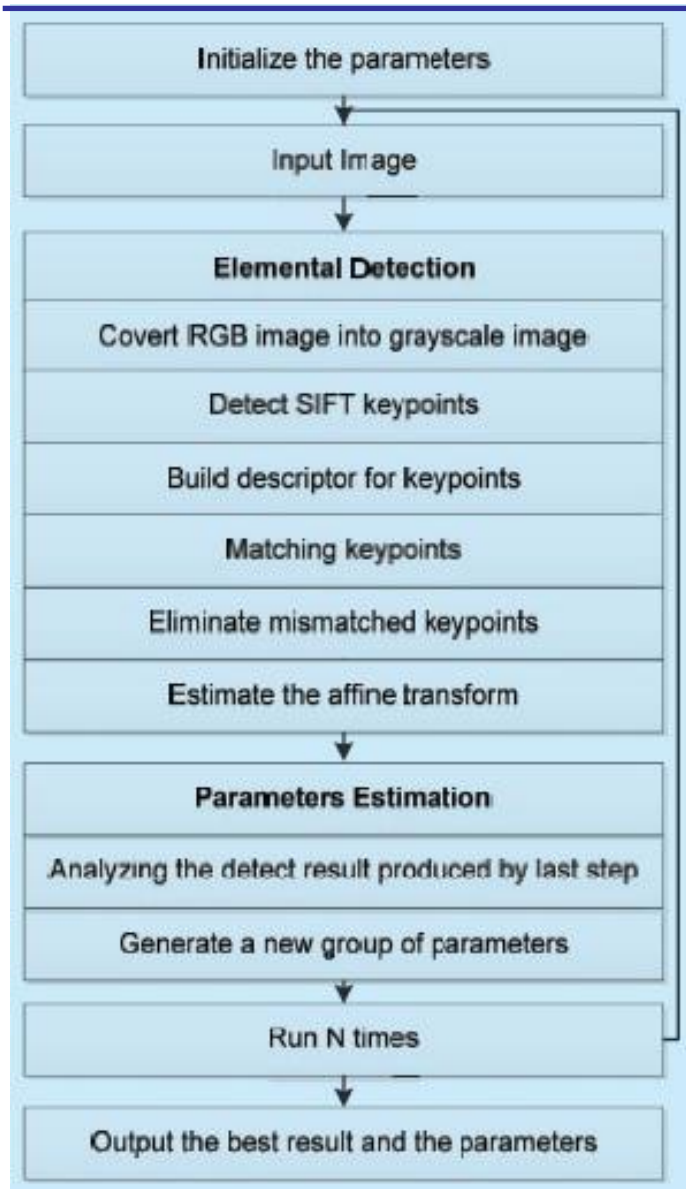


Fig. 3. The SIFT CMF Detection using PSO.

1) The Elemental Detection: This component consist of 5 steps that are similar to those of the SIFT based framework. In preprocessing, a RGB image should be converted into a gray scale image. In Keypoint Detection and Feature Extraction, the keypoints are detected from the test images and the SIFT descriptors a 128 dimensional feature vector, is built for the corresponding keypoints. In matching, the best bin first algorithm[2] is applied to match keypoints. In Filtering, the mismatched keypoints should be eliminated. If the distance between two matched keypoints is too small, this pair of matched keypoints will possibly be a mismatch. The descriptor of such pair of matched key points may be very similar. In this paper if the distance of the paired is smaller than a preset value Dis_{min} they will be removed, which can reduce the probability of mismatching keypoints. The other mismatched keypoints are eliminated by RANSAC algorithm[5].

2) Parameter Estimation: The parameters of the SIFT framework are optimized. The reason for the choice of these parameters will make evidence for final detection

results. $S, \sigma, Thresh$: They are used in keypoint detection. Chose $S=3, \sigma = 1:6, Thresh = 0.03$. Rob Hess chose $thresh=0.04$. Accord-ing to the literature and our experience the domains of the three parameters are set as $S \in [3; 6]; \sigma \in [1; 2]; Thresh \in [0:0001; 0:1]$: It is used in matching. Pan et al used $\sigma = 0:5, Haung$ chose $\sigma = 0:45$, Amerini et al and Irene Amerini set. $\sigma = 0:6$ The domain of σ is set as $[0:01; 1]$. Dis_{min} :It is used in filtering. Pan chose default values of $M=100$ and R which is used in RANSAC is decided by the PSO[4] algorithm. The domain of

R is set as $R \in [1; 10]$

a) Evaluation Function: Although the metric for de-tection approach are various in different literature, the core ideas are similar: More True Matched Keypoints(TMKS)[12], less mismatched keypoints(MMKs) and less missing matched keypoints(Miss-MKs). The evaluation function is defined as

$$P_{match} = \frac{T_{MK_t} + \sigma}{T_{MK_t}} \quad ; \quad \begin{cases} 10 & ; \text{if}(MMK_t \leq 10) \\ MMK_t & ; \text{if}(MMK_t > 10) \end{cases} \quad (1)$$

The parameter estimation will chose the highest value of P_{match} as the best result.

III. PROBLEMS IN CURRENT SIFT CMF DETECTION

The detection result of SIFT CMFD highly depends on the selection of parameter value in it each step of detection process is an obvious drawback exist in existing CMF detection approaches. Normally these parameter values are determined by experience or result of test against a no:of forgery images. However, different research teams chose different values, which are only applicable for certain images. When these experiment parameter values are applied for a large no:of images the limitations such as: The duplication regions cannot produce keypoints or keypoints in the duplicated regions are not stable and hence are eliminated in filtering. No matching keypoints pairs satisfy the match conditions. If there are too many similar objects in an image and parameter values are chosen inappropriately some similar regions may mistakenly regarded as duplicate regions. Using EPVs, there may be very few keypoints being found in some duplicated regions, or even no keypoints can be found. In this situation, it is difficult to estimate duplicated regions accurately.

PSO integrated SIFT based CMF detection approach is robust against various attack, which include plain copy move, Gaussian noise, JPEG Compression, rotation and scaling. Duplicated region is move to the target location without any additional modification thus it is robust against plain copy move attack. The images intensities are normalized between 0 and 1 and added zero mean gaussian noise with standard deviation of 0.02, 0.04, 0.06, 0.08, and 0.10 to the duplicated regions.Hence it is robust against Gaussian noise attack. JPEG Compression is a common global disturbance, here the quality

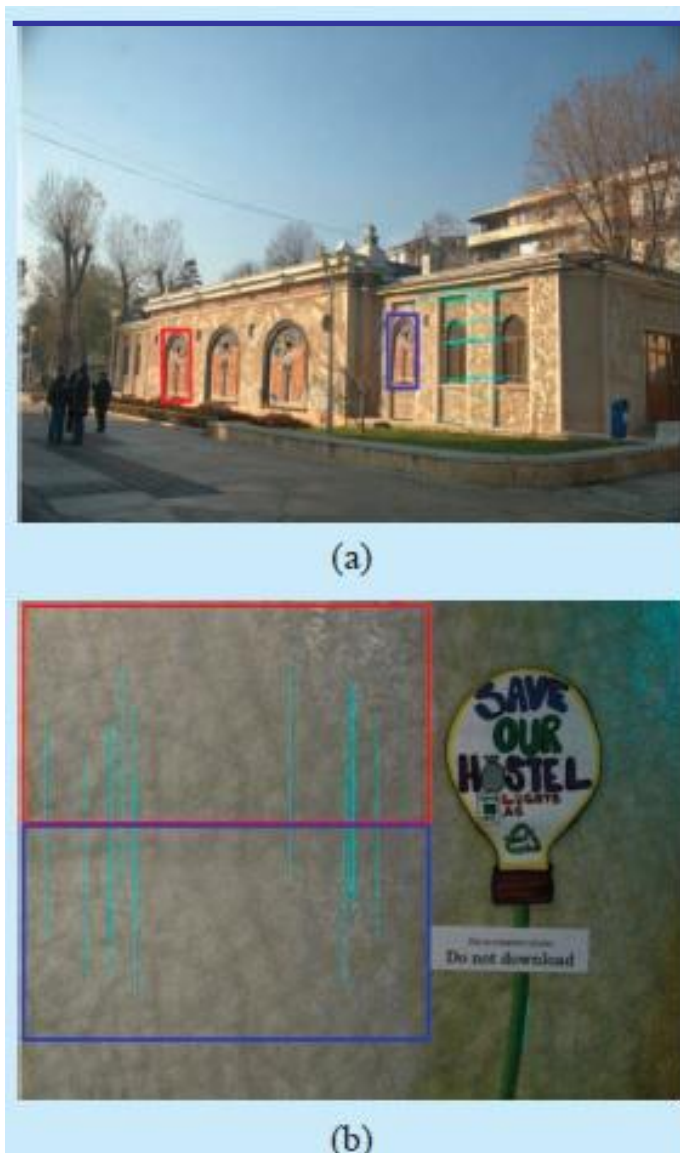


Fig. 4. Images detected by EPV-SIFT. a) error result is shown and b) The true matched keypoints are too less to estimate duplicated regions accurately.

factor varied between 100 and 20 in step of 10 degree. The duplicated regions are rotated between 2 to 10 degree in steps of 2 degree, and larger rotation angles of 20, 40, 60 and 80 degree. Thus it is rotationally invariant. The duplicated regions are rescaled by 50%, 80%, 101%, 103%, 105%, 107%, 120% and 200%. So this algorithm is robust against scaling attack. The PSO can automatically generate customized parameter values for images, which are independent of neither experience nor experiment. According to our observation PSO integrated SIFT can achieve much better result than EPV-SIFT.

But CMFD-PSO also produce error result if the image contains salt and pepper noise. In these situations the forged area may not be identified correctly even though after several iterations since it produce different feature descriptors for those noised areas. Fat-tail distributed or impulsive noise is

sometimes called salt and pepper noise or spike noise. An image containing salt and pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise is caused by analog to digital converter errors, bit errors in transmission, etc.

IV. PROPOSED SYSTEM

Here an improved CMF Detection method using PSO algorithm is proposed. For getting efficient detection result we should make the image noise free. Image denoising is the process of eliminating or reducing noise from a degraded image with an objective to recover the original image. Image denoising is done in the field of military, aerospace, scientific research, forensic etc for better analysis, for better compression, for making image visually pleasant we need to perform image restoration from noisy image.

Noise is a quality of degradation factor. They are unwanted unrelated information present in images. The noise get introduced into images via: Electrical system used for storage, Transmission through communication channels, Processing or acquisition, Environmental conditions, etc. The noise get distributed into images in terms of non correlated neighboring pixels. Based on its distribution it is represented as some mathematical or statistical model. Noises are classified into many types such as Impulse Noise, Poisson Noise, Exponential Noise, Thermal Noise, etc. Among these, impulse noise frequently corrupts the images due to the limitations and defects in the process and/or media of acquisition and transmission. This noise gets distributed over the image in terms of non-correlated neighboring pixels. The impulse noise is categorized into fixed-value impulse noise and random-value impulse noise.

The image denoising or filtering technique can be mainly classified into two groups such as linear filter and non linear filter. The mean and weiner filter is an example of linear filters. Where as median filtering is a non linear technique. The nonlinear filters are good for removing impulse noise. Here in the proposed system we are adding a module for image denoising. In this system an effective non linear filtering method is used so as to denoise the image from impulse noise. An adaptive median filtering technique is introduced.

A. Median Filtering

The median filter, originating from the robust estimation theory and well studied in the literature, is a popular nonlinear filter. Its statistical and deterministic properties have been thoroughly studied from a theoretical point of view. Although it is simple in formulation, the median filter yields good edge preservation and impulsive noise suppression characteristics that are highly desirable in image processing. This is evidenced by the amount of research work published and the widespread deployment of the median filter in a variety of applications. Its disadvantages, mainly the inflexibility in the filter structure, the destruction of fine image details, and its relatively poor performance in attenuating additive Gaussian noise and other short-tailed noise, have led to the development of various

modifications and extensions of the fundamental median filter. It used $N \times N$ size of filtering window for noise removal. This $N \times N$ matrix contains N^2 element. Median filter operation first sorts all the elements of filtering window, then it select the central element of that sorted sequence called median value. The central pixel of filtering window will then replace with this median value. Median filtering algorithm uses a window containing an odd number of pixels. For digital image, there is a window with an odd matrix, then calculate the median value of the odd matrix as the output pixels. The filtering effect mainly depends on the size of the matrix and the number of pixels.[8]

The median filter was extended to various rank-orderbased filters, such as the loweruppermiddle filters the fuzzy rank filters and the rank-conditioned rank-selection filters[8]. To tackle the problem of the destruction of image details, a lot of image detail-preserving filters were proposed, such as multistage median filters, FIRmedian hybrid filters, truncation filters, and various noise adaptive switching median filters based on some noise detection mechanisms.

In this paper an adaptive median filter[13] is used where the size of median filter window will change adaptively. As we know, the size of detection window affects the result of noise removal. Small filter window limits inhibition capability of noise but can preserve the image details better, on the contrary, large filter window strengthens the inhibition capability of noise but loses much more details which results in blur. Furthermore, using a fixed window size in the whole image is not very reasonable. For example, classic filters which use fixed window size have good performance in removing low density of noise but show ineffectiveness in removing high density of noise. With respect to the density of noise and the feature of different parts of image, the proposed algorithm adaptively varying the detection window size to improve the noise removal ability. We start from a 3×3 windows. If the median pixel in this window is the extreme pixel, we enlarge the detection window size. The step is repeated and stopped when the median pixel is not the extreme pixel or the window size reaches to a given maximum window size which is related with the intensity of noise. Thus in the preprocessing module of CMF Detection using PSO we are integrating an additional process of image filtering through adaptive median filter to get better detection results.

V. RESULTS

Had proved the concept of integrating PSO to the SIFT based framework for better detection of CMF images. The PSO can automatically generate customized parameter values for images, which are independent of neither experience nor experiment. According to our observation PSO integrated SIFT can achieve much better result than EPV-SIFT. Due to the denoising step added to the preprocessing had improved the detection accuracy. As well as normalizing the pixel values in the preprocessing had made the detection result more illumination invariant.

VI. CONCLUSION

In this paper we propose a novel approach, for improving the CMF detection. Comparing with the existing work this paper is trying to make enhancement such as put forward the concept of applying the PSO algorithm to the CMF detection. It integrates the PSO algorithm into the SIFT based framework and also an efficient median filtering process in the preprocessing step to perform the CMF detection.

Although CMF detection using PSO is applicable to most of the CMF images, accidentally, we find that the approaches uses SIFT-based framework cannot find reliable keypoints in uniform texture regions or when the duplicated regions are too small, as a future work we want to focus on new ways to improve the detection performance for such cases.

REFERENCES

- [1] Irene Amerini, Lamberto Ballan, Roberto Caldelli, Alberto Del Bimbo, and Giuseppe Serra. A sift-based forensic method for copy-move attack detection and transformation recovery. *IEEE Transactions on Information Forensics and Security*, 6(3):1099–1110, 2011.
- [2] Jeffrey S Beis and David G Lowe. Shape indexing using approximate nearest-neighbour search in high-dimensional spaces. In *Computer Vision and Pattern Recognition, 1997. Proceedings., 1997 IEEE Computer Society Conference on*, pages 1000–1006. IEEE, 1997.
- [3] Vincent Christlein, Christian Riess, Johannes Jordan, Corinna Riess, and Elli Angelopoulou. An evaluation of popular copy-move forgery detection approaches. *IEEE Transactions on information forensics and security*, 7(6):1841–1854, 2012.
- [4] Russ C Eberhart, James Kennedy, et al. A new optimizer using particle swarm theory. In *Proceedings of the sixth international symposium on micro machine and human science*, volume 1, pages 39–43. New York, NY, 1995.
- [5] Martin A Fischler and Robert C Bolles. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM*, 24(6):381–395, 1981.
- [6] Hailing Huang, Weiqiang Guo, and Yu Zhang. Detection of copy-move forgery in digital images using sift algorithm. In *Computational Intelligence and Industrial Application, 2008. PACIIA'08. Pacific-Asia Workshop on*, volume 2, pages 272–276. IEEE, 2008.
- [7] James Kennedy. Particle swarm optimization. In *Encyclopedia of machine learning*, pages 760–766. Springer, 2011.
- [8] Heng Liu and Ningning Zhou. An improved filtering algorithm based on median filtering algorithm and medium filtering algorithm. In *Advanced Computational Intelligence (ICACI), 2012 IEEE Fifth International Conference on*, pages 574–578. IEEE, 2012.
- [9] David G Lowe. Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60(2):91–110, 2004.
- [10] Xunyu Pan and Siwei Lyu. Detecting image region duplication using sift features. In *ICASSP*, pages 1706–1709. Citeseer, 2010.
- [11] Xunyu Pan and Siwei Lyu. Region duplication detection using image feature matching. *IEEE Transactions on Information Forensics and Security*, 5(4):857–867, 2010.
- [12] Shi Wenchang, Zhao Fei, Qin Bo, and Liang Bin. Improving image copy-move forgery detection with particle swarm optimization techniques. *China Communications*, 13(1):139–149, 2016.
- [13] Ningning Zhou and Shaobai Zhang. An adaptive image mixed noise removal algorithm based on mmtd. In *Digital Information Processing, Data Mining, and Wireless Communications (DIPDMWC), 2016 Third International Conference on*, pages 93–98. IEEE, 2016.