Enhancing Image Copy-Move Forgery Detection using Particle Swarm Optimization Techniques

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ABSTRACT: Copy-Move Forgery (CMF) is a simple and effective operation to generate forged digital images. Recent, techniques on Scale Invariant Features Transform (SIFT) are commonly used to detect CMF. Various approaches under the SIFT- framework are the most acceptable ways to CMF detection due to the robust performance of SIFT. However, for some CMF images, these approaches cannot produce satisfactory detection results. For instance, the number of the matched keypoints may be too less to prove an image to be a CMF image or to produce an accurate result. These values are only applicable for few images, which limits their application. To solve the problem, a novel approach names as CMF Detection with Particle Swarm Optimizations (PSO) algorithm into the SIFT-based framework. Sometimes these approaches may even produce error results. According to our observations, one of the reasons is that detection results produced by the SIFT-based framework are highly depending on parameters whose values are often determined with experiences. It utilizes the PSO algorithm to generate customized parameter values for images, which are used for CMF detection under the SIFT=based framework. Experimental results show that CMFD-PSO has good performance.

Keywords: CMF: Enhancing copy-move forgery detection: SIFT: region duplication: digital image forensics.

I INTRODUCTION

Copy-Move Forgery (CMF) is a simple and typical operation that tampers with an image by copying at least one part of the image and pasting it to a different location of the same image [6]. The Scale-Invariant Features Transform (SIFT)\ has been proved to have robust performance in detecting this kind of forgery.

Image security is a key issue in any field that makes use of digital images. Images have long been a part of the forensic investigation and law enforcement, an example of which include images of criminals, images of crime scenes, biometric images, etc. However, with the development of the sophisticated techniques for digital image forgery and the low cost to obtain a high-quality digital image, anyone can manipulate a digital image easily without leaving visible clues. Accordingly, digital image forensics has emerged as an important research field.

Unfortunately, all classical CMF detection approaches under the SIFT-based framework have one common drawback, i.e., their detection effects 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 experience or some experiments on a number of forgery images. However, these experience parameter values (EPV) are only applicable to few images. The approaches under the SIFT-based framework, which use the EPV, are names EPV-SIFT in this paper. Sometimes, duplicated regions identified by PEV-SIFT are false while true duplicated regions in a forged image are missed. Sometimes, the number of true matched key points (TMKs) indicated by EPV-SIFT is too less to estimate the duplicated regions accurately. Two examples are shown in Fig.1.

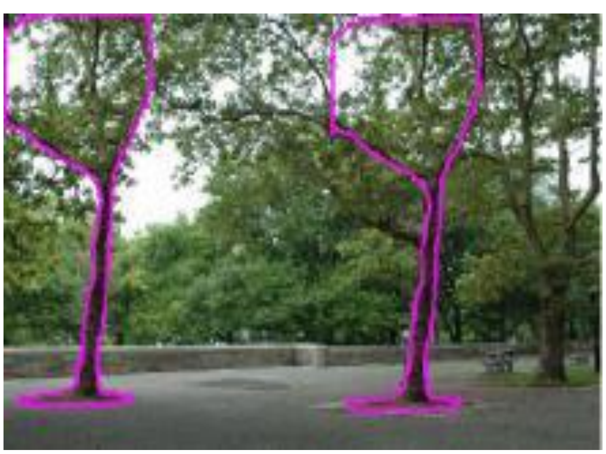
To handle the issue of EPV-SIFT parameters setting, we integrate the Particle Swarm Optimization (PSO) algorithm into the SIFT framework and propose a new approach to detecting CMF. We name our approach as CMF Detection with PSO, or CMFD-PSO, which automatically determines customized parameter values (CPV) for images. With the help of CPV, forged images that cannot be detected by EPV-SIFT will be detected easily. In a word, detection with CPV can obtain much better results than that with EPV.

The rest of this paper is organized as follows. Section II introduces related work. Section III analyzes problems exist in classical SIFT-based CMF detection with EPV. Section IV presents the design of our new approach. Section V devises experiments to test and evaluate our approach. Section VI concludes the paper.

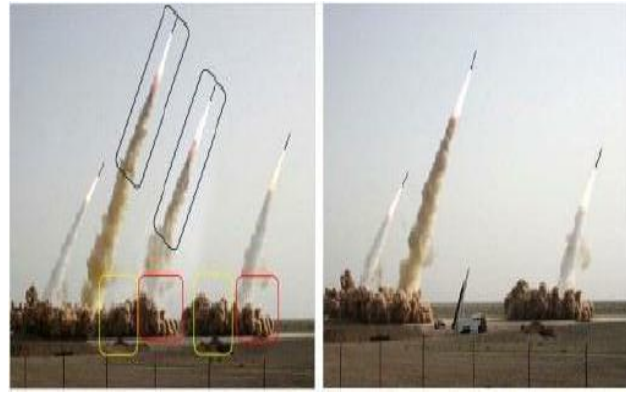
II. RELATED WORK

Several techniques in digital images forensics are employed to detect CMF images. In recent years, approaches under the SIFT-based framework are widely applied to detect based CMF, because they have robust performance in detecting the duplicated regions with geometrical or illumination adjustments. Huang etel. Proposed a preliminary SIFT-based framework in 2008 [3]. They detected SIFT key points and built SIFT descriptors using SIFT algorithm, and then matched these key points to find generally duplicated regions. They noticed that a parameter setting is important for detection results so that they made many experiments find the best parameter value. However, they just found the importance of one parameter but ignored the others.

Amerini et al. [7], Pan and Lyu [6,9], all of them paid high attention to estimating duplicated regions. Although noticing the influence of parameters, they only set specific parameters for their image database. Jing-Ming Guo et al. used DAISY descriptor to detect uniform texture images [10]. There are many efforts similar to Jing-Mingo Guo, which changed some algorithms of theSIFT-based framework to meet some detection purposes.



(a)EPV-SIFT: An error result is shown



(b) Key points to estimate duplicated regions

Fig.1 Images are detected by EPV-SIFT. (a) An error result is shown. (b) The true matched key points are too few to estimate duplicated regions accurately counter-forensics of SIFT-based copy-move detection, the essence of which is to process some key points and make those key points to be ignored by dissatisfying detection condition. However, the detection condition is proposed basing on some parameters. In conclusion, setting parameters is very important for forensics and counter-forensics. With the development of digital images, there are many mature tools that can detect images directly, such an extract image key points, build descriptors, and match key points, etc.

III. FORMULATION OF PROBLEMS

This section analyzes problems in parameter setting after a brief description of the SIFT-based framework.

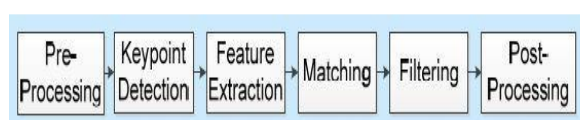


Fig 2: Common workflow of SIFT-based CMF framework

3.1 The SIFT-based framework

Pre-Processing is to prepare an image for detection, such as converting an RGB image into a grayscale image with standard color space conversion.

CMF detection approaches under the SIFT-based framework work in a general waythat may be divided into

Pre-Processing. Keypoint detection.Feature Extraction, Matching, Filtering, and Post-Processing, as shown in Fig 2.

Feature Extraction is to build a descriptor, i.e. a feature vector, for each key point based on its relationship with the surrounding pixels.

Keypoint Detection is to find points that are stable for geometric transformation and illumination transformation as key points.

Filtering is to eliminate mismatch key points, which are identified as matched key points during Matching, bu actually they are not.

Matching is to determine matched key points based on feature vectors. The regions around the matched key points are probably duplicated regions.

Post-processing is to delete duplicated regions, or estimate geometric transformation parameters, and so on, when necessary. It depends on different detection purposes.

The effects of the CMF detection workflow may be shown as Fig. 3.

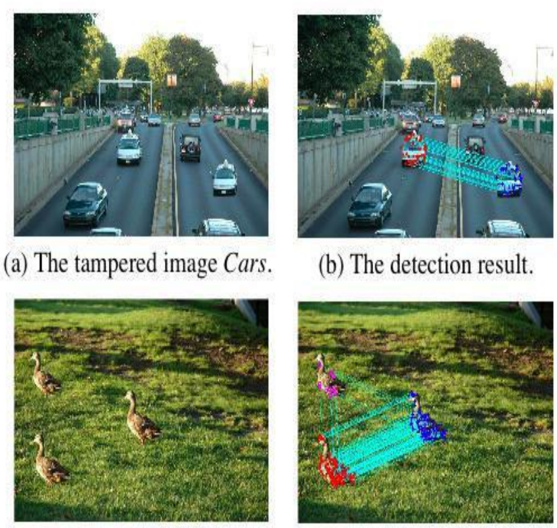
3.2 Problems in parameter values selection

As detection results depend on the selection of parameter values, an obvious drawback exists in existing CMF detection approaches. Normally, these parameter values are determined by experiences or results of thetest against a number of forgery images. However, different research teams choose different values, which are only applicable to certain images. When they are used to detect a large number of images, the following limitations appear.

1) The number of the matched key points is limited. Using EPVs, there may be very few key points being found in some duplicated regions, or even no key point can be found. In this situation, it is difficult to estimate duplicated regions accurately. To prove that the image is a CMF one with so few matched key points. Some typical examples are shown in Fig 1 (b).
2) Duplicated regions cannot be detected. There are two scenarios. First, the duplicated regions cannot produce key points, or the key points in the duplicated regions are not stable and hence are eliminated in Filtering. Second, no matched key point pairs satisfy the match conditions.
3) Detected regions are not duplicated ones. If there are too many similar objects in an image and parameter values are chosen inappropriately, some similar regions may be mistakenly regarded as duplicated regions, though actually they are native regions in the original image.

IV. DESIGN OF OUR APPROACH

The goal of our approach, CMFD-PSO, is to automatically generate suitable parameter values for each test image. The flow chart of CMFD-PSO is shown in Fig 4. It includes two components, one of which is Elemental Detection.



(a) The tampered image *Cars*. (b) The detection result.

(c) The tampered image *Goslings*. (d) The detection result.

Fig. 3 Detecting CMF under SIFT-based framework

Elemental Detection is derived from the SIFT-based framework. Its task is to detect CMF images. Parameters Estimation is a new component, which can generate suitable parameter values for each image. Using these values to detect the corresponding image may produce a satisfactory result. The PSO algorithm [15,16] is applied to estimate parameter values. To our knowledge, none of the existing CMF detection approaches use the PSO algorithm.

4.1 Overview of CMFD-PSO

CMFD-PSO generates suitable parameter values automatically for each image according to the features of the image. With these parameter values, Elemental Detection can produce better results.

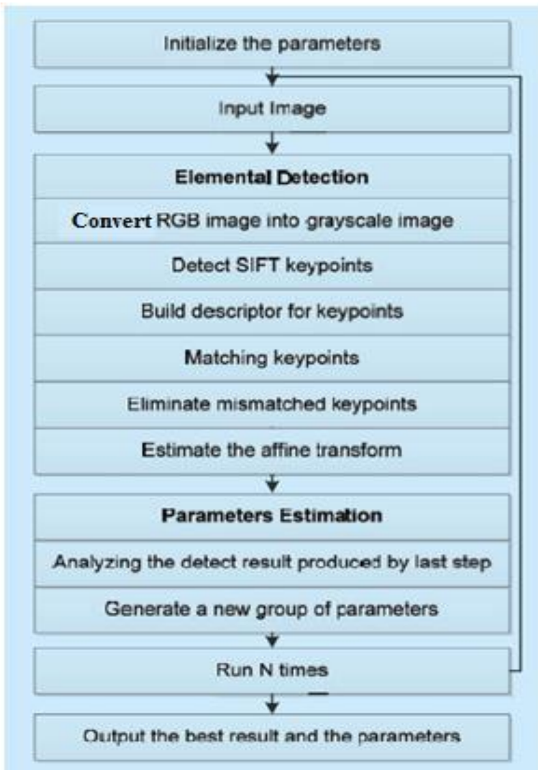


Fig. 4 the flow chart of our approach, CMFD-PSO

The first step is to identify the input and the output of the SIFT-based framework. The input includes an image and a group of parameters. The output is only the number of matched key points, which is used to evaluate whether the results is good. We turn parameter value estimation into an issue of theoptional solution. An evaluation criterion is created to make detection decision. The criterion is formed by the number of matched key points. When the criterion reaches extreme value, theoptional solution will turn out. In PSO, the parameter value estimation issue can be expressed as:

$$D_{Result} = f(X), \quad X = (x_1, x_2, x_3, x_4 \ldots)$$

X is a group of input parameters: f(x) is detection process. Dresult is the detection result. By adjusting the values of X, Dresult can converge to the extreme value.

In this paper, the PSO algorithm is applied to solve the optimal solution problem. The PSO algorithm is proposed by Eberhart and Kennedy in 1996 to model thesocial behavior of bird flocking or fish schooling. The algorithm is suitable for solving minimization or maximization problems.

Usually, there are some solutions for the optimal solution problem. If the method of exhaustion is used, it will cost a lot of time. It may take more than one year to detect one image. It is impractical.

Using CMFD-PSO to detect images, initially, random or manually generated initialization parameter values are used, then, the following two operations are executed N times.

(1) According to the result of theoperation (1), a new group of parameter values is generated by Parameters Estimation. Then deliver this group of parameter values to operation (1) and start the next round.
(2) Elemental Detection detects the input image with the detection parameter values and then delivers the detection result to operation (2).

The best detection result is chosen from the operations of the N rounds. Then this result and relevant parameter values are output. In our experiment, we set the value of N to 100.

4.2 The elemental detection

In Pre-Processing, an RGB image should be converted into a gray-scale image. In Keypoint Detection and Feature Extraction, the key points are detected from the test images and the SIFT descriptor, a 128-dimensional feature vector, is built for the corresponding key points.

This component consists of five steps that are similar to those of the SIFT-based framework, which is shown in Fig 2. The details of each step are shown in the following instructions.

In Filtering, the mismatched key points should be eliminated. If the distance between two matched key points is too small, this pair of matched key points will possibly be a mismatch. The descriptors of such pair of matched key points may be very similar. In this paper, if the s=distance of the paired key points is smaller than a preset value Dts min they will be removed, which can reduce the probability of mismatching key points. The other mismatched key points are eliminated by the Random Sample Consensus (RANSAC) algorithm [8]. Given two matched key points sets from a region and its duplicate as P and P*, respectively. They are related by an affine transform specified by a matrix T and shift P0 vector as P*=TP+P0. The following steps will run M times: Three pairs of non-collinear matched key points are randomly selected to obtain a transform parameter T and shift vector P0. Then, all pairs of matched key points are classified into inliers or outliers. Specifically, a pair of matched key points (P, P*) is an inlier if ||P*-TP-P0|| < R. otherwise, it is an outlier.

In Matching, the best-bin-first algorithm (BBF) [5] is applied to match key points. When looking for matching with feature vector f1, another feature vector f2 should be found according to the smallest Euclidean distance l1 between the vectors. Then, a third feature vector f3 other than f1 and f2 should be found, where the Euclidean distance l2 between f1 and f3 is the second smallest. The match condition is l1 < rl2, where r is a threshold and r E (0, 1).

T and P0 are estimated basing on the number of inliers, choosing the largest number of inliers from M times estimate results. If the matched key points do not meet the conditions that they will be regarded as the mismatch.

4.3 The parameters estimation

The PSO algorithm is used to search the adjustable parameters. The PSO algorithm is suitable for solving minimization or maximization problems. Before using PSO to find customized parameter values, we should endeavor to explicitly answer two questions that inevitably emerge:

(1) How to build the evaluation function to choose the customized parameters?
(2) Which detection parameters of the SIFT-based framework need to be optimized?

4.3.1 Parameters for elemental detection

The parameters of the SIFT-based framework need to be optimized and their boundaries are listed in Table 1. The reason for the choice of these parameters is that these parameters will make anevident effect for final detection results.

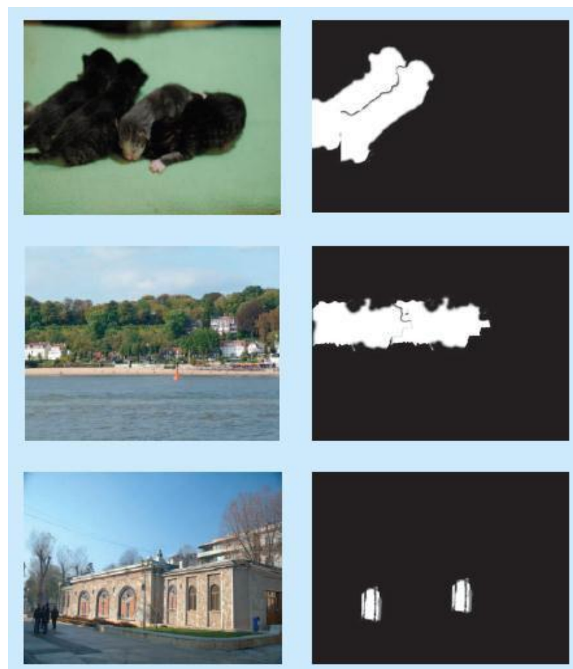


Fig. 5 Examples used in our comparisons

CONCLUSIONS

In this paper, propose a novel approach, CMFD-PSO, to detecting CMF in digital images. Comparing with existing work, thepaper makes three contributions.

(1) It derives rules to automatically determine customized parameter values for given images that are to be detected.
(2) It puts forward the concept of applying the PSO algorithm to CMF detection

(3) It integrates the PSO algorithm into the SIFT-based framework to perform CMF detection.

Fig. 6 Three CMF images that cannot be detected by neither CMFD-PSO nor EPV-SIFT

We proof the concept of CMDF-PSO by experiments. Experimental results show that CMFD-PSO can automatically generate customized parameter values for images, which are independent of neither experiences nor experiments.

Three examples are shown in Fig 6. As a future work, we will figure out new ways to improve the detection performance for such cases. CMFD-PSO can achieve much better results than EPV-SIFT in that it can identifies matched points that its counterparts cannot, and it can dramatically increase the number of true matched key points, which make the detection of region duplication more accurate and more acceptable.

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