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Copy-Move Forgery Detection: A State-of-the-Art Technical Review and Analysis

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ABSTRACT This paper presents the state-of-the-art technical reviews and analysis of recent copy-move forgery detection (CMFD) techniques. A new CMFD process pipeline was introduced. In addition, the techniques used in each stage of the CMFD pipeline are summarized and classified into small categories. Furthermore, the tables of comparison are provided as a quick reference. This technical review paper is expected to help provide useful insights and updated information regarding recent advancements in CMFD to researchers in the field.

INDEX TERMS Copy-move forgery, detection, CMFD, survey, digital forensics.

I. INTRODUCTION

Digital media tampering and counterfeit information have become a serious issue in modern information systems. Owing to the emergence of easy-to-use photo editing software, realistic tampering of a digital photo has been simplified greatly. To tackle this problem, many studies have been focused on how to detect, manually and automatically, this type of manipulated media or information. There are currently two main types of digital image forgeries: splicing and copy-move forgery (CMF).

Splicing usually refers to a tampering technique performed by replacing some parts of the target digital image with image fragments from the other sources. Detecting of a spliced image involves checking inconsistencies of some properties, values or attributes within the target image. Unlike splicing, copy-move forgery (CMF) duplicates fragments from the target image and place it back somewhere in the same image to cause misleading or misinterpretation.

To develop a copy-move forgery detection (CMFD) technique, many factors must be considered. First, a CMFD method is required to provide detection results with high accuracy and reliability. However, in practice, the developed method should also be efficient in terms of speed and computational complexity. Therefore, solving the problem of the speed–accuracy trade-off is currently challenging. Moreover, an efficient CMFD method should be robust against various types of attack and manipulation techniques (e.g., noise addition, compression, scaling, and rotation).

Recently, there have been surveys and summaries of CMFD techniques proposed in the literature. Warif et al. [1], presented details of the CMFD process, a classification of feature extraction techniques, and popular datasets that were publicly available. The review by Singh and Kaur [2] classified block-based CMFD methods into five sub-categories (i.e., intensity-based, movement-based, dimensionality reduction-based, texture-based, and frequency-based) of CMFD mechanisms. Meanwhile, in February 2018, Lin et al. [3] and Zhang et al. [4] introduced the latest updated reviews on passive digital image forensics and passive techniques for CMFD, respectively. In [4], the mathematical model of CMF and the framework for the CMFD process were introduced. Detection techniques were classified in two main categories (block-based and keypoint-based approaches) and details of the feature description techniques belonging to each category were provided.

In this work, a state-of-the-art review and analysis of CMFD techniques are presented. Unlike previous technical reviews, this work introduces a new model of the CMFD process pipeline that differs from the traditional one. Each component in the pipeline is analyzed and explained in detail with diagrams and details of the related research. Furthermore, this review involves only the latest findings (2015 to 2018) retrieved from the IEEE and ScienceDirect digital libraries.

The rest of this paper is structured as follows. In Section 2, the model of the copy-move forgery (CMF) problem is first

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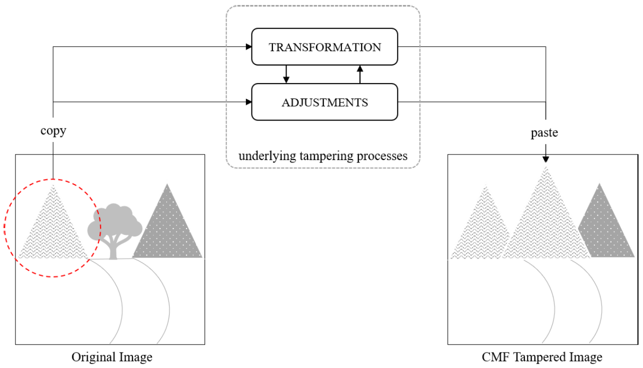

FIGURE 1. Model of copy-move forgery.

defined together with the new framework/process pipeline of the CMFD process. Detailed analysis and comparison of preprocessing techniques are then presented in Section 3. Section 4 explains the basic idea of keypoint detection. Details of some important and well-known techniques (e.g., SIFT [5]) are also briefly discussed. In Section 5 and 6, the feature extraction and matching processes are categorized and discussed, respectively. In Section 7, a general idea is given of the false matching removal process with details of some recently proposed techniques. Regarding visualization of the detection results, techniques for localizing CMF tampered regions are presented in Section 8. Techniques for optimizing and enhancing the quality of detection results are introduced in Section 9. Finally, we draw conclusions in Section 10.

II. COPY-MOVE FORGERY (CMF) AND DETECTION PROCESS

Copy-move forgery (CMF) is a typical type of digital image manipulation in which parts of the original image are duplicated and then replaced or pasted back to the same image. Prior to the replacement process, the duplicated parts of the target image may undergo some transformations (e.g., scaling, rotation) or parameter adjustments (e.g., brightness or contrast adjustments). Figure 1 shows the general concept of CMF.

Regarding detection of copy-move forgery, many CMFD techniques have been proposed so far. Most of them, however, share some common procedures. In this section, a new CMFD process pipeline is introduced. Unlike the existing frameworks, in this paper, CMFD techniques are no longer divided into block-based and keypoint-based techniques but are integrated into a single framework. The order of some processes in this framework are interchangeable. Some elements or stages are also deemed optional and can be skipped for a specific purpose. Figure 2 shows the new CMFD process pipeline. Sections III to IX then explain the general idea, structure, and sample techniques that belong to each stage, in detail.

III. PREPROCESSING

Preprocessing is the first stage in the CMFD framework. It is an optional process referring to the conversion or

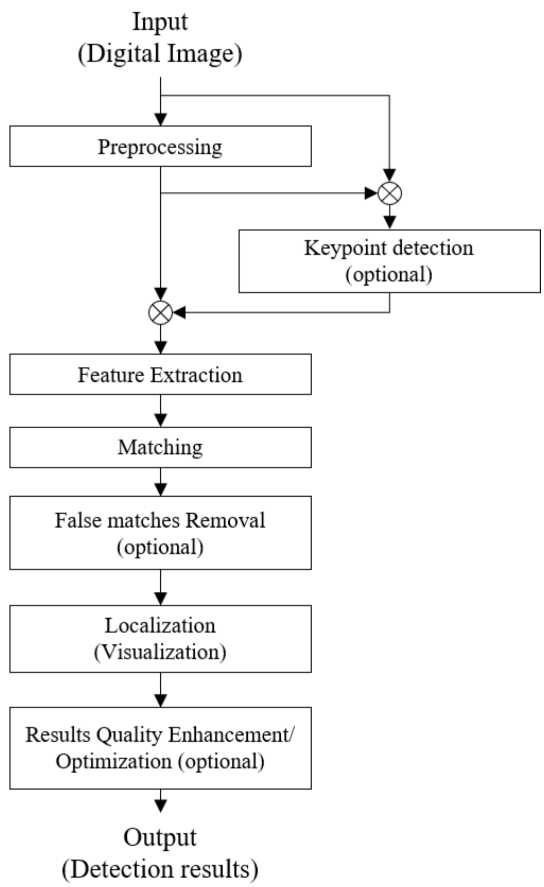

FIGURE 2. New CMFD framework.

information reduction of the original image. Generally, preprocessed information will usually make the following CMFD processes more efficient, resulting in faster detection speed or higher detection accuracy. Some examples of the preprocessing techniques are conversion of RGB to grayscale [6], [7], [8], HSV [9], [10] or YCbCr [11], [12], [13] color space, local binary pattern (LBP) [14], median filter [9], [15], discrete wavelet transform (DWT) [16], [17], and principal component analysis (PCA) [18]. In this paper, not only conversion and dimensionality reduction techniques, but also block division and segmentation are also included in preprocessing (e.g., SLIC [15], [19]). These techniques are used to divide the target digital image into fixed or non-fixed size blocks, sub-blocks, patches, or superpixels.

Figure 3 shows the structure of the preprocessing stage consisting of two main components: conversion or dimensionality reduction-related and segmentation-related units. In this stage, the order of the processes are interchangeable and each unit can be visited/performed more than once. For example, the preprocessing could start by dividing the target image into fixed-size square blocks and then wavelet decomposition (e.g., DWT) could be performed on each individual block. Moreover, each block could also be divided into many

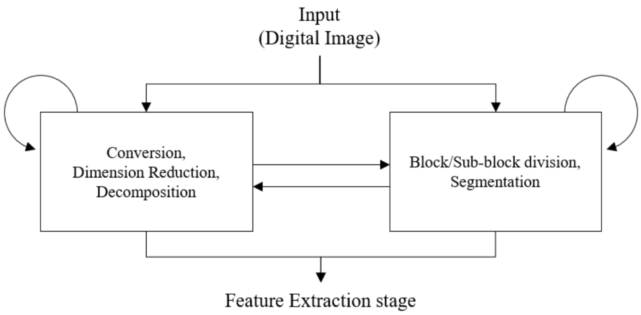

FIGURE 3. **Main components of the CMFD preprocessing stage.**

sub-blocks depending on the design and underlying feature extraction method or algorithm.

Li et al. [20], introduced the use of dynamic image segmentation prior to the actual CMFD process. In [20], the target image was segmented into meaningful patches and features were extracted and matched among these patches. This preprocessing method offers an efficient way to search and match features, in which features retrieved from the same patch will not be compared. In [9], a Sobel operator (Sobel edge detection) [21], morphological opening [22], and median filter [23] were used to remove unnecessary small objects from the target digital image. This resulted in greater precision in the following feature extraction process. Moreover, Utsubioglu et al. [13], converted the digital image into a YCbCr [24] color space prior to the feature extraction process to reduce the dimensionality and also used them as intensity-based features resulting in a new feature description method with higher discriminative power.

IV. KEYPOINT DETECTION

Keypoint detection is an optional stage in the CMFD pipeline in which interest points (so-called "keypoints") are detected. Pixels in the area around each keypoint are used as input for keypoint-based feature description/extraction techniques. Each interest point holds a high level of uniqueness resulting in high discriminative power of the extracted feature. There are many ways to detect keypoints within the target digital image, depending on the detection criteria. Some methods use edges of objects within the image as the main criteria for choosing a good keypoint. Therefore, the current research on keypoint detection techniques can be classified into three main categories depending on these criteria: edge, corner, and blob.

Unfortunately, not all keypoint detection techniques are suitable for CMFD. There are only a small number of detection techniques being used and studied so far. Harris corner detection [25] and Laplacian of Gaussian (LoG) [26] are excellent examples of popular keypoint detection techniques for CMFD. The Harris detector is a corner-based keypoint-detection method that achieves its goal of corner detection by using the sum of vertical and horizontal gradients over a small window to discriminate between corner and non-corner images. Utilizing Eigenvalues decomposition, the Harris keypoint detector is robust against rotation. A good example of using Harris keypoint detector in CMFD was proposed in 2016 by Uliyan et al. [8].

Laplacian of Gaussian (LoG) is a two-step image filtering process in which a Gaussian filter is applied before applying the Laplacian process. LoG was adopted in a SIFT feature descriptor, which is a robust feature description technique well-known in the field. Keypoint detection using LoG is a blob-based detector that begins by applying LoG to the image with different scaling parameters σ. Therefore, searching for local maxima locations across the scale and space will result in a list of potential keypoint (x, y, σ). These processes are done in many octaves of the image in the Gaussian Pyramid [26]. Because the Laplacian of Gaussian is computationally expensive, the difference of Gaussian (DoG) [27] is in practical use to compute LoG, which results in significant reduction of computational cost. Examples of recently proposed techniques utilizing LoG and DoG are presented [20], [28]–[30].

To design or utilize a keypoint detection method, there are three main factors of concern: speed, uniqueness, and robustness. In terms of speed, some keypoint detection techniques (LoG, for example) are not suitable for systems that require real-time or near real-time processing speed. Regarding the uniqueness of keypoint, a detection method that detects many keypoints with close or similar characteristics are more likely to create false matches during the feature matching stage owing to the low discriminative power of the extracted features. Finally, depending on the system, the keypoint detection process should be robust against some types of changes and transformations: noise addition, rotation, and scaling, for example. In CMF, where parts of the target image are duplicated, an efficient keypoint detection method is expected to detect the same keypoints on both the original and the duplicated area, even after some transformations (e.g., rotation, scaling) or a noise-added condition.

V. FEATURE EXTRACTION

Feature extraction is a crucial step determining both accuracy and efficiency of the detection system. In this stage, feature descriptors are generated from each block or keypoint obtained from previous processes. These descriptors are vectors derived from the image data, which hold a high level of discriminative power. Therefore, in CMF, the original and duplicated image should generate a set of feature descriptors that are similar or closely related to each other. With a robust extraction technique, each generated descriptor will have a high level of discriminative power that will finally be reflected in the overall accuracy of the detection system.

Not only for determining overall detection accuracy, this stage is also one of the key factors in determining the processing speed of the system. In practice, there are a large number of keypoints or blocks within a single image, especially in a high resolution image. Hence, producing feature descriptors for all block/keypoint is a challenging task. In practical forensic investigation where authenticity of all digital images needs to be verified, the detection speed should be fast enough not to hinder, and should allow subsequent investigation processes to go smoothly.

Because the feature extraction process is a crucial stage and acts as the core of the CMFD system, there are a huge number of research studies reported in the literature. In this section, feature extraction techniques are classified into groups. Moreover, some recently proposed techniques will be discussed in the following subsections. Figure 4 shows a classification of the feature extraction techniques.

A. TRANSFORMATION-BASED TECHNIQUES

Transformation-based techniques involve the conversion of the original image data from spatial domain (i.e., image plane) into frequency or spatial-frequency domain. Utilizing frequency domain, the method can remove some information (e.g., edges or high frequency components) from the target image that is generally unnecessary for the detection. It can also highlight some essential components (e.g., low frequency components) leading to more accurate and efficient ways to extract a feature descriptor. In addition, conversion of pixel coordinates (e.g., Polar Complex Exponential Transform: PCET) [9]) is also included in this category.

Cozzolino et al. [31], proposed a CMFD method applying circular harmonic transform-based techniques (e.g., Zernike moments [32], Polar Cosine Transform (PCT) [33], and Fourier-Mellin transform (FMT) [34]) to the overlapping image patches to detect copy-move forgeries. Combined with the proposed modified PatchMatch algorithm (see [35] for further details on PatchMatch), the method is claimed to be more robust against rotation and scaling. In 2017, Fadl and Semary [6] introduced the use of polar coordinate transformation with one dimensional fast Fourier transform (FFT) [36] to detect forgeries. In this method, the image pixels are converted from a traditional Cartesian system to a polar system. Geometric transformation (scaling or rotation, for example) in the Cartesian coordinate system will result in shifting (translation) in the converted polar system, which is much easier to deal with. Therefore, the method efficiently illustrates an important advantage of polar coordinate transformation in term of geometric transformation invariant. Moreover, Zandi et al. [37] proposed an iterative method for CMFD using PCT as a core feature extraction technique. The method relies on the creation of a uniqueness metric and calculation of local capacity, in order to determine a good interest point and resulting in a set of selected keypoints. PCT is then applied to each keypoint to generate a set of robust feature descriptors. Although a high level of distinctiveness (discriminative power) of the descriptor and a high degree of invariance are hard to achieve simultaneously, this method is claimed to be robust against rotation and slight scaling, while offering a high level of distinctiveness.

Mahmood et al. [12], Ustubioglu et al. [13], and Hilal et al. [18], presented new CMFD techniques utilizing DCT [38] as the core of their feature-description technique. In [12], stationary wavelet transform (SWT) [39] was applied to the target image. DCT was then applied to the *LL* sub-band of the SWT output to create the reduced feature descriptors. In [13], DCT-phase terms were utilized to limit the range of the feature vector to $[-1, 1]$. The feature descriptor was then generated by applying zigzag scanning to extract the first 16 elements from the DCT output, concatenating with the average Y, Cb, and Cr obtained from RGB to YCbCr conversion. Combining this with the use of Benford's law to identify the compression history of the target image, the method is claimed to give a higher accuracy ratio than existing techniques do.

B. HASHING

An excellent example of using hashing in CMFD is the work of Bi et al. [40] proposed in 2018. Bi et al. [40] introduced the use of the proposed enhanced coherency sensitive hashing (CSH) in detecting CMF. Previously proposed by Korman and Avidan [41] in 2016, CSH is a combination of the previous locality sensitivity hashing (LSH) [42] and the well-known PatchMatch algorithm [35]. CSH is generally designed for finding and matching of image patches, and is claimed to have more accuracy with three to four times faster processing speed than the PatchMatch algorithm. In [40], the author introduces an iterative method for detecting CMF starting by applying enhanced CSH to the host/target image to obtain feature correspondence maps. Then, the algorithm applies local bidirectional coherency error-based refining process to the obtained feature correspondences. The entire process is repeated if the retrieved level of error is still not stable. After the refinement, the final detection result/map is detected using some morphological operations.

C. LOCAL BINARY PATTERN (LBP)-BASED TECHNIQUES

A local binary pattern (LBP) is a statistical method for texture analysis. The original concept of this technique was first introduced by He and Wang [43] in 1990. LBP is a technique that transforms a cell/block of image data into statistical texture information. For the image being examined, LBP is performed on each individual pixel by comparing the intensity of each pixel with that of its surrounding eight neighbors. The comparison with neighboring pixels can be done in either clockwise or counter-clockwise manner. For each comparison, there are two possible results: 0 or 1. If the value of a neighbor pixel is smaller than the center pixel, the result will be 0; otherwise, the result is 1. For each pixel, this results in an 8-bit binary pattern that is usually converted to decimal form (for easier comparison) and then combined with the histogram-based approach (histogram of oriented gradients: HOG) [44], for example, to improve the detection accuracy. The mathematical expression of LBP at a pixel location can be shown in the following equation (1).

$$\begin{aligned} LBP(x, y) = \{&G_{xy}(x-1, y+1), G_{xy}(x, y+1), \\ &G_{xy}(x+1, y+1), G_{xy}(x+1, y), \end{aligned}$$

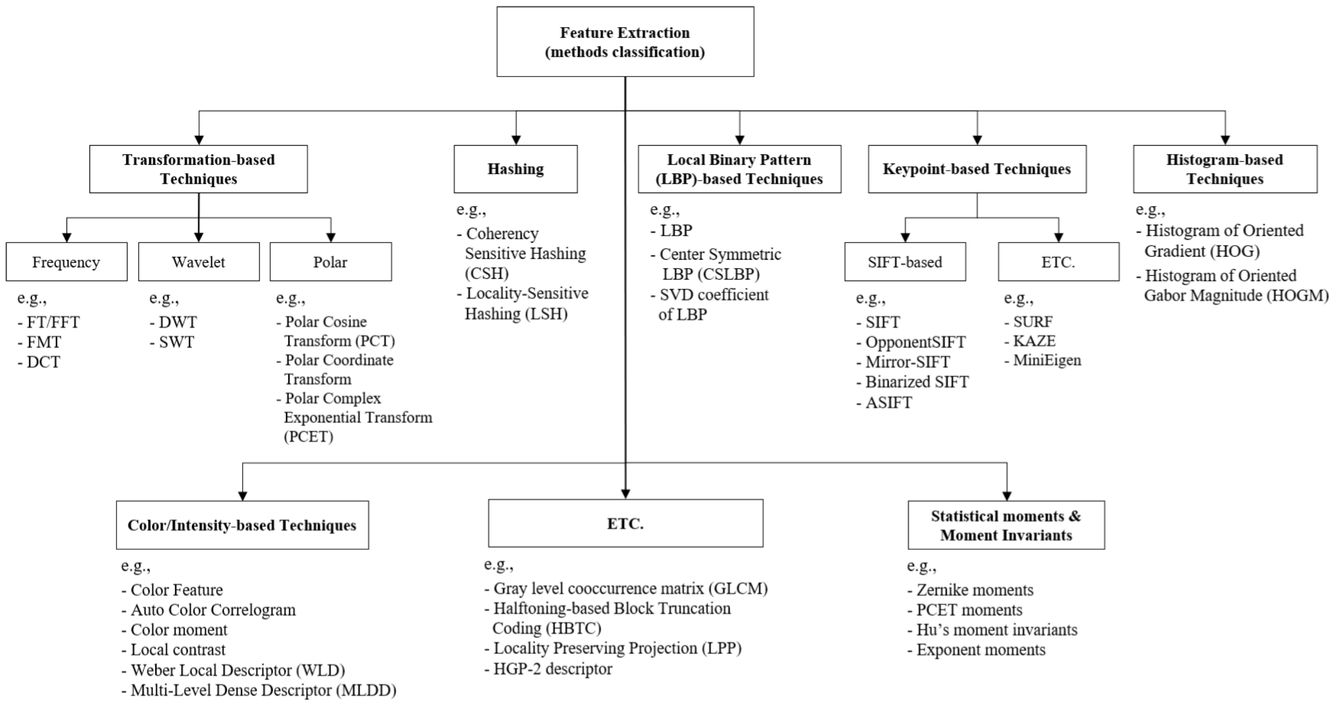

FIGURE 4. Classification of feature extraction techniques proposed from 2015 to 2018.

$$G_{xy}(x+1, y-1), G_{xy}(x, y-1), G_{xy}(x-1, y-1), G_{xy}(x-1, y)\} \quad (1)$$

$$G_{xy}(i,j) = \begin{cases} 1, & \text{if } I(i,j) - I(x,y) \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

In (1), x and y refer to pixel location (row and column) in the target image, while $I(x, y)$ represents an intensity value of the pixel at location (x, y).

Recently, the idea of LBP has become more attractive in the field of CMFD. Some recent examples utilizing LBP as a feature description technique to detect CMF are proposed in [45], [46], [16], [47], [48]. Mahmood et al. [45], presents a new CMFD technique using stationary wavelets [39] together with LBP variance to detect anomalies within the digital image. The method begins with performing grayscale conversion and SWT on the target image during the preprocessing process. The low-frequency component (*LL* channel) of SWT is then selected for further processing. Local binary pattern variance (LBPV) is then utilized to create a feature descriptor from each circular block within the target image. The technique shows an interesting way to solve the CMFD problem using an LBP-based method; the method is also claimed to be robust against scaling and rotation.

Wang et al. [46] presents a CMFD technique using LBP and SVD [49]. This technique shows an interesting way to create feature descriptors from the target image block using a special vector containing sign information of the SVD coefficients computed from a previously processed LBP labeled image. Jwaid and Baraskar [16], in 2017, proposed a method to detect CMF using LBP with DWT and PCA. This technique uses LBP as a core feature extraction mechanism. The detection method is claimed to have achieved a high level of accuracy. To detect CMF accurately within the target image, the technique requires a reference (original) image for comparison. This can be considered a significant drawback of this technique, making it unsuitable for practical use.

Kalsi and Rai [47], in 2017, proposed a CMFD technique based on using approximation image LBP (AILBP) for detecting copy-move forgeries. AILBP was performed by applying 2-level wavelet decomposition to the target image. LBP was then performed on the decomposed image with the lowest frequency components. The author claims that combining wavelet decomposition with LBP is effective in terms of accuracy and computational time. Last, in 2015, Sharma and Ghanekar [48] proposed a CMFD technique for medical images using rotational invariant features. The feature extraction process was done using the center symmetric local binary pattern (CSLBP) [50], which is a LBP variant producing a shorter length version of the LBP histogram, making it more robust against noise.

D. KEYPOINT-BASED TECHNIQUES

Regarding keypoint-based feature extraction, there is no denying that scale-invariant feature transform (SIFT) [5] is a classic, yet still popular approach in this field. SIFT offers a feature description technique with a 128-element length feature. The generated feature is robust against both scale and rotational changes making its feature descriptor very suitable for CMFD application. SIFT, however, is not an ultimate solution without any drawbacks. In fact, SIFT suffers from its high computational cost and complexity. This makes it unsuitable for some practical applications, in which a large number of images need to be processed or real-time processing speed is required. To overcome this problem, many approaches have been studied and steps proposed to speed up or improve various aspects of SIFT. Some recent SIFT-based methods for CMFD are proposed in [51], [52], [53], [54], [55], [56], [57], [58].

In [54], Muzaffer and Ulutas proposed a CMFD technique using binarized SIFT by which the value of each element in a SIFT descriptor is binarized to zero or one. This technique is claimed to improve the overall speed of detection by allowing the following matching process to perform faster owing to less complex (simplified) feature descriptors. Jin and Wan [55], proposed a technique to improve SIFT detection against smooth regions. The OpponentSIFT technique is employed to increase the discriminative power of the descriptors at low contrast keypoints. The technique offers a very robust way to overcome one of the biggest current SIFT problems: its inability to deal with low contrast (smooth) regions. Moreover, in 2016, Shahroudnejad and Rahmati [56] proposed an interesting approach for detecting CMF using Affine-SIFT (ASIFT). The proposed method applied the affine camera model prior to SIFT in order to simulate and obtain more information on possible affine distortions. The method is claimed to be fully affine invariant and also robust against transformations and deformation of the CMF tampered regions.

E. HISTOGRAM-BASED TECHNIQUES

In the field of computer vision, especially regarding feature extraction, a histogram is a very useful tool that can be applied to many applications. For example, a histogram was used in SIFT [5] in assigning the orientation of each keypoint. Some histogram-based CMFD techniques have been proposed recently. Lee et al. [7], proposed a method for CMFD using a histogram of oriented gradient (HOG). The CMF detection is done by applying HOG to an image converted to grayscale and then divided into overlapping image blocks. The proposed method was tested against the CoMoFoD public dataset [59] and images from Google search. The experimental results show robustness of the proposed method against typical CMF and small rotation. Later in the same year, the same author proposed a new technique utilizing Gabor magnitude [60] for detecting copy-move forgery. The detection was first done by applying a Gabor filter to the image. Using the filtered image, the Gabor magnitude of each image block was then computed. Last, using the magnitude information, the histogram of oriented Gabor magnitude (HOGM) was then created for each block. According to the experimental results, the proposed technique not only demonstrated the ability to deal with slight rotation, scaling, JPEG compression, and blurring, but was also capable of detecting multiple CMFs in the same image.

F. COLOR/INTENSITY-BASED TECHNIQUES

The color or pixel intensity-based method is one of the most straightforward feature extraction techniques. Bi and Pun [61] introduced an iterative refining technique for detecting CMF in digital images. For each patch of the image, the method employs an array of simple color features in RGB channels as a feature descriptor. The results of the following feature matching are then refined using the proposed iterative method, resulting in higher quality CMF detection results. Harjito and Prasetyo [62], proposed a passive method for CMF detection using a halftoning-based block truncation coding (HBTC) feature. The feature extraction method relies on the underlying proposed color feature (CF) and bit pattern feature (BF). This technique shows an interesting way of using HBTC with a color feature. However, the proposed method is a supervised approach requiring a set of training images in creating color and bit pattern codebooks before generating both CF and BF. This makes this technique less practical.

Another good example of using the intensity-based technique during a feature extraction process was introduced by Pun and Chung [15]. In this work, Pun and Chung [15] proposed a two-stage localization for CMFD. The technique utilizes the Weber local descriptor (WLD), proposed by Chen et al. [63], to performing rough localization of the CMF regions. There are two main components in WLD: orientation and differential excitation. The orientation component contains information related to gradient orientation of the current pixel. Differential excitation utilizes the intensity-based approach to create descriptors for CMF rough localization by calculating the ratio between the relative differences of the current central pixel with its neighbors. The proposed CMFD is claimed to be robust against both scaling and rotational changes.

Last, Moussa [64] proposed a new simple method for CMFD using the sum of pixel intensities as feature descriptors. The detection algorithm begins by dividing the target digital image into overlapping square blocks. For each block B_i, the detection method will again split B_i block into k sub-blocks. The method will then compute the sum of pixel intensities within each sub-block and use the results from all the k sub-blocks as the feature descriptor representing B_i. This CMFD technique offers a fast and very simple way to tackle the problem of CMF. However, it was also mentioned that the detection performance would drop in the case of geometric transformation (i.e., rotation or scale). Therefore, the technique is still far from practical use for CMFD in which forged images undergo various types of adjustment and transformation.

G. STATISTICAL MOMENTS AND MOMENT INVARIANTS

Until now, there have been a number of statistical moments and moment invariant-based CMFD techniques proposed in the literature. Some recent approaches were proposed in [11], [9], [65], [66]. Wang et al. [65], in 2017, proposed a keypoint-based CMFD method for small smooth regions. The method utilizes superpixel classification and adaptive keypoint extraction technique in finding keypoints for both high and low contrast (smooth) areas. Inspired by exponent moments, originally proposed by Meng and Ping [67] in 2011, exponent moments magnitudes was proposed as a new local visual feature claimed and experimentally proven to be robust against scaling, rotation, or highly compressed images. The technique is also claimed to deal effectively with the low-contrast problem (smooth regions). The method, however, suffers from its high complexity and cost, making it unfit for real-time or near real-time applications.

Bi et al. [11] introduced a hierarchical feature matching process for CMFD using the proposed multi-level dense descriptor (MLDD). MLDD consists of two main parts: a color texture descriptor (MLDD_CT) and an invariant moment descriptor (MLDD_IM). MLDD_IM relies on calculation of the PCET moments of each pixel. The PCET moment is an orthogonal moment defined in a circular area in which its magnitude is invariant to scaling or rotation. Therefore, the PCET moment is chosen as a geometric invariant feature for this reason and its low computational complexity. The paper above also comes with detailed experimental results showing its robustness against various types of changes and modifications (geometric transform, noise addition, and JPEG compression, for example). Furthermore, using a similar technique, Hosny et al. [9], in 2018, proposed the use of PCET moments (order 15) for CMFD. The feature extraction process is done by applying PCET moments to the edge detected image previously processed with RGB to HSV conversion, and a Sobel operator, respectively. The method is claimed to be robust against scale, rotation, Gaussian noise, and JPEG compression. The visual experimental results presented in the paper; however, show the detection results against only the most straightforward CMF attack (i.e., without scaling or rotation). Therefore, it is hard to ensure the effectiveness of this technique against each type of attack.

H. OTHER FEATURE EXTRACTION TECHNIQUES

In this paper, there are some more recent CMFD techniques that are yet to be classified. Also, at the time of writing, some recently proposed techniques may not be included in this paper. Therefore, details of some unclassified CMFD techniques are discussed in this subsection.

In 2015, Cao et al. [68] utilized the locality preserving projections (LPP) technique to detect copy-move regions in digital images. With this technique, LPP is employed during the feature extraction process for dimensionality reduction of the image block. After dividing the image into blocks, LPP is applied to each block to create the projection matrix that will later be processed into a feature descriptor. This work introduces an interesting way to tackle the CMF problem. The technique, however, was tested against only a few images tampered with using a straightforward CMF attack.

Uliyan et al. [8], in 2016, introduced a CMFD method using angular radial partitioning together with Harris keypoints. In this work, two types of segmentation, angular radial partitioning (ARP) and then the Harris keypoint detection method, were applied to the target image. For each keypoint, the feature extraction process involves creating two types of descriptor: 1) chain code, generated from the total number of Harris corners in each sector within the same cluster. The chain code is used only during the preliminary matching process. 2) The HGP-2 descriptor, introduced by Trujillo in 2012, is used as a feature descriptor for further texture-based matching processing.

Last, in 2018, Teerakanok and Uehara [69] presented a GLCM-based rotational invariant feature description technique for CMFD. The method first utilizes SURF to detect keypoints within the target image. GLCM with various offset values is then applied to pixels around each keypoint to obtain co-occurrence matrices. For each keypoint, the algorithm computes the sum of all co-occurrence matrices in a column-based manner resulting in a feature descriptor representing each keypoint. The method was tested against the CoMoFoD [59] public dataset and showed that it could properly deal with rotation. This method, however, still has the drawback of rapid changes in scale, which hinders it from being used in practice.

VI. MATCHING

Upon retrieving feature descriptors from the previous stage, the feature matching process is then performed to find potential matches between original image patches and copy-move areas. In this paper, we define the feature matching processes to include two fundamental components: searching methods and similarity measuring techniques. Search methods involve the algorithms or methods used to find efficiently the matches between original image and CMF areas. These methods usually involve dimensional or cost reduction techniques (e.g., PCA, sorting, etc.) and some accuracy enhancement techniques (e.g., clustering or segmentation). To determine similarity between two feature descriptors, the underlying similarity methods are essential. Figure 5 shows the main components of the feature matching processes together with techniques belonging to each component. These are classified into various categories. In this paper, the CMF searching techniques are divided into six categories. The details of searching-related techniques and similarity measuring techniques are briefly explained in the following subsections VI-A and VI-B respectively.

A. SEARCHING-RELATED TECHNIQUES

1) SORTING

Sorting is a popular approach usually adopted in the CMFD technique. Because a large number of feature descriptors are extracted from a single digital image, especially from high resolution images, matching among all descriptors becomes a computationally challenging task.

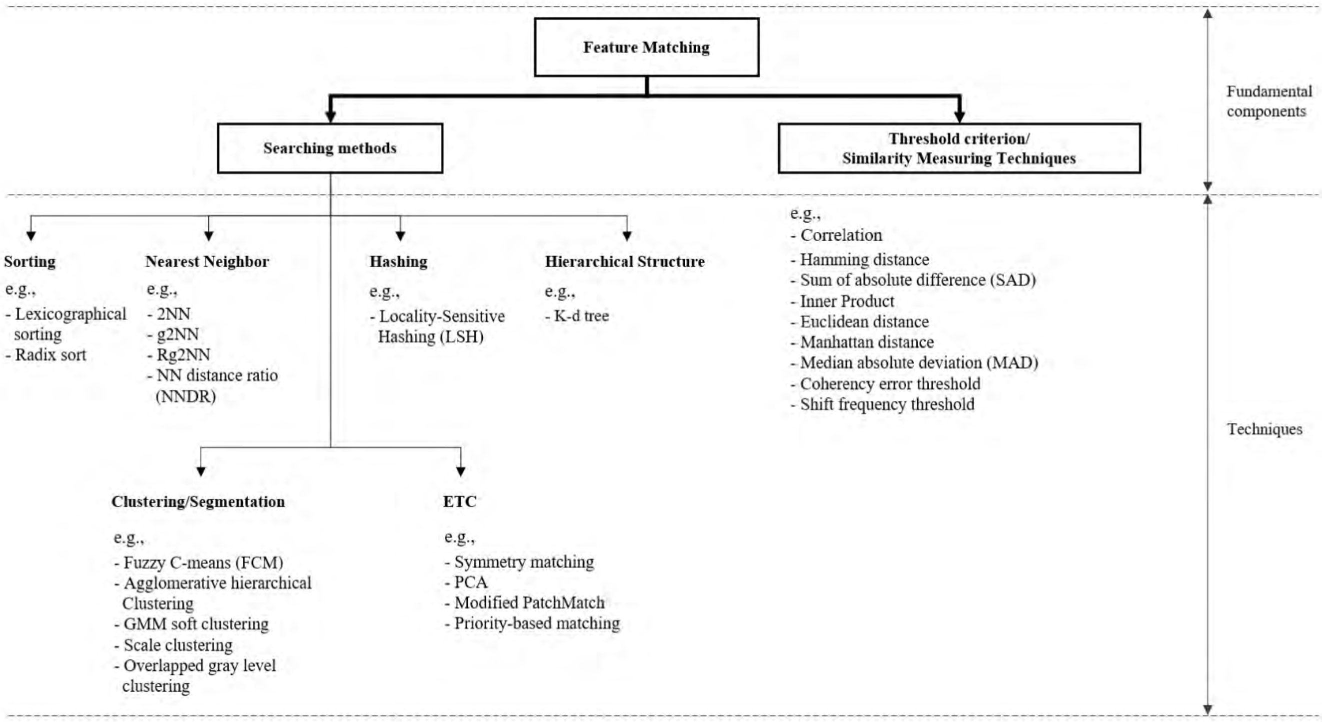

FIGURE 5. **Main components and classification of feature matching techniques.**

Therefore, sorting is usually employed to speed up the matching
process.

Some examples of using sorting to speed up the detection process were introduced in [6], [60], [11], [37], [12], [13]. Fadl and Semary [6] performed CMF matching by applying a radix sort to one-dimensional Fourier transform-based feature descriptors. Bi et al. [11] performed color texture descriptor-based sorting to increase the speed of feature matching during the preliminary matching process. Last, Lee [60], Zandi et al. [37], Mahmood et al. [12], and Ustubioglu et al. [13] demonstrated the use of lexicographical sorting during the feature matching process.

2) NEAREST NEIGHBOR-BASED TECHNIQUES

Nearest neighbor (NN)-based techniques are popular approaches usually employed in CMFD. The two nearest-neighbor (2NN) technique measures the distance ratio between the first and the second nearest neighbors (NN). Therefore, two features are considered a match if the distance ratio between the first and second NN is less than a predefined threshold. The 2NN technique is usually performed with some underlying similarity measuring methods (i.e., Euclidean distance [70]) or arccos of dot products distance. Yang et al. [30], in 2017, proposed a CMF technique using hybrid features between SIFT and KAZE [71] keypoint descriptors. This technique employs 2NN with a minimum spatial distance criterion in which the comparison between a pair of descriptors is skipped or omitted if both corresponding keypoints are located too close to each other. With this technique a predefined minimum spatial distance threshold is required.

Utilizing the general idea of 2NN, the generalized 2 nearest-neighbor (g2NN) technique was introduced by Amerini et al. [72] in 2011. Instead of measuring only the distance ratio between the first and second NN, g2NN introduces the idea of measuring the distance ratio between the i-th and $(i + 1)$-th nearest neighbor. G2NN has been proposed to overcome the current problem of multiple copy-move regions. Some recent research using g2NN and reversed g2NN (Rg2NN) as the main matching techniques were proposed in [28], [55], [52] and [65], respectively.

3) HASHING

Hashing is a technique in which the feature descriptor is digested into a shorter and easier-to-compare form. By using the digested descriptors in performing a rough comparison, the speed of the matching process can be significantly improved. Muzaffer and Ulutas [54], 2017, proposed a CMFD technique using binarized SIFT. The 128-bit binarized SIFT feature is then hashed using the proposed hashing algorithm. Such method is claimed to decrease the search dimension; therefore, greatly improving the processing/detection speed with little loss of accuracy compared to a traditional SIFT-based approach. Furthermore, Pun and Chung [15] utilized locality-sensitive hashing (LSH) [42] during the feature matching stage. In this work, LSH was adopted to filter the candidate block matches. LSH relies on performing a series of hash functions on the feature vectors and search features with the same hash values to determine matches. As LSH was designed to work well with a huge amount of data, it is claimed that this technique can speed up the detection process. Unfortunately, there was no benchmark data presented in the paper.

4) HIERARCHICAL STRUCTURE-BASED TECHNIQUES

Hierarchical structure (e.g., *k-d* tree [73]) offers a faster and well-organized way to match features by grouping relevant descriptors close to each other in the hierarchical structure. In 2017, Emam et al. [74] proposed an interesting CMFD technique for detecting anomalies within smooth regions. The method utilized the multi-support region order-based gradient histogram (MROGH) feature extraction technique. During the matching process, *k-d* tree is employed to search for k nearest neighbors. Moreover, the matching algorithm uses g2NN to iterate nearest neighbor tests to look for multiple matches. Moussa [64] introduced a fast CMFD method using simple pixel intensity-based descriptors. *k-d* tree (with 1-norm distance) was adopted to store all the feature descriptors information and search for nearest neighbors during the matching process. Lastly, Li et al. [20] also utilized the *k-d* tree approach to speed up the matching process. The technique is proven to reduce the computational complexity of matching from $O(n^2)$ to $O(n \log n)$.

5) CLUSTERING AND SEGMENTATION

has recently become more and more popular in this CMFD feature matching process. Using segmentation (e.g., SLIC [75]), the target image can be segmented into meaningful superpixels/patches. Matching between patches was proved to have higher efficiency in term of both accuracy and speed because the matching of two descriptors will be performed only between descriptors from different patches. In 2015, Yadav and Kapdi [52] proposed a SIFT-based CMFD technique utilizing Gaussian Mixture Model (GMM) clustering [76]. The method first generates SIFT descriptors from the target digital image. The SIFT keypoints are then clustered using the GMM soft clustering technique. The initial number of clusters in the GMM was empirically determined. Clustering SIFT keypoints using GMM reduces the number of keypoints that need to be analyzed; therefore, GMM can help speed up the matching process. Moreover, Alberry et al., in 2018, proposed an interesting way of using Fuzzy C-means (FCM) clustering during the matching process. The technique applies FCM to cluster the detected SIFT keypoints prior to the actual matching step. This results in reduction of the computational complexity leading to a speeded up matching process. Although the paper presents a number of testing results against various datasets, there is, unfortunately, no performance comparison with traditional/existing CMFD techniques.

6) OTHER SEARCHING-RELATED TECHNIQUES

In 2017, Bi and Pub [61] proposed a fast reflexive off-set guided searching method for CMFD. The method utilized the proposed iterative priority-based matching technique in searching for CMF tampered regions. At the initialization stage, the preliminary matching process generates mapping offsets (MO) and uses MOs to calculate the initial reflective offsets (RO). The first reflective offset will then be fed to start the iterative priority-based matching process. This method shows an interesting way of refining the matching results using an iterative method: the priority-based matching technique. However, it also relies on the approximate nearest neighbor field (ANNF) to search for nearest neighbors rather than using an exhaustive search. This makes it more practical for near real-time application. Cozzolino et al. [31] uses the proposed modified PatchMatch algorithm for CMF feature matching. The modified PatchMatch algorithm not only offers a fast approximate nearest neighbor search, the algorithm is also modified to deal efficiently with invariant features resulting in better robustness against scaling and rotation.

Furthermore, Warif et al. [28] proposed a two-stage matching process using g2NN and the proposed symmetry matching technique. The g2NN technique was first applied during the preliminary matching stage. To search for reflection-based CMF attacks, the author proposed the use of mirror-SIFT features along with the proposed symmetry matching process. Symmetry matching relies on combination of scale and phase weighting information to calculate symmetry magnitude. This magnitude is then used to determine the dominant symmetry axis between pairs of features through the linear Hough transform [77]. This work addressed the importance of reflection-based CMF attacks and also proposed an interesting way to deal with it.

B. SIMILARITY MEASURING TECHNIQUES

During the searching process, the matching algorithm looks for possible matches by searching for nearest or approximate nearest neighbors. The similarity measuring techniques serve as underlying mechanisms used for actual comparison between a pair of descriptors.

According to recent research, Euclidean distance [70] is undoubtedly the most simple and frequently used technique. Examples of some selected recent research utilizing Euclidean distance during their feature matching stage were proposed in [61], [9], [60], [37], [45]. Instead of Euclidean distance, Malviya and Ladhake, in [66] and [78], utilized Manhattan distance [79] as an alternative to Euclidean distance to determine the relationship between pairs of matching features. Hosny et al. [9] utilizes Euclidean distance with correlation technique to compare between a pair of PCET moments-based feature descriptors. Zandi et al. [37] uses Euclidean distance with the proposed adaptive threshold in comparing features. Furthermore, Sharma and Ghanekar [48] performed comparison and matching between pairs of descriptors using a shift frequency threshold and Euclidean distance threshold.

In addition, similar to the matching technique used by Lowe [5], Ustubioglu et al. [29] utilized the sorted inverse cosine of inner product between features together with the predefined threshold to determine the similarity between two feature descriptors. In [13], the same author, introduced the use of element-by-element comparison with the automatic threshold value generated using Benford's generalized law and the statistical characteristics of the image. Lastly, Muzaffer and Ulutas [54], in 2017, applied the hashing technique to digest the feature descriptors and used Hamming distance [80] between hashed features to determine the similarity between features.

VII. FALSE MATCHES REMOVAL

After the feature matching process, there are always some false positive matches, in which non-tampered areas labeled as tampered, appeared among the matching results. To remove these false matches, some false match removal techniques are adopted and utilized. In this section, false match removal techniques used in recent research are categorized and briefly introduced. In this paper, false match removal techniques are classified into four categories as follows.

A. CLUSTERING/SEGMENTATION-BASED TECHNIQUES

In reducing false matches, clustering or segmentation techniques are usually used to separate authentic and tampered areas. Moreover, the spatial distance between clusters can help to confirm the existence of CMF tampered regions. Wang et al. [65], 2017, utilized hierarchical agglomerative clustering [81] to create a tree of clusters. Each keypoint was assigned to a cluster. The algorithm then calculated the spatial distance between clusters and then repeatedly searched for the pair of clusters with the closest distance and merged them. This approach offers an efficient way to distinguish different matched regions. Combining this with a robust estimation technique (i.e., Random Sample Consensus algorithm (RANSAC) [82]), the proposed technique offers an effective way to remove false matches. Using a quite similar technique, Al-Hammadi and Emmmanuel [83] applied hierarchical clustering to the matching results to reduce the number of false matches.

Furthermore, Emam et al. [74], in 2017, applied hierarchical agglomerative clustering to the matching results both before and after applying RANSAC to remove any possible outliers from the matching results. Last, to reduce false alarms (false matches) while still maintaining low computational cost, Yang et al. [30] and Zandi et al. [37], using almost the same underlying methods, both proposed new filter algorithms for false match removal based on the SLIC segmenation technique [75] and RANSAC algorithm. The CMF regions are usually chosen from meaningful image segments. Therefore, rather than using clustering based on all matched keypoints, which is computationally costly, SLIC was used to separate the image into meaningful segments. This is a faster and more attractive approach to achieve the same goal of false match removal.

B. THRESHOLD, CONSTRAINTS, AND CRITERIA-BASED TECHNIQUES

Fadl and Semary [6], 2017, utilized a spatial distance-based threshold to remove false matches during each round of feature matching. In this work, a pair of matched features were considered CMF tampered only if the spatial distance between them was larger than a predefined threshold. Pun and Chung [15] also used the spatial distance between a pair of matched blocks to determine the authenticity of CMF matches. The Euclidean distance was employed in this work to measure the spatial distance between image blocks. The detection output is marked with different colors if the distance between blocks is greater than a predetermined threshold value. Lee et al. [7] divided the detection results into non-overlapping blocks. For each block, the number of white pixels indicating the matched blocks were counted. All the blocks were discarded from the final detection result if the number of white pixels was less than a predefined threshold. According to empirical testing against 500 tampered images, 16×16 block size and threshold value of 64 were suggested.

Novozámský and Šorel [84] presents a false match reducing method using JPEG constraint verification. The method first saved the target image with 10, 20, ..., 90, 95, 98 compression qualities. Each image was then reloaded, after which the proposed JPEG verifying procedure was performed. According to the experimental results, the number of false matches significantly decreased at qualities higher than 90 and no false match was found at quality of 98. Cozzolino et al. [31] used a median filter together with the dense linear fitting (DLF) post-processing technique. The median filtration removes outliers (false matches) while still leaving the linear behavior of the signal unaltered. Furthermore, Bi et al. (2016), proposed an adaptive distance and orientation-based filtering method to remove the redundant pixels from the detection results. The method relies on the classification of pixel pairs into symmetrical (SPP) and unsymmetrical (UPP) pixel pairs. Distribution of the distance and orientation of both SPP and UPP are then computed. The adaptive thresholds for SPP and UPP are then calculated. Using the mentioned soft-threshold, the outliers are removed from the detection results. This algorithm offers a very interesting way to filter out outliers from the final results.

C. TRANSFORM ESTIMATION-BASED TECHNIQUES

To remove outliers, in many studies, attempts have been made to estimate the relationship between each CMF region and its corresponding original image region. Regarding affine transform estimation, the random sample consensus (RANSAC) algorithm, originally proposed by Fischler and Bolles [82] in 1981, is undoubtedly one of the most robust and frequently used algorithms. Moreover, many recent CMFD techniques have attempted to compute a transformation matrix by

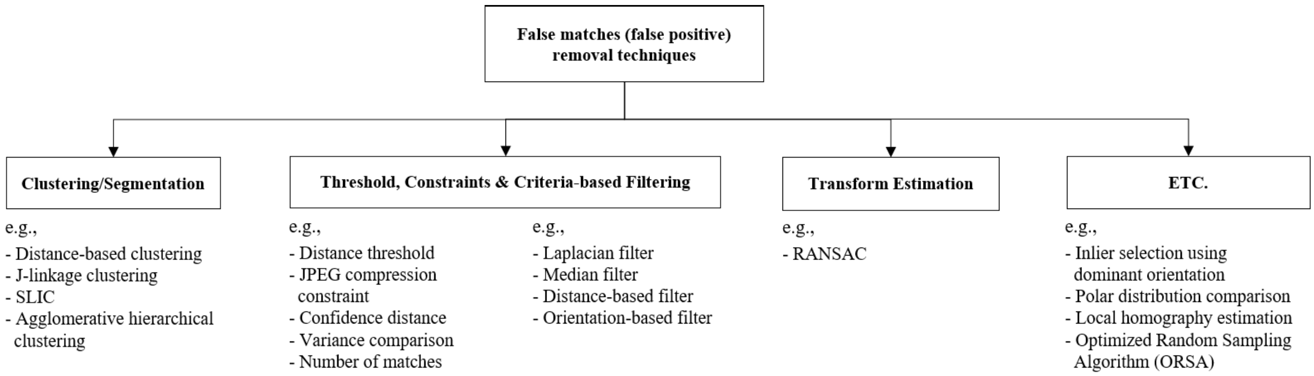

FIGURE 6. **Classification of current false match removal methods.**

which to help filter out outliers and increase overall detection accuracy of a detection system. Some recent works using RANSAC-based methods for false match removal are presented in [37], [28], [65], [30], [16].

Zandi et al. [37] proposed an outlier filtering algorithm using SLIC segmentation, PCT phase, and RANSAC transform estimation. In 2017, Warif et al. [28] adopted hierarchical agglomerative clustering and the RANSAC algorithm, to cluster matched keypoints and estimate the geometrical transformation among clusters. Using a similar set of techniques, Yang et al. [30] used hierarchical clustering, which is capable of detecting multiple CMF regions with the RANSAC algorithm, to remove any possible false matches.

Unlike previously mentioned work, Li et al. [20] proposed a two-stage matching process. In the first matching stage, RANSAC was employed to eliminate noise in the keypoints detection process. However, during the second matching stage, the author proposed an iterative approach for re-estimation of a transform matrix. The method relies on distinguishing the CMF region from the background, which will also remove any outliers that are not located inside CMF regions. This work offers an interesting way of using an iterative method such as the EM algorithm [85] to achieve this goal. Last, Shahroudnejad and Rahmati [56] selected optimized random sampling algorithm (ORSA), proposed by Moisam and Stival [86] in 2004, as an alternative to RANSAC to remove outliers from the detection results.

D. OTHER RELATED TECHNIQUES

To remove false matches or noise (i.e., small isolated pixels) in the detection output, the morphological operation is one of the most commonly used methods so far. Erosion [87] is a morphological method suitable for removing isolated pixels (noise) from the output image. The technique scans the target image I with the structuring element (or kernel) K. As K scans over I, the algorithm calculates the minimal pixel value and then replace the image pixel at the center of the kernel with the calculated value. Using erosion, objects within the target image will become thinner. Therefore, groups of noise pixels, which are actually small, will finally be removed. An excellent example of using erosion to remove isolated noise pixels from the detection image was introduced by Pun and Chung [15] in 2018. Furthermore, Sharma and Ghanekar [48], and Mahmood et al. [45], [12] utilized the morphological opening [22] technique to remove small falsely detected objects and noise pixels. Morphological opening is a technique developed from the combination of erosion and dilation [88]. The image is first eroded, resulting in the removal of small noise pixels. Then, image dilation is performed to counter the effect of erosion (i.e., objects become thinner) making the shape of objects in the image revert back to normal.

VIII. LOCALIZATION

Localization is an optional stage in the CMFD process pipeline involving visualization of the detection results. Generally, the detection output is generated using a binary image (i.e., black and white image), which makes it easier to see the detected CMF region within the target image. In this section, only a few techniques are introduced. Jin and Wan [55], in 2017, computed a region correlation map between the original image and the computed warped image using affine and inverse affine transform matrixes. A Gaussian filter with size of 7 pixels and binary threshold at the value of 0.55 were then applied to the obtained region correlation map to create the output binary image.

Furthermore, Yadav and Kapdi [52] employed a Laplacian filter and boundary tracing operation to highlight the CMF tampered regions. Interestingly, the final output of this method is not a binary image, but the original image with the border of the tampered objects being highlighted.

IX. OPTIMIZATION & QUALITY ENHANCEMENT

Optimization and quality enhancement is the last and also an optional stage in the CMFD pipeline. In some case, a detected CMF region may be incomplete; some holes (i.e., false negative results) may be included. Therefore, the goal of this stage involves removing these false negative results by filling the holes within the detected tampered regions making the

TABLE 1. Table of summary (2015 - 2018).

Authors	Techniques			Dataset
Moussa 2015 [64]	**Pre.:** overlapping blocks and non-overlapping sub-blocks **Search:** *kd*-tree **Loc.:** -	**KD:** - **SM:** sum of absolute difference **Opt.:** -	**FE:** sum of pixel intensities **FMR:** - **Invar.:** -	Silva et al. [10]
Malviya & Ladhake 2015 [66]	**Pre:** noise removal, 8Z affine transform and non-overlapping blocks **Search:** Sorting (n/a) **Loc.:** -	**KD:** - **SM:** Manhattan distance **Opt.:** -	**FE:** auto color correlogram and color moment **FMR:** - **Invar.:** scale, rotation	MICC-F220 [72]
Ustubioglu et al. 2015 [29]	**Pre:** local phase quantization-based texture feature extraction **Search:** n/a **Loc.:** -	**KD:** Laplacian of Gaussian (LoG) **SM:** inner product, inverse cosine, and predefined threshold **Opt.:** -	**FE:** SIFT **FMR:** - **Invar.:** scale, rotation	private dataset
Cozzolino et al. 2015 [31]	**Pre:** overlapping patches **Search:** modified PatchMatch **Loc.:** magnitude of offset field	**KD:** - **SM:** n/a **Opt.:** -	**FE:** circular harmonic transform (CHT) based methods **FMR:** median filter, fitting error, thresholding **Invar.:** scale, rotation	Christlein et al. [90], GRIP [31]
Silva et al. 2015 [10]	**Pre:** HSV conversion **Search:** nearest neighbor distance ratio (NNDR) **Loc.:** pyramidal decomposition, multiscale analysis and voting	**KD:** SURF **SM:** Euclidean distance **Opt.:** -	**FE:** SURF **FMR:** spatial proximity and correspondence angle based clustering **Invar.:** scale, rotation	CMH [10], CMEN [10]
Cao et al. 2015 [68]	**Pre:** overlapping square blocks **Search:** lexicographical sorting **Loc.:** -	**KD:** - **SM:** n/a **Opt.:** -	**FE:** locality preserving projections (LPP) **FMR:** confidence distance threshold **Invar.:** n/a	n/a
Lee 2015 [60]	**Pre:** grayscale conversion, overlapping blocks **Search:** lexicographical sorting **Loc.:** -	**KD:** - **SM:** Euclidean distance **Opt.:** -	**FE:** histogram of oriented Gabor magnitude (HOGM) **FMR:** proposed noise removal algorithm **Invar.:** medium scale, small rotation	CoMoFoD [59], Christlein et al. [90]
Lee et al. 2015 [7]	**Pre:** grayscale conversion, overlapping blocks **Search:** lexicographical sorting **Loc.:** -	**KD:** - **SM:** Euclidean distance **Opt.:** -	**FE:** histogram of oriented gradient (HOG) **FMR:** number of matches-based threshold **Invar.:** scale, rotation	CoMoFoD [59], Google image
Li et al. 2015 [20]	**Pre:** dynamic image segmentation **Search:** *kd*-tree **Loc.:** -	**KD:** Laplacian of Gaussian (LoG) **SM:** Euclidean distance with soft thresholding **Opt.:** -	**FE:** SIFT **FMR:** matching between patches, iterative re-estimation of transform matrix, RANSAC **Invar.:** rotation	Christlein et al. [90], MICC-F600 [91]
Yadav and Kapdi 2015 [52]	**Pre:** grayscale conversion **Search:** GMM-based soft clustering, G2NN **Loc.:** boundary trace operations	**KD:** Laplacian of Gaussian (LoG) **SM:** Euclidean distance **Opt.:** -	**FE:** SIFT **FMR:** Laplacian filter **Invar.:** scale, rotation	CoMoFoD [59]

Pre.: Preprocessing **KD:** Keypoint detection **FE:** Feature extraction
Search: Searching algorithm **SM:** Similarity measuring method **FMR:** False matches removal technique
Loc: Localization **Opt.:** Enhancement and optimization **Invar.:** Invariant properties

final detection results more complete. The goal of this stage is somewhat different from removal of false matches where the isolated pixels (or false positive matches) are removed.

The main techniques to achieve this are morphological dilation [88] and closing [89] methods. Dilation [88] is opposite to the previously introduced morphological erosion

TABLE 2. Table of summary (2015 - 2018) (continue).

Authors	Techniques			Dataset
Sharma and Ghanekar 2015 [48]	**Pre:** grayscale conversion, overlapping square blocks **Search:** lexicographical sort **Loc.:** -	**KD:** - **SM:** shift frequency threshold, Euclidean distance **Opt.:** -	**FE:** center symmetric local binary pattern (CSLBP) [50] **FMR:** morphological opening **Invar.:** rotation	Heikkila et al. [92], Visualonline database (n/a)
Malviya and Ladhake 2016 [78]	**Pre:** 8Z affine transform, non-overlapping blocks **Search:** - **Loc.:** -	**KD:** - **SM:** Manhattan distance **Opt.:** -	**FE:** auto color correlogram **FMR:** - **Invar.:** scale, rotation	CoMoFoD [59]
Shahroudnejad and Rahmati 2016 [56]	**Pre:** - **Search:** 2NN **Loc.:** SLIC [75]	**KD:** Affine-SIFT (ASIFT) **SM:** Euclidean distance **Opt.:** morphological operations	**FE:** Affine-SIFT (ASIFT) **FMR:** ORSA [86], morphological operations **Invar.:** scale, rotation	CASIA TIDE v2.0 [93]
Ustubioglu et al. 2016 [13]	**Pre:** YCbCr conversion, overlapping blocks **Search:** lexicographical sorting **Loc.:** -	**KD:** - **SM:** element-by-element comparison, soft-threshold using Benford's law **Opt.:** -	**FE:** DCT, quantization, and zigzag scanning **FMR:** - **Invar.:** -	CoMoFoD [59], Google seach, KLTCI [94]
Uliyan et al. 2016 [8]	**Pre:** grayscale conversion, statistical region merging (SRM), Tamura texture, Clustering, ARP **Search:** 2-level matching algorithm **Loc.:** -	**KD:** Harris keypoint detection on each ARP sector **SM:** - **Opt.:** -	**FE:** developed chaincode (preliminary matching), HGP-2 descriptor (further matching) **FMR:** Euclidean distance (apply on chaincode), median absolute deviation (MAD)(for HGP-2 descriptors) **Invar.:** scale, rotation	MICC-220 [72], Christlein et al. [90]
Al-Hammadi and Emmanuel 2016 [83]	**Pre:** single image super resolution (SISR) algorithm **Search:** - **Loc.:** -	**KD:** SURF **SM:** Euclidean distance **Opt.:** -	**FE:** SURF **FMR:** Hierarchical clustering **Invar.:** scale, rotation	CoMoFoD [59]
Zandi et al. 2016 [37]	**Pre:** - **Search:** lexicographical sorting **Loc.:** proposed iterative interest point verification method	**KD:** proposed detection method using uniqueness of data **SM:** Euclidean distance with proposed adaptive thresholding **Opt.:** -	**FE:** polar cosine transform (PCT) **FMR:** minimum distance criterion, proposed filter algorithm using SLIC and RANSAC **Invar.:** scale, rotation	Christlein et al. [90], SBU-CM16 [95]
Nithiya and Veluchamy 2016 [19]	**Pre:** grayscale conversion, DWT (L-channel), adaptive blocks size computation, SLIC **Search:** - **Loc.:** color feature comparison	**KD:** SIFT **SM:** - **Opt.:** morphological operations	**FE:** SIFT **FMR:** Euclidean distance **Invar.:** scale, rotation	n/a
Bi et al. 2016 [11]	**Pre:** YCbCr conversion **Search:** color texture descriptor based sorting and proposed geometrically invariant moment based matching **Loc.:** -	**KD:** - **SM:** Euclidean distance **Opt.:** morphological closing	**FE:** proposed MLDD descriptor **FMR:** proposed adaptive distance and orientation based filtering method **Invar.:** scale, rotation	Christlein et al. [90]
Bi et al. 2016 [96]	**Pre:** - **Search:** n/a **Loc.:** -	**KD:** - **SM:** n/a **Opt.:** morphological closing	**FE:** proposed MLDD descriptor **FMR:** pixel pairs classification, polar distribution calculation, adaptive threshold-based filtering **Invar.:** scale, rotation	Christlein et al. [90]

technique. Dilation makes the edge/border of the objects become thicker, resulting in small holes within the image being filled. An excellent use of dilation in recent work was introduced by Pun and Chung [15] in 2018. In this work, the authors employed morphological dilation to remove the small holes within the detection results during

TABLE 3. Table of summary (2015 - 2018) (continue).

Authors	Techniques			Dataset
Bi and Pun 2017 [61]	**Pre:** overlapping patches **Search:** reflective offset-guided searching using proposed priority-based matching algorithm **Loc.:** morphological operations (n/a)	**KD:** - **SM:** squared Euclidean distance **Opt.:** -	**FE:** color feature in RGB channel **FMR:** pixels's reflective offset fitting **Invar.:** scale, rotation	Christlein et al. [90]
Fadl and Semary 2017 [6]	**Pre:** grayscale conversion, overlapping blockss **Search:** radix sort **Loc.:** -	**KD:** - **SM:** correlation **Opt.:** -	**FE:** polar coordinate transformation and 1-D FFT **FMR:** spatial distance threshold **Invar.:** scale, rotation	DVMM (n/a)
Harjito and Prasetyo 2017 [62]	**Pre:** overlapping blocks and non-overlapping sub-blocks **Search:** lexicographical sorting **Loc.:** -	**KD:** - **SM:** shift frequency threshold **Opt.:** -	**FE:** color image compression using HBTC, proposed color and bit pattern features **FMR:** isolated regions removal (n/a) **Invar.:** -	SIPI-USC (n/a)
Kuznetsov and Myasnikov 2017 [14]	**Pre:** intensity range reduction, gradient calculation, adaptive linear contrast enhancement, LBP, overlapping blocks **Search:** hash table **Loc.:** -	**KD:** - **SM:** n/a **Opt.:** -	**FE:** Rabin-Karp hash function-based method **FMR:** - **Invar.:** -	private dataset
Warif et al. 2017 [28]	**Pre:** - **Search:** g2NN (preliminary matching) and proposed symmetry matching (further matching) **Loc.:** -	**KD:** Laplacian of Gaussian (LoG) **SM:** n/a **Opt.:** -	**FE:** SIFT and proposed mirror-SIFT **FMR:** hierarchical Agglomerative clustering, RANSAC **Invar.:** scale, rotation	private NB-CASIA dataset
Wang et al. 2017 [65]	**Pre:** non-overlapping segmentation using ERS algorithm **Search:** Rg2NN [97] **Loc.:** zero mean normalized cross-correlation	**KD:** Superpixel classification, Adaptive keypoint extraction using probability density-based SURF detector and adaptive Hessian response threshold **SM:** Euclidean distance **Opt.:** -	**FE:** exponent moment magnitudes **FMR:** hierarchical Agglomerative clustering, RANSAC **Invar.:** slight scale, rotation	Christlein et al. [90], GRIP [31]
Yang 2017 [30]	**Pre:** - **Search:** 2NN **Loc.:** correlation map	**KD:** Laplacian of Gaussian (LoG) and KAZE [71] **SM:** predefined threshold (n/a) **Opt.:** morphological operations (n/a)	**FE:** SIFT and KAZE **FMR:** minimum distance criterion, proposed filtering algorithm using SLIC segmentation and RANSAC **Invar.:** scale, rotation	Christlein et al. [90]
Mahmood et al. 2017 [45]	**Pre:** grayscale conversion, SWT(LL channel), overlapping circular blocks **Search:** lexicographical sorting **Loc.:** -	**KD:** - **SM:** Euclidean distance **Opt.:** morphological closing	**FE:** LBPV **FMR:** - **Invar.:** scale, rotation	CoMoFoD [59], KLTCI [94]
Wang et al. 2017 [46]	**Pre:** YCbCr conversion, overlapping blocks **Search:** lexicographical sorting **Loc.:** -	**KD:** - **SM:** element-by-element comparison **Opt.:** -	**FE:** SVD coefficient of LBP of Y-channel image, and average of each Y, Cb, Cr channels **FMR:** - **Invar.:** rotation (180 degree only)	CASIA [98], Google search
Jwaid and Baraskar [16]	**Pre:** Ycbcr conversion (use Cb and Cr channels), DWT (LL channel), overlapping blocks **Search:** PCA **Loc.:** SVM	**KD:** - **SM:** n/a **Opt.:** -	**FE:** LBP **FMR:** - **Invar.:** -	CoMoFoD [59]

TABLE 4. Table of summary (2015 - 2018) (continue).

Authors	Techniques			Dataset
Hilal et al. 2017 [18]	**Pre:** PCA, non-overlapping square blocks **Search:** lexicographical sorting **Loc.:** -	**KD:** - **SM:** n/a **Opt.:** -	**FE:** local contrast, DCT **FMR:** - **Invar.:** -	private dataset
Dixit et al. 2017 [17]	**Pre:** grayscale conversion, DWT (LL channel), overlapping square blocks **Search:** row sorting (n/a) **Loc.:** -	**KD:** - **SM:** Euclidean distance **Opt.:** -	**FE:** statistical mean **FMR:** statistical variance comparison **Invar.:** -	CoMoFoD [59]
Kalsi and Rai 2017 [47]	**Pre:** wavelet decomposition (LL channel), overlapping blocks **Search:** - **Loc.:** -	**KD:** - **SM:** n/a **Opt.:** -	**FE:** LBP **FMR:** - **Invar.:** -	private dataset
Emam et al. 2017 [74]	**Pre:** - **Search:** *kd*-tree, g2NN **Loc.:** -	**KD:** difference of Gaussian (DoG) **SM:** Euclidean distance **Opt.:** morphological dilation and closing	**FE:** multi-support region order-based gradient histogram (MROGH) **FMR:** distance-based clustering criterion **Invar.:** scale, rotation	Christlein et al. [90]
Muzaffer and Ulutas 2017 [54]	**Pre:** - **Search:** - **Loc.:** -	**KD:** Laplacian of Gaussian (LoG) **SM:** hashing, hamming distance between hashed features **Opt.:** -	**FE:** binarized-SIFT **FMR:** RANSAC **Invar.:** rotation	CoMoFoD [59]
Jin and Wan 2017 [55]	**Pre:** - **Search:** g2NN **Loc.:** region correlation map, Gaussian kernel, binary threshold	**KD:** Laplaian of Gaussian (LoG) with zero contrast threshold, non-maximum value suppression (NMS) keypoint selection **SM:** n/a **Opt.:** morhpological closing	**FE:** OpponentSIFT **FMR:** proposed optimized J-linkage clustering using image segmentation, J-linkage algorithm and RANSAC **Invar.:** scale, rotation	Christlein et al. [90], GRIP [31], MICC-F600 [91]
Resmi and Vishnukumar 2017 [57]	**Pre:** grayscale conversion, canny edge detection, and SLIC **Search:** two-stage matching (n/a on the first stage and oversegmentation method on the latter) **Loc.:** -	**KD:** Laplacian of Gaussian (LoG) **SM:** Euclidean distance **Opt.:** -	**FE:** SIFT **FMR:** Transform estimation (n/a) **Invar.:** scale, rotation	MICC-F220 [72], MICC-F8multi [72]
Alberry et al. 2018 [51]	**Pre:** - **Search:** Fuzzy C-means (FCM) clustering **Loc.:** -	**KD:** Laplacian of Gaussian (LoG) **SM:** n/a **Opt.:** -	**FE:** SIFT **FMR:** - **Invar.:** scale, rotation	MICC-F220 [72], private dataset
Novozámský and Šorel [84]	**Pre:** - **Search:** - **Loc.:**	**KD:** - **SM:** - **Opt.:**	**FE:** - **FMR:** faster variant of alternating projection for verification of the JPEG copy-move constraint **Invar.:**	Silva et al. [10], CoMoFoD [59], private dataset

the first stage of their proposed two-stage detection process.

Using the idea of dilation and erosion, morphological closing was introduced in the field of image processing. Morphological closing [89] is a method opposite to the morphological opening [22] technique. The method is done by respectively performing dilation and erosion on the target image. Dilation first removes the small holes within the image; however, objects inside the image will become thicker as well. To counter this effect, the erosion process is then performed.

TABLE 5. Table of summary (2015 - 2018) (continue).

Authors	Techniques			Dataset
Pun and Chung 2018 [15]	**Pre:** median filter, SLIC (1^{st} stage matching), adaptive overlapping circular blocks (2^{nd} stage matching) **Search:** descending order sorting (1^{st} stage matching), LSH-based matching (2^{nd} stage matching) **Loc.:** -	**KD:** - **SM:** Euclidean distance **Opt.:** geometrical morphological operations (hole filling)	**FE:** Weber local descriptor (1^{st} stage matching), discrete analytic Fourier-Mellin transform (DAFMT) (2^{nd} stage matching) **FMR:** minimum distance criterion, geometrical morphological operations (isolated pixels elimination) **Invar.:** scale, rotation	Christlein et al. [90], CMH [10]
Hosny et al. 2018 [9]	**Pre:** HSV conversion, Sobel operator [21], morphological opening, median filter, object bouding box detection **Search:** - **Loc.:** -	**KD:** - **SM:** Euclidean distance **Opt.:** -	**FE:** PCET moments (order 15) **FMR:** **Invar.:** scale, rotation	Ardizzone et al. [99], private dataset
Das et al. 2018 [53]	**Pre:** grayscale conversion, 2-level SWT **Search:** Hierarchical agglomerative clustering (in 2^{nd} matching) **Loc.:** -	**KD:** Laplacian of Gaussian (LoG) **SM:** Euclidean distance (in 1^{st} matching) **Opt.:** -	**FE:** SIFT **FMR:** RANSAC **Invar.:** scale, rotation	MICC-F220 [72], private dataset
Teerakanok and Uehara 2018 [69]	**Pre:** grayscale conversion **Search:** lexicographical sorting **Loc.:** -	**KD:** SURF **SM:** inner product, inverse cosine and predefined threshold **Opt.:** -	**FE:** sum of GLCM **FMR:** minimum distance criterion **Invar.:** -	Ardizzone et al. [99]
Mahmood et al. 2018 [12]	**Pre:** YCbCr conversion, overlapping blocks **Search:** lexicographical sorting **Loc.:** -	**KD:** - **SM:** n/a **Opt.:** -	**FE:** SWT, DCT **FMR:** minimum distance criterion **Invar.:** -	CoMoFoD [59], UCID v2 [100]
Khan et al. 2018 [101]	**Pre:** grayscale conversion, overlapping square blocks **Search:** - **Loc.:** -	**KD:** SURF/MinEigen [102] **SM:** Threshold (n/a) **Opt.:** -	**FE:** SURF/MinEigen **FMR:** - **Invar.:** -	MICC-F220 [72]
Bi and Pun 2018 [40]	**Pre:** - **Search:** enhanced coherency sensitive hashing **Loc.:** -	**KD:** - **SM:** coherency error threshold **Opt.:** -	**FE:** enhanced coherency sensitive hashing **FMR:** iterative local bi-direction coherency error refinement, morphological operations (n/a) **Invar.:** scale, rotation	Christlein et al. [90], GRIP [31]
Li and Zhou 2018 [58]	**Pre:** image enlarging (scaling) **Search:** group matching using scale clustering, overlapped gray level clustering **Loc.:** proposed localization method using scale and color information	**KD:** contrast threshold lowered SIFT **SM:** n/a **Opt.:** -	**FE:** SIFT **FMR:** minimum distance criteria, local homography estimation, dominant orientation-based inlier selection **Invar.:** scale, rotation	MICC-F220 [72], MICC-F600 [91], CMH [10], COVERAGE [103], CMH+GRIPori, GRIP [31], Christlein et al. [90]

Morphological closing is a popular techniques used in much recent CMFD research. Some examples of using morphological closing to enhance the quality of the final detection output were presented in [45], [55], [74].

X. CONCLUSIONS

In this paper, the state-of-the-art advances in copy-move forgery detection (CMFD) are briefly summarized. A new CMFD process pipeline is introduced together with details of each individual processing stage including goals, basic ideas, and associated techniques. To the best of our knowledge, some stages in the proposed pipeline may currently have only a few associated techniques. However, we plan to update and perform more surveys regarding this in the near future. This paper is expected to provide insights and updated information on recent studies for researchers in the field. Last, for quick reference, the broken down details of each recent technique, together with a comparison between it and the others are presented in the following table 1 to 5.

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