Copy-move image forgery detection using direct fuzzy transform and ring projection

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Abstract: Cloning (copy-move) image forgery detection (CMFD) is a pure image processing method without any support of embedded security information. Fuzzy transform (F-Transform) is a powerful tool that encompasses both classical transforms as well as approximation technique using fuzzy IF-THEN rules studied in fuzzy modelling. Ring projection transform (RPT) for features extraction is a very effective tool as it transforms two-dimensional data into one-dimensional with a very few component which significantly reduces the computational complexity. We propose a new and comprise scheme of fuzzy transform and RPT for CMFD. Firstly, the F-transform is employed on the input image to yield highly reduced dimension representation, which is split into fixed size overlapping blocks. Further, RPT is applied to every block for calculating their features. These feature vectors are lexicographically sorted. Finally, the duplicated blocks are filtered out using correlation coefficient. The proposed algorithm is faster and efficient in terms of execution time and accuracy.

Keywords: CMFD; copy-move image forgery detection; RPT; ring projection transform; fuzzy transform; basic functions; correlation coefficient; feature extraction.

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1 Introduction

Digital images play a wide role in our daily life as we are living in the digital and technical era. These images can be personal or official and can be used as various important purposes such as evidence in the court of law, a news item, financial record etc. Forge image are being used as an original image to disguise and can be presented as false evidence. Furthermore, image processing softwares, editing tools and the internet make this process quite easy. Anyone can doctored images without leaving any visual clues. Therefore, there is a necessity of some effective algorithm which can detect image forgery automatically for the authenticity of the digital images.

Forgeries were extremely hard when computers, digital camera and smartphone are not easily available. Nowadays the recognition of smartphones and digital cameras has made the task acquirement of digital images easier. Moreover, current photo editing tools such as Photoshop makes it comparatively easy to produce digital image forgeries. Additionally, humans cannot distinguish the dissimilarities between the original and its tempered version. The cloning image forgery is the very popular type of technique, perform to create a digital image doctoring. Additionally, in which a specific block of image or object is copied and then pasted it to the other portion of the same image to accomplish information hiding. As the copied region move from the same image, its important properties such as noise, colour palette as well as texture, will be well-matched with the remaining part of the image. It will lead to a great remonstrance in identifying and locating the forgery regions.

Various approaches (Fridrich et al., 2003; Tsai and Chiang, 2002; Ansari et al., 2014; Liu et al., 2011; Pan and Lyu, 2010) have been reported for detecting copy-move forgery which can be categorised to block-based as well as keypoint-based. Fridrich et al. (2003) propose the first technique for detecting CMFD. They have used block matching detection scheme with the help of discrete cosine transform (DCT). Further, quantised DCT coefficient has been calculated and then lexicographical sort was applied to detect copy-move region. Similarly, Popescu and Farid (2004) propose a PCA based CMFD approach, which distinct in its demonstration of over-lapping blocks based on the principal component analysis (PCA) rather than DCT. Further, Luo et al. (2006) detached image into four sub-blocks then they have performed a matching operation on the basis of average red, blue and green colour values. Additionally, this technique is has proven ability to work on the various types of attacks such as additive noise, JPEG compression and Gaussian blurring. Similarly, Kang and Wei (2008) used singular value decomposition (SVD) to yield reduced dimension of the input image, They have found the SV matrix and then lexicographical sort is applied to find the similar region. This method proved to be efficient after applying noise distortion. Ansari and Ghrera (2018) and Ansari and Ghrera (2016) have proposed a technique for extracting texture feature from the given image. Further, these extracted feature vector can be applied to identify CMFD. Additionally, they have also developed edge detection (Ansari et al., 2017b, 2016b) techniques, copy-move forgery can be identified after edge detection. Furthermore, Li et al. (2007) developed a sorted neighbourhood technique with the help of discrete wavelet transform (DWT) and SVD. Firstly, DWT is employed on given image after that SVD is applied to low frequency elements to minimise their dimensions. lexicographical sort is employed on SV vectors for making identical blocks nearby in the sorted list. Further, doctored regions were identified. The DWT, as well as SVD techniques, are very time consuming and computationally complicated. Bayram et al. (2009) have applied scale as well as rotation invariant Fourier Mellin transform (FMT) and the notion of bloom filters to identify cloning part of the image. This approach was computationally efficient and also able to identify cloning part in highly compressed images.

In this paper, we have only focused on a block-based method for CMFD. Firstly, fuzzy transform was applied to a given image to yield a highly minimise dimension demonstration.This highly reduced dimension representation is split into fixed size over-lapping blocks and ring projection transform (RPT) is employed to every block for characterising their features. Furthermore, to make feature vectors nearby lexicographical sort is applied. Finally, the identical blocks are identified using correlation coefficient.

2 Fuzzy transform

Fuzzy transform was developed by Perfilieva (2004a) and Perfilieva (2004b). It is a factual technique of the fuzzy approximation of a continuous function. In this section, we present the overviews of main definitions and concept of the F-transform technique.

2.1 Fuzzy partition: basic functions

Definition 1: A fuzzy partition of a given real compact interval $[a, b]$ is defined by a decomposition $\mathbb{P} = \{a = x_1 < x_2 < \cdots < x_n = b\}$ of $[a, b]$ into $n-1$ subintervals $[x_{k-1}, x_k]$, $k = 2, \ldots, n$ and by a family $\mathbb{A} = \{A_1, A_2, \ldots, A_n\}$ of n fuzzy numbers (basic functions), identified by their membership functions $A_k : [a, b] \to [0, 1], k = 1, \ldots, n$, if they fulfil the following conditions:

- $A_k : [a, b] \to [0, 1]$ is continuous with $A_k(x_k) = 1$
- $A_k(x) = 0$ if $x \notin (x_{k-1}, x_{k+1})$
- for $k = 2, \ldots, n$, A_k is increasing on $[x_{k-1}, x_k]$ and decreasing on $[x_k, x_{k+1}]$
- A_1 is decreasing on $[a, x_2]$ and A_n is increasing on $[x_{n-1}, b]$
- for all $x \in [a, b]$ the partition of unity condition holds $\sum_{k=1}^{n} A_k(x) = 1.$

Let a fuzzy partition of $[a, b]$ be given by the fuzzy numbers $A_1, A_2, \ldots, A_n$ with the help of Definition 2. We say that it is uniform if the nodes $x_1 < \cdots < x_n$, $n \geq 3$, are equidistant, i.e., $x_k = a + h(k-1)$, $k = 1, \ldots, n$, where $h = (b-a)/(n-1)$ and the following two additional properties are met:

- $A_k(x_k - x) = A_k(x_k + x), \forall x \in [0, h], k = 2, \ldots, n-1$
- $A_{k+1}(x) = A_k(x - h), \forall x \in [a + h, b], k = 2, \ldots, n-1.$

Remark 1: In the case of a uniform partition, h is a length of the support of A_1 or A_n, while $2h$ is a length of the support of other basic functions A_k, $k = 2, \ldots, n-1$.

An example of the non-uniform partition of an interval by fuzzy sets with triangular shaped membership functions is depicted in Figure 1 while Figure 2 shows a uniform partition of an interval by fuzzy sets with sinusoidal shaped basic functions. The following formulas give the formal representation of such triangular and sinusoidal-shaped membership functions, respectively:

$$A_1(x) = \begin{cases} 1 - \frac{(x-x_1)}{h_1}, x \in [x_1, x_2]; \\ 0 \quad \text{otherwise}, \end{cases}$$

$$A_2(x) = \begin{cases} \frac{(x-x_{k-1})}{h_{k-1}}, \quad x \in [x_{k-1}, x_k]; \\ 1 - \frac{(x-x_k)}{h_k} \text{ if } x \in [x_k, x_{k+1}]; \\ 0 \quad \text{otherwise}, \end{cases}$$

$$A_n(x) = \begin{cases} \frac{(x-x_{n-1})}{h_{n-1}}, x \in [x_{n-1}, x_n]; \\ 0 \quad \text{otherwise}, \end{cases},$$

where $k = 2, \ldots, n-1$ and $h_k = x_{k+1} - x_k$.

$$A_1(x) = \begin{cases} 0.5 \left(\cos \frac{\pi}{h}(x - x_1) + 1\right), x \in [x_1, x_2]; \\ 0 \quad \text{otherwise}, \end{cases}$$

$$A_k(x) = \begin{cases} 0.5 \left(\cos \frac{\pi}{h}(x - x_k) + 1\right), x \in [x_{k-1}, x_{k+1}]; \\ 0 \quad \text{otherwise}, \end{cases},$$

where $k = 2, \ldots, n-1$ and

$$A_n(x) = \begin{cases} 0.5 \left(\cos \frac{\pi}{h}(x - x_n) + 1\right), x \in [x_{n-1}, x_n]; \\ 0 \quad \text{otherwise}. \end{cases}.$$

First, let us recall the following lemma proved in Perfilieva (2004b) confirming that the definite integral of a basic function from a uniform fuzzy partition does not depend on its shape.

Lemma 1: *Let a uniform fuzzy partition of* $[a, b]$ *be given by basic functions* $A_1, A_2, \ldots, A_n$, $n \geq 2$. *Then* $\int_a^b A_1(x)\mathrm{d}x = \int_a^b A_n(x)\mathrm{d}x = \frac{h}{2}$ *and for* $i = 2, \ldots, n-1$, $\int_a^b A_n(x)\mathrm{d}x = h$.

Figure 1 A non-uniform fuzzy partition of $[1, 4]$ by triangular membership functions (see online version for colours)

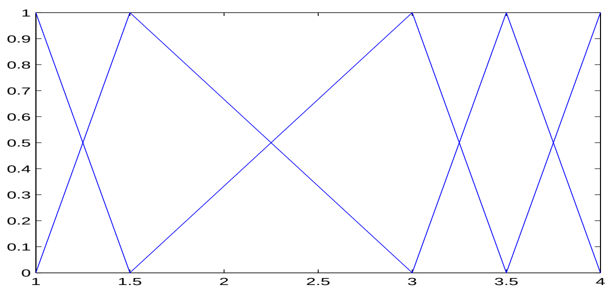
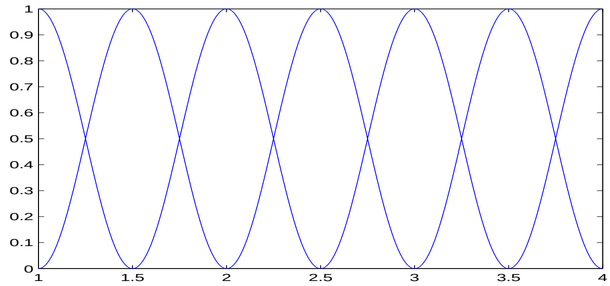


Figure 2 Uniform fuzzy partition of $[1, 4]$ by sinusoidal membership functions (see online version for colours)



2.2 *Direct fuzzy transform*

Definition 2: Let a fuzzy partition of $D = [a, b]$ be given by basic functions $A_1, \ldots, A_n \subseteq D$, $n > 2$ and let $f : D \to R$ be an arbitrary function from $C(D)$. The n-tuple of real numbers $[F_1, F_2, \ldots, F_n]$ given by

$$F_i = \frac{\int_a^b f(x)A_i(x)\mathrm{d}x}{\int_a^b A_i(x)\mathrm{d}x}, \; i = 1, 2, \ldots, n \tag{1}$$

is the direct fuzzy transform (F-transform) of f with respect to the given fuzzy partition and $[F_1, F_2, \ldots, F_n]$ are the components of the F-transform of f.

Definition 3: Let $A_1, A_2, \ldots, A_n$ be basic functions which form a fuzzy partition of $[a, b]$ and f be a function from $C([a, b])$. Let $F_n[f] = [F_1, F_2, \ldots, F_n]$ be the integral F-transform of f with respect to $A_1, A_2, \ldots, A_n$. Then the function

$$f_{F,n}(x) = \sum_{k=1}^{n} F_k A_k(x) \tag{2}$$

is called the inverse F-transform.

Definition 4: Let a fuzzy partition of $D = [a, b]$ be given by basic functions $A_1, \ldots, A_n \subseteq D$, $n > 2$ and let $f : D \to R$ be a function known at nodes $p_1, p_2, \ldots, p_N$ such that for each $i = 1, 2, \ldots, n$, there exists $k = 1, 2, \ldots, N$: $A_i(p_k) > 0$. The n-tuple of reals $[F_1, F_2, \ldots, F_n]$ given by

$$F_i = \frac{\sum_{k=1}^{N} f(p_k)A_i(p_k)}{\sum_{k=1}^{N} A_i(p_k)}, \; i = 1, 2, \ldots, n \tag{3}$$

is the discrete direct F-transform of f with respect to the given fuzzy partition.

Similarly, as in equation (2), we call the discrete inverse F-transform of f with respect to $A_1, A_2, \ldots, A_n$ for defining the following function in the same points $p_1, p_2, \ldots, p_N$ of $[a, b]$:

Definition 5: Let $A_1, A_2, \ldots, A_n$ be basic functions which form a fuzzy partition of $[a, b]$ and f be a function from $C([a, b])$. Let $F_n[f] = [F_1, F_2, \ldots, F_n]$ be the integral F-transform of f with respect to $A_1, A_2, \ldots, A_n$. Then the function

$$f_{F,n}(p_j) = \sum_{k=1}^{n} F_i A_i(P_j) \tag{4}$$

is called the inverse F-transform.

2.3 F-Transform in two variables

The direct and inverse F-transforms of a function with two and more variables can be introduced as a direct generalisation of the case of one variable. We will give its brief review and refer to Di Martino et al. (2008) for more details.

Assume that our universe of discourse is the rectangle $[a, b] \times [c, d]$ and let $n, m > 2$, $x_1, x_2, \ldots, x_n \in [a, b]$ and $y_1, y_2, \ldots, y_m \in [c, d]$ be $n+m$ assigned points, called nodes, such that $a = x_1 < x_2 < \ldots < x_n = b$ and $c = y_1 < y_2 < \ldots < y_m = d$. Furthermore, let $A_1, A_2, \ldots, A_n : [a, b] \to [0, 1]$ be a fuzzy partition of $[a, b]$ and $B_1, B_2, \ldots, B_m : [c, d] \to [0, 1]$ be a fuzzy partition of $[c, d]$ and $f(x, y)$ be a continuous function on $[a, b] \times [c, d]$. Then we can define the $n \times m$ matrix $[F_{kl}]$ as the F-transform of f with respect to $\{A_1, A_2, \ldots, A_n\}$ and $\{B_1, B_2, \ldots, B_m\}$ if we have for each $k = 1, 2, \ldots, n$ and $l = 1, 2, \ldots, m$, $x \in [a, b]$ and $y \in [c, d]$:

$$F_{kl} = \frac{\int_a^b \int_c^d f(x, y) A_k(x) B_l(y)}{\int_a^b \int_c^d A_k(x) B_l(y)}. \quad (5)$$

In the discrete case, we assume that the function f determined values in some points $(p_j, q_j) \in [a, b] \times [c, d]$, where $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, M$. Moreover, the sets $P = \{p_1, p_2, \ldots, p_N\}$ and $Q = \{q_1, q_2, \ldots, q_M\}$ of these nodes are sufficiently dense with respect to the chosen partitions, i.e., for each $i = 1, 2, \ldots, N$ there exists an index $k \in \{1, \ldots, n\}$ such that $A_i(p_k) > 0$ and for each $j = 1, 2, \ldots, M$ there exists an index $l \in \{1, \ldots, m\}$ such that $B_j(q_l) > 0$.

In this case, we may define the matrix $[F_{kl}]$ to be the discrete F-transform which is the extension of (3), of f with respect to $A_1, A_2, \ldots, A_n$ and $B_1, B_2, \ldots, B_m$ if we have for each $k = 1, 2, \ldots, n$ and $l = 1, 2, \ldots, m$:

$$F_{kl} = \frac{\sum_{j=1}^{M} \sum_{i=1}^{N} f(p_i, q_j) A_k(p_i) B_l(q_j)}{\sum_{j=1}^{M} \sum_{i=1}^{N} A_k(p_i) B_l(q_j)}. \quad (6)$$

Similarly, by extending equation (4) to the case of two variables, we give the discrete inverse F-transform of f with respect to $A_1, A_2, \ldots, A_n$ and $B_1, B_2, \ldots, B_m$ to be the following function defined in the same points $(p_j, q_j) \in [a, b] \times [c, d]$, with $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, M$, as

$$f_{nm}^F(p_i, q_j) = \sum_{k=1}^{n} \sum_{l=1}^{m} F_{kl} A_k(p_i) B_l(q_j). \quad (7)$$

3 Principle of image compression by the F-Transform method

Let an image I of the size $N \times M$ pixels be represented by a function of two variables (a fuzzy relation) $f_I : N \times N \to [0, 1]$ partially defined at nodes $(i, j)2[1, N] \to [1, M]$. The value $f_I(i, j)$ represents an intensity range of each pixel. A compression of the image I is represented by the $n \times m$ matrix $F_{nm}[f_I]$ of the discrete F-transform components of f_I :

$$F_{nm}[f_I] = \begin{pmatrix} F_{11} \cdots F_{1m} \\ \vdots \quad \vdots \quad \vdots \\ F_{n1} \cdots F_{nm} \end{pmatrix}$$

where

$$F_{kl} = \frac{\sum_{j=1}^{M} \sum_{i=1}^{N} f_I(i, j) A_k(i) B_l(j)}{\sum_{j=1}^{M} \sum_{i=1}^{N} A_k(i) B_l(j)}. \quad (8)$$

for each pair $k = 1, 2, \ldots, n$; $l = 1, 2, \ldots, m$. The basic functions $A_1, A_2, \ldots, A_n$ and $B_1, B_2, \ldots, B_m$ establish fuzzy partitions of $[1, N]$ and $[1, M]$ respectively, and $n < N$, $m < M$. The value $\rho = \frac{nm}{NM}$ is called the compression ratio.

A reconstruction of the image I (function f_I) is given by the inverse F-transform of f_I adapted to the domain $[1, N] \times [1, M]$:

$$f_{nm}^F(i, j) = \sum_{k=1}^{n} \sum_{l=1}^{m} F_{kl} A_k(i) B_l(j). \quad (9)$$

Remark 2: A comparison among three techniques: F-transform, FEQ and JPEG have been attempted (Di Martino et al., 2008). It has been shown that the technique of F-transform is better than FEQ technique, but it is worse than the JPEG technique. However, a complexity of the F-transform based compression is less than the complexity of JPEG technique.

3.1 Features extraction using ring projection transform (RPT)

Features extraction using RPT is a very useful tool in the field of image processing and pattern recognition. In order to make matching invariant to rotation, the RPT (Tsai and Chiang, 2002; Tang et al., 1991, 1998; Choi and Kim, 2002) technique was proposed. The RPT converts a 2D image into a rotation-invariant representation in the 1D ring projection space. The template of size $m \times n$ is denoted by $T(x, y)$. The RPT process of the template is given as follows: First, the centre point of $T(x, y)$, denoted as (x_c, y_c), is derived, and subsequently, the template $T(x, y)$ Cartesian frame is transformed into a polar frame based on the following relations:

$$x = r \cos \theta, \quad (10)$$

$$y = r \sin \theta, \quad (11)$$

where $r = \text{Int}[(x - x_c)^2 + (y - y_c)^2]^{1/2}, r \in [0, R], R = \min(M, N)$ and $\theta \in [0, 2\pi]$.

The ring-projection of image $T(x, y)$ at radius r, denoted by $P_T(r)$, is defined as the mean value of $T(r \cos \theta, r \sin \theta)$ at the specific radius r. That is,

$$P_T(r) = \frac{1}{2\pi r} \int_0^{2\pi} T(r \cos \theta, r \sin \theta). \quad (12)$$

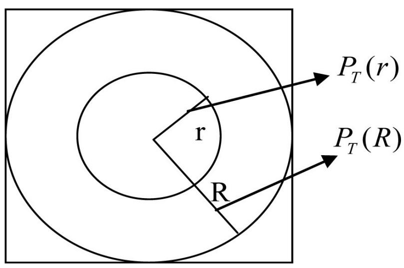
$$\langle P_T,\, P_K\rangle = \frac{\left[(R+1)\sum_{r=0}^{R} P_T(r)P_S(r) - \sum_{r=0}^{R} P_T(r)\sum_{r=0}^{R} P_S(r)\right]^2 \times 100}{\left\{(R+1)\sum_{r=0}^{R} P_T(r)^2 - \left[\sum_{r=0}^{R} P_T(r)\right]^2\right\}\left\{(R+1)\sum_{r=0}^{R} P_S(r)^2 - \left[\sum_{r=0}^{R} P_S(r)\right]^2\right\}} \tag{14}$$

Taking the mean of stimulus values for each specific ring reduces the effect of noise. The discrete representation of $P_T(r)$ is given by

$$P_T(r) = \frac{1}{S_r}\sum_{i=1}^{n} T(r\,\cos\,\theta_k,\, r\,\sin\,\theta_k), \tag{13}$$

where S_r is the total number of pixels falling on the circle of radius $r = 0, 1, 2, \ldots, R$. Since $P_T(r)$ is defined as the mean of pixel intensities along the circle, centred on the template of radius r (as shown in Figure 3). $P_T(r)$ values of all rings in the template have equal importance in the computation of correlation (Tang et al., 1998). Furthermore, as RPT is constructed along circular rings of increasing radii, the derived one-dimensional ring projection template is invariant to rotation of its corresponding two-dimensional image template.

Figure 3 Concept of RPT template



The correlation coefficient is a measurement of the strength of the linear relationship between two variables or sets of data. For the matching process, the normalised correlation (NC) is adopted in the measurement of similarity. Let $P_T = [P_T(0),\, P_T(1),\, P_T(2),\, \ldots P_T(R)]$ and $P_S = [P_S(0),\, P_S(1),\, P_S(2),\, \ldots, P_S(R)]$ Then normalised correlation coefficient between two different RPTs P_T and P_S is given by the formula:

The value of $\langle P_T,\, P_K\rangle$ is unaffected by rotations and linear changes (constant gain and offset) between two different RPTs P_T and P_S. Additionally, the dimensional length of the ring projection vector is only $R+1$. This significantly reduces the computational complexity for $\langle P_T,\, P_K\rangle$.

4 Copy-move image forgery detection (CMFD) algorithm

The block-based CMFD techniques, the majority of the techniques are analogous to that developed by Popescu and Farid (2004). It indicates that more computational work is necessary for dimension lessening, matching control as well as similarity filtering for big numbers of image blocks. Generally, as test images grow bigger, the nature of copy-move forgery detection algorithms requires many iterations and comparisons. For example, suppose that a grey-scale image of size $m \times n$ pixels can be divided into small overlapping blocks of size $b \times b$ pixels, then the total number of image blocks is $N = (m - b + 1) \times (n - b + 1)$ generated by sliding the window of $b \times b$ pixels over the whole image by one pixel every time from upper left to bottom right corner. MATLAB is working with matrices; however, it is less optimised when faced with multiple loops. Therefore, it will be extremely important that the should be minimal. Moreover, CMFD algorithm turns out to be computationally proscribed when the number of image blocks is higher which inexorably leads to high computational load for consequent feature extraction as well as similarity matching. Therefore, CMFD generally performs on a reduced image size to decrease the computational cost; However, information loss is inevitable.

Based on this scheme, we develop a boosting scheme to decrease the computational overhead and number of estimated blocks every time and it turns out to decrease the time and memory drastically. The proposed technique (as shown in Figure 4) has been applied to grey-scale images as follows:

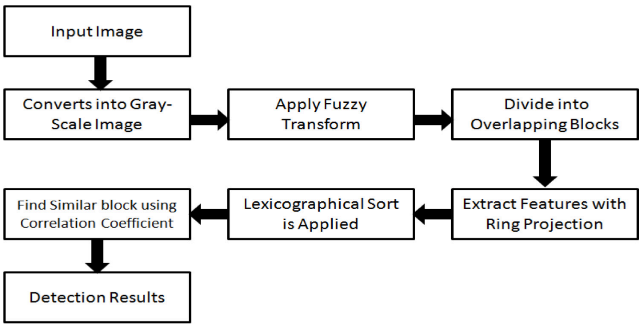
- Let I be a grey image partitioned in $N \times M$ pixels. It can be seen as a fuzzy relation $I : (i, j) \in \{1, \ldots, N\}\{1, \ldots, M\} \rightarrow [0, 1]$, $I(i,\, j)$ being the normalised value of the pixel $P(i,\, j)$, that is $I(i,\, j) = P(i,\, j)/255$ if the length of the grey-scale, has 256 levels.
- The image I is compressed by using a discrete F-transform in two variables $[F_{kl}]$ (formula (8)) defined for each $k = 1, 2, \ldots, n$ and $l = 1, 2, \ldots, m$, as

  $$F_{kl} = \frac{\sum_{j=1}^{M}\sum_{i=1}^{N} f_I(i,\, j)A_k(i)B_l(j)}{\sum_{j=1}^{M}\sum_{i=1}^{N} A_k(i)B_l(j)}. \tag{15}$$

  The basic functions $A_1, A_2, \ldots, A_n$ and $B_1, B_2, \ldots, B_m$ establish fuzzy partitions of $[1,\, N]$ and $[1,\, M]$ respectively.
- Overlapping blocks of size $b \times b$ are created in reduced image with one-pixel shifting and the total number of overlapping blocks is given by $N_{ovr} = (M - b + 1) \times (N - b + 1)$.
- Ignore the blocks whose contrast is greater than the predefined threshold 'CTR' to reduce the false positive.

   - Transform each overlapping $b \times b$ into a $1D$ RPT vector of size $R + 1$.
   - The feature vectors extracted from Step (a) are arranged into a matrix and denoted as A with the size of $(M - b + 1)(N - b + 1) \times R + 1$.
   - Form another matrix P of two columns for storing top-left coordinates.
- Apply lexicographical sort to the matrix A for making similar blocks consecutive.
- For every adjacent row of matrix A,
   - Compute the normalised correlation coefficient between the pair of sorted rows using the equation (14)
   - If the computed correlation coefficient exceeds a preset threshold value 'C_t', then extract the corresponding blocks position from the matrix P, and marked the location of these forged blocks in the original image by setting pixel values to zero.
- Finally, the copy-move region is detected automatically without applying post-processing operation.

Figure 4 Proposed model



5 Results and discussion

Accuracy, true positive rate (TPR), False Positive Rate (FPR) were calculated to prove the robustness of the proposed algorithm.The experiments were carried out on MATLAB R2013a, RAM 4 GB and core i3 processor. The database of 100 images was composed where 50 images were original and 50 were tempered. This database is having different type of image format (.jpg, .png and .tiff) and various resolutions like 256×256, 512×512, 640×480 etc. The forged images are constructed with the help of Photoshop in which the forge area or object is randomly selected and pasted into the same image. Furthermore, one public database MICC-F220 (http://www.micc.unii.it/ballan/research/image-forensics/) was also used for the comparative analysis of proposed algorithm with other reported techniques.This database are having total 220 images, from them 110 are original and 110 are forged. Additionally, various types of attacks such as scaling, rotation and blurring were also applied on tempered images of both databases to check the robustness of the proposed algorithm.

The image is converted into grey-scale then a direct fuzzy transform is applied and basic function is used to establish fuzzy partitions. The number of points covered by basis functions is different. It may be noted that the less number of points covered by basic functions may give the less detection results and also increases the execution time of the algorithm. As we increase the number of points covered by basic functions, the size of the original image will reduce, consequently, the execution time of algorithm will be decreased. However, a higher number of points covered by the basic functions may also give the false detection results. Therefore, baseLen parameter was used in the proposed algorithm to control the quality of detection results as well as the execution time of the algorithm. The optimal value of baseLen parameter leads to the better detection results in a very less time, which shows the feasibility and effectiveness of proposed method. In proposed algorithm, the parameter 'CTR' was also introduced to ignore the low contrast blocks, which reduces the false positive. Lesser the number of blocks are, the faster is the process.

The performance of the proposed technique has been observed by calculating the True Positive Rate (TPR), the False Positive Rate (FPR), and the Accuracy. They can be estimated as follows:
True Positive (TP): Tempered image detected as tempered
False Positive (FP): Original image detected as tempered
True Negative (TN): Original image detected as original
False Negative (FN): Tempered image detected as original

From these above measures, we can define various performance evolution metrics: TPR, FPR and Accuracy as follows:

$$\text{Accuracy} = \frac{\text{Number of correctly identified images}}{\text{Total number of images}} \times 100$$

$$\text{True Positive Rate(TPR)} = \frac{\text{Number of tempered images identified as tempered}}{\text{Total number of tempered images}}$$

$$\text{False Positive Rate(FPR)} = \frac{\text{Number of original images identified as tempered}}{\text{Total number of original images}}.$$

The performance of proposed method is depicted in Tables 1–3, which shows that proposed method perform better than state of the art techniques (Fridrich et al., 2003; Popescu and Farid, 2004). Table 1 shows the accuracy of proposed algorithm in 100 images with various attacks and varying block sizes.The overall accuracy of proposed method was 91.25%. Table 2 shows the accuracy of proposed algorithm and execution time on MICC-F220 database. Moreover, Table 3 shows that the proposed algorithm is able to reduce dimensions drastically in comparison to other reported methods (Fridrich et al., 2003; Popescu and Farid, 2004; Amerini et al., 2011;

Bayram et al., 2009; Luo et al., 2006). Reduced dimension leads to less of computational time; Therefore, proposed algorithm is faster as compare to other existing algorithm as shown in Table 2.

Table 1 Accuracy results

Block-size	*No. of images*	*Identified correctly*	*Identified incorrectly*	*Accuracy (%)*
4×4	100	94	6	94
8×8	100	93	7	93
16×16	100	91	9	91
32×32	100	87	13	87
Total	400	365	35	91.25

Table 2 TPR, FPR and execution time comparison for each method on MICC-F220

Methods	*TPR*	*FPR*	*Execution time in seconds*
Fridrich et al. (2003)	89	84	294.96
Popescu and Farid (2004)	87	86	70.97
Pan and Lyu (2010)	89	1	10
Amerini et al. (2011)	100	8	4.94
Proposed method	90	34	3.80

Table 3 Feature dimension comparison with existing algorithm

Methods	*Extraction domain*	*Total blocks*	*Feature dimension*
Fridrich et al. (2003)	DCT	255025	64
Popescu and Farid (2004)	PCA	255025	32
Amerini et al. (2011)	SIFT	2700 key points	128
Zimba and Sun (2011)	DWT-PCA	12789	16
Ghorbani et al. (2011)	DWT-DCT	12769	16
Hu et al. (2011)	Grouped DCT	45024	8
Luo et al. (2006)	Spatial domain	247009	5
Proposed method	FT and RPT	1156	4

The images are shown in Figures 5–9 represent the results of copy move forgery detection marked on the tampered image. The row is composed of four images: original image, tampered image, fuzzy transform image and resultant image from left to right.

Figure 5 Copy-move forgery detection: (a) original image; (b) grey-scale forgery image of (a); (c) Fuzzy Transform image and (d) forgery detection (see online version for colours)

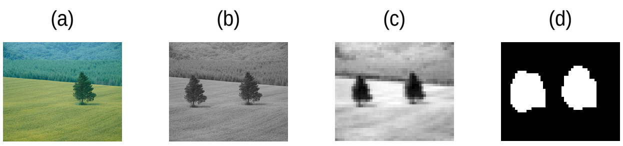


Figure 6 Copy-move forgery detection: (a) original image; (b) grey-scale forgery image of (a); (c) fuzzy transform image and (d) forgery detection (see online version for colours)

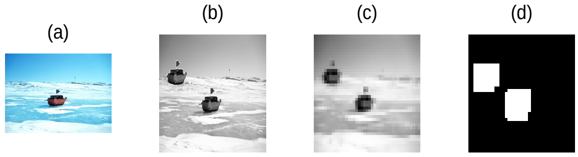


Figure 7 Forgery detection on MICC-220 Databse: (a) original image; (b) forgery image of (a); (c) fuzzy transform image and (d) forgery detection (see online version for colours)

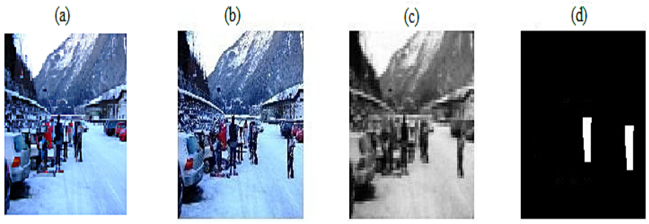


Figure 8 Forgery detection on MICC-220 Databse: (a) original image; (b) forgery image of (a); (c) fuzzy transform image and (d) forgery detection (see online version for colours)

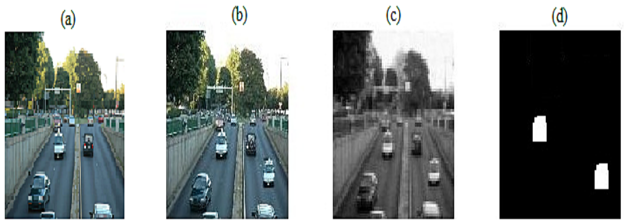


Figure 9 Forgery detection on MICC-220 Databse: (a) original image; (b) forgery image of (a); (c) fuzzy transform image and (d) forgery detection (see online version for colours)

6 Conclusion

A novel method to detect copy-move image forgery based on fuzzy transform and RPT is presented. The comprises scheme of fuzzy transform and RPT greatly improved the time and memory. Due to the inherently rotation-invariant feature of the RPT method, large angle rotation of tampered region can be successfully detected. Additionally, the proposed method is able to detect copy-move region effectively with various attack i.e., scaling, rotation and Gaussian noise. Moreover, it drastically reduces the computational time, as well as feature dimensions, compare to other reported algorithms. In future, the proposed algorithm can be applied for detecting copy move forgery in colour, highly compressed and noisy images.

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Website

http://www.micc.unii.it/ballan/research/image-forensics/