Journal of Software Engineering

ISSN 1819-4311

Academic Journals Inc.

www.academicjournals.com

Journal of Software Engineering 9 (3): 487-503, 2015
ISSN 1819-4311 / DOI: 10.3923/jse.2015.487.503

A Copy-Move Forgery Image Blind Authentication Approach Based on Radon-Pseudo-Fourier-Mellin-Transform

[1]Junliu Zhong and [2]Yanfen Gan
[1]School of Information Engineering, Guangdong Mechanical and Electrical College,
[2]Department of Information Science and Technology, Guangdong University of Foreign Studies South China Business College, Guangzhou, 510545, China

Corresponding Author: Yanfen Gan, Department of Information Science and Technology, Guangdong University of Foreign Studies South China Business College, Guangzhou, 510545, China

ABSTRACT
Copy-move forgery is a common type of image forgery. In the past decades, various types of copy-move forgery image blind authentication approaches have been proposed and these approaches have been used to detect blind forgery images in a number of applications fields. But the robustness of these previously blind authentication approaches against noise and geometric deformation is poor. In this study, the moment invariants which were review are successfully applied in the field of forgery image detection and authentication. Then a new novel approach was proposed for copy-move forgery which is to construct its rotation and scaling moment invariants by using Radon-Pseudo-Fourier-Mellin-Transforms (RPFMT) approach. The experimental results show that the proposed approach can detect copy-move region accurately, even when the copied region was undergone a large angel rotation and scaling tampered. In addition, the robustness of the proposed approach to additive-White Gaussian Noise is greatly improved in comparison with some recent approaches.

Key words: Copy-move, forgery image, blind authentication, robustness, geometric deformation, rotation and scaling moment invariants, radon-pseudo-fourier-mellin-transform

INTRODUCTION
In recent years, the common users have become extremely easy to produce good quality forgery images with the development of the powerful digital photo-editing tools. While these editing tools and technologies have achieved many exciting advances in art and science but also led to some serious social, legal and scientific issues. There are many image forgery issues had been ever happened in the world. The first image forgery issue happened in 1860, forgers placed Lincoln's head in Senator John Calhoun's body in a image aim to obtain desired political benefits. Original image is shown in Fig. 1a, forged image is shown in Fig. 1b. If these issues used in scientific discovery, court evidence, news reports and other occasions will have the potential negative impact on society. So, proceed with digital image forgery authentication research will be of great significance.

There are many methods for image forgery. Farid (2004) classified image forgery authentication schemes into six representative categories: Enhanced, composited, morphed, re-touched, painted, computer generated. The image composited operation is also called as the copy-move forgery. It is the most common digital image forgery (Nguyen and Katzenbeisser, 2012;

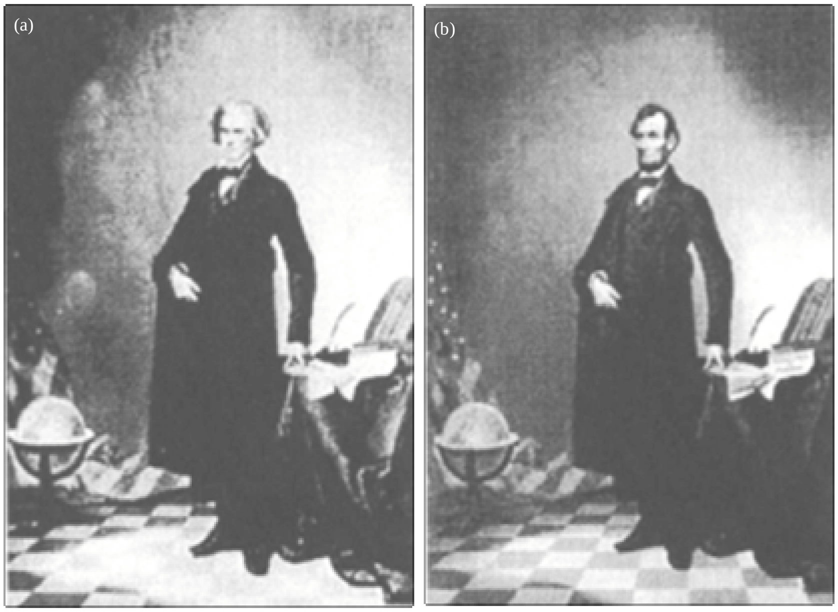

Fig. 1(a-b): (a) Original image and (b) Forged image

Hsu and Chang, 2007; Kumar *et al*., 2011) in which a part of a digital image is copied and pasted to another part in the same image in order to cover an important image feature (Bayram *et al*., 2009). In the actual application, it is likely to be subjected to rotation, scaling, or additive noise for better covering the forgery marks and achieving the blended purposes. In the past decades, many approaches about copy-move blind forgery are proposed. Fridrich *et al*. (2003) extracted Discrete Cosine Transform (DCT) coefficients which are robust to low-pass filtering and compression. Popescu and Farid (2004) proposed to apply Principal Components Analysis (PCA) to obtain compact representations for the blocks. And then they (Popescu and Farid, 2005) employed Expectation-Maximization approach to expose resample traces. Zhao (2012) proposed an approach based on PCA of projection feature. As tampered image is divided into many overlapped small image blocks. The horizontal projection and vertical projection of each image block regained to build up a matrix. And the experiment shows that the computation of this approach is more rapid than Posucue approach. Li *et al*. (2007) proposed a blind forensics approach based on Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD) to detect the specific artifact. Since the robustness of these previously blind authentication approaches against noise and geometric deformation especial anti-rotation and anti-scaling is poor. Qian *et al*. (2013) proposed a rotation angle estimation approach. It based on pixel variance periodicity introduced by interpolation and established a mapping between image rotation angle and the periodicity of pixel variance. But the approach is robust for rotation angles between 5° and 45°. Hence, it must be consider a novel approach to detect a good accuracy for a large angle rotation and scaling.

Hu (1962) proposed a theory of Two-Dimensional (2-D) moment invariants for planar geometric figures. His fundamental theorem method is well-known as HU moments. Hu (1962) used geometric figures linear transforms to construct classic invariant moments containing translation, rotation and scale etc. It is laid the foundation for the image moment invariant theory. Hu (1962) moment invariants are no scaling moment invariants. Later, people found that many improved moment invariants. The representative approaches have the Zernike moments (Liao and Pawlak, 1998), Legendre moments (Yap and Paramesran, 2005), Tchebichef moments (Mukundan *et al.*, 2001), Krawtchouk moments (Yap *et al.*, 2003) and orthogonal Fourier-Mellin moments (Derrode and Ghorbel, 2001). Orthogonal moment invariant is superiority to non-orthogonal moment invariant. But the problem of the orthogonal moment invariant for image geometric moment invariant analysis is lack of essentially scaling invariance (Teh and Chin, 1988). So some improved approaches are proposed. Huang *et al.* (2008) proposed an approach to detect copy-move forgery in digital images by extracting Scale Invariant Feature Transform (SIFT) descriptors of an image which are invariant to changes in illumination, rotation, scaling etc. Owing to the similarity between copied region and pasted region, descriptors are matched between each other to seek for any possible forgery in images. Chihaoui *et al.* (2014) proposed an approach uses the Scale Invariant Feature Transform (SIFT) and uses the Singular Value Decomposition (SVD) by matching between identical features. He and Wang (2010) proposed a approach use the radon transform to construct moment invariants. Lei *et al.* (2011) proposed a novel robust hashing approach for image authentication based on Radon and Discrete Fourier Transform (DFT). Kakar and Sudha, (2012) proposed an authentication approach based on transform-invariant features. But the authentication approach is limited by modifying the MPEG-7 image signature tools descriptors. Yap *et al.* (2010) proposed an approach which is called Polar Harmonic Transforms (PHTs), namely, Polar Complex Exponential Transform (PCET), Polar Cosine Transform (PCT) and Polar Sine Transform (PST). These a set of transforms can be used to generate rotation moment invariant. The experiments conducted shown that unlike the well-known Zernike and pseudo-Zernike moments, the kernel computation of PHTs is extremely simple and has no numerical stability issue. This implies that PHTs encompass the orthogonality and invariance advantages of Zernike and pseudo-Zernike moments but are free from their inherent limitations. The problem of this approach is also lack of scaling invariants. Wang *et al.* (2009) proposed rotational invariance based on Fourier analysis in polar and spherical coordinates. Zhang *et al.* (2010) proposed a general approach to construct a complete set of Orthogonal Fourier-Mellin Moment (OFMM) invariants. By establishing a relationship between the OFMMs of the original image and those of the image having the same shape but distinct orientation and scale, a complete set of scaling and rotation invariants is derived. Sheng and Shen (1994) proved that anti-rotation, anti-scaling and orthogonality performance of the Fourier-mellin-moment-invariants are better than Zemike and Hu moments. And the feature description ability, especially the description of the small image performance is also better. Papakostas *et al.* (2007) pointed out OFMMS can be widely applied in many fields such as image blind authentication. since the radial polynomials used in OFMMs have much more zeros than those of the other orthogonal moments, the OFMMs have the capability to describe high spatial frequency components of an image.

In general, one of the challenge here is the geometric moment invariants applied to detect the image forgery, especially applied to the copy-move blind image authentication are less. Another challenge is to find the robust representations for the approach, that the copy-move blocks can be detected more accuracy under modifications. In view of this, we focus on these two aspects and propose an approach to extract Radon-Pseudo-Fourier-Mellin-Moment-Invariants (RPFMMIs) features from the image blocks by using Radon-Pseudo-Fourier-Mellin-Transform (RPFMT). These features would be not only applied to robust to Gaussian noise addition but also applied to rotation and scaling moment invariants.

AUTHENTICATION APPROACH BASED ON RADON-PSEUDO-FOURIER-MELLIN-TRANSFORM

Radon and Fourier-Mellin transforms are the fundamental tools used in the proposed approach. In this section we first briefly review these transforms and their properties in order to establish the proper ties of the proposed approach.

Radon-transform: Mathematician Radon (1917) proposed Linear Radon transform. The basic idea of radon transform is the duality of point and line. It has a good anti-noise performance, can detect the image translation, rotation, scaling and other geometric transform.

In mathematics, the classical Radon transform in Two-Dimensions (2-D) is the integral transform consisting of the integral of a function over straight lines (Galigekere *et al*., 2000; Beylkin, 1987; Jafari-Khouzani and Soltanian-Zadeh, 2005a) Radon transform reflects the relationship between the image and its projection. Now supposed a 2-D function $f(x, y)\epsilon L^2(D)$, its Radon transform $R(r, \theta)$ is a function defined on the space of straight lines L in 2-D plane by the line integral along each such line. The Radon transform of a 2-D function $f_D(x, y)$ is defined as:

$$R(r, \theta)\{f_D(x, y)\} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f_D(x, y)\delta(r - x\cos\theta - y\sin\theta)dxdy \tag{1}$$

where, δ is a Dirac Delta function. The value of the r on a given straight line is the integral of $f_D(x, y)$ along this line and θ is the angle between the line and the y-axis (Beylkin, 1987; Jafari-Khouzani and Soltanian-Zadeh, 2005a, b). Radon transform is given in Fig. 2. Due to the inherent properties of the Radon transform, it is a useful tool to detect linear trends in images and capture the directional information of the images.

From Eq. 1, the discrete Radon transform equation is defined as:

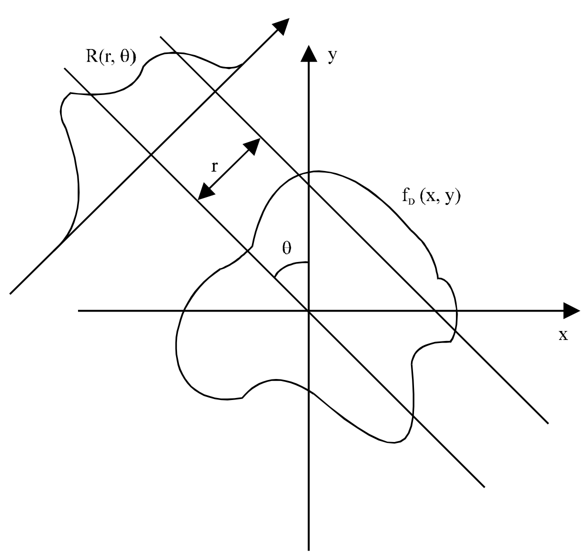

Fig. 2: Radon transform of $f_D(x, y)$

$$R(r,\theta)=\sum_{x=1}^{M}\sum_{y=1}^{N} f_D(x,y)\delta(r-x\cos\theta-y\sin\theta) \tag{2}$$

where, M and N are the dimensions of rows and columns in the image matrix.

From Eq. 1, R (r, θ) is the integral of $f_D(x, y)$ along this line L:

$$r = x\cos\theta+y\sin\theta \tag{3}$$

Suppose $r_1, r_2,...,r_n$ is the perpendicular distance of a line from the origin and projection angle $\theta_1, \theta_2,...,\theta_m$ is the angle formed corresponds to $r_1, r_2,...,r_n$ by the distance vector. The $R(r_i, \theta_k)$ represents the Radon transform of point (r_i, θ_k). Radon transform matrix (Gan and He, 2011) is defined in Eq. 4:

$$R(r_i,\theta_k)=\begin{bmatrix} R(r_1,\theta_1) & R(r_1,\theta_2) & \cdots & R(r_1,\theta_n) \\ R(r_2,\theta_1) & R(r_2,\theta_2) & \cdots & R(r_2,\theta_n) \\ \vdots & \vdots & \cdots & \vdots \\ R(r_m,\theta_1) & R(r_m,\theta_2) & \cdots & R(r_m,\theta_n) \end{bmatrix} \tag{4}$$

The normal form of the affine transform is defined as:

$$\begin{cases} x' = ax+by+e \\ y' = cx+dy+f \end{cases} \tag{5}$$

where, $\Delta = \begin{vmatrix} a & b \\ c & d \end{vmatrix} \neq 0$ is a Det.

The translation, scaling and rotation expressions of the Radon transform (Hu, 1962) is given as:

$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \lambda \begin{bmatrix} \cos\varphi & \sin\varphi \\ -\sin\varphi & \cos\varphi \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} \tag{6}$$

where, λ is scaling factor, i = 1,2,3... ., x_i' and y_i' are new coordinates after the Radon transform.

Rotation feature of Radon transform: From Eq. 6, it can be write that:

$$g_D(x,y)=f_D(x',y')=f_D(x\cos\varphi+y\sin\varphi,\ -x\sin\varphi+y\cos\varphi) \tag{7}$$

where, $g_D(x', y')$ is $f_D(x, y)$ rotate to a new coordinate.

Suppose:

$$x' = x\cos\varphi+y\sin\varphi,\ y' = -x\sin\varphi+y\cos\varphi$$

where, $dx' = \cos\varphi\, dx$, $dy' = \cos\varphi$ d.

In both Eq. 1, 6 and 7, rotation feature of Radon transform is defined as:

$$\begin{aligned}
R_g(r,\theta) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g_D(x,y)\delta(r - x\cos\theta - y\sin\theta)dxdy \\
&= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_D(x',y')\delta(r - x\cos\theta - y\sin\theta)dxdy \\
&= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_D(x\cos\varphi + y\sin\varphi, -x\sin\varphi + y\cos\varphi)\delta(r - x\cos\theta - y\sin\theta)dxdy \\
&= \frac{1}{\cos^2\phi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_D(x\cos\varphi + y\sin\varphi, -x\sin\varphi + y\cos\varphi)\delta\{r - [(x'\cos\varphi - y'\sin\varphi)\cos\theta + (x'\sin\varphi + y'\cos\varphi)\sin\theta)dx'dy' \\
&= \frac{1}{\cos^2\phi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_D(x',y')\delta\{r - [x'(\cos\theta\cos\varphi + \sin\theta\sin\varphi) + y'(\sin\theta\cos\varphi - \cos\theta\sin\varphi)]\}dx'dy' \\
&= \frac{1}{\cos^2\phi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_D(x',y')\delta\{r - [x'\cos(\theta - \varphi) + y'\sin(\theta - \varphi)]\}dx'dy' \\
&= \frac{1}{\cos^2\varphi}R_f(r,\theta - \varphi)
\end{aligned} \tag{8}$$

Scaling feature of Radon transform: From Eq. 6, the scaling factor is simplified as:

$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \lambda \begin{bmatrix} x_i \\ y_i \end{bmatrix} \tag{9}$$

Suppose $\lambda > 0$ then:

$$g_D(x, y) = f_D(x', y') = f_D(\lambda x, \lambda y) \tag{10}$$

where, g_D (x, y) is a new scaling function of fD (x', y').

From Eq. 1 and 10, scaling feature of Radon transform is defined as:

$$\begin{aligned}
R_g(r,\theta) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g_D(x,y)\delta(r - x\cos\theta - y\sin\theta)dxdy \\
&= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_D(\lambda x,\lambda y)\delta(r - x\cos\theta - y\sin\theta)dxdy \\
&= \frac{1}{\lambda^2}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_D(x',y')\delta[\frac{1}{\lambda}(\lambda r - x'\cos\theta - y'\sin\theta)]dx'dy' \\
&= \frac{1}{\lambda}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_D(x',y')\delta(\lambda r - x'\cos\theta - y'\sin\theta)dx'dy' \\
&= \frac{1}{\lambda}R_f(\lambda r,\theta)
\end{aligned} \tag{11}$$

The Radon transform of $g_D(x, y)$ by rotation and scaling is defined as:

$$R_g(r,\theta) = \frac{1}{\lambda\cos^2\varphi} R_f(\lambda r, \theta - \varphi) \tag{12}$$

Radon-pseudo-fourier-mellin-transform: The radial moments of order r with repetition of image intensity function are defined as D(s, k). For detecting the forgery image, Wang *et al*. (2008), Jing *et al*. (2010), Liu *et al*. (2011) and Derrode and Ghorbel (2001) introduced a set of Fourier-Mellin-Transform moments. In Two-Dimension (2-D) polar coordinates, D(s, k) is the Radon-Fourier-Mellin-Transform of a 2-D function g(s, k) with order s^{-1} and it can be defined as:

$$D(s,k) = \int_0^{\infty}\int_0^{2\pi} g(s,k) r^{s-1} e^{-ik\theta} d\theta dr \tag{13}$$

where, s is complex number, $e^{-ik\theta}$ is complex exponential, k = 0, ±1, ±2 is order of circular harmonic function. To simplify the Eq. 13, further improvement are suggested in Eq. 14 by using real number u to display complex numbers. Equation 14 is defined as:

$$D(s,k) = \int_0^{\infty}\int_0^{2\pi} g(s,k) r^{u-1} e^{-ik\theta} d\theta dr \tag{14}$$

where, k = 0, ±1, ±2,..., u = 1, 2, 3... are real numbers and the priors k and u are supposed to be equal to 2 in this study.

Construct Radon-Pseudo-Fourier-Mellin-Transform moment invariants: From Eq. 12 and 14, it can be supposed that:

$$\beta = \theta - \varphi,\ \rho = \lambda r,\ r = \frac{\rho}{\lambda},\ dr = \frac{d\rho}{\lambda},\ d\theta = d\beta$$

The rotation and scaling of Radon-Pseudo-Fourier-Mellin-Transform moment invariant is defined as:

$$\begin{aligned} D_g(u,k) &= \iint R_g(r,\theta) r^{u-1} e^{-ik\theta} dr d\theta \\ &= \iint \frac{1}{\lambda\cos^2\varphi} R_f(\lambda r, \theta-\varphi) r^{u-1} e^{-ik\theta} dr d\theta \\ &= \frac{1}{\lambda\cos^2\varphi} \iint R_f(\rho,\beta) (\frac{\rho}{\lambda})^{u-1} e^{-ik(\beta+\varphi)} \frac{d\rho}{\lambda} d\beta \\ &= \frac{1}{\cos^2\varphi} (\frac{1}{\lambda})^{u+1} e^{-ik\varphi} \iint R_f(\rho,\beta) \rho^{u-1} e^{-ik\beta} d\rho d\beta \\ &= \lambda^{-(u+1)} e^{-ik\varphi} (\cos\varphi)^{-2} D_f(u,k) \end{aligned} \tag{15}$$

where, $D_f(u, k)$ can be transformed from $R_f(u, k)$ by using Radon-Pseudo-Fourier-mellin-Transform (RPFMT). $D_g(u, k)$ is Radon-Pseudo-Fourier-Mellin-Transform of $R_f(u, k)$. From Eq. 15, a function

$R_f(u, k)$ can be transformed from a scaling factor to magnitude factor and transformed from a rotate factor to a phase factor by using RPFMT approach. From Eq. 15, we also can construct scaling and rotation moment invariants of $Z_f(u, k)$ by using RPFMT approach:

$$\begin{aligned} Z_g(u,k) &= \frac{D_g(0,0)D_g(u,k)}{D_g(u,0)D_g(0,k)} \\ &= \frac{\lambda^{-1}D_f(0,0)\lambda^{-(u+1)}e^{-ik\varphi}D_f(u,k)}{\lambda^{-(u+1)}D_f(u,0)\lambda^{-1}e^{-ik\varphi}D_f(0,k)} \\ &= \frac{D_f(0,0)D_f(u,k)}{D_f(u,0)D_f(0,k)} \\ &= Z_f(u,k) = Z(u,k) \end{aligned} \tag{16}$$

Given a RPFMT moment invariant function Z(u, k), we can construct its mean, standard deviation, skewness, kurtosis. Equation 17-22 are defined as following forms:

$$f_1 = \frac{1}{M \times N}\sum_{u=1}^{M}\sum_{k=1}^{N} Z(u,k) = \mu \tag{17}$$

$$f_2 = \sum_{u=1}^{M}\sum_{k=1}^{N} | Z(u,k) | \tag{18}$$

$$f_3 = \sqrt{\sum_{u=1}^{M}\sum_{k=1}^{N} | Z(u,k) |^2} \tag{19}$$

$$f_4 = \sqrt{\frac{1}{M \times N}\sum_{u=1}^{M}\sum_{k=1}^{N} |Z(u,k) - \mu|^2} = \sigma \tag{20}$$

$$\begin{aligned} f_5 &= \frac{(M \times N)\sum_{u=1}^{M}\sum_{k=1}^{N} | Z(u,k) - \mu |^3}{(M \times N - 1)(M \times N - 2)\left(\sqrt{\frac{1}{(M \times N)}\sum_{u=1}^{M}\sum_{k=1}^{N} | Z(u,k) - \mu |^2}\right)^3} \\ &= \frac{(M \times N)\sum_{u=1}^{M}\sum_{k=1}^{N} | Z(u,k) - \mu |^3}{(M \times N - 1)(M \times N - 2)\sigma^3} \end{aligned} \tag{21}$$

$$f_6 = \frac{(M \times N)\sum_{u=1}^{M}\sum_{k=1}^{N} | Z(u,k) - \mu |^4}{(M \times N - 1)\left(\sqrt{\sum_{u=1}^{M}\sum_{k=1}^{N} | Z(u,k) - \mu |^2}\right)^4} \tag{22}$$

where, Eq. 17 is Z(u, k) mean value, Eq. 18 is magnitude, Eq. 19 is absolute value of magnitude, Eq. 20 is standard deviation, Eq. 21 is skewness and Eq. 22 is kurtosis.

These six eigenvalues with scaling and rotation moment invariants can be detected scaling and rotation tampered for copy-move image. Hence, we can detect the overlapping square blocks of image and extract six eigenvalues of each pixel from these overlapping blocks to construct feature matrix. Three-Dimension (3-D) feature matrix of image can be defined as:

$$H = [6, d, d] = [f_1, f_2, f_3, f_4, f_5, f_6]^T \tag{23}$$

The size of overlapping-block image matrix is d×d. In order to simplify the feature matrix and apply lexicographic sorting to detect forgery image, Eq. 23 can be divided to six categories 2-D feature matrix and improved the authentication accuracy by multiply authentication. Equation 24 is defined as:

$$H[6,d,d] = \begin{bmatrix} H_{f1}[d,d] \\ H_{f2}[d,d] \\ H_{f3}[d,d] \\ H_{f4}[d,d] \\ H_{f5}[d,d] \\ H_{f6}[d,d] \end{bmatrix} \tag{24}$$

where, $H_{f1}[d, d]$ is a 2-D matrix for function f_1 in Eq. 17.

MATERIALS AND METHODS

Proposed technique approach steps: In this study, our approach is applied to detect copy-move forgery image. If the target image is RGB image, we use standard color space conversion to converted it to gray-scale image firstly. Then the gray-scale image is divided into overlapping blocks. The overlapping blocks is projected to construct planar projective transform matrixes from projection space by Radon transform, extract the overlapping blocks scaling and rotation feature to construct moment invariants for the next step. Based on the above scaling and rotation feature, a Radon-Pseudo-Fourier-Mellin-Transform approach was proposed to construct moment invariants feature matrixes and then eigenvalues are extracted. Lexicographic Sorting is applied to matrices and finally it is judged, detected and located forgery region based on the confidence distance whether the well-ordered adjacent images are copy-move image blocks.

The experimental results show that the proposed approach has a good robustness and it can detect and authenticate types of a large angle rotation and scaling transform to copy-move images. The approach has more accuracy compared above approaches.

The detailed steps of the proposed approach are described as follows:

Step 1: Using standard color space conversion transform original RGB image into gray-scale image S which image size is M×N

Step 2: Divide S into fixed-sized overlapping square blocks which block size is d×d. The number of overlapping blocks is L= [M-d+1] ×[N-d+1]

Step 3: Using Radon-Pseudo-Fourier-Mellin-Transforms approach to construct 3-D moment invariants matrix from Eq. 23 or six 2-D moment invariants matrixes from Eq. 24 for each overlapping block and extract its eigenvalues. Using 3-D feature matrix of each overlapping-block to construct 4D feature matrix of S and extract its eigenvalues

Step 4: Each 3-D matrix of block is also consisted of six such 2-D matrixes from Eq. 24 which is suitable for Lexicographic matrix. Form a row vector matrix K using the feature vectors, where i is the row vector number of a overlapping block. The total number of row vectors is L. The obtained matrix K has a dimension of L×H, where, H is the number of elements in each row vector

Step 5: Lexicographic matrix K in a dictionary sequence. Denote the sorted matrix as K1 which is the same dimension as K. K1i is the i th row vector of K1. Record the overlapping block in K and K1i with (Xi, Yi) as its top left corner coordinates

Step 6: Conduct the matching authentication of similar blocks and identify the forgery position. During the window movement, when the matching function value is the maximum or over a level, the center corresponding to the window will be the position of matching similar point

Step 7: Repeat the 4-6 steps six times by using Eq. 24 and detect, locate, identify the forgery region more accuracy

RESULTS AND DISCUSSION

In the present experiments, all experiments are operated on the computers architecture with Intel (R) Core™2 Duo CPU T8300 at 2.4 GHz, 2 GB RAM and Windows XP system. Image overlapping blocks are square overlapping block of 16×16. MATLAB 7.0 processing software is applied to realize the approach in this study and other relevant approaches.

In this experiment, the performance of the proposed approach was analyzed in the presence of forgery images which have scaled and rotated copy-move region. To further demonstrate the benefit of Radon-pseudo-Fourier-Mellin-Transform approach in this study, an image named "HelloKity-cake" was forged whose size is 1024×768 as an example. This image region was tampered with the translation, ±10% scaling, 30°, 60°, 90° clockwise rotation and additive Gaussian noise by using PhotoShop software. The detection results were presented in anti-translation, anti-scaling, anti-rotation and anti-Gaussian Noise and then the accuracy rates (percents) for the authentication of copy-move forgery image by using RPFMT were also presented. In the last experiment, the performance of the approaches in study were also compared (Popescu and Farid, 2004; Qian *et al.*, 2013; Yap *et al.*, 2010) with the present proposed approach.

Authentication in translation tampered testing: The authentication results for tampered "HelloKity-Cake" images are shown in Fig. 3. Figure 3a is the original image without tampered operation, the copied region translated in Fig. 3b and 3c is the authentication with the present approach.

Authentication in scaling tampered testing: The authentication results for tampered "HelloKity-Cake" images are shown in Fig. 4. Figure 4a is the copied region scaled 10% and Fig. 4c is the authentication with the proposed approach.

The authentication results for tampered "HelloKity-Cake" images are shown in Fig. 5. Figure 5a is copied region scaled -10% and Fig. 5c is the authentication with the present proposed approach.

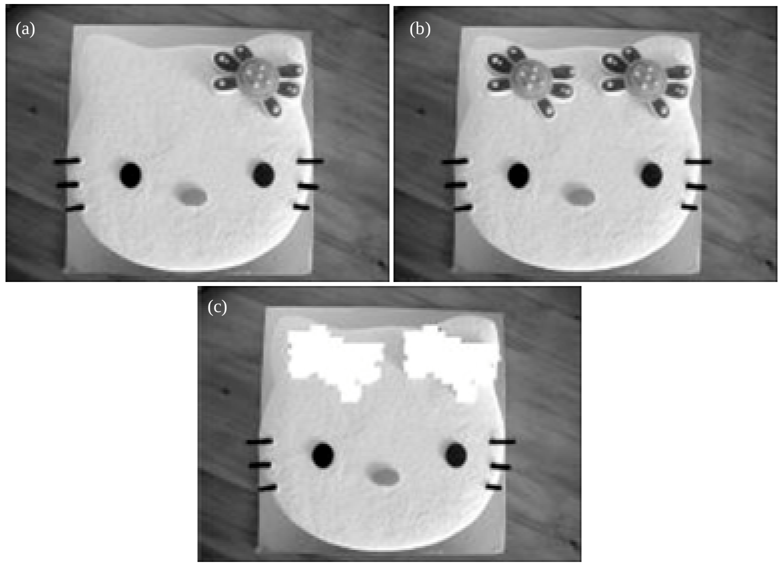

Fig. 3(a-c): Authentication for translation tampered (a) Original image, (b) Copy-move forgery image and (c) Detected image

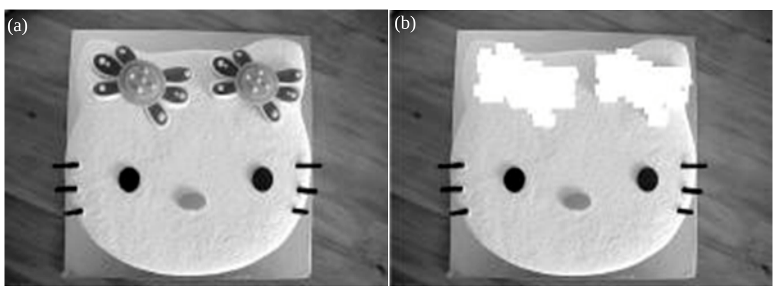

Fig. 4(a-b): Authentication for 10% scaling tampered, (a) Copy-move forgery image and (b) Detected image

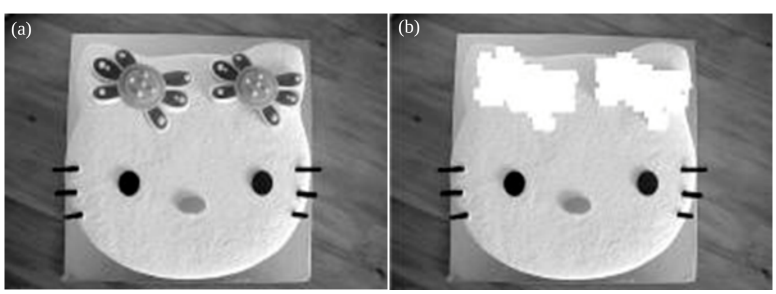

Fig. 5(a-b): Authentication for -10% scaling tampered, (a) Copy-move forgery image and (b) Detected image

Authentication in rotation tampered testing: The authentication results for tampered "HelloKity-Cake"images are shown in Fig. 6. Figure 6a is the copied region rotated 30° clockwise and Fig. 6b is the authentication with the proposed approach.

The authentication results for tampered "HelloKity-Cake" images are shown in Fig. 7. Figure 7a is the copied region rotated 60° clockwise and Fig. 7b is the authentication with the proposed approach.

The authentication results for tampered "HelloKity-Cake" images are shown in Fig. 8. Figure 8a is the copied region rotated 90° clockwise and Fig. 8b is the authentication with the proposed approach.

Authentication in added Gaussian noise tampered testing: The authentication results for tampered "HelloKity-Cake" images are shown in Fig. 9. Figure 9a is the copied region added Gaussian noise ($\mu = 0.01$, $\delta^2 = 0.01$) and Fig. 9b is the authentication with the present proposed approach.

The authentication results for tampered "HelloKity-Cake" images are shown in Fig. 10. Figure 10a is the copied region added Gaussian noise ($\mu = 0.05$, $\delta_2 = 0.1$) and Fig. 10b is the authentication with the present proposed approach.

Performances of authentication approach: Hundred natural images were downloaded from the Internet used for experiment. Then images were tampered with the above-said manner. We

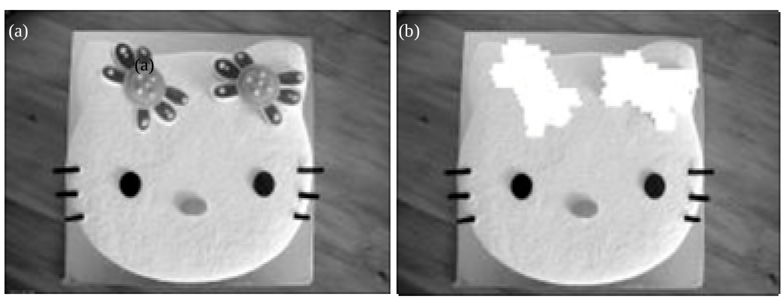

Fig. 6(a-b): Authentication for 30° clockwise rotation tampered, (a) Copy-move forgery image and (b) Detected image

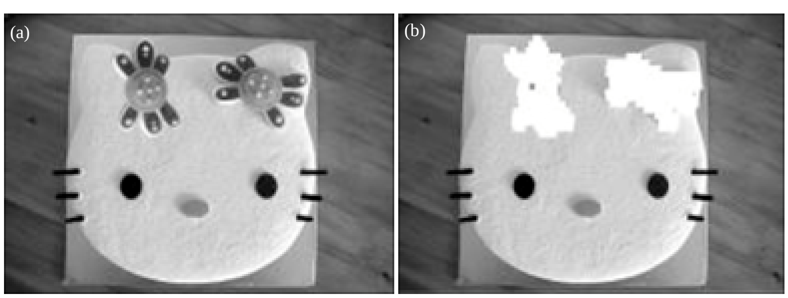

Fig. 7(a-b): Authentication for 60° clockwise rotation tampered, (a) Copy-move forgery image and (b) Detected image

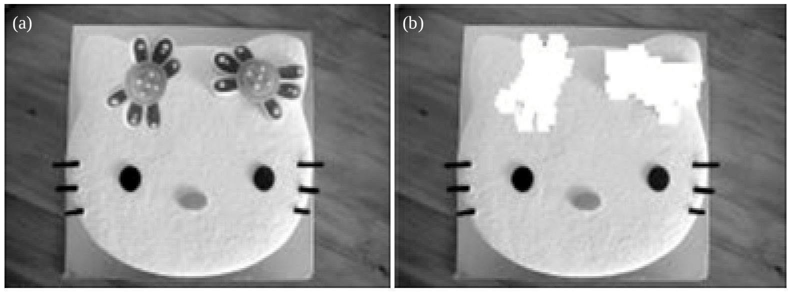

Fig. 8(a-b): Authentication for 90° clockwise rotation tampered, (a) Copy-move forgery image and (b) Detected image

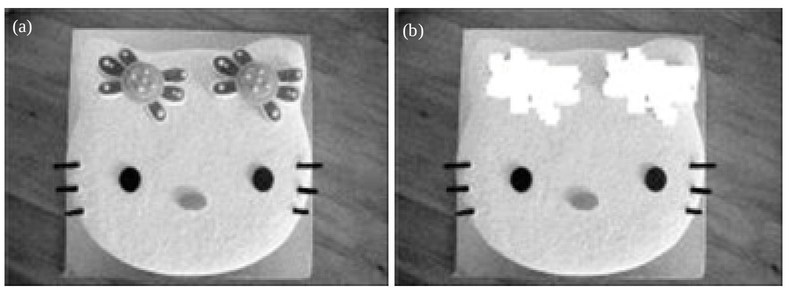

Fig. 9(a-b): Authentication for additive Gaussian noise tampered, (a) Copy-move forgery image and (b) Detected image

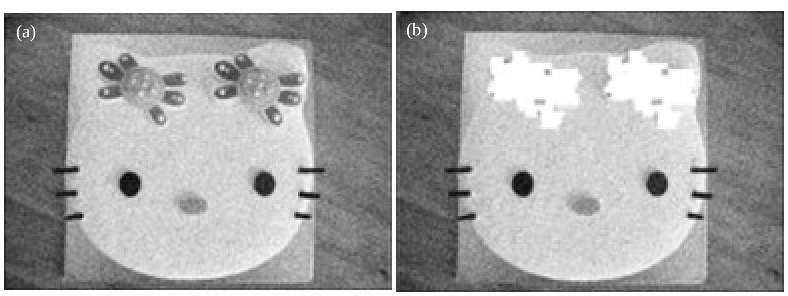

Fig. 10(a-b): Authentication for additive Gaussian noise tampered, (a) Copy-move forgery image and (b) Detected image

tampered the image region with the translation, ±10% scaling, 30, 60 and 90° clockwise rotation and additive Gaussian noise by using Ps. We used d = 16 as a block size and slide the blocks one pixel each time to detect image. It was supposed that the smallest size of duplication would be at least 32×32. In this case, if a image size is there would be (32-16+1)×(32-16+1) = 289 connected duplicated blocks. The above tampered image samples are tested with the approach in this paper and the testing results are showed in Table 1.

Table 1: Authentication rates of the present proposed approach on 100 forgery images with copy-move regions undergone different types of distortion

Copy-move image	Total No. of images	Authentication rate of approach in this study (%)
Scaling by 10%	100	81
Rotation by -10%	100	87
1Rotation by 30°	100	85
Rotation by 60°	100	80
Rotation by 90°	100	80
Translation	100	92
Additive gaussian noise (F = 0.5, δ^2 = 0.01)	100	90
Additive gaussian noise (F = 0.1, δ^2 = 0.05)	100	83

Table 2: Comparison for copy-move forgery image authentication approaches

Manner	Popescu (2004)	Qian (2013)	Yap (2010)	This study
Translation	√	√	√	√
±10% scaling	-	√	-	√
0~45° rotation	-	√	√	√
45~90° rotation	-	-	-	√
Additive noise	√	√	√	√

Table 1 shows that the present proposed approach has relatively high authentication. The authentication rates is at least 80%, even if the copied region of tampered images is undergone translation, scaling, rotation and added Gaussian noise tampered.

Comparison for copy-move authentication approaches: The approaches, described by Popescu and Farid (2004), Qian *et al.* (2013) and Yap *et al.* (2010) were implemented and the robustness of these approaches was also compared in Table 2.

From Table 2, the approach of Popescu and Farid (2004) has the poorer robustness for the copy-move forgery detection. This approach only can detect translated forgery. The approach of study (Qian *et al.*, 2013) is an improved approach and it has the fairly good robustness, can detect such as translation, some certain extent scaling, some small degrees rotated forgery region but can not detect a large degree rotated forgery region which rotated degrees is larger than 45°. The approach based on the Radon-Pseudo-Fourier-Mellin-Transform in this study has more superiority than the compared approaches.

CONCLUSION

Copy-move forgery is a very common type of image forgery approach and this approach belongs to blind authentication which is applied so widely. In this study, we study the problem of copy-move blind forgery authentication, the image geometric structure and focus on its scaling and rotation invariant moments. To detect the forgeries under the modifications, we proposed the Radon-Pseudo-Fourier-Mellin-Transform (RPFMT) approach which is invariant to scaling and rotation. The present experimental results show that we have achieved good results and we can detect copy-move forgery very accurately even if the forged image is scaled ±10%, large angle rotated. And we also compared the robustness of our approach with the previously proposed approaches which use PCA and Periodicity within pixel variances, PHTs and we showed that our approach is more robust to various types of processing and the approach can be used in regions like copy-move image forgery authentication. Our experiments for all schemes are going on for additive Gaussian noise. But our approach in paper uses the Lexicographic Sorting that make the authentication efficient low. For example, if the image is large size, such as size of M×N, The numbers of sub-block are L = (M-d+1) ×(N-d+1), the numbers of image pixels are W = (M-d+1)×(N-d+1 ×d×d). The eigenvalues of 3-D in each pixel may be calculated in Lexicographic Sorting approach that will result in computationally very expensive.

REFERENCES

Bayram, S., H.T. Sencar and N. Memon, 2009. An efficient and robust method for detecting copy-move forgery. Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, April 19-24, 2009, Taipei, Taiwan, pp: 1053-1056.

Beylkin, G., 1987. Discrete radon transform. IEEE Trans. Acoustics Speech Signal Process., 35: 162-172.

Chihaoui, T., S. Bourouis and K. Hamrouni, 2014. Copy-move image forgery detection based on SIFT descriptors and SVD-matching. Proceedings of the 1st International Conference on Advanced Technologies for Signal and Image Processing, March 17-19, 2014, Sousse, Tunisia, pp: 125-129.

Derrode, S. and F. Ghorbel, 2001. Robust and efficient Fourier-Mellin transform approximations for gray-level image reconstruction and complete invariant description. Comput. Vision Image Understand., 83: 57-78.

Farid, H., 2004. Creating and detecting doctored and virtual images: Implications to The child pornography prevention act. Technical Report No. TR2004-518, Department of Computer Science, Dartmouth College, New Hampshire, USA., pp: 1-13.

Fridrich, J., D. Soukal and J. Lukas, 2003. Detection of copy-move forgery in digital images. Proceedings of the Digital Forensic Research Workshop, August 6-8, 2003, Cleveland, OH., USA., pp: 55-61.

Galigekere, R.R., D.W. Holdsworth, M.N.S. Swamy and A. Fenster, 2000. Moment patterns in the Radon space. Opt. Eng., 39: 1088-1097.

Gan, J.Y. and S.B. He, 2011. Nonlinear radon transform and its application to face recognition. Pattern Recognit. Artif. Intell., 4: 405-409.

He, B. and X. Wang, 2010. Robust digital watermarking image method based on Radon invariant moments. Comput. Eng. Applic., 46: 98-101.

Hsu, Y.F. and S.F. Chang, 2007. Image splicing detection using camera response function consistency and automatic segmentation. Proceedings of the International Conference on Multimedia and Expo, July 2-5, 2007, China, pp: 28-31.

Hu, M.K., 1962. Visual pattern recognition by moment invariants. IEEE Trans. Inform. Theory, 8: 179-187.

Huang, H., W. Guo and Y. Zhang, 2008. Detection of copy-move forgery in digital images using SIFT algorithm. Proceedings of the Pacific-Asia Workshop on Computational Intelligence and Industrial Application, Volume 2, December 19-20, 2008, Wuhan, China, pp: 272-276.

Jafari-Khouzani, K. and H. Soltanian-Zadeh, 2005a. Radon transform orientation estimation for rotation invariant texture analysis. IEEE Trans. Pattern Anal. Mach. Intell., 27: 1004-1008.

Jafari-Khouzani, K. and H. Soltanian-Zadeh, 2005b. Rotation-invariant multiresolution texture analysis using radon and wavelet transforms. IEEE Trans. Image Process., 14: 783-795.

Jing, T., X. Li and F. Zhang, 2010. Image tamper detection algorithm based on Radon and Fourier-Mellin transform. Proceedings of the IEEE International Conference on Information Theory and Information Security, December 17-19, 2010, Beijing, China, pp: 212-215.

Kakar, P. and N. Sudha, 2012. Exposing postprocessed copy-paste forgeries through transform-invariant features. IEEE Trans. Inform. Forensics Secur., 7: 1018-1028.

Kumar, S., S.P. Das and S. Mukherjee, 2011. Copy-move forgery detection in digital images: Progress and challenges. Int. J. Comput. Sci. Eng., 3: 652-663.

Lei, Y., Y. Wang and J. Huang, 2011. Robust image hash in Radon transform domain for authentication. Signal Process.: Image Commun., 26: 280-288.

Li, G., Q. Wu, D. Tu and S. Sun, 2007. A sorted neighborhood approach for detecting duplicated regions in image forgeries based on DWT and SVD. Proceedings of the IEEE International Conference on Multimedia and Expo, July 2-5, 2007, China, pp: 1750-1753.

Liao, S.X. and M. Pawlak, 1998. On the accuracy of Zernike moments for image analysis. IEEE Trans. Pattern Anal. Mach. Intell., 20: 1358-1364.

Liu, Q., H. Zhu and Q. Li, 2011. Object recognition by combined invariants of orthogonal Fourier-Mellin moments. Proceedings of the 8th International Conference on Information, Communications and Signal Processing, December 13-16, 2011, Singapore, pp: 1-5.

Mukundan, R., S.H. Ong and P.A. Lee, 2001. Image analysis by Tchebichef moments. IEEE Trans. Image Process., 10: 1357-1364.

Nguyen, H.C. and S. Katzenbeisser, 2012. Detection of copy-move forgery in digital images using Radon transformation and phase correlation. Proceedings of the 8th International Conference on Intelligent Information Hiding and Multimedia Signal Processing, July 18-20, 2012, Piraeus, Greece, pp: 134-137.

Papakostas, G.A., Y.S. Boutalis, D.A. Karras and B.G. Mertzios, 2007. Fast computation of orthogonal Fourier-Mellin moments using modified direct method. Proceedings of the 14th International Workshop on Systems, Signals and Image and 6th EURASIP Conference Focused on Speech and Image Processing, Multimedia Communications and Services, June 27-30, 2007, Maribor, Slovenia, pp: 153-156.

Popescu, A.C. and H. Farid, 2004. Exposing digital forgeries by detecting duplicated image regions. Technical Report No. TR2004-515, Department of Computer Science, Dartmouth College. http://www.cs.dartmouth.edu/reports/TR2004-515.pdf.

Popescu, A.C. and H. Farid, 2005. Exposing digital forgeries by detecting traces of resampling. IEEE Trans. Signal Process., 2: 758-767.

Qian, R., W. Li and N. Yu, 2013. High precision rotation angle estimation for rotated images. Proceedings of the IEEE International Conference on Multimedia and Expo Workshops, July 15-19, 2013, San Jose, CA., USA., pp: 1-4.

Radon, J., 1917. The integral transform consisting of the integral of a function over straight lines. Leipzig Math. Phys. Kl, 69: 262-267, (In German).

Sheng, Y. and L. Shen, 1994. Orthogonal Fourier-Mellin moments for invariant pattern recognition. J. Opt. Soc. Am., 11: 1748-1757.

Teh, C.H. and R.T. Chin, 1988. On image analysis by the methods of moments. IEEE Trans. Pattern Anal. Mach. Intell., 10: 496-513.

Wang, Q., O. Ronneberger and H. Burkhardt, 2009. Rotational invariance based on fourier analysis in polar and spherical coordinates. IEEE Trans. Pattern Anal. Mach. Intell., 31: 1715-1722.

Wang, X., B. Xiao and J.F. Ma, 2008. Scaling and rotation invariant analysis approach to object recognition based on radon and analytic Fourier-Mellin transforms. J. Image Graphics, 13: 2157-2162.

Yap, P.T. and R. Paramesran, 2005. An efficient method for the computation of Legendre moments. IEEE Trans. Pattern Anal. Mach. Intell., 27: 1996-2002.

Yap, P.T., R. Parameshan and S.H. Ong, 2003. Image analysis by Krawtchouk moments. IEEE Trans. Image Process., 12: 1367-1377.

Yap, P.T., X. Jiang and A.C. Kot, 2010. Two-dimensional polar harmonic transforms for invariant image representation. IEEE Trans. Pattern Anal. Mach. Intell., 32: 1259-1270.

Zhang, H., H.Z. Shu, P. Haigron, B.S. Li and L.M. Luo, 2010. Construction of a complete set of orthogonal Fourier-Mellin moment invariants for pattern recognition applications. Image Vision Comput., 28: 38-44.

Zhao, J.H., 2012. Authentication algorithm of image forgery based on principal components analysis of projection data. Comput. Eng., 38: 203-205.