Applied Intelligence (2022) 52:15417–15435
https://doi.org/10.1007/s10489-022-03215-x

CBRW: a novel approach for cancelable biometric template generation based on 1-D random walk

Nitin Kumar[1] · Manisha [1]

Accepted: 24 December 2021 / Published online: 15 March 2022

Abstract

Cancelable Biometric is a challenging research field in which security of an original biometric image is ensured by transforming the original biometric into another irreversible domain. Several approaches have been suggested in literature for generating cancelable biometric templates. In this paper, two novel and simple cancelable biometric template generation methods based on Random Walk (CBRW) have been proposed. By employing random walk and other steps given in the proposed two algorithms *viz. CBRW-BitXOR* and *CBRW-BitCMP*, the original biometric is transformed into a cancelable template. The performance of the proposed methods is compared with other state-of-the-art methods. Experiments have been performed on eight publicly available gray and color datasets i.e. CP (ear) (gray and color), UTIRIS (iris) (gray and color), ORL (face) (gray), IIT Delhi (iris) (gray and color), and AR (face) (color). Performance of the generated templates is measured in terms of Correlation Coefficient (Cr), Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), Structural Similarity (SSIM), Mean Absolute Error (MAE), Number of Pixel Change Rate (NPCR), and Unified Average Changing Intensity (UACI). By experimental results, it has been proved that proposed methods are superior than other state-of-the-art methods in qualitative as well as quantitative analysis. Furthermore, CBRW performs better on both gray as well as color images.

Keywords Cancelable · Random walk · Performance · Gray · Color

1 Introduction

Biometric recognition [1] has been widely used for user authentication. However, there are privacy and security concerns associated with biometric recognition. One of the ways to enhance the privacy and security of traditional biometrics is provided by cancelable biometric. Different methods of cancelable biometric template generation proposed by researchers are discussed in research work [2]. In traditional biometric based application, user provides his biometric credentials to a sensor device. This sensor device will scan his biometric trait and discriminating features obtained from any machine learning method. These extracted features are stored into some standalone database. This whole process is known as Enrolment process in traditional biometric based systems. Afterwards, when a user presents his biometric credential at sensor device, again same features are extracted same as enrolment process and matching is performed with the stored representations. This matching process results in either granting access to the user or denial of the access. This process is known as authentication.

In contemporary scenarios with the evolution of new methods or techniques, it is possible to gain unauthorized access to the standalone database using software and/or hardware devices. It may result into compromise of the original biometric credentials. Due to the outspread of the corona virus disease (COVID), most activities are being performed in online mode which further increases the risk of private information such as user credentials i.e. username and password. Increased online activities have also increased the number of accounts corresponding to a single user i.e. accounts on e-commerce websites, internet banking and online learning platforms etc. and hence the need for user authentication has gone up sharply. If any of the sensitive user information such as password or biometric

✉ Nitin Kumar
nitin@nituk.ac.in

Manisha
manisharawatphd@nituk.ac.in

[1] National Institute of Technology, Uttarakhand, India

trait of one account is compromised, then it may also put on risk the security and privacy of other accounts. As humans have limited count of biometric traits such as iris, face, fingerprint, palmprint, ECG and voice etc. Hence, keep them secure from an adversarial attack is mandatory.

Cancelable biometric [2] plays an important role in providing security to biometric traits by transforming the original biometric in another irreversible domain. In cancelable biometric, instead of storing the original features directly into the database, firstly these features are destroyed/deformed by some transformation functions. The templates obtained after this transformation are totally meaningless in comparison to the original biometric as shown in Fig. 1. Further, these distorted versions of original biometric are stored in the database. There are four important characteristics [3] associated with these cancelable templates: (i) Diverse (ii) Non-invertible (iii) Revocable (iv) Performance. *Diverse* generally means each cancelable biometric template should be different from others or in other words no two persons should be allotted same cancelable biometric template. *Non-invertible* means original biometric features cannot be extracted with these cancelable biometric templates while *Revocable* property states that if cancelable biometric template of a person gets stolen or compromised then a new cancelable template will be allotted to him/her without compromising original biometric identity. *Performance* property states that cancelable biometric based system's recognition rate should be same as traditional biometric based systems. It simply means recognition rate should not deteriorate using cancelable biometric template. The word *cancelable* means if one's allotted cancelable biometric template gets compromised, a new template will be allotted to him by cancelling the previous one as happens in the case of Automatic Teller Machine (ATM) password. A strong transformation function is typically required for generation of strong cancelable biometric template.

Random walk [4] (a.k.a. drunker's walk) is a method which has been extensively used in image segmentation [5, 6]. In this method, a drunker randomly walks in left, right, up or down positions from the current position. Motivated by this concept, in this research work, two cancelable biometric template generation methods based on random walk (CBRW) have been proposed. As a biometric image may be thought of as a matrix of intensity values, we have tried to exploit random walk model to transform the current intensity values into other intensity values such that the original biometric is distorted. A sample image of cancelable biometric template corresponding to a face image is depicted in Fig. 1.

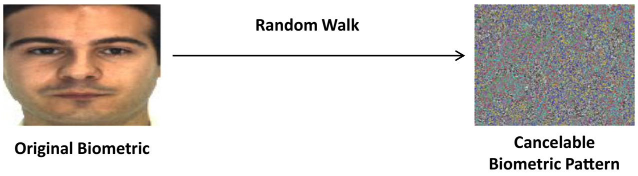


Fig. 1 Example of cancelable biometric template generated by proposed method

1.1 Contribution

In this paper, we have made following contributions:

(i) Proposed two novel methods based on random walk model for generating cancelable biometric templates.
(ii) Extensive experiments have been performed on eight publicly available gray and color biometric datasets.
(iii) Proposed approaches are independent of the biometric trait used and hence experiments can be easily performed with other biometric modalities. In this work, experiments have been performed on three different biometric modalities i.e. face, iris and ear.

Besides the above contributions, there are some advantages of the proposed methods such as (a) Both methods are equally applicable to gray as well as color images (b) Performance of the proposed methods is superior than several other compared methods in qualitative as well as quantitative terms.

The rest of the paper is organized as follows: Section 2 briefly provides related work in cancelable biometric while Section 3 describes the proposed method in detail. In Section 4, experimental setup and results with qualitative, quantitative and histogram analysis are presented and discussed. Concluding remarks and future work are given in Section 5 at the end.

2 Related work

In literature, various methods for cancelable biometric template generation have been suggested. These methods are further classified into six categories [2]: (i) Cryptography (ii) Transformation (iii) Filter (iv) Hybrid (v) Multimodal and (vi) Others. Each of these categories is further contained several template generation methods.

Proposed methods comes under transformation based category which is one of the pioneer technique in the domain of cancelable biometric template generation in which original features are changed using different types of transformation such as Cartesian, Polar and Hadamard etc. In *Cartesian transformation* [3], image registration is required which is further followed by estimating position and orientation of singular points with respective minutiae positions. Fixed size cells are retrieved after dividing whole coordinate system. Cancelable biometric templates are formed by applying the changes in the cell positions. In *Polar transformation* [8], corresponding to the core position in polar coordinate, minutiae positions are calculated. In this transformation, polar regions are retrieved from the coordinate space. Further, changes are applied on these polar regions. Both these transformations are suffered from deviation problem such that if minutiae positions are changed in small scale in original biometric image, it can reflect a large deviation in the transformed minutiae domain. Fingerprint biometric is the most popular trait used in Cartesian and Polar transformation.

Hadamard transform is a non-sinusoidal, orthogonal transformation which is used for projection on to walsh functions. Walsh functions are set of square or rectangular waveforms whose elements consists with values of $+1$ and -1, used for projection. Hadamard transformation used Hadamard matrix in which pairwise orthogonal row vectors have values $+1$ and -1. Two variants of Hadamard transform are known namely partial Hadamard and full Hadamard. Partial Hadamard [11] matrix is obtained after selecting some rows from full Hadamard and is non invertible in nature while full Hadamard transformation matrix is invertible in nature. Two important advantages of partial Hadamard includes low computational cost and low storage requirement. Uhl et al. [12] have generated cancelable iris templates which used wavelet transformation as a transformation key matrix. The main advantage of this method includes no occurrence of data loss and no requirement of features alignment. In *Multiplicative transform* [13], cancelable biometric templates are formed by element wise multiplication of original features with some random vector. Sorting method is applied on indexes of this resulting vector which is further used for retrieval of biometric template.

Random Projection (RP) [14] is a non-invertible method. In this method, the extracted feature vector $\mathbf{x} \in \mathbb{R}^N$ from a biometric is projected onto a random subspace $\mathbf{A} = [a_{ij}]$ (where $\mathbf{A} \in \mathbb{R}^{n*N}$ with $n < N$). Here, each entry a_{ij} of $\mathbf{A}$ is an independent realization of a random variable. This process is described as follows:

$$\mathbf{y} = \mathbf{A}\mathbf{x} \tag{1}$$

Here $\mathbf{y}$ is the n dimensional Random Projection vector and N dimensional feature vectors are embedded in a lower dimension space n [15]. Pillai et al. [17] have used Sectored Random Projections for generation of cancelable iris template. In this approach iris image is divided into many parts which are known as sectors. Further, random projection is applied on individual sectors. Lastly, these transformed sectors are again concatenated to form cancelable iris template. Punithavathi et al. [16] have proposed extended version of this method in which individual sectors are projected on *Dynamic Random Projection Matrix* (DRPM) which finally generates cancelable iris template. Here, DRPM matrix is retrieved from the iris features which remove the requirement of any external matrix for transformation. Kim et al. [18] have used *Sparse Random Projection* for generation of cancelable face template. In this method, random matrix has the value -1, 0 and +1. The values used in random matrix is used for accelerating enrolment and authentication process.

3 Cancelable biometric template generation based on random walk

In this section, firstly generation of random walk matrix $\mathbf{R}_W$ based on the popular random walk model is defined and then two methods for cancelable biometric template generation are proposed which are based on $\mathbf{R}_W$. In the following, the original biometric image is denoted as $\mathbf{S}$ of size $a \times b$ and another image $\mathbf{R}$ which is generated using uniform distribution and is of the same size as the secret image.

3.1 Generation of random walk matrix $\mathbf{R}_W$

In random walk or drunker's walk method, a person is initially assumed to be present at the origin of the two dimensional plane and then he can move one step in any of the four directions i.e. left, right, up and down. Subsequently, he can move again in the four directions based on the position after the first step and so on. In this proposed work, one dimensional horizontal walk is used as shown in Fig. 2. There are two directions for random movement i.e. (i) Forward (towards positive x-axis) (ii) Backward (towards negative x-axis). The main objective is to transform the pixel values in $\mathbf{S}$ with the help of random matrix $\mathbf{R}$ as shown for a sample sub-image of size 10×10 in Fig. 3.

Based on random matrix $\mathbf{R}$, the pixel values is modified in the original biometric image $\mathbf{S}$. Suppose p and r are pixels location in matrix $\mathbf{S}$ and $\mathbf{R}$ respectively as shown in Fig. 3. Procedure for generation of $\mathbf{R}_W$ is given in Algorithm 1. In the proposed Algorithm, (i, j) is the location for any pixel in two dimensional entities i.e. where i and j represent row and column number respectively.

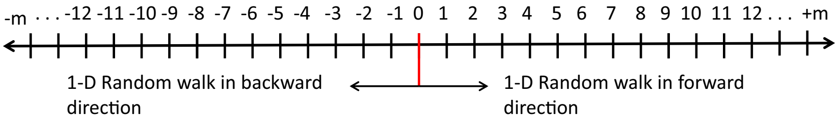

-m . . . -12 -11 -10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 11 12 . . . +m
1-D Random walk in backward direction
1-D Random walk in forward direction

Fig. 2 Example of one dimensional horizontal walk

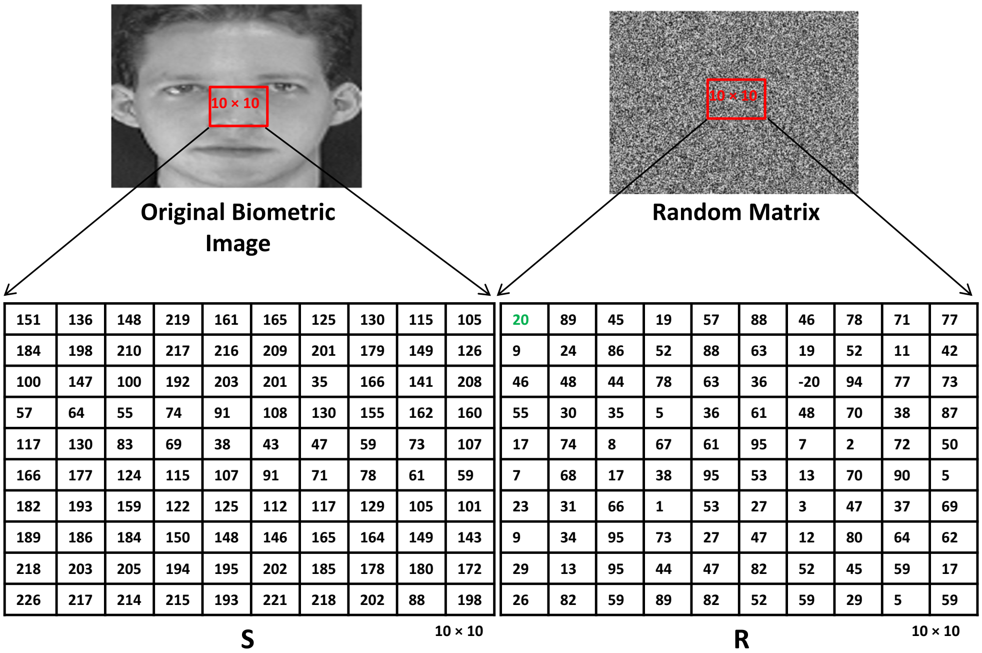
Algorithm 1 Generation_RWM(**S**, **R**).

```
Input: Secret image $\mathbf{S}$ and random matrix $\mathbf{R}$
Output: Random walk matrix $\mathbf{R}_W$
For $i = 1\ to\ a$ and $j = 1\ to\ b$, repeat the following two steps
If $\mathbf{R}(i, j) > 0$ then
    $\mathbf{X}(i, j) = \mathbf{S}(i, j) + \mathbf{S}[(i, j) + \mathbf{R}(i, j)]$ (See Fig. 4a).
If $\mathbf{R}(i, j) < 0$ then
    $\mathbf{X}(i, j) = \mathbf{S}(i, j) + \mathbf{S}[(i, j) - \mathbf{R}(i, j)]$ (See Fig. 4b).
$\mathbf{R}_W(i, j) = \mathbf{X}(i, j)\ mod\ 256$
```

While moving forward, it may happen that we reach the lower rightmost pixel of **S** i.e. (a, b) and still we have to go forward. This condition is termed as *Overflow* and we start moving forward from the upper left corner of image (i.e. position (1,1) of the image) as illustrated in Fig. 4c. Similarly, while moving backward, it may happen that we reach the upper left corner i.e. location (1,1) in the image and we still need to move backward. In this case, the backward movement is done from the bottom rightmost pixel i.e. (a, b) backward. This condition is termed as *Underflow*. The Algorithm 1 above represents the generation of random walk matrix for a gray scale image. For finding the random walk matrix for a color image, this Algorithm is applied on each of the channels (R,G,B). Next, two cancelable biometric template generation methods are discussed in which templates are generated with the help of $\mathbf{R}_W$ matrix.

Step-by-step procedure of generation of random walk $\mathbf{R}_W$ matrix: For elaboration purpose 10×10 dimension sub-image **S** is selected but experiments have been accomplished on image size of 320×240. The following steps will be applicable on any image of any dimensions for generation of $\mathbf{R}_W$ matrix :

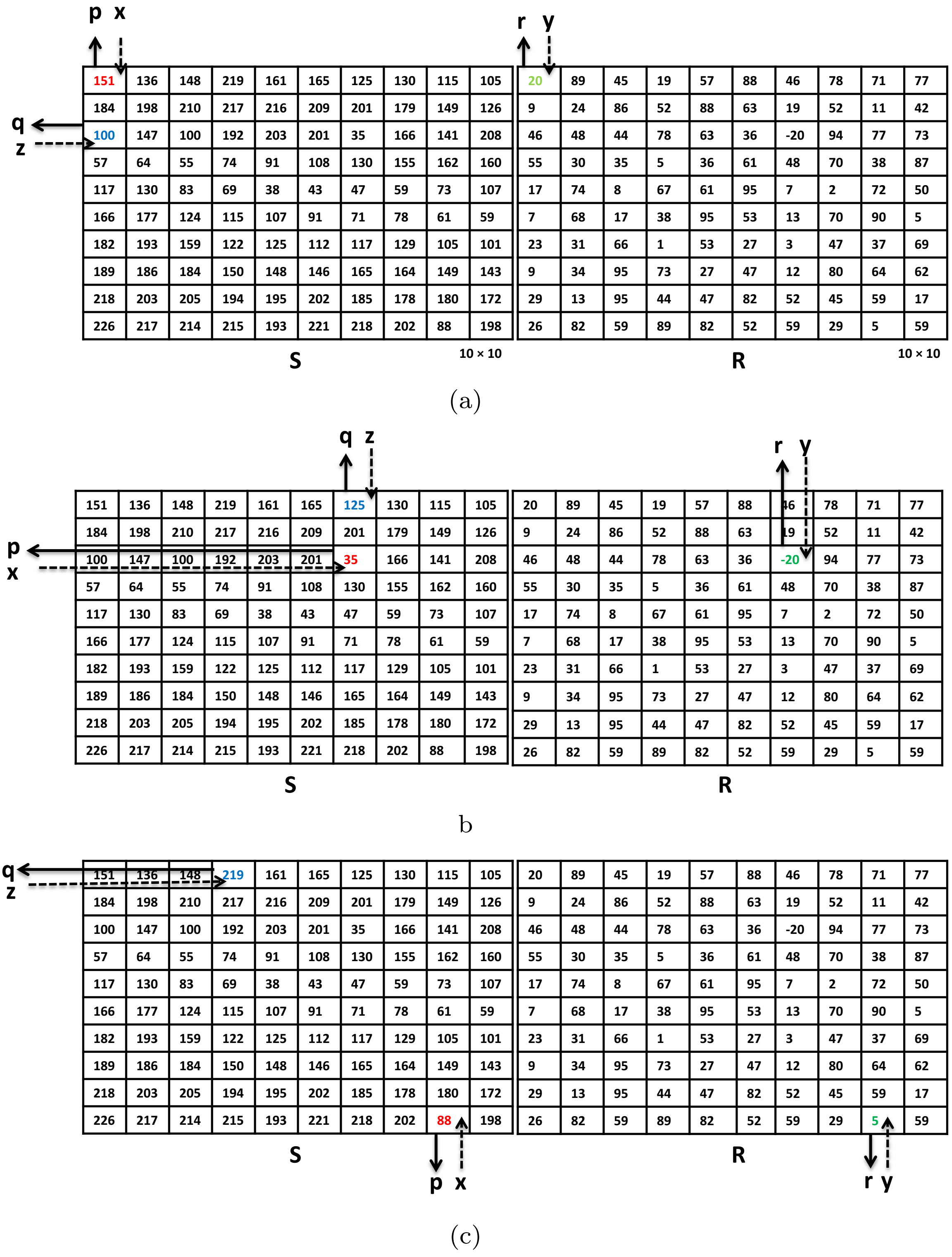
1. Both **S** and **R** matrices should be of same dimensions. The **R** matrix contains both positive and negative integers. One null $\mathbf{R}_W$ matrix of same size as **S** and **R** is created for storing the transformed pixels. Pixels in **S** will move in forward and backward direction according to value in **R**.
2. x is the pixel value at p^{th} location in **S** and corresponding to same location, another pixel value y is chosen from r^{th} location in **R**.
3. If the pixel value y at r^{th} location in **R** is +ve then pixel value x at p^{th} location in **S** will move in forward direction. Similarly, for -ve pixel value in **R**, pixel value x will step backward in **S**.
4. Let's take a small example of one pixel value x at p^{th} location in **S** has a value 151, corresponding to this pixel location, in **R** at r^{th} location y pixel value is 20 as shown in Fig. 4a. According to proposed work, p^{th} pixel will move in forward direction 20 steps ahead and



151	136	148	219	161	165	125	130	115	105
184	198	210	217	216	209	201	179	149	126
100	147	100	192	203	201	35	166	141	208
57	64	55	74	91	108	130	155	162	160
117	130	83	69	38	43	47	59	73	107
166	177	124	115	107	91	71	78	61	59
182	193	159	122	125	112	117	129	105	101
189	186	184	150	148	146	165	164	149	143
218	203	205	194	195	202	185	178	180	172
226	217	214	215	193	221	218	202	88	198

20	89	45	19	57	88	46	78	71	77
9	24	86	52	88	63	19	52	11	42
46	48	44	78	63	36	-20	94	77	73
55	30	35	5	36	61	48	70	38	87
17	74	8	67	61	95	7	2	72	50
7	68	17	38	95	53	13	70	90	5
23	31	66	1	53	27	3	47	37	69
9	34	95	73	27	47	12	80	64	62
29	13	95	44	47	82	52	45	59	17
26	82	59	89	82	52	59	29	5	59

Fig. 3 Selection of 10 × 10 size sub-image from original biometric and random image and named them as secret image **S** and random matrix **R**



S

151	136	148	219	161	165	125	130	115	105
184	198	210	217	216	209	201	179	149	126
100	147	100	192	203	201	35	166	141	208
57	64	55	74	91	108	130	155	162	160
117	130	83	69	38	43	47	59	73	107
166	177	124	115	107	91	71	78	61	59
182	193	159	122	125	112	117	129	105	101
189	186	184	150	148	146	165	164	149	143
218	203	205	194	195	202	185	178	180	172
226	217	214	215	193	221	218	202	88	198

R

20	89	45	19	57	88	46	78	71	77
9	24	86	52	88	63	19	52	11	42
46	48	44	78	63	36	-20	94	77	73
55	30	35	5	36	61	48	70	38	87
17	74	8	67	61	95	7	2	72	50
7	68	17	38	95	53	13	70	90	5
23	31	66	1	53	27	3	47	37	69
9	34	95	73	27	47	12	80	64	62
29	13	95	44	47	82	52	45	59	17
26	82	59	89	82	52	59	29	5	59

(a)

S

151	136	148	219	161	165	125	130	115	105
184	198	210	217	216	209	201	179	149	126
100	147	100	192	203	201	35	166	141	208
57	64	55	74	91	108	130	155	162	160
117	130	83	69	38	43	47	59	73	107
166	177	124	115	107	91	71	78	61	59
182	193	159	122	125	112	117	129	105	101
189	186	184	150	148	146	165	164	149	143
218	203	205	194	195	202	185	178	180	172
226	217	214	215	193	221	218	202	88	198

R

20	89	45	19	57	88	46	78	71	77
9	24	86	52	88	63	19	52	11	42
46	48	44	78	63	36	-20	94	77	73
55	30	35	5	36	61	48	70	38	87
17	74	8	67	61	95	7	2	72	50
7	68	17	38	95	53	13	70	90	5
23	31	66	1	53	27	3	47	37	69
9	34	95	73	27	47	12	80	64	62
29	13	95	44	47	82	52	45	59	17
26	82	59	89	82	52	59	29	5	59

b

S

151	136	148	219	161	165	125	130	115	105
184	198	210	217	216	209	201	179	149	126
100	147	100	192	203	201	35	166	141	208
57	64	55	74	91	108	130	155	162	160
117	130	83	69	38	43	47	59	73	107
166	177	124	115	107	91	71	78	61	59
182	193	159	122	125	112	117	129	105	101
189	186	184	150	148	146	165	164	149	143
218	203	205	194	195	202	185	178	180	172
226	217	214	215	193	221	218	202	88	198

R

20	89	45	19	57	88	46	78	71	77
9	24	86	52	88	63	19	52	11	42
46	48	44	78	63	36	-20	94	77	73
55	30	35	5	36	61	48	70	38	87
17	74	8	67	61	95	7	2	72	50
7	68	17	38	95	53	13	70	90	5
23	31	66	1	53	27	3	47	37	69
9	34	95	73	27	47	12	80	64	62
29	13	95	44	47	82	52	45	59	17
26	82	59	89	82	52	59	29	5	59

(c)

Fig. 4 Illustration for computation of $\mathbf{R}_W$ matrix (**a**) $\mathbf{R}(i, j) > 0$ (**b**) $\mathbf{R}(i, j) < 0$ (**c**) *Overflow*

reaches at q^{th} location which is at 21^{st} place and has pixel value $z = 100$. Now, add this pixel value $z = 100$ with original value x which is 151, this will give $x + z = 251$. Further, to keep the pixel in between 0 to 255 range modulus operation by 256 is used. Finally, we got 251 as transformed pixel value of x at p^{th} location and stored in $\mathbf{R_w}$. The x value at p^{th} in original biometric has now transformed to value 251 instead of

151 in transformed domain and stored in corresponding location in $\mathbf{R_w}$. Similarly, all other pixels will also have converted in same manner.

5. In case of color image, each channel (R, G, B) pixel values are ranged between 0 and 255. For maintaining this pixel range we have used mod function. The effectiveness of mod operation is illustrated by following example. Suppose x value in **S** is chosen at 4^{th} location and has pixel value 219, corresponding to this location, y value in **R** is 19. As per proposed Algorithm 1, x will move in forward direction 19 steps ahead in **S** and reached at location 23^{rd}, which has pixel value $z = 100$. Further addition of these two values $x + z$ will result in 319. This resultant value is beyond standard pixel range. To resolve this problem, we have used mod function, 319 mod 256 results in 63. This 63 will now become new transformed value of x at 4^{th} location in transformed domain and stored in $\mathbf{R_w}$.
6. A 10 × 10 dimensions image results in total of 100 pixels. We need to perform transformation at 98^{th} location in **S**, which has pixel value 88 and corresponding to this location, **R** contains pixel value 5 at 98^{th} location. According to our method, we have to move 5 steps ahead in **S**, which results in pixel location 103^{rd}, which is out of range as total number of pixels are 100. For handling this problem, we have provided solution of circular loop using mod function by 100 e.g. 103 mod 100, which results in 3. Now, in original biometric we stepped forward by 3 positions beyond 100^{th} location and reached at 3^{rd} location in **S**. The value at 3^{rd} place is 148. Now, addition is performed between 148 and 88, which results in new pixel value 236. Now 236 $\ mod\ $ 255 is 236, which is to assign for 98^{th} location in transformed domain in **R**. The final value for 98^{th} pixel is 236 instead of 88 in transformed domain. Same solution will work for underflow condition with negative values in **R**, which leads to move in backward direction.

3.2 Cancelable biometric template based on random walk using bit XOR (CBRW-BitXOR)

Algorithm 2 CBRW-BitXOR.

```
Input: Original biometric image $\mathbf{S}$ and random image
       $\mathbf{R}$
Output: Cancelable template $\mathbf{C}$
$\mathbf{R}_W$ = Generate_RWM($\mathbf{S}$, $\mathbf{R}$) // Obtain random walk
  matrix using Algorithm 1
$\mathbf{C}$=$\mathbf{S} \oplus \mathbf{R}_W$ // Find the cancelable biometric template
  using XOR of $\mathbf{S}$ and $\mathbf{R}_W$
```

Here, we describe the method for generation of cancelable biometric template using BitXOR. The step-by-step procedure for cancelable biometric template generation using BitXOR method is given in Algorithm 2.

Initially, the random walk matrix is obtained using Algorithm 1. Next, XOR operation between **S** and $\mathbf{R}_W$ is performed for generation of cancelable biometric template. Some sample images of ear, iris and face biometrics together with their corresponding cancelable biometric templates generated by proposed methods (BitXOR and BitCMP) and other popular methods are shown in Fig. 5. It can be seen from Figure that templates generated by proposed methods do not contain any traces of the original biometric while other methods do.

3.3 Cancelable biometric template based on random walk using bit complement (CBRW-BitCMP)

Algorithm 3 CBRW-BitCMP.

```
Input: Original biometric image $\mathbf{S}$ and random image
       $\mathbf{R}$
Output: Cancelable biometric template $\mathbf{C}$
$\mathbf{R}_W$ = Generate_RWM($\mathbf{S}$, $\mathbf{R}$) // Obtain random walk
  matrix using Algorithm 1
$\mathbf{I}$=$\mathbf{S} \oplus \mathbf{R}_W$ // Generate intermediate template
$\mathbf{C}$=$BitCMP(\mathbf{I})$ // Generate cancelable template
```

Similar to the above Algorithm, in this subsection the method for generation of cancelable biometric template using Bit Complement is described. The proposed method uses random walk matrix $\mathbf{R}_W$ for generating cancelable biometric templates. Further, Algorithm 3 presents step-by-step procedure of template generation using BitXOR method.

Initially, random walk matrix is obtained using Algorithm 1. Intermediate share **I** is generated by XOR operation performed between **S** and $\mathbf{R}_W$. Finally, the Bit Complement of the intermediate share is performed to get the cancelable biometric template. Some sample images of ear, iris, and face biometrics together with cancelable templates generated using proposed methods and other popular methods are shown in Fig. 5. It can be seen from Figure that no original credentials are revealed by both proposed methods while other methods are unable to distort the original biometric without revealing them.

The main difference between two proposed methods is that, the second method consist with one more step of bit complement $BitCMP$ operation in addition to BitXOR operation whose output is taken as intermediate template **I** as described in Algorithm 3.

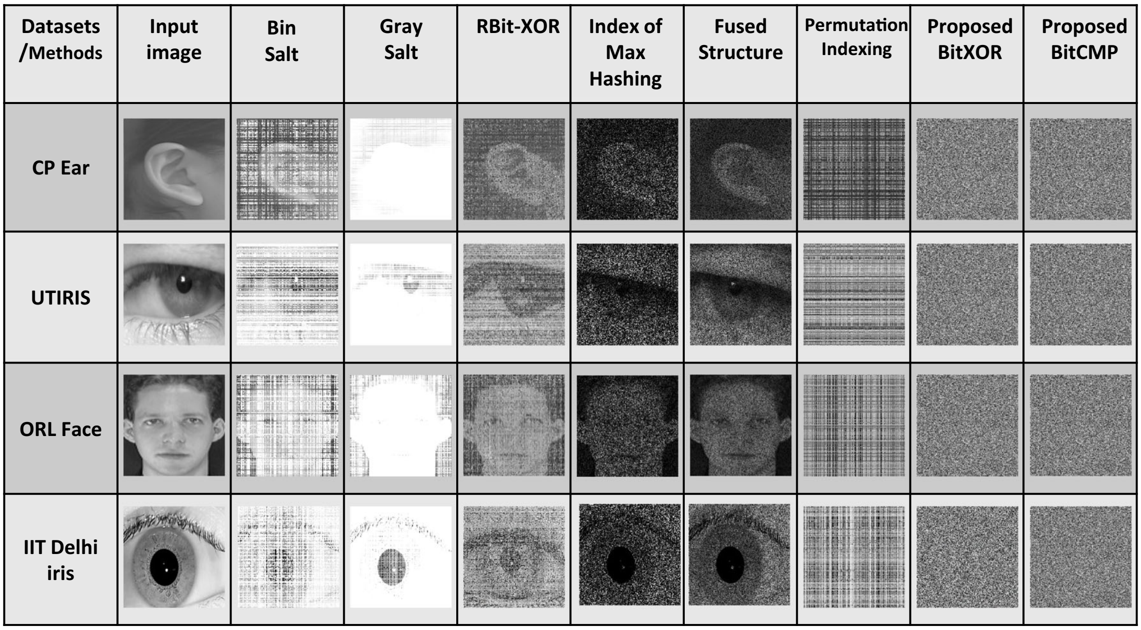


Fig. 5 Qualitative analysis among color cancelable biometric template generated using Bin Salt [25], Gray Salt [25], RBit-XOR [19], Index of Max Hashing [9], Fused Structure [10], Permutation Indexing [7], CBRW-BitXOR (proposed) and CBRW-BitCMP (proposed) on CP ear [23], UTIRIS [24], ORL face [20] and IIT Delhi iris [22] datasets

4 Experimental setup and results

4.1 Dataset description

Experiments have been performed of both proposed methods on three biometrics (both gray and color) *viz.* (i) Ear (ii) Iris and (iii) Face. The **C**arreira-**P**erpinan(CP) [23] ear dataset is publicly available dataset which consists with total of 102 ears images of 17 peoples. This dataset consists of both gray and color images. The **U**niversity of **T**ehran **IRIS** (UTIRIS) [24] dataset consists with 1540 iris images of 79 individuals. The dimensions of color dataset are 2048×1360 and for gray dataset dimensions are 1000×776. The **O**livetti **R**esearch **L**aboratory (ORL) face [20] dataset formerly known as American Telephone & Telegraph company. This dataset is formed by 400 gray images of 40 different subjects with various facial expressions. **A**leix Martinez and **R**obert Benavente (AR) face [21] dataset consists with 4000 images of 126 different individuals (70 males and 56 females). In **IIT D**elhi (IITD) iris [22] dataset (version 1.0) has 1120 iris images captured from 224 users (176 males and 48 females). A brief description about these datasets are provided in Table 1.

The proposed method is free from minutiae points, iris codes, and minutiae cylinder codes. In this proposed work, cancelable biometric templates are generated for the whole image by giving equal weightage to all the pixels in the original biometric image. The size of an image as per our proposed work is 320×240 which means total number of 76800 pixels as features have been used while in the compared methods, Permutation Indexing [7], Index of Max Hashing [9], Fused Structure [10], Bin Salt [25], Gray Salt [25], typically 10 to 200 features have been used. For comparison of the proposed method with state of the art methods, we have used all the pixels in the image as features and rest of the method is kept same. The cancelable biometric templates generated by the proposed method and state-of-the-art methods are shown in Figs. 5 and 6 respectively. As we have not extracted any features from the image so that the proposed method is free from the alignment process. Further, in this method one random matrix is used for generation of cancelable biometric templates. This matrix is registered corresponding to a key or password. The user verification is performed when the user presents his/her cancelable template along with PIN or

Table 1 Datasets description

Dataset	# Identities	Total Images	Image Size
ORL face [20]	40	400	112 × 92
AR face [21]	126	4000	768 × 576
IIT Delhi iris [22]	224	1120	320 × 240
CP ear (gray) [23]	17	102	300×400
CP ear (color) [23]	60	185	80×150
UTIRIS color [24]	79	1540	2048 × 1360
UTIRIS gray [24]	79	1540	1000×776

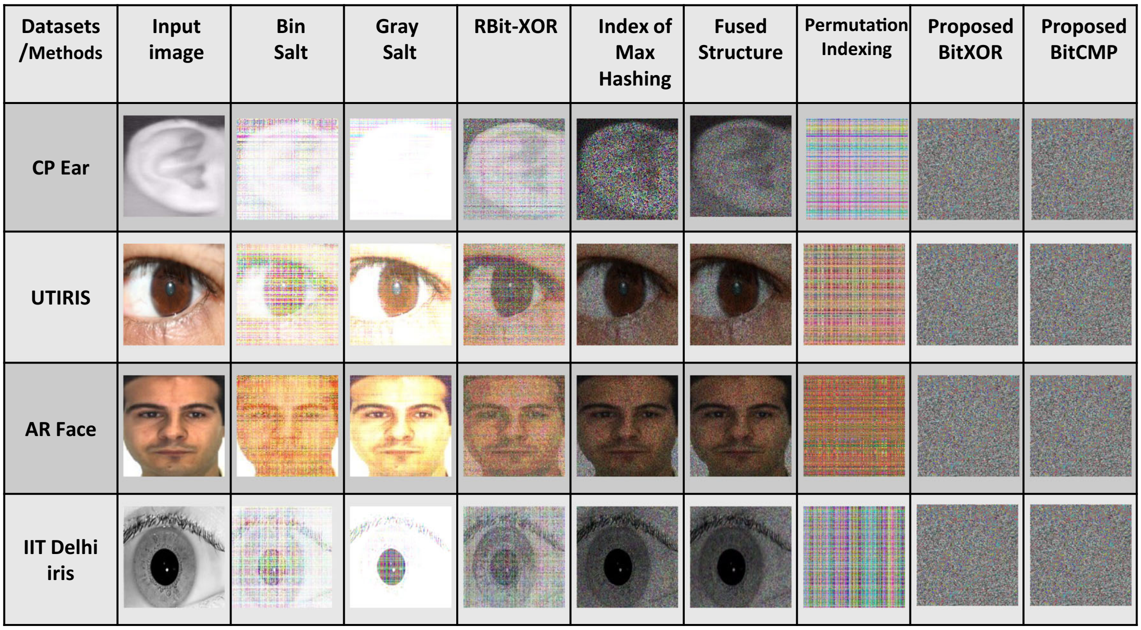


Fig. 6 Qualitative analysis among color cancelable biometric template generated using Bin Salt [25], Gray Salt [25], RBit-XOR [19], Index of Max Hashing [9], Fused Structure [10], Permutation Indexing [7], CBRW-BitXOR (proposed) and CBRW-BitCMP (proposed) on CP ear [23], UTIRIS [24], AR face [21] and IIT Delhi iris [22] datasets

password. This method is useful for verification and results are presented in Table 7.

4.2 Qualitative analysis

Here, a qualitative analysis of cancelable biometric templates generated by proposed methods is presented. The quality of cancelable biometric templates generated by proposed method and other compared methods are shown in Fig. 5 for gray datasets while Fig. 6 shows cancelable biometric templates for color datasets. It can be seen from both these Figs. 5 and 6 that templates generated by proposed method for all datasets do not reveal any information about the original biometric while others methods do. A histogram analysis between original biometric **S** and cancelable biometric template **C** generated by proposed methods is also carried out. A histogram analysis between **S** and **C** is shown in Fig. 7 for gray datasets and Fig. 8 represents for color datasets using both proposed methods. It is easy to observe that histogram of cancelable template is flattened in most cases (except the color iris image) in comparison to respective original image histogram. This analysis concludes that the intruder cannot gain any information from the cancelable biometric template as they are totally distorted.

4.3 Quantitative analysis

A quantitative analysis is also carried out for cancelable templates generated by proposed methods and other compared methods. The performance of templates is measured in terms of Correlation (Cr), Mean Absolute Error (MAE), Number of Pixel Change Rate (NPCR), Peak Signal to Noise Ratio (PSNR), RMSE (Root Mean Square Error), SSIM (Structural Similarity) and UACI (Unified Average Changing Intensity). The ideal value for above mentioned measures for two similar images are given as: Correlation value is $+1$ and -1, MAE is 0, NPCR is 0, PSNR is infinite, RMSE is 0, SSIM is $+1$ and -1 and UACI is 0. In cancelable biometric based system, original biometric **S** and generated cancelable biometric template **C** should not be similar. Hence, the value for above mentioned performance measure in cancelable biometric domain should be opposite to ideal values. The values of these parameters in the case of cancelable biometric system should be minimum for Correlation, PSNR and SSIM. While for MAE, NPCR, RMSE, UACI values should be maximum. The computation formulae of above mentioned performance measures are given in Table 2. The quantitative results for both gray and color images are given in Tables 3–6. The detail description of seven performance measures is given below:

- **Correlation Coefficient**: It is used to present the relation between the two images. Two images are related to each other in terms of three types of correlation values i.e. (i) Zero (ii) Positive and (iii) Negative correlation. The possible value of correlation is between -1.0 to $+1.0$. The zero value of correlation between **C** and **S** denotes that they are totally dissimilar. However, the negative value of correlation denotes that

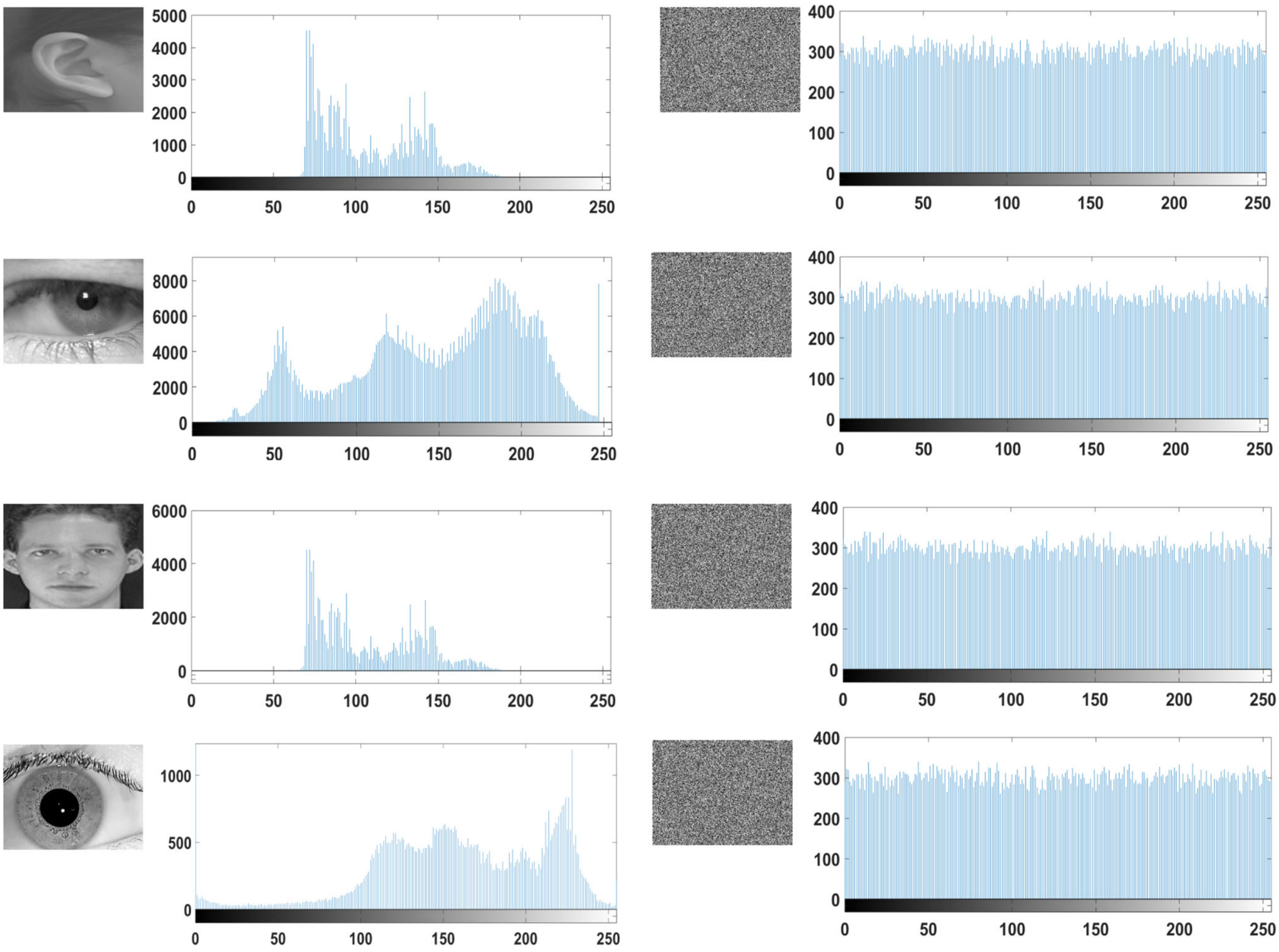


Fig. 7 Histogram analysis between gray original biometric **S** and cancelable biometric template **C** generated by CBRW-BitXOR (proposed) on CP ear [23], UTIRIS [24], ORL face [20] and IIT Delhi iris [22] datasets

the cancelable template **C** resembles with the negative of the original biometric image **S**. While, the positive value denotes that cancelable biometric template **C** resembles the original biometric **S**. In cancelable biometric system, correlation coefficient should be near to zero.

$$C_r = \frac{\sum_m \sum_n \left(S_{mn} - \bar{S}\right)\left(C_{mn} - \bar{C}\right)}{\sqrt{\left(\sum_m \sum_n \left(I_{mn} - \bar{I}\right)\right)^2 - \left(\sum_m \sum_n \left(S_{mn} - \bar{S}\right)\right)^2}} \tag{2}$$

Here **S** is the original biometric image and **C** is the cancelable biometric template corresponding to **S**. And, m and n are the row and column number respectively. Though, $\mathbf{S}_{mn}$ and $\mathbf{C}_{mn}$ represents the pixel intensity at a location in **S** and **C**. Here, $\bar{S}$ and $\bar{C}$ are the mean of the **S** and **C** respectively. For color image, this method is applied on each channel (red, green and blue) followed by taking their average i.e. divided by number of channels i.e. three.

- **Mean Square Error**: It denotes the sum of square of difference between the pixel intensity of two images at particular location. In this proposed work, the difference between the pixel intensity at each location in **C** and **S** is taken and squared. Further for taking the mean square error this resultant value is divided by the total number of pixels present in an image.

$$MSE = \frac{1}{W \times H} \sum_{i=1}^{W} \sum_{i=1}^{H} \left(S\left(i, j\right) - C\left(i, j\right)\right)^2 \tag{3}$$

Here, $S(i, j) - C(i, j)$ is error and $W \times H$ is the one image size or total number of pixels in an image. Its value can range from 0 to ∞. For two similar images its value is 0 while for cancelable biometric based system its value should far from 0. Higher the distortion among two images higher will be the value of MSE.

- **Root Mean Square Error**: It is a standard way of representing the mean square error in quantitative data. It is square root of mean square error as depicted in

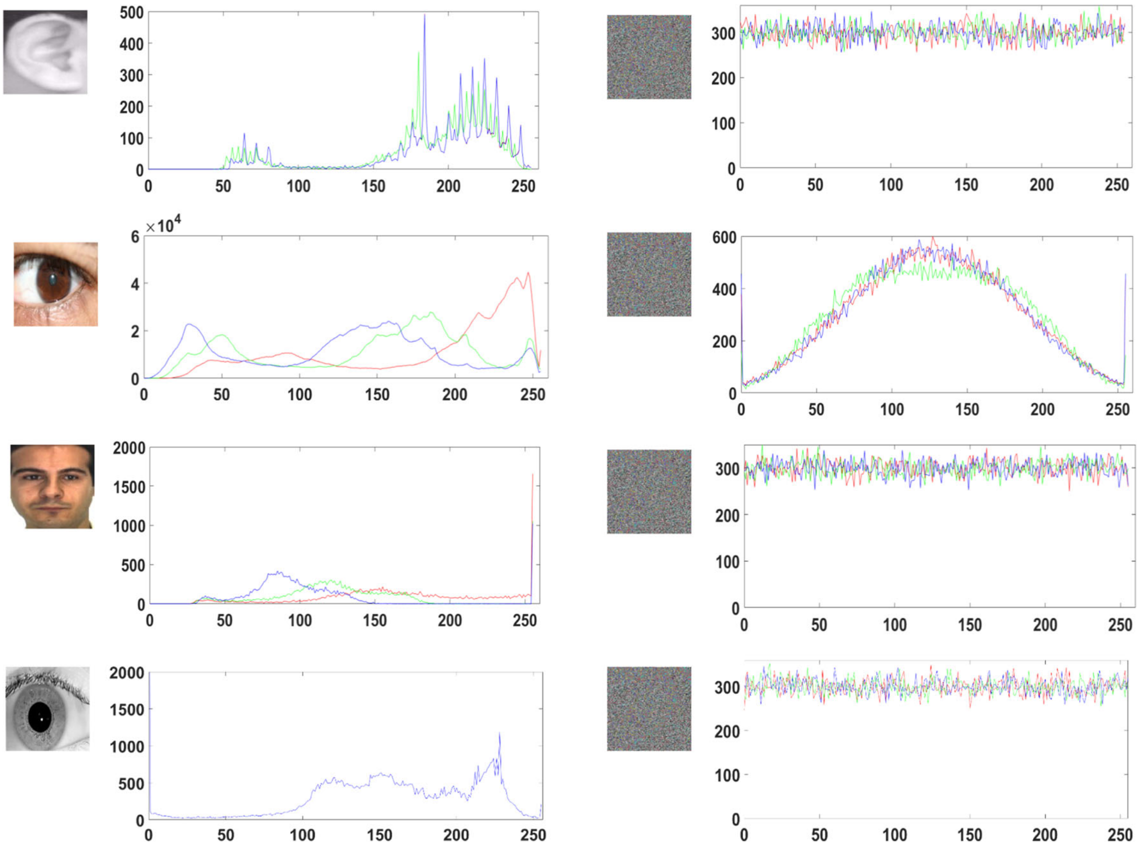


Fig. 8 Histogram analysis between color original Biometric **S** and color Cancelable Biometric **C** template by CBRW-BitXOR (proposed) on CP ear [23], UTIRIS [24], AR face [21], and IIT Delhi iris [22] datasets

below equation. Like MSE, the value of RMSE also ranges between 0 to ∞. The value of RMSE for two similar images is 0 while for cancelable biometric based system its value should far from 0. Higher value of RMSE denotes the two images are highly distorted to each other.

$$RMSE = \sqrt{MSE} \tag{4}$$

Here, MSE is Mean Square Error.

- **Peak Signal to Noise ratio**: It is the ratio between the maximum possible intensity value power of an image and the power of noise that effect the image quality. In other words, it is ratio between maximum pixel intensity value and Root Mean Square Error.

$$PSNR\,(db) = 20\log_{10}\frac{255}{\sqrt{MSE}} \tag{5}$$

Here, 255 is the maximum value of single channel. The relation between PSNR and MSE can be seen in above relation Which shows that if MSE between **C** and **S** is high then PSNR value will be low and vice versa. In case of cancelable biometric system, the value of MSE should be high which results in lower value of PSNR i.e. noise among the two images should be high.

- **Structural Similarity**: It is another measure to represent how much difference is present between the two images. The value range of SSIM is between -1 to 1. For two similar images the SSIM value is 1. In case of cancelable biometric system the value of SSIM should approach to 0.

$$SSIM(S,C) = \frac{(2\mu_S\mu_C + T_1)\,(2\sigma_{SC} + T_2)}{\left(\mu_S^2 + \mu_C^2 + T_1\right)\left(\sigma_S^2 + \sigma_C^2 + T_2\right)} \tag{6}$$

Here μ_S, μ_C are mean and σ_S, σ_C are variance and σ_{SC} is covariance between original image **S** and cancelable template **C**. However, T_1 and T_2 are constants

- **Mean Absolute Error**: It is an absolute average value used to represent the distortion provided in the original biometric image. Its value also ranges between 0 to ∞. For two similar images the value of MAE is 0 while for dissimilar images its value far from 0. In case of cancelable biometric system the value of MAE should be maximum.

$$MAE = \frac{1}{W \times H}\sum_{i=1}^{W}\sum_{i=1}^{H}|S\,(i,\,j) - C\,(i,\,j)\,| \tag{7}$$

Table 2 Performance measures used in proposed work

Measure	Formula	Description
Correlation Coefficient	$C_r = \frac{\sum_m \sum_n (S_{mn} - \bar{S})(C_{mn} - \bar{C})}{\sqrt{(\sum_m \sum_n (S_{mn} - \bar{S}))^2 - (\sum_m \sum_n (C_{mn} - \bar{C}))^2}}$	Here S and C are original and cancelable template images respectively.
Mean Square Error	MSE=$\frac{1}{W \times H} \sum_{i=1}^{W} \sum_{j=1}^{H} (S\,(i,\,j) - C\,(i,\,j))^2$	Here, $S\,(i,\,j) - C\,(i,\,j)$ is error and $W \times H$ image size.
Root Mean Square Error	RMSE=$\sqrt{MSE}$	Here, MSE is Mean Square Error
Peak Signal to Noise ratio	$PSNR\,(db)$=20 $\log_{10} \frac{255}{\sqrt{MSE}}$	Here, 255 is the maximum value of single channel.
Structural Similarity	SSIM (S,C)=$\frac{(2\mu_S \mu_C + T_1)(2\sigma_{SC} + T_2)}{(\mu_S^2 + \mu_C^2 + T_1)(\sigma_S^2 + \sigma_C^2 + T_2)}$	μ_S, μ_C are means and σ_S, σ_C are variance and σ_{SC} is covariance between images **S** and **C** respectively. And, T_1 and T_2 are constants
Mean Absolute Error	MAE=$\frac{1}{W \times H} \sum_{i=1}^{W} \sum_{i=1}^{H} \vert S\,(i,\,j) - C\,(i,\,j)\,\vert$	Here, $S\,(i,\,j) - C\,(i,\,j)$ is error and $W \times H$ is image size or total number of pixels in an image
Number of Pixel Change Rate	NPCR=$\left(S_i,\,C_j\right) = \frac{\sum_{i,j} D(i,j)}{W \times H} \times 100\%$	Here $D\,(i,\,j) = 0$; if $S\,(i,\,j) = C\,(i,\,j)$ and $D\,(i,\,j) = 1$; if $S\,(i,\,j) \neq C\,(i,\,j)$
Unified Average Changing Intensity	UACI=$\frac{1}{W \times H} \times \frac{\sum_{i=1}^{W} \sum_{j=1}^{H} \vert S(i,j) - C(i,j)\vert}{255} \times 100\%$	Here, $S\,(i,\,j) - C\,(i,\,j)$ is error and $W \times H$ is image size or total number of pixels in an image. And, 255 is maximum color value in single channel.

Here, $S(i, j) - C(i, j)$ is error between original image and corresponding cancelable biometric template. While $W \times H$ is the image size or total number of pixels in an image

- **Number of Pixel Change Rate**: This measure is used to calculate the randomness between the two images. For two dissimilar images the value of NPCR is high. In cancelable biometric, its value should be high which represents the high extent of distortion in the cancelable template.

$$NPCR = \left(S_i, C_j\right) = \frac{\sum_{i,j} D(i, j)}{W \times H} \times 100\% \tag{8}$$

Here (i) $D(i, j) = 0$; if $I(i, j) = S(i, j)$ and (ii) $D(i, j) = 1$; if $I(i, j) \neq S(i, j)$.

- **Unified Average Changing Intensity**: It is normalized form of the mean absolute error. It is also used to check the difference between the intensity value among two images. In cancelable biometric system, the value of UACI should be high. From our experimental results, it has been observed that some state-of-the-art methods have high value of UACI but still they are unable to hide glimpses of original biometric in corresponding cancelable templates.

$$UACI = \frac{1}{W \times H} \times \frac{\sum_{i=1}^{W} \sum_{i=1}^{H} |I(i, j) - S(i, j)|}{255} \times 100\% \tag{9}$$

Here, 255 is maximum intensity value in single channel and $I(i, j) - S(i, j)$ is error while $W \times H$ is image size

The quantitative results of above performance measures obtained from proposed methods and state-of-the-art methods are given in Tables 3 and 4 for gray datasets while Tables 5 and 6 represents results for color datasets. It can be noticed from Tables 3 and 4 that the average Correlation between the original biometric and cancelable biometric template, generated by proposed methods, is almost zero which signifies that these two entities are not correlated. Although, for other compared methods the correlation between **S** and **C** is present. Further, the value of NPCR is highest for the proposed methods while lowest for PSNR. The RMSE is also maximum for the proposed methods while SSIM value is minimum which signifies that two patterns are structurally dissimilar. Hence, it can be seen that proposed methods outperform all the compared methods in terms of almost all performance measures except one or two on a variety of biometrics. Similar observations can be made on the experimental results on color images as shown in Tables 5 and 6 respectively. The performance of the proposed methods and state-of-the-art methods is also compared in terms of Equal Error Rate (EER), False Acceptance Rate (FAR), False Rejection Rate (FRR), Genuine Acceptance Rate (GAR). The results of verification measures are presented in Table 7.

The red and blue entries in a column denote the method stood at first and second place respectively in terms of various performance measures. Both proposed methods have been compared with six other methods i.e. Bin Salt [25], Gray Salt [25], RBit-XOR [19], Index of Max Hashing [9], Fused Structure [10] and Permutation Indexing [7]. In a single result table, total 28 first and 28 second comparisons are present. This shows number of times a single method stood first and second places among total of 28 first and 28 second places. Total four Tables are present for all datasets (both gray and color). In this way, a total of 112 (= 28 first/second places in single Table × 4 Tables) first places and 112 second places are available in all the tables. Number of times individual method stood first and second place in all Tables is depicted by bar graph as shown in Fig. 9. From the bar graph, it can be seen that the proposed methods stood at first place 55 times out of 112 first places and second place 23 times out of 112 second places. Similarly, Index of Max Hashing stood 32 times first and 30 times second, Permutation Indexing stood 13 times first and 19 times second, Fused Structure stood 8 times first and 36 times second. However, RBit-XOR stood four times first and two times second, Bin Salt stood two times second while Gray Salt didn't secure a single place in terms of performance measures.

4.4 How performance measures satisfies the characteristics of cancelable biometric?

The main characteristics of cancelable biometric system is that the generated template should be distorted version of the original biometric. It should not reveal any information regarding its original credentials. In this proposed work, seven performance measures have been used for finding the relationship between original image (**S**) and cancelable biometric template (**C**) generated corresponding to the original image. The relation between performance measures and cancelable biometric characteristics is discussed below which is inspired from research work of Trivedi et al. [26]:

- **Diversity** property in cancelable biometric template states that templates generated corresponding to single identity should be different. In this proposed work, cancelable templates are generated using BitXOR between original biometric **S** and random walk matrix $\mathbf{R}_W$. Further, this $\mathbf{R}_W$ matrix is obtained from random matrix **R**. Hence for generating the different cancelable templates for same user, this random matrix needs to change which result in different templates for same user. The difference between old and new

Table 3 Quantitative results for gray images on CP ear, UTIRIS iris, ORL face and IIT Delhi iris datasets using proposed Algorithm 2

Methods	Cr	MAE	NPCR	PSNR	RMSE	SSIM	UACI
			CP ear				
Bin Salt	0.3685	26.6611	35.4147	29.7650	9.0401	0.3141	0.03510
Gray Salt	0.2874	0.1326	38.4164	Inf	0.4737	0.3019	0.00003
RBit-XOR	0.3178	18.1543	51.3793	29.4138	8.6877	0.1744	0.02750
Index of Max Hashing	-0.0033	41.4980	49.9003	30.5797	8.4266	0.0247	24.11690
Fused Structure	0.1568	38.7793	50.0025	30.9976	8.8739	0.0283	23.05070
Permutation Indexing	0.0005	31.6737	99.5364	29.6212	7.9331	0.0295	16.34260
Proposed	–0.0012	31.4192	99.9895	27.8996	10.3203	0.0103	12.32120
			UTIRIS				
Bin Salt	0.3358	15.4143	42.4160	31.4486	7.3453	0.3016	0.02570
Gray Salt	0.2707	0.0055	35.4165	68.6364	0.1569	0.2247	0.00001
RBit-XOR	0.3359	21.5205	51.3869	28.6801	9.3937	0.1845	0.03770
Index of Max Hashing	–0.0148	60.6443	49.9675	28.2759	9.8967	0.0262	27.70360
Fused Structure	–0.1283	55.4433	50.0502	27.7256	9.9323	0.0230	21.74250
Permutation Indexing	0.0015	29.8329	99.3266	28.4457	9.8249	0.0302	11.69920
Proposed	–0.0023	36.3812	99.9956	27.5930	10.6848	0.0101	14.26720
			ORL face				
Bin Salt	0.3575	18.2217	36.4149	29.8268	8.4661	0.3436	0.03160
Gray Salt	0.3607	0.0270	24.4163	57.4669	0.4177	0.2505	0.00009
RBit-XOR	0.3504	25.9038	47.3863	27.8707	10.3721	0.1970	0.05080
Index of Max Hashing	–0.0055	54.0264	49.9366	28.5310	9.4937	0.0355	25.10840
Fused Structure	0.1574	50.0738	49.9951	28.9516	9.9148	0.0263	23.55830
Permutation Indexing	–0.0017	23.7709	99.4188	28.3948	9.7281	0.0292	9.32190
Proposed	–0.0025	29.3690	99.9956	28.1091	10.0471	0.0098	11.51720
			IITD iris				
Bin Salt	0.3275	18.3122	49.5682	32.0333	6.8382	0.3043	7.18130
Gray Salt	0.2879	0.0005	46.1307	Inf	0.0009	0.1846	0.00080
RBit-XOR	0.3935	25.0757	43.2950	28.4284	9.6652	0.2394	9.83360
Index of Max Hashing	–0.0059	95.3870	48.0685	27.1983	14.0205	0.0075	37.40670
Fused Structure	–0.0577	40.5832	49.8713	30.3754	9.0572	0.0290	15.91500
Permutation Indexing	0.0061	36.5739	98.8301	27.5929	10.6394	0.0143	14.34270
Proposed	–0.0031	42.1365	99.9898	26.3531	10.9573	0.0070	16.52410

templates can be found by above discussed seven performance measures. The diversity between two templates generated for same user is shown in Table 8. From this Table, it can be seen that results are satisfying the dissimilar properties of two images. Hence, two templates generated for same user are different to each other. The results are presented for cancelable biometric templates generated by proposed Algorithm 2 for gray datasets. Similar results have been obtained for templates generated with Algorithm 3 and color datasets.

– **Non-invertible** property states that intruder should not able to retrieve the original credentials after accessing the cancelable templates. It simply means no reverse engineering process could reveal the original credential from the distorted ones. For satisfying this property, we have used computational complexity method which shows how much computational difficult is to obtain the original credential from cancelable template generated by proposed method. For generating the cancelable biometric templates three important steps are there. (i) Uniform distributed random image **R** (ii) Random walk

Table 4 Quantitative results for gray images on CP ear, UTIRIS iris, ORL face and IIT Delhi iris datasets using proposed Algorithm 3

Methods	Cr	MAE	NPCR	PSNR	RMSE	SSIM	UACI
			CP ear				
Bin Salt	0.3685	26.6611	35.4147	29.7650	9.0401	0.3141	0.03510
Gray Salt	0.2874	0.1326	38.4164	Inf	0.4737	0.3019	0.00003
RBit-XOR	0.3178	18.1543	51.3793	29.4138	8.6877	0.1744	0.02750
Index of Max Hashing	-0.0033	41.4980	49.9003	30.5797	8.4266	0.0247	24.11690
Fused Structure	0.1568	38.7793	50.0025	30.9976	8.8739	0.0283	23.05070
Permutation Indexing	0.0005	31.6737	99.5364	26.6212	7.9331	0.0295	16.34260
Proposed	0.0023	31.2946	99.6106	27.9150	10.3016	0.0104	12.27290
			UTIRIS				
Bin Salt	0.3358	15.4143	42.4160	31.4486	7.3453	0.3016	0.02570
Gray Salt	0.2707	0.0055	35.4165	68.6364	0.1569	0.2247	0.00001
RBit-XOR	0.3359	21.5205	51.3869	28.6801	9.3937	0.1845	0.03770
Index of Max Hashing	–0.0148	60.6443	49.9675	28.2759	9.8967	0.0262	27.70360
Fused Structure	-0.1283	55.4433	50.0502	27.7256	9.9323	0.0230	21.74250
Permutation Indexing	0.0015	29.8329	99.3266	28.4457	9.8249	0.0302	11.69920
Proposed	0.0028	36.2451	99.6096	27.6059	10.6688	0.0102	14.21370
			ORL face				
Bin Salt	0.3575	18.2217	36.4149	29.8268	8.4661	0.3436	0.03160
Gray Salt	0.3607	0.0270	24.4163	57.4669	0.4177	0.2505	0.00009
RBit-XOR	0.3504	25.9038	47.3863	27.8707	10.3721	0.1970	0.05080
Index of Max Hashing	–0.0055	54.0264	49.9366	28.5310	9.4937	0.0355	25.10840
Fused Structure	0.1574	50.0738	49.9951	28.9516	9.9148	0.0263	23.55830
Permutation Indexing	–0.0017	23.7709	99.4188	28.3948	9.7281	0.0292	9.32190
Proposed	0.0030	29.2166	99.6133	28.1275	10.0250	0.0100	11.45750
			IITD iris				
Bin Salt	0.3275	18.3122	49.5682	32.0333	6.8382	0.3043	7.18130
Gray Salt	0.2879	0.0005	46.1307	Inf	0.0009	0.1846	0.00080
RBit-XOR	0.3935	25.0757	43.2950	28.4284	9.6652	0.2394	9.83360
Index of Max Hashing	–0.0059	95.3870	48.0685	27.1983	14.0205	0.0075	37.40670
Fused Structure	–0.0577	40.5832	49.8713	30.3754	9.0572	0.0290	15.91500
Permutation Indexing	0.0061	36.5739	98.8301	27.5929	10.6394	0.0143	14.34270
Proposed	0.0032	41.9214	99.6133	26.3722	10.9329	0.0065	16.43970

matrix $\mathbf{R}_W$ and (iii) Cancelable template generation using BitXOR operation. In this proposed work, 320×240 uniform distributed random image is used, from which by using proposed Algorithms another same size $\mathbf{R}_W$ matrix is generated. Finally, this $\mathbf{R}_W$ matrix is operated with original biometric $\mathbf{S}$ for generation of cancelable biometric template. Hence, the proposed method consists with many steps for providing distortion in original biometric.

A rough computation complexity can be seen as 320×240 is the image size which results in total number of 76800 pixels and each image is represented by 8 bits per pixel. So the possible combination will be 76800^{256} or 76800^{2^8}. This results in very huge number of images. If the number of bits required to represent single pixel is 16 bits then complexity will be 76800^{65536}. In case of color image, these combinations will become $76800^{16777216}$ (8 bits for single pixel i in each channel so total channels are three) i.e. RGB (3×8=24 bits for each pixel). This is for one image e.g. random image. For random walk matrix, same complexity will be applicable which results in 76800^{256} and $76800^{16777216}$ combinations for gray and color image respectively. Hence, the total complexity will be 2×76800^{256} and

Table 5 Quantitative results for color images on CP ear, UTIRIS iris, AR face and IIT Delhi iris datasets using proposed Algorithm 2

Methods	Cr	MAE	NPCR	PSNR	RMSE	SSIM	UACI
			CP ear				
BIN Salt	0.3726	16.1243	60.3736	Inf	8.7680	0.2136	21.6780
Gray Salt	0.3419	17.3465	96.9898	Inf	8.6750	0.6716	20.5436
RBit-XOR	0.4196	18.7189	98.4661	28.7543	9.3166	0.0552	22.0222
Index of Max Hashing	0.2192	91.6883	72.4308	27.0778	11.2889	0.0105	80.8686
Fused Structure	-0.0626	75.7431	98.4153	27.9853	10.1690	0.0060	81.1095
Permutation Indexing	0.0002	34.3336	98.7996	27.3449	11.0118	0.0286	40.3925
Proposed	0.0024	70.2292	99.7851	25.7906	13.1121	0.0102	82.6226
			UTIRIS				
Bin Salt	0.2892	11.5604	97.8171	32.9566	6.3329	0.2832	13.6005
Gray Salt	0.3683	0.0205	97.1941	58.5614	0.3726	0.2679	0.0241
RBit-XOR	0.4304	20.9749	98.5574	28.0217	10.1323	0.2249	24.6764
Index of Max Hashing	0.0007	73.4919	99.3238	28.1113	9.1623	0.0247	86.4611
Fused Structure	0.2965	58.3934	99.0590	28.9269	8.0080	0.2867	68.6981
Permutation Indexing	0.0009	31.7332	99.1744	27.3341	10.9630	0.0321	37.3332
Proposed	–0.0024	31.6639	100.0000	27.0757	11.0936	0.0096	37.2516
			AR face				
Bin Salt	0.2867	17.6261	95.7843	29.6312	8.6082	0.2683	20.7366
Gray Salt	0.3151	0.0084	95.2613	68.2847	0.1932	0.2331	0.0099
RBit-XOR	0.3603	18.7915	92.1341	29.0458	9.0152	0.2134	22.1076
Index of Max Hashing	0.0009	59.6217	99.6712	29.3985	9.7028	0.0264	70.1432
Fused Structure	0.3814	64.0564	96.0148	29.8593	9.1332	0.2562	75.3605
Permutation Indexing	–0.0003	31.1703	99.0873	27.1549	11.1931	0.0358	36.6710
Proposed	–0.0040	40.5696	99.8917	27.1298	11.2967	0.0186	47.7289
			IITD iris				
Bin Salt	0.3281	18.1737	98.6803	32.0936	6.8063	0.3042	21.3808
Gray Salt	0.2856	0.0765	91.9948	Inf	0.0356	0.1844	0.0897
RBit-XOR	0.3894	25.1371	86.2976	28.4296	9.6640	0.2389	29.5731
Index of Max Hashing	0.0011	77.0563	99.0258	27.4080	13.6843	0.0111	90.6545
Fused Structure	0.3506	63.6589	99.3264	26.1429	12.7390	0.3004	50.8928
Permutation Indexing	0.0009	36.7071	98.8589	27.5912	10.6413	0.0144	43.1848
Proposed	–0.0030	42.1678	100.0000	27.3507	10.9602	0.0086	49.6092

$2 \times 76800^{16777216}$ for gray and color image. This means these number of combination will be required for getting the glimpse of the original biometric which is not computationally feasible.

- **Revocable** property states that in case of adversary attack the previous allotted cancelable template should be discarded and a new should be allotted to the genuine user. In this proposed work, random walk matrix $\mathbf{R}_W$ is used to provide the distortion in the original biometric which in turn depends on the random matrix $\mathbf{R}$ generated using uniform distribution method. With the help of this $\mathbf{R}_W$ matrix, we can generate many cancelable biometric template and given to the genuine user in case of compromise. For experimental work, we have used 320×240 size images. For gray image, we can generate 76800^{256} (for 8 bits per pixel representation) number of possible combinations for uniform distributed random image $\mathbf{R}$. For color image, these combinations will become $76800^{16777216}$ (24 bits for each pixel), which are very huge in count. By selecting any one of these combination (except the one used before), different cancelable biometric template can be allotted to the genuine user in case of compromise or adversarial attack.

Table 6 Quantitative results for color images on CP ear, UTIRIS iris, AR face and IIT Delhi iris datasets by proposed Algorithm 3

Methods	Cr	MAE	NPCR	PSNR	RMSE	SSIM	UACI
			CP ear				
BIN Salt	0.3726	16.1243	60.3736	Inf	8.7680	0.2136	21.6780
Gray Salt	0.3419	17.3465	96.9898	Inf	8.6750	0.6716	20.5436
RBit-XOR	0.4196	18.7189	98.4661	28.7543	9.3166	0.0552	22.0222
Index of Max Hashing	0.2192	91.6883	72.4308	27.0778	11.2889	0.0105	80.8686
Fused Structure	-0.0626	75.7431	98.4153	27.9853	10.1690	0.0060	81.1095
Permutation Indexing	0.0002	34.3336	98.7996	27.3449	11.0118	0.0286	40.3925
Proposed	0.0022	70.2373	99.8110	25.7899	13.1132	0.0103	82.6322
			UTIRIS				
Bin Salt	0.2892	11.5604	97.8171	32.9566	6.3329	0.2832	13.6005
Gray Salt	0.3683	0.0205	97.1941	58.5614	0.3726	0.2679	0.0241
RBit-XOR	0.4304	20.9749	98.5574	28.0217	10.1323	0.2249	24.6764
Index of Max Hashing	0.0007	73.4919	99.3238	28.1113	9.1623	0.0247	86.4611
Fused Structure	0.2965	58.3934	99.0590	28.9269	8.0080	0.2867	68.6981
Permutation Indexing	0.0009	31.7332	99.1744	27.3341	10.9630	0.0321	37.3332
Proposed	0.0020	31.5300	99.6074	27.0897	10.9972	0.0098	37.0941
			AR face				
Bin Salt	0.2867	17.6261	95.7843	29.6312	8.6082	0.2683	20.7366
Gray Salt	0.3151	0.0084	95.2613	68.2847	0.1932	0.2331	0.0099
RBit-XOR	0.3603	18.7915	92.1341	29.0458	9.0152	0.2134	22.1076
Index of Max Hashing	0.0009	59.6217	99.6712	29.3985	9.7028	0.0264	70.1432
Fused Structure	0.3814	64.0564	96.0148	29.8593	9.1332	0.2562	75.3605
Permutation Indexing	-0.0003	31.1703	99.0873	27.1549	11.1931	0.0358	36.6710
Proposed	0.0038	40.3595	99.8984	27.1335	11.2915	0.0189	47.4818
			IITD iris				
Bin Salt	0.3281	18.1737	98.6803	32.0936	6.8063	0.3042	21.3808
Gray Salt	0.2856	0.0765	91.9948	Inf	0.0356	0.1844	0.0897
RBit-XOR	0.3894	25.1371	86.2976	28.4296	9.6640	0.2389	29.5731
Index of Max Hashing	0.0011	77.0563	99.0258	27.4080	13.6843	0.0111	90.6545
Fused Structure	0.3506	63.6589	99.3264	26.1429	12.7390	0.3004	50.8928
Permutation Indexing	0.0009	36.7071	98.8589	27.5912	10.6413	0.0144	43.1848
Proposed	0.0034	41.9519	99.6082	27.3683	10.9379	0.0093	49.3551

Table 7 The performance of the proposed and state-of-the-art methods in terms of Genuine Accept Rate (GAR), False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER) for gray images on CP ear dataset using Bin Salt [25], Gray Salt [25], RBit-XOR [19], Index of Max Hashing [9], Fused Structure [10], Permutation Indexing [7] and proposed method

Bin Salt	46.75	53.32	53.25	53.28
Gray Salt	47.62	52.46	52.38	52.42
RBit-XOR	44.00	53.46	53.44	52.55
Index of Max Hashing	45.89	53.76	54.11	53.94
Fused Structure	46.75	53.49	53.25	53.37
Permutation Indexing	46.85	52.49	53.35	53.67
Proposed	54.98	44.81	45.02	44.91

Table 8 Performance measures used for showing the diversity property between two cancelable template generated for same user

Datasets	Cr	MAE	NPCR	PSNR	RMSE	SSIM	UACI
CP ear	0.0031	42.5028	99.6484	27.4472	10.8189	0.0090	16.6678
UTIRIS	0.0012	42.6492	99.6068	27.4517	10.8133	0.0069	16.7252
ORL face	0.0011	42.5290	99.6185	27.4431	10.8239	0.0070	16.6781
IITD iris	-0.0001	42.9074	99.6328	27.4377	10.8306	0.0054	16.8264

The two templates are generated for same user using different random matrix **R**

- **Performance**: The cancelable biometric templates generated by proposed methods are secure than templates generated by state-of-the-art methods as proved by quantitative and qualitative analysis. Hence it can be ensured that performance of the system will not deteriorate.

4.5 Discussion

Here, we critically analyse the experimental results presented in Tables 3–6. As already described, the proposed methods work equally well on gray as well as color biometric images. The proposed methods outperform all other methods in qualitative as well as quantitative terms. A qualitative analysis was done in Section 4.2 where the original biometric and the corresponding cancelable templates were shown. The reason behind other state-of-the-art methods revealing partial and full information about original biometric is that these methods use the original biometric along with other natural images while the proposed methods introduce randomness in the original image using random walk model. Further, histogram analysis shows that cancelable templates generated by proposed methods do not reveal any information regarding original image. This strengthens the fact that for any intruder, it would be extremely difficult to know about the original image. Afterwards, a quantitative analysis has also been presented for both gray and color datasets. A comparison between cancelable biometric templates generated by proposed methods and other methods has been presented based on several performance measures including Cr, RMSE, PSNR, SSIM, MAE, NPCR and UACI. Bar graph as shown in Fig. 9 represents which method performed better than others in terms of quantitative performance measures. In the bar graph, x-axis shows the method name while y-axis denotes the number of times a method stood first or second in quantitative results. It is clear from the bar graph that proposed methods stood first at many places.

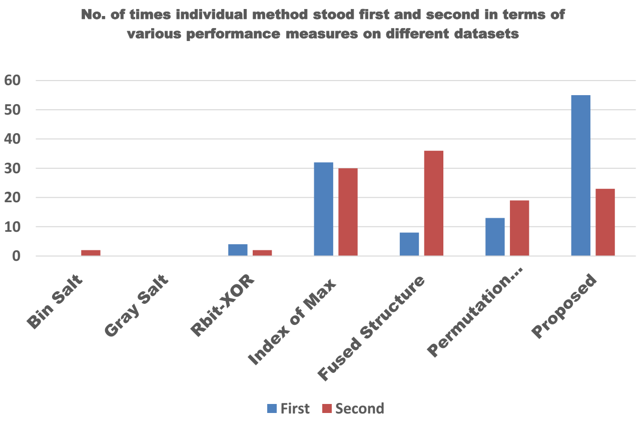


Fig. 9 Number of times following methods i.e. Bin Salt [25], Gray Salt [25], RBit-XOR [19], Index of Max Hashing [9], Fused Structure [10], Permutation Indexing [7] and Proposed method stood at first and second place in terms of quantitative measures

4.6 Comparison of proposed method with state-of-the-art methods

In Bin Salt [25] and Gray Salt [25] methods, auxiliary data is added with original biometric to generate a cancelable template and this addition of auxiliary data is known as salting method. The main advantage of this method is simple for implementation while main disadvantage is to know the amount of auxiliary data needed to add with the original biometric image for cancelable template generation. Proposed methods are different from other methods in terms of security as template generated by these methods reveal partial and full information about the original biometric as depicted by Figs. 5–6. Both Bin Salt and Gray Salt methods used simple addition and subtraction operations which are invertible in nature. Both these methods are tested on only gray iris dataset. Proposed methods are different from the Index of Max Hashing [9] and Fused Structure [10] methods on the basis of quality of templates, limited number of biometric modalities and feature sets. For different datasets, templates generated by these methods reveal partial and full information about original credentials which is not reveal by proposed method. A comparative study among all methods is presented in Table 9. Further, comparison among proposed method with the state-of-the-art methods is also carried out in terms of histogram analysis.

Table 9 Comparison of the Proposed method with state-of-the-art methods

Factor	Bin Salt	Gray Salt	RBit-XOR	Index of Max	Fused Structure	Permutation Indexing	Proposed
Random Image							√
Random Walk							√
BitXOR			√				√
Gray Images	√	√	√	√	√	√	√
Color Images							√
Histogram Analysis							√
Number of Datasets	1	1	1	2	2	3	8
Biometric Modalities	iris	iris	iris	fingerprint	fingerprint	face, fingerprint, fingervein	ear, face, iris
Glimpses in templates	√	√	√	√	√	√	
Limited feature sets	√	√		√	√	√	

5 Conclusion and future work

This research work has proposed two novel methods for generation of cancelable biometric templates using random walk method. Towards this effect two methods are proposed *viz.* (a) Cancelable Biometric template generation based on Random Walk using Bit XOR (CBRW-BitXOR) (b) Cancelable Biometric template generation based on Random Walk using Bit Complement (CBRW-BitCMP) have been suggested and two novel algorithms have been proposed. Both of these algorithms employ another proposed algorithm for generation of random walk matrix. Extensive experiments are performed on a various biometric datasets including ear, iris and face. Proposed methods have been compared with other methods by qualitative and quantitative analysis. The qualitative analysis shows that proposed methods are able to transform original credentials without revealing them while other compared methods do reveal some structure of the original biometric. The quantitative analysis shows that the proposed methods outperform other compared methods in terms of seven performance measures i.e. Cr, MAE, RMSE, PSNR, UACI, SSIM and NPCR. The advantages of the proposed methods include: (i) Independence from the fact whether original biometric image is gray or color and (ii) No information about original credentials is revealed by proposed methods. In future work, new methods will be explored which result better in both qualitative and quantitative measures.

Acknowledgements We acknowledge Ministry of Human Resource Development, Govt. of India for supporting this research by providing fellowship to one of the authors, Ms. Manisha. One of the authors, Dr. Nitin Kumar is thankful to Uttarakhand State Council for Science and Technology, Dehradun, Uttarakhand, India for providing financial support towards this research work (Sanction No. UCS & T/R & D-05/18-19/15202/1 dated 28-09-2018)

References

1. Prabhakar S, Pankati S, Jain AK (2003) Biometric recognition: security and privacy concerns. IEEE Secur Priv 1:33–42
2. Manisha, Kumar N (2019) Cancelable biometrics: a comprehensive survey. Artif Intell Rev Springer Netherlands. https://doi.org/10.1007/s10462-019-09767-8
3. Patel VM, Ratha NK, Chellappa R (2015) Cancelable biometrics: a review. IEEE Signal Process Mag 32(5):54–65
4. Grady L (2006) Random walks for image segmentation. IEEE Trans Pattern Anal Machine Intell 28(11):1768–1783
5. Bampis CG, Maragos P, Bovik AC (2016) Graph-driven diffusion and random walk schemes for image segmentation. IEEE Trans Image Process 26(1):35–50
6. Bertasius G, Torresani L, Yu SX, Shi J (2017) Convolutional random walk networks for semantic image segmentation. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 858–866
7. Murakami T, Fujita R, Ohki T, Kaga Y, Fujio M, Takahashi K (2019) Cancelable permutation-based indexing for secure and efficient biometric identification. IEEE Access 7:45563–45582
8. Ratha NK, Chikkerur S, Connell JH, Bolle RM (2007) Generating cancelable fingerprint templates. IEEE Trans Pattern Anal Mach Intell 29(4):561–572
9. Jin Z, Hwang JY, Lai YL, Kim S, Teoh ABJ (2018) Ranking-based locality sensitive hashing-enabled cancelable biometrics: index-of-max hashing. IEEE Trans Inform Forens Secur 13(2):393–407
10. Sandhya M, Prasad MV (2016) Securing fingerprint templates using fused structures. IET Biometr 6(3):173–182
11. Wang S, Hu J (2013) A Hadamard transform-based method for the design of cancellable fingerprint templates. In IEEE International Congress on Image and Signal Processing (CISP) 3(6):1682–1687
12. Hämmerle-Uhl J, Pschernig E, Uhl A (2013) Cancelable iris-templates using key-dependent wavelet transforms. In: IEEE International conference on biometrics (ICB), pp 1–8
13. Wang Y, Hatzinakos D (2010) Cancelable face recognition using random multiplicative transform. In IEEE International Conference on Pattern Recognition 20:1261–1264
14. Pillai JK, Patel VM, Chellappa R, Ratha NK (2011) Secure and robust iris recognition using random projections and sparse representations. IEEE Trans Pattern Anal Mach Intell 33(9):1877–1893

15. Lingli Z, Jianghuang L (2010) Security algorithm of face recognition based on binary pattern and random projection. In IEEE Cognitive Informatics (ICCI) 9:733–738
16. Punithavathi P, Geetha S (2016) Dynamic sectored random projection for cancelable iris template. In IEEE International conference on advances in computing communications and informatics (ICACCI), pp 711–715
17. Pillai JK, Patel VM, Chellappa R, Ratha NK (2010) Sectored random projections for cancelable iris biometrics. In: IEEE International conference on acoustics speech and signal processing, pp 1838–1841
18. Kim Y, Toh KA (2008) Sparse random projection for efficient cancelable face feature extraction. In IEEE Conference on Industrial Electronics and Applications 3:2139–2144
19. Manisha, Kumar N (2020) On generating cancelable biometric template using reverse of Boolean XOR. In: Proceedings of international conference on emerging trends in communication, control and computing (ICONC3), Lakshmangarh, Sikar, India,1-4. https://doi.org/10.1109/ICONC345789.2020.9117459
20. Samaria FS, Harter AC (1994) Parameterisation of a stochastic model for human face identification. In: Proceedings of IEEE workshop on applications of computer vision, pp 138–142
21. Martinez AM (1998) The AR face database CVC Technical Report24
22. Kumar A, Passi A (2010) Comparison and combination of iris matchers for reliable personal authentication. Pattern Recogn 43(3):1016–1026
23. Emersic Z, Struc V, Peer P (2017) Ear recognition: more than a survey. Neurocomputing 255:26–39
24. Hosseini MS, Araabi BN, Soltanian-Zadeh H (2010) Pigment melanin: pattern for iris recognition. IEEE Trans Instrum Meas 59(4):792–804
25. Zuo J, Ratha NK, Connell JH (2008) Cancelable iris biometric. In: IEEE 19th international conference on pattern recognition, pp 1–4
26. Trivedi AK, Thounaojam DM, Pal S (2020) Non-Invertible cancellable fingerprint template for fingerprint biometric. Comput Secur 90:101690

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Dr. Nitin Kumar received his Doctor of Philosophy and Master of Technol-ogy from Schoolof Computer and System Sciences, Jawaharlal Nehru Univer- sity, New Delhi. He is currentlyworking as Assistant Professor in the Department of Computer Science and Engineering at National Institute ofTechnology, Uttarakhand, India. His current research include visualattentionmodeling, pattern recognition, face recognition and image processing.

Ms. Manisha received her M.Sc.in Computer Science from Kurukshetra University, Kurukshetra. She has completed her Doctor of Philosophy in Computer Science and Engineering at National Institute of Technology, Uttarakhand. Her current research interests include Cancelable Biometrics, Pattern Recognition and Image Processing.