Securing Mass Biometric Templates Using Blockwise Multi-Resolution Clustering Watermarking

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Abstract. High resolution grayscale face templates are widely used in access control applications. Securing such images using computational intelligence optimization is complex. The high volume of templates in access control applications adds more complexity to securing these templates in real world using modest resources. The dimension of search space is huge due to traditional representation of all image blocks in candidate solutions to find their optimal embedding parameters. In this paper, a Blockwise Multi-Resolution Clustering (BMRC) framework is proposed to watermark streams of grayscale high resolution face images using modest computational resources. BMRC stores multi-objective optimization results for all blocks of similar texture in an associative memory. Multi-resolution clustering of blocks is used to store this knowledge for different number of blocks clusters in texture feature space. Thus the high dimensional optimization problem for face image is decomposed into smaller problems for 8×8 blocks, then previous optimization results statistics for these blocks are recalled from associative memory using the texture features of these blocks. Solutions representing different resolutions are ranked and optimal resolution is concluded at the end of the watermarking process. Experimental results show complexity reduction up to 93.5% in fitness evaluations for a stream of only 40 images. The solutions produced are of the same quality as full optimization for all face image blocks.

Keywords: Intelligent Watermarking, Population Based Incremental Learning, Biometrics Security, Clustering, Computational Intelligence, Bio-watermarking, Multi-Hypothesis

1 Introduction

Biometrics are the means to recognize individuals using intrinsic physical or behavioral characteristics. Biometrics is synergistically merged into the digital watermarking technology to secure biometric templates, also to hide biometric traits invisibly inside other biometric templates to improve recognition rates using multiple biometrics traits. High resolution face templates are widely used in biometric based access control applications [8]. Digital watermarking has been used to secure grayscale images by embedding watermarks into these images to ensure their authenticity. Finding optimal embedding parameters is a complex problem with conflicting objectives of image quality and watermark robustness. Image quality is associated with the distortion resulting from watermark embedding while watermark robustness relates to the resistance of the embedded watermark against manipulations on the watermarked image.

In intelligent watermarking (IW), different computational intelligence techniques have been proposed to find optimal embedding parameters. Authors have proposed using evolutionary computation optimization techniques like Genetic Algorithms (GA) [11], Particle Swarm Optimization (PSO) [15], and combinations of GA and PSO [5] to find embedding parameters that maximize the fitness for both quality and robustness [12]. Most of these traditional methods are based on representing all cover image 8×8 pixels blocks in candidate solutions according to their positional order, and iteratively improve the fitness until convergence is reached [11]. These methods use single aggregated objective [11]. To date, few authors have proposed mutli-objective formulation [3, 7], where the two objectives are optimized simultaneously and multiple non-dominated solutions are located forming a Pareto front. This last approach provides more operational flexibility.

Most of the EC techniques suffer from convergence problems due to the complexity of the search space associated with high resolution images. Handling constraints for large sized candidate solutions is computationally complex. Such constraints avoid using the same frequency coefficient for embedding more than once for the same image block. In this paper, mass grayscale face biometric templates are considered to be secured. For this type of images, the traditional representation [11] implies that shifting slightly the face pixels inside the image is considered as a new optimization problem, and consequently costly re-optimizations are required. And thus watermarking a stream of high resolution grayscale face images results in a stream of computationally complex optimization problems.

In this paper, a Blockwise Multi-Resolution Clustering (BMRC) framework is proposed for rapid intelligent watermarking. The proposed technique is capable of finding optimal embedding parameters in a computationally efficient manner. BMRC is based on a multi-objective formulation which satisfies the trade-off between watermark quality and robustness, and thus allows adaptability for different application domains, where the objectives priority vary, without the need for costly re-optimizations.

During the training phase, the multi-objective optimization results, obtained on few training images, are stored in an associative Block Cluster Memory (BCM). After the full optimization results are obtained, the optimal solution is selected from the resulting Pareto front based on the application domain priorities. This optimal solution represents optimal embedding parameters for all training image 8×8 pixels blocks, it is used to collect the most frequent embedding parameters for all image blocks having the same texture. This information is stored for multi-resolution clustering of face image blocks based on their texture features, where clustering resolution represents the number of clusters. BMRC uses an incremental learning scheme in training phase, such that the multi-resolution clusterings and their corresponding most frequent embedding parameters are calculated for the first training images and get updated for subsequent training images.

During generalization phase, texture features are extracted from 8×8 pixels blocks of the unseen stream of images, then these blocks are categorized using the recalled multi-resolution clustering prototypes from BCM. The watermark fitness is calculated for different resolutions stored in BCM, and then solutions are ranked to choose the optimal clustering resolution for each face in the stream. And thus BMRC implements multi-hypothesis approach where all alternative solutions associated with multi-resolution clusterings are stored in associative BCM memory, and the hard decision is taken at the end of the watermarking process.

Proof of concept simulations are performed using the PUT database [4] of high resolution face images, and compared against reference method in terms of complexity and quality of solutions. Simulation results demonstrate that BMRC results in a significant reduction of the computational cost for intelligent watermarking by replacing costly optimization operations with associative memory recalls. The resulting solutions have nearly the same quality and robustness as those obtained with full optimization of each face image.

This paper is organized as follows. Section 2 introduces watermarking concepts, metrics, and terminology needed to understand the paper, then an overview for different intelligent watermarking approaches proposed in literature. This section also introduces Population Based Incremental Learning (PBIL), and texture feature extraction for grayscale images. Section 3 describes the proposed framework for rapid blockwise intelligent watermarking for mass high resolution grayscale facial images. The proposed experimental methodology is described in Section 4. Results and analysis are presented in Section 5.

2 Intelligent Watermarking of Grayscale Images

Most digital watermarking techniques proposed for grayscale images use different transform domains to embed a watermark that minimizes the visual impact, and to deal with the uncorrelated coefficients in the transform domain. The most commonly used transform domains in watermarking literature are Discrete Cosine Transform (DCT) [11] and Discrete Wavelet Transform (DWT) [5]. Using DCT transform inheriting robustness against JPEG compression which is based on DCT transform as well, the host image is divided into small blocks of pixels (8×8 pixels), transformed to frequency domain, and watermark bits are distributed among these blocks by changing frequency

bands coefficients of these blocks according to the value of the watermark bit to be embedded. Few authors have considered other transforms based on DFT [6] to improve robustness against geometric attacks since these transforms are more resistant to geometric manipulations.

2.1 Watermarking Metrics

Digital watermarking system can be characterized using three main aspects: watermark quality, robustness, and capacity. Watermark quality measures the distortion resulting from watermark embedding, there are limits defined in literature [14], where the human vision cannot recognize the distortion resulting from the embedding. Watermark robustness measures the resistance to different manipulations and processing on the watermarked image, this is measured by the correlation between the extracted watermark after the manipulations and the original watermark. Watermark capacity measures the number of embedded bits per block given thresholds for watermark quality and/or watermark robustness.

Watermark quality and robustness are commonly measured using Weighted Peak Signal-To-Noise Ratio (wPSNR) and Normalized Correlation (NC) respectively. These metrics have been defined in [9, 10].

2.2 Intelligent Watermarking

Modifications in certain frequency bands are less perceptible than others, and modifications in other frequency coefficients are more robust against manipulations. Many authors have therefore proposed using different evolutionary optimization techniques to find optimal frequency bands for embedding the watermark bits to maximize the fitness for both watermark quality and robustness objectives. The embedding parameters for frequency domain watermark embedding and extraction algorithms are represented using frequency coefficients altered due to watermark bits embedding which are commonly called embedding bands in literature.

Evolutionary computation (EC) methods like GA and PSO have attracted authors attention due to simplicity of these techniques and the ease in adapting them to many different types of watermarking systems. Moreover EC does not assume a distribution of the parameters space represented by selected frequency bands for embedding [11]. EC methods, inspired by biological evolution, are generally characterized by having candidate solutions which evolves iteratively to reach the target of optimization based on the guidance of objectives fitness evaluation. These candidate solutions are referred to as chromosome in GA, and more generally individuals of the population of candidate solutions.

In these traditional methods, all cover image blocks are represented in optimization candidate solutions. The selected embedding bands are altered along optimization iteratively to maximize the fitness for watermark quality and robustness. This representation allow distribution of watermark bits among blocks. The optimization problem can be formalized as:

$$\begin{aligned}
\max_{EB_{X_c}} \quad & \{QF(EB_{X_c}), RF(EB_{X_c})\} \\
EB_{X_c} &= \{eb_1, eb_2, ..., eb_i, ..., eb_{NB}\}, \text{ where } NB = (M_c/8) \times (N_c/8) \\
eb_i &= \{a_1, a_2, ..., a_e, ..., a_{C_i}\}, \text{ where } a_e \text{ is 6-bit binary representation} \\
& \quad \text{for embedding bands index for block } b_i \text{ with } a_e \in [0, 1, ..., 63] \\
\text{s.t. } a_e &\neq 0, \text{ where } 1 < e < C_i \text{ ,and } 1 < i < NB \\
a_{e1} &\neq a_{e2}, \text{ where } 1 < e1, e2 < C_i
\end{aligned} \tag{1}$$

where b_i represents the 8×8 block in cover image of resolution $M_c \times N_c$, the total number of blocks NB which is equal to $(M_c/8) \times (N_c/8)$, a_e represents the $\underline{e}$th embedding band for block b_i belonging to the set of embedding bands for this block eb_i, and the embedding capacity for block b_i is C_i. The first constraint considered ensures avoiding DC coefficient a_e for embedding, and the second constraint considered ensures avoiding using the same embedding bands for the same block.

Many authors have proposed aggregating both quality and robustness fitness into one objective for simplicity utilizing different aggregation weights for the objectives to resolve the issue of different scaling of these different types of objectives, and to favor one objective over the others using these weights. Shieh *et al* [11] have used Genetic Algorithm for optimizing the aggregated fitness for both quality and robustness, while Wang *et al* [15] have used Particle Swarm Optimization for optimization. Other authors [5] have proposed combining both GA and PSO.

Different formulations for watermark embedding optimization have been evaluated and compared in literature [7]. Multi-objective formulation corresponds to the trade-off among different quality and robustness objectives. It provides multiple optimal non-dominated solutions (Pareto front) which gives a system operator the ability to choose among multiple solutions to tune the watermarking system resolving the challenge of operating flexibility [7].

2.3 Population Based Incremental Learning (PBIL)

The salient feature of Population Based Incremental Learning (PBIL) is the introduction of a real valued probability vector. The value of each element of the vector is the probability of having a 1 in that particular bit position of the encoded chromosome. PBIL has proved efficiency with intelligent watermarking problem where utilizing the previous experience in subsequent generations ensures better convergence properties [7] compared to GA and PSO. Also the probability vector is considered a good representation for optimization landscape that can be recalled to reproduce the landscape without the need to go through complex iterations. Bureerat and Sriworamas [1] proposed changes to PBIL algorithm to handle multi-objective optimization problems. In this algorithm the probability vector is replaced with probability matrix, where each row in this matrix represents the probability vector to create sub-population individuals.

2.4 Texture Features of Grayscale Images

Texture features are extracted from the grayscale images using 8×8 pixels blocks granularity. The most commonly used texture features can be classified into spatial features like Gray Level Covariance Matrix (GLCM), and other domains features like Discrete Cosine Transform (DCT). Taking the computational complexity into consideration, using spatial features would have lower complexity compared to other domains features. However the watermark embedding and extraction methods based on spatial domain would have lower robustness against different image alterations, and lower watermark embedding capacity. In literature, many authors have considered DCT for extracting texture features of grayscale images. Yu *et al.* [16] have proposed zoning method using the most significant 39 coefficients.

The watermark embedding/extracting algorithm considered in this paper is an algorithm proposed by Shieh *et al* [11] based on DCT domain, where the original cover image is not required during extraction of the watermark, this reduces the required space needed to store the original cover images. Having the DCT coefficients ready for watermark embedding and extraction eliminates the additional complexity for texture feature extraction.

Therefore, the computational complexity of traditional methods described in this section is not affordable using modest computational resources, and thus a novel formulation is essential for intelligent watermarking a stream of high resolution images. Most of authors in intelligent watermarking were focusing on single image watermarking, and did not pay enough attention to high volume of grayscale images watermarking. Only for high volume bi-tonal images, Vellasques *et al.* [13] proposed a high throughout watermarking by considering optimization of a stream of images as single dynamic optimization problem. This approach is not efficient with grayscale face images [9] due to positional representation of blocks.

3 Blockwise Multi-Resolution Clustering (BMRC) Watermarking

BMRC shown in Figure 1 finds optimal embedding bands for a stream of high resolution face images using modest computational complexity. This is accomplished by replacing computational expensive full optimization with memory recalls from an associative memory representing prior

optimization knowledge acquired during training. Face images blocks are clustered according to their texture, and then optimal embedding bands for all of blocks of same texture are selected together using prior knowledge stored in associative Block Cluster Memory (BCM). In this paper only even embedding is considered with equal embedding capacity for all blocks, uneven embedding scheme is detailed in [10]. Texture metric and watermark bit assignment algorithm are required to distribute bits among different blocks according to their texture in the uneven scheme.

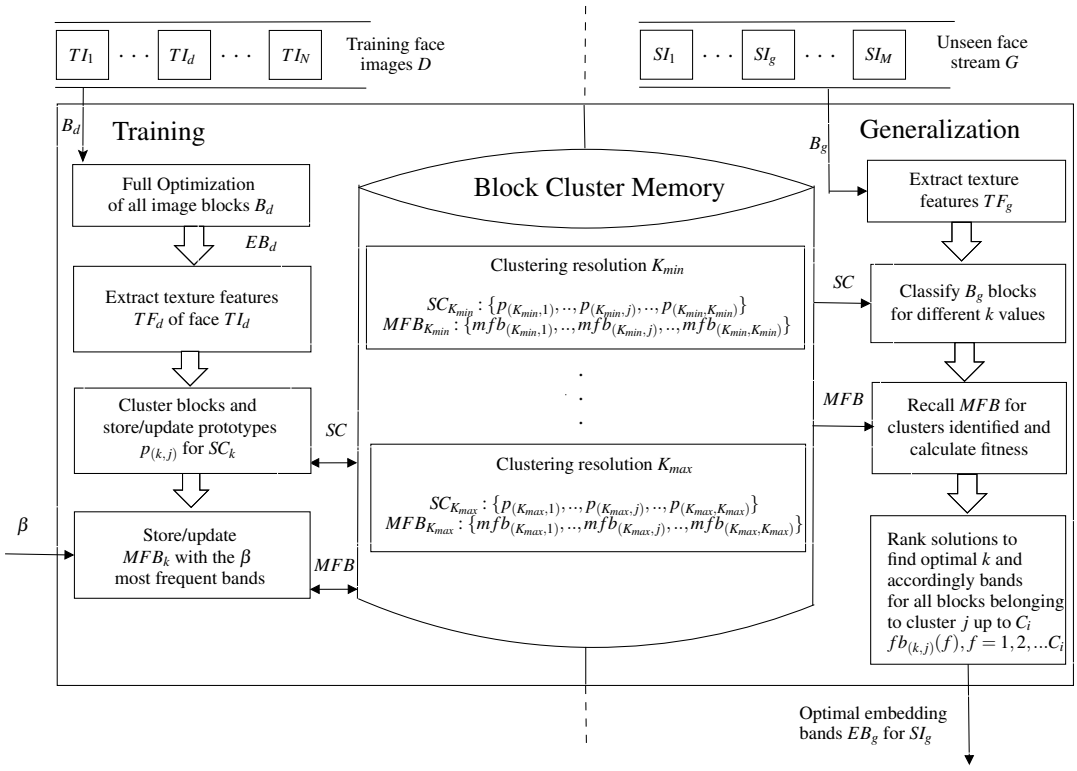

Fig. 1: General overview of BMRC architecture and processing steps for training and generalization phases. BCM is organized based on clustering resolution k ranging from K_{min} to K_{max}.

3.1 Training

The training set D consists of training face images defined as $D = \{TI_1, TI_2, ..., TI_d, ..., TI_N\}$, where TI_d represents face image of index d from the training set D of resolution $M_c \times N_c$. The number of face images in the training set is equal to N. For each training face image TI_d, the image is divided into 8×8 pixels blocks $B_d = \{b_i\}$, where $i = m_c \times (M_c/8) + n_c$ with m_c, and n_c defines the row and column index of 8×8 blocks respectively. The total number of blocks $NB = (M_c/8) \times (N_c/8)$, and thus $i = [1, 2, ..., NB]$.

Training face image blocks B_d are transformed into DCT domain $DCT_d = \{dct_i\}$, where $dct_i = \{ac_0, ac_1, ..., ac_a, ..., ac_{63}\}$ with ac_0 defines the DC coefficient of the 8×8 block b_i, and ac_a defines the $\underline{a}$th DCT coefficient of the same block b_i.

After the full multi-objective optimization process for face image TI_d, the optimal solution is selected among Pareto front based on application domain priorities as shown in Figure 2. The optimal embedding bands EB_d are concluded for face image TI_d, where $EB_d = \{eb_i\}$ with eb_i representing the optimal embedding bands for block b_i. The embedding bands defines the index of DCT coefficients which are modified during embedding the watermark. It can be defined as $eb_i = \{a_1, a_2, ..., a_e, ..., a_{C_i}\}$ with e is the index of the embedding bands in eb_i, and C_i is the number of embedding bands for block b_i representing the embedding capacity for b_i.

Multi-objective optimization results in multiple optimal solutions called non-dominated solutions, where improving one objective fitness results in suffering for other objective considered. Choosing the optimal solution among these solutions is based on the priority of objectives in the application domain. This feature ensures the adaptability of the proposed system in different application domains without computationally expensive re-optimizations.

For example, quality is the most important issue with medical imaging applications where the watermarked image still goes through feature extraction process, on the other hand robustness is the most important issue with biometrics application where the embedded watermark represents biometric traits which are used for recognition after watermark bits extraction. In this research, we employ a fixed trade-off between robustness and quality by fixing quality requirements for optimal solution weighted PSNR at 42 dB [14] which is considered acceptable from a Human Vision System (HVS) standpoint as shown in Figure 2 for training set face images TI_1, TI_2, and TI_3.

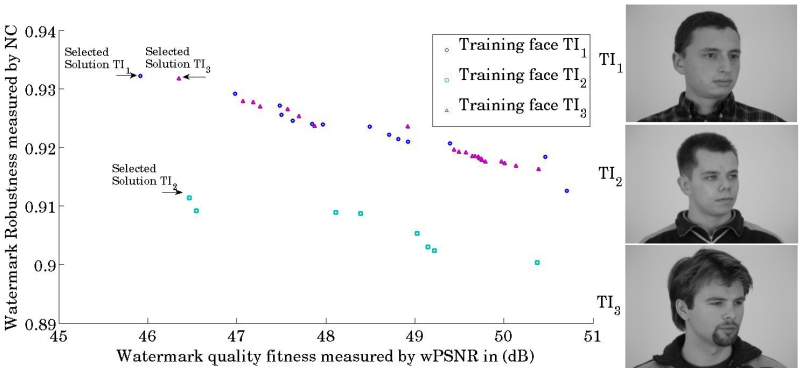

Fig. 2: Selecting solution among Pareto front for training set face images TI_d from PUT database [4] based on application domain objectives priorities, where embedding capacity is 8 bits per block.

The texture features TF_d are extracted from DCT_d, where TF_d defines the most significant DCT coefficients from DCT_d for training face image TI_d. The texture feature vectors are defined as $TF_d = \{tf_i\}$, where tf_i defines the texture feature vector of block b_i. This feature vector is defined as $tf_i = \{ac_a\}$, where $a \in [0, 1, ..., 63]$, and $a = \{a_1, a_2, ..., a_t, ..., a_T\}$. The number of coefficients used to extract features is equal to T, and t is the index of texture feature in the feature vector tf_i as shown in Figure 3.

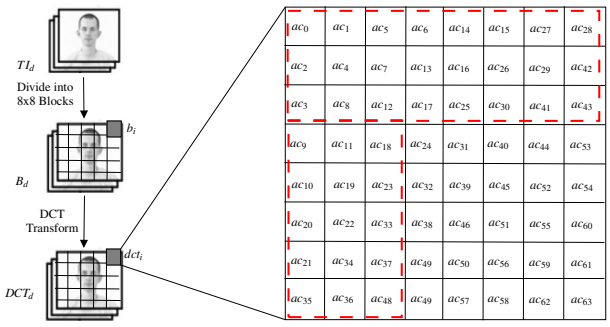

Fig. 3: Zoning method to select the most significant DCT coefficients to extract texture features tf_i for block b_i [16], $tf_i = \{ac_a\}$, where $a = \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 25, 26, 27, 28, 29, 30, 33, 34, 35, 36, 37, 41, 42, 43, 48\}$

The prior knowledge is represented by blockwise multi-resolution clustering of face image blocks b_i for different number of clusters k using texture feature vectors tf_i. The set of clusterings

SC:{$SC_{K_{min}}$, $SC_{K_{min}+1}$, ..., SC_k, ..., $SC_{K_{max}}$} are stored in associative memory. Each clustering SC_k consists of cluster prototypes $p_{(k,j)}$ with $j = 1, 2, ..., k$ representing jth cluster for clustering resolution k, where SC_k:{$p_{(k,1)}$, $p_{(k,2)}$, ..., $p_{(k,j)}$, ..., $p_{(k,k)}$}. This set of clusterings SC are updated along training phase to update prototypes based on face images in the training dataset D.

The Most Frequent embedding Bands (MFB_k) for all blocks belonging to the same blocks cluster are calculated for training set D using previous optimization results. These results are represented by optimal embedding bands eb_i for all blocks b_i of training face image TI_d. For each clustering SC_k there is MFB_k set, where $MFB_k = \{mfb_{(k,1)}, mfb_{(k,2)}, ..., mfb_{(k,j)}, ..., mfb_{(k,k)}\}$. $mfb_{(k,j)}$ is associated with cluster prototype $p_{(k,j)}$ representing most frequent embedding bands using clustering resolution k for jth cluster. The set of most frequent bands is defined as $mfb_{(k,j)} = \{fb_{(k,j)}(1), fb_{(k,j)}(2), ..., fb_{(k,j)}(f), ..., fb_{(k,j)}(\beta)\}$ and $fb_{(k,j)}(f) \in [1, 2, ..., 63]$. $mfb_{(k,j)}$ is ordered descendingly with respect to the frequency of occurrence of embedding bands, where $fb_{(k,j)}(1)$ is the index of the most frequent embedding band for jth cluster using resolution k represented by prototype $p_{(k,j)}$, and $fb_{(k,j)}(\beta)$ is the index of the least frequent band. The parameter β is tunable for the proposed system defining the size of $mfb_{(k,j)}$ representing the maximum number of frequent bands stored in BCM.

3.2 Generalization

The generalization set of unseen face image G is defined as $G = \{SI_1, SI_2, ..., SI_g, ..., SI_M\}$, where the size of generalization set equals to M. The subscript g is used instead of d for the data structures used in generalization phase. Thus B_g, DCT_g, and TF_g defines the 8×8 blocks, the DCT transformed blocks, and the texture features of the face image SI_g respectively.

In the generalization phase, texture features tf_g are extracted from SI_g, then face image SI_g blocks are compared against cluster centroids recalled from BCM for different resolutions k. Each block b_i is associated with the nearest centroid for each value of k in texture space. As shown in Figure 4, the block is compared to the recalled centroids for multi-resolution clustering k in texture feature space. In this example, the face image block b_i is associated with clusters 1, 3, 2, and 6 for number of clusters k equals to 3, 4, 5, and 6 respectively in texture feature space.

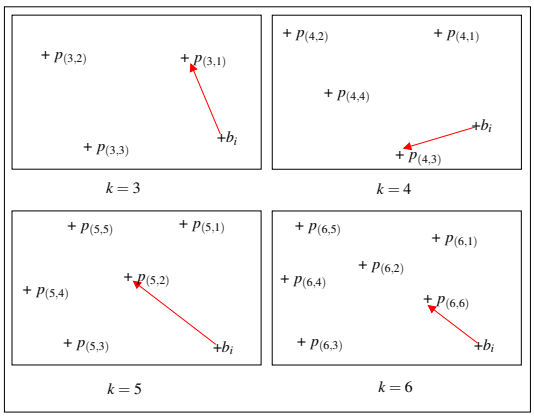

Fig. 4: Classifying block b_i for different k values in texture feature space.

The most frequent embedding bands $mfb_{(k,j)}$ associated with prototypes $p_{(k,j)}$ of clusters found in face image SI_g are recalled from BCM. These most frequent embedding bands are used as optimal embedding bands for all face image blocks belonging to the same cluster of blocks based on their texture features. This recall is performed for different resolutions k to find optimal embedding bands for all blocks, then watermark quality and robustness fitness are calculated using these bands.

As shown in Figure 5 for $k = 3$, each block b_i is classified using the distance to the prototypes $p_{(k,j)}$ of defined blocks clusters in texture feature space, then $mfb_{(k,j)}$ associated with $p_{(k,j)}$ are recalled. The embedding capacity C_i of b_i decides how many embedding bands $fb_{(k,j)}(f)$ are

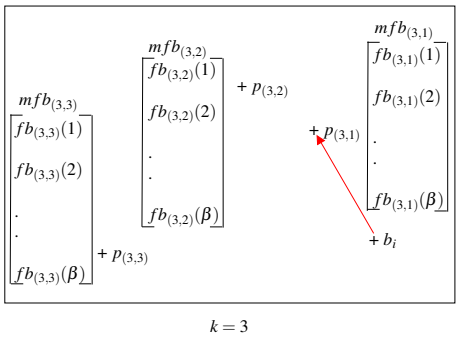

Fig. 5: Classifying block b_i in texture feature space and recall $mfb_{(k,j)}$ associated with prototypes $p_{(k,j)}$ for $k = 3$, where $SC_3 = \{p_{(3,1)}, p_{(3,2)}, p_{(3,3)}\}$,and $MFB_3 = \{mfb_{(3,1)}, mfb_{(3,2)}, mfb_{(3,3)}\}$

selected from $mfb_{(k,j)}$ to be used for embedding, such that if the capacity is equal to 1 bit-per-block, only the embedding band $fb_{(k,j)}(1)$ is selected for embedding, on the other hand if the capacity is equal to 3 bits-per-block, then $fb_{(k,j)}(1)$, $fb_{(k,j)}(2)$, and $fb_{(k,j)}(3)$ are selected.

Using the watermark fitness calculated for different values of k, solutions are proposed to be ranked to find the optimal number of cluster k to accomplish maximum watermark fitness. Ranking solutions based on two conflicting objectives like watermark quality and robustness would involve decision based on the priorities of the application domain.

4 Experimental Methodology

The database for face images used in experiments is proposed to be PUT [4] face database which consists of 100 individuals with 100 poses for each individual. Color face images of resolution 2048x1536 are converted to grayscale level. Using the first pose of each individual (face images of name pattern IIII1001.JPG where IIII is the individual number in 4 digits), the first 40 face images are used for verification, the next 10 individuals face images for training with full optimization to populate associative memory. The training set and verification set is used for system design and parameters tuning.

Multi-objective PBIL optimization [1] of both the baseline and BMRC training is performed using 24 individuals and 5 sub-populations, with maximum number of iterations equals to 40, external archive maximum size is 20, and convergence is assumed if the Pareto front produced is the same for 15 iterations.

The watermark to be embedded is a binary logo of resolution 221×221. The watermark embedding/extracting algorithm used in experiments is an algorithm proposed by Shieh *et al* [11]. The metrics used in experimentation for measuring watermark quality and robustness are wPSNR and NC respectively as defined in [9, 10]. Only robustness against JPEG compression of quality factor 80% is considered in experimentation.

The experimental study compares BMRC with the baseline system representing traditional methods with full optimization for all face image blocks. The comparison is based on quality of solutions produced and complexity reduction measured in number of fitness evaluations. In this experiment, the minimum number of clusters K_{min} is set to 3 and maximum number K_{max} is set to 40. The maximum training capacity β is set to 20 bits-per-block. The training set size N equals to 1, and the size of unseen stream M equals to 40 high resolution face images. The training phase invloves multi-objective optimization for one training face image using embedding capacity equals to 8 bits-per-block.

5 Experimental Results

Table 1 shows the complexity reduction measured by number of fitness evaluation, where results show significant reduction of 93.5% when considering the training fitness evaluations with

Fitness Evaluation	Baseline	BMRC
Training	N/A	960
Generalization	38400	1520
Complexity Reduction		
Generalization only	96.0%	
Overall Reduction	93.5%	

Table 1: Computational complexity reduction of the proposed system compared to baseline system for a stream of 40 face images using training set size $N = 1$, measured in number of fitness evaluations for the stream.

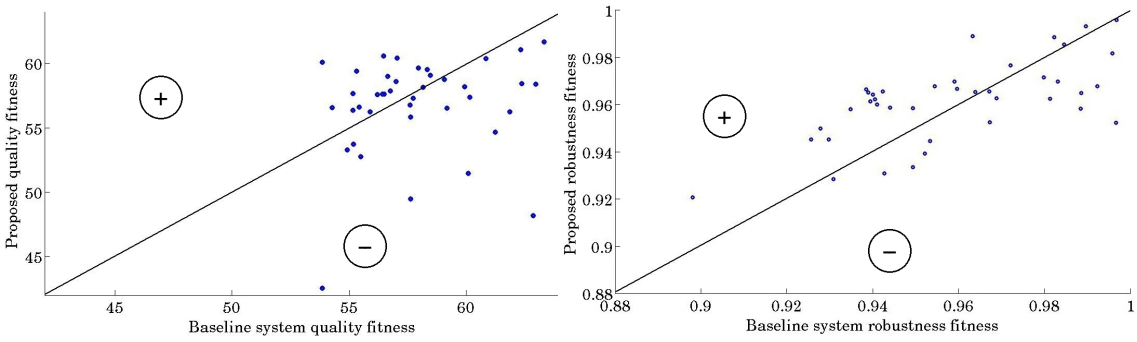

Fig. 6: Fitness comparison of BMRC compared to baseline system.

generalization for a stream of 40 face images. The fitness comparison of the set of 40 face images is shown in Figure 6.

Table 2 shows mean fitness for stream of 40 face images where there is improvement in robustness fitness and slight degradation in quality fitness within the acceptable quality according to HVS using significantly reduced computational resources.

Mean Fitness	Quality [wPSNR]	Robustness [NC]
MOGA [2]	58.41±3.35	0.9393±0.0061
Baseline	57.93±2.71	0.9589±0.0240
BMRC	56.79±3.76	0.9617±0.0171

Table 2: Mean watermark quality and robustness fitness defined in Section 2.1 for the set of 40 face images using baseline system, and MOGA [2] compared to BMRC.

6 Conclusion

Intelligent watermarking for streams of high resolution grayscale face images using evolutionary optimization is a very costly process, it has large dimension of search space due to representing all image blocks in the population of candidate solutions. The positional representation of these blocks in traditional methods for grayscale face images results in expensive re-optimizations when shifting face image pixels inside the image. Also the application domain priorities variations result in costly re-optimizations for single objective optimization formulation to adjust the aggregation according to the priorities change.

In this paper, we presented BMRC framework which replaces stream of similar optimization problems with BCM associative memory recalls. This BCM memory holds optimization solutions statistics for 8×8 pixels blocks grouped according to their texture, such that the most frequent embedding parameters for all blocks of the same texture are selected together during generalization phase. The training phase of BMRC is based on multi-objective optimization to populate BCM,

such that the selected solution from Pareto front based on objectives priorities is used. If the objectives priorities vary, no costly re-optimizations are needed because only another solution from the Pareto front will be selected to populate BCM. The proposed BCM holds the optimization solutions for different clustering resolutions in texture feature space and postpone the hard decision for the optimal clustering resolution till the end of the watermarking process.

Simulation results show a significant complexity reduction measured in number of fitness evaluations including the training phase of BMRC. This complexity reduction is 93.5% for a stream of 40 face images. The solutions produced by the proposed framework are almost of the same accuracy as full optimization.

The concept presented in this paper can be generalized on any stream of optimization problems with large search space, where the candidate solutions consist of smaller granularity problems that affect the overall solution. The challenge for applying this approach is to find the significant feature for this smaller granularity that affects the overall optimization problem.

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