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Optimized Features of SIFT Transform Function for Digital Image Watermarking using Hybrid Swarm Intelligence and Neural Network

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Abstract: ***Authentication of digital multi-media is a challenging task in the current scenario of internet technology for the authentication of digital multi-media data used digital watermarking techniques. The feature-based watermarking techniques provide the robustness of digital watermarking methods. In this paper proposed optimized features based digital watermarking techniques using a neural network. For the process of features, optimization used hybrid swarm intelligence algorithms. The hybrid algorithms are a combination of PSO and ACO. The PSO used as feature optimizer and ACO used for the selection of features point for the processing of neural network models. Two neural networks models used BP and RBF. The property of both models is different for the processing of data and desired output for the enhancement of the proposed model used cascaded neural network models using BP and RBF. The cascaded models generate dynamic patterns for the embedding of a digital watermark. The dynamic patterns provide the randomness of the pixel value and decrease the value of attack predication. The proposed algorithms have been tested on an extensive database of 300 images. The analysis of the proposed algorithm is satisfactory against different types of attacks and enhance the strength of robustness.***

Keywords : ACO, Digital Image Watermarking, Neural Network, PSO, SFIT, Swarm intelligence.

I. INTRODUCTION

The generation of multimedia data is increasing in the current age of technology. The generated data transmitted over the internet faced a problem of integrity and authentication [1, 2]. The lack of authentication and integrity data easily tampered and distributed. For the prevention of misuse of multimedia data required copyright protection methods. The digital watermarking techniques provide copyright protection. The implementation of digital watermarking techniques in multimedia data in two different modes of operation one is pixel-based methods, and others are feature-based methods. The pixel-based methods work based on shifting of pixel left to right and randomness of the pixel in the source image and symbol image [1-4]. The robustness of pixel-based image watermarking algorithms is a week and easily tampered by the attacker. Instead of pixel-based methods, the feature-based watermarking algorithm is much robust. The feature-based watermarking techniques used a transform-based function such as discreet wavelet transforms function (DWT), scale-invariant feature transform, and many more Fourier based function [5-8]. The transform-based function enriches property of texture in this paper proposed feature-based watermarking techniques.

The process of features extraction extracts the all features property of raw images. The extracted features are a collection of low intensity, high intensity, and some distorted intensity of data. The distorted intensity of data creates the week pattern of watermark embedding. The week embedding process easily threats very attacker. For the better selection of features used features optimization process. The process of features optimization used swarm-based optimization algorithms [9, 10, 21]. The swarm-based algorithms are multi-objective and multi constraint-based fitness function and generate a better optimal solution instead of unguided algorithms for the optimization of features used particle swarm optimization and ant colony optimization [13-18]. The particle and ant colony optimization both are used features optimization for better selection and generation of patterns. For the betterment of features, optimization combined both swarm algorithms and improved the performance of features optimization [20]. The improved features optimization normalized the value of noise. The normalized value of noise increases the strength of features. Besides, the preservation of edge and quality of texture data is very important during the extraction of texture features form the raw image. If the edge and texture features cannot preserve the quality of watermarking image is decline and watermark image easy to attack. Due to fast and effective learning of cascaded neural network improved the robustness and imperceptibility of watermarking instead of conventional neural network models []. For the generation of a dynamic pattern used cascaded neural network models. The cascading of neural network models used two models BP neural network models and RBF neural networks models. The RBF neural network models generate the pattern randomness of optimized features. Several improved features-based models have been proposed [11, 19, 23, 39].

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The embedding process of watermarking based on neural network assure the full copyright protection, but the process of network is very sensitive against attacks. The performance of neural network-based methods has poor due to minimum randomness of patterns, so direct acceptability of models in watermarking approach is not good.

The scale factor of neural network-based image watermarking is sensitive Against noise attack. Each feature point of watermark image required scale factor, for the improvement of scale factor. The process has used optimization algorithm for the improvement of scale factor. The process needs optimization algorithm such as genetic algorithm (GA), particle swarm optimization (PSO) and other swarm-based optimization algorithms. The used optimization algorithms improved the value of scale factor and enhanced the robustness of digital image watermarking. The proposed watermarking algorithms improved the robustness of digital image watermarking.

In this paper, the proposed algorithms simulated in MATLAB software and tested with a collection of 300 image dataset. The image dataset is a collection of different categories of images. The rest of paper is organized as follows in section II. SHIFT transform function. In section III, discuss the swarm optimization process in section, IV discuss neural network models and cascaded algorithms for the process of embedding. In section, V discuss the experimental process based on geometrical attacks and finally discuss the conclusion and future work direction in VI.

II. SFIT TRANSFORM FUNCTION

The process of SIFT function generates features key point of digital image. The process of features extraction describes here *[29-32]:*

Step 1 – Scaling of Space:

The process of mapping pf 2D image data into 2D SIFT transform the process of transfer used linear kernel scaling factor the derivation as:

$$f_{out} = K_n * f_{in}$$

Where,

K_n – kernel

f_{in} - input signal

$*$ - convolution operation

Scale-space $S(x, y, \sigma)$ of image $I(x, y)$ is expressed mathematically as:

$$S(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where,

$G(x, y, \sigma)$ - scale variable Gaussian function

(x, y) - spatial coordinates

σ - scale-space factor (using image's smoothness)

The feature point value denoted by σ. The maximum value of σ denoted a good feature value and the minimum value of σ extract minimum feature.

The process of $DOG(difference\ of\ Gaussian)$ space describe mathematically as:

$$D(x, y, \sigma) = [G(x, y, k\sigma) - G(x, y, \sigma)] * I(x, y) = S(x, y, k\sigma) - S(x, y, \sigma)$$

Where,

$I(x, y)$ - input image

k - multiple of 2 neighboring scale-spaces

$*$ - convolution operation.

To measure high and low value of $D(x, y, \sigma)$, each feature points matched with its neighbor.

Step 2 – calculate the feature points:

The orientation and location of the feature points, the inner points of orientation is called feature point and left outer point is calculated in step 3 formula.

Step 3 - formula:

$$\begin{cases} \theta(x,y) = \tan^{-1} 2\{[I_L(x,y+1) - I_L(x,y-1)]/[I_L(x+1,y) - I_L(x-1,y)]\} \\ g(x,y) = \sqrt{[I_L(x+1,y) - I_L(x-1,y)]^2 + [I_L(x,y+1) - I_L(x,y-1)]^2} \end{cases}$$

Where,

$\theta(x, y)$ - orientation of the gradient

$g(x, y)$ - magnitude

The direction of key points is visualized by histogram the maximum gradient direction of feature key points collects as feature descriptor. The collected feature point creates feature matrix. The collected feature matrix shown in figure 1:

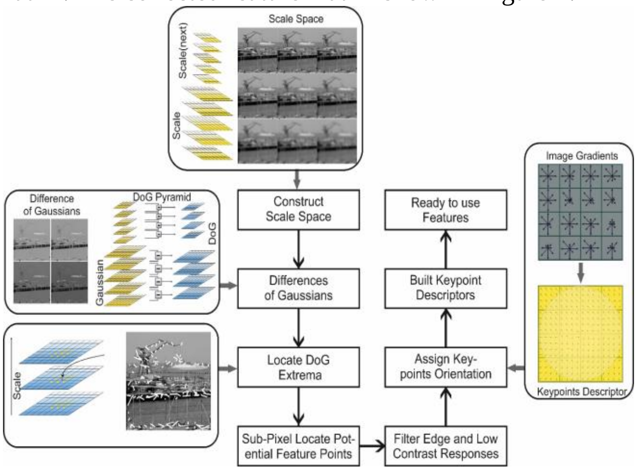


Fig. 1. Process block diagram of feature extraction process of SIFT transform function.

III. SWARM INTELLIGENCE ALGORITHMS

Swarm intelligence inspired by the biological flying kits and nature inspired function in artificial intelligence. The nature of swarm intelligence is meta-heuristic and diverse solution of define problem[33-36]. In this section describe the two swarm-based algorithms such as PSO and ACO algorithm. Also describe the process of hybrid swarm optimization in the process of features optimization[37, 38].**ACO (Ant colony optimization)**

ACO algorithm was discussed by Dorigo (1992). It is based on population heuristic evolutionary algorithm; it is inspired by the biological ant and its grouped working of the ants. It has been confirmed that defined algorithm finds on a comparable good optimization result's solution in solving issues[39, 40, 41, 42, 43]. The ACO algorithm based on the action of many separately and responding of information. Although the acting of ant is normal, the actions of complete group of ant is acceptable. The ACO algorithm has the distributed computing's properties, heuristic search and positive feedback. It is a heuristic global optimization algorithm in the evolutionary algorithm. In process of the evolution, the information interaction based on pheromone performs main role. Due to the merit of the ACO algorithm, it is widely applied in sort-out the combinatorial optimization issues, likes traveling salesman, assignment, job-shop scheduling, vehicle routing, graph coloring, network routing and so on[44-48].

A. PSO (Particle swarm optimization)

Eberhart and Kennedy discussed the vital useful metaheuristic technique is PSO ($particle\ swarm\ optimization$) in 1995. It is based on behavior of social words for searching the food. In that technique, the position x_i of each object shows the solution of the given issue and the best solution shows the solution's source. Each object has its self-information storage to store the recent best position reached by the object and the global best situation of the whole population. In the manner of data information saved in the storage of all objects and its velocity v_i it can update its position $x_i(t+1)$ as in below figure[49-50].

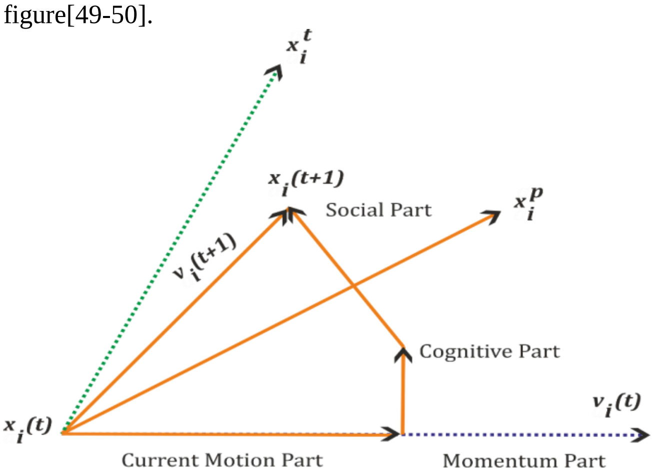


Fig. 2. PSO Algorithm: Velocity and position updates of objects.

B. Hybrid swarm intelligence (ASPO)

The combination of ACO and PSO play vital role in feature optimization in digital watermarking. The nature of meta-heuristic function creates diverse solution of given problem. In the combination of ACO and PSO works in the mode of feature selection and features reduction[37-42]. The collection of feature data proceeds by the ant colony optimization and the selection of data proceed by the particle swarm optimization. The process of algorithms describes here.

Some parameters define for the processing of algorithms

F=f_1, f_2,……………….f_n is the feature point of SIFT transform function.

W is the weight factor of features.

τ

$is\ the\ constant\ value\ of\ pheromones\ of\ ants, v_1\ and\ v_2\ is\ velocity\ of\ particle$,

$c_1\ and\ c_2\ is\ acceleration\ constant\ of\ particle$

The process of hybrid swarm intelligence describes as.

Step1. Process of features set F1{f1,f2,…………fn} with population of particle of swarm optimization .

a. Define the initial value of V1=0, V2=0, and weight of particle Wi.

b. Define the selection function of ACO

$F\_optimal(s) =$

$\frac{(Fst-Fst)}{st}, wi\epsilon f(f1, f2 \ldots\ldots fn) \ldots\ldots\ldots\ldots (1)$

Here

$if\ the\ value\ of\ Rd\ is\ zero\ the\ feature\ is\ optimal\ point$

$Fst\ is\ SIFT\ r\ and\ w\ is\ set\ of\ feature\ points\ of\ sum\ sets$

$is\ phenomenon\ value\ of\ ants\ and\ LI\ is\ value\ of\ least\ interface\ of\ ants$

Step2. The $Pbest$ value set to $Gbest$

Proceed the value of next step selection of ants feature points

1. Estimate the difference value of local ants

$\mathrm{Rf} = \frac{\mathrm{LSI}}{\mathrm{Wd}}$ Here

$Lsi\ is\ interference\ value\ of\ ants\ and\ Wd\ is\ sum\ value\ of\ PSO\ space$

The $PSO\ space\ creates\ the\ space\ of\ feature\ space$

$$FS=\begin{cases} \frac{\max\ (RF)\ -F(s)}{\max_{h=1}(WS)} & if\ \ s_i \in f_j \\ 0 & otherwise \end{cases} \qquad (3)$$

2. $Create\ the\ relative\ FS\ difference\ value$

$$\mathrm{Rd} = \sum_{\mathrm{fd}=1}^{\mathrm{n}} \sum_{\mathrm{pf}=1}^{\mathrm{m}} (\mathrm{xi} - \mathrm{fs}) \ldots\ldots\ldots\ldots\ldots (4)$$

IV. PROPOSED ALGORITHMS

The proposed algorithms used for the digital watermarking. This section describes three algorithms such as SIFT-RBF-PSO, SIFT-BP-PSO and cascaded BP and RBF with optimized features of raw image for the processing of watermarking.

SHIFT-RBF-PSO

The RBF neural network is very fast processing and dynamic pattern generation algorithms. The hybrid algorithms used SIFT feature transform and PSO. The PSO processes the feature optimization function for the SIFT feature matrix. The optimal features matrix converted into vector and process through the RBF network input.

1. Input: set of feature points $F = \{f1, \ldots\ldots, f_n\}$
Population size of PSO limit of $m\ (assign\ b:\ c = m - b)$
2. Output: set of $DP = \{DP(f_1), \ldots\ldots.., DP(f_n)\}$
3. $Wi \leftarrow 0$; {step}
4. for all $f_t \in f$ do
5. $DP(f_t) \leftarrow$ update velocity (V_t)
6. if the number of features points =b then
7. $M^i \leftarrow \{f_{i\frac{b}{2}+m}\ m \in \{1, \ldots\ldots, \frac{b}{2}\}\}$
8. $(k^i, m^i) \leftarrow c - RBF\ (C^i)$ {or $Flexible\ c - means\ (C^i)$
9. for all $velocity_j^i \in V^i$ do
10. estimate $k - distance\ (V), DP(V), DP(M)$
11. end for
12. define learning function @=a-p;
13. if $Wi >$ 0 the
$(CR;\ W)$Weighted $c - means(V \cup DP(V), N^i \cup$
14. $DP(M))$
15. for all $CR_j \in CR$ do
Compute $k - distance\ (CR_j)$
16. end for
17. $cr \leftarrow CRJ$

18. $Pattern^i \leftarrow \{\sum_{wI\in W_1} w_I, \dots \dots \dots, \sum_{wI\in W_c} W_I\}$
19. Update Wi *of neural input*
20. *end if*
21. $i \leftarrow i+1$;
22. *end if*
23. *end for*
24. *return* $DP(dynmaic\ pattern)$

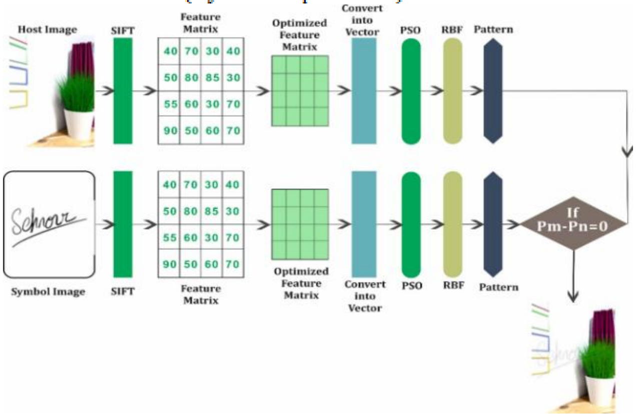


Fig.3. process block diagram of watermarking using RBF neural network and particle swarm optimization.

SHIFT-BP-ACO

Process the input vector of feature points$F_t \in \Re^D$ at the stage of input vector of *BP Neural Network* model. The constraints function of learning of *BP Neural Network* model is $m << n$. The optimal process of SIFT process through ACO and reduces the dissimilarity of features points. The process of algorithms describes here.

1. Input: a SIFT feature point for the BP model
2. Output: $dynamic\ pattern\ DP_{Pf)}$
3. Compute $D_{(P_t,k)}$ and $k - disimarilty(p_t)$
4. for all $DP \in BP_{(f_t,k)}$ do
5. estimate local pattern$-Lp(f_t, DP)$
6. end for
7. $W_{\text{update}} \leftarrow ACO\ \{the\ set\ of\ ants\}$
8. for all $DP \in W_{\text{update}}$ and $FP \in M_{(DG,K)}$ do
9. Update $k - disimarilty(DP)$ and $cluester - ds(ACO, DP)$
10. if $DP_{(FP,k)}$ then
11. $W_{\text{update}} \leftarrow W_{\text{update}} \cup \{DP\}$
12. end if
13. end for
14. for all $DP \in W_{\text{update}}$ do
15. Update $FD(DP)$ and $FD(\{ACO_{o,k}\})$
16. end for
17. return $DP(dynamic\ pattern)$

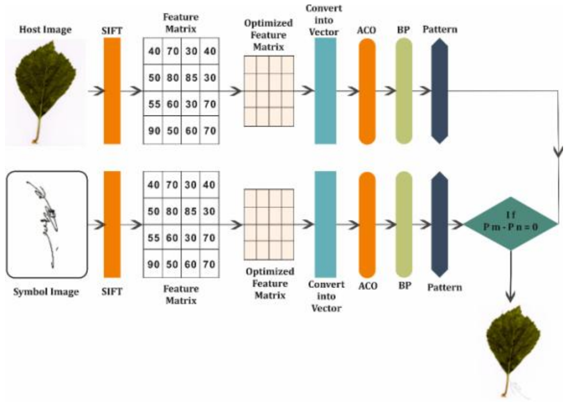


Fig.4. process block diagram of watermarking using BP neural network and ant colony optimization.

CASCADED ALGORITHMS

The cascading of BP and RBF neural network. The cascading of BP function of two stage and RBF function used in single step process. The training pattern of optimal features process with pattern of clustered generated by BP neural network [57].

1. If $BP = 0)$, define the all value of initial input state
2. If $RBF > 0)$ the condition of cluster pattern with minimization of minimum desired output.
3. If $F\_optimal < 0)$, the condition of features processing for the pattern generation.

Algorithm 1. Cascading process of algorithms
Input: set the value of neural network input $NN = \{NNi, i = 1, \dots \dots \dots, n\}$
Output: O – the dynamic pattern of watermark.
Begin
Step 1. Process the value of learning factor $L = \emptyset$
Step 2. Estimate $PC(BP;\ NNi)$ for each input of network, $i = 1, \dots \dots \dots, n$
Step 3. $P_f = RBF$; pattern of features assign NNi
Then, set
$Pf \leftarrow PC\{NNi\}; Pf \leftarrow PC \cup \{NNi\};\ n\ Pf_s = pf_s - 1$
Step 4. while $pf \neq \emptyset$ **do**
Estimate the value of $F\_optimal$ to find NN_i where $i \in \{1,2, \dots \dots, Fs\}$;
$Pf = pf - 1$;
if $(RBF > 0)$ **then**
$Pf \leftarrow Pf \cup \{W_i\}$
end
end
Step 5 find the optimal pattern for the process of embedding.
return Pf

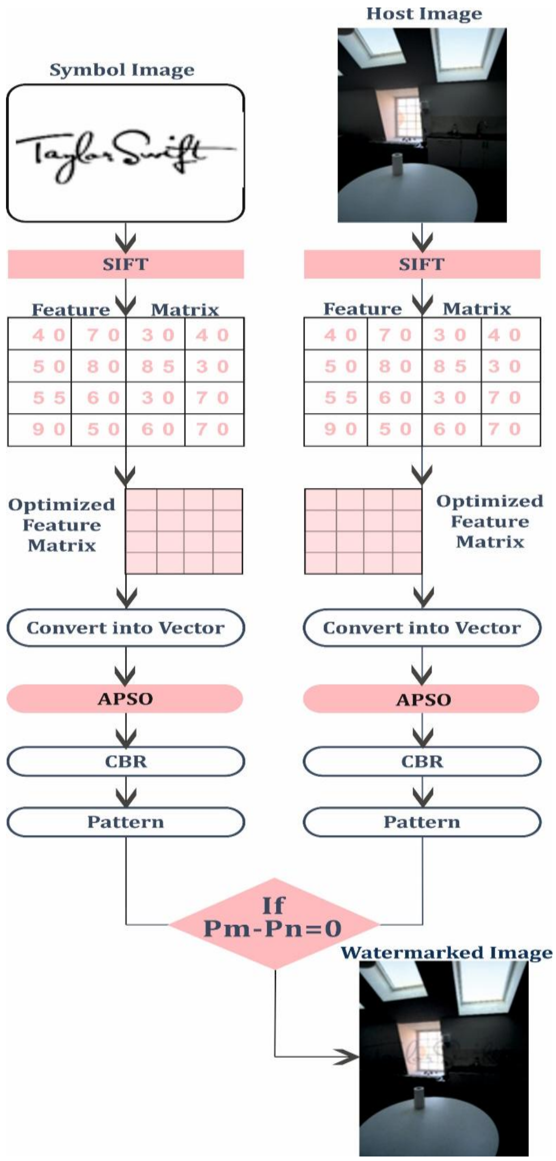


Fig.5. process block diagram of watermarking using CBR neural network and APSO.

V. EXPERIMENTAL RESULT ANALYSIS

The proposed algorithms of watermarking are tested on 300 color image datasets. the datasets of color image consist of different categories such as person, flower, peppers and etc. these image datasets collected from CVG_UGR datasets. For the analysis of algorithms used following hardware and operating system, (1) the machine equid with intel core 7 process with operating system windows 10. (2) in this operating system used MATLAB software for the implementation of algorithms. Measuring the performance of algorithms used following formula according to our define objective.

RMSE factor estimate the error deference value of source image and final watermark image [42,45,23,29].

$$RMSE = \sqrt{\frac{1}{m\times n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I_{image}(i,j) - I''_{image}(i,j)]^2} \ldots$$ …….(5)

where $m \times n$ is the resolution of I (i, j) is the pixel location, I_{image} is the source image, and I''_{image} is the watermarked image. Then PSNR value is calculated as

$$PSNR = 20log_{10}\frac{Max(I_{image})}{RMSE}$$ ………(6)

Calculated value of robustness used this formula as

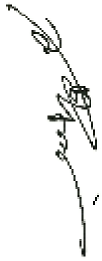
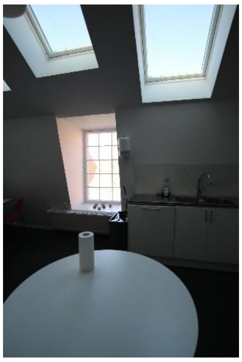
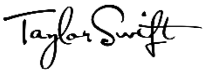
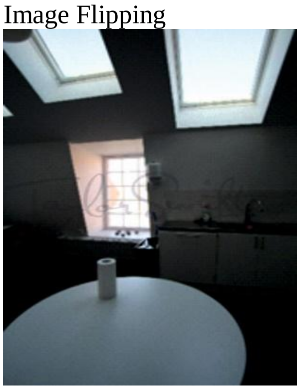
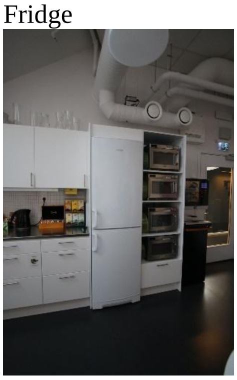
$$NC = \left(\frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} W_f(i,j)-W_d(i,j)}{\sqrt{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} W_o^2(i,j)}\times\sqrt{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} W_E^2(i,j)}}\right)$$……..(7)

Where Wf is the source watermark and Wd is decoded watermark

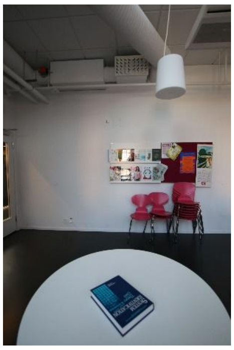
The similarity percentage is estimated as

$$sim = \left(1 - \frac{RMSE}{MAX(Iimage)} \times 100\right)\% \ldots \ldots \ldots (8)$$

Table 1 discuss the process of watermark embedding with host image and symbol image and finally generated with the watermark image. Also try to attack for watermark image such as cropping, scaling, Row-Column Blanking, rotation, image flapling, noise attack and etc.

Sr. No.	Host	Symbol	Watermarked Image
1.	Leaf 	Roger 	Cropping 
2.	Grass 	Schoner 	Rotation 
3.	Kitchen 	Taylor 	Image Flipping 
4.	Fridge 	Kings 	Row-Column Blanking 

5. Furniture



Lara

Scaling

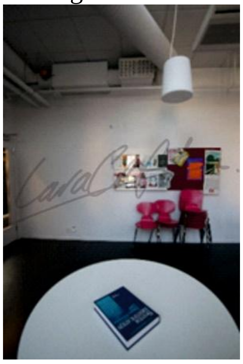
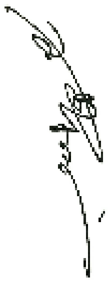


Table 2 shows the experimental analysis of watermark image with different types of attacks and estimate their variation in concern of PSNR, NC and percentage of similarity of target image. The cascaded neural network methods achieve high performance value and great strength against attacks.

Method	Size	Host Image	Symbol Image	Watermarked Image
1. SIFT-BP-ACO 2. SIFT-BP-PSO 3. CBR-ACO 4. CBR-PSO 5. SIFT-BP-APSO	256x256	Leaf.jpg	Roger.jpg	



SALT NOISE ATTACK

Method	SIM (%)	PSNR(DB)	NC
SIFT-BP-ACO	78.77	92.3822	0.9889
SIFT-BP-PSO	88.47	96.5151	0.8674
CBR-ACO	91.41	97.1486	1
CBR-PSO	92.67	97.3845	0.9621
SIFT-BP-APSO	94.41	98.4454	0.8221

GAUSSIAN NOISE ATTACK

Method	SIM (%)	PSNR(DB)	NC
SIFT-BP-ACO	75.15	88.4759	0.7792
SIFT-BP-PSO	85.34	79.9587	0.7878
CBR-ACO	81.21	87.2234	0.7902
CBR-PSO	96.32	90.4748	0.7448
SIFT-BP-APSO	98.67	91.4724	0.7048

CROPPING ATTACK

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SIFT-BP-ACO	52.07	72.2454	0.6824
SIFT-BP-PSO	72.61	70.4829	1
CBR-ACO	77.49	75.2487	0.8624
CBR-PSO	61.42	79.1157	0.7124
SIFT-BP-APSO	78.11	82.1197	0.6521

SCALING ATTACK

SIFT-BP-ACO	70.18	67.2792	0.8834
SIFT-BP-PSO	80.34	68.3537	0.7928
CBR-ACO	82.37	65.1734	0.9124
CBR-PSO	72.44	69.3948	0.8621
SIFT-BP-APSO	86.67	69.8929	0.7424

ROTATION ATTACK

SIFT-BP-ACO	62.48	78.1467	0.8854
SIFT-BP-PSO	60.39	74.6829	0.8584
CBR-ACO	66.42	77.2415	0.8814
CBR-PSO	75.36	79.2425	0.8223
SIFT-BP-APSO	79.46	85.2438	0.8028

Method	Size	Host Image	Symbol Image	Watermarked Image
1. SIFT-BP-ACO 2. SIFT-BP-PSO 3. CBR-ACO 4. CBR-PSO 5. SIFT-BP-APSO	512x512	Grass.jpg 	Schoner.jpg 	

SALT NOISE ATTACK

Method	Encoding Time	SIM	PSNR	NC
SIFT-BP-ACO		84.27	75.0229	0.5784
SIFT-BP-PSO		88.69	75.1424	0.5636
CBR-ACO		77.62	78.6924	0.6241
CBR-PSO		67.07	79.4521	0.6027
SIFT-BP-APSO		92.18	80.1534	0.5429

GAUSSIAN NOISE ATTACK

SIFT-BP-ACO	87.61	93.5852	0.9026
SIFT-BP-PSO	87.31	91.2457	0.9561
CBR-ACO	88.24	89.6952	0.9647
CBR-PSO	89.49	91.2536	0.8729
SIFT-BP-APSO	90.48	94.2561	0.8451

CROPPING ATTACK

SIFT-BP-ACO	89.24	67.5968	0.9641
SIFT-BP-PSO	81.63	69.6834	1
CBR-ACO	80.37	62.4834	0.9789
CBR-PSO	91.11	73.2464	0.9045
SIFT-BP-APSO	93.12	76.2444	0.8954

SCALING ATTACK

SIFT-BP-ACO	45.14	81.3434	1
SIFT-BP-PSO	52.64	85.4828	0.8725
CBR-ACO	52.42	82.3661	1
CBR-PSO	55.38	87.0192	0.8924
SIFT-BP-APSO	56.62	89.0157	0.5692

ROTATION ATTACK

SIFT-BP-ACO	67.62	61.3434	0.7021
SIFT-BP-PSO	77.86	55.4828	0.7537
CBR-ACO	68.83	72.3661	0.8668
CBR-PSO	69.40	57.0192	0.8747
SIFT-BP-APSO	82.71	75.0157	0.6496

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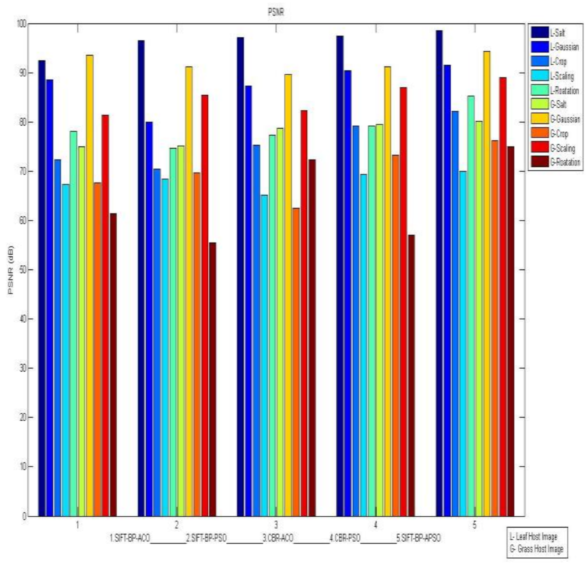

Fig.6. window show that the comparative analysis of PSNR using SIFT-BP-ACO, SIFT-BP-PSO, CBR-ACO, CBR-PSO and SIFT-BP-APSO techniques with different host images (Leaf and Grass) and symbol images (Roger and Schoner). With the help of performance graph indicate the high performance of SIFT-BP-APSO tehnique because it shows high numeric result value of PSNR compared to all techniques these are SIFT-BP-ACO, SIFT-BP-PSO, CBR-ACO, CBR-PSO.

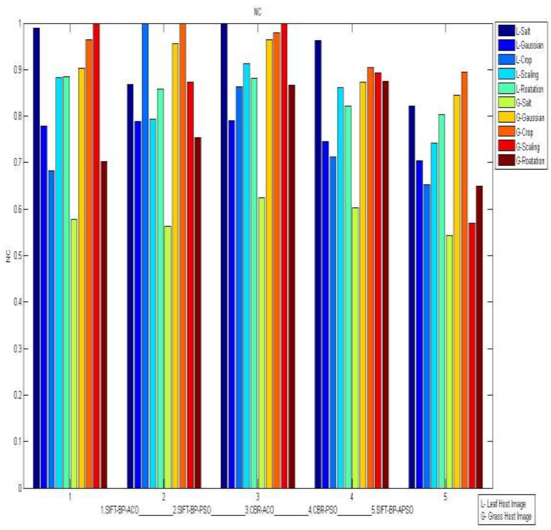

Fig.7. window show that the comparative analysis of NC using SIFT-BP-ACO, SIFT-BP-PSO, CBR-ACO, CBR-PSO and SIFT-BP-APSO techniques with different host images (Leaf and Grass) and symbol images (Roger and Schoner). With the help of performance graph indicate the high performance of SIFT-BP-APSO tehnique because it shows low numeric result value of NC compared to all techniques these are SIFT-BP-ACO, SIFT-BP-PSO, CBR-ACO, CBR-PSO.

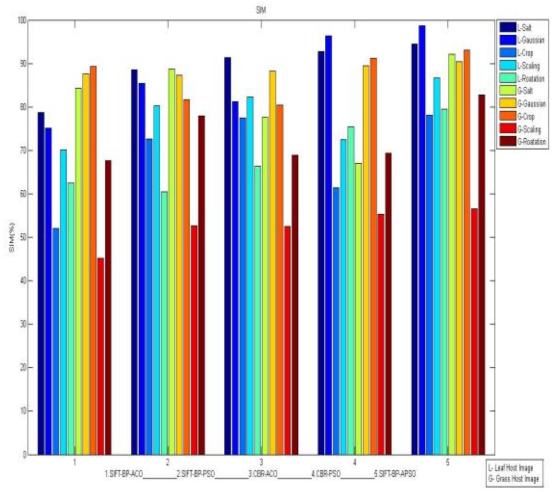

Fig.8. window show that the comparative analysis of SIM using SIFT-BP-ACO, SIFT-BP-PSO, CBR-ACO, CBR-PSO and SIFT-BP-APSO techniques with different host images (Leaf and Grass) and symbol images (Roger and Schoner). With the help of performance graph indicate the high performance of SIFT-BP-APSO tehnique because it shows high numeric percentage result value of SIM compared to all techniques these are SIFT-BP-ACO, SIFT-BP-PSO, CBR-ACO, CBR-PSO.

VI. CONCLUSION & FUTURE WORK

To emphasize the security strength and quality of the watermarking image of the proposed algorithm. It is compared with the other two neural network algorithms for image watermarking. The variation of results shows in table 2. The comparative table of results indicates that the performance of proposed algorithms is better than two neural network-based algorithms. The result indicates that the proposed algorithm balanced the performance of robustness and imperceptibility. The high value of similarity of proposed algorithms shows that the better quality of watermark image. The process of analysis finds that the detection accuracy in reasonable condition has NC values above 99%. The performance of proposed algorithms proved that the secured watermarking process against attacks. In case of noise attack, the variation of noise value increase, but the value of Nc is not decreasing. The increased value of NC shows the high strength of the security of the watermark process. The high value of PSNR also indicates the better predication of the watermark image. The point of trust of proposed algorithms is to justify the concept of dynamic pattern generation in the case of cascaded neural network models. The concept of dynamic pattern generation shows more randomness of patterns, and the perception of pattern prediction is decreased in the future, using the proposed algorithms in other fields of multimedia data such as video and audio.

REFERENCES

1. Islam M, Roy A, Laskar RH. Neural network based robust image watermarking technique in LWT domain. Journal of Intelligent & Fuzzy Systems. 2018 Jan 1;34(3):1691-700.

2. Zhou NR, Luo AW, Zou WP. Secure and robust watermark scheme based on multiple transforms and particle swarm optimization algorithm. Multimedia Tools and Applications. 2019 Jan 1;78(2):2507-23.
3. Zheng Z, Saxena N, Mishra KK, Sangaiah AK. Guided dynamic particle swarm optimization for optimizing digital image watermarking in industry applications. Future Generation Computer Systems. 2018 Nov 1;88:92-106.
4. Ali M, Ahn CW. An optimal image watermarking approach through cuckoo search algorithm in wavelet domain. International Journal of System Assurance Engineering and Management. 2018 Jun 1;9(3):602-11.
5. Ansari IA, Pant M, Ahn CW. Artificial bee colony optimized robust-reversible image watermarking. Multimedia Tools and Applications. 2017 Sep 1;76(17):18001-25.
6. Bahrami Z, Tab FA. A new robust video watermarking algorithm based on SURF features and block classification. Multimedia Tools and Applications. 2018 Jan 1;77(1):327-45.
7. Balasamy K, Ramakrishnan S. An intelligent reversible watermarking system for authenticating medical images using wavelet and PSO. Cluster Computing. 2018:1-2.
8. Chatterjee S, Sarkar S, Hore S, Dey N, Ashour AS, Balas VE. Particle swarm optimization trained neural network for structural failure prediction of multistoried RC buildings. Neural Computing and Applications. 2017 Aug 1;28(8):2005-16.
9. Li D, Deng L, Gupta BB, Wang H, Choi C. A novel CNN based security guaranteed image watermarking generation scenario for smart city applications. Information Sciences. 2019 Apr 1;479:432-47.
10. Makbol NM, Khoo BE, Rassem TH, Loukhaoukha K. A new reliable optimized image watermarking scheme based on the integer wavelet transform and singular value decomposition for copyright protection. Information Sciences. 2017 Nov 1;417:381-400.
11. Mehta R, Rajpal N, Vishwakarma VP. A robust and efficient image watermarking scheme based on Lagrangian SVR and lifting wavelet transform. International Journal of Machine Learning and Cybernetics. 2017 Apr 1;8(2):379-95.
12. Mitashe MR, Habib AR, Razzaque A, Tanima IA, Uddin J. An adaptive digital image watermarking scheme with PSO, DWT and XFCM. In2017 IEEE International Conference on Imaging, Vision & Pattern Recognition (icIVPR) 2017 Feb 13 (pp. 1-5). IEEE.
13. Saxena N, Mishra KK. Improved multi-objective particle swarm optimization algorithm for optimizing watermark strength in color image watermarking. Applied Intelligence. 2017 Sep 1;47(2):362-81.
14. Shih FY, Zhong X, Chang IC, Satoh SI. An adjustable-purpose image watermarking technique by particle swarm optimization. Multimedia Tools and Applications. 2018 Jan 1;77(2):1623-42.
15. Sun L, Xu J, Liu S, Zhang S, Li Y, Shen CA. A robust image watermarking scheme using Arnold transform and BP neural network. Neural Computing and Applications. 2018 Oct 1;30(8):2425-40.
16. Thakkar FN, Srivastava VK. A fast watermarking algorithm with enhanced security using compressive sensing and principle components and its performance analysis against a set of standard attacks. Multimedia Tools and Applications. 2017 Jul 1;76(14):15191-219.
17. Yang J, Liu K, Kang X, Wong E, Shi Y. Steganalysis based on awareness of selection-channel and deep learning. InInternational Workshop on Digital Watermarking 2017 Aug 23 (pp. 263-272). Springer, Cham.
18. Brandao AS, Jorge DC. Artificial neural networks applied to image steganography. IEEE Latin America Transactions. 2016 Apr 26;14(3):1361-6.
19. Rehman A, Naz S, Razzak MI, Hameed IA. Automatic visual features for writer identification: a deep learning approach. IEEE Access. 2019 Jan 21;7:17149-57.
20. Iftikhar S, Kamran M, Munir EU, Khan SU. A reversible watermarking technique for social network data sets for enabling data trust in cyber, physical, and social computing. IEEE Systems Journal. 2015 Apr 20;11(1):197-206.
21. Chang CS, Shen JJ. Features classification forest: a novel development that is adaptable to robust blind watermarking techniques. IEEE Transactions on Image Processing. 2017 May 19;26(8):3921-35.
22. [22]. Islam M, Laskar RH. Geometric distortion correction based robust watermarking scheme in LWT-SVD domain with digital watermark extraction using SVM. Multimedia Tools and Applications. 2018 Jun 1;77(11):14407-34.
23. Singh AK, Kumar B, Singh SK, Ghrera SP, Mohan A. Multiple watermarking technique for securing online social network contents using back propagation neural network. Future Generation Computer Systems. 2018 Sep 1;86:926-39.
24. Yahya AN, Jalab HA, Wahid A, Noor RM. Robust watermarking algorithm for digital images using discrete wavelet and probabilistic neural network. Journal of King saud university-Computer and Information sciences. 2015 Oct 1;27(4):393-401.
25. Merrer EL, Perez P, Trédan G. Adversarial frontier stitching for remote neural network watermarking. arXiv preprint arXiv:1711.01894. 2017 Nov 6.
26. Adi Y, Baum C, Cisse M, Pinkas B, Keshet J. Turning your weakness into a strength: Watermarking deep neural networks by backdooring. In27th {USENIX} Security Symposium ({USENIX} Security 18) 2018 (pp. 1615-1631).
27. Zhang J, Gu Z, Jang J, Wu H, Stoecklin MP, Huang H, Molloy I. Protecting intellectual property of deep neural networks with watermarking. InProceedings of the 2018 on Asia Conference on Computer and Communications Security 2018 May 29 (pp. 159-172). ACM.
28. Jagadeesh B, Kumar PR, Reddy PC. Robust digital image watermarking based on fuzzy inference system and back propagation neural networks using DCT. Soft Computing. 2016 Sep 1;20(9):3679-86.
29. Yen CT, Huang YJ. Frequency domain digital watermark recognition using image code sequences with a back-propagation neural network. Multimedia Tools and Applications. 2016 Aug 1;75(16):9745-55.
30. Kandi H, Mishra D, Gorthi SR. Exploring the learning capabilities of convolutional neural networks for robust image watermarking. Computers & Security. 2017 Mar 1;65:247-68.
31. Sun L, Xu J, Liu S, Zhang S, Li Y, Shen CA. A robust image watermarking scheme using Arnold transform and BP neural network. Neural Computing and Applications. 2018 Oct 1;30(8):2425-40.
32. Hsu LY, Hu HT. Blind image watermarking via exploitation of inter-block prediction and visibility threshold in DCT domain. Journal of Visual Communication and Image Representation. 2015 Oct 1;32:130-43.
33. Loganathan A, Kaliyaperumal G. An adaptive HVS based video watermarking scheme for multiple watermarks using BAM neural networks and fuzzy inference system. Expert Systems with Applications. 2016 Nov 30;63:412-34.
34. Uchida Y, Nagai Y, Sakazawa S, Satoh SI. Embedding watermarks into deep neural networks. InProceedings of the 2017 ACM on International Conference on Multimedia Retrieval 2017 Jun 6 (pp. 269-277). ACM.
35. Rajpal A, Mishra A, Bala R. Multiple scaling factors based Semi-Blind watermarking of grayscale images using OS-ELM neural network. In2016 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC) 2016 Aug 5 (pp. 1-6). IEEE.
36. Singh DA, Leavline EJ, Valliyappan K, Srinivasan M. Enhancing the performance of classifier using particle swarm optimization (PSO)-based dimensionality reduction. International Journal of Energy, Information and Communications. 2015;6(5):19-26.
37. Agarwal C, Mishra A, Sharma A. A novel gray-scale image watermarking using hybrid Fuzzy-BPN architecture. Egyptian Informatics Journal. 2015 Mar 1;16(1):83-102.
38. Mishra A, Agarwal C. Toward optimal watermarking of grayscale images using the multiple scaling factor–based cuckoo search technique. InBio-Inspired Computation and Applications in Image Processing 2016 Jan 1 (pp. 131-155). Academic Press.
39. Khowaja SA, Ismaili IA. Image compression using moving average histogram and RBF network. Mehran University Research Journal of Engineering & Technology. 2015 Oct;34(4):359.
40. Mishra A, Agarwal C. Toward optimal watermarking of grayscale images using the multiple scaling factor–based cuckoo search technique. InBio-Inspired Computation and Applications in Image Processing 2016 Jan 1 (pp. 131-155). Academic Press.
41. Durga KV, Mamatha G, Bindu CH. SVD based image watermarking with firefly algorithm. In2015 International Conference on Computer Communication and Informatics (ICCCI) 2015 Jan 8 (pp. 1-7). IEEE.
42. Singh G, Kad S. Comparative Study of Watermarking an Image Using GA and BFO with GA and HBO Technique. InProceedings of the Second International Conference on Information and Communication Technology for Competitive Strategies 2016 Mar 4 (p. 5). ACM.

43. Waleed J, Jun HD, Hameed S, Kamil M. Optimal positions selection for watermark inclusion based on a nature inspired algorithm. International Journal of Signal Processing, Image Processing and Pattern Recognition. 2015 Jan;8(1):147-60.
44. Steganography OT. Current Status: Comparative Analysis Of Optimization Techniques Used In Steganography Schemes.
45. Agarwal C, Mishra A, Sharma A. A novel gray-scale image watermarking using hybrid Fuzzy-BPN architecture. Egyptian Informatics Journal. 2015 Mar 1;16(1):83-102.
46. Upadhyay S, Jain K. Genetic Algorithm based High Quality Image Watermarking using Multi Resolution Wavelet Transform.
47. Anand S, Singh a watermarking relational database based on 5-level dwt using genetic algorithm & PSO, J. International Journal Of Engineering Sciences & Research Technology, 2016.
48. Gupta M. Optimized Digital Image Watermarking for Uncorrelated Color Space (Doctoral dissertation, Rajasthan Technical University, Kota).
49. Verma V, Srivastava VK, Thakkar F. DWT-SVD based digital image watermarking using swarm intelligence. In2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT) 2016 Mar 3 (pp. 3198-3203). IEEE.
50. Sengupta A, Bhadauria S. Exploring low cost optimal watermark for reusable IP cores during high level synthesis. IEEE Access. 2016 Apr 7;4:2198-215.