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Self-Organizing Hierarchical Particle Swarm Optimization of Correlation Filters for Object Recognition

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***Abstract*—Advanced correlation filters are an effective tool for target detection within a particular class. Most correlation filters are derived from a complex filter equation leading to a closed form filter solution. The response of the correlation filter depends upon the selected values of the optimal trade-off (OT) parameters. In this paper, the OT parameters are optimized using particle swarm optimization with respect to two different cost functions. The optimization has been made generic and is applied to each target separately in order to achieve the best possible result for each scenario. The filters obtained using standard particle swarm optimization (PSO) and hierarchal particle swarm optimization (HPSO) algorithms have been compared for various test images with the filter solutions available in the literature. It has been shown that optimization improves the performance of the filters significantly.**

***Index Terms*—Correlation filter, Optimal trade-off, Hierarchical particle swarm optimization, Object recognition.**

I. Introduction

CORRELATION filters have been widely used in numerous domains including Pattern Recognition, Signal Processing and Image Processing for various applications such as automatic target recognition (ATR) [1]–[5], biometric recognition [6]–[8] and object tracking [9], [10]. The correlation filters is constructed to generate correlation peaks for targeted objects in the image whilst yielding a low response to background noise, clutter and illumination changes. Advanced correlation filters (CFs) were introduced to offer distortion tolerant object recognition more than three decades ago [11]. Over time, the accuracy of correlation filters has been improved [12]–[15].

Correlation filters are effective for accurate detection of target objects. The Maximum Average Correlation Height (MACH) and Minimum Average Correlation Energy (MACE) filters have been used to cater noise and clutter distortion to give output in form of a correlation peak [16]. The MACE filter yields pronounced peaks for easy detection of the filter output but sensitive to noises and distortions [17]. Unlike the MACE, the MACH filter generates maximum relative height of the correlation peak with respect to the expected distortion but produces broader peaks [18].

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Correlation filters can be implemented in software using the complex filter equation. Different correlation filters can be implemented by varying the values of optimal trade-off parameters of filter equation. Until now, researchers simply tuned these parameters through experimental trials. The motivation for this study is to optimize the OT-parameters of a correlation filter as no optimization process has, to date, been implemented and in this way determine the best possible values for these parameters. Particle swarm optimization (PSO) is a population based stochastic optimization technique proposed by Eberhart and Kennedy [19] inspired by the social behavior of animals such as bird flocking or fish schooling. The PSO algorithm defined in [20] is now referred as standard PSO. One of the most prominent variants of the PSO algorithm is the Self-Organizing Hierarchical PSO (HPSO) algorithm, proposed by Ratnaweera *et al.* [21]. These algorithms have been used for optimization in various applications [22]–[28].

This paper proposes the optimization of the OT parameters using the standard PSO and HPSO algorithms. Optimization is based on the cost functions that are used by the MACE and MACH filters. Resulting filters are not generic as the values of the parameters change for each target object. However, the proposed method is generic as it can be applied to any target object to give optimum performance with respect to both cost functions.

The rest of the paper is organized as follows. Problem statement is described in section 2. Combined framework of the optimized algorithm and correlation filter is discussed in section 3. Comparative results are analyzed in section 4 and conclusion is given in section 5.

II. Literature Review

The motivation for using an enhanced correlation filter is to suppress the presence of extraneous correlation peaks that make detection difficult. Linear combination of correlation templates employed in multiplexed filters does not yield a sharp peak in the correlation plane and often produces side lobes of high intensity. MACE filter ensures a sharp correlation peak that results in easy detection in the correlation plane, is sensitive to distortion. Correlation function level is reduced all over the correlation plane except at the center in the MACE filter. This is similar to minimizing the Average Correlation Energy (ACE) of the plane while retaining intensity constraints at the origin. On the other hand, peak of the MACH filter

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is broader but it possesses high tolerance against several distortions. Average Similarity Matrix (ASM) is minimized for the implementation of the MACH filter. This can be more accurate in terms of average dissimilarity measure as minimization of ASM reduces dissimilarity between correlation planes. Amplitude of the MACH filter correlation peak is higher as compared to the MACE filter [17], [18].

Energy equation of correlation filter is given by [29]:

$$E(h) = \alpha(ONV) + \beta(ACE) + \gamma(ASM) - \delta(ACH) \quad (1)$$

The ASM is given by [18]:

$$ASM = h^{+}\left[\frac{1}{N}\sum_{i=1}^{N}\left(X_i - \overline{X}\right)^{*}\left(X_i - \overline{X}\right)\right]h = h^{+}S_x h \quad (2)$$

where h is the designed filter and the superscript + shows the conjugate transpose in which:

$$S_x = \frac{1}{N}\sum_{i=1}^{N}(X_i - \overline{X})^{*}(X_i - \overline{X}) \quad (3)$$

and the Average Correlation Energy (ACE) is [18]:

$$ACE = h^{+}\left(\frac{1}{N}\sum_{i=1}^{N}X_i X_i^{*}\right)h = h^{+}D_x h \quad (4)$$

where

$$D_x = \frac{1}{N}\sum_{i=1}^{N}X_i{}^{*}X_i \quad (5)$$

The output noise variance is [18]:

$$ONV = h^{+}Ph \quad (6)$$

where $P = \delta^2 I$ and the average correlation height is [29]:

$$ACH = h^{t}m_x \quad (7)$$

Equation (1) is minimized to [29]:

$$E(h) = h^{+}Ih - \delta\left|h^{t}m_x\right| \quad (8)$$

where $I = \alpha P + \beta D_x + \gamma S_x$

So, the filter equation becomes [29]:

$$h^{o} = (\delta/2)\, I^{-1}m_x \quad (9)$$

where o denotes the optimal complex filter equation and δ is a scaling factor. The values of the OT parameters α, β and γ control the behavior of filter and their choice is not obvious. When $\alpha \approx 0$ and $\beta \approx 0$, the filter behaves as a MACH filter which minimizes the ASM of the correlation plane. When $\alpha \approx 0$ and $\gamma \approx 0$, the filter behaves as a MACE filter, which minimizes the ACE of the correlation plane. Finally, when $\beta \approx 0$ and $\gamma \approx 0$, the filter behaves as a MVSDF filter [29] (which is not being considered due to very high computational complexity [18]). Until now, the values of these parameters, as proposed by Bone *et al.*, were fixed as $\alpha = 0.01$, $\beta = 0.1$ and $\gamma = 0.3$ for the MACH filter [16]. As a result, the correlation filter did not always provide optimal results. A novel approach has been proposed in this work for optimization of the OT parameters to yield the best possible filter response for a particular application.

III. Proposed Methodology

A combined framework of a correlation filter transfer function and an optimization algorithm has been proposed in this work. Resulting correlation filters yield optimum results as the OT parameters are optimized for specific target objects. Results achieved through PSO and HPSO are compared for an ATR application

A. Particle Swarm Optimization (PSO)

PSO algorithm is based upon animal social systems such as birds flocking or fish schooling which is commonly used as an optimization technique. There are several particles donating a set of optimization particles which search for the best solution in a multi-dimensional search space. This algorithm finds the best optimized value for each particle by convergence. Optimized value is estimated using some cost function which defines the best value for that fitness function. Each particle has two main parameters: one is particle position, $x(i)$ and the second is particle velocity $v(i)$ where i denotes the iteration index. Afterwards the best values, attained from all the particles, combine to get the best value for the whole swarm. For a swarm of N particles traversing a D-dimensional space, the velocity and position of each particle are updated as:

$$\begin{aligned} v_k^d(i+1) &= v_k^d(i) + c_1 \cdot r_{1,k}(i) \cdot \left(p_k^d - x_k^d(i)\right) \\ &\quad + c_2 \cdot r_{2,k}(i) \cdot \left(g^d - x_k^d(i)\right) \quad (10) \\ x_k^d(i+1) &= x_k^d(i) + v_k^d(i+1), \quad (11) \end{aligned}$$

where $d = 1, ..., D$ denotes the dimension of the particles and is the $k = 1, ..., N$ particle index. The constants c_1 and c_2 are called cognitive and social parameters. Variables v_k^d and x_k^d are velocity and position of the k-th particle corresponding to its d-th dimension while g^d and p_k^d are the swarms global best positions and particles local best positions for the d-th dimension, respectively. The variables $r_{1,k}$ and $r_{2,k}$ are drawn from a uniform random distribution $[0, 1]$ and source of randomness in the search behavior of the swarm.

Eberhart and Shi proposed one of the variants of PSO containing an inertia-weight model [20], which multiplies the velocity of current iteration with a factor, known as the inertia weight:

$$\begin{aligned} v_k^d(i+1) &= w.v_k^d(i) + c_1 \cdot r_{1,k}(i) \cdot \left(p_k^d - x_k^d(i)\right) \\ &\quad + c_2 \cdot r_{2,k}(i) \cdot \left(g^d - x_k^d(i)\right), \quad (12) \end{aligned}$$

Inertia weight $w \in [0, 1]$ converges and controls momentum of the particle. If value of w is too small, very little momentum is preserved from the previous iteration which quickly changes the direction, whereas a large value of w gives a delayed change in direction of a particle and slow convergence. If $w = 0$, the particle moves without knowing the past velocity value. This particular variant of the PSO is now commonly referred as the Standard PSO [30], [31].

There are several applications of optimization algorithms. Grosan *et al.* proposed the application of PSO algorithm in the data mining domain. [26] Pandey *et al.* used the particle swarm optimization algorithm for a cloud computing application in which optimization of cloud resources was done to schedule applications. This technique minimized the computational and data transmission cost by three times as compared to the best resource selection heuristic technique and can be used for optimization of any number of tasks and resources. [23] Merwe *et al.* proposed the application of PSO for data vector clustering. The PSO algorithm was used to find the centorid of data clusters specified by a user. This optimization algorithm was compared with k-means clustering and produced minimized errors with the best convergence. The proposed algorithm has been used for the refinement of clusters formed by k-means. [24] Omran *et al.* also used this optimization algorithm for image clustering in comparison with k means clustering algorithm. Its application are in MRI and satellite imaging. [25]

The most effective and commonly used variant of PSO is the Self-Organizing Hierarchical PSO algorithm which has time-varying acceleration coefficients (HPSO) [21]. Inertia weight term is removed and only the acceleration coefficients guide the movement of the particle towards the optimum solution. Acceleration coefficients vary linearly with time. Therefore if the velocity goes to zero at some point, the particle is re-initialized using a predefined starting velocity. The HPSO algorithm achieves outstanding results due to its self-organizing and self-restarting property. whereas improvement of the acceleration coefficients enhances the particles global capability of search in the earlier stages and moves particles to the global optima at the end stage which is how the capability of convergence is enhanced. Large cognitive and small social parameters are used at the beginning and small cognitive and large social parameters are used in the latter stages in HPSO. The mathematical representation of HPSO is given as follows:

$$v_k^d(i+1) = c_1 \cdot r_{1,k}(i) \cdot \left(p_k^d - x_k^d(i)\right) + c_2 \cdot r_{2,k}(i) \cdot \left(g^d - x_k^d(i)\right), \quad (13)$$

where

$$c_1 = (c_{1f} - c_{1i}) \times \frac{k}{\max ITER} + c_{1i} \quad (14)$$

$$c_2 = (c_{2f} - c_{2i}) \times \frac{k}{\max ITER} + c_{2i} \quad (15)$$

The velocity and position of the k-th particle are updated using eqn. (13) and (11), respectively.

B. Optimization Algorithms for Correlation Filter Design

OT correlation filters are implemented by the complex filter equation which depends on the selection of OT parameter values. Values employed was determined through experiments by several researchers. For example, fixed values of OT parameters was used in the work of Bone *et al.* [16]. The choice of selecting the most suitable values for specific target recognition applications was not obvious. A novel framework is proposed in this paper for the selection of the most suitable values of OT parameters corresponding to the filter response. The value of parameter α is updated using the equation 11

$$\alpha_k(t+1) = \alpha_k(t) + v_{k,\alpha}(t+1) \quad (16)$$

TABLE I: Summary of the steps for correlation filter parameter optimization via PSO.

	Description of OT correlation filter with PSO
1:	Randomly initialize the position and velocity of each particle.
2:	Calculate the fitness value of each particle using equation 17 / 18.
3:	Calculate the best for each particle
4:	Calculate the global best for the swarm.
5:	Update the velocity using equation 12
6:	Update the position using equation 11
7:	Calculate the fitness value of each particle using equation 17 / 18
8:	Update the local best of each particle
9:	Update the global best of the swarm.
10:	Terminate the algorithm if the stopping condition is reached, otherwise go to step 5.

Using equations 11 and 13, similar updated equations for β and γ are formed for optimization purposes. HPSO finds the best values of OT parameters by convergence of the fitness function for a specific object recognition application
Correlation Output Peak Intensity (COPI) and Peak to Correlation Energy (PCE) are performance measures used for characterizing correlation plane [32]:

$$COPI = \max\{|C(x,y)|^2\} \quad (17)$$

C(x,y) is the correlation peak output at the location of (x,y) and:

$$PCE = \frac{COPI - \overline{|C(x,y)|^2}}{\left\{\sum \frac{\left[|C(x,y)|^2 - \overline{|C(x,y)|^2}\right]^2}{N_x N_y - 1}\right\}^{1/2}} \quad (18)$$

where $\overline{|C(x,y)|^2} = \sum |C(x,y)|^2 / N_x N_y$ is the average value of the correlation output plane intensity.
The MACE filter minimizes the Average Correlation Energy (ACE) of the correlation plane so the value of PCE maximizes. The MACH filter minimizes Average Similarity Matrix (ASM) due to which the height of the correlation peak maximizes. The correlation peak height and peak to correlation energy values have been used as a fitness function in the optimization algorithms. A summary of these steps in the implementation of optimization algorithms is given below.

IV. Results and Discussion

Publically available dataset of the Amsterdam library has been used for experimentation [33]. Ten different datasets of size 128x128 are used for comparing the results of the optimization algorithms with those available in the literature [16].

A. Parameter Settings

Experiments are carried out for the correlation filters in order to evaluate the optimum values for the OT parameters

TABLE II: Summary of the steps for correlation filter parameter optimization via HPSO.

	Description of OT correlation filter with HPSO
1:	Randomly initialize the position and velocity of each particle.
2:	Calculate the fitness value of each particle using equation 17 / 18.
3:	Calculate the local best for each particle
4:	Calculate the global best for the swarm.
5:	Update the velocity using equation 13
6:	If the velocity is equal to 0 then reinitialize the velocity.
7:	Update the position using equation 11
8:	Calculate the fitness value of each particle using equation 17 / 18
9:	Update the local best of each particle
10:	Update the global best of the swarm.
11:	Terminate the algorithm if the stopping condition is reached, otherwise go to step 5.

Fig. 1: Example images from the ten datasets from the Amsterdam library of object images

through both the PSO and HPSO algorithms. Parameters chosen for the simulations are given in table III.

Correlation filters have been implemented with a slight modification. Due to the possibility of a particle giving a negative value for a particular parameter, only the magnitude of the value has been considered while the sign has been ignored. Lower limit has not been set to 0 as even the magnitude of the negative value could be significant. The results show this assertion to be justified.

Parameters	Values
Iterations	300
Dimensions	3
Experiments	100
Particles	10
V_{min}	-0.1
V_{max}	0.1
X_{min}	-1
X_{max}	1
c_1, c_2	2
w	0.9

TABLE III: Parameter values for PSO.

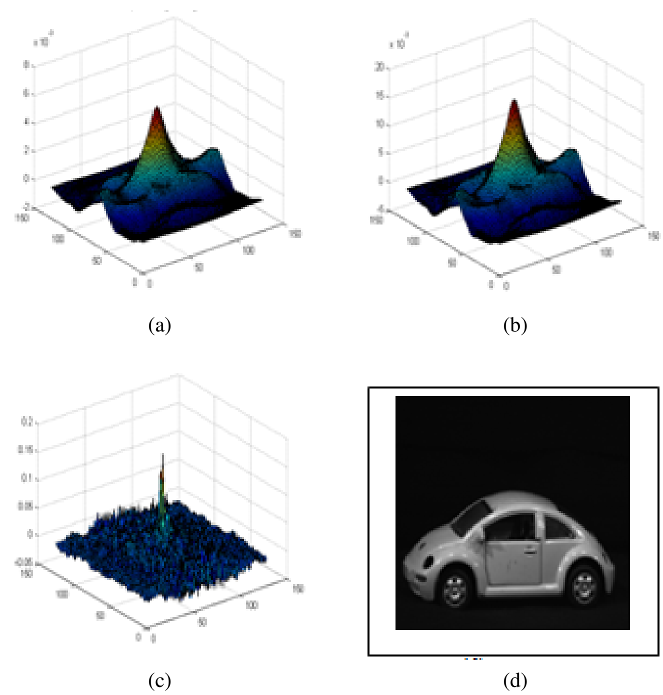

Fig. 2: (a) Correlation plane resulting from Bone's [16] choice of values: $\alpha = 0.01$, $\beta = 0.1$, $\gamma = 0.3$; (b) Correlation plane using PSO optimized values $\alpha = 0.0035$, $\beta = 0.0402$, $\gamma = 0.0461$; (c) Correlation plane using HPSO optimized values $\alpha = 4.52E-05$, $\beta = 0.1097$, $\gamma = 0.221$; (d) test image employed

B. Results for comparison of PSO and HPSO

Ten different publically available datasets, examples of which are shown in Fig. 1, have been taken to compare the results of the optimization algorithms in order to analyze the optimized values corresponding to the dataset. The out-of-plane rotated $0-40$ training images have been used with a difference of 10 between images. The test images are taken within this range. Cost function has been selected on the basis of targeted requirement. The PCE and COPI values have been taken as cost functions separately to compare the results of HPSO and PSO with the values suggested by Bone [16].

Test images for different rotations and from different data sets are used in experiments to analyze the pattern of optimized values. The values of α, β and γ for the COPI cost function are 0.01, 0.1 and 0.3, respectively, as proposed by Bone *et al.* [16]. In Table IV, comparison of COPI values has made for the optimized values and Bones proposed values. From these results, it can be seen that the height of the correlation peaks generated by the HPSO optimization algorithm is better for values obtained with the PSO and Bones values.

Correlation planes from the optimization algorithms and the values proposed by Bone *et al.* have been analyzed for one of the datasets from Table IV. Cost function for the optimization algorithms in this case is the COPI value. Optimized values from HPSO give the best performance in terms of COPI as compared to PSO and Bones work [16], as shown in Fig. 2. Test image is 15^o out plane rotated. The values of the COPI in

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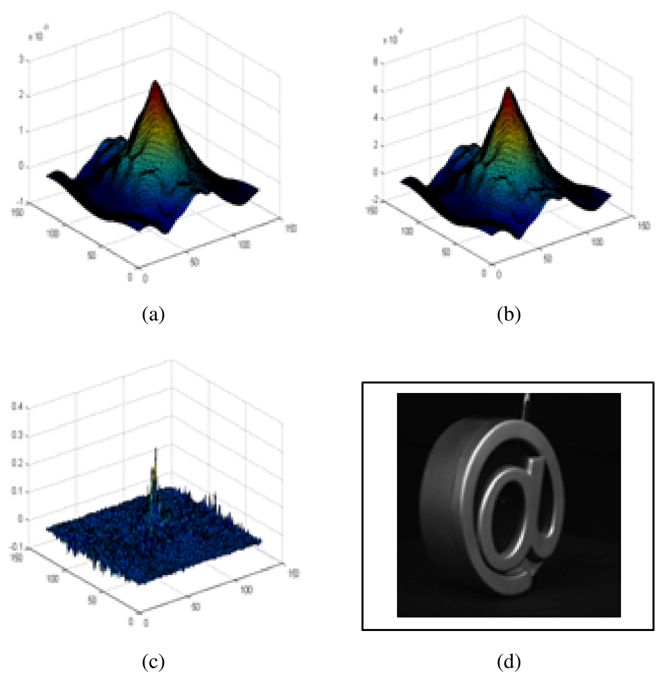
TABLE IV: The value of COPI from PSO, HPSO optimized values and existing values.

Data set	Test image (Deg)	Bones values COPI	PSO				HPSO			
			α	β	γ	COPI	α	β	γ	COPI
1	5	$4.10E-5$	0.0039	0.0401	0.0472	$2.71E-4$	$9.45E-9$	0.0962	0.1737	$2.57E-1$
2	5	$4.94E-5$	0.0039	0.0433	0.0508	$3.16E-4$	$7.28E-9$	0.0927	0.2081	$1.25E-1$
3	5	$1.56E-5$	0.0048	0.0403	0.0467	$7.99E-5$	$2.03E-8$	0.0606	0.2344	$1.95E-1$
4	15	$1.19E-4$	0.0033	0.0384	0.0527	$1.01E-3$	$1.14E-8$	0.1419	0.2418	$1.22E+0$
5	15	$4.98E-5$	0.0035	0.0427	0.05	$3.71E-4$	$1.49E-8$	0.1179	0.1776	$1.42E-1$
6	25	$4.12E-5$	0.0036	0.0392	0.0471	$2.99E-4$	$4.24E-9$	0.1056	0.2826	$1.23E+0$
7	25	$7.06E-5$	0.0041	0.0402	0.0489	$4.40E-4$	$2.94E-8$	0.1534	0.1906	$1.27E-1$
8	25	$2.33E-5$	0.0039	0.0379	0.0474	$1.59E-4$	$8.40E-8$	0.1519	0.2093	$5.42E-2$
9	45	$8.36E-6$	0.0041	0.0386	0.0478	$5.46E-5$	$3.13E-9$	0.0974	0.1786	$4.11E-2$
10	45	$1.43E-5$	0.0039	0.0413	0.0434	$9.51E-5$	$6.30E-8$	0.1024	0.1877	$3.42E-2$



(a) (b) (c) (d)

Fig. 3: (a) Correlation plane resulting from Bones [16] value choice of values: $\alpha = 0.01$, $\beta = 0.1$, $\gamma = 0.3$ (b) Correlation plane using PSO optimized values $\alpha = 0.0039$, $\beta = 0.0413$, $\gamma = 0.0434$ (c) Correlation plane using HPSO optimized values $\alpha = 6.30E-08$, $\beta = 0.1024$, $\gamma = 0.1877$ (d) example test image employed.

the cases of PSO, HPSO and Bones values are: $9.51E-05$, $3.42E-02$ and $1.43E-05$ respectively. In Fig. 2 (a) and (b), the peaks of Bone's values and PSO optimized values are apparently the same but the results of applying PSO are better than from those achieved from the parameter values proposed by Bone *et al.* COPI result obtained from HPSO optimized values is better than both Bone's result and the PSO optimized result as shown in fig. 2 (c). The results of HPSO are better as compared to Bone's work and PSO optimized results for other performance measures also, as shown in fig. 3, 4 and 5

In Fig. 3, the test image is 45^o out of plane rotated. The values of the COPI from the PSO, HPSO and Bones choice of values are: $5.46E-05$, $4.11E-02$ and $8.36E-06$, respectively. The reason for the side lobes present in the correlation plane resulting from the HPSO optimized values is due to the small contribution of the ONV term and the full correlation that has been used in the experimentation i.e. the full test image has been correlated with the trained filter. Results of the HPSO optimization are better as compared to the results obtained with other values in terms of the COPI performance measure.

The minimized value of ACE leads to the maximum value of the PCE performance measure. It gives sharp and prominent peaks as compared to the other filters examined. Test images from different datasets with different out-of-plane rotations have been used in the experimentation to analyze the pattern of optimized values. The values of α, β and γ for the PCE cost function are 0.01, 0.3 and 0.1, respectively according to the values proposed by Bone *et al.* [16]. In Table V, comparisons have been made between the PSO and HPSO optimized values and the originally proposed values by Bone [16] for the PCE cost function. As for the performance measure, the value of the PCE using HPSO optimized parameter values is better than the PCE values obtained using PSO and the originally starting value. The correlation plane for the PCE cost function has been analyzed for some datasets. In Fig. 4, the test image is 45^o out-of-plane rotated. The value of the PCE from the PSO and HPSO optimized values and the values proposed by Bone *et al.* [16] are: $7.27E+01$, $2.26E+02$ and $2.69E+01$, respectively. Again, the results obtained using HPSO are better than those obtained from other values in terms of the PCE performance measure, optimization is giving a sharper peak in comparison to the other methods.

The test image is 15^o out-of-plane rotated in Fig. 5. The correlation peak from the optimized values obtained from HPSO is sharper as compared to those obtained from PSO and Bones proposed values shown in Fig. 5. The values of the PCE using PSO, HPSO and Bones parameter values [16] are $3.67E+02$, $4.49E+03$ and $1.18E+02$, respectively. Thus the results obtained using PSO optimization are also better than those achieved from the values proposed by Bone *et al.* [16]. But again, the optimized value given from HPSO gives the best result as compared to the PSO technique and Bones proposed

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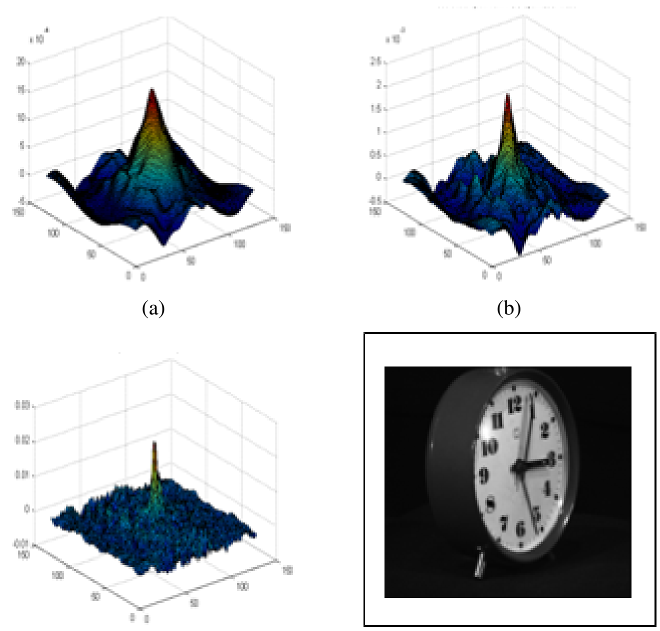
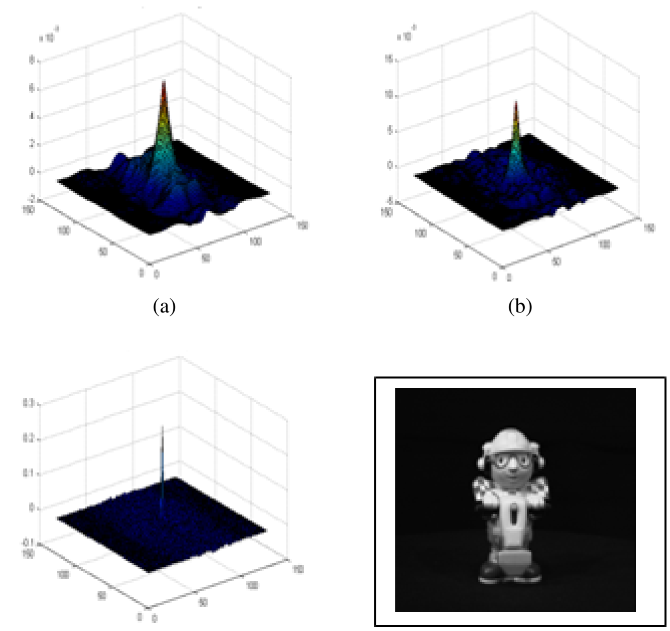
TABLE V: The values of PCE resulting from the PSO and HPSO optimized parameters and their unoptimized values.

Data set	Test image (Deg)	Bones values PCE	PSO α	PSO β	PSO γ	PSO PCE	HPSO α	HPSO β	HPSO γ	HPSO PCE
1	5	$6.16E+1$	0.0032	0.7475	0.5519	$1.59E+2$	$3.16E-6$	0.7007	0.4695	$7.68E+2$
2	5	$5.04E+1$	0.0038	0.7638	0.566	$9.06E+1$	$1.26E-6$	0.7137	0.4402	$6.74E+2$
3	5	$5.35E+1$	0.0027	0.7351	0.5389	$1.60E+2$	$1.85E-5$	0.7515	0.2495	$9.42E+2$
4	5	$2.43E+1$	0.0037	0.6879	0.5232	$6.66E+1$	$7.83E-8$	0.6561	0.5438	$5.38E+2$
5	15	$1.18E+2$	0.0034	0.7139	0.5433	$3.67E+2$	$2.38E-7$	0.7199	0.4175	$4.49E+3$
6	15	$7.97E+1$	0.0031	0.7497	0.5165	$2.11E+2$	$1.73E-5$	0.7842	0.2776	$7.83E+2$
7	25	$4.56E+1$	0.003	0.7136	0.5402	$1.32E+2$	$5.01E-8$	0.7152	0.4497	$3.68E+3$
8	25	$8.78E+1$	0.0037	0.7454	0.5619	$2.32E+2$	$8.90E-6$	0.7395	0.3128	$1.10E+3$
9	45	$2.69E+1$	0.0033	0.7583	0.5106	$7.27E+1$	$7.52E-6$	0.4861	0.6633	$2.26E+2$
10	45	$4.94E+1$	0.0032	0.7337	0.4818	$1.20E+2$	$4.12E-5$	0.7494	0.3425	$3.76E+2$



(a) (b) (c) (d)

Fig. 4: (a) Correlation plane resulting from Bones [16] choice of values: $\alpha = 0.01$, $\beta = 0.3$, $\gamma = 0.1$; (b) correlation plane using PSO optimized values $\alpha = 0.0033$, $\beta = 0.7583$, $\gamma = 0.5106$; (c) Correlation plane using HPSO optimized values $\alpha = 7.52E-06$, $\beta = 0.4861$, $\gamma = 0.6633$. (d) Test image employed.



(a) (b) (c) (d)

Fig. 5: Correlation plane resulting from use Bones [16] choice of values: $\alpha = 0.01$, $\beta = 0.3$, $\gamma = 0.1$; (b) Correlation plane using PSO optimized values $\alpha = 0.0034$, $\beta = 0.7139$, $\gamma = 0.5433$; (c) Correlation plane using HPSO optimized values $\alpha = 2.38E-07$, $\beta = 0.7199$, $\gamma = 0.4175$; (d) test image employed.

values for both the COPI and PCE cost functions. Otimized values vary for all the datasets. The most suitable value of the OT parameters depends on the dataset and cost functions. Optimized value obtained using PSO can converge to a local best value nevertheless, PSO still gives better results than those obtainable using existing unoptimized parameter values.

V. Conclusion

In this paper, a novel approach of combining OT correlation filter and optimization algorithms has been proposed to improve correlation filter results. The aim of this study has been to optimize the optimal trade-off parameters of correlation filters which has not accomplished in the past. The optimized values obtained using the PSO and HPSO methods have been compared to parameter values that have been previously employed related to the cost functions for a specified target detection application. The values of the optimal trade-off parameters are not fixed for all applications and neither are the cost functions but the selection of the values are varied according to the requirements. The optimized values obtained with HPSO suppress the output noise variance (ONV) factor.The results obtained with this optimization algorithm are more accurate than those achieved with optimized parameter values obtained using PSO and previously suggested values.

The PSO algorithm is a relatively simple heuristic algorithm. In future work, we will compare PSO and HPSO with other advanced heuristic algorithms to attempt to further enhance the performance of pattern recognition correlation filters.

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