AN EFFICIENT METHOD FOR THE CLASSIFICATION OF SEGMENTED IMAGES BASED ON PARTICLE SWARM OPTIMIZATION , KARHUNEN-LOEVE TRANSFORMATION AND SUPPORT VECTOR MACHINES

Mircea WEINGART
University Politehnica of Bucharest , Romania
e-mail:mirceaw201@yahoo.com

Keywords: particle swarm optimization, support vector machines, Karhunen-Loeve transformation, image classification

Abstract: *The subject of this article is to present an efficient method of image segmentation based on a nature inspired optimization technique namely Particle Swarm Optimization and a classification of the segmented images with support vector machines (SVM linear classifier .The classification is performed on the segmented image itself in one case and on the segmented image pre-processed by applying a Karhunen-Loeve transformation that de-correlates and compress the image in the other case.*

1. INTRODUCTION

Image segmentation is a digital image processing technique that partitions an image into multiple regions of interest . Image segmentation has vast applications from medical imagery to industrial applications . Its increasing importance contributed to the development of better methods of optimized segmentation . Such methods are based on nature inspired optimization , due to the study of bees , ants , birds and fish , on how they organize especially for the task of food search .

All these use the shortest path to food .

Particle swarm optimization(PSO) models the behavior of such collective living organisms. A particle may be a bird , a bee or an ant.

Each individual intelligence and also the collective intelligence are factors in the optimization process. The swarm has a fixed size with the initial position of particles randomly distributed.

Besides the position , the particles have also velocities. Every particle travels for finding food and remembers the best positions to food.

Particles communicate between them and change the positions and velocities based on the best positions found by the other particles.

The swarm has cohesion , since the particles stay together , the particles are separated in the sense that they don't come too close and keep an alignment moving in the general direction of the swarm. The model of PSO maximizes an objective function f(X) , where X are particles' coordinates. The Ant Colony Optimization(ACO) concept is based on ant colonies cooperation to find the best path to food as in [1]. Each of the N ants from the colony travels through a multi-layer graph representing the ant's path to food from the first to the last layer, and the nodes visited by the ant are an eventual solution . When the path is completed the ant deposits pheromone on the path based on an update rule. After the whole colony of ants finish their paths , a the pheromones on the global best path is updated based on a specific rule. The optimum solution is the path that will be used by all ants , and this path will have the largest amount of pheromone.

ACO has been used for image classification in this way : ants collect information from the image and the choice of pixel path is a function of the label of the pixel. The favourite paths are those from the same image segment as presented in [2]. In [3] an ant colony algorithm is used for fuzzy clustering in image segmentation.

Based on these methods an image can be optimally segmented in terms of speed of algorithm's convergence and by achieving a good segmentation. A comparative study of Artificial Bee Colony(ABC) is presented in [4]. This model is based on the concepts of food sources, employed foragers and unemployed foragers . In order to select o food resource checks the food source by some properties such as taste of nectar , closeness to the hive . The employed foragers are employed at a certain food resource that they are currently exploiting and they give information about this food source to other bees . The unemployed foragers can be one of two categories: a scout that searches at random for a food source, or an onlooker that tries to get to a food resource based on the employed foragers information that she received.
The ABC algorithm steps comprise the following:

Initialization of the population;
Loop
Repeat
Employed bees are placed on the sources of food;
Onlooker bees are placed on food sources depending on the nectar quantities;
Scout bees are sent to search for new food sources;
Best food source is kept in memory;
till requirements are met

As it is presented in [5] an Artificial Bee Colony (ABC) based image clustering method is used to find clusters of an image where the number of clusters is specified.

2. THE DESCRIPTION OF THE PROPOSED SOLUTION FOR SEGMENTED IMAGES CLASSIFICATION

The proposed solution for the classification of segmented images has two scenarios:

The first scenario uses a Particle Swarm Algorithm for the segmentation of the original Lena and Barbara images , then images are classified by using a support vector machine technique .

The second scenario uses the same Particle Swarm Optimization algorithm that is applied to the same images that were pre-processed by a feature selection using the Karhunen-Loeve transform . As is shown later in this article will be selected 35, 115 and 415 principal components of the two images.

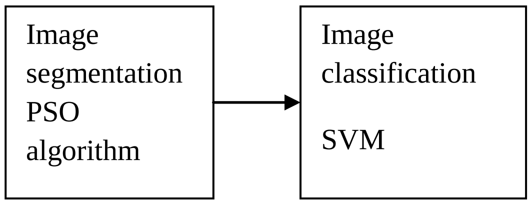

Fig.1 Image classification of segmented images. First scenario

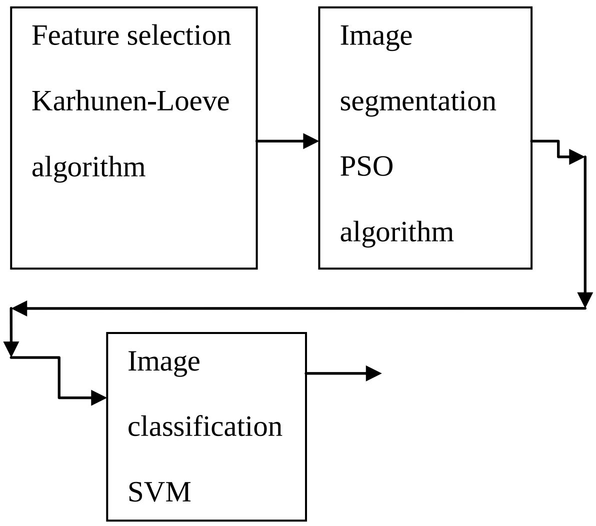

Fig.2 Image classification of segmented images. Second scenario

The PSO(Particle Swarm Optimization) basic algorithm implementation is as follows (as in [1]).We have to maximize f(X) with
$X(l) \leq X \leq X(u)$, X(l) and X(u) are the lower and upper bounds of X. PSO algorithm steps, considered for the unconstrained case:

1. Initialize swarm size N , usually 20 to 30 particles
2. Generate initial population of X in the range defined above : X_1 , X_2, … X_N. Particle j in iteration i has position X_j^i and velocity V^i_j. . Compute the initial value of the objective function

$f(X_1(0), X_2(0), \dots X_N(0))$

3. Find velocities of all particles. , initially all velocities are zero. Set i=1, first iteration
4. In iteration i , for particle j we get historical best value of the objective function for particle j in all previous iterations : $P_{best,j}$ and historical best value for all particles in previous iterations : G_{best} .
   Find velocity for particle j , iteration i
   $V_j(i)=V_j(i-1)+c_1r_1[P_{best,j}-X_j(i-1)]+c_2r_2[G_{best} - X_j(i-1)]$; j=1,2,……,N , with c_1 and c_2 are the individual (cognitive) and social learning rates , r_1 , r_2 uniform distributed random numbers in the interval [0 1].
   Find the position of particle j for iteration i: $X_j(i)= X_j(i-1)]+ V_j(i)$ for =1,2,……,N.
   Objective function evaluation at iteration i: $f[X_1(i)],f[X_2(i)], \dots ,f[X_N(i)]$
5. The convergence of the current solution is verified and if the positions of all particles converged to the same values , the algorithm also converged. If not, step 4 is repeated for i=i+1 and re-compute $P_{best,j}$ and G_{best} until all particles converged to the same best(optimum) solution .

In [6] is mentioned that PSO algorithm may be trapped in local optimum that may cause problems and some improvements proposed to tackle this . One solution is the Darwinian Particle Swarm Optimization where many swarms of test solutions co-exist at any time., with each swarm performing it's own PSO. There are also rules governing all swarms that simulate theoretically the natural selection. Another improved PSO-based method is the fractional order PSO (FODPSO) proposed in [6] for controlling the convergence rate of the algorithm by using the fractional calculus based on the concept of fractional differential of a signal x(t):

$$D^{\alpha}[x(t)]= \frac{1}{T^{\alpha}} \sum_{k=0}^{r} \frac{(-1)^k \Gamma(\alpha+1)x(t-kT)}{\Gamma(K+1)\Gamma(\alpha-k+1)}$$

with Γ the gamma function , T , the sampling period and r the truncation order. Fractional calculus is well-suited for a keeping a "memory" of past events .Re-writing the velocity of the particle in terms of the fractional differential we get for the first 4 terms of the fractional differential:

$$V_j(i) = \alpha V_j(i-1) + \tfrac{1}{2}\alpha V_j(i-2) + \tfrac{1}{6}\alpha(1-\alpha) V_j(i-3) + \tfrac{1}{24}\alpha(1-\alpha)(2-\alpha) V_j(i-4)+ c_1r_1[P_{best,j}X_j-(i-1)]+c_2r_2[G_{best}- X_j(i-1)]$$

For α=1, FODPSO becomes the DPSO case (no "memory").As an application of FODPSO is presented here an image segmentation method based on optimal thresholding as proposed in [6]. This method searches for optimal thresholds that makes histogram based classes reach the desired properties. This is done through optimization of an objective function. Multilevel image segmentation applied to a color – R,G,B – image is modeled with three parameters in [6],namely is defined a function of n-1 thresholds , considering L levels of intensity for each channel of the RGB image. Based on this function the image is divided in n classes that may represent multiple objects and specific features of these objects. It is mentioned that the simplest way to optimize thresholding is by considering maximization of the between-class variance , defined as:

$$(\sigma_B{}^C)^2= \sum_{j=1}^{n} w_j^C \, (\mu_j^C - \mu_T^C)^2$$

, where j is class , w_j^C is the probability of this class and μ_j^C is the mean of the class. Then the n-level thresholding is an optimization problem to find the thresholds t_j^C that maximize the fitness function (actually three objective functions-one for each RGB component):

$\Phi^C=\max(\sigma_B{}^C)^2(t_j^C)$, for $1< t_j^C<L$ and j=1,…,n-1 C=(R,G,B). Here comes into play the PSO,DPSO and FODPSO techniques to do this optimization efficiently.

Short description of the Karhunen-Loeve transform (used for feature selection)

X represents a set of n vectors and each vector has K components .

T : X → Y = T(X- m_X **)** is a transformation that makes the covariance matrix of Y diagonal.

m_X **= E{X} =** $(m_1,m_2,\dots m_n)^T$ is the mean vector of X , m_i is the mean of vector x_i .

$$\sum\nolimits_X = \mathbf{E}\{(X- m_X)(X-m_X)^T\}$$

is the covariance matrix of X.

The rows of T are orthogonal eigenvectors (the principal components) of $\sum_X$ ordered corresponding to decaying eigenvalues , $\sum_Y$ is a diagonal covariance matrix of Y with the diagonal elements the eigenvalues of $\sum_X$,and this does the de-correlation of pixels in the coordinate basis system formed by the principal components and also with the preservation of variance . References are in [7] .

Short description of Support Vector Machines(SVM) classifier

These linear classifiers have as objective a partition into classes of given feature vectors [8]. For the two-classes case-considered here as illustrative for the SVMs description , let x_i be N training feature vectors that belong to classes ω_1 and ω_2 that are linearly separable , our task being to find an optimum hyperplane that correctly separates in the two classes the given vectors.

The hyperplane quation defining it is :

$h(x) = w^T x + w_0 = 0$

The optimality is in the sense that by determining the direction w and exact position in space w_0 is needed also to have a margin of selection that hyperplane equally distanced from the closest points in ω_1 and ω_2 respectively .The solution is :

$w = \sum_{i=1}^{N} \lambda_i y_i x_i$ with

$\sum_{i=1}^{N} \lambda_i y_i = 0$

λ_i are lagrange multipliers , y_i are class indicators (y_i =+1 for ω_1 and -1 for ω_2).

Some λ_i are zero , and only N_P are not zero. Then the vector optimal hyperplane is: $w = \sum_{i=1}^{N_P} \lambda_i y_i x_i$, and is called support vector machine., that is the support vectors lie on one of the two hyperplanes :

$w^T x + w_0 = \pm 1$, and they are the training vectors that are closest to the linear classifier.

The proposed complete solution is in short: the input system reads the clean training images (Lena and Barbara) and trains a SVM (Support Vector Machine).

In the first scenario the same images are segmented by PSO, DPSO and FODPSO methods and they are classified with the trained SVM.The same images are also pre-processed in the second scenario by taking the first principal components, then segmented with the same algorithms and then classified by using SVM.

3. EXPERIMENTAL RESULTS AND THEIR INTERPRETATION

Two tables with results are presented next:

Table 1 SVM based classification rate of segmented images results

Method	LENA Image(%)	BARBARA Image(%)
PSO	100	100
DPSO	100	100
FODPSO	100	100

Table 2 SVM based classification rate of segmented images pre-processed with Karhunen-Loeve.Results

Method	LENA Image(%)	BARBARA Image(%)
PSO For 35, 115 and 415 selected principal components	100	100
DPSO For 35, 115 and 415 selected principal components	100	100
FODPSO For 35, 115 and 415 selected principal components	100	100

As presented in the above tables 1 and 2 the classification rate was 100% correct for the two segmented images using the PSO, DPSO and FODPSO segmentation methods and a SVM classifier.The segmentation levels used were : 2,3,4,5 and 6.The average computation time for the Karhunen-Loeve, segmentation and classification was 27.5 seconds for each case , namely for each image , method and segmentation level. The first 35, 115 and 415 principal components wre selected by using the Karhunen-Loeve transform applied to the two images. As can be seen from the results , the two images can be classified even they are segmented and compressed with Karhunen-Loeve , and in this way the proposed system can be used as a rapid automated classification of images that were segmented with PSO, DPSO, and FODPSO methods, and were de-correlated and compressed with Karhunen-Loeve transform. Examples of segmented images are presented next.

FODPSO
Barbara-3 levels of segmentation

FODPSO
Lena-3 levels of segmentation

PSO
Lena-5 levels of segmentation

DPSO
Barbara-5 levels of segmentation

Fig. 3 Examples of segmented images

4. CONCLUSIONS

The proposed system can be used for a fast classification of images that had to be segmented for a better analyze of them for example , or for a selection of some regions of interest from the image(s). In the case of remote presence of the person that has to analyze the images the image compression increase the speed of image transmission , so for example in case of medical imagery when a good and fast diagnostic has to be carried out of segmented images , the use of Karhunen-Loeve transform applied before segmentation can perform this image compression and also doing a de-correlation pixel-wise.

5. ACKNOWLEDGMENT

I wish to thank Professor Victor Neagoe for the constant help and guidance, and to Manuel Couceiro , for his very kind support regarding PSO, DPSO and FODPSO methods, through his article and implementation on this matter.

6. REFERENCES

[1]. Rao, S. S., "*Engineering optimization Theory and practice*" fourth ed., John Wiley and Sons, Inc., 2009

[2]. Le Hegarat-Mascle S., Kallel A., Descombes X., "*Ant Colony Optimization for Image Regularization Based on a Nonstationary Markov Modeling*" IEEE Transactions on image Processing ,vol. 16,.no. 3, march 2007

[3]. Han Y., Shi P., "*An improved ant colony algorithm for fuzzy clustering in image segmentation"* Elsevier, Neurocomputing 70(2007) 665-671

[4]. Karaboga, D. ,Akay B., "*A comparative study of Artificial Bee Colony algorithm*" Elsevier, Applied Mathematics and Computation 214(2009) 108-132

[5]. Hancer, E., Ozturk, C., Karaboga, D. *"Artificial Bee Colony based image clustering method"*, IEEE Congress on Evolutionary Computation(CEC),2012

[6]. Ghamisi, P., Couceiro, M. S.,Benediktsson, J. A., Ferreira, N. M. G.,"*An efficient method for segmentation of images based on fractional calculus and natural selection*", Elsevier, Expert Systems with Applications 39(2012),12407-12417

[7]. Neagoe, V., Stanasila, O., "*The theory of pattern recognition*" , Editura Academiei Romane, Bucharest,1992,134-137

[8]. Theodoridis, S., Koutroumbas, K., *"Pattern Recognition"*Elsevier,2009,119-124