



Nonlinear adaptive filters based on Particle Swarm Optimization

Faten BEN ARFIA, Mohamed BEN MESSAOUD, Mohamed ABID

*CES Computer Engineering System design Laboratory
National Engineering School of Sfax: Tunisia.*

E-mails: benarfia_faten@yahoo.fr, M.benMessaoud@enis.rnu.tn,
mohamed.abid@enis.rnu.tn

Abstract

This paper presents a particle swarm optimization (PSO) algorithm to adjust the parameters of the nonlinear filter and to make this type of the filters more powerful for the elimination of the Gaussian noise and also the impulse noise. In this paper we apply the particle swarm optimization to the rational filters and we completed this work with the comparison between our results and other adaptive nonlinear filters like the LMS adaptive median filters and the no-adaptive rational filter.

Keywords

Nonlinear filter, rational filter, Particle Swarm Optimization, Gaussian noise, impulse noise.

Introduction

The suppression of noise is one of the most important tasks in image filtering. Traditionally, linear processing methods are employed for this domain because are easy to implement and design but they are many disadvantage e.g. in the presence of impulse noise, the performance of linear filter deteriorates severely and they tend to reduce the important image feature so to better preserve those feature, non linear filter are used in image denoising

[1]. To be more powerful, this type of filter must be adaptive so many adaptive algorithms are used to finding an optimal filtering function [2].

PSO is recently developed as a new approach for the adaptation of nonlinear image filtering. In this work this technique is a probabilistic optimization algorithm proposed as a simulation of social behavior [3].

The paper is organized as follows: Section 2 presents the rational filter as an adaptive non-linear image filtering. Section 3 describes the formulation of the particle swarm optimization and it's detailed this algorithm in image filtering. In section 4 are experiment results on the rational filter adapted with the adaptive algorithm PSO. Finally, a conclusion and perspectives is presented in section 5.

Adaptive nonlinear rational filter

Rational filter are one of the recent and major classes of nonlinear filter. It is the successful tool for application in image enhancement, interpolation and denoising.

This type of non linear filter is the ratio of two polynomials function; it is recently proposed to represent the input-output relation in a nonlinear signal processing system [4] [5].

A rational function, used as a filter, can be expressed as

$$y = \frac{a + \sum_{m=0}^{N-1} a_{m1} x(n-m_1) + \sum_{m_1=0}^{N-1} \sum_{m_2=0}^{N-1} a_{m1,m2} x(n-m_1)x(n-m_2) + \dots}{b + \sum_{m=0}^{N-1} b_{m1} x(n-m_1) + \sum_{m_1=0}^{N-1} \sum_{m_2=0}^{N-1} b_{m1,m2} x(n-m_1)x(n-m_2) + \dots}$$

where

x is the input and y is the output of the rational filter.

This rational function is composed of a linear numerator and a linear denominator; these two types of function are widely used in enhancement, filtering and interpolation [6].

A major obstacle of this function can again be their complexity: if the order of the rational function is higher, many parameters will be required, and this will cause slow convergence.

The rational filter used in this application with two windows forms of 3*3, illustrated in Figure 1

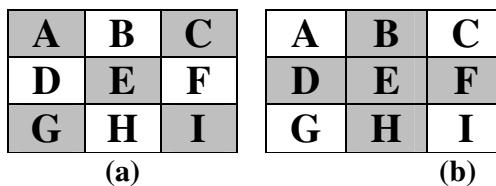


Figure 1. Restrained neighborhoods.

(a) Type I: Cross shaped neighborhood. (b) Type II: x-shaped neighborhood.

Particle Swarm Optimisation

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995[7], inspired by social behavior of bird flocking or fish schooling. The PSO is a population-based optimization technique, where the population is called swarm.

The basic PSO algorithm can be described as follows: Each particle in the swarm represents a possible solution to the optimization problem existing. During PSO iteration, every particle accelerates independently in the direction of its own personal best solution found so far, as well as the direction of the global best solution discovered so far by any other particle [8]. Therefore, if a particle finds a promising new solution, all other particles will move closer to it, exploring the solution space more thoroughly [9].

Let s denotes the swarm size. Each particle $1 \leq i \leq s$ is characterized by three attributes [10]:

- (1) The particle position vector Y_i ;
- (2) The particle position change (velocity) vector V_i ;
- (3) The personal (local) best position achieved by the particle so far \hat{Y}_i . Moreover, let G denote the best particle in the swarm.

Particle Swarm Optimization Algorithm

This algorithm can be resumed as follows:

1. Initialize Y_i and V_i , and set $\hat{Y}_i = Y_i$ for $i = 1, 2 \dots s$.
2. Evaluate each particle Y_i for $i = 1, 2 \dots s$.
3. Let G to be the best particle in $\{\hat{Y}_1, \hat{Y}_2 \dots \hat{Y}_s\}$
4. For $i = 1, 2 \dots s$. do:

 Update V_i according to:

$$V_i = w V_i + c_1 r_1 (\hat{Y}_i - Y_i) + c_2 r_2 (G - Y_i)$$

Update Y_i according to:

$$Y_i = Y_i + V_i$$

5. Go to Step 3, and repeat until convergence.

where

w inertia weight factor;

c_1, c_2 self-confidence factor and swarm-confidence factor, respectively;

r_1, r_2 two random numbers uniformly distributed between 0 and 1.

If Y_i is better than \hat{Y}_i , then $\hat{Y}_i = Y_i$

5. Go to Step 3, and repeat until convergence.

Particles' velocities on each dimension are clamped to a maximum velocity V_{max} . The velocity on that dimension is limited to V_{max} , if the sum of accelerations would cause the velocity on that dimension to exceed V_{max} , which is a parameter specified by the user.

This algorithm is illustrated in figure 3.

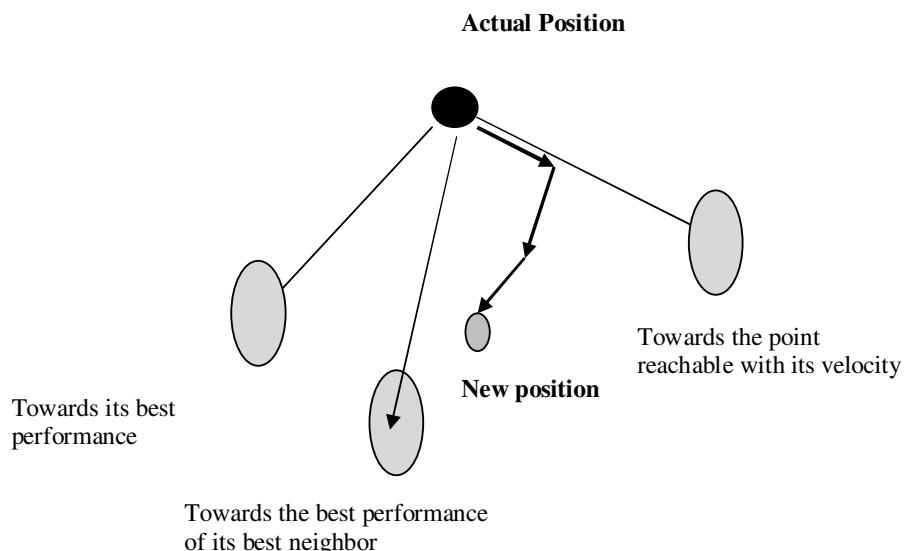


Figure 2. Principe of the movement of a particle

This approach is applied to adjust the parameters of nonlinear adaptive filters such as adaptive rational filter explained in paragraph 2.

Experimental results

In our application we have applied the PSO algorithm to solve the parameter estimation problem for nonlinear rational filters. Each pixel of the noisy image is taken in the form of a particle in the terminology of PSO. The proposed PSO algorithm applies the velocity updating and position updating formulas to the population composed of many particles such that better particles are generated.

In our contribution, to find optimum parameters of function for this filter, we need to initialize firstly the coefficients of the PSO approach. The Table 1 gives the initialized coefficients of PSO.

Table 1. The initialized coefficients of the PSO.

coefficients	value
w	0,7
Vmax	2,5
Number of particle s	5
self-confidence factor c1	1,3
swarm-confidence factor c2	1,3

Table 2. Performance of the different algorithm denoising in Gaussian noise ($\delta=20$).

Lena.bmp			
	PSNR	SNR	MSE
Median -LMS	22,53	25,17	340,52
No-adaptive Rational filter	37,65	24,28	285,37
PSO-Rational filter	38,75	32,82	124,69

Table 3. Performance of the different algorithm denoising in impulse noise (20%).

Lena.bmp			
	PSNR	SNR	MSE
Median -LMS	17,83	7,92	1194
No-adaptive Rational filter	38,89	28,89	179,91
PSO-Rational filter	39,63	35,03	96,79



Figure 3. Gaussian noise ($\delta=20$) (a) Original image. (b) Noisy image. (c) Image filtered with non-adaptive rational filter. (d) Image filtered with LMS median filter. (e) Image filtered with PSO rational filter.



Figure 4. impulse noise (20%) (a) Original image. (b) Noisy image. (c) Image filtered with non-adaptive rational filter. (d) Image filtered with LMS median filter. (e) image filtered with PSO rational filter.

In this work we applied a particle swarm optimization (PSO) algorithm to solve the parameter estimation problem for nonlinear adaptive rational filters. This filter is applied to the test image lena.bmp noised with two types of noise: Gaussian noise with $\delta=20$ and impulse noise with 20%.

We compared the rational filter level PSNR (peak- signal-to-noise ratio), MSE(Mean Square Error) and the SNR(Signal Noise Ratio) to another adaptive non-linear filter adapted by another approach explained in the two tables 2 and 3: the median filter approach adapted by the LMS (Last Mean Square) and the no-adaptive rational filter for both types of noise: Gaussian and impulse noise .

We have demonstrated that this approach (PSO) applied on a rational filter has shown the efficiency in three criteria: PSNR, SNR and MSE compared to other approaches used, especially for the impulse noise.

It was noticed that the PSO rational filter is more effective for impulse noise than other used filters.

Conclusions

This contribution consists on applying the PSO approach (particle swarm optimization) for the adaptation of a nonlinear adaptive rational filter.

The application of this new approach in the denoising field gives a better performance compared with other technique.

During implementation of this approach it was found that the PSO technique cannot ameliorate the results of the filtered images by increasing the number of iterations. Although it can ameliorates the results with the change of these parameters to achieve an optimal function that gives the best filtered image. So these coefficients must be the right choice to find better results.

Future work includes funding an optimum function for the PSO approach to get the coefficients of the rational filter that gives the best results for image filtered , Also changed some criteria for the image as the block size of the image and the particle size in PSO approach.

References

1. Ben HAMZA, H. KRIM «Image Denoising: A Nonlinear Robust Statistical Approach», IEEE Transactions On Signal Processing, Vol. 49, No. 12, December 2001
2. C. KOTROPOULOS, I. PITAS «Adaptive LMS L-filters for noise suppression in images» IEEE Transactions on Image Processing, Volume 5, Number 12, December 1996.
3. H.TALBIL, M. C. BATOUCHÉ «Particle swarm optimization for image registration» International Conference on Computer Theory and Applications, IEEE Press, Damascus, Syria, April 2004. IEEE Catalog Number 04EX852, ISBN 0-7803-8484-2.
4. Ramponi G., «The Rational Filter for Image Smoothing », IEEE Signal Processing Letters, Vol.3 (3), 1996.
5. L.Khriji , M.Gabbouj «Vector Median-Rational Hybrid Filters for Multichannel Image Processing », IEEE Signal Processing Letters, Vol.6, No.7,pp.186-190, July 1999.

6. Leung H., Haykin S, «Detection and Estimation Using an Adaptive Rational Function Filters » IEEE Trans. on Signal Processing, Vol.42 (12), 1994.
7. J. KENNEDY, R.C. EBERHART. «Particle Swarm Optimisation», Proceedings of the IEEE International Conference on Neural Networks, 1995, pp. 1942-1948, IEEE Press.
8. M.G.H. OMRAN, Particle Swarm Optimization Methods for Pattern Recognition and Image Processing, PhD Thesis, University of Pretoria, November 2004.
9. M.G.H. OMRAN, A. P. ENGELBRECHT, A. SALMAN «Differential Evolution Based Particle Swarm Optimisation», IEEE Swarm Intelligence Symposium, Proceedings of the 2007.
10. I.C. TRELEA «The particle swarm optimization algorithm: convergence analysis and parameter selection» Information Processing Letters, Vol. 85, pp. 317-325, 2003.