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A Novel Approach of 2D Adaptive Filter Based on MPSO Technique for Biomedical Image

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Abstract

In this paper, extension of the 1-D adaptive filter schemes to 2D formation and the new 2D adaptive filters are designed. The results of proposed scheme are compared with 2D variable step-size normalized least mean squares, the 2D VSS affine projection algorithms, the 2D set-membership NLMS, and 2D SM APA. The performance of proposed scheme is compared with other reported methods for 2D adaptive filter design. Based on simulation results, it is demonstrated that the proposed method can achieve 85% and 90% reduction in normalized mean square error and normalized maximum error mean, respectively. Moreover, the proposed 2D-ANC filter applied for reconstruction of a biomedical image shows 6 dB signal-to-noise ratio improved as compared to recently reported algorithm.

Keywords 2D ANC · 2D VSS NLMS · 2D SM NLMS · 2D SM APA · Biomedical image

Introduction

Adaptive filter algorithms have numerous applications in electrical engineering [1–3]. For the past two decades, one-dimensional as well as the two-dimensional adaptive filter has received a lot of thoughts [4] and the attributes of these filters of taking into consideration the nonstationary statistical property as well as statistical correlation of the two-dimensional space make this scheme attractive to researchers. The application of this filter scheme for the field of image processing ranges from de-noising of image, enhancement, cancellation of noise, two-dimensional line enhancer and identification of system. The least mean squares adaptive scheme (LMS) which was originally proposed in 1D was stretched out to two-dimensional spaces in [5]. This scheme was used for measurements of nonstationary images. In paper [6], another two-dimensional LMS scheme is presented which uses the block diagonal-based scheme for filter designing. This scheme was used for the McClellan transformation. The scheme presented in [5] is a stretched out version of its 1D opposite match.

The 2D scheme is an intriguing concept with the advantage of simple architecture, but this scheme is highly delicate for changes in eigenvalues, and the rate of convergence is too slow which is not desirable. For overcoming these problems, the normalized LMS (NLMS) scheme was presented. In this scheme, the effect of magnitude on rate of convergence was taken into consideration. In paper [7], filter presented relies on affine projection scheme (APA). The presented scheme gives the advantage of freely selecting the projection vectors. The efficiency of the presented scheme increases when the host data possess a strong correlation. Unfortunately, this improvement comes at the expense of increased algorithm complexity. In paper [7], another APA scheme was presented for linear filtering. The simulation results display the fast convergence and good track down attributes of the scheme. In paper [8], a recursive LMS scheme is presented in two-dimensional spaces. When the scheme was extended from 1D to 2D space, the complexity of algorithm increased.

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The 2D RLS has good performance in many applications, but the cost that we have to pay to enjoy its abilities is so expensive; therefore, we did not consider this algorithm. In 2D adaptive filter algorithms, the small changes of the step sizes can produce a considerable change in adaptation speed and accuracy.

Therefore, the optimal step-size selection is important in different applications. This selection is usually attained by trial and error method. Furthermore, an adaptive system with a constant step size cannot efficiently control its parameters. To overcome this problem, the time-varying step-size technique was presented in [7]. In [7], the variable step-size APA (VSS APA) and variable step-size NLMS (VSS NLMS) algorithms for one-dimensional case were presented. The same approach in [8] was successfully extended to the other adaptive filter algorithms in [8]. In this paper, with the purpose of using variable step size in 2D applications, we extend the approach in [5–8] to establish two new 2D adaptive filter schemes which are referred 2D VSS APA and 2D VSS NLMS algorithms. In simulation results section, we demonstrate the good performance of the proposed algorithms in adaptive noise cancellation in digital images for image de-noising. Unfortunately, when we use time-varying step size, we have to pay its cost, because of increasing the computational complexity. Another way to overcome the problem of existence trade-off between low misadjustment and high convergence speed contemporaneous is using the concept of set-membership (SM) filtering. In this method, by definition an upper bound on the estimation error, the number of adaptation of filter coefficients is reduced. The one-dimensional SM NLMS algorithm and the SM APA were proposed in [7, 8], respectively. For reducing the complexity in two-dimensional spaces applications, a new 2D SM adaptive scheme was developed. The simulation results of the two-dimensional SM NLMS and SM APA confirm the higher efficiency of the scheme in noise elimination. In the traditional filter schemes, the coefficients of filter are updated to full extent. For reducing the difficulty, other filter schemes making use of partially updated coefficients were brought forth. Based on this approach, the filter coefficients to be modified are opted in a manner so as to maximize the efficiency [6–9].

The one-dimensional schemes like SPU NLMS and SPU APA are popular cases of adaptive filters [6–9]. To reduce the computational complexity of conventional 2D NLMS and 2D APA algorithms, we extend the SPU approach to 2D structure to establish the 2D SPUNLMS and 2D SPU APA. In two-dimensional filter schemes, selection of parameters is not clearly defined. These parameters are usually adopted by means of trial and error method. In the presented paper, we study both previous and new two-dimensional spaces schemes simultaneously. As we know, each algorithm has different behaviour in various applications of adaptive filters. So, we consider the performance of the presented algorithms in 2D ANC for de-noising of images.

These schemes are faced by many obstacles which include rate of convergence, analysis of nonlinear and nonstationary process, partial complete overlap of the signal and bandwidth of noise signal. These setbacks are countered by means of evolutionary schemes commonly referred as particle swarm optimization (PSO) employed for 2D adaptive filter design. Literature survey reveals the 2D ANC filter based on MPSO has not yet been reported. The main inspiration for this work is to develop a 2D ANC filter relying on PSO for intelligent recovery of biomedical image. This is shown that this scheme attains much satisfactory performance parameters in comparison with filter relying on LMS, NLMS, VSS NLMS, VSS APA, SM APA and SPUNLMS schemes in two-dimensional spaces. The architecture of presented ANC filter scheme in two-dimensional spaces is an intelligent approach for removing noise from bio-medical images which give better SNR, MSE, ME and correlation factor.

Design 2D-ANC Filter Using Particle Swarm Optimization Technique

Based on the chronological order of research finding which includes the design presented, procedure proposed the adaptive filters are said to posses the ability of self-learning. This property is very useful in reducing the noise of a host signal; with every iteration the error is minimized [10–17].

The filter scheme presented relies on gradient-based approaches like LMS and RMS schemes [14]. In past few years, evolutionary schemes like MPSO, PSO, CS, MCS and ABC, ABC-MR were used for selection of most favourable filter parameter values for intelligent reconstruction of one-dimensional signal [14]. Hence, in the presented paper MPSO and gradient relying approaches are used for designing the ANC filter.

The flow diagram of 2D-ANC filter based on MPSO is displayed in Fig. 1. The noisy MRI brain image ($d(i, j)$) involves the pure image ($x(i, j)$) and noise ($v(i, j)$). In case of MRI brain image, $v(i, j$ consists of Gaussian disturbance. These types of disturbances are additive and posses very less correlation with ($x(i, j)$). In the presented work, $d(i, j)$ is input from data base of MIT-BIH [18]. In Fig. 1, $v_1(i, j)$ is the disturbances generated using MATLAB. It is observed that the $v_1(i, j)$ is correlated with $v(i, j)$ but have very less correlation with ($x(i, j)$). The $v_1(i, j)$ is standard noise disturbance (input) of linear FIR model in two-dimensional spaces, which is clearly defined in lattice space

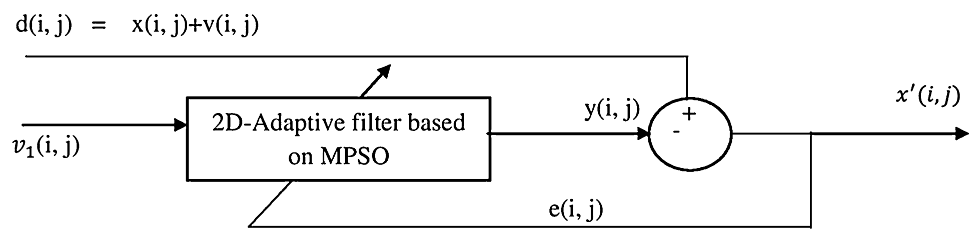

Fig. 1 A obstruct figure of 2D ANC filter with MPSO technique

of regular interval (i, j) ε $[N_1, N_2]$, where N_1 and N_2 represent order of input. The outcome of the FIR digital filter in two-dimensional spaces is given as below:

$$y(i,j) = \sum_{t=o}^{M_1}\sum_{l=0}^{M_2}\alpha(t,l)x(i-t,j-l) \quad (1)$$

where $x(i, j)$ is the reference signal, $\alpha(t, l)$ is coefficients of the model, and M_1 and M_2 represent order of FIR filter. Typically, the two-dimensional spaces signal is represented in the form of matrix. Therefore, the weight matrix $\alpha(i, j)$ and the input matrix $x(i, j)$ are introduced as

$$\alpha_k(i,j) = \begin{bmatrix} \alpha(0,0) & \ldots & .. & \alpha(0,M_2-1) \\ \alpha(1,0) & \ldots & \ldots & \alpha(1,M_2-1) \\ . & . & . & . \\ \alpha(M_1-1,0) & \ldots & \ldots & \alpha(M_1-1,M_2-1) \end{bmatrix} \quad (2)$$

$$x_k(i,j) = \begin{bmatrix} x(i,j) & \ldots & .. & x(i,j-M_2+1) \\ \cdots & \cdots & \cdots & \ldots.. \\ . & . & . & . \\ x(i-M_1+1,j) & \ldots & \ldots & x(i-M_1+1,j-M_2+1) \end{bmatrix} \quad (3)$$

where k is number of iterations and $0 \le k \le N_1N_2$. Hadhoud expressed in [5] that the weight matrix and the host matrix can be mapped into one-dimensional structure by lexicographic ordering. Equations (4) and (5) present the one-dimensional form of Eqs. (2) and (3).

$$\alpha_k(i,j) = [\alpha(0,0)\ldots..\alpha(0,M_2-1)\alpha(1,0)\ldots\alpha(M_1-1,M_2-1)]^T \quad (4)$$

$$x_k(i,j) = [x(i,j)\ldots..x(i,j-M_2+1)x(i-1,0)\ldots x(i-M_1+1,j-M_2+1)]^T \quad (5)$$

Both vectors $x(i, j)$ and $\alpha(i, j)$ have dimensions $(M_1M_2) \times 1$. From Eqs. (4) and (5), Eq. (1) can be stated as

$$y_k(i,j) = \alpha_k^T(i,j)x_k(i,j) \quad (6)$$

The error signal $(e(i, j))$ is computed as the difference of $d(i, j)$ and $y(i, j)$. This in turn is input to the ANC filter in every loop run. The iteration continues until $e(i, j)$ noise is minimum. The final outcome $(x'(i, j))$ is almost equivalent to $x(i, j)$. The cost function for $e(i, j)$ is defined as:

$$\xi_k(i,j) = E\left[e_k^2(i,j)\right] \quad (7)$$

where $e_k(i, j)$ is the error signal at the kth iteration and is given by

$$e_k(i,j) = d_k(i,j) - \alpha_k^T(i,j)x_k(i,j) \quad (8)$$

where $d_k(i, j)$ is the desired signal. The aim of 2D-LMS scheme is to obtained the most favourable weight matrix so that the cost function, $\xi_k(i, j)$, is minimum. To solve non-linear Eq. 7, the MPSO technique can be used. This scheme starts with initialization of arbitrary swarm having population M and R unidentified parameters whose most favourable values are to be calculated. This scheme remembers and in a sequential pattern substitutes the most favourable position parameter of every individual particle (p_{best}, $i = 1, 2, \ldots, M$) along with the group velocity parameter (g_{best}). The traditional PSO schemes encounter several obstacles when the population size is large. In order to avoid these conditions, PSO is modified by bringing a new parameter in the equation known as the inertia weight (w). In MPSO, the velocity $(v_{ij}(n+1))$ and position $(v_{ij}(n+1))$ of each particle are modified in accordance with the following eq:

$$v_{ij}(n+1) = w \times v_{ij}(n) + c_1 \times r(0,1) \times \left(g_{\text{best}} - p_{ij}(n)\right) + c_2 \times r(0,1) \times \left(p_{\text{best}_{ij}} - p_{ij}(n)\right) \quad (9)$$

$$p_{ij}(n+1) = p_{ij}(n) + v_{ij}(n+1) \quad (10)$$

where $v_{ij}(n)$ represent velocity vector at nth loop count, $r(0, 1)$ represent vector of arbitrary values in range of (0, 1), and c_1, c_2 represent coefficients of acceleration in the direction of g_{best} and p_{best}, respectively. The location improvisation is carried out at the scenario when current location $p(n + 1)$ has better performance than previous location $p(n)$. The PSO technique is used to minimize the objective function (Eq. 7) which provides the coefficients ($h(n)$, $n = 1, 2,\ldots, m$) of optimum 2D-ANC-MPSO. In this process, the main objective is to evaluate the p_{best} and g_{best} for each particle and update their values in every iteration. The iteration ends when the fitness function $((\varphi_1))$ given below becomes less than a pre-specified tolerance value ($\varepsilon_p = 0.1$).

$$\varphi_1 = \min(\xi_k) \tag{11}$$

where K is the initial input of MPSO. It may be noted that exploration and exploitation are two main characteristics of MPSO. Exploration shows how more search area can be covered by the technique for better performance, whereas exploitation indicates accurate convergence to a particular point. These characteristics depend upon the w parameter. A higher value of w gives more exploration, while exploitation is better for lower value of w. Therefore, w is a critical parameter which must be updated carefully. Initially, the w is assigned a high value which is lowered as iteration goes towards the end. The implementation steps of MPSO are as follows:

Step 1 Start with the initialization of position and velocity for every particle of the population.
Step 2 Evaluate the fitness value $((\varphi_1))$ of every individual point of the population using Eq. 11.
Step 3 Evaluate the point with largest fitness value and reset its position to obtain lowest fitness value. If lowest fitness value is acceptable, then update the position otherwise assign new random value to the particle according to Eqs. 9 and 10 for position and velocity.
Step 4 For every point, perform comparison of the fitness value with p_{best} and update the value only if it is superior than the p_{best}.
Step 5 Evaluate the best point in accordance with its fitness value and update if it is superior than g_{best}.
Step 6 Perform the check for final criterion, if satisfied stop the loop, otherwise repeat from step 3.

From Eqs. 9 and 10, it is clear that w is an important parameter affecting the velocity and position of each particle in PSO. Depending on selection of w, the PSO technique is classified into different categories. In Constant Weight Inertia (CWI) PSO, the w is kept constant between 0 and 1 for each particle and at any time instant, the inertia weight (w_t) is given by:

$$w_t = c \tag{12}$$

However, a constant value of w_t may not lead to optimum exploitation and exploration in the simulation process for various signals. Therefore, for better performance of MPSO, adaptability in w_t is required. In case of Dynamic Inertia (DI) MPSO [11], the w_t is updated in each iteration as:

$$W_t = 0.5 + \frac{\text{Rand}(\cdot)_t}{2} \tag{13}$$

where $\text{Rand}(.)_t$ is the random function that generates numbers uniformly distributed between 0 and 1. Since new w_t obtained in each iteration has no relation with the previous value, there is difficult to choose the random value to achieve better exploitation and exploration. To overcome this, a linear decay inertia (LDI) MPSO is used in which w_t is updated in each iteration linearly between maximum and minimum values. The iteration process starts with maximum value of w_t and decremented as the iteration progresses. For LDI MPSO, the w_t after each iteration is written as:

$$W_t = w_{\max} - \frac{(w_{\max} - w_{\min}) \times t}{t_{\max}} \tag{14}$$

where $w_{\min}$ and $w_{\max}$ are the minimum and maximum values of w_t, respectively, and $t_{\max}$ denotes the maximum time of iterations. Although LDI MPSO provides better results for exploitation, exploration is not optimized as per requirement. For improving exploration, the nonlinear inertia (NLI) MPSO is used in which Eq. 9 is modified by introducing nonlinearity as:

$$W_t = w_{\max} - \frac{(w_{\max} - w_{\min}) \times (t_{\max} - t)^n}{t_{\max}^n} \tag{15}$$

where n is the nonlinear modulation index.

Table 1 represents the computation difficulty of 2D adaptive schemes which were established in this paper. It is clearly observed that the computation difficulty of 2D ANC PSO is less than conventional 2D NLMS and 2D NLMS algorithms

Simulations and Results

The performance of 2D adaptive noise filter is designed with MPSO evaluated on brain image corrupted with 10 dB noise as discussed in [16]. In this work, the reference noise is considered as the Gaussian noise as generated from MATLAB software. The fidelity parameters such as output signal-to-noise ratio (SNR), normalized root-mean-square error (NRMSE), and normalized root maximum error (NRME) are calculated by different input SNR. These fidelity parameters are calculated using following equations [8]:

$$\text{Input SNR}_{\text{dB}} = 10\log_{10}\frac{\left(x_{\text{pure}}(i,j)\right)^2}{\left(d_{\text{noisy}}(i,j) - x_{\text{pure}}(i,j)\right)^2} \tag{16}$$

$$\text{Ouput SNR}_{\text{dB}} = 10\log_{10}\frac{\left(x_{\text{pure}}(i,j)\right)^2}{\left(x'_{\text{filtered}}(i,j) - x_{\text{pure}}(i,j)\right)^2} \tag{17}$$

$$\text{NRMSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(x'_{\text{filtered}}(i,j) - x_{\text{pure}}(i,j)\right)^2}{\sum_{i=1}^{N}\left(x_{\text{pure}}(i,j)\right)^2} \times 100} \tag{18}$$

Table 1 Computation difficulty of various algorithms

Techniques	Product operation	Add operation
2D-ANC(LMS) [13]	$3M_1M_2 + 1$	$(M_1 + 3)(M_2 + 5) + M_1M_2$
2D-ANC(NLMS)	$2M_1M_2 + 1$	$(M_1 + 3)(M_2 + 5) + 8$
2D-ANC (PSO)	$M_1M_2 + 1$	$M_1 + M_2 + 1$

$$\mathrm{NRME} = \sqrt{\frac{\mathrm{abs}\left(x'_{\mathrm{filtered}}(i,j) - x_{\mathrm{pure}}(i,j)\right)}{\mathrm{abs}\left(x_{\mathrm{pure}}(i,j)\right)}} \times 100 \tag{19}$$

In response to the noise brain image, the enhanced image of 2D ANC output using LMS, NLMS, and MPSO schemes is represented in Fig. 2. The image sources of Fig. 2a represent the corrupted brain-axial image, Fig. 2b represents the enhanced brain-axial image based on 2D ANC VSS NLMS, Fig. 2c represents the enhanced brain-axial image based on 2D ANC MPSO, Fig. 2d represents the corrupted brain-web image, Fig. 2e represents the enhanced brain-axial image based on 2D VSS NLMS, Fig. 2f represents the enhanced brain-axial image based on 2D ANC MPSO, Fig. 2g represents the corrupted brain-nerve image, Fig. 2h represents the enhanced brain-nerve image based on 2D VSS NLMS, and Fig. 2i represents the enhanced brain-nerve image based on 2D ANC MPSO. It is can be seen that the 2D ANC filter with MPSO technique improved the quality of brain image. This means brain image information can be more accurately detected using 2D ANC MPSO technique. Figure 3 compares the variation of output SNR with input SNR for four different algorithms. As observed, the output SNR performance of 2D ANC MPSO technique is better as compared to that of 2D ANC VSS LMS and 2D ANC SM NLMS algorithms. The proposed 2D ANC MPSO technique gives nearly 6 dB improvement in average output SNR in comparison with recently reported 2D-ANC VSS NLMS technique [14]. Figure 4 illustrates the changes of NRMSE as a function of different input SNR for 2D adaptive filter based on four various schemes. As observed, the NRMSE of 2D adaptive filter using MPSO technique is much lower as in comparison with other algorithms. Typically, the 2D ANC MPSO algorithm achieves 85% reduction in average NRMSE as compared to the 2D ANC VSS NLMS algorithm. Figure 5 represents NRME of output MRI brain image for various levels of input SNR. 2D adaptive filter with MPSO technique provides considerable decrease in NRME as compared to other algorithms for all values of input SNR. The average NRME of filtered brain image with MPSO algorithm is found to be 90% lower in comparison with 2D ANC VSS NLMS technique. The performance fidelity parameters of proposed 2D ANC filter using MPSO technique are also compared with other reported 2D ANC VSS

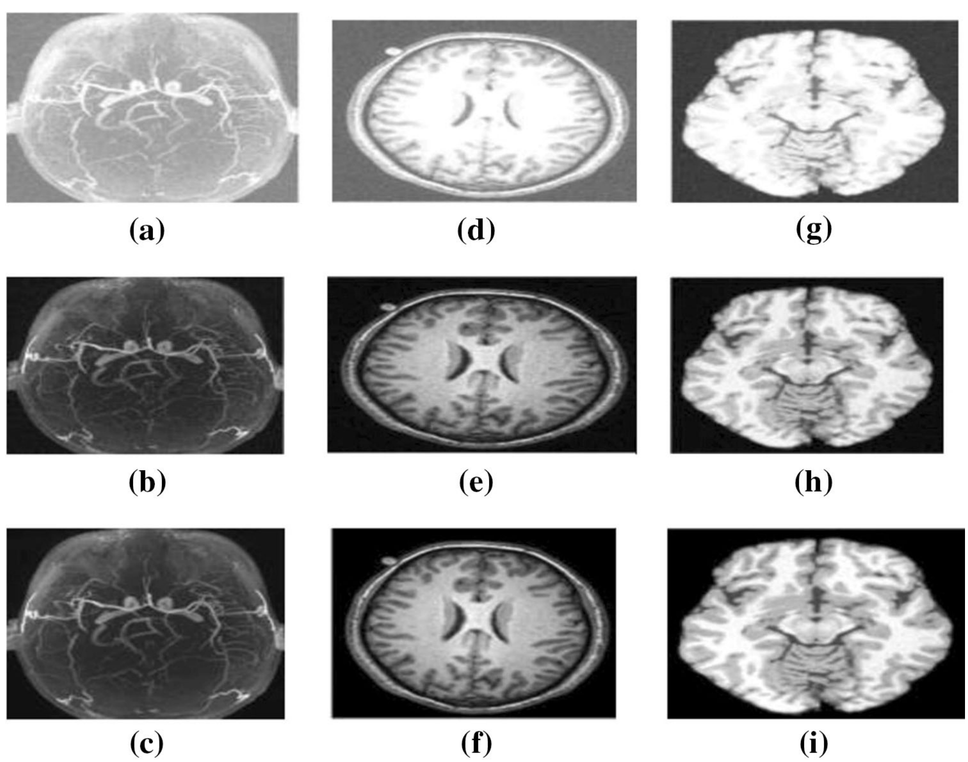

Fig. 2 **a** The corrupted brain-axial image. **b** The enhanced brain-axial image based on 2D ANC VSS NLMS. **c** The enhanced brain-axial image based on 2D ANC MPSO. **d** The corrupted brain-web image. **e** The enhanced brain-axial image based on 2D VSS NLMS. **f** The enhanced brain-axial image based on 2D ANC MPSO. **g** The corrupted brain-nerve image and **h** The enhanced brain-nerve image based on 2D VSS NLMS. **i** The enhanced brain-nerve image based on 2D ANC MPSO

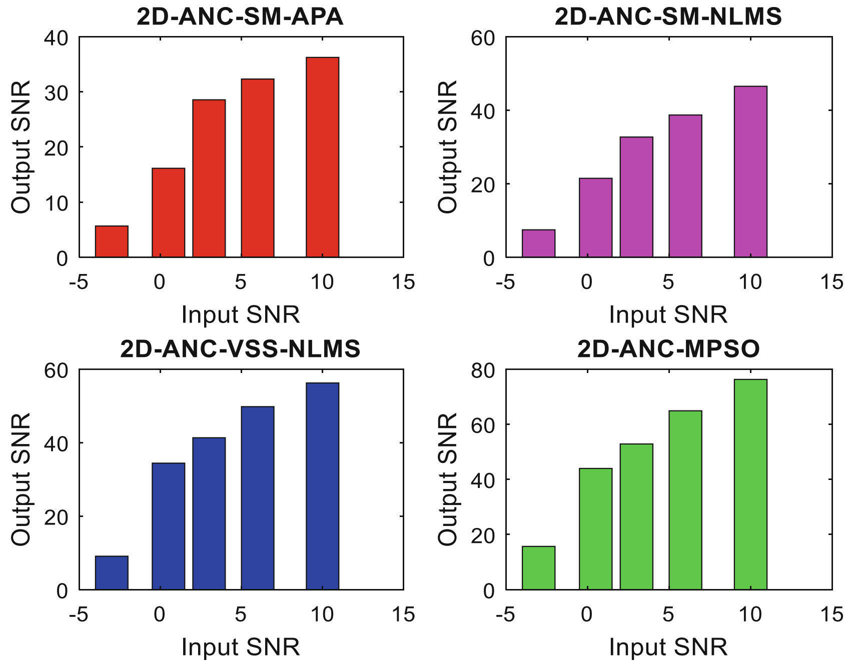

Fig. 3 SNR comparison of the 2D-ANC filter using MPSO, VSS NLMS, SM NLMS and SM APA algorithms

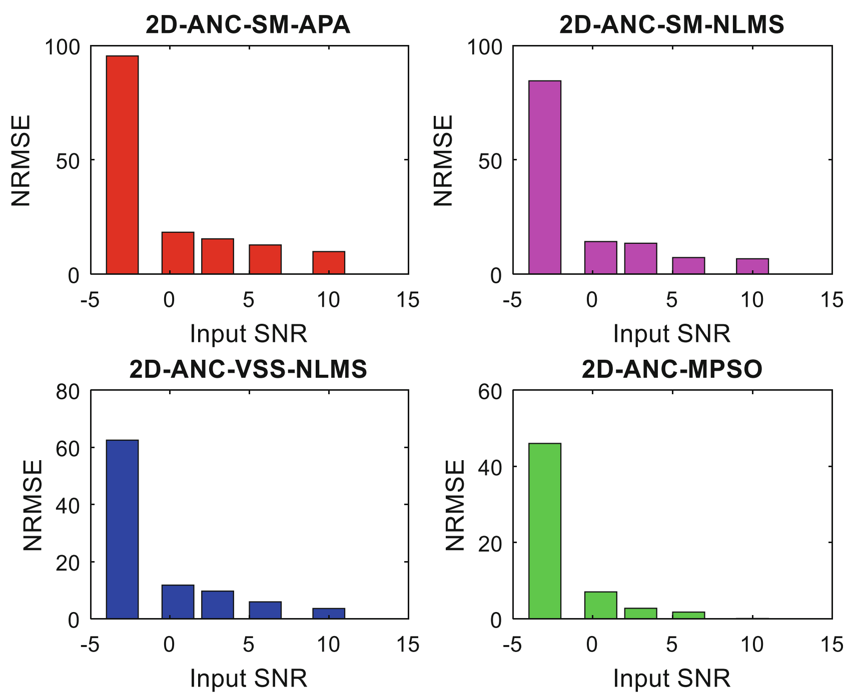

Fig. 4 Change of NRME with different input SNR for the 2D ANC filter using SM APA, SM NLMS, VSS NLMS and MPSO algorithms

NLMS, 2D ANC SM NLMS technique applied on MRI brain image. Table 2 gives the output SNR for different values of input SNR for various techniques. The simulation results given in Table 3 clearly indicate that the output SNR with 2D ANC filter based on MPSO technique is much higher as compared to other techniques for all values of input SNR. The NRMSE and NRME of filtered brain image are given in Tables 4 and 5, respectively, for different techniques.

It is observed that 2D ANC filter with MPSO technique provides much lower value of both NRMSE and NRME in comparison with other reported algorithms. For the testing of adaptation time, the square error of 2D adaptive filters is analysed with mean and standard deviation. Table 5 lists the mean and standard deviation (SD) of various schemes along with CPU time. The MPSO-based 2D adaptive filters are having smallest mean, SD and computation difficulty.

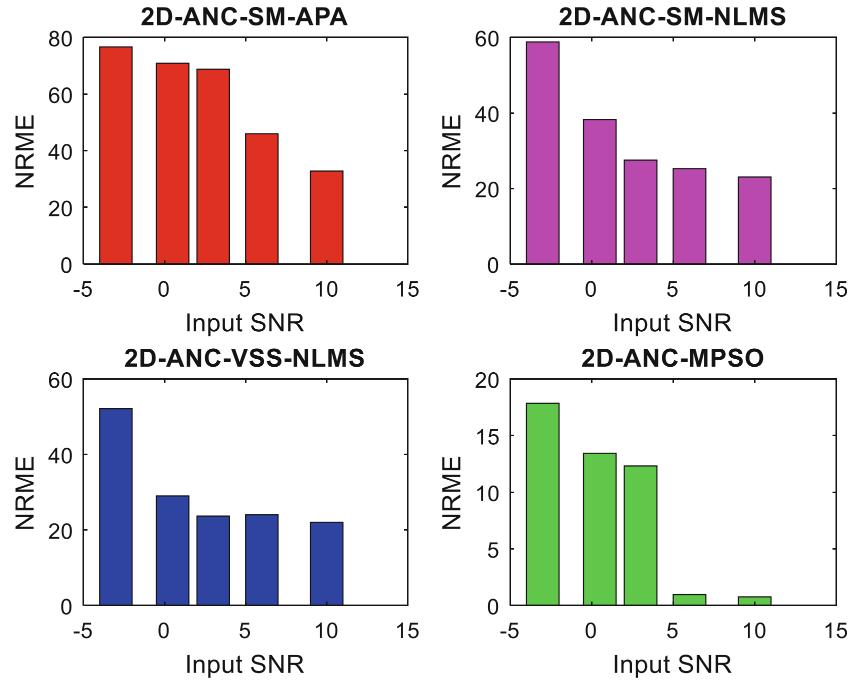

Fig. 5 Change of NRMSE with different input SNR for the 2D ANC filter using SM APA, SM NLMS, VSS NLMS and MPSO algorithms

Table 2 SNR comparison of different schemes on MRI image

SNR_{in} (dB)	SNR_{out} (dB)			
	2D SM APA	2D SM NLMS	2D VSS NLMS	2D ANC MPSO
− 3.0	5.65	7.44	9.09	15.67
0.5	16.12	21.45	34.41	43.96
3.0	28.54	32.69	41.32	52.84
6.0	32.31	38.68	49.78	64.87
10	36.23	46.49	56.23	76.25

Table 3 NRMSE performance of MRI image for different schemes

SNR_{in} (dB)	NRMSE ($\times 10^{-4}$)			
	2D SM APA	2D SM NLMS	2D VSS NLMS	2D ANC MPSO
− 3.0	95.43	84.54	62.51	46.02
0.5	18.32	14.24	11.78	7.06
3.0	15.43	13.50	9.69	2.76
6.0	12.76	7.25	5.93	1.76
10	9.86	6.72	3.61	0.08

Table 4 NRME performance of various schemes

SNR_{in} (dB)	NRME ($\times 10^{-3}$)			
	2D SM APA	2D SM NLMS	2D VSS NLMS	2D ANC MPSO
− 3.0	76.64	58.80	52.10	17.86
0.5	70.87	38.26	29.02	13.44
3.0	68.76	27.50	23.69	12.32
6.0	45.98	25.25	24.03	0.96
10	32.80	23.02	22.01	0.76

Table 5 Mean, SD and CPU time of adaptive filters

Parameter	2D SM APA	2D SM NLMS	2D VSS NLMS	2D ANC MPSO
Mean	2.78	3.76	2.98	1.34
SD	38.67	26.56	22.54	16.21
CPU time (s)	2.43	1.897	0.651	0.084

Conclusion

An efficient 2D adaptive filter using MPSO technique has been developed for enhancing the MRI image. A performance comparison of proposed 2D adaptive filter using MPSO technique has been carried out with other reported techniques. The simulation results demonstrate that significant improvement in SNR, NRMSE, NRME, and coherence factor can be achieved from proposed 2D adaptive filter design when compared with, 2D VSS NLMS, 2D SM NLMS and 2D SM APA algorithms. Moreover, the 2D adaptive filter based on MPSO scheme requires lesser computation time. Therefore, the 2D adaptive filter with MPSO algorithm is a most efficient approach for de-noising the MRI image.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Human and Animal Rights Authors used the data available in [18] for their study and did not collect data from any human participant or animal.

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