Adaptive comprehensive particle swarm optimisation-based functional-link neural network filter model for denoising ultrasound images

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Abstract
Multiplicative speckle is a dominant type of noise that spoils the inherent features of the medical ultrasound (US) images. Apart from the speckle, impulse and Gaussian noises also appear in the US image due to the error encountered during the data transmission and transition of switching circuits and sensors. The noise not only deteriorates the visual quality of the US but also creates complications in the diagnosis. In this study, an adaptive comprehensive particle swarm optimisation-based functional-link neural network (ACPSO-FLNN) filter has been proposed and implemented in filtering noisy US images in different noise conditions. The proposed filter is compared with some state-of-the-art filtering techniques. Quantitative and qualitative measures such as training time, time complexity, convergence rate, and statistical test are included to study the performance of the proposed filter. Furthermore, sensitivity, computational complexity, and order of the proposed filter are also investigated. Friedman’s test with 50 images is performed for statistical validation. The lower rank, that is, 6 and critical value of $21 \times 10^{-4}$ of the proposed ACPSO-FLNN filter validates its dominance over other filters.

1 | INTRODUCTION

Medical imaging has emerged as one of the indispensable non-invasive processes of creating visual information of the internal body parts suitable for further clinical analysis and decision-making. Developments in image acquisition hardware technology and computing algorithms have helped a lot to avail the amazing visuals of internal organs. However, noise may get added to the image at the time of the acquisition, storing and transmission. It may be generated from switching circuits and heating of electronic components as well as sensors. In such a scenario, denoising is essential. Most of the conventional denoising filters are noise-specific. Intelligent filters can identify as well as remove any kind of noise from the medical images. Ultrasound (US) imaging is one of the modern non-hazardous medical imaging modalities. It is relatively more inexpensive, portable and free from ionic radiation than the other medical imaging modalities, such as X-ray or computed tomography (CT) [1]. It provides good quality real-time images of the soft tissues, such as tumour, foetus, muscles and arteries. In US imaging, the acoustic echoes reflected from the tissues or organs are captured by the transducer and transformed into electrical signals. The information regarding the amplitude and time taken by the acoustic echoes to travel through the organs is utilised to form the image.

The most prominent noise in US imaging is speckle noise. It introduces granular patches and consequently annoying appearances of images [2]. Similarly, impulse and Gaussian noises also deteriorate the quality of US images. Impulse and Gaussian noises are generated because of the error encountered during the data transmission and imitations of the switching circuits and sensors. Processes like characterisation and measurement of...
noise are tedious tasks. Choosing an appropriate filter is a challenge for a radiologist. Inappropriate selection of the filter may suppress diagnostically significant features in the US images.

There are many linear spatial filters that are used to eliminate noise from medical images. These filters require prior knowledge of the noise characteristics for the filtering process to be effective. The major drawback is that they are effective only for a specific noise type. In a real-time scenario, noise in images is mixed and sometimes not separable. To get rid of the mixed noise, the filter should be self-adaptive to the noise characteristics. The Wiener filter is an example of such an adaptive filter. It has a demerit that it considerably blurs the edges. Moreover, it is computationally extensive as compared to some of the other competitive filters [3, 4]. To overcome the constraints of the Wiener filter, non-linear neural network (NN) filters were proposed [5–7], but their performance depends upon the training algorithm. The training algorithm is intended to determine the optimum weights and other system parameters of the NN. Most of the time, combinations of gradient-based algorithms and evolutionary techniques are used as training algorithms [8]. Though the gradient-based algorithms quickly converge to the optimal solution, they fail when the cost functions are quite flat and highly random [9]. Moreover, if the cost function becomes discontinuous or multimodal, then the difficulty is enhanced manifold. To overcome these hurdles, evolutionary techniques, such as genetic algorithm (GA), particle swarm optimisation (PSO), cat swarm optimisation and so forth have been used. Such algorithms search and find the optimum value from the random population. These techniques are different from derivative-based approaches and are suitably applied in different optimisation problems [10, 11].

Researchers have successfully applied derivative-free learning-based NN filters for eliminating the noise from images [12–14]. Among these filters, the heuristic-based NN filter models are noticed to be quite effective. Among these heuristic algorithms, the PSO is relatively easier in implementation and computationally effective with reduced memory requirement as compared to GA [15]. PSO is a popular algorithm helpful to optimise the learning process in artificial NN (ANN) [16–19]. Apart from that, PSO is successfully utilised in various optimisation as well as engineering problems [20–24]. In [25], functional-link NN (FLNN) filter has been employed for removing noise from X-ray images. The gradient descent least mean squares (LMS) and conventional PSO techniques to update the weights were used in this approach. Marginal enhancement in peak signal-to-noise ratio (PSNR) was noticed in the PSO-based NN filter as compared to the LMS-based NN filter. Slow tuning and trapping at local minima are the major shortcomings in the conventional PSO. Arumugam and Rao have recommended various modified versions of the PSO that not only avoid the above-mentioned problems but also help in fixing the optimised values of the controlling parameters. Such modifications improve the efficiency and convergence speed of the PSO [26].

In this study, an improved version of the PSO is proposed and named as adaptive comprehensive PSO (ACPSO). In this technique, two of the controlling parameters of PSO, that is, inertia and the acceleration constant are adaptive. In the conventional PSO, both local and global best position values are required for updating the velocity. However, in the ACPSO, the velocity of the particle depends only on the global best position. To the best of the authors’ knowledge, ACPSO optimisation for updating the weights of the FLNN filter used for suppressing the noise in the US images has not been reported in the literature yet. The main contributions of this study are outlined as follows:

1. An effortless FLNN model is implemented for designing the filtering network, and in the place of the conventional PSO, the ACPSO is utilised for updating the weight of the NNs. Thus, the proposed NN filter is named as ACPSO-FLNN.
2. In this study, the controlling parameters of the proposed ACPSO, that is, inertia and the acceleration constant are adaptive, and in each iteration, these are acclimatised completely in an automated way.
3. The US image data were collected from Medanta hospital, Ranchi, India, for utilisation on experimentation purposes only.
4. The developed filter is applicable in different noise conditions and in suppressing dominant speckle as well as mixed noise of US images. The proposed filtering parameters can be learned offline, and after achieving the optimum value, it can be applied to any other noisy images having different noise characteristics for online noise suppression.

The layout of the study is as follows: Section 2 describes the related study in the field of image denoising using the NN filter and optimisation techniques. The methodology for designing the ACPSO-FLNN filter is discussed in Section 3. The experimental results of the qualitative and quantitative analysis are presented in Section 4. Finally, the conclusion of this study is given in Section 5.

2 RELATED WORK

This section presents the recent developments in FLNN network that have been carried out for denoising purpose, which plays a vital role in many subsequent applications. Some of the related research studies are discussed and analysed below to highlight the significance of the proposed technique. In recent years, several ANN techniques have been reported for various signal and image processing as well as engineering applications [27–29]. These methods are mainly employed in different image processing tasks such as image denoising, restoration, deblurring, and inpainting [30–34]. In the beginning, the feed-forward multilayer perceptron (MLP) network is utilised mostly to get rid of the noise. However, the MLP has more than one hidden
layer, and the selection of these layers is quite intuitive. It also takes additional time in training, and due to its complicated structure, programming complexity increases [35, 36]. FLNN is first introduced by Pao to eradicate the constraint of the multilayer network [37]. The FLNN is a novel single-layer network and introduces non-linearity through various functionally expanded inputs. This network can form subjectively complex decision regions and provide quality results in comparison with the feed-forward network. Behera et al. have developed a non-linear active noise canceller using FLNN to get rid of different noises [38]. Similarly, authors in [39] have applied the same NN to control noise from acoustic signals. They used LMS as a learning algorithm for the training. Similarly, other gradient techniques such as leaky LMS, normalised LMS, mean squares error (MSE), recursive least squares, backpropagation (BP) and so forth can also be applied for the training. Currently, evolutionary and nature-inspired optimisation techniques are attracting the attention of researchers because of their ability to work in a dynamic or non-linear environment. Bhumireddy et al. have recommended GA as a learning algorithm for the training of FLNN and radial basis functions (RBF) network [40]. Isiet and Gadala have discussed several types of PSO and specifically highlighted such PSO techniques which are self-adapting in [41]. Roy et al. applied the PSO, NN and fuzzy logic in solving the forecasting problem [42]. Kumar et al. used the heuristic learning-based simple neural filter model that suppress the Gaussian and impulse noises from the CT images [43]. Similarly, Kumar and Mishra have presented a comprehensive review of the nature-inspired NN-based adaptive filter for eliminating noise from the various medical images [44]. Qiao et al. presented an adaptive PSO (APSO)-based NN model and applied it in the prediction task [45]. Ben and Zhang demonstrate a PSO-based convolutional NN model for the classification of images [46]. Kumar and Mishra have applied parameterless heuristic techniques like teaching learning-based optimisation and Jaya for the training of the NN filters and successfully suppressed the dominant noise of magnetic resonance image (MRI) and US images [47, 48]. Duan and Wang have introduced image filter based upon NN with pigeon-inspired optimisation, which is efficiently applied for restoring several images [49]. Likewise, another heuristic algorithm, that is, bat optimisation-based NN model is developed for the enhancement of MRI images [50]. Therefore, the above-mentioned research studies inspired us to work in the area of US images since this technology is almost available everywhere in developing and underdeveloped countries. Also, we are trying to eliminate different noises from the US image which appear due to known or unknown sources. An advanced deep-learning network like convolutional neural network (CNN) is applied to develop an image filter in [51, 52]. Twenty convolutional layers and a regression layer are used to design the denoised CNN (DnCNN) filter in [53]. Similarly, some of the recently proposed state-of-the-art filtering approaches such as speckle-reducing bilateral filter (SRBF) [54], non-local means-based speckle filter (NLM-SF) [55] and low-rank matrix-approximation despeckling filter (LMDF) [56] are also considered to be effective for denoising purpose.

The proposed methodology is discussed in the next section.

### 3 | PROPOSED APPROACH

#### 3.1 | ACPSO

PSO, a member of the family of nature-inspired algorithms was introduced by Eberhart and Kennedy in 1995. They mathematically modelled it by observing the behaviour of bird flocking and fish schooling [57]. The PSO is one of the well-adopted heuristic techniques which can solve optimisation problems and can be applied in many industrial applications [58, 59]. In this approach of optimisation, swarms are considered as particles, and their position is termed as the potential solution of some associated objective function. The velocity as well as the direction of each particle roaming alongside each dimension of the problem space will be updated along with the upcoming succeeding movement. PSO velocity and position rule for updating the *p*th particle at the *t*th generation are given below:

\[
\text{Velocity} : v(t) = v(t-1) + c_1 \times r_1 \times (p_{best} - x(t)) + c_2 \times r_2 \times (g_{best} - x(t))
\]

\[
\text{Position} : x(t) = x(t-1) + v(t)
\]

where, \(c_1, c_2\) are cognitive and social learning factors that attract the particle toward its own success, that is, local best ‘\(p_{best}\)’ as well as the swarm’s best ‘\(g_{best}\)’. Similarly, \(r_1, r_2\) are the random values, and these two values range between 0 and 1. The selection of these parameters is very crucial for algorithm efficiency, speed and convergence. Another controlling parameter, that is, \(\beta\) was introduced and initially a value was fixed to a certain constant point, that is, 0.8 by researchers. Also, from various empirical experiments, it was observed that the inertia linearly varies between 0.9 and 0.4, and due to such adaptation execution, the efficiency of the algorithm significantly improved [60]. The larger value of inertia facilitates global exploration and the smaller value provides efficient local search. Similarly, in APSO [26], neither can \(\epsilon\) and \(\beta\) be fixed to a constant nor linearly decrease. Controlling the parameters’ values depends upon the global and local search of the particles. Hence, it helps to reduce the burden of finding the optimal values of the cognitive factors and inertia. The APSO is mathematically expressed in Equations (3) and (4) as

\[
\text{velocity} : v(t) = \beta \times v(t-1) + \epsilon \times r_1 \times (p_{best} - x(t)) + \epsilon \times r_2 \times (g_{best} - x(t))
\]

\[
\text{Position} : x(t) = x(t-1) + v(t)
\]

where \(\beta = (1.1 - \frac{g_{best}}{g_{best\_average}})\) and \(\epsilon = (1 + \frac{g_{best}}{p_{best}})\).

In APSO, \(\beta\) becomes minimum when \(g_{best}\) is equal to \(g_{best\_average}\) and the acceleration constant \(\epsilon\) will be around 2 when
$\hat{g}_{best}$ is equal to $g_{best}$. It allows the particles to search near the global optima, and these parameters provide better performance than the conventional PSO. However, at the same time, the programming complexity of APSO is increased compared to the conventional PSO because of more number of controlling parameters. Liang et al. have shown the potential of the comprehensive learning PSO to avoid premature convergence and discussed another variant of PSO in which the solution is majorly depended only upon the global best particle [61]. Hence, a research initiative of [61] inspired us to develop a hybrid heuristic technique for this study, and it is named as ACPSO. This technique not only reduces the programming complexity but also minimises the premature convergence because the momentum of the search is majorly depended on the global best position, $g_{best}$. It is not only simple in design but also the selection of all the algorithmic parameters is performed at a fully automated level since it reduces the burden of finding the local best solution for updating the velocity of the particle in Equation (5). The controlling parameters such as acceleration constant and inertia are iteratively fixed on the $\hat{g}_{best}$, $\bar{g}_{best}$, and (gi) average values. The ACPSO is mathematically modelled as

\[
\text{velocity : } v^i(t) = \beta \times v^i(t-1) + \epsilon \times r \times (\hat{g}_{best} - x^i) \tag{5}
\]

\[
\text{position : } x^i(t) = x^i(t-1) + v^i(t) \tag{6}
\]

where $\beta = (1.1 - \frac{\hat{g}_{best}}{\bar{g}_{best}})$ and $\epsilon = (1 + \frac{\hat{g}_{best}}{gi})$

### 3.2 Proposed ACPSO-FLNN Filter

In the proposed ACPSO-FLNN filter, overlapping kernels with a contextual pixel and its eight-connected pixels of the noisy image are considered as an input. These pixel intensities are expanded exponentially and given as

\[
T_i = \{x_i, e^{2x_i}, \ldots, e^{(P-1)x_i}\} \tag{7}
\]

where $i = 1, 2, 3, \ldots, (2K+1)^2$, $K = \{-1, 0, 1\}$

For an eight-connected neighborhood of the size $3 \times 3$, $P$ is an arbitrarily defined constant that determines the length of the exponential series in Equation (7).

Given, $X = \{x_1, x_2, \ldots, x_i, \ldots, x_{(2K+1)^2}\} | x_i \in X$ \tag{8}

The total set of expanded pixel intensities in the block can be represented as

\[
T = \{T_1, T_2, \ldots, T_{(2K+1)^2}\} \tag{9}
\]

The expanded intensities are non-linearly weighted using a set of random weights. The corresponding set of weights at the $j$th iteration is

\[
W^j = \{w_1, w_2, \ldots, w_{L}\} \tag{10}
\]

where $L$ is the total of the weights given by, $L = (2K + 1)^2 P$ (7) and Equation (8) implies

\[
T = \left\{x_1, e^{x_1}, e^{2x_1}, \ldots, e^{(p-1)x_1}, \ldots, x_{(2K+1)^2}, e^{(2K+1)x_1}, \ldots, e^{(2K+1)^2}\right\} \tag{11}
\]

The set of weights $W$ and the expanded series of input $T$ contain $L$ terms such that

\[
T = \{t_1, t_2, \ldots, t_L\}, T_i = \{t_1, t_2, \ldots, t_P\}
\]

and

\[
T_2 = \{t_{p+1}, t_{p+2}, \ldots, t_{2P}\}, \ldots
\]

Similarly $W = \{w_1, w_2, \ldots, w_L\}$

The restored intensity value is

\[
\hat{y}(m, n) = \varphi \left( \sum_{q=1}^{L} \frac{1}{t_q} w_q \right) \tag{14}
\]

The estimated error will be

\[
\hat{e}(m, n) = \hat{y}(m, n) - y_R(m, n) \tag{15}
\]

\[
\hat{e} = \frac{1}{(M-1)(N-1)} \sum_{a=1}^{M-1} \sum_{b=1}^{N-1} \hat{e}(m, n) - y_R(m, n) \tag{16}
\]

where $y_R(m, n)$ is the reference image and the structure of the proposed filter is depicted in Figure 1, and Figure 2 presents the noisy image kernel as ACPSO-FLNN filter inputs where $y_R(m, n)$ is the desired intensity which is the contextual pixel of the reference image kernel. Here, the reference image is the noise-free US image. Similarly, $\varphi$ is the activation function of the FLNN network. At the $(t+1)$th iteration, the set of weights are updated using PSO. In ACPSO, initially $S$ numbers of the normalised set of random velocities and set of normalised positions are generated, and the position in the first iteration at $j = 1$ is shown in Equation (17).

\[
P_j = \{P_{j1}, P_{j2}, P_{j3}, \ldots, P_{jL}\}; \tag{17}
\]

\[
V_j = \{V_{j1}, V_{j2}, V_{j3}, \ldots, V_{jL}\}\]
FIGURE 1  Structure of adaptive comprehensive particle swarm optimisation (ACPSO)-based functional-link neural network (FLNN) filter network

\[ P(j) = \begin{bmatrix}
p_{11} & p_{12} & \cdots & p_{1L} \\
p_{21} & p_{22} & \cdots & p_{2L} \\
\vdots & \vdots & \ddots & \vdots \\
p_{l1} & p_{l2} & \cdots & p_{lL}
\end{bmatrix}; \]

\[ V(j) = \begin{bmatrix}
v_{11} & v_{12} & \cdots & v_{1L} \\
v_{21} & v_{22} & \cdots & v_{2L} \\
\vdots & \vdots & \ddots & \vdots \\
v_{l1} & v_{l2} & \cdots & v_{lL}
\end{bmatrix} \]

Here, the length of \( S \) is selected as 10 in the ACPSO-FLNN filter. The set of positions constitutes the set of weights of ACPSO-FLNN in Equation (10). The position of ACPSO-

\[ (n-1) \rightarrow (n) \rightarrow (n+1) \]

\begin{align*}
(m-1) & \quad X_1 \\
& \quad X_c(m-1,n-1) \\
& \quad X_2 \\
& \quad X_c(m-1,n) \\
& \quad X_3 \\
& \quad X_c(m-1,n+1) \\
& \quad X_4 \\
& \quad X_c(m,n-1) \\
& \quad X_5 \\
& \quad X_c(m,n) \\
& \quad X_6 \\
& \quad X_c(m,n+1) \\
& \quad X_7 \\
& \quad X_c(m+1,n-1) \\
& \quad X_8 \\
& \quad X_c(m+1,n) \\
& \quad X_9 \\
& \quad X_c(m+1,n+1)
\end{align*}

FIGURE 2  Noisy 3 × 3 image kernel as FLNN inputs

where \( l = 1, 2, 3 \ldots \ldots, S, P_l \in P \) and \( V_l \in V \)

\[ W(j) = P_j(j) \quad (19) \]

For each set of positions, \( P_l \) the corresponding error \( e_l \) is computed, and for \( S \) number of positions, the set of errors is to be calculated. The local best position and respective velocity are given as

\[ P_l(j) = \{ P_{l1}, P_{l2}, P_{l3}, \ldots \ldots, P_{lL} \} \]

\[ V_l(j) = \{ V_{l1}, V_{l2}, V_{l3}, \ldots \ldots, V_{lL} \} \]

The best positions yielded by the minimum error is given as

\[ P_b = P_l; \quad e_l < e_l \forall i, l, i = 1, 2, \ldots, S \quad \text{and} \quad l = 1, 2, \ldots, S \quad (20) \]
By using Equations (22) and (23) of ACPSO, the updated sets of velocities are

\[ V^{(j+1)} = \beta \times V^{(j)} + \epsilon \times r \times (P_{gb}^{(j)} - P^{(j)}) \quad (22) \]

Similarly, the updated set of weights positions are

\[ P^{(j+1)} = P^{(j)} + V^{(j+1)} \quad (23) \]

where \( \beta = (1.1 - \frac{R^{(j)}}{(P_{gb}^{(j)})_{average}}) \) and \( \epsilon = (1 + \frac{R^{(j)}}{P_{gb}^{(j)}}) \) where \( \beta \), \( \epsilon \) and \( r \) are the inertia, acceleration constant and random values, respectively. The value of \( r \) will be between 0 and 1.

Similarly, \( P_{gb}^{(j)} \), \( P^{(j)} \) and \( (P_{gb}^{(j)})_{average} \) are the best, local, and average weights position at the \( j^{th} \) iteration. Once the weights are updated, error (i.e. objective function) will be calculated again by using the new sets of weights. According to the minimum error, the respective weights will be saved so that it can be compared.
with the previous minimum error. If the current error is lesser than the previous one, then the current one is saved or else the previous one is kept. After a certain epoch, error change will be saturated, then the program will be terminated and the optimum will be reported and expressed as

$$W_{opt} = P_{opt} = P_b \left( \chi \right)$$ \hspace{1cm} (24)

The number of iterations is \( j = 1, 2, \ldots, \gamma \). The optimum sets of weights suitable for a particular class or modality of images, if derived once, can be utilised later for the restoration of any images from that class with the least computational complexity. The ACPSO provides the final sets of optimum weights that are fed to the FLNN. The developed ACPSO-FLNN filter is applicable for the restoration of any other US noise image. The equation for the corrupted image is mathematically expressed as

The first step in adding the impulse noise to the ground-truth image is constructing a two-dimensional vector of random probability values with the standard uniform distribution within the range 0 to 1 and described by

$$R_p \sim U (0, 1)$$ \hspace{1cm} (25)

The cumulative distribution of the support of \( R_p \) is

$$f \left( R_p \right) = P \left( R_p \leq r_p \right) = r_p, \hspace{0.5cm} r_p \in R_p, \hspace{0.5cm} 0 \leq r_p \leq 1$$ \hspace{1cm} (26)

The resultant image with the simulated impulse noise is

$$X_i = \begin{cases} 0 & \text{if } 0 \leq R_p \left( m, n \right) \leq d/2 \\ \max \{ X \} & d/2 \leq R_p \left( m, n \right) \leq d \\ X \left( m, n \right) & \text{Otherwise} \\ 1 \leq m \leq M \text{ and } 1 \leq n \leq N \end{cases}$$ \hspace{1cm} (27)

In Equation (27), \( X \) denotes the ground-truth image. The variables, \( M \) and \( N \) are the numbers of rows and columns in the ground-truth image. The variable \( d \) describes the noise density. The number of pixels to which the value \( 0 \) is assigned is restricted to \((d/2)MN\). The same constraint is applicable to the number of pixels to which the value \( \max \{ X \} \) is assigned. After the process of adding the Gaussian noise to the ground-truth image, the mathematical expression of the corrupted image is

$$X = X + \eta_G$$ \hspace{1cm} (28)

The variable \( \eta_G \) in Equation (28) is the two-dimensional noise vector comprising the Gaussian distributed random values characterised by the probability distribution,

$$P \left( \eta_G \right) = \frac{1}{\sqrt{2\pi \sigma_G}} e^{-\left( \eta_G - \mu_G \right)^2 / 2\sigma_G^2}$$ \hspace{1cm} (29)

In Equation (29), the variable \( \mu_G \) is the mean and \( \sigma_G \) is the standard deviation of the noise vector \( \eta_G \). In this study, \( \mu_G \) is set to 0. Simulating the speckle in the ground-truth yields

$$X_i = X + \Gamma \left( \eta_G, X \right), \hspace{0.5cm} \eta_G \sim U \left( 0, 1 \right)$$ \hspace{1cm} (30)

In Equation (30), \( \eta_G \) is a two-dimensional vector comprising uniformly distributed random values with 0 mean and standard deviation \( \sigma_G \). \( \Gamma \) depicts the speckle density. The operator, \( \Gamma \) in Equation (30) indicates the inner product. In our simulation, the speckle, Gaussian and impulse noises are added to the ground-truth in three consecutive steps. As the performance of the proposed ACPSO-FLNN filter relies upon the network error, it can be improved by minimising the error which depends upon the assigned weights. Hence, the error in Equation (16) will become the fitness function and it can be minimised on the basis of the best weights of FLNN. In the current research study, the ACPSO optimisation technique is applied to search such optimum sets of weights from the initialised weight population. ACPSO will provide the best solution in terms of FLNN weights and after achieving this, the proposed ACPSO-FLNN filter can be utilised as a filter coefficient for eradicating various spurious noises. The pseudo-code of the proposed ACPSO-FLNN filtering algorithm is as follows:

For iteration \( j \)

For image row \( M - 1 \)

For image column \( N - 1 \)

For each weight particle

Initialise weight particle’s position \( P \)

Initialise weight particle’s velocity \( V \)

End

Do

For each weight particle

Compute the fitness value

If the current fitness value is better than the previous fitness value \( (P_i) \) in past

Fix the current value as the new \( P_i \)

End

Choose the particle with the best fitness value of all the particles position as the \( P_i \) and average particle position as the \( P_i \) (average)

For each particle

Update the weight \( \times \) particle velocity by (22)

Update the weight’s particles position by (23)

Update ACPSO’s controlling parameters \( \beta \) & \( \epsilon \)

End

End

End

Stop while the maximum iteration or the minimum error criteria is attained
41 EXPERIMENTAL RESULTS AND DISCUSSION

The MATLAB® platform is used for simulation tasks, and Intel (R) Core (TM) i3-2365 M CPU @ 1.40 GHz and 4Gb RAM are the specifications of the computer hardware. The images shown in Figures 4(a) and (b) are considered as a reference and noisy images, respectively, for the training of the proposed filter. The image shown in Figure 4(a) is a noise-free US image of a 10-week foetus, and Figure 4(b) is the same noise image that is contaminated with speckle, Gaussian and impulse noises. Here, the mean \( \mu \) and variance \( \sigma \) of speckle noise are 0 and 0.004, respectively. Similarly, the mean and variance of Gaussian noise are 0 and 0.001, respectively, and the density of impulse noise is

![Figure 4](image-url)
TABLE 1 Parameters for NN filtres

| Sl. No. | NN filtres | Parameters | Symbol | Value/function |
|--------|------------|------------|--------|----------------|
| 1      | PSO-FLNN   | No. of weights | $W$ | $\{9 \times 5 \times 10\} = 450$ |
|        |            | Acceleration constant | $c_1$ | 2               |
|        |            |                      | $c_2$ | 2               |
|        |            | Randomly generated number | $r_1$ | (0-1) |
|        |            |                      | $r_2$ | (0-1) |
|        |            | Activation function   | $\varphi(\cdot)$ | tanh(\cdot) |
| 2      | APSO-FLNN and ACPSO-FLNN (proposed) | No. of weights | $W$ | $\{9 \times 5 \times 10\} = 450$ |
|        |            | Inertia            | $\beta$ | $\beta = (1 - \frac{P_i(j)}{P_{\text{ave}}})$ |
|        |            | Acceleration constant | $C_c$ | $C_c = (1 + \frac{g_{\text{i}}}{p_{\text{best}}})$ |
|        |            | Randomly generated number | $R$ | [0-1] |
|        |            | Activation function   | $\varphi(\cdot)$ | tanh(\cdot) |
| 3      | LMS-FLNN   | No. weights       | $W$ | $\{9 \times 5\} = 45$ |
|        |            | Learning rate      | $\mu$ | 0.02 |
| 4      | BP-MLP     | No. of weights     | $W$ | $\{27 \times 6 \times 2\} = 324$ |
|        |            | Activation function | $\varphi(\cdot)$ | tanh(\cdot) |
|        |            | Learning rate      | $\mu$ | 0.02 |

Note: ACPSO, adaptive comprehensive particle swarm optimisation; APSO, adaptive particle swarm optimisation; BP, backpropagation; LMS, least mean squares; PSO, particle swarm optimisation; FLNN, functional-link neural network; MLP, multilayer perceptron.

considered to be 0.001. The pixel of Figure 4(b) will be the input of the proposed ACPSO-FLNN network, and the contextual pixel of the noise-free image will be a target during the training of the filtre network. The nine pixels of the kernel at the top-left corner of the noisy US image in Figure 4(b) will be the first set of input and the middle pixel of the corresponding kernel of US image in Figure 4(a) as the target for the first iteration. This process occurs iteratively till the bottom right kernel is reached. The files of the US images are in digital imaging and communications in medicine format. All the US images were collected from Medanta Hospital, Ranchi, Jharkhand, India, and these data are taken anonymously so that the patient information is not disclosed anywhere. The size of the image was $640 \times 480$ during the training and testing of the filtre network. The number of iterations is fixed as 1000 times for all the implemented ANNs filtering techniques. A linear adaptive filtre is also employed for comparative studies. The outer row and column pixels are padded to the input image so that the size of the denoised image remains unchanged during processing; this step helps us to find the exact image quality metrics data. The controlling parameters of all competitive filtres, such as PSO-FLNN, LMS-FLNN and BP-MLP are obtained empirically and are depicted in Table 1. Similarly, APSO-FLNN and the proposed ACPSO-FLNN get adapted iteratively. Parameters like the inertia and acceleration constant of APSO and ACPSO are presented in Table 1 where they are updated on the basis of the various particle positions of the employed heuristic optimisation techniques. In the case of heuristic-based approach, PSO-FLNN hyperparameters are manually tuned and the best filtering result achieved when the value of $c_1$ and $c_2$ are fixed as 2. Similarly, hyperparameters are fixed in the derivative-based approach such as LMS-FLNN and BP-FLNN. However, such parameters are fixed in an automated manner in the APSO-FLNN and the proposed ACPSO-FLNN filtre. Here, parameters are adaptive and inertia as well as acceleration constant get tuned with the execution of the filtering algorithm iteratively. Some of the other state-of-the-art filtering approaches, such as an advanced deep-learning network, that is, DnCNN, SRBF, NLMSF and LMDF are also considered for comparative study.

4.1 Subjective evaluation

Figure 4 presents the visual aspect and the removal of different noises by the proposed ACPSO-FLNN filtre. Figure 4(c) is obtained after applying the proposed filtre, and it demonstrates the cancellation of the mixed noise which is present in Figure 4(b). Similarly, Figure 4(d) shows the US image of the heart chambers, which is corrupted by speckle and Gaussian noises. The density of both noises present in this image is mentioned in Figure 4(d) caption. The same image is filtered by the proposed filtre and is depicted in Figure 4(e). In fact, this image demonstrates that the proposed filtre can filtre embedded speckle and Gaussian noises simultaneously. Likewise, Figure 4(f) presents the US image of the breast which is degraded by speckle and impulse noises. Here, the speckle noise density has a mean zero and variance of 0.002, which is different from the specification of the noisy image (Figure 4(b)) which is used in the
TABLE 2  Quality metric data of Experiment I

| Image Filtres      | Image quality metrics |  |  |
|--------------------|-----------------------|---|---|
| US image of foetus | SSIM 0.5347           | 0.7061 | 23.65 | 18.13 | -21.66 |
|                    | BP-MLP 0.8114         | 0.8114 | 24.42 | 19.16 | -22.07 |
|                    | LMS-FLNN 0.8166       | 0.8166 | 24.59 | 19.40 | -22.56 |
|                    | PSO-FLNN 0.8431       | 0.8431 | 25.49 | 20.11 | -23.04 |
| Noisy              | APSO-FLNN 0.8506      | 0.8506 | 26.54 | 20.55 | -24.02 |
|                    | ACPF-FLNN 0.8533      | 0.8533 | 26.68 | 20.91 | -25.97 |

Notes: SSIM, structural similarity index; PSNR, peak signal-to-noise ratio; NRDB, noise reduction in decibels; NMSE, normalised mean squares error.

TABLE 3  Quality metric data of Experiment II

| Image Filtres      | Image quality metrics |  |  |
|--------------------|-----------------------|---|---|
| US image of heart chamber | SSIM 0.6447 | 0.7061 | 26.65 | 20.07 | -24.29 |
|                    | BP-MLP 0.7305         | 0.7305 | 27.44 | 20.16 | -24.63 |
|                    | LMS-FLNN 0.7348       | 0.7348 | 27.19 | 21.37 | -25.74 |
|                    | PSO-FLNN 0.7429       | 0.7429 | 27.90 | 21.39 | -25.81 |
| Noisy              | APSO-FLNN 0.7532      | 0.7532 | 28.33 | 22.06 | -26.42 |
|                    | ACPF-FLNN 0.7684      | 0.7684 | 28.20 | 22.34 |       |

4.2 Quality measure

The MSE, PSNR, structural similarity index (SSIM), normalised MSE (NMSE) and noise reduction in decibels (NRDB) are estimated to measure the quantitative significance of all NN filters. The MSE and PSNR techniques quantify the pixel’s difference between the noisy as well as filtered images. PSNR is one of the most adopted metrics that is widely used for measuring the performance of any digital image filter. Similarly, the quality metric SSIM evaluates the structural resemblance by associating the local shape of pixel intensities. It is based on the human visual system for acquiring information from an object, and it is formulated on three parameters such as luminance, contrast, and structure. Similarly, NMSE is a metric of denoising efficacy and provides information about image detail preservation during the restoration. The efficiency of denoising techniques can be quantified on the basis of NRDB. It is a logarithmic ratio of $MSE_{IN}$ and $MSE_{OUT}$, where $MSE_{IN}$ is the MSE between the reference and noisy images. Similarly, $MSE_{OUT}$ is the MSE between the reference and filtered images. The above-mentioned image qualitative metrics are mathematically formulated by using Equations (31) to (36). The proposed ACPF-FLNN filter has been compared with the other five competitive filters. The data obtained from different experiments are presented in Tables 2–4.

\[
MSE = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} (X(m,n) - \hat{Y}(m,n))^2
\]  

PSNR:

\[
PSNR = 10 \times \log_{10} \left( \frac{M \times N}{MSE} \right)
\]  

SSIM:

\[
SSIM(x, y) = \frac{1}{M} \sum_{i=1}^{M} \left( \frac{2\mu_x \mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \right) \left( \frac{2\sigma_{xy} + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \right)
\]  

NRDB:

\[
NRDB = 10 \times \log_{10} \left( \frac{MSE_{IN}}{MSE_{OUT}} \right)
\]  

\[
NMSE \text{ in dB} = -10 \log_{10} (NMSE)
\]
NMSE:

\[ NMSE = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} (X(m,n) - \hat{Y}(m,n))^2}{\sum_{m=1}^{M} \sum_{n=1}^{N} (X(m,n))^2} \]  (36)

where \( X(m,n) \) and \( \hat{Y}(m,n) \) are the noisy and filtered images, respectively. Similarly, \( \mu_x, \mu_y, \sigma_x^2, \sigma_y^2 \) and \( \sigma_{xy} \) are the mean brightness of the noisy image, mean brightness of the denoised image, the global variance of a noisy image, the global variance of denoised image and covariance between the noisy and the restored image, respectively. Similarly, \( C_1 \) and \( C_2 \) are the arbitrary constants.

The data of Experiment I is obtained from the denoising of the US image of the foetus, and it is presented in Table 2. The proposed ACPSO-FLNN is compared with the other five filters such as Wiener, BP-MLP, LMS-FLNN, PSO-FLNN and APSO-FLNN. If we observe Table 2, the PSNR and SSIM data of the noisy US image are 19.72 and 0.5347 dB, respectively, and are depicted vertically in the given table. After applying different filtering algorithms, the PSNR and SSIM values improve and reaches up to 26.68 and 0.8533 dB, respectively.

Similarly, the values of NRDB and NMSE accomplished show that the different variants of the PSO-based NN filter provide a better result than the linear (Wiener) adaptive filter and derivative leaning-based NN filters such as BP-MLP and LMS-FLNN. The figure of the proposed filter is boldfaced. Similarly, Tables 3 and 4 provide the data of different denoising schemes that are applied for eliminating the noise of the heart chamber and breast US images. These experimental data exhibit that the proposed ACPSO-FLNN filter provides a superior outcome than that of the other competitive adaptive image filters.

The sensitivity of the proposed ACPSO-FLNN filter with consideration of two controlling parameters, that is, inertia \( \dot{\beta} \) and acceleration constant \( C \), are presented in Figure 5(a) and (b). Here, iteration is fixed to 1000 during the evaluation of sensitivity. The sensitivity is investigated by considering the PSNR as the performance metric with respect to ACPSO-controlling parameters, that is, \( \dot{\beta} \) and \( C \). From Figure 5(a), it is clear that, varying the inertia values from 1.1 to 0.4, the PSNR value reached up to the maximum, that is, 29 dB. Similarly, Figure 5(b) depicts the sensitivity plot of \( C \) and PSNR while varying the acceleration constant from 1.17 to 1.98.

The comparative performance study is also carried out between the proposed ACPSO-FLNN filter with DnCNN, SRBF, NLMSF, LMDF filters, in terms of PSNR. The denoised US image of breast and foetus using DnCNN is shown in Figure 9, and it is presented in the Appendix. Twenty convolutional layers and a regression layer are used in the DnCNN filter. The blockiness artefact is observed in the filtered images. However, it clears the background noise of the US images. It is

### Table 4: Quality metric data of Experiment III

| Image                  | Filters | SSIM     | PSNR (dB) | NRDB (dB) | NMSE (dB) |
|------------------------|---------|----------|-----------|-----------|-----------|
| US image of breast     | SSIM    | 0.6447   | 28.02     | 20.07     | −23.88    |
|                        | Wiener  |          | 28.11     | 21.37     | −24.69    |
|                        | BP-MLP  | 0.7237   | 28.16     | 21.39     | −25.11    |
| PSNR (dB)              | 23.55   | LMS-FLNN | 28.24     | 22.06     | −27.40    |
|                        | PSO-FLNN | 0.7361  | 28.19     | 22.34     | −28.87    |
| Noisy                  | APSO-FLNN | 0.7444 | 28.45     | 22.06     | −28.87    |
|                        | ACPSO-FLNN | 0.7790 | 29.07     | 22.34     | −26.35    |
observed from Table 5 that the DnCNN filter, PSNR value of the denoised US foetus image is 26.16 dB. Similarly, the PSNR of the filtered US foetus, breast and heart images by implementing SRBF are 25.46, 27.08 and 27.09, respectively. By observing all the columns of Table 5, it can be concluded that the proposed ACPSO-FLNN is superior in performance as compared to others.

The performance measures such as the average computational time, convergence rate and statistical test are also incorporated to judge the effectiveness of these filters. Figure 6 presents the average computational time taken for training by all the NN filters. These algorithms are executed for the same number of iterations, that is, 1000, and the execution time is monitored for the completion of each filtering algorithm. During experimentation, the LMS-FLNN and BP-MLP have taken a training time of 2000 and 5536 s, respectively, which are the lowest and highest among all the NN filters. This happens because of the multiple numbers of hidden layers present in MLP. Similarly, among the PSO-based NN filters, the proposed ACPSO-FLNN filter takes the minimum time of 2400 s as compared to the PSO-FLNN and APSO-FLNN filters. The time complexity and order of the proposed ACPSO-FLNN filter is presented in Table 6. After comparing both the tables, it is evident that the proposed ACPSO-FLNN filter is less complex than the APSO-FLNN filter because, for updating, the velocity of the ACPSO weight local particle position is not required and this velocity is further utilized to update the particle position.

Table 8 demonstrates the use of symbols which are used in the time complexity and order of the ACPSO-FLNN and APSO-FLNN filters. On the other hand, the proposed ACPSO-FLNN filter is more accurate than any other competitive filters, which is the major concern in medical applications. Figure 7 presents the region of convergence characteristics of the employed NN filters for this study, and it is plotted with respect to the iterations and NMSE. The proposed ACPSO-FLNN filter has a better convergence rate than the other competitive filtering algorithms.

All the competitive filters are applied on 50 noisy US images, and it is also observed that occasionally the PSO-FLNN filter provides a better result or equivalent result in comparison with the APSO-FLNN filter. It is because these algorithms are

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**TABLE 5** PSNR of various state-of-the-art image filters

| Image filters | PSNR (dB) |
|---------------|-----------|
| US images     |           |
| Foetus        | 19.72     |
| Heart chamber | 21.72     |
| Breast        | 23.55     |
| DnCNN [58]    | 26.16     |
| SRBF [59]     | 25.46     |
| NLMS [60]     | 25.57     |
| LMDF [61]     | 24.46     |
| ACPSO-FLNN    | 26.68     |

**FIGURE 6** Average computational time of various image filters

---

**TABLE 6** Time complexity and order of ACPSO-FLNN filter

| Algorithm steps     | Time complexity |
|---------------------|-----------------|
| Fitness evolution   | $f^*(n^*m^*+(p^*)+l^*+(p^*(n^*+l^*)+))$ |
| Global best         | $m^*n$          |
| Velocity            | $m^*p+n^*c^*$   |
| Weighted position   | $l^*m$          |
| Stopping criteria   | $m^*p+n$        |
| Overall time complexity and order | $T(n) = f^*(n^*m^*+(p^*)+l^*+(p^*(n^*+l^*)+)) + m^*n + (m^*p+n^*c^*)+ (l^*m) + (n^*p+l^*)$ |
|                      | $= O_j^*(n^*m^*+(p^*+l^*)+m^*n + P^*c^*)$ |
FIGURE 7  Convergence characteristics of neural network (NN) filters

TABLE 7  Time complexity and order of ACPSO-FLNN filter

| Algorithm Steps       | Time complexity                                                                 |
|-----------------------|---------------------------------------------------------------------------------|
| Fitness evolution     | \( j*(a^m*(p^l)+l/p*(a+l)) \)                                                   |
| Global best           | \( m^*n \)                                                                       |
| Velocity              | \( m^*n+p^*o+c^*p+c^*r \)                                                        |
| Weighted position     | \( l^*m \)                                                                       |
| Stopping criteria     | \( m^*n+p \)                                                                     |
| Overall time complexity| \( T(n) = j*(a^m*(p^l)+l/p*(a+l)) + m^*n + (m^*n+p^*o+c^*p+c^*r) \)            |

TABLE 8  Symbols used in finding time complexity and order

| Symbols | Meaning                                                                 |
|---------|-------------------------------------------------------------------------|
| \( T(n) \) | Time complexity of the model of \( m^*n \) number of solutions         |
| \( O \)  | Big-O asymptotic notation                                               |
| \( m^*n \) | Number of weighted-sets in population                                  |
| \( l \)  | Weighted sum of input pixel                                             |
| \( o \)  | Minimum error weight position                                           |
| \( p \)  | Number of weight position                                               |
| \( c \)  | Constant time                                                           |
| \( j \)  | Number of function in each functionality attended                      |

Annova-2 and evaluates the significance as well as the repeatability of the results. This test is performed on the data of PSNR that are collected during the different experiments. The values of Friedman’s test are depicted in Tables 9 and 10, respectively. The lower-ranking and critical value, that is, \( p \) is 0.0021, shows the effectiveness of the proposed ACPSO-FLNN filter and outplays the other competitive filters. The critical value will compare column effects in a two-way layout and this non-parametric statistical tests. Here, the null hypothesis that the column effects are entirely identical against the alternative that they are not similar.

Also, the proposed filter has a reasonable time for training, which is an indispensable requirement for any digital adaptive filter. Apart from the several advantages of the proposed filter mentioned in the section above, ACPSO is a two-stage algorithm and for the optimum solution, the particle velocity,
as well as the respective position, should be updated carefully. Also, this algorithm is parameter-specific, and inertia, as well as acceleration, will play a major role in finding a solution that enhances the programming complexity since the target of this study is the automatic selection of the controlling parameters of PSO by using ACPSO. However, a heuristic technique which is simple in implementation as well as having fewer parameters is to be studied.

5 | CONCLUSION

An adaptive noise cancellation filter based on the ACPSO-FLNN was proposed in this study for cancelling the mixture of speckle, Gaussian and impulse noises from the US images. From the simulation output, it is evident that the proposed filter is quite effective in different noise conditions and can handle specific as well as mixed noise. To maximise the performance of the FLNN filter, ACPSO was used to automatically tune its hyperparameters. The qualitative and quantitative assessment reflected the superiority of the proposed ACPSO-FLNN filter over eight other competitive filters. The training time, time complexity, convergence characteristics and Friedman's statistical data exhibited by the ACPSO-FLNN filter were observed to be remarkably effective. The proposed ACPSO-FLNN filter can be tested on other noise-types and artefacts. Any advanced NNs model may also be tested and studied on other medical imaging modalities. Also, a heuristic technique that is simple in implementation as well as having fewer parameters is to be explored.

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CONFLICT OF INTEREST

There is no conflict of interest between the authors.

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