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A novel fuzzy system for edge detection in noisy image using bacterial foraging

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Abstract Bio-inspired edge detection using fuzzy logic has achieved great attention in the recent years. The bacterial foraging (BF) algorithm, introduced in Passino (IEEE Control Syst Mag 22(3):52–67, 2002) is one of the powerful bio-inspired optimization algorithms. It attempts to imitate a single bacterium or groups of *E. Coli* bacteria. In BF algorithm, a set of bacteria forages towards a nutrient rich medium to get more nutrients. A new edge detection technique is proposed to deal with the noisy image using fuzzy derivative and bacterial foraging algorithm. The bacteria detect edge pixels as well as noisy pixels in its path during the foraging. The new fuzzy inference rules are devised and the direction of movement of each bacterium is found using these rules. During the foraging if a bacterium encounters a noisy pixel, it first removes the noisy pixel using an adaptive fuzzy switching median filter in Toh and Isa (IEEE Signal Process Lett 17(3):281–284, 2010). If the bacterium does not encounter any noisy pixel then it searches only the edge pixel in the image and draws the edge map. This approach can detect the edges in an image in the presence of impulse noise up to 30%.

Keywords Bacterial foraging · Edge detection · Fuzzy derivative · Impulse noise · Membership function · Histogram · Probable-edge

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1 Introduction

Edge detection is one of the basic problems of image analysis with fundamental importance. Edges are the significant local changes of intensity in an image. Many of the important features can be extracted from the edges of an image (e.g., corners, lines, curves). Edges are present at the boundary between two dissimilar regions. Edges can be detected easily because differences in the pixel values among regions are relatively easy to calculate. But in the presence of noise, detection of edges becomes very difficult because both edges and noise are characterized by high frequency. Erroneous edge detection may lead to artifacts in severe cases like medical, security and biometrics. Most of the works in the area of edge detection follow three basic steps: (1) Smoothing, (2) Detection, and (3) Localization.

Noise removal from images has been one of the important and challenging areas. Numerous attempts have been made to remove noise without affecting the image features. Luo (2006) proposes detection of the salt and pepper noise based on histogram. Two peaks at the ends of a histogram give the intensity values of salt and pepper noise. These noisy pixels are then replaced with the median of the noise free pixels. Toh et al. (2008) have adopted the method of Luo (2006) for the detection of noisy pixels and the maximum value of gradient in neighborhood with fuzzy reasoning is used to reduce the noise. Similar approach is adopted in Toh and Isa (2010). The noise removal in color images proposed by Verma et al. (2009b, 2010a), utilizes fuzzy reasoning. Schulte et al. (2006) present a fuzzy detection and reduction method based on the fuzzy averaging of the neighborhood pixels. In Guo et al. (2005), Lee et al. (2005) Genetic algorithm is used to optimize the fuzzy membership function, which is used to remove impulse noise. All these methods are applicable to the removal of impulse noise only.

Some of the earlier edge detection methods such as Prewitt and Sobel operators in Gonzalez and Woods (2008), used for the local gradients only detect the edges along certain orientations and they perform poorly on the blurred or the noisy images. The Prewitt operator calculates two derivatives: one for the horizontal changes and other for the vertical. These derivatives are 3×3 kernels to be convolved with the original image. Similarly Sobel Edge Detector in Nalawa (1993) calculates the gradients of the image intensity at each point, giving the direction of the largest possible increase from light to dark pixels and the rate of change of intensity in that direction. The Canny (1986) edge detector counters the noise problems by convolving an image with the first-order derivative of the Gaussian function in the local gradient direction and performs edge detection by thresholding.

Edge detection in the presence of impulse noise is a very difficult task. All the classical edge detectors and many recent edge detectors fail to detect edges in the presence of noise. This is because impulse noise and edges show similar characteristics with respect to changes in the intensity levels. If the edges of an object in an image are not clearly visible then the fuzzy reasoning is able to extract useful attributes from the approximate and incomplete image data and improves the task of edge detection. The fuzzy theory, since its inception by Zadeh (1965), has evolved into a mature theory and found applications in several fields. It utilizes human reasoning through the use of linguistic variables to find solutions for engineering problems. The imprecision that exists in nature is accurately modeled by the fuzzy logic. The application of fuzzy techniques in image processing is a promising research field. As a result the fuzzy techniques have percolated into several tasks of image processing (e.g., Filtering, interpolation, and morphology), and have found numerous applications (e.g., in industrial and medical image processing). Abdallah and Ayman (2009) have proposed a fuzzy logic reasoning strategy for edge detection in digital images just by segmenting an image into a window of size of 3×3 and without determining the threshold value. The approach in

Verma et al. (2009a, 2010b) for edge detection utilizes ant colony optimization coupled with fuzzy derivative technique.

The evolutionary algorithms (Dorigo et al. 1991; Passino 2002; Hanmandlu et al. 2009; Roomi et al. 2010) are increasingly sought for finding optimum solutions to the engineering problems. Ant Colony Optimization (ACO), proposed by Dorigo et al. (1991) is inspired by foraging behavior of an ant colony. The advantages of ACO comprise: (1) Exploitation of the sensing capabilities of the group, (2) Avoidance of premature convergence by way of distributed computing. But there are also some disadvantages associated with ACO like: (1) No centralized methodology exists to guide the ant colony toward good solutions, (2) It suffers from slow convergence, and (3) It also fails to tackle large and complex problems. Owing to these problems, modified ACO approaches have come into the fore like that of Ho et al. (2006). Another evolutionary technique is Particle Swarm Optimization (PSO) (Setayesh et al. 2009; Roomi et al. 2010). PSO algorithm employs a swarm of particles. The movements of the particles are guided by the swarm's local best position as well as global best position in the search-space.

Passino (2002) have proposed another evolutionary bio-inspired algorithm, known as bacterial foraging (BF) algorithm. BF algorithm is the offshoot of the behavior of some species of bacteria like *E. coli*. There are four stages in the life cycle of bacteria namely: (1) Chemo taxis, (2) Swarming, (3) Reproduction and (4) Elimination and Dispersal. These stages in the search space generate an optimum solution to the problem of optimization. But there are some drawbacks associated with traditional BF like: (1) Poor convergence behavior while dealing with complex optimization problems in comparison to other nature-inspired optimization techniques such as genetic algorithm (GA) and particle swarm optimization (PSO), (2) Bacteria foraging with fixed step size suffers from two main problems. Firstly, if the step size is very high then the precision gets low although the bacterium reaches the vicinity of a food source (the optimum point) quickly. It moves around the maxima in the remaining chemotactic steps. Secondly, if the step size is very small then it takes many chemotactic steps to reach the optimum point. So the rate of convergence decreases. Some good features of BF are: (1) Search strategy of bacteria is salutary (like common fish) in nature and (2) Bacteria can sense, decide and act which make them better than ants in ACO and particles in PSO. As regards GA, it sidesteps the property that edges are continuous in nature. Rather it just seeks for the edges in the whole search space. The BF is favored for its ability to search for the next edge pixel in the surrounding edge pixels. This makes the BF computationally more luring than GA.

Many researchers have hybridized BF with the help of other evolutionary methods. In this context mention may be made of Kim et al. (2007) who hybridized BF with Genetic algorithm (GA) called GA-BF and Biswas et al. (2007) who hybridized BF with PSO. Bacterial Foraging Algorithm (BFA) has been successfully applied to real world problems like optimal controller design (Kim et al. 2007; Yuksel 2007; Setayesh et al. 2009), harmonic estimation in Mishra (2005), transmission loss reduction in Tripathy et al. (2006), and machine learning in Kim and Cho (2005). The hybridization of BFA-Differential Evolution (DE) in Biswas et al. (2007) and an Adaptive Bacterial Foraging Optimization Algorithm (ABFOA) in Dasgupta et al. (2009) for the function optimization are also undertaken. It has made a way into the optimization of antenna array for faster convergence (Datta et al. 2008).

Hanmandlu et al. (2007) have used BF for the recognition of the Handwritten Hindi numerals and Hanmandlu et al. (2009) have applied BF for color image enhancement where the optimization of both entropy and visual factors is dealt with. A fuzzy inference scheme is proposed in Mishra (2005) for selecting the optimal chemotactic step size in BF. An automatic detection of circular shapes from complicated and noisy images based on Bacterial Foraging

Optimization (BFO) is presented by Dasgupta et al. (2008), where a fuzzy function has been derived for the edge map of a given image. Recently Verma et al. (2011) have developed an algorithm for edge detection using BF in which direction of movement of bacteria is found using a directional probability matrix derived from ACO. But this algorithm fails to deliver goods on noisy images. In this work, we propose an algorithm for finding the edges not only in the images corrupted with impulse noise but also in the normal images. The edge detection technique of Russo (1998) adopts fuzzy reasoning to obtain edge information from noisy images. The approach in Civicioglu and Alci (2004), first removes the impulse noise using a statistical method then tries to detect edges. Yuksel (2007) has devised a neuro-fuzzy (NF) operator for the edge detection in images corrupted with the impulse noise.

In the proposed approach, we differ from the traditional methods where the noise is removed first then the edges are found. Here BF is modified to perform the task of edge detection in noisy images. In this bacteria search for the optimal paths, i.e. edges, with the help of fuzzy rules. Noisy pixels present in the edges are identified by taking the histogram of a noisy image as described in (Luo 2006; Toh et al. 2008; Toh and Isa 2010). We deal with only those noisy pixels which are present in edges, i.e. those which are encountered by bacteria on the optimal paths. The noise in the pixels is removed by bacteria utilizing the noise adaptive fuzzy switching median filter (Toh and Isa 2010). The adaptive behavior enables the filter to expand the size of the filtering window according to the local noise density, making it possible to filter out the high-density impulse noise. This selective removal of noisy pixels from the edges not only reduces the computational complexity greatly but also preserves the fine edges.

This paper is organized as follows: The modified bacterial foraging technique is discussed for edge detection in Sect. 2. A brief introduction to the filtering stage of Noise Adaptive Fuzzy Switching Median Filter is presented in Sect. 3. Section 4 gives the experimental results and conclusions are given in Sect. 5.

2 The modified bacterial foraging technique for edge detection

The BF algorithm (Passino 2002), described briefly in “Appendix A”, is modified here for the edge detection. Here an objective function is posed as the effort or a cost incurred by the bacteria in search of edges. A set of bacteria tries to reach an optimum cost by following four stages such as chemotaxis, swarming, reproduction, and elimination and dispersal. In the present application, swarming step does not play any major role but only increases the complexity of the problem. Therefore, we ignore the swarming step of BF algorithm. The following steps form part of the edge detection using the Modified BF:

2.1 Search space

The area in which bacteria forage for nutrients is the 2-D search space consisting of x and y coordinates of pixels in an image. Being limited by the image dimensions, i.e. horizontal and vertical pixels of the image, there are basically two main characteristics of the search space, namely: (1) it is finite and (2) it can take only discrete values. In our approach bacteria are placed at random pixels in 2-D noisy image.

2.2 Chemo taxis

The differences in the pixel intensities suggest the presence of edges but at the same time this information can be misleading in the case of noisy images. The ambiguity between

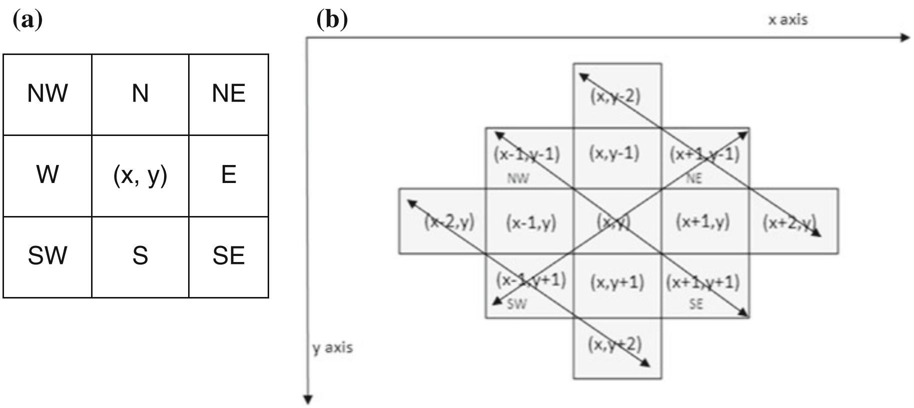

Fig. 1 **a** Pixel (x, y) with its neighborhood pixel. **b** The edge pixels under consideration in SW–NE direction

edge pixel and noisy pixel is dealt with by fuzzy reasoning. A bacterium determines the next location from a set of eight neighboring pixels, i.e. in one of the 8 directions: $D \in \{E, W, N, S, NE, SE, NW, SW\}$. To find the next position for the movement of bacteria, fuzzy derivative approach is used. Consider the neighborhood of a pixel (x, y) in Fig. 1a. The derivative at the central pixel position (x, y) in the direction D is defined as the difference between an intensity of the pixel at (x, y) and its neighboring pixel in the same direction. This difference (also called derivative) is denoted by $\nabla(x, y)$.
For example

$$
\begin{aligned}
\nabla_N(x, y) &= I(x, y-1) - I(x, y) \\
\nabla_{NW}(x, y) &= I(x-1, y-1) - I(x, y)
\end{aligned} \tag{1}
$$

For an edge in the SW–NE direction (Fig. 1b), the three derivative values are calculated as:

$$
\begin{aligned}
\nabla_{NW}(x, y) &= I(x-1, y-1) - I(x, y) \\
\nabla_{NW}(x-1, y+1) &= I(x-2, y) - I(x-1, y+1) \\
\nabla_{NW}(x+1, y-1) &= I(x, y-2) - I(x+1, y-1)
\end{aligned} \tag{2}
$$

Fuzzy Sets: The above differences do not distinguish clearly between a noisy pixel and an edge pixel. Since fuzzy sets have a smooth boundary, we fuzzify the differences to enable them find the direction of an edge. So the derivative values in (2) are fuzzified using the membership function **Large**, defined as:

$$
\mu(\nabla) = \begin{cases} 0, & \text{if } \nabla < a \\ \frac{\nabla - a}{b - a}, & \text{if } a \le \nabla \le b \\ 1, & \text{if } \nabla > b \end{cases} \tag{3}
$$

Fuzzy Rules:

The following fuzzy rules have their output as the fuzzy set called, "**probable-edge**". This is used to obtain the direction of bacteria movement:

IF $\nabla_{NW}(x, y)$ is **Large** AND $\nabla_{NW}(x-1, y+1)$ is **Large** AND $\nabla_{NW}(x+1, y-1)$ is **Large**
THEN NE is **probable-edge**.
IF $\nabla_{SE}(x, y)$ is **Large** AND $\nabla_{SE}(x-1, y+1)$ is **Large** AND $\nabla_{SE}(x+1, y-1)$ is **Large**
THEN SW is **probable-edge**.

Similar fuzzy rules are devised for edges in other directions as:

IF $\nabla_{N}(x, y)$ is **Large** AND $\nabla_{N}(x-1, y)$ is **Large** AND $\nabla_{N}(x+1, y)$ is **Large**
THEN E is **probable-edge**.
IF $\nabla_{S}(x, y)$ is **Large** AND $\nabla_{S}(x-1, y)$ is **Large** AND $\nabla_{S}(x+1, y)$ is **Large**
THEN W is **probable-edge**.
IF $\nabla_{NE}(x, y)$ is **Large** AND $\nabla_{NE}(x-1, y-1)$ is **Large** AND $\nabla_{NE}(x+1, y+1)$ is **Large**
THEN SE is **probable-edge**.
IF $\nabla_{SW}(x, y)$ is **Large** AND $\nabla_{SW}(x-1, y-1)$ is **Large** AND $\nabla_{SW}(x+1, y+1)$ is **Large**
THEN NW is probable-edge.
IF $\nabla_{E}(x, y)$ is **Large** AND $\nabla_{E}(x, y-1)$ is **Large** AND $\nabla_{E}(x, y+1)$ is **Large**
THEN S is **probable-edge**.
IF $\nabla_{W}(x, y)$ is **Large** AND $\nabla_{W}(x, y-1)$ is **Large** AND $\nabla_{W}(x, y+1)$ is **Large**
THEN N is **probable-edge**.

The fuzzy set **probable-edge** is defuzzified using the maximum value to obtain the direction vector $\Delta(i)$ of ith bacterium. For finding the next direction of tumbling of ith bacteria $\theta^i(j+1)$ we use:

$$\theta^i(j+1) = \theta^i(j) + c(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{4}$$

where, $\Delta^T(i)$ is the transpose of $\Delta(i)$ and $c(i)$ indicates the step size length. After moving to the pixel, we (bacteria) check for the noisy pixel using the histogram technique. The histogram (Gonzalez and Woods 2008) of a digital image with intensity levels in the range [0, L-1] is a discrete function $h(r_k) = n_k$, where r_k is kth intensity value and n_k in the number of pixels in the image with intensity r_k. For the pixels corrupted with the impulse noise, histogram will have peaks at both the ends, say H_{lower} and H_{upper}.

$$\begin{aligned} H_{lower} &= \max\{h(r_k)\} \quad \text{for } k = 0, \ldots, L/8 \\ \text{and } H_{upper} &= \max\{h(r_k)\} \quad \text{for } k = 7L/8, \ldots, L-1 \end{aligned} \tag{5}$$

The pixel at which bacterium is currently located, will be compared with the intensity value of H_{lower} and H_{upper}.

An impulse noise flag is created for the identification of "noisy pixels" by using

$$N(i, j) = \begin{cases} 1, & \text{if } I(i, j) = H_{lower} \text{ or } H_{upper} \\ 0, & \text{else} \end{cases} \tag{6}$$

where $I(i, j)$ is the intensity of pixel and $N(i, j) = 1$ represents "noisy pixels", which can be filtered. In our approach we use the filtering stage of the noise adaptive fuzzy switching median filter of Toh and Isa (2010). So $N(i, j) = 0$ represents the "noise free pixels" from

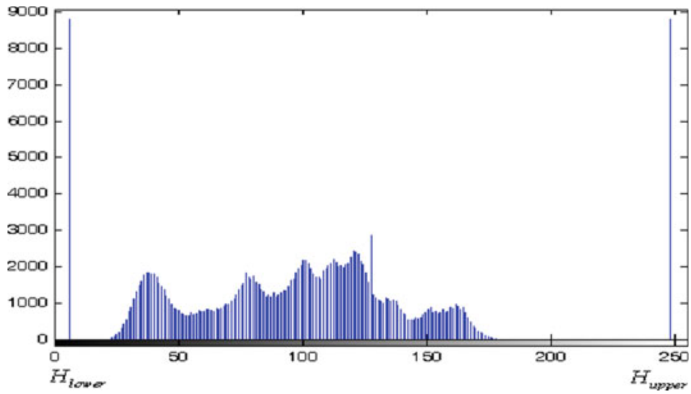

Fig. 2 Histogram of Image Lena with 30% impulse noise

which the bacteria can directly check for the edge pixels. H_{lower} and H_{upper} are the minimum and maximum values of intensity for the impulse noise in the histogram shown in Fig. 2.

2.3 Elimination and reproduction step

The elimination step removes the bacteria that deviate from the actual path whereas the reproduction step increases the number of bacteria for better foraging. We select a threshold value (β) by which to discard certain bacteria. At the end of one step of movement of all bacteria, if the intensity of a pixel where bacteria have reached is less than this threshold (β) the bacteria are less healthy; hence eliminated. The same number of bacteria eliminated is replaced with healthy bacteria.

At the end of all stages a bacterium along the optimal path having intensity greater than α is considered as the final edge detected. Thus the movement of bacteria throughout the image results in the removal of noise from the edges providing an optimal path.

3 Impulse noise removal

The Noise Adaptive Fuzzy Switching Median Filter (NAFSM) (Toh and Isa 2010) is a double-stage recursive filter. In this, a flag is set up in a flag matrix at the location of the noisy pixel. At the filtering stage the noisy pixels are subject to changes. The flag also helps to identify the noise free pixels from getting changed. This is done to preserve the originality of the image. The NAFSM filter uses a square filtering window $W_{2R+1}(x, y)$ with the size $(2R + 1) \times (2R + 1)$ given by:

$$W_{2R+1}(i, j) = \{I(i + m, j + n)\} \quad \text{where } m, n \in (-R, R) \tag{7}$$

If the current window $W_{2R+1}(x, y)$ has no noise-free pixel then the filtering-window will be expanded by one pixel on four sides. This procedure is repeated until sufficient number of noise-free pixels is found. For each detected noisy pixel, the size of the window is initialized to 3×3, i.e. $R = 1$. These noise-free pixels will be used as candidates for selecting the median pixel $M(i, j)$ given by:

$$M(i, j) = median\, \{I(i + m, j + n)\} \quad \text{for } N(i, j) = 0 \tag{8}$$

Preparing for the possibility that the search for "noise-free pixels" would be halted if the window size reaches to 7×7, the four pixels in the 3×3 window is given by:

$$W_3(i, j) = I(i + k, j + l) - I(i, j) \quad \text{where } k, l \in (-1, 1) \tag{9}$$

The four "noise-free pixels" in the upper-left diagonal will yield a more accurate median pixel denoted by $M(i, j)$, instead of all 8-connected neighboring pixels. After that, the local information is taken as the maximum absolute luminance difference in the window of size 3×3:

$$D(i, j) = \max \{|I(i + k, j + l) - I(i, j)|\} \quad \text{where } k, l \in (-1, 1) \text{ and } k \neq 0, l \neq 0 \tag{10}$$

For the fuzzification of $D(i, j)$, the fuzzy membership function "**Large**" is made use of:

$$\mu(D(i, j)) = \begin{cases} 0, & \text{if } D(i, j) < \gamma_1 \\ \frac{D(i,j)-\gamma_1}{\gamma_2-\gamma_1}, & \text{if } \gamma_1 \leq D(i, j) \leq \gamma_2 \\ 1, & \text{if } D(i, j) > \gamma_2 \end{cases} \tag{11}$$

where γ_1 and γ_2 are the experimentally determined parameters. Finally, the detected "noisy pixel" is corrected using the correction term $\rho(i, j)$ given by

$$\rho(i, j) = [1 - \mu(D(i, j))]I(i, j) + \mu(D(i, j))M(i, j) \tag{12}$$

We will present an algorithm that removes the noisy pixels on the optimal path of bacteria, i.e. edges. Thus bacteria will replace the intensity of the noisy pixels with the correction term.

Algorithm:

Step: 1. Initialize all the bacteria with the random positions.
Step: 2. for each bacterium from 1:N_b
For each chemotaxis (iterate for 1 to 16)
For reproduction and elimination (iterate for 1 to 4)
i. Find all the pixels that are the neighbors of the initial position of bacteria.
ii. Move the bacteria to the neighboring pixels.
iii. If the neighbor's pixels or the initial pixel are noisy, then remove the noise using NAFSM and get back to the initial pixel.
iv. Use the fuzzy rules to determine the direction vector $\Delta(i)$ for further movement, i.e. the edge direction.
v. Move the bacteria in the next direction using $\Delta(i)$.
vi. If the value of $\Delta(i) >$ threshold α, put the current pixel into a set of edge pixels.
vii. If the intensity of pixel is less than threshold β then eliminate the bacteria.
viii. Replace the same number of bacteria that are discarded with the healthy bacteria.

The flow chart of the proposed algorithm is shown in Fig. 3:

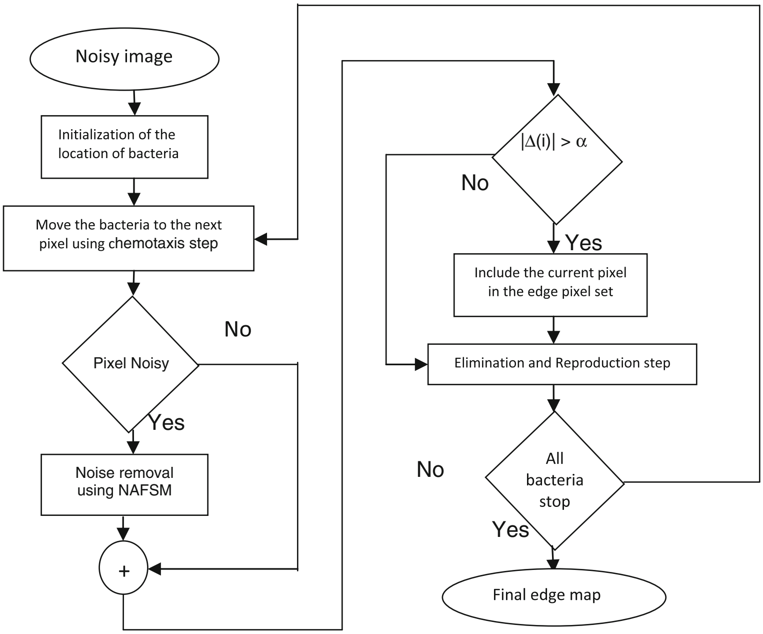

Fig. 3 A flow chart of the proposed edge detection approach

4 Results and discussion

The computer simulations are performed on three test images, viz. Lena, Cameraman and Peppers using MATLAB 7.10 to assess the performance of the proposed algorithm with different levels of impulse noise ranging from 5 to 30% while finding edges.

Next, the performance of the algorithm is compared with Sobel, Canny, ACO and GA operators for 0% impulse noise and then with Gudmundsson et al. (1998), Yuksel (2007), Danafar et al. (2006) for low impulse noise followed by a comparison with Civicioglu and Alci (2004), Yuksel (2007) for high impulse noise.

The simulation results for varying number of bacteria are shown in Fig. 4. The results suggest that number of bacteria, N_b to be used should be 3,500 approximately. The lower number of bacteria results in loss of edges as seen in Fig. 4a, b or distorted edges as observed in Fig. 4c, d. The high number of bacteria increases the computational complexity without the requisite effect. Results of Lena images are shown with 30% impulse noise and it has been confirmed by simulations that this level of impulse noise on other images is also tolerated.

Initialization of the parameters is as follows:

- Total number of bacteria $N_b = 3{,}500$ approx.
- Step size $(c) = 1$
- Number of chemotactic steps $N_c = 16$
- Number of elimination–dispersion events $N_{ed} = 4$
- Bacteria split ratio=2:1
- Threshold value $(\alpha) = 0.7$
- Threshold value for deciding number of bacteria to eliminate/reproduce $(\beta) = 30$

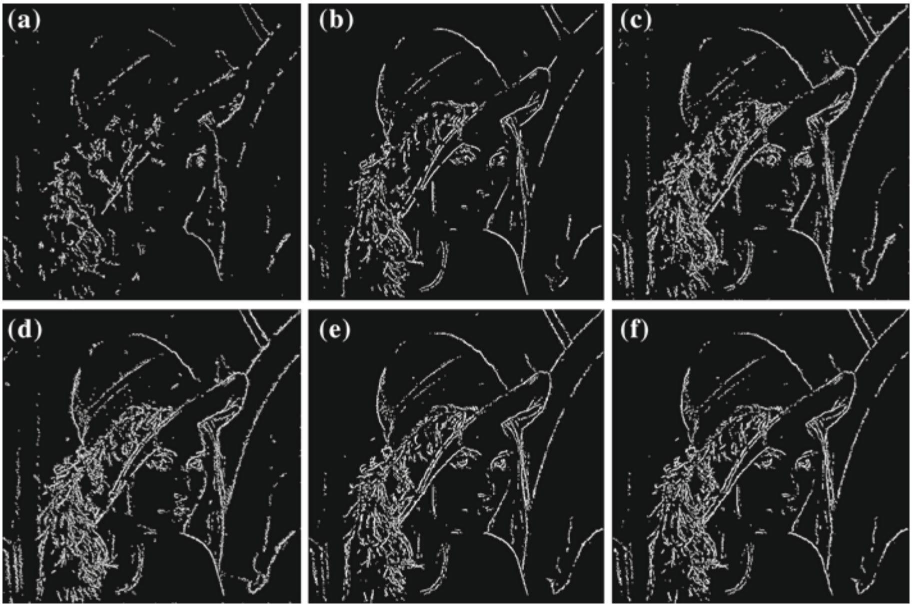

Fig. 4 Results on Lena images by the proposed algorithm with varied number of bacteria at 30% noise. **a** $N_b = 300$, **b** $N_b = 1{,}500$, **c** $N_b = 2{,}000$, **d** $N_b = 3{,}000$, **e** $N_b = 3{,}500$, **f** $N_b = 4{,}000$

The fuzzy reasoning helps find the direction of bacteria movement and fuzzy membership function used in this case is "**Large**". The parameters involved in "**Large**" are "a" and "b". The proposed algorithm is not found to be sensitive to the values of "a" and "b". Thus a range of values is fixed experimentally for parameters: "a" (5–15) and "b" (80–110). The membership function "**Large**" is also found useful for the noise removal if the parameters γ_1 and γ_2 are varied in the range 8–15 and 25–30 respectively.

4.1 Performance analysis

Performance of the proposed algorithm for the noise free images is compared with Sobel and Canny edge detectors, EDIACO of Lu and Chen (2008) and EDMGA of Gudmundsson et al. (1998). Results of these techniques are shown in Fig. 5. It is observed from these results that the best connectivity of edges is provided by Canny edge detector in Fig. 5c. But the increased connectivity gives a lot of false edges as well. Sobel edge detector on the other hand gives less number of edges in Fig. 5b. Figure 5d shows the outcome of EDIACO, which increases the connectivity of edges found from Sobel edge detector using ACO. Figure 5d points out the misleading edges. The same is also true of the results in Fig 5e obtained by the GA based algorithm of Gudmundsson et al. (1998). The result of the proposed algorithm is shown in Fig. 5f. It can be seen that the proposed method gives more connected edges and also removes the misleading edges.

The performance of the proposed algorithm on the noisy images is now discussed for different levels of impulse noise and also a comparison with other algorithms such as EDNFR of Russo (1998), NAEDF of Danafar et al. (2006) and EDHPSO of Setayesh et al. (2009). These algorithms perform best at low noise levels, so we have used 5% impulse noise in our experiments. The resulting images after the application of our approach are shown in Fig. 6.

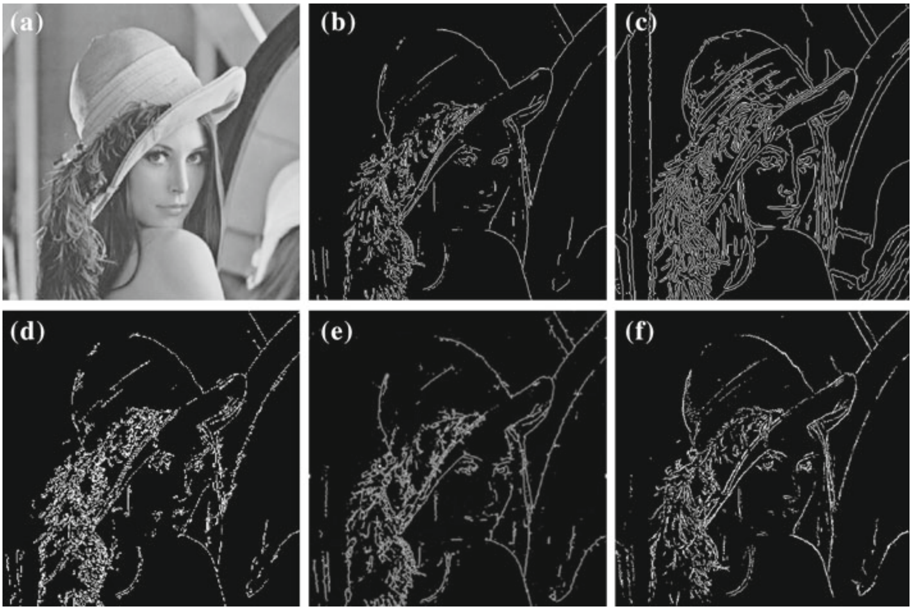

Fig. 5 Results of Lena images of edge detectors with 0% noise. **a** Original image, **b** Sobel edge detector, **c** Canny edge detector, **d** EDIACO, **e** EDMGA, **f** the proposed algorithm

Algorithms in Russo (1998), Danafar et al. (2006) are based on the fuzzy technique while the method in Setayesh et al. (2009) utilizes PSO for edge detection. Visual perception of these results vindicates the superiority of our algorithm. Figure 6c shows thick edges and a lot of false edges as can be seen in Fig. 6b and d. The result of the proposed image is shown in Fig. 5e. It is observed that our algorithm gives good edge map and also removes the noise.

Next, a comparison of our algorithm is made with some existing algorithms such as EDHDS of Civicioglu and Alci (2004) and EDNNF of Yuksel (2007) for the edge detection with higher impulse noise. The level of impulse noise taken is 20% and the results are shown in Fig. 7. The algorithm in Civicioglu and Alci (2004) first removes the noise from a noisy image then edge detection is made; but this step wise process increases the time complexity and results in the false edges as can be observed in Fig. 7b. On the other hand, the algorithm in Canny (1986) performs two steps: noise removal and edge detection simultaneously. Even then some residual noise can still be observed on the top of Lena's hat in Fig. 7c. Figure 7d shows the results of the proposed approach.

The simulation results on cameraman and peppers with different impulse noise levels are shown in Figs. 8, 9, 10. It can be seen from the results that our algorithm gives good edge information on all images up to 30% impulse noise. However the algorithm fails to detect optimal paths for bacteria (good edges) in the highly corrupted images as the number of noise-free pixels is insufficient. The computational complexity of this algorithm is comparable to the existing techniques for edge detection. As this algorithm performs both noise detection and noise removal only on the optimal paths, i.e. edges, computation is reduced drastically. One more feather on the cap is that the parameters needed in the algorithm are independent of the type of images. To summarize our algorithm is suitable for edge detection in the noisy images up to 30% impulse.

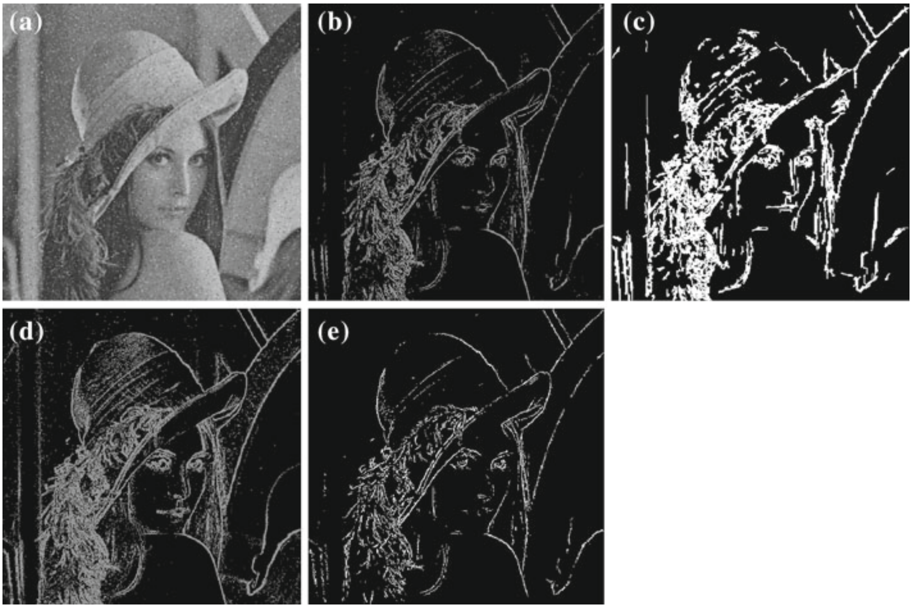

Fig. 6 Results of comparison. **a** Lena image with 5% impulse noise, **b** EDNFR, **c** NAEDF, **d** EDHPSO, **e** the proposed algorithm

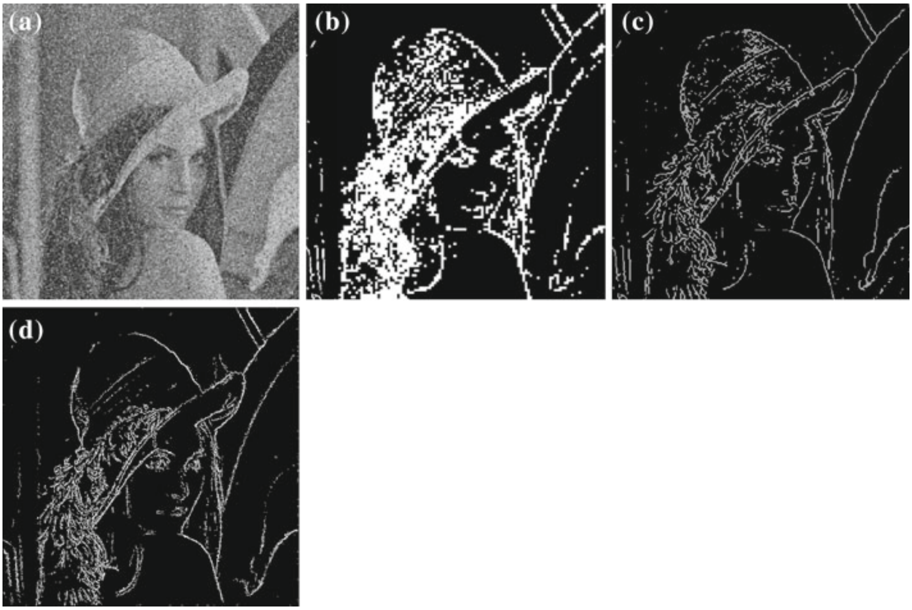

Fig. 7 Results of comparison. **a** Lena with 20% impulse noise, **b** EDHDS, **c** EDNNF, **d** the proposed algorithm

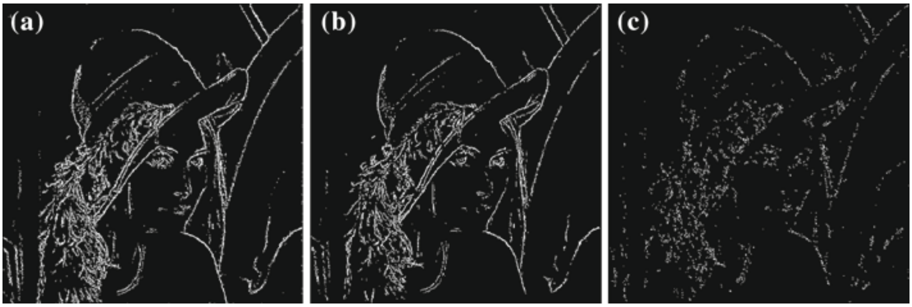

Fig. 8 Results of the proposed algorithm on Lena with different percentages of impulse noise. **a** 10% impulse noise, **b** 30% impulse noise, **c** 50% impulse noise

Fig. 9 Results of the proposed algorithm or camera man with different percentages of impulse noise. **a** 0% impulse noise, **b** 20% impulse noise, **c** 30% impulse noise

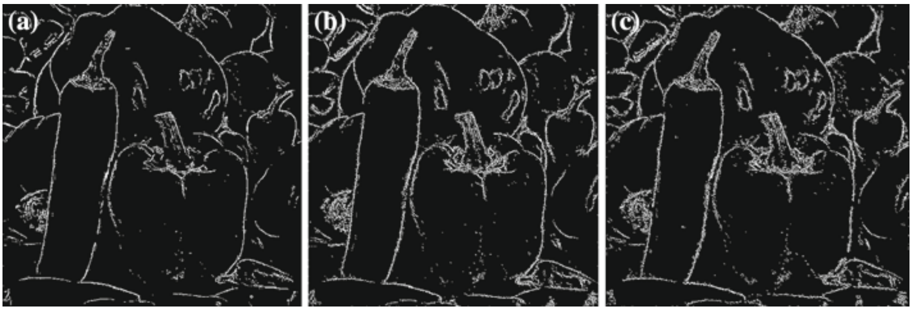

Fig. 10 Results of the proposed algorithm on Peppers with different percentages of impulse noise. **a** 0% impulse noise, **b** 20% impulse noise, **c** 30% impulse noise

5 Conclusions

An edge detection technique is presented for images corrupted with impulse noise. An algorithm developed based on 'Bacterial foraging', that associates the 'Fuzzy reasoning' to the bacteria movement, locates the edge pixels and invokes the 'Noise Adaptive Fuzzy Switching Median Filter' for the removal of noise from the noisy edges. The proposed approach yields superior performance on the images having up to 30% of impulse noise as seen in our experiments. The main contribution of this paper is the detection of edges in the presence of noise using BF with reduced computational complexity. A comparison with some edge detection operators such as Sobel, Canny, ACO and GA vindicate the superiority of the new fuzzy edge detector.

Appendix A: Ho et al. (2006); Roomi et al. (2010)

The study of foraging behavior of several generations of species has established that poor foraging either leads to their elimination or modifies them into better ones. Foraging is treated as an optimization process because species try to move in the direction of higher concentration of food by maximizing the energy intake per unit time. If they lie in low concentration of food patch they change their direction of movement. Social (group) forging is always better than individual foraging. In social foraging members of group communicate about availability of food in their respective region using some mechanism. It helps to find food rich region; thus collective intelligence of group results in more successful foraging.

Bacteria foraging is one of the recent evolutionary learning technique based on the foraging behavior of *E. coli* bacterium. *E. coli* bacterium make two kinds of movements: swim (run) and tumble. The bacterium spends its life between these two activities in search of food. The concentration of food (chemical) in a region decides how long it swims before a tumble. The motion patterns (taxis) generated by bacterium are thus called “chemotaxis”. The bacterium in a neutral substance (neither food nor noxious) will alternately tumble and run. If the medium changes to a nutrient region with constant concentration, mean run time increases. In case of positive nutrient gradient, bacterium spends most of time in swim and a negative gradient encourages tumbling.

Escherichia coli bacteria are supposed to have some chemical signaling between them contributing towards a group intelligent behavior. They move as a group and this behavior is termed as “swarming”. In nutrient rich healthy environment, *E. coli* grows longer and then divides into two daughters. This event is termed as “reproduction”. The events happen in the local environment, where bacteria get killed or group is dispersed to other places. It is called “elimination and dispersal event”. It can weaken foraging sometimes, but can also place bacteria in the food rich region.

There are four steps in bacterium’s life cycle, i.e. Chemotaxis, Swarming, Reproduction, and Elimination-dispersal. The number of bacteria (N_b) is kept much lesser than a practical situation to keep computation low. Population of bacteria is also kept constant, i.e. number of bacteria reproduced is equal to number of bacteria eliminated. Consider a function $J(\theta^i), \theta^i \in R^{D_m}$, which represents the concentration of nutrients in the search space R^{D_m} of the dimension D_m. The position of ith bacterium in the search space, after pth chemotactic, qth reproductive and rth elimination-dispersal steps is denoted by $\theta^i(p, q, r)$ or simply θ^i. Each bacterium will move in the direction of the nutrient rich region judged by the value of the cost function $J(\theta^i)$. Initial positions of bacteria are either decided by the initial information or chosen randomly.

(1) **Chemotaxis**: The kind of movement of bacteria is determined by the nutrients present in the search space, characterized by a value of the cost function $J(\theta^i)$ i.e. bacteria will move in the direction of better value of cost function. Let $c(i)$ be the step size taken during run in the random direction. If a bacterium finds the new position more nutrient-rich, it will take another step in the same direction. This swim will continue

till the cost function keeps on reducing or the maximum number of steps reaches N_s. If new position has constant nutrients or nutrient gradient is negative, swim is followed a by tumble. The direction of movement after tumble is represented by the random vector $\Delta(i)$ and the movement is expressed as:

$$\theta^i(p+1,q,r) = \theta^i(p,q,r) + c(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}(A.1) \tag{A.1}$$

In our work, the direction of bacteria movement is not random but decided by the fuzzy logic (see Sect. 2.2).

Swarming: The moving bacteria do not make cell-to-cell communication rather use some sort of chemical signaling, which is modeled in BFO with the help of some attractant and repellent parameters. This feature is emphasized in our work as we are interested in the optimum path (edge), not the global optimum.

(2) **Reproduction:** This is achieved by sorting all bacteria in the ascending order. The healthiest bacteria, N_{br} split into two to be placed in the same location. To make the population constant N_{br} the least healthy bacteria die, i.e. elimination. Note that $N_{br} = N_b/2$, and let N_{re} be the total number of reproduction steps.

(3) **Elimination and dispersal**: This step regulates the population of bacteria by eliminating the bacteria that land in low nutrient or noxious regions. Dispersal on the other hand locates the bacteria in new regions, which might remain unexplored with limited number of bacteria taken. This step is not used in our algorithm as we do not search for the global optimum.

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