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Performance evaluation of the fast forward quantum optimization algorithm in digital image clustering

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***Abstract*—The primary objective of clustering in image analysis is to establish a meaningful correspondence between image features and clusters. This process is instrumental in extracting higher-level semantic information from digital images. In this study, we propose a novel image clustering approach that integrates the fast forward quantum optimization algorithm (FFQOA) with the K-means clustering (KMC) algorithm, forming a hybrid method referred to as FFQOA + KMC. The FFQOA + KMC initiates clustering based on the grayscale values of images using KMC and then refines the clustering outcome through FFQOA to achieve optimal segmentation. Subsequently, FFQOA + KMC is applied to several benchmark grayscale images, with results compared to those from alternative clustering techniques. Experimental findings confirm the robustness and superiority of FFQOA + KMC through both visual inspections and statistical metrics.**

***Index Terms*— Fast forward quantum optimization algorithm (FFQOA), Quantum optimization, K-means clustering (KMC), Digital image clustering**.

I. Introduction

Digital image clustering is one of the most computationally intensive tasks in pattern discovery and image processing. The primary objective of image clustering is to distinguish each object from others within the image [1–3]. It involves partitioning an image into segments or clusters, where each cluster represents a distinct region [4].

During image clustering, features are assigned to specific clusters using appropriate distance metrics [5]. The resulting clusters consist of features that exhibit a high degree of similarity within their own group, relative to features in other clusters. Typically, clusters are represented by a set of feature vectors known as centroids [6]. In digital image processing, achieving effective clustering with well-separated centroids is a challenging task due to various complicating factors [7], such as contrast, brightness, and noise.

These factors introduce several fundamental challenges in image clustering:

How can one feature be distinguished from another when their colors tend to blend together?

How can features be separated from the background when their color saturation levels are similar?

How can color levels be accurately characterized to ensure that each feature is correctly assigned to its corresponding cluster?

One of the most widely used algorithms in clustering is the K-means clustering (KMC) algorithm [8]. In KMC, a user-defined number of centroids are initialized randomly [9, 10]. Then, based on similarity metrics such as the Euclidean distance, the distance between each feature and the centroids is calculated, and each feature is assigned to its nearest centroid. This iterative process continues until either the algorithm reaches the predetermined maximum number of iterations or the centroids no longer change.

Despite its simplicity and relatively low computational complexity, KMC suffers from two major limitations [11]:

The random initialization of centroids, and

The algorithm tends to converge to the nearest local optimum.

By incorporating fuzzy set theory [12] into the KMC algorithm, a novel algorithm known as the fuzzy C-means (FCM) algorithm was introduced [13]. FCM is less sensitive to uncertainty in feature values and aims to minimize a fuzzy variant of the least squares error metric [14]. Compared to KMC, FCM generally achieves superior performance. However, similar to KMC, FCM is still prone to convergence at local minima and remains highly susceptible to noise and image distortions [15]. Several researchers have proposed enhancements to the FCM algorithm. For instance, Krishnapuram and Keller [16] introduced a probabilistic modification to FCM by designing an objective function whose minimization yields a meaningful probabilistic partition of the data. Pham [17] generalized the FCM objective function by incorporating spatial penalties on membership functions. Zhao et al. [18] further extended the generalized FCM by integrating a kernel distance function. Wu and Kang [19] developed a clustering method based on picture fuzzy sets and the principle of maximum entropy. Shi et al. [20] proposed an ensemble-based fuzzy clustering approach using a membership reconstruction method. To enhance similarity calculations in the FCM framework, Surono and Putri [21] adopted Minkowski and Chebyshev distance metrics.

Numerous metaheuristic techniques have been proposed by researchers to obtain optimized solutions to complex problems [22]. Prominent examples include the genetic algorithm (GA) [23, 24], cultural algorithm (CA) [25], simulated annealing (SA) algorithm [28], particle swarm optimization (PSO) [31, 32], and so on. FFQOA addresses the problems with the KMC algorithm by using quantum wavefunctions that make it easier to explore and get out of local minima. FFQOA is different from PSO and GA because it changes its search distribution using quantum wavefunctions. This makes the global search stronger and less sensitive to random centroid initialization. This makes it easier to discover cluster centroids that are consistent throughout the simulation.

This study assesses the clustering performance of FFQOA+KMC on a diverse set of grayscale images [33], and compares it with six established methods: KMC [9], FCM [21], GA+KMC [27], SA+KMC [30], CA+KMC, and PSO+KMC [31]. The comparison is based on multiple evaluation metrics, including mean squared error (MSE), Peak signal-to-noise ratio (PSNR), and F-measure (FM), demonstrating the superiority of FFQOA+KMC. The proposed hybrid uses FFQOA to determine the best initial centroids by searching the global solution space of the objective function used in the KMC before the clustering process starts. FFQOA makes KMC less likely to converge to local minima by giving it better centroid options. This procedure makes the segmentation more robust overall.

The remainder of this article is organized as follows. **Section II** provides the basics of FFQOA. Experimental results are presented in **Section III**. Finally, conclusion is discussed in **Section IV**.

II. Overview of FFQOA

This section presents the mathematical modeling of FFQOA [34-37]. In this work, terms like "wavefunction," "quantum movement factor," and "displacement" are used as quantum-inspired comparisons instead of strict quantum-mechanical ideas. These analogous operators are meant to act like probabilistic searches, and you shouldn't consider them as real quantum states. Instead, they are considered mathematical tools that make stochastic exploration easier during the optimization process.

Each step of the FFQOA is discussed next.

Let

$$S = [R^{LB}, R^{UB}] \subset \mathbb{R}^{Dim} \quad (1)$$

denote a Dim-dimensional search space, where $R^{LB} < 0$ and $R^{UB} > 0$ represent the lower and upper bounds, respectively, for each dimension.

Let $f : S \rightarrow \mathbb{R}$ be an objective function defined over S. The goal of an optimization problem is to find the global optimal solution $g^* \in S$ such that:

$$f(g^*) = \min f(g) \quad (2)$$

depending on whether the problem is formulated as a minimization or maximization task. Although f need not be continuous, the optimal solution g^* must lie within the bounded interval $[R^{LB}, R^{UB}]$ for each dimension. Here, R^{LB} and R^{UB} denote the lower and upper bounds of the search space S, respectively.

Step 1: Initialization Using Quantum Wavefunctions.

The matter waves associated with quantum particles can be interpreted using wavefunctions. A set of wavefunctions is considered as the initial feasible solution to the objective function f, with the solutions uniformly distributed over the search space S.

This set of wavefunctions is denoted by $\Phi(z)$ and defined as:

$$\Phi(z) = [\varphi_1(z), \varphi_2(z), \ldots, \varphi\_Q(z)] \sim [R^{LB}, R^{UB}] \quad (3)$$

Here, q = 1, 2, …, Q, where Q denotes the total number of wavefunctions in S, and z = 1, 2, …, Z, where Z represents the maximum number of iterations.

Each individual wavefunction $\varphi_q(z)$ in Eq. (3) can be represented as a linear combination of two component functions:

$$\Phi_q(z) = \tau \cdot G_q(z) + (1 - \tau) \cdot H_q(z) \quad (4)$$

In Eq. (4), $G_q(z)$ and $H_q(z)$ are defined as:

$$G_q(z) = R^{UB} + \beta_1 \cdot (R^{UB} - R^{LB}) \quad (5)$$
$$H_q(z) = R^{LB} + \beta_2 \cdot (R^{UB} - R^{LB}) \quad (6)$$

Where, $\beta_1, \beta_2 \in [0, 1]$ are random numbers drawn from a uniform distribution. In Eq. (4), τ is a complex-valued coefficient with magnitude $|\tau| = \sqrt{(x^2 + y^2)}$, where x and y are the real and imaginary parts, respectively.

Step 2: Define Location $L_q(z)$ of Each $\Phi_q(z)$ as:

$$L_q(z) = 1 / \Phi_q(z) \cdot e(-2/\Phi_q(z)) \quad (7)$$

Step 3: Define Movement $M_q(z)$ of Each $\Phi_q(z)$ as:

$$M_q(z) = |\Phi_q(z)| - (L_q(t)/2) \ln(1/|\eta|) \quad (8)$$

Here, $\eta \in [0,1]$ denotes the quantum movement factor of $\Phi_q(z)$.

Step 4: Define Displacement $D_q(z)$ of Each $\Phi_q(z)$ as:

$$D_q(z) = 2 \cdot |L_q(z) - M_q(z)| \quad (9)$$

Step 5: Prepare the Set of Displacements $\rho(z)$ as:

$$\rho(z) = \{D_1(z), D_2(z), \ldots, D_qQ(z), \mathit{LocalDis}_q(z), \mathit{GlobalDis}\} \qquad (10)$$

Each $LocalDis_q(z)$ term acts as the local best displacement for $\Phi_q(z)$, while GlobalDis represents the global best displacement obtained so far in $\rho(z)$.

Step 6: Supply $\rho(z)$ as input to the objective function as:

$$\min f(\rho(z)) \qquad (11)$$

Step 7: Evaluate fitness and apply acceleration mechanism as:

$$A_q(z+1) = \varphi \cdot A_q(z) + \ln(1/\eta)\, \beta_1 [LocalDis_q(z) - D_q(z)] + \ln(1/\eta)\, \beta_2 [GlobalDis - D_q(z)] \qquad (12)$$

In Eq. (12), φ is referred to as the quantum acceleration factor, defined as:

$$\varphi = \varphi_{max} - z \cdot (\varphi_{max} - \varphi_{min})/Z \qquad (13)$$

Here, φ_{min}, $\varphi_{max} \in [0.1, 0.9]$, with $\varphi_{max} > \varphi_{min}$. The parameter η is a small positive number, and $\beta_1, \beta_2 \in [0, 1]$ are random numbers.

The terms $LocalDis_q(z)$ and GlobalDis represent the best local and global displacement vectors at iteration z, respectively.

Step 8: Update the Displacement as:

$$D_q(z+1) = D_q(z) + A_q(z+1) \qquad (14)$$

III. Experimental Results

This section presents the performance analysis of FFQOA+KMC in terms of digital image clustering. The performance of the proposed FFQOA+KMC was compared with KMC, FCM, GA+KMC, SA+KMC, CA+KMC, and PSO+KMC.

3.1 Dataset description and evaluation metrics

The FFQOA+KMC algorithm was applied to a diverse set of monochrome images for clustering. The images used in the experiments were sourced from Alpert et al. [33]. The performance of FFQOA + KMC was assessed by measuring the consistency between the clustered images and the ground truth images. Well-established metrics were employed for this evaluation, including Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and F-measure (FM).

3.2 Digital image clustering

In Fig. 1 (columns (a) and (b)), the original images and their corresponding ground truth images are presented for the training, validation, and testing sets, respectively. Columns (c) through (g) of the same figures show the clustered images obtained using KMC, FCM, GA+KMC, SA+KMC, CA+KMC, and PSO+KMC, respectively. The clustered images produced by the FFQKCA are illustrated in column (h). Visual inspection reveals that the KMC, FCM, GA+KMC, SA+KMC, CA+KMC, and PSO+KMC methods did not consistently cluster all elements. In contrast, the clustered images from FFQOA+KMC demonstrate clear and consistent object clustering across the training, validation, and testing sets.

3.3 Statistical analysis

Statistical analyses of FFQOA+KMC and the existing clustering methods were conducted using the MSE, PSNR, and FM metrics. Table 1 provides a comparative summary of FFQOA+KMC against KMC, FCM, GA+KMC, SA+KMC, CA+KMC, and PSO+KMC for the selected images. Results show that FFQOA+KMC achieves an average MSE of 219.12, which is substantially lower than the corresponding values of all other methods. Likewise, the PSNR value for FFQOA+KMC is 24.72, indicating a clear enhancement in reconstruction quality. The FM score of 0.3220 also reflects a consistent improvement over competing methods, while remaining within a plausible range for unsupervised clustering. Overall, these statistically consistent results confirm that FFQOA+KMC delivers superior performance compared to all benchmarked techniques.

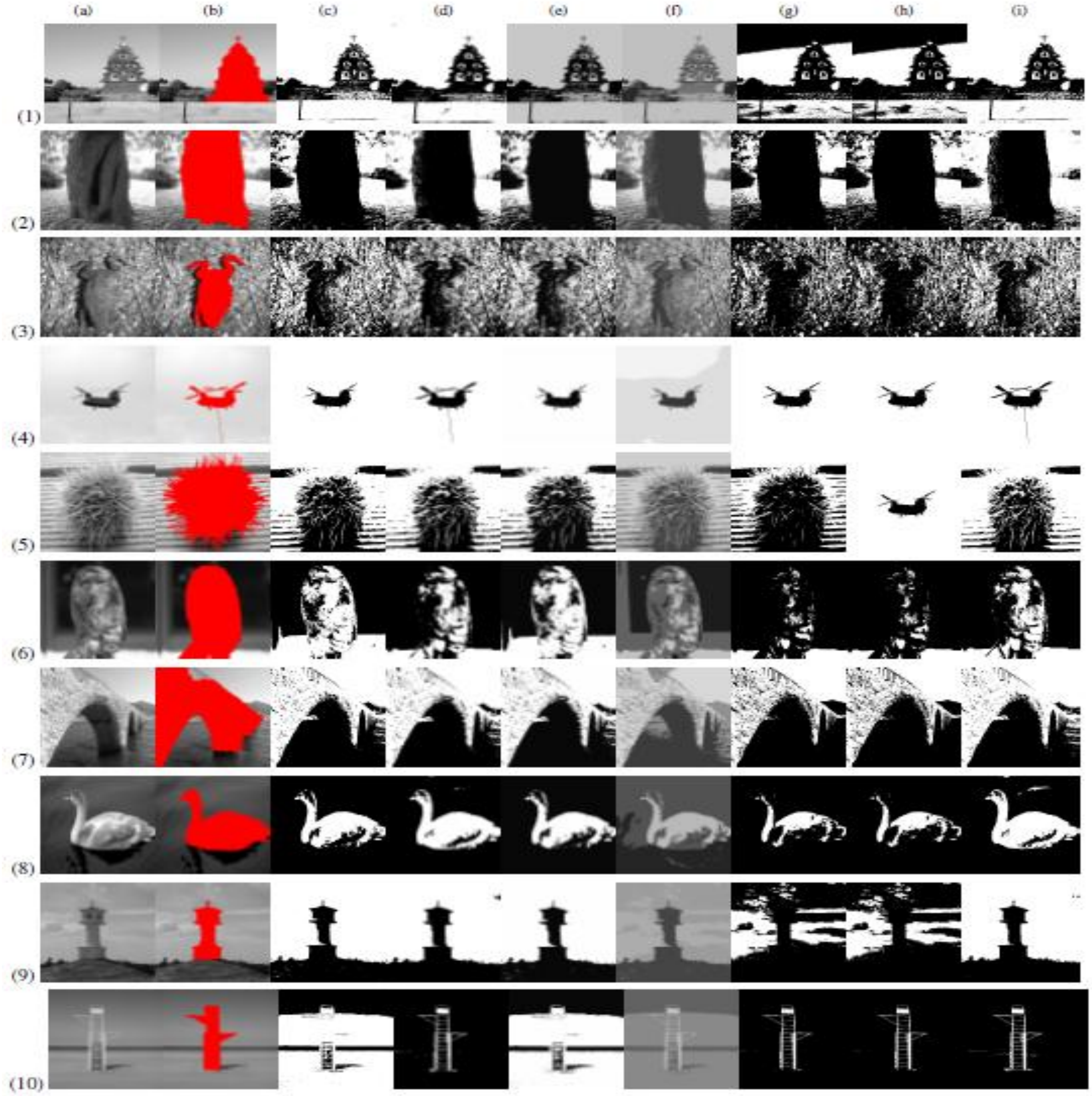

Figure 1. Clustering of images (1-10): (a) original image, (b) ground truth image, (c) KMC, (d) FCM, (e) GA+KMC, (f) SA+KMC, (g) CA+KMC, (h) PSO+KMC, and (i) FFQOA+KMC.

Table 1. The results of the FFQOA+KMC on selected images, including the MSE, PSNR, and FM.

Method	**MSE (↓)**	**PSNR (↑)**	**FM (↑)**
KMC	25400.19	4.08	0.0024
FCM	23892.83	4.35	0.0010
GA+KMC	3072.23	13.26	0.0021
SA+KMC	1267.23	17.10	0.0032
CA+KMC	1156.23	17.50	0.1134
PSO+KMC	1052.23	17.91	0.2134
FFQOA+KMC	**219.12**	**24.72**	**0.3220**

IV. Conclusions and Future Directions

Clustering is a broad and significant research area with numerous practical applications. In this study, we employed the FFQOA+KMC, which integrates the FFQOA with the KMC clustering algorithm. Then, FFQOA+KMC was applied to cluster various grayscale images. Visual inspection and statistical analysis revealed that FFQOA+KMC consistently produced higher-quality clustered images and statistically significant improvements compared to other clustering methods, including KMC, FCM, GA+KMC, SA+KMC, CA+KMC, and PSO+KMC. These findings indicate that FFQOA effectively enhances KMC's clustering performance by optimizing cluster centroids.

Despite the experimental results demonstrating clear improvements over existing methods, the evidence remains limited to a small number of grayscale images. Therefore, a wider evaluation across different datasets and image types is required.

There are also certain challenges with the proposed FFQOA+KMC approach. The method adds more computational overhead because of FFQOA's iterative optimization process and requires careful tuning of quantum-inspired parameters. Furthermore, when external evaluation metrics are used, performance may depend on the number of reference labels.

In future, the FFQOA can be applied in various biomedical imaging datasets [38-42], time series forecasting [43-45], traveling salesman problem [46], optimal decision-making [47, 48], and various domain specific problems [49-51]. FFQOA is intended to enhance global exploration and avoid early convergence, so it might work in a similar way for these problem classes; however, this needs to be verified in the future.

REFERENCES

[1] O. J. Tobias and R. Seara, "Image segmentation by histogram thresholding using fuzzy sets," IEEE Trans. on Image Processing, vol. 11, no. 12, pp. 1457–1465, 2002.

[2] Yaorui Tang, Bo Yang, Hong Peng, and Xiaohui Luo, "Industrial defect detection and location based on greedy membrane clustering algorithm," Digital Signal Processing, vol. 149, p. 104470, 2024.

[3] Xuemin Hu, Dan Xiong, and Li Chai, "Robust multi-view clustering via structure regularization concept factorization," Digital Signal Processing, vol. 155, p. 104713, 2024.

[4] Yi Yang, Dong Xu, Feiping Nie, Shuicheng Yan, and Yueting Zhuang, "Image clustering using local discriminant models and global integration," IEEE Trans. on Image Processing, vol. 19, no. 10, pp. 2761–2773, 2010.

[5] A. K. Jain, M. N. Murty, and P. J. Flynn, "Data clustering: A review," ACM Computing Surveys (CSUR), vol. 31, no. 3, pp. 264–323, 1999.

[6] C. Carpineto and G. Romano, "A lattice conceptual clustering system and its application to browsing retrieval," Machine Learning, vol. 24, pp. 95–122, 1996.

[7] X. Yang, W. Zhao, Y. Chen, and X. Fang, "Image segmentation with a fuzzy clustering algorithm based on ant-tree," Signal Processing, vol. 88, no. 10, pp. 2453–2462, 2008.

[8] J. MacQueen, "Some methods for classification and analysis of multivariate observations," in Proc. 5th Berkeley Symp. Math. Stat. Probab., vol. 1, pp. 281–297, Oakland, CA, USA, 1967.

[9] L.-H. Juang and M.-N. Wu, "MRI brain lesion image detection based on color-converted K-means clustering segmentation," Measurement, vol. 43, no. 7, pp. 941–949, 2010.

[10] K. Shao, G. Mei, and Y. Wu, "Investigating changes in global distribution of ozone in 2018 using K-means clustering algorithm," J. Comput. Math. Data Sci., vol. 3, p. 100028, 2022.

[11] P. Fränti and S. Sieranoja, "How much can K-means be improved by using better initialization and repeats?," Pattern Recognition, vol. 93, pp. 95–112, 2019.

[12] L. A. Zadeh, "Fuzzy sets," Information and Control, vol. 8, no. 3, pp. 338–353, 1965.

[13] J. C. Bezdek, Pattern Recognition with Fuzzy Objective Function Algorithms. New York: Plenum Press, 2013.

[14] A. W. C. Liew, S. H. Leung, and W. H. Lau, "Fuzzy image clustering incorporating spatial continuity," IEE Proc. Vision, Image and Signal Processing, vol. 147, no. 2, pp. 185–192, 2000.

[15] M. Forouzanfar, N. Forghani, and M. Teshnehlab, "Parameter optimization of improved fuzzy C-means clustering algorithm for brain MR image segmentation," Eng. Appl. Artif. Intell., vol. 23, no. 2, pp. 160–168, 2010.

[16] R. Krishnapuram and J. M. Keller, "A possibilistic approach to clustering," IEEE Trans. Fuzzy Syst., vol. 1, no. 2, pp. 98–110, 1993.

[17] D. L. Pham, "Spatial models for fuzzy clustering," Comput. Vis. Image Underst., vol. 84, no. 2, pp. 285–297, 2001.

[18] F. Zhao, L. Jiao, and H. Liu, "Kernel generalized fuzzy C-means clustering with spatial information for image segmentation," Digital Signal Processing, vol. 23, no. 1, pp. 184–199, 2013.

[19] C. Wu and Z. Kang, "Robust entropy-based symmetric regularized picture fuzzy clustering for image segmentation," Digital Signal Processing, vol. 110, p. 102905, 2021.

[20] P. Shi, L. Guo, H. Cui, and L. Chen, "Geometric consistent fuzzy cluster ensemble with membership reconstruction for image segmentation," Digital Signal Processing, vol. 134, p. 103901, 2023.

[21] S. Surono and R. D. A. Putri, "Optimization of fuzzy C-means clustering algorithm with combination of Minkowski and Chebyshev distance using principal component analysis," Int. J. Fuzzy Syst., vol. 23, no. 1, pp. 139–144, 2021.

[22] I. Boussad, J. Lepagnot, and P. Siarry, "A survey on optimization metaheuristics," Information Sciences, vol. 237, pp. 82–117, 2013.

[23] D. E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning. New York: Addison-Wesley, 1989.

[24] J. R. Koza, "Genetic programming as a means for programming computers by natural selection," Stat. Comput., vol. 4, no. 2, pp. 87–112, 1994.

[25] R. G. Reynolds, "An introduction to cultural algorithms," in Proc. 3rd Annu. Conf. Evol. Program., River Edge, NJ, vol. 24, pp. 131–139, Feb. 1994.

[26] D.-X. Chang, X.-D. Zhang, and C.-W. Zheng, "A genetic algorithm with gene rearrangement for K-means clustering," Pattern Recognition, vol. 42, no. 7, pp. 1210–1222, 2009.

[27] M. Z. Islam, V. Estivill-Castro, M. A. Rahman, and T. Bossomaier, "Combining K-means and a genetic algorithm through a novel arrangement of genetic operators for high-quality clustering," Expert Syst. Appl., vol. 91, pp. 402–417, 2018.

[28] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing," Science, vol. 220, no. 4598, pp. 671–680, 1983.

[29] S. Z. Selim and K. Alsultan, "A simulated annealing algorithm for the clustering problem," Pattern Recognition, vol. 24, no. 10, pp. 1003–1008, 1991.

[30] J. Lee and D. Perkins, "A simulated annealing algorithm with a dual perturbation method for clustering," Pattern Recognition, vol. 112, p. 107713, 2021.

[31] S. Carstensen and J. C.-W. Lin, "An efficient PSO-based evolutionary model for closed high-utility itemset mining," Appl. Intell., vol. 55, no. 4, pp. 1–17, 2025.

[32] S. Zhao, T. Zhang, S. Ma, and M. Wang, "Sea-horse optimizer: A novel nature-inspired meta-heuristic for global optimization problems," Appl. Intell., vol. 53, no. 10, pp. 11833–11860, 2023.

[33] S. Alpert, M. Galun, A. Brandt, and R. Basri, "Image segmentation by probabilistic bottom-up aggregation and cue integration," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 2, pp. 315–327, 2012.

[34] P. Singh, A Journey into Quantum Wavefunction Optimization Algorithm: Exploring the Path to the Optimal Solution. Cambridge, UK: Cambridge University Press, UK, 2025.

[35] P. Singh, "The Fast Forward Quantum Optimization Algorithm: A study of convergence and novel unconstrained optimization," *Comput. Methods Appl. Mech. Eng.*, vol. 443, p. 118039, 2025.

[36] P. Singh and S. S. Bose, "A Quantum-Clustering Optimization Method for COVID-19 CT Scan Image Segmentation," *Expert Syst. Appl.*, vol. 185, p. 115637, 2021.

[37] P. Singh, "FQTSFM: A fuzzy-quantum time series forecasting model," *Inf. Sci.*, vol. 556, pp. 57–79, 2021.

[38] M. K. Muchahari, P. Singh, and S. Das, "Automated White Matter Lesions Segmentation of MRIs for Multiple Sclerosis Detection Using Fuzzy-Entropy Algorithm," *Int. J. Fuzzy Syst.*, vol. 27, pp. 1875–1886, 2025.
[39] P. Singh and Y.-P. Huang, "AKDC: Ambiguous Kernel Distance Clustering Algorithm for COVID-19 CT Scans Analysis," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 54, no. 10, pp. 6218–6229, 2024.
[40] P. Singh and Y.-P. Huang, "An ambiguous edge detection method for computed tomography scans of coronavirus disease 2019 cases," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 54, no. 1, pp. 352–364, 2024.
[41] P. Singh and S. S. Bose, "Ambiguous D-means fusion clustering algorithm based on ambiguous set theory: Special application in clustering of CT scan images of COVID-19," *Knowl.-Based Syst.*, vol. 231, p. 107432, 2021.
[42] P. Singh, "A Type-2 Neutrosophic-Entropy-Fusion Based Multiple Thresholding Method for the Brain Tumor Tissue Structures Segmentation," *Appl. Soft Comput.*, vol. 103, p. 107119, 2021.
[43] P. Singh, "A novel model to deal with ambiguous and complex time series: Application to sunspots forecasting," *Knowl.-Based Syst.*, p. 114257, 2025.
[44] P. Singh and Y.-P. Huang, "A new hybrid time series forecasting model based on the neutrosophic set and quantum optimization algorithm," *Comput. Ind.*, vol. 111, pp. 121–139, 2019.
[45] P. Singh and B. Borah, "An effective neural network and fuzzy time series-based hybridized model to handle forecasting problems of two factors," *Knowl. Inf. Syst.*, vol. 38, pp. 669–690, 2014.
[46] P. Singh, "Quantum wavefunction optimization algorithm: Application in solving traveling salesman problem," *Int. J. Mach. Learn. Cybern.*, vol. 16, pp. 3557–3585, 2025.
[47] P. Singh and T. W. Liao, "Multi-criteria group decision-making using ambiguous sets, Weibull distribution, and aggregation operators: A case study in optimal vendor selection for office supplies," *Syst. Soft Comput.*, vol. 7, p. 200283, 2025.
[48] P. Singh, "Data-driven ambiguous cognitive map for complex decision-making in supply chain management," *J. Comput. Math. Data Sci.*, vol. 14, p. 100110, 2025.
[49] G. Oise, C. Nwabuokei, R. IGBUNU, and P. EJENARHOME, "Revisiting Parasitic Computing: Ethical and Technical Dimensions in Resource Optimization", Vokasi Unesa Bull. Eng. Technol. Appl. Sci., vol. 2, no. 3, pp. 376–386, 2025.
[50] D. Oliva, F. Soleimanian Gharehchopogh, V. Hacimahmud Abdullayev, W. aribowo, A. Asmunin, and A. Iwan Nurhidayat, "A Novel Modified Tornado optimizer with Coriolis force Based On Levy Flight to Optimize Proportional Integral Derivative Parameters of DC Motor", Vokasi Unesa Bull. Eng. Technol. Appl. Sci., vol. 2, no. 3, pp. 387–400, 2025.
[51] Kabiru Abubakar Tureta, A. SABO, and Y. Abdulrazak, "A Optimal Placement of Phasor Measurement Units on Shiroro 330kv Grid Network using Binary Grey Wolf Optimization Algorithm", Vokasi Unesa Bull. Eng. Technol. Appl. Sci., vol. 2, no. 3, pp. 444–459, 2025.

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