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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.

1. 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 challenging due to complicating factors such as contrast, brightness, and noise [7]. These factors introduce several fundamental challenges in image clustering:

a) How can one feature be distinguished from another when their colors tend to blend together?
b) How can features be separated from the background when their color saturation levels are similar?
c) 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 clustering algorithms is K-means clustering (KMC) [8]. In KMC, a user-defined number of centroids is 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 stop changing. Despite its simplicity and relatively low computational complexity, KMC suffers from two major limitations [11]:

a) The random initialization of centroids, and the algorithm tends to converge to the nearest local optimum.

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By incorporating fuzzy set theory [12] into the KMC algorithm, a novel algorithm, 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) [28], particle swarm optimization (PSO) [31][32], and others. FFQOA addresses the problems with the KMC algorithm by using quantum wavefunctions, which make it easier to explore and escape local minima. FFQOA differs from PSO and GA in that it adapts 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.

2. METHOD

2.1 Overview of Fast Forward Quantum Optimization Algorithm (FFQOA)

This section presents the mathematical modeling of FFQOA [34]-[37]. In this work, terms such as “wavefunction,” “quantum movement factor,” and “displacement” are used as quantum-inspired analogies rather than strict quantum-mechanical concepts. 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.

$$S = [RLB, RUB] \subset \mathbb{R}Dim \tag{1}$$

Denote a D-dimensional search space, where $R^{LB} < 0$ and $R^{UB} > 0$ represent the lower and upper bounds, respectively, for each dimension.
Let $f : S \to \mathbb{R}$ 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:

$$f(g*) = min\, f(g) \tag{2}$$

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:

$$\Phi(z) = [\varphi_1(z), \varphi_2(z), \ldots, \varphi\_Q(z)] \sim [RLB, RUB] \tag{3}$$

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:

$$\Phi q(z) = \tau \cdot Gq(z) + (1 - \tau) \cdot Hq(z) \tag{4}$$

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

$$Gq(z) = RUB + \beta_1 \cdot (RUB - RLB) \tag{5}$$
$$Hq(z) = RLB + \beta_2 \cdot (RUB - RLB) \tag{6}$$

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:

$$Lq(z) = 1 / \Phi q(z) \cdot e(-2/\Phi q(z)) \tag{7}$$

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

$$Mq(z) = |\Phi q(z)| - (Lq(t)/2)\, ln(1/|\eta|) \tag{8}$$

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:

$$Dq(z) = 2 \cdot |Lq(z) - Mq(z)| \tag{9}$$

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

$$\rho(z) = \{D_1(z), D_2(z), \ldots, DqQ(z), LocalDisq(z), GlobalDis\} \tag{10}$$

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:

$$min\, f(\rho(z)) \tag{11}$$

Step 7: Evaluate fitness and apply acceleration mechanism as:

$$Aq(z+1) = \varphi \cdot Aq(z) + ln(1/\eta)\, \beta_1 [LocalDisq(z) - Dq(z)] + ln(1/\eta)\, \beta_2 [GlobalDis - Dq(z)] \tag{12}$$

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

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

Here, $\varphi_{min}, \varphi_{max} \in [0.1, 0.9]$, 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:

$$Dq(z+1) = Dq(z) + Aq(z+1) \tag{14}$$

3. 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 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).

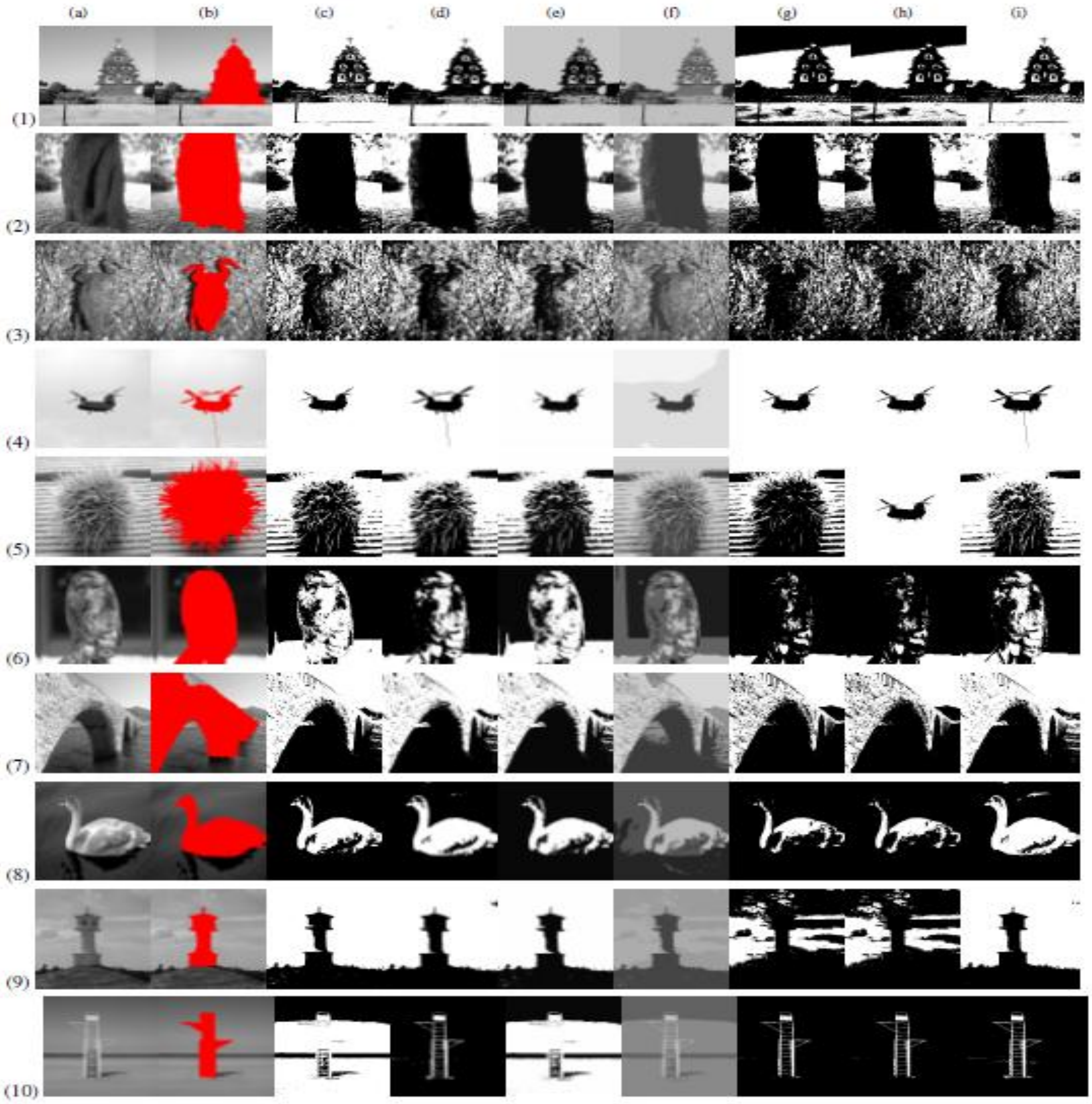

Figure 1. Clustering of images (1-10): (a) original image, (b) ground truth image, (c) KMC, (d) FCM, (e) GA+KMC, (f) SA+KMC, (g) CA+KMC, (h) PSO+KMC, and (i) FFQOA+KMC.

In Figure 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.

3.2 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, substantially lower than the corresponding values for 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.

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	0.001
GA+KMC	3072.23	13.26	0.0021
SA+KMC	1267.23	17.1	0.0032
CA+KMC	1156.23	17.5	0.1134
PSO+KMC	1052.23	17.91	0.2134
FFQOA+KMC	**219.12**	24.72	**0.322**

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

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