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REVIEW

Quantum medical images processing foundations and applications

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Abstract

Medical imaging is considered one of the most important areas within scientific imaging due to the rapid and ongoing development in computer-aided medical image visualisation, advances in analysis approaches, and computer-aided diagnosis. Here, the principles of quantum computation and information to develop the field of medical image processing will be reviewed. The advancement of quantum computation in image processing has proved its outstanding properties for processing and storage capacity compared to the classical methods. This review provides a comprehensive summary of the common advanced approaches, methodologies and advanced applications in medical images based on quantum computation.

KEYWORDS

Image Processing, Medical Images, Quantum Information

1 | INTRODUCTION

Image processing represents the technique for utilising and manipulating images to achieve a specific objective, such as obtaining data automatically or supporting the interpretation of various human behaviours. The principle of image processing has become significant since the development of visual knowledge for personal analysis and data processing for autonomous machine perception [1]. The rapid innovation in image processing and investigation practices in recent years and their implementations have inspired growth in computer vision systems and other related fields. Image processing has proved its efficiency for various domains such as astronomy, defence, biology, medicine, and industry. Digital image processing is now being applied to explain a broad range of problems, related to improving the information for human visual analysis and testing. Digital image processing has emerged as an applied and useful tool with diverse applications, especially in medical informatics [2].

Medical informatics is described as a discipline involving approaches to medical data processing and specifying methods for the diagnosis and cure of patients [3]. It includes a mixture of fields such as medical image processing, medical image classification, medical image watermarking, medical decision support system, health informatics system, biostatics, and bio-signal analysis, clinical support systems, medical computer-based training, and medical networking systems. Medical image applications such as processing of magnetic resonance imaging (MRI), X-rays, electron micrographs, and ultrasonic scanning are almost no longer achievable without computers [4]. Moreover, computer-based tools can be used for effective ways of minimising costs, optimising clinical results, and providing better treatment. The principal strength of the application of computers in medical imaging remains in the use of image processing techniques for quantitative analysis [3]. Medical images rely on visual analysis by human observers, which can lead to inadequacies caused by inter-observer dissimilarities and errors due to weakness, distractions, and limited experience. While the interpretation of an image by an expert illustrates his/her experience and knowledge, there is almost always a subjective component. When computer analysis is performed with the appropriate care and logic, it can be an actual strength which can potentially add to the interpretation of the expert. Thus, it becomes achievable to enhance the diagnostic precision and confidence to compete with an expert with many years of experience. However, these medical data processing approaches are still prone to challenges regarding consistency, effectiveness, and an inadequate level of security. Contrasted with classical computation, quantum computation demonstrates several outstanding characteristics by employing quantum mechanics to denote and process information, such as quantum entanglement, parallel quantum computing, and quantum superposition [5].

Quantum computation investigates the computational power and other properties of computers based on quantum mechanical principles. The field was introduced in the early 1980s with suggestions for analogue quantum computers by Paul Benioff [6]. Richard Feynman has shown that quantum mechanical systems cannot be replicated efficiently and proficiently by using classical schemes. Additionally, he suggested that developing the construction of a quantum computer only depends on quantum theories and rules. The no-cloning theorem and its inspiration in quantum computing have been identified in Ref. [7, 8]. The no-cloning theorem prevents the realization of identical copies of an unknown quantum state. The quantum system can solve complex computational problems faster and more effectively than the classical system is demonstrated in Ref. [6]. The present model for realizing quantum algorithms is the gate model, where the algorithms are implemented as a succession of simple gates operating on one or more quantum bits. The manipulation of a quantum computer consists of a series of unitary transformations which influence each component of the superposition concurrently. It produces considerable parallel data processing which reduces the execution time. The development of quantum computation and information has appeared in various areas of science, such as biology, chemistry, and computer systems. Quantum image processing is mainly dedicated to exploiting quantum computing and quantum information processing to generate and operate with quantum images. So, it is expected that quantum image processing technologies will propose abilities and performances that are not yet achieved by classical methods [9]. These developments could be in terms of processing speed, security, and minimisation of storage requirements etc.

The review is organised as follows; in Section 2, the principles of medical image processing operations are discussed. Various quantum image representation and features are explained in Section 3. Section 4 discusses the different aspects of quantum computation-based medical images. Finally, Section 5 includes a summary and conclusion.

2 | MEDICAL IMAGE PROCESSING OPERATIONS

This section introduces different procedures of medical image processing, including generation, visualisation, examination, and control. The terminology of processing biomedical images involves the manipulation of the digital image in the field of biomedical sciences and the main domains of digital image processing are shown in Figure 1:

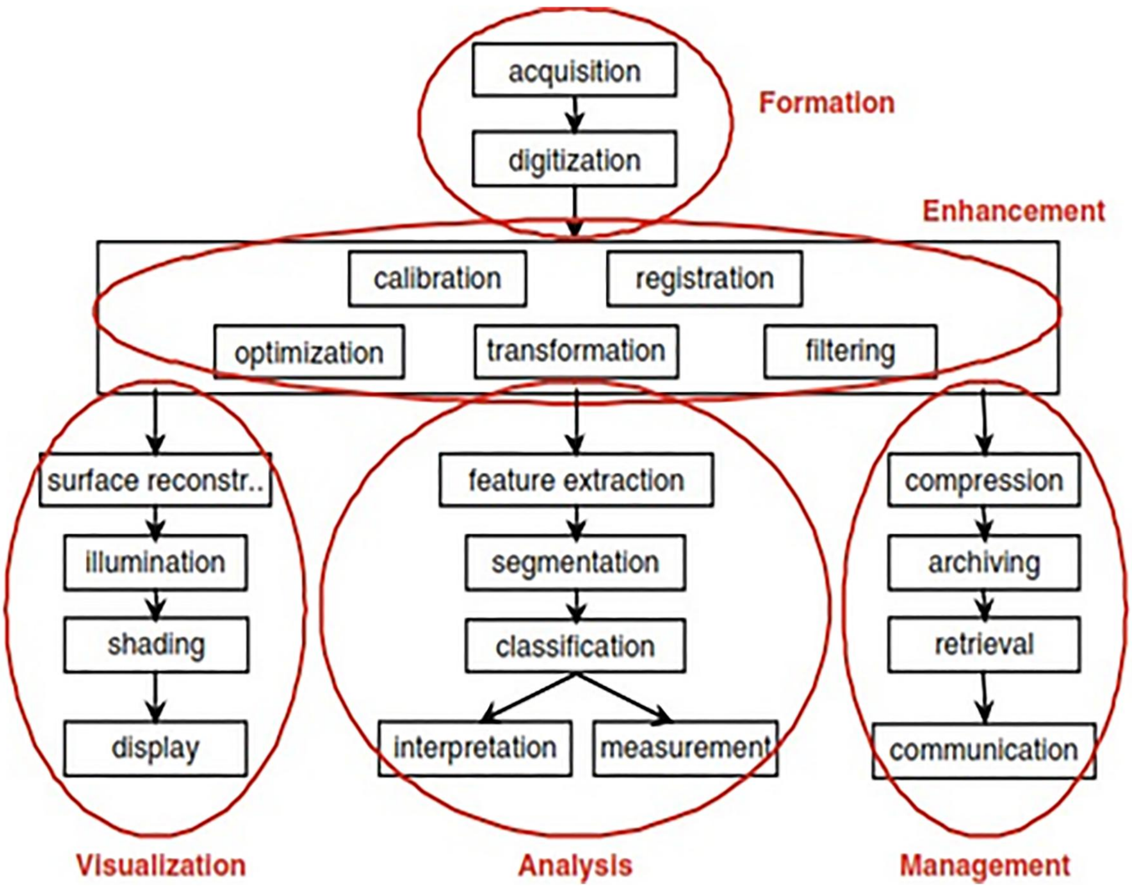


FIGURE 1 Various modules of image processing [10]

2.1 | Medical image formation

Image construction incorporates the whole process from obtaining the image through creating a digital image pattern. Medical images have been a significant part of diagnostics, medication devising and planning, and follow-up inquiries since the development of X-rays. Moreover, medical images are used for learning, documentation, and analysis, explaining morphology, biological, and physical applications in different dimensions of image data [10]. Now, a broad category of imaging techniques has been investigated, which concerns transferring, absorption or refraction of light, scattering, temperature, sound, or rotation. The contrast against image quality for the imaging modality has been highlighted in Figure 2. An algorithm for representing a specific vertebrae pattern which operates by individual imaging modality and it cannot be transferred immediately to a different modality.

2.1.1 | X-ray imaging

Röntgen initially proposed calling the process X-ray when he observed that radiation could be generated when the electron dropped from a flying projectile towards a vacant position of an internal scale [10]. The difference between energy levels is produced in the form of a photon. The vacant positions of an internal range are produced by firing electrons into the atom. The acceleration of released particles from a wire has resulted from the extraordinary energy between the cathode and anode. The acceleration energy is transformed to kinetic energy and loaded onto the particles. The most important kind of intercommunications may happen, that is the particle speeds up and communicates with the nucleus. It occurs when the electron is decreased down with the coulomb field of the protons, and potential energy corresponds to the destruction of the kinetic energy of the particle when it emits a photon. When x-radiation moves within a material, the X-ray photons can communicate, including the nucleus or the shell appearing in absorption or scattering. Absorption occurs when the photon has wholly disappeared, transferring the total potential energy to the absorbing matter. This influence is dangerous and produces the destruction of existing cells; however it is necessary to get a contrasted image. Scattering happens in the case of generating a coherent or incoherent secondary photon and is utilised for filtering the diffused radiation resulting from the wrong direction and location of the secondary photon.

2.1.2 | Computed tomography (CT)

X-ray imaging performs a combination of images consisting of each reduction coefficient when the paths are combined. Usually, we cannot discover the series of overlapping objects of an individual image [3]. This situation is different when the image is computed tomography since the absorption is achieved within 3-D for all volume elements (voxel). The volume is obtained slice by slice, and every slice is restored from various measures under different angulations. Both back and filtered back projections are the most popular methodologies employed for image restoring. The principles of arithmetic operations performed in CT can be explained by assuming the slice of the image is broken into four pixels, and two identical rays are moving it in two opposite directions. Consequently, the outcome is four independent formulas which enable the computation of the various four absorption measurements. Furthermore, there is a positive relationship between the number of identical rays, angles, rows, and columns of CT images. In another words, when the number of parallel rays and angles are increased, the number of columns and rows of CT images is increased. Now, the development to speed up the attainment of CT images is achieved by scanners and fan ray gantries [10].

2.1.3 | Magnetic resonance imaging (MRI)

The principle of MRI is like the one introduced for CT, as both are presented to work in the field of medicine. But the invention of MRI depends on the influence of electromagnetic waves on the nucleus [3]. The MRI technology is concentrated on hydrogen atoms since most of the body of a human consists of water. The movement of the hydrogen nucleus is a self-

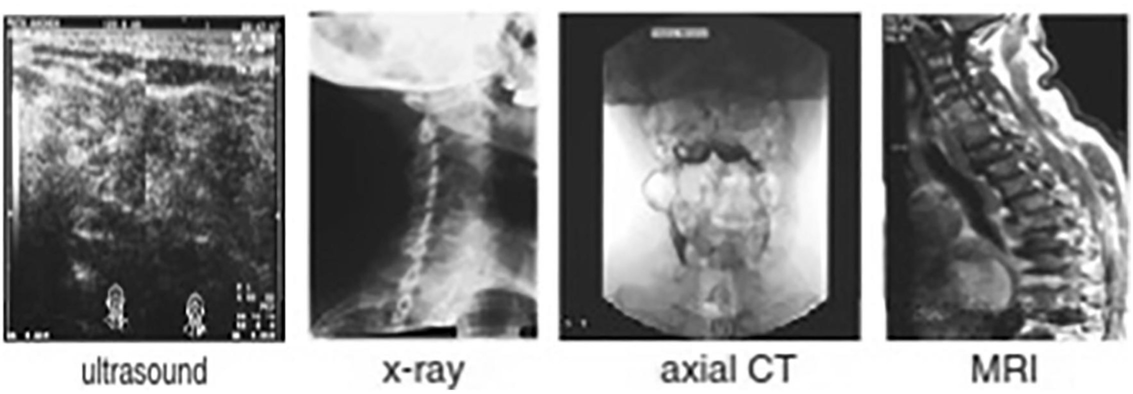


FIGURE 2 Medical imaging modalities

rotation or in other words, like spinning and has a magnetic moment. The reality of understanding the MRI corresponds to the macroscopic aspect of billions of hydrogen atoms where the total effect of spins is equivalent to a macroscopic magnetic moment. The first component of MRI is the magnetic moment, which can be parallel or anti-parallel according to the direction of the external magnetic field. The second component of MRI is the impulse of radio frequency (RF), which can charge the systems of protons' rotation in case both electromagnetic and precession frequencies are identical. Besides, the excitement of RF is supported by exponential relaxation since the system has to recover its equilibrium. The relaxation process is complicated and affected by two factors, which are spin and spin-lattice [10].

2.1.4 | Ultrasound

Compared to MRI and CT, the technology of ultrasound was invented for medical imaging processing according to the principle of sound wave reflection. The transducer and 1-Dimensional to 4-Dimensional is represented as the source of data for ultrasound technology [3]. In case of the 1-Dimensional, where the sound wave is moving in the same or opposite direction to the distribution of the wave, the changes between various materials correspond to the partially reflected and transferred sound wave [10]. The creation of an ultrasound image is dependent on the signal of pulse-echo from the transducer, and there are five prospects, which are

- The amplitude method represents the relationship between the strength of the echo and the depth.
- The echo strength encoded by the brightness method with the grey levels and allows it to produce a simultaneous series of transducers which scan plane through the body.
- The time-motion method visualises the flow of the sound-reflecting tissue edges and provides practical analysis.
- The motion method is the most popular method in clinical ultrasound as a chain of quickly obtained brightness method scans are illustrated as a moving picture.

2.2 | Image enhancement

The procedures of image enhancement focus on two-level methodologies for processing images which are algorithms and techniques. These algorithms and techniques are employed without any known previous knowledge about the content of a particular image and especially in the post or pre-processing steps.

Accordingly, the fundamental techniques are morphological filtering, convolution, and histograms [3, 10]. In the case the prepared images are medical one, methods for registration and calibration are presented. The histogram represents a scheme to display and explore the hidden distribution of frequency for a set of sequential data. The various operations of image pixels are based on the image histogram, and changing the values of the pixels will result in individual transformations from their perspective positions and their next neighbourhood. Therefore, this kind of transformation is identified as a point operation, and the histogram can achieve the description of simple pixel transformation. For example, enhanced mentor contrast in the image can be obtained by spanning the grey scales of the image. If the initial histogram of the image does not include any feasible grey layer, the distance among neighboured pixels of the grayscale is extended and results in the enhanced contrast of the image. In contradiction to histogram transformation, the estimated pixels are merged with their neighbouring states while discrete filtering is implemented.

The template is used as a characterisation of the underlying mathematical formula and it is a principally squared mask of ordinarily different lateral length. This template is reflected on two axes and is located at the definite edge of the input image. The image pixels below the mask are called the kernel. In a couple of similar templates, pixel values and the core are multiplied and then added to each other. Consequently, the outcome is stored at the location of the mask of the centre pixel and the template is moved either in the direction of columns or rows to the following locations on the input image until all the places are hit and the resulted image has been measured entirely. The values of template pixels are used to determine the effect of the filter system. In the case of values of a template, the pixel is positive, the average value is measured in the local area of all the pixels, and the outcome image is polished and causes decreased noise [10].

The morphology of mathematics can be used as another method for filtering the binary image. The technique for filtering is employed on each pixel of the image and indicates either true or false for each pixel. Generally, if the binary image contains a white pixel, then it means the essential parts. Otherwise, the pixels are black and show the background. On the other hand, the mentioned process is altered in the situation of the printing of the image. There are various logical operations applied to the binary image for reduction, opening, expansion, closing, and skeleton.

The decline of the image is achieved by applying an operation among the pixels, while the extension is obtained by using an operation among the pixels. Excluding the tiny details on the boundary of fragments or the background without changing the associated size of the entire region is achieved by the opening process. The closing operation can eliminate gaps in the heart of a region and polish its shape. The skeleton represents the route along with the thickness of one pixel, which is positioned in the middle of the segment [3, 10].

2.3 | Medical image visualisation

Image visualisation applies to every kind of manipulation of the image pattern, occurring in an optimised outcome of the image. Following the idea of visualisation of the image, we reviewed everything that transforms, which assists the streamlined production of the model. In medicine, this involves the practical presentation of 3D essential data. The aforementioned procedures have found broad applicability in different research areas particularly in medical diagnostics, medication plans, and therapy. In contradiction the difficulties in the overall field of computer graphics, the reproduced objectives for medical purposes are not entirely provided by precise, mathematical formulations but by a specific set of voxels. Consequently, techniques have been developed for medical visualisation. Those techniques have relied either on surface restoration or the visualisation of a straight volume, brightness, and shading [1].

The algorithm of the marching cube was developed explicitly for surface restoration from medical volumes. Here, the voxel is no longer represented as a cube of limited edge distance but like a point. It is equal to a point grid for imagining volumes. In this volume, a cube is viewed with four corners in all the two neighbouring layers. Through employing symmetry, the complicated puzzle of surface generation is decreased to just 15 various topologies, which can be determined to be most active because the polygon classifications regarding the essential hierarchies can be saved in a searchable table [10].

Comparable to the method of spatial convolution, the cube is located successively at every point in the volume dataset. Following the fulfilment of the marching cube algorithm, a divided volume is converted into a triangulated surface. However, the surface is created from a substantial number of triangles, which may be diminished significantly by heuristic methods without any apparent deterioration of quality. Decreasing the number of components to be imagined supports real-time visualisation of the volume.

The analogue simulation of illumination for real scenes is used to create photo-realistic displays of the volume surface. Concerning the illumination design by Phong, ambient light is generated by projecting various observations; diffuse scattering on non-bright surfaces, and straightforward mirroring on bright surfaces. While the power of the ambient light continues constantly in the scene for each surface portion, the concentrations of diffuse and speckle reflections depend on the orientation and properties of surfaces as well as their distances and routes to the origin of the light and the inspection of the point.

We can identify the fundamental triangles by excluding shading, and it represents a critical object in computer graphics. Accordingly, multiple approaches for shading have been produced to enhance the visual impression extensively. For example, *Gouraud* shading effects on solid rough surfaces and Phong shading produce genuine reflections. Furthermore, textures or different bitmaps on the surfaces can be forecasted to achieve a higher practical impact of the scene [10].

The primary visualisation of volume has declined from a preparatory consideration of the surface object. Representation of the visualisation is achieved instantly on the voxel data, and it is feasible without unspecified segmentation. The specified approach enables the visualisation of various medical data representations in both 3D and 4D by radiologists to an interactive localization of pathological fields. The processing of volume is managed by either incorporating different layers of data or an imagined ray of light. The ray of light will be preceded according to the position of the observer. Many difficulties result from the discrete radiation of the pixel hierarchy which has pointed to many algorithmic alternatives, while considerably sensible visualisations can be afforded to the observer [3].

The extracted characteristics from the intensity of the voxel with the rays are utilised to represent the value of the equivalent grey and colour positions in the viewing surface. This pointed method is well-known as shading. In the case of placing the source of the light and the image surface on the same plane of the object, the object is positioned between the observer and the source of the light. We can create incredibly effective scenes by combining the approaches of direct volume and surface based.

2.4 | Medical image analysis

The analysis of image processing consists of different stages to achieve the computations and conceptual descriptions of biomedical images. These stages involve previous information about the characteristics and content of the images which need to combined with the specified algorithm towards a high level of abstraction. Therefore, the implemented algorithms can rarely be assigned instantly into different application areas since the process of image analysis is significant.

2.4.1 | Feature extraction

The first step of the process of image analysis is extracting the features of the image. Secondly, the breakdown and classification of an image should be performed on a high level of image abstraction and not on the level of the pixel. The primary purpose of extracting the features is to highlight essential information in the image at a particular level and to distribute them to the operating algorithms. Accordingly, the given information from the remaining levels will be ignored, and the reduction of the data to represent the unique features is achieved. The process of extracting the features and segmentation of the image can be accomplished sequentially, and at several degrees of abstraction before performing the classification process at the highest stage of abstraction. Furthermore, we must take into consideration the feature extraction of the regional level process for implementing before classification [1].

2.4.2 | Edge detection

The primary input of the computer vision cycle is the image, and it can contain a considerable amount of data to be managed. Therefore, reduction of the processed data can be obtained by extracting only the significant features of the image [1]. The primary features that have no information about existing shapes and are derived automatically from the image are described as low-level. On the other hand, the features that include information regarding the shapes and elements of objects that appear in the image are defined as high-level. The elements and shapes varied according to the proposed system. For example, if the proposed system is to detect the face, then the elements can be eyes, ears, and nose. But the components can be wheels, taillights, and headlights if the system is to detect a vehicle. Those features are typically applied for high-level processes such as object classification. Detection of the edge is one of the critical allow-level feature detection components within image processing.

The primary purpose of edge detection is to determine the borders of areas in an image according to the featured attributes such as strength and texture. The number of processed data can be reduced by employing the detection edge of the image and maintaining the principal shape of existing objects in an image. Numerous parameters affect the shape of edges, such as the triangular and optical characteristics of an image, the noise level in the image, and the illumination conditions. The edge map is the result of the edge detection process and is regularly a binary image. The edge map illustrates the classification of every individual pixel in the image and various edge properties, such as dimension and orientation. The detection of the edge process is employed by three complex operations to develop a useful edge map. These operations are smoothing and noise reduction, image differentiation, and labelling levels. Firstly, to minimise the effect of noise and normalise the image for numerical differentiation, the smoothing algorithm is applied. Secondly, to determine anticipated derivatives by performing numerical differentiation on the image. Finally, a labelling process is adopted on the image to distinguish the pixels as edges or non-edges [11–14].

2.4.3 | Segmentation

The process of segmentation involves breaking an image into combined areas. Therefore, the produced area is featured and indicated as the preceding step of the classification procedure. Other descriptions emphasise the different diagnostically or therapeutically appropriate image regions and concentrate on the best universal applicability of medicinal imaging, specifically, the distinction between the structures of normal anatomical and unhealthy tissue [1, 3]. The effect of the segmentation process is regularly carried out on the local level of abstraction. Accordingly, the various pixel, texture, edge, or area-oriented methods can be classified methodically concerning the number of feature extraction components used as an input to the segmentation process. Also, there are composite strategies, which appear from a mixture of individual methods.

2.4.4 | Classification

The primary responsibility of the classification stage is to designate every combined area gathered from the segmentation process and to form mainly defined classes of objects. Commonly, area-based characteristics that sufficiently summarise the features of the objects are applied to control the classification process. In this situation, different feature extraction levels are conducted between segmentation and classification. Those characteristics need to be sufficiently selective and well adapted to the application because they primarily affect the causing quality of the classifier [10].

The models of classifiers can be categorised into three main types, which are supervised, unsupervised, and learning classification. In the case of clustering the pixels and classifying them into similar groups, the employed classifier algorithm is unsupervised. On the other hand, if the goal of classification is to recognise the objects, it will require global principles or an excellent ready reference to generate the ground accuracy of classification [3]. After that, the extracted features from those representations are utilised to parameterise and improve the classifier. During the training process, the execution of the classifier can significantly improve.

Nevertheless, the classification of objects through a supervised approach is always challenging if the classified objects are surprisingly different from the trained objects. In before-mentioned circumstances, the training patterns do not sufficiently display the actual system. A learning classifier is being used to overcome the stated problem since it turns its parameterisation, including every applied classification, also after the training stage. Generally, the different features can be defined by various schemes and shortened either to digital/binary feature vectors (signature) or possible sequences of symbols. For instance, if we can represent the contour in a closed state either by employing the components of Fourier as a significant feature vector or by employing essential line pieces such as 'concave', 'convex', and 'straight' we create a symbol string [1].

2.5 | Medical image management

The management of medical images contains all the possible techniques to maintain the outstanding efficiency in storing, communicating, transferring, archiving, and retrieving information contained in medical images. Therefore, we can consider that telemedicine approaches are part of the medical management process. The development of short and long-term, transfer (transmission) and retrieval (access) in medical and healthcare applications will motivate the team to find better solutions [10].

The discovery of computed tomography and its combination with the medical system has the potential for originating the first picture-archiving and communication-system (PACS) to store the data of medical images. The massive number and dimensions of medical images represent the essential difficulty of storing medical images. For example, more than 10-megabytes of storage space are required to save a single radiography image that is 40 × 40 cm, the resolution is five-line pairs per millimetre, and it consists of various 1024 grey levels for each pixel. Furthermore, if an obtained image has a high-resolution like digital mammography for breasts, the required storage space will be increased and can be 250 megabytes or more for every test [1, 3].

The expectations of storing high-resolution CT, radiography, and MRI images will be increased tenfold. For example, a university hospital requires two terabytes to save the image data per year. Accordingly, adequate storage, access, and transmission of medical images have involved efficient compression procedures, and a high-speed communication system is required since the data must be stored for a long time. The compression loss of medical images resulted from the noise has a small effect on the rates of compression of two or three. Recently, hybrid storage approaches to overcome these problems have become available [3].

Medical information systems represent a significant component of medical image processing to deliver the correct information at the exact time and place. Therefore, the transmission of the image data through various medical departments and between broadly distributed hospitals requires a well-developed communication network. The main issue with transferring the medical information is the standardisation process since the whole data (including images 'with different formats and dimensions', the medical information for patients, 'e.g., name, identification' and the hospital information, 'e.g., study, device') should be transmitted in a standard format. Consequently, the Digital-Imaging and Communications in Medicine (DICOM) has developed standards to send various medical data and includes the following:

- Classes of objects to organise the structural information regarding the contents of the medical data.
- Classes of services to provide instructions on what should happen to the medical data.
- The protocols that are used to transmit the data over the network.

The medical images can be restored regularly from the stored database in case the name, the date of birth, or unique identification of the patient is known. Unil now, the recovery of stored medical image information has depended on its alphanumerical features. It is apparent that the achievement of PACS diagnostic system is significantly increasing efficiency concerning the immediate availability of images from the related content of a provided sample image [10].

The model for implementing query by example (QBE) is a significant responsibility of upcoming systems for content-based image-retrieval (CBIR). Since there are various and complicated development approaches of diagnostic data, the field of biomedical imaging needs different conceptual strategies for success. The framework indicates the series of processes starting with check-in, the characteristic extraction, segmentation, and the identification of the image patterns approaching the peak of the pyramid, which is the typical presentation for the analysis of the particular scene. The image data, which is essential for retrieval, is continuously compressed and extracted. A bitmap image is symbolically described by a semantic chain (hierarchical tree structure). The tree nodes include specific knowledge of the described regions (segments) of the image. Its structure defines the contiguous and/or temporary limitations of every included pattern. By utilizing this technology, radiologists and physicians are encouraged about the potential for patient administration, investigation, and education.

3 | REPRESENTATION OF QUANTUM IMAGES

The evolution of quantum computation and information has emerged in several domains of science [15–67]. One of the most prominent areas is quantum image processing, which concentrates on improving the different classical image processing tasks and operations by integrating the laws of quantum mechanics. The idea of applying the principles of quantum mechanics to represent the images was initiated in 1996 when Vlasov wrote a paper about the recognition of orthogonal images [68]. The developed concept of recognition depended on employing a unitary operator that rotated an orthogonal set of images to an orthogonal set of primary vectors of a measurement tool, as shown in Figure 3.

Beach et al. [16] worked on pose determination and a reality delegation scheme for distinguishing objects in a chaotic visual environment by using one or more cameras as its inputs. They showed that current quantum algorithms (such as Grover's algorithm) are suitable for image processing tasks. They used Grover's algorithm to conduct searches inside their pose determination system and proved higher performance compared to a classical approach. Also, they mentioned another advantage of the quantum system regarding the required memory to store the required vertices for image processing since it needed 3.1 GBytes of classical memory compared to only 35 quantum bits.

Venegas-Andraca and Bose [29] studied the idea of storing and retrieving an image in a multi-particle quantum system (see Figure 4). They discussed three approaches to storing: 1) storing the image without any colour and representing the real values by their natural parameters such as frequency instead of

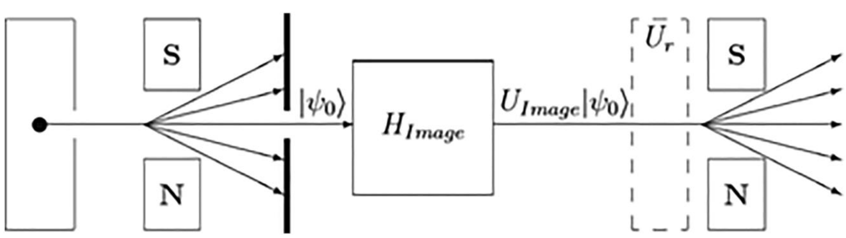


FIGURE 3 Recognition of orthogonal images [68]

a linear combination of Red-Green-Blue (RGB) representation, 2) storing a colour in a quantum bit by using a machine that can detect the frequencies of electromagnetic waves and generate a quantum state as output, and 3) storing an image in a set of qubit lattices. Also, they considered two methods for retrieval, which either recover a single frequency of the image or the full image. The development of encoding quantum images by employing the representation of the quantum bit lattice has been introduced [29]. Subsequently, several quantum image representations are proposed [21–25].

3.1 | Flexible representation for quantum images

One of the most important representations of quantum images is the flexible representation for quantum images 'FRQI'. The architecture of FRQI consists of three main stages, which are preparation of the FRQI image state from the original one, compression, and processing operations as storing, detection and retrieving. The representation of quantum images using the flexible one is like the description of the pixel in images on classical computers. The process of representation is performed by capturing the vital information of both the colours and the similar positions for each pixel at each point in an image. Later, the resulting pixels are integrated to form the quantum state as represented in Equations (1) and (2) as

$$|I> = \frac{1}{2^n}\sum_{i=0}^{2^{2n}-1}|ci> \oplus |i>, \tag{1}$$

$$|ci> = \cos\theta_i|0> + \sin\theta_i|1> \tag{2}$$

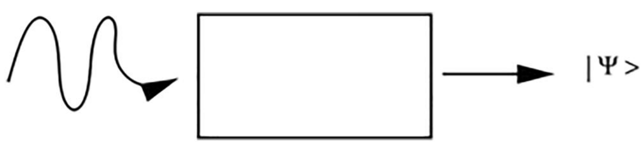


FIGURE 4 Frequency to quantum state apparatus

Where $|0>$ and $|1>$ denotes the two dimensions of quantum computational basis, $|i>$, $i = 1, 2, 3, \ldots 2^{2n-1}$, and θ represents a series of angles (vector) of the encrypted colour. The flexible representation of quantum image consists of two main parts which $|c_i>$ and $|i>$. $|c_i>$ and $|i>$ encrypt the information regarding both the colours and its corresponding positions of the image. An illustrative example of a flexible representation of a 2×2 quantum image and its corresponding state is shown in Figure 5. The transformation of the initially prepared quantum state to the desired quantum image state is required to develop the representation process [22].

3.2 | Multi-Channel Quantum Image Representation

Multi-Channel Quantum Image Representation 'MCQI' provides a way to characterise the various colour information of the quantum image. It is accomplished by extending the representation of FRQI grayscale to express the diverse knowledge of colour images and maintain the normalised state. It is achieved by selecting three quantum bits to encrypt colour information of images. According to the MCQI representation, the whole RGB information of the image will be stored concurrently [27, 28]. MCQI representation is shown in Equation (3). An illustrative example of an MCQI of a 2 × 2 quantum image and its corresponding state is shown in Figure 6.

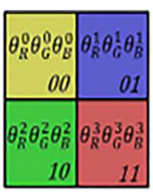
$$|I> = \frac{1}{2^{n+1}}\sum_{i=0}^{2^{2n}-1}|c^i_{RGB\alpha}> \oplus |i>, \tag{3}$$

where the colour information $|c^i_{RGB\alpha}>$ encrypting the RGB channels information is defined as in Equation (4)

$$\begin{aligned}|c^i_{RGB\alpha}> = {} & \cos\theta^i_R|000> + \cos\theta^i_G|001\rangle + \cos\theta^i_B|010\rangle \\ & + \cos\theta_\alpha|011\rangle + \sin\theta^i_R|100\rangle + \sin\theta^i_G|101\rangle \\ & + \sin\theta^i_B|110\rangle + \sin\theta_\alpha|111\rangle\end{aligned} \tag{4}$$

$$|I\rangle = \frac{1}{2}[(\cos\theta_0|0\rangle + \sin\theta_0|1\rangle)\otimes|00\rangle + (\cos\theta_1|0\rangle + \sin\theta_1|1\rangle)\otimes|01\rangle + (\cos\theta_2|0\rangle + \sin\theta_2|1\rangle)\otimes|10\rangle + (\cos\theta_3|0\rangle + \sin\theta_3|1\rangle)\otimes|11\rangle]$$

FIGURE 5 A simple 2 × 2 image and its FRQI



$$\begin{aligned}|I\rangle = \frac{1}{4}[& (\cos\theta^0_R|000\rangle + \cos\theta^0_G|001\rangle + \cos\theta^0_B|010\rangle + \sin\theta^0_R|100\rangle + \sin\theta^0_G|101\rangle + \sin\theta^0_B|110\rangle)\otimes|00\rangle \\ & + (\cos\theta^1_R|000\rangle + \cos\theta^1_G|001\rangle + \cos\theta^1_B|010\rangle + \sin\theta^1_R|100\rangle + \sin\theta^1_G|101\rangle + \sin\theta^1_B|110\rangle)\otimes|01\rangle \\ & + (\cos\theta^2_R|000\rangle + \cos\theta^2_G|001\rangle + \cos\theta^2_B|010\rangle + \sin\theta^2_R|100\rangle + \sin\theta^2_G|101\rangle + \sin\theta^2_B|110\rangle)\otimes|10\rangle \\ & + (\cos\theta^3_R|000\rangle + \cos\theta^3_G|001\rangle + \cos\theta^3_B|010\rangle + \sin\theta^3_R|100\rangle + \sin\theta^3_G|101\rangle + \sin\theta^3_B|110\rangle)\otimes|11\rangle]\end{aligned}$$

FIGURE 6 A simple 2 × 2 image and its MCQI

MCQI has three main advantages, which are as follows: Firstly, MCQI utilised the principle of quantum parallelism to encrypt the colour information and their prospective positions. Therefore, the required number of quantum bits is fewer than the quantum lattice representation [29] and consequently requires fewer computing resources. Secondly, the transformation of colour information performed on the entire image is achieved by using the unitary quantum gates regardless of the qubit's positions. This obtained a natural way with lower complexity to create the transformation operation. Finally, the MCQI design provides the ability to develop a quantum cryptographic scheme for the colour image based on watermarking.

3.3 | NEQR representation and its features

A novel enhanced quantum representation 'NEQR' is developed to represent digital images by storing the grayscale value for each pixel by using the basis state of a qubit string rather than an angle encrypted in a qubit in FRQI. Accordingly, the whole image can be stored using two entangled qubit sequences, one for the grayscale and other for the positional information for each pixel [32].

The representative expression of a $2^n \times 2^n$ form of NEQR representation can be written as in Equation (5)

$$
\begin{aligned}
|I> &= \frac{1}{2^n} \sum_{y=0}^{2^n-1} \sum_{x=0}^{2^n-1} |f(y,x) > |yx> \\
&= \frac{1}{2^n} \sum_{y=0}^{2^n-1} \sum_{x=0}^{2^n-1} \oplus_{i=0}^{q-1} \left| c_{yx}^{i} > \right| yx >
\end{aligned} \tag{5}
$$

An illustrative example of a NEQR representation of a 2×2 quantum image and its corresponding state is shown in Figure 7. The preparation of a quantum image in the form of NEQR is divided into two main steps; the first step is capturing the vital information of both the colours and the similar positions for each pixel at each point in an image which is the same as FRQI. The second step is divided into 2^{2n} sub-operations for setting the grayscale value for each pixel [32]. The time complexity of preparing the NEQR quantum image shows almost a quadratic reduction contrary to FRQI, since NEQR uses the basic state of a qubit sequence for storing the grayscale value for each pixel rather than the probability amplitude of an individual qubit applied in the FRQI representation.

Furthermore, NEQR can retrieve the original classical image with a deterministic and accurate approach by employing the quantum measurements compared to a probabilistic approach such as FRQI. Another critical characteristic of NEQR is that the number of performed complex image operations is more than FRQI. NEQR required more qubits to encode the quantum image since it needed $q + 2n$ qubits to represent a $2^n \times 2^n$ quantum image with grey range 2^q [32].

3.4 | CQIR representation and its features

Caraiman's quantum image representation 'CQIR' encoded the colour information of the quantum image by using the sequence of quantum bits, which is the same as NEQR [31]. The essential characteristic of Caraiman's approach is the ability to generate a corresponding histogram of the quantum image, which provided a better way for processing various operations as negativity and binarisation. To encode L grey levels of an image using CQIR, we will require m qubits [10]. CQIR approach can improve the features of an image by enhancing the contrast of the image. The representation of an image utilising the CQIR approach is given in Equation (6):

$$
|I> = |c>_m \times |p>_{2n} = \frac{1}{2^n} \sum_{i=0}^{2^{2n}-1} \sum_{j=0}^{2^m-1} \alpha_{ij} |j>|i> \tag{6}
$$

where $|P>$ stored the encoded pixel positions by $2n$ qubits, $m = \log_2 L$ is used to encode L grey level of an image and represent the colour information for every pixel. The complexity cost of preparing the entire quantum image is less than $o(\log_2 L.n.2^{2n})$ [17]. The coefficients $\propto_{ij}$ present the colour of the pixel with its position, including the superposition of every possible colour. An illustrative example of a CQIR representation of a 2×2 quantum image and its corresponding state is shown in Figure 8.

3.5 | QUALPI representation and its features

Quantum image representation for log-polar images 'QUALPI' provides an improved technique to solve the limitations of storing and processing images presented in Cartesian coordinates. These limitations lead to the difficulty of performing complex transformations requiring many immutable interpolations such as rotation and scaling. The idea of QUALPI

$$
\begin{aligned}
|I\rangle &= \frac{1}{2}(|0\rangle \otimes |00\rangle + |100\rangle \otimes |01\rangle + |200\rangle \otimes |10\rangle + |255\rangle \otimes |11\rangle) \\
&= \frac{1}{2}(|00000000\rangle \otimes |00\rangle + |01100100\rangle \otimes |01\rangle \\
&\quad + |11001000\rangle \otimes |10\rangle + |01100100\rangle \otimes |01\rangle)
\end{aligned}
$$

FIGURE 7 A 2×2 NEQR quantum image and it's quantum state depends on storing and processing the log-polar of the image. The log-polar of the image consists of log-radius 2^m and the angular orientations 2^n [32]. The entire quantum image is stored in a normalised quantum superposition state where every basic state describes one pixel. The representation of an image utilising QUALPI approach is given in Equation (6):

$$|I> = \frac{1}{\sqrt{2^{m+n}}} \sum_{\rho=0}^{2^m-1} \sum_{\theta=0}^{2^n-1} |g(\rho,\theta) > \oplus |\rho > \oplus |\theta > \qquad (7)$$

The tensor product of the angular position, the grayscale and log-radius position constitute the base state of QUALPI, as shown in Equation (7). The complexity cost of preparing the entire quantum image using the QUALPI technique is less than $o(q(m+n).2^{m+n})$ for a 2^m and 2^n log-polar quantum image with grayscale 2^q [32]. An illustrative example of a QUALPI representation of a 2 × 8 log-polar quantum image and its corresponding state is shown in Figure 9.

4 | QUANTUM COMPUTATION-BASED MEDICAL IMAGES

This section provides a brief discussion of the essential tasks of quantum computation in medical image processing, including edge detection, segmentation, watermarking, encryption, feature selection, and classification.

4.1 | Medical image edge detection

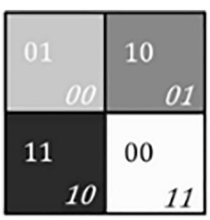
A new quantum edge detection algorithm to identify and improve the fuzzy and complicated features of medical images with the essence of the fundamental concepts and principles of quantum signal processing is proposed in [69]. The operation of the proposed protocol is divided into two main stages. Firstly, the operator of image improvement is generated according to the superposition of the quantum state and the corresponding pixel qubit. The operator is merged with a grey correlative feature of the pixels in 3 × 3 neighbourhood windows. Secondly, to obtain edge detection, an edge determination operator concerning fuzzy entropy is adapted to the quantum improvement image. The experimental results showed that the proposed algorithm is more practical and efficient compared to the classical edge detection algorithms as it can extract both strong and weak edges of medical images.

4.2 | Medical image segmentation

A microscopic image segmentation using a quantum inspired evolutionary algorithm has been proposed in Ref. [70]. It is evident that image segmentation has become an important research area for various medical imaging fields. The automated complex analytical process makes it a substantial time-consuming procedure. The intention to achieve microscopic image segmentation is to extract the cellular, nuclear, or tissue components. This is considered a challenging process due to the significant variations of features of these components (size, shape, orientation, or texture). This paper describes a novel approach to dealing with rats. Microscopic hippocampus image segmentation based on the hybrid evolutionary strategy (ES) is proposed. The proposed work used the quantum-inspired evolutionary algorithm (QIEA) to establish the optimal level for the multilevel thresholding. The QIEA depends on both quantum and evolutionary computing. Intensive work for automatic hippocampus segmentation is performed on a database of 179 images. The acquired results have demonstrated that the proposed algorithm provides superior segmentation with eight levels that offer the highest correlation between the original and the segmented image.

4.3 | Medical image watermarking

The comparison between imperceptibility and flexibility represent one of the most genuine difficulties in developing a digital



$$|I\rangle = \frac{1}{2}(|01\rangle \otimes |00\rangle + |10\rangle \otimes |01\rangle + |11\rangle \otimes |10\rangle + |00\rangle \otimes |11\rangle)$$

FIGURE 8 A 2 × 2 CQIR quantum image and its state. CQIR, Caraiman's quantum image representation

$$|I\rangle = \frac{1}{4}[|11111111\rangle \otimes (|0000\rangle + |0001\rangle + |1000\rangle + |1001\rangle) + |11110000\rangle \otimes (|0010\rangle + |0011\rangle + |1010\rangle + |1011\rangle) + |01111111\rangle \otimes (|0100\rangle + |0101\rangle + |1100\rangle + |1101\rangle) + |01110000\rangle \otimes (|0110\rangle + |0111\rangle + |1110\rangle + |1111\rangle)]$$

FIGURE 9 A 2 × 2 QUALPI quantum image and its state. QUALPI, Quantum image representation for log-polar images watermarking framework. The development of the quantum particle swarm optimization approach to watermarking the medical images for ownership security and authentication has been discussed in Ref. [71]. The idea behind the proposed algorithm is to consider solving the watermarking as an optimization problem. Therefore, the optimization problem was resolved by employing the features of the human visual system and, quantum particle swarm optimization approach in adaptive quantization index modulation and the breakdown of singular value combined with both discrete wavelet and discrete cosine transforms. The performance of the proposed algorithm proves its efficiencies from the perspective of visual fidelity and against many types of attacks such as PEG compression, filtering, image scaling, and cropping.

4.4 | Medical images encryption

The protection of medical images is critical and necessary to assure the security and confidentiality of the patients' information. Therefore, an approach to applying the chaos-based quantum encryption procedure for medical images is proposed in Ref. [72]. The method is employed when two distinct employers would like to transfer the medical images of patients, and they communicate through the cloud. In this case, the first employer encrypts the image and moves it to the cloud, and the other employer receives the encrypted images from the cloud. Afterward, he decrypts the received medical images and securely can access the patient's information. Furthermore, an effective quantum encryption algorithm to secure the medical media by employing both the grey cypher and a chaotic map is suggested. The idea of the algorithm is summarised by mixing the image with the quantum grey code and then encoding it by applying a quantum XOR operation. The XOR operation is performed according to a key generator managed by the logistic-sine map. The analysis of the proposed algorithm is used for its robustness, reliability, and high efficiency contrasted.

4.5 | Medical image feature selection and classification

The classification and feature extraction of cells to identify cervical cancer by employing a combination of quantum particle swarm optimization and fuzzy k-nearest neighbours have been proposed in Ref. [73]. The accuracy of cell identification and representation is an essential aspect and particularly in multiple image-based treatments for disease analysis. To improve the efficiency of classification of cells in applied cervical images, they suggested a combined feature extraction method that merges the power of the quantum particle swarm optimization (QPSO) along with the flexibility of the fuzzy k-nearest neighbours (Fuzzy k-NN). The proposed algorithm works first by utilising the properties of QPSO to decide the best-minimised combination of features, original number of gathered features is equal to 17 and is reduced to a group of seven features.

Verification of the strength of the proposed algorithm is achieved by employing the Herlev dataset, which consists of 1000 images and applying two different experimental scenarios for detecting cervical cancer. The outcome of these experiments proved improvement in the accuracy by combining quantum with the Fuzzy k-NN approach compared to the classical particle swarm optimization and Fuzzy k-NN approach. A third experiment was performed to test the harmony between QPSO and the Fuzzy k-NN approach compared to applying QPSO with another classification method like Naïve Bayes (NB) networks. The result of the third experiment was that the adaptive search ability of the quantum-behaved QPSO algorithm is adequately achieved by the intuitionistic rationality essential to the Fuzzy k-NN technique. Consequently, the proposed hybrid algorithm exceeded the different strategies of QPSO combined with the Naïve Bayes and supports the vector machine with simple average improvements varying from 2% to 11% concerning the classification parameters that were evaluated. These achievements would enhance the efficiency of image-based methods applied in cervical cancer investigation and treatment.

5 | CONCLUSION

In this paper, we highlighted several aspects of quantum medical image processing. We provided a compendium of the advances made in the new and exciting sub-field of quantum computing for medical images. We presented a comprehensive overview of the potential of applying the various medical image processing operations such as encoding and enhancement on the quantum platform instead of the classical one. The review provides a roadmap to achieve safe and effective images on quantum computers since the research progress of quantum computing still has a long way to go, and therefore, further investigation is required in the field of quantum image processing.

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CONFLICT OF INTEREST

The author of this manuscript state that there is no conflict of interests to submit this manuscript.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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