Sumer University Journal for Pure Science (ISSN: 2790-7031)
SUJPS 2022 (November), Vol. 1, No. 1, p.p.: 612-625

(QPIE:QHED) Edge Detection Using Optimal Feature Subset Selection Based on Detection of for Quantum Image Processing

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Abstract

Image processing and detection are natural extensions of detecting the edges, curves, and areas of sudden changes in brightness or, more specifically, missing pixels. Edge detection is a set of mathematical algorithms. Change detection is a term used to describe the process of identifying discrete changes in single-digit data. The dimension. The ability to detect and remove image edges is fundamental to image processing and computer and machine vision. One way to detect and remove features from images is to use edge detection. In this work, we first provide an overview of research in this area, and then list some of the concerns that have been raised regarding rapid development and its achievement. We see “quantum image classification and recognition” as the ideal application to showcase the potential of quantum technology. Quantum Probabilistic Image Encoding (QPIE:QHED) was used in our study to transform classical data into quantum states. It is necessary to apply quantum algorithms to classical problems, a method for quantum Hadamard edge detection, and also uses them to process quantum image data, often produced by QPIE, using QHED, a modern edge detection technique. Quite simply, QHED is a technology for precise edge detection in images that uses quantum computing.

Keywords: Edge Detection, , Quantum Hadamard Edges, Quantum Probability Image Encoding QPIE, Quantum Image Processing QHED, Optimal Feature Subset Selection, Quantum Principal Component**.**

(QPIE:QHED) اكتشاف الحواف باستخدام التحديد الأمثل للمجموعة الفرعية للميزات استنادًا إلى اكتشاف معالجة الصور الكمومية

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الخلاصة

تعد معالجة الصور واكتشافها امتدادات طبيعية لاكتشاف حواف الصورة الرقمية ومنحنياتها والمناطق ذات التغييرات المفاجئة في السطوع أو، بشكل أكثر تحديدًا، وحدات البكسل المفقودة هي مهمة اكتشاف الحواف، وهي مجموعة من الخوارزميات الرياضية، واكتشاف التغيير هو مصطلح يستخدم لوصف عملية تحديد التغييرات المنفصلة في البيانات أحادية البعد. تعد القدرة على اكتشاف حواف الصورة وإزالتها أمرًا أساسيًا لمعالجة الصور ورؤية الكمبيوتر والآلة. تتمثل إحدى طرق اكتشاف الميزات وإزالتها من الصور في استخدام ميزة اكتشاف الحواف. في هذا العمل، نقدم أولاً نظرة عامة على الأبحاث في هذا المجال، ثم نقوم بإدراج بعض المخاوف التي أثيرت فيما يتعلق بالتنمية السريعة وتحقيقها. نحن نرى أن "تصنيف الصور الكمومية والتعرف عليها" هو التطبيق المثالي لعرض إمكانات تكنولوجيا الكم. تم استخدام ترميز الصور الاحتمالية الكمومية (QPIE:QHED) في دراستنا لتحويل البيانات الكلاسيكية إلى حالات كمومية. من الضروري تطبيق خوارزميات الكم على القضايا الكلاسيكية، وهي طريقة للكشف عن حافة هادامارد الكمومية، و تستخدمها أيضًا لمعالجة بيانات الصورة الكمومية، التي غالبًا ما تنتجهاQPIE ، باستخدام QHED، وهي تقنية حديثة للكشف عن الحواف. بكل بساطة، QHEDهي تقنية للكشف الدقيق عن الحواف في الصور التي تستخدم الحوسبة الكمومية.

1. Introduction

If an edge detector is doing its job well, it should be able to extract a network of curves from an image that indicate the locations of objects, surface marks, and orientation changes. By applying an edge detection approach to a picture, we may significantly lessen the amount of data processing required without losing any of the picture's important structural properties. If the edge detection works as expected, deciphering the image could be a breeze. It isn't always feasible to achieve such sharp boundaries, even with fairly straightforward real-world images. Problems with non-simple images might arise when edges aren't connected, when there aren't enough edges, or when they don't correspond to anything interesting in the picture. It is increasingly difficult to understand the pictures because of this. The first and most important stage in many analysis, pattern recognition, and computer vision approaches is to find the edges of the picture.

algorithm for large numbers has been a primary motivator for advancing the field of quantum computation (Quantum Probability Image Encoding QPIE, Quantum Image Processing QHED). One notable motivation behind the use of QPIE, QHED is that they require substantially fewer qubits than pixels in classical images. If you have an N-pixel image, you only need $\log_2(N)$ qubits. For every n qubit, you also have the ability to create 2^n states with superposition; therefore, improved processing power and computation times are used even with large and complex data sets, so the number of pixels used is minimized, leading to the best possible processing.

Two separate types of edges may be identified in a two-dimensional picture of a three-dimensional picture. The perspective from which the picture was taken is an important consideration in one approach. You may learn a lot about a three-dimensional object's shape and marks from its edges, which are always visible no matter where you are. A viewpoint dependent edge is one whose appearance changes when the observer moves their point of view. When one object obscures another's vision, for example, this type of edge usually represents the geometry of the scene [1], [2].

For instance, a common edge may be the border between the red and yellow blocks that are next to each other. Contrarily, a line must to be a few pixels broad and a different color on a background that is otherwise static. A ridge detector can pick this up. Two lines can be considered to have one edge each [3].

Quantum picture processing is one area of research within the broader field of quantum data and computation. One kind of quantum data is quantum information protocols, more often known as QIPs. It delves into the prospect of showing pictures on a quantum computer that use quantum physics and then doing different things with those pictures depending on how they're shown. Since QIP takes advantage of quantum parallel computing, it naturally outperforms traditional image processing []. The reason behind this is the fact that quantum states can be entangled or superimposed. Even if some works use the idea of quantum superiority to make things more complicated, there is a lot of talk about QIP.

Most often used methods for finding edges are search-based techniques and zero-crossing-based methods. In order to find edges, most people use search-based methods, which initially find an edge strength measure such the gradient magnitude. Next, they look for local directional maximums of the gradient magnitude using a computed estimate of the edge's local orientation, like the direction of the gradient [4]. Finding edges in an image is accomplished using zero-crossing based techniques by looking for places where the resultant second-order derivatives expression crosses zero. No straight line may pass across the Laplacian with the expression, and thus leads to what are known as zero-crossings. Prior to looking for edges in a picture, the smoothing stage, also known as Gaussian smoothing, is usually performed [5].

Figure 1. Edge Analytics

There are a number of different edge detection approaches that vary mostly in the smoothing filters they employ and the strength metrics they utilize. Not all edge recognition techniques utilize the same filters to determine x- and y-coordinate picture gradients[6].

2. Related work

John Canny investigated the computational difficulty of finding the best smoothing filter to meet specific needs in detection of edges, localization, and reduction. Here, he proved that the best filter is the result of adding four exponential components[7],[8]. Additionally, he proved that this filter, being a first-order derivatives of Gaussians, provides a decent estimate [9]. In addition, he brought up the concept of "non-maximum suppression," which means that when the presmoothing filter is applied, the edge points are those places where the amplitude of the gradient has a local maximum along the gradient's direction. The idea of looking at gradients direction for a zero crossing of the second derivatives was first proposed by [10]. That took fewer than twenty years to understand in terms of modern geometric variation, to paraphrase the operator. The zero-crossing of the Laplacian is foundational to the Marr-Hildreth edges detectors, which it is linked to. Alfred Bruckstein and Ron Kimmel both put forth this concept in [11].

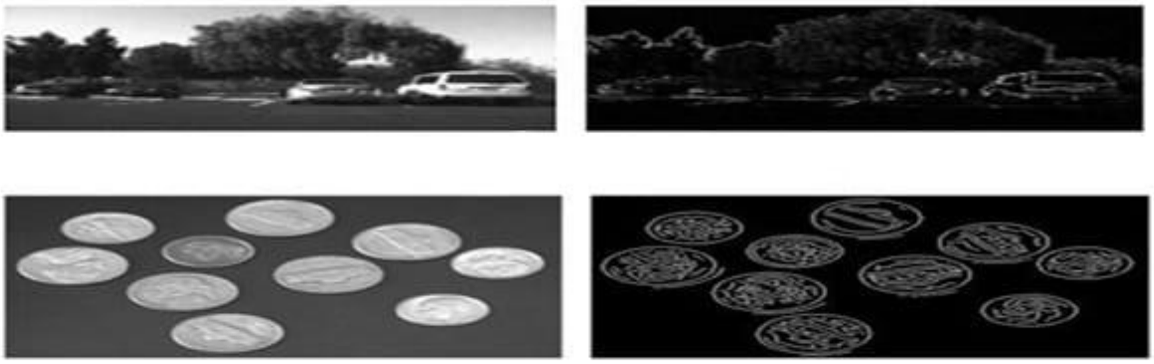


Figure 2. Canny Based Edge Evaluations

Although his work is rooted in the early days of computer vision, the Canny edge detection (and all its variants) remain the best method for discovering edges in a computer image. More parameters or more computation time is required for edge detectors that are stronger than the Canny[10][27]. The Canny-Deriche detector is similar to the Canny edge detector in theory, but it takes a different approach, using recursive filters to smooth out images instead of exponential or Gaussian ones [12].

One way to look at the following differential edge detector is as a scale space representation-based reinterpretation of Canny's technique using differential invariants [13]. Both theoretical studies and real-world applications at the sub-pixel level can profit from this. That is why the Log Gabor filter works in the actual world when it comes to finding edges [13, 14].

Removing extraneous detail from an image's edges is what "thinning the margins" is all about. This approach can be applied after the image has undergone noise filtering (with a median or Gaussian filter, for example), edge detection using the edge operator, and edge smoothing with the appropriate threshold value. When done correctly, this removes unnecessary points and produces elements with edges which are precisely one pixel thick[15],[16].

3. Thresholding

After that, we'll use a threshold to check if a certain pixel in the image has any edges. Once an edge strength measure, such the gradient magnitude, has been calculated, this is executed. With a lower threshold, the picture is more susceptible to noise and characteristics that don't exist. On the other hand, you risk missing nuanced nuances or giving the idea that they are shaky if your threshold is exceptionally high[17][18].

Typically, thick edges will be produced when the edge is applied just to the gradient magnitude picture. This need post-processing edge thinning in order to thin them out. The edge curves for edges that aren't completely suppressed are narrow by definition, and an edge linking (edge tracking) method can join edge pixels to form an edge polygon[19]. For a discrete grid, non-maximum suppression may be achieved by using first-order derivatives to determine the gradient direction, rounding it down to multiples of 45 degrees, then comparing the magnitude values of the gradient in that direction to the values on the grid.

One common approach to the problem of establishing suitable thresholds is hysteresis-based thresholding. Using a mixture of criteria, this technique detects edges. We first use the higher threshold to find the first stage in an edge's creation [20]. We mark an edge as we go along by tracking its movement across an image pixel by pixel and stopping when we reach a specific threshold. We cease to demarcate the region whenever the number falls below a specific threshold [21]. The underlying premise of this method is that edges will normally be located along continuous curves. Without classifying each and every noisy pixel as an edge, we may instead follow a faint trace of an edge that we are already familiar with. The ideal thresholding values may change over an image, thus it's important to pick the right ones [22].

4. Problem Statement

While maintaining the same amount of true positives, Optimal Feature Selection halves the number of features with no true positives . Choosing the correct variables is a breeze, which simplifies and improves the model's readability and accuracy. In the high-dimensional process of text categorization, you need to pick characteristics that are relevant. Typically, an optimization procedure is employed to select the optimal subset of features from a massive feature space when feature selection is being considered. A text classifier's efficiency and accuracy are both enhanced by carefully selecting its characteristics[23].

5. Objective

The purpose of choosing features is to identify the most effective collection of characteristics to employ in light of the assessment function. There is a significant financial and time investment required to search through all potential feature subsets. Though they can't guarantee the world's finest outcomes, the other suboptimal approaches are more effective and realistic.

6. The quantum edge approach and its main contribution to work

In the field of image processing, several potential applications of quantum computing have been identified. The emergence of quantum image representations approaches suggests that several image processing algorithms can potentially outperform their "traditional" counterparts by an exponential amount by leveraging quantum properties such as entanglement and superposition. We improve a quantum edges recognition method in this study after quickly going over some of the fundamental ways to show quantum images [24][25].

7. Quantum Image Processing:

a. Encoding of Quantum Probability Images (EQPI):

One major benefit of EQPI is the fact that it uses a lot less qubits compared to traditional picture pixels. You will only require $\log_2(N)$ qubits if your image has N pixels. With superposition, you can produce 2^n states for every n qubits[26].

Research in the area known as artificial intelligence (AI) aims to give computers the ability to "think" and make rational decisions in the same way that people do. "Seeing" data may also be retrieved using computer vision techniques. As a branch of computer vision, image recognition is able to recognize and understand the pictures used for training. See figure. 1

Figurer. 1. Automated Street Object Detection Using Computer Vision.

Edge Detection serves as a crucial technique for identifying picture components, and image processing helps us grasp what's happening in an image. Edge detection involves finding the perimeters of components in order to identify them, as the name suggests. While edge detection is within the purview of conventional classical image processing, it isn't always the most effective method[27][28], especially when dealing with huge pictures that require a lot of calculations per pixel. An effective substitute that uses its own technique for edge detection is quantum image processing. See fig. 2.

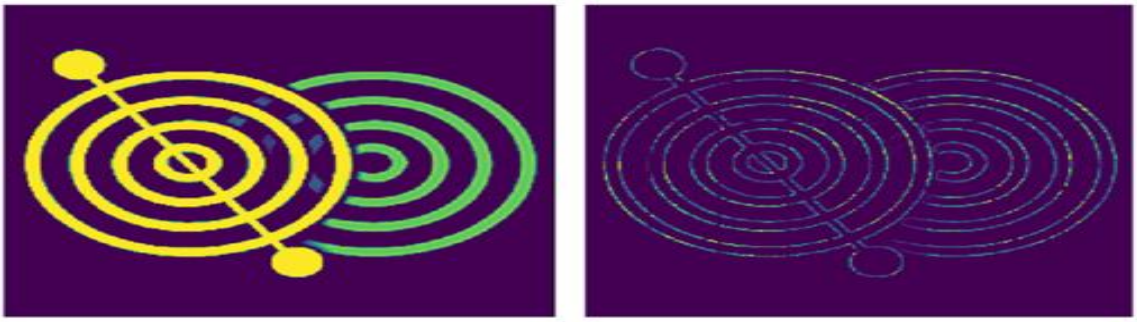
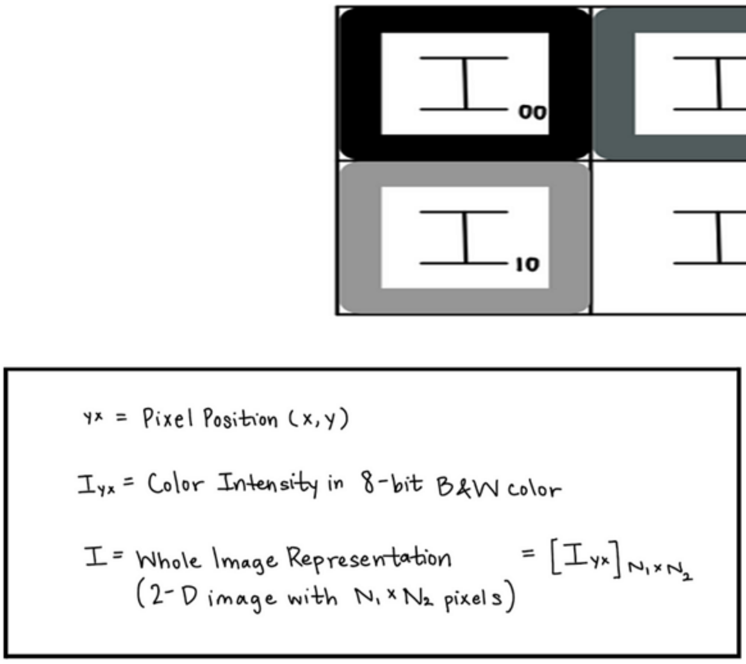


Figure. 2. Quantum Image Processed Product.

Converting pictures used with conventional image processing to quantum images is necessary for doing quantum image processing upon such images. Quantum Probability Imaging Encoding is one of several quantum picture representations.

One major benefit of QPIE is the fact that it uses a lot less qubits compared to traditional picture pixels. You will only require $\log_2(N)$ qubits if your image has N pixels. With superposition, you can produce 2^n states for every n qubits. To illustrate the point, four qubits and sixteen states would be required for a sixteen-pixel picture. Therefore, how may this advantageous conversion be carried out. See fig. 3.



yx = Pixel Position (x, y)

I_{yx} = Color Intensity in 8-bit B&W color

I = Whole Image Representation = $[I_{yx}]_{N_1 \times N_2}$
(2-D image with $N_1 \times N_2$ pixels)

Figure. 3. Classical 2 × 2 Image 4 Pixels.

We can identify the location of each pixel in this typical $2x2$ picture ($4\,pixels$) example. yx is a subscript. An $8-bit$ black-and-white color representing the pixel's location label and color intensity will be used. The complete two-dimensional picture may be represented by a set of all these separate pixel representations[29][30].

The entire picture is still represented by pixel intensities; by normalizing, we may transform them into probability amplitudes for a quantum state (such as QPIE). In this case, the amplitudes' total of squares would be 1. And Bringing Pixel Intensities Up to Probability Amplitude Criteria. See figure 4

$$\frac{I_{yx}}{\sqrt{\sum I_{ys}^2}} \tag{1}$$

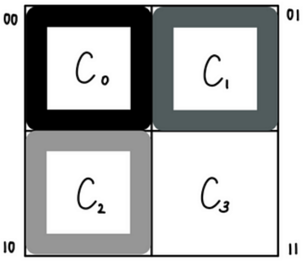


Figure. 4. Enhancing Quantum Image Pixel Intensities to Meet Probability Amplitude Requirements

Superposition of states that are quantum is the way to express this now that the picture has been transformed from classical to quantum. It is possible to generalize the state for this 2x2 picture as

$$|\mathrm{Img}\rangle = c_0|00\rangle + c_1|01\rangle + c_2|10\rangle + c_3|11\rangle \tag{2}$$

The generalization might be expressed as for a picture with n qubits:

$$|\mathrm{Img}\rangle = \sum_{i=0}^{2^n-1} c_i|i\rangle \tag{3}$$

a. **Detection of Quantum Hadamard Edges (DQHE):**

Finding the pixel-intensity gradients is the traditional method for identifying an image's edge. This results in a

complexity is O(N) for images with N pixels as it requires processing for each pixel. Large pictures are affected by this because the number of pixels increases at an exponential rate as the image size increases. the pixel-intensity gradients may be calculated using a quantum method with complexity $O(1)$, independent of the picture size, by capitalizing on the superposition caused by the Hadamard gate. The rate of acceleration is exponential. In addition, a 2^n pixel picture only requires n qubits[31][32].
Let's have a look at a $3 \times 3 = 9$ pixel images and see how the DQHE technique works. This requires 4 data qubits as well as 1 ancilla qubit, which is equal to $\log(9)$. The intensity of each pixel can be represented by an amplitude c^k. Our data qubits are first initialized to equation 4

C_0	C_1	C_2
C_3	C_4	C_5
C_6	C_7	C_8

$$\sum[\mathrm{i}=0 \text{ to } \mathrm{N}-1]\mathrm{C_i}\,|\mathrm{i}\rangle = \left(\mathrm{C}-0,\mathrm{C}-1,\dots,(\mathrm{N}-1)\right)^{\mathrm{T}} \tag{4}$$

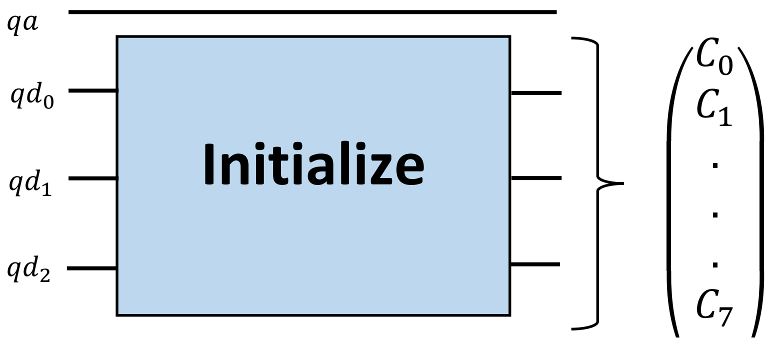
together with our auxiliary qubit to $|0\rangle$. Thus, the general situation is:

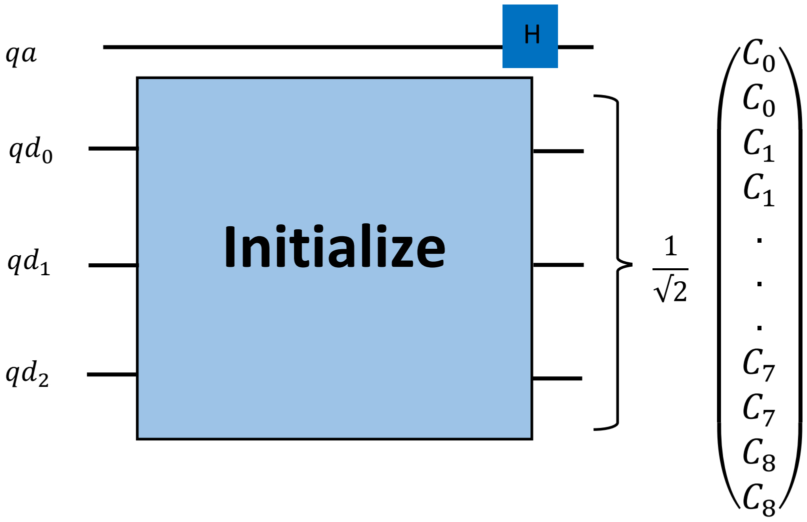
$$\left(\mathrm{C}-0,\mathrm{C}-1,\dots,\mathrm{C}-(\mathrm{N}-1)\right)^{T} \otimes |0\rangle \tag{5}$$

After that, we use a Hadamard gate on our ancilla qubit. Therefore, our current situation is:

$$\left(\mathrm{C}-0,\mathrm{C}-1,\dots,\mathrm{C}-(\mathrm{N}-1)\right)^{T} \otimes |0\rangle + |1\rangle)/\sqrt{2} \tag{6}$$

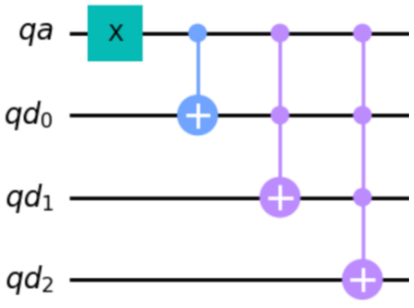
This doubles each amplitude C_{i} since the total number of binary states is doubled.





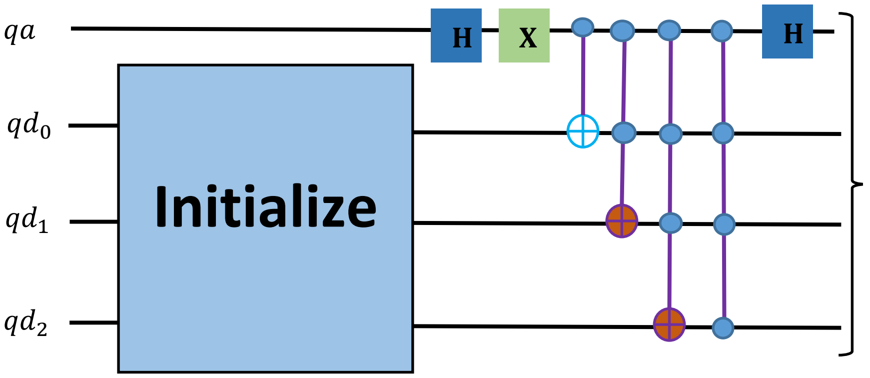
The next step is to activate a decrement gate for each qubit. An amplitude's assignment can be "shifted" upwards by one using the decrement gate[30]. So, the strength of $|j-1\rangle$ becomes $c-i$. Combining $X-$gates with controlled $\times -gates$, the decrement gate forms a unitary operation. For a total of five qubits, it appears as follows:

$$D=\begin{pmatrix} 0 & 1 & 0 & . & . & . & 0 & 0 \\ 0 & 0 & 1 & . & . & . & 0 & 0 \\ 0 & 0 & 0 & . & . & . & 0 & 0 \\ . & . & . & . & & & . & \\ . & . & . & & . & & . & \\ . & . & . & & & . & . & \\ 0 & 0 & 0 & . & . & . & 0 & 1 \\ 1 & 0 & 0 & . & . & . & 0 & 0 \end{pmatrix}$$



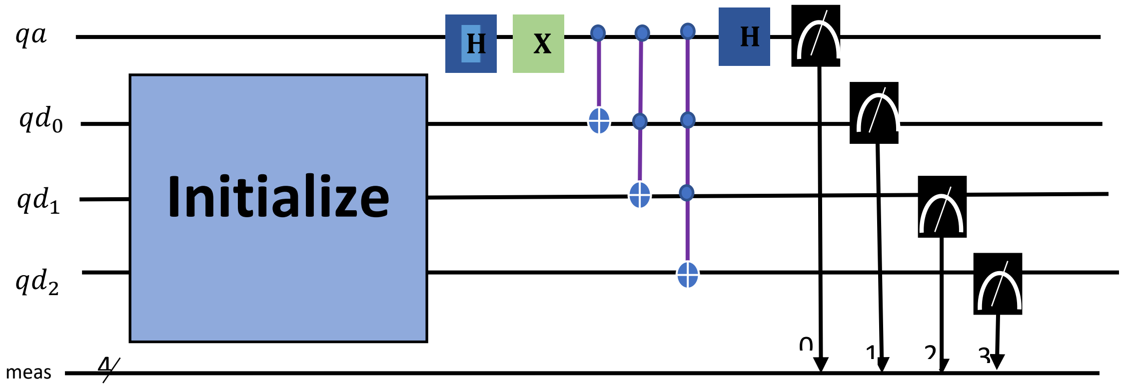
The result of implementing the decrement gate is:

Lastly, the ancilla qubit is subjected to a Hadamard. For even states $|j\rangle$, this adds the nearby amplitudes, while for odd states $|j\rangle$, it subtracts them. The wave function is then encoded with this gradient information[33].

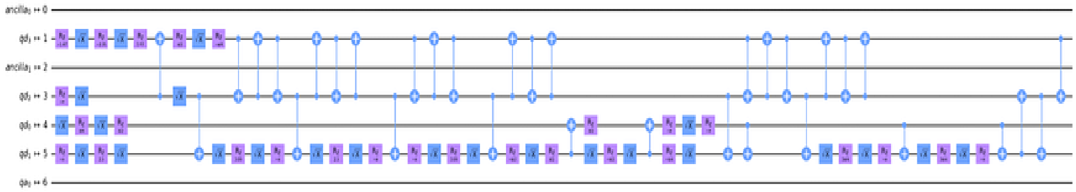


$$\frac{1}{\sqrt{2}}\begin{pmatrix} c_0 + c_1 \\ c_0 - c_1 \\ c_1 + c_2 \\ c_1 - c_2 \\ . \\ . \\ . \\ c_7 + c_8 \\ c_7 - c_8 \\ c_8 + c_0 \\ c_8 - c_0 \end{pmatrix}$$

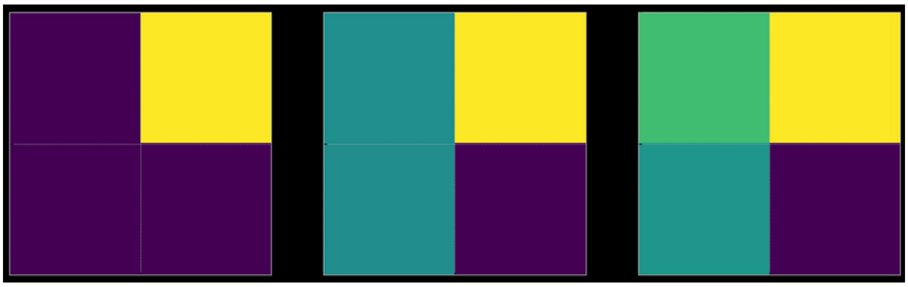
All of the qubits can now be measured. What matters is the difference between the amplitudes of the nearby states, which is represented as $c_k - c\ (k+1)$in the odd states. Pixel gradients will be bigger since we tend to measure states using larger amplitudes.



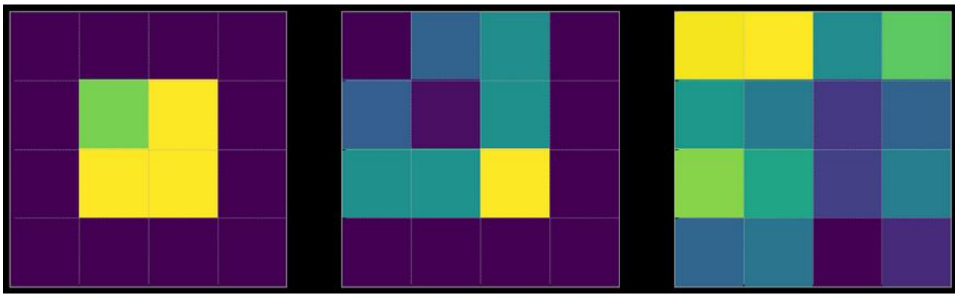
A distribution of measurable states is obtained by running this circuit a certain number of times. We can plot the total amount of measurements versus. pixel position ($|2\mathrm{i}+1\rangle$ corresponds to pixel i) and the odd-numbered states provide us with the gradient data we desire. a horizontal and vertical scan are required to do this for an actual image. To achieve the vertical scan, simply flip the original image over and start the process all over again. Finally, the output picture is generated by adding all of the vertical and horizontal scan data. scaling this method to any possible number of qubits is likewise a piece of cake. To construct the complete decrement gate, just keep adding multi-controlled X-gates. No matter how many qubits are used, the algorithm's underlying principle remains unchanged[34][35]. While other gates make up the initialization "black box" and multi-controlled $X-gates$, the basis gates do not make up the quantum circuit we shown above. Perhaps you're curious in the implications for the IBM quantum computer in terms of the basic gates that can be implemented. The $7-qubit$ ibm-lagos computers is represented by the precise circuit mentioned before, which is given for an initialized state $(c-0, c-1, \ldots., (N-1))^T$. Gate for Initialization & The remaining algorithmic steps up to the measurement:



We started with a basic quantum algorithm and ended up with hundreds of gates! This implies additional gates for qubits with greater data. We know full well the limits of the quantum computers we have now. If our quantum computers achieves 0.999 $gate$ fidelity, following 100 gates we are going to have just ~90% overall fidelity. Of course, there are other causes of mistake and noise in quantum computers, such decoherence. [36][37][38]. Thus, in actuality, we should anticipate losing the majority of the information in the process with a circuit that deep. Let's examine the differences between a simulated quantum computer (QASM simulator) and an actual one ($7-qubit$ ibm-lagos) as we go from 2 to 4 to 6 information qubits.

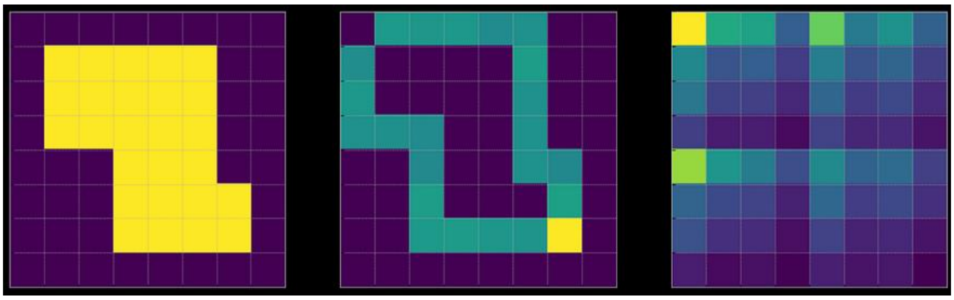


From the left to the right: picture input, output from the QASM backend, and output from the IBM Lagos backend.
The real quantum computers gives the same answer as the computer simulation.
(2 Data Qubits).



From the left to the right: picture input, output from the QASM backend, and output from the IBM Lagos backend. You can't really tell what the real quantum computers says, but it might be similar to what you saw in the simulation.

(4 Data Qubits).



From the left to the right: picture input, output from the QASM backend, and output from the IBM Lagos backend. The real quantum computers basically just makes garbage. Along the way, we lost all of our data in the circuit. (6 Data Qubits).

Our project's results show that while QHED promises to be exponentially faster than a standard computer, our own real quantum computing devices are still a long way from being able to consistently do these kinds of calculations. [39]We think that quantum picture processing is a cool way to use quantum computing, and we hope that it will be possible within the next ten years. additionally, we want to show the potential of QHED in the presence of a trustworthy quantum computer[40]. The input that we utilized was the 6.S089 logo, which has dimensions of 256×256 pixels. We generated code that divided the picture into $32x32$, or 2^10, pixel pieces. Afterwards, the next phase of edge-detected output was generated by utilizing the QASM simulation backend using 10 data qubits plus 1 ancilla the qubit for each 2^10 pixel chunk. In an ideal world, you could process such $256x256 =$ 2^16 pixels picture using just 16 data qubits. Unfortunately, our Python kernel continued to crash whenever we attempted this. See fig. 5

Figure 5. Edge evaluations using quantum algorithms.

The input picture is the 6.S089 logo, and the output image is a quantum Hadamard image with edges recognized. with any luck, you have gained some useful knowledge on quantum Hadamard detection of edges and quantum image processing. The chance to experiment with an actual quantum computer was certainly fun. fig. 6. Techniques for Edge Evaluations[41].

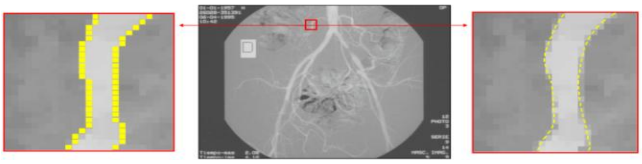


Figure 6. Circuit with Quantum Implementation in Edge Evaluation.

It is possible to show how a classical image becomes a quantum image by employing Quantum Image Representations (QImRs), such as the Flexible The recently created Enhanced Quantum Representations (NEQR) and the Quantum Image (FRQI) representation. A picture archive format is QPIE. In this paper, a Detecting Quantum Hadamard Edges (DQHE) and (QPIE) Quantum Probability Image Encoding method is detailed for using these (QImRs) for edge detection. It is possible to use quantum physics to determine the likelihood of an occurrence. See figure7.

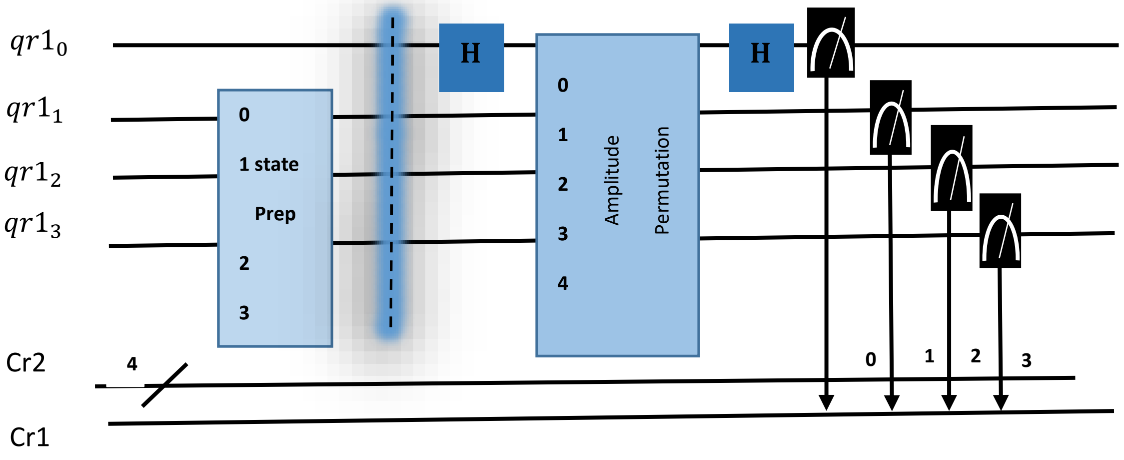


Figure 7. Circuit with Quantum Implementation in Edge Evaluation.

Applications that facilitate the processing and manipulation of pictures more rapidly, such as in games and movies, will proliferate as quantum technology advances. Although it's true because we can partially analyze massive volumes of data, such as 4K films and photos, until quantum technology can manage mistakes[42][43]. See figure. 8.

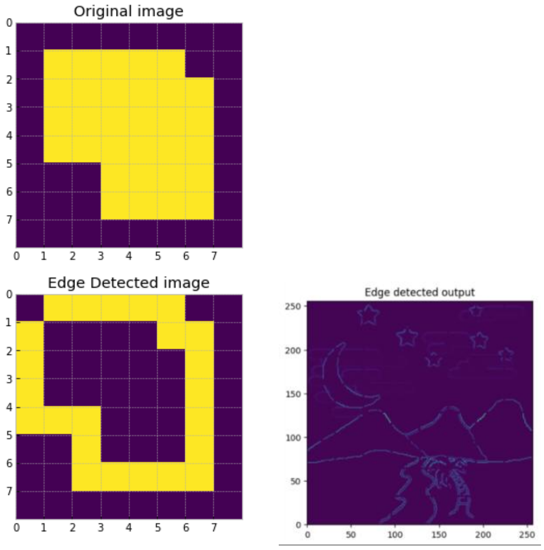


Figure. 8 Comparing Quantum Evaluations with Edge Evaluations

8. Discussion and Results

Edge detection is an absolute must when trying to extract image characteristics. The ability of modern image processing algorithms to identify edges is crucial for understanding the structure of objects as well as features in a picture. There is great potential in the new field of quantum image processing. When compared to traditional image processing, quantum image processing may be superior in some situations. The speed of edges identification for classic photo processing is not great for really huge photos since most traditional edge recognition algorithms demand high resolution as well as pixel-by-pixel calculation. As a result, the process is extremely slow.

9. Conclusion

Quantum computing has several interesting applications in image processing. Utilizing quantum properties like entanglement and superposition can significantly speed up many image processing processes when compared to their "traditional" equivalents. One typical use case in quantum computing and quantum information processing is the creation and manipulation of quantum images. One area of computer science is known as quantum processing of images, or QIP. Computing speed, security, as well as storage requirements are just a few areas where QIP technologies are expected to surpass their conventional counterparts. This is all down to the unique properties of quantum computing, such as entanglement and parallelism. Developing techniques to modify the color and position data included in the many types of flexible representations of quantum images (FRQI) has been a major focus of QIP. A primary motivation for developing FRQI was the need to limit the scope of fast geometric operations like (two-point) swapping, flipping, as well as (orthogonal) rotations to a localized area of a picture. There has been some recent talk on quantum picture scaling and quantum image translation utilizing NEQR. These methods can be used to change the size of a quantum picture. First, single qubit gates like X, Z, and H gates were used to show the possibilities of FRQI-based color transformations. Afterwards, Multi-Channel Quantum Images-based channels interest (CoI) operators were used to change the grayscale value of the chosen color channel. A technique called "channel swapping," or the CS operator, was employed to change the grayscale value for both channels. In order to demonstrate the practicality of QIMP methodologies and applications, researchers are continuously using QIRs, and we must already begin to simulate the processing of image projects. Extraction of quantum picture properties and comparing quantum images are only two examples of the many applications of quantum gates that include operations like these that researchers have been using for some time. Additionally, they have been employed for the stabilization, filtering, and classification of quantum images. Researchers have shown a great deal of interest in security solutions based on QIMP, as will be shown later on. All of these technologies have been utilized because they are the main ones used for security in this industry. The majority of studies in this field have focused on finding ways to make QIMP hardware work, enhancing QIMP's utility to run more traditional digital image processing algorithms, or identifying problems that could make certain QIMP protocols impossible to implement.

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