

QR Denoising using a Hopfield Network

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Abstract - In this research paper, we will train and test the Hopfield neural network for recognizing QR codes. We propose an algorithm for denoising QR codes using the concept of parallel Hopfield neural network. One of the biggest drawbacks of the noisy QR code is its poor performance and low storage capacity. Using Hopfield we can easily denoise the QR code and thereby increasing the storage capacity.

Key Words: QR Code, Hopfield network, noisy QR code, denoising

I. INTRODUCTION

Quick response code or commonly known as QR code is a square barcode which was first developed in Japan. A barcode is a machine-readable optical label that contains a piece of information. Today, QR codes are everywhere. One can easily find them on products for their identification and tracking, business cards, presentations, payment apps. People use it for storing information that can easily be decoded with the help of imaging devices such as camera, scanner. In recent times, the QR code has become so popular because of its fast readability and huge storage capacity. A QR code uses four standardized encoding modes i.e. numeric, alphanumeric, kanji and byte/binary.

QR codes store the data using patterns of black dots and white spaces, arranged in a square grid. These are scanned and can be translated into the human-readable language using imaging devices such as a scanner or a camera. The easiest way to scan a QR code is by using a smartphone's camera until the pattern is recognized. The required data is then extracted from the scanned patterns that are present in both horizontal and vertical components of the image.

There are various versions of QR codes available. For this research, we are using version 6(41*41).

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques.

A Hopfield network is a form of recurrent neural network, developed by John Hopfield in 1982. Hopfield network serves as an associative memory systems with binary threshold nodes. The network is initially trained to store a number of patterns.

Then only it is able to recognize any of the learned patterns by exposure to only partial or even some corrupted information about that pattern, i.e., it eventually settles down and returns the closest pattern or the best guess. In the testing phase, the network will come across noisy QR codes as well. We propose an algorithm for denoising the noisy QR codes using the parallel Hopfield network. By using Hopfield network, we will be able to achieve higher storage capacity and thereby increasing better performance.

II. RELATED WORKS

The technology of QR code recognition has been studied in recent years. We can simply divide the recognition into two steps: Preprocessing of images and extraction of the QR code [1,2,3].

Some researchers focus on image denotation or camera shaking in image preprocessing. A previous work uses the super-resolution technique that generates a high - resolution image from multiple low - resolution images to improve the performance of low - resolution QR code recognition. [4,5,6,7]

In addition, some researchers use various binarizations to improve the non - uniform background and uneven light problems. Researchers propose several different methods for locating and extracting QR image code in the extraction of the QR code. Some researchers use the finder pattern feature to find a rough QR code. They effectively extract the QR code from the images after estimating the four corners of the QR code using the rough QR code position [8,9,10,11,12] They use edge detection in research to find a rough barcode area. Morphological dilation and closure are then used to create more compact areas. Finally, the QR image code position can be detected.

Although these studies have their contributions, we can improve some of the shortcomings. Researchers focus only on image denoising, but finding the position of the QR code is an important part of QR decoding [13,14,15,16,17] They did not propose their method for dealing with this problem. Previous work requires a great deal of calculation.

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Table 1 Literature Survey

Paper name and year	Proposed method and study	Algorithm	Gap Identified	Conclusion
The capacity of Hopfield associative memory[2003]	The proposed structure makes it possible to use higher order information without needing approximations or infeasibly large amounts of memory	Outer product construction	Feed forward and recurrent networks exhibit outer product derivative structure but convolutional neural networks do not	Provides insights into geometry of neural network optima
Network traffic prediction based on the wavelet analysis and Hopfield neural network[2013]	Network traffic is normalised and wavelet transform then reconstructed the components into AR model and send high frequency to hopfield neural network	Alpha trous wavelet algorithm	Traditional single network flow model does not simulate the complex characteristics of network traffic. Proposing a hybrid model for prediction	This model improves the prediction accuracy and has good adaptability to the network traffic.
Study of Hopfield neural network[2013]	Shows limitations of the model as pattern recognize the proving that all images with a single black point can be recognized by a fully connected network	Minimum cut algorithm	Graph partition problems are solved with additional constraints suggest balancing sizes of two sides of the cut	Exploring the term, capacity of neural network model showing that very large class of mappings are not feasible by neural nets.
Research of QR code image correction based on image grey feature[2017,IEEE]	Proposes an algorithm for accurate reading and rapid correction of QR Code location information	In this paper, mathematical morphology using digital image processing	This algorithm solves problems influenced on QR code by light, shooting impact angle, correction algorithm robustness etc	QR code image solving the problem of accurate recognition and fast correction achieves good results n practical engineering applications.

III. ALGORITHM

In our algorithm, we have trained the networks with the denoised QR codes, which will help in recognizing the noisy QR codes and denoising them. Steps followed are:

A. Data generation

We have used an open source generator called PHP QR Code for the generation of datasets [18,19,20,21,22] We have generated around 6000 QR codes 41x41 (Version-6) with error correction level L. We generated the QR Code using random strings of 250 characters using random string generator



Fig 1 Original QR code

B. Training Algorithm

We have randomly divided these 6000 QR codes into a set of 15 containing 400 each. This is done because the number of nodes in the Hopfield network is equal to the number of pixels in the QR code. In this case number of pixels = 41 x 41 = 1681 and hence the number of nodes in the Hopfield network = 41 x 41 = 1681. And before using these 41 x 41 QR Codes for training the network they are converted into 1681 x 1 vectors. Also, as stated by the Hebbian Rule of

Learning the maximum capacity of a Hopfield associative network is similar to $0.15n$ [13].

The simplest hence the most common way to train the neural network is applying Hebb's rule, which is immediate and incremental but has an overestimated capacity of $n/2 * \ln(n)$. So we use the pseudo-inverse learning rule which does not have the functionality of Hebb's rule and also, it's not incremental but has the capacity almost equal to n [23,24,25,26]

As we have a large set of QR codes it is not possible to use the network with a capacity of $<n$. So, we divide these QR codes into a set of 15 Hopfield network at random and use the algorithm given in the parallel algorithm section.

The pseudo-inverse rule states that firstly we have to train the network with normal Hebbian Rule and by doing so we have to find out the weight matrix W with diagonal elements 0 i.e. no self-loops which will provide greater stability. After that, we have to find the pseudo-inverse's weight matrix which can be calculated by taking the inverse of W and making the diagonal elements 0. In mathematical form it can be represented as follows:

$$W_1 = W_{\text{hebbian}} \text{ (where } W_{ii} = 0\text{)}$$

$$W_2 = (W_1)^{-1}$$

$$W_{\text{pseudo-inverse}} = W_2 \text{ having } W_{ii} = 0$$

C. Noisy QR's preparations

There are 3 different types – Gaussian, Salt, and Pepper of noise which we can use for the preparation of noisy QR codes. We used these 2 types of noise for testing our networks.

1) Gaussian noise: It is a noise which has a probability function which is equal to the normal distribution. The values this noise take is Gaussian-distributed. We have used MATLAB to add noise to our QR Codes and to test our network. It can be done in the following steps:

```
I = imread('example.jpeg');
J = imnoise(I,'gaussian',0,0.1)
imshow(J);
```


Here, in imnoise we have used GAUSSIAN method with mean 0 and variance 0.1.

After adding the noise to the QR code, we will convert the resultant image to the Binary image. It can be done in the following way:

```
BW = im2bw(J,0.1)
imshow(BW);
```



Fig 2 : QR code

2) Salt and Pepper noise: We have also performed a test on our network using salt and pepper noise having fraction equals to the 0.4 of the total pixels being affected [27,28,29,30] It can be done in the following way:

```
I = imread('ex1.png');
J = imnoise(I,'salt & pepper',0.1);
imshow(J)
```



Fig 3 : Noisy QR

On each set of QR codes, we train a Hopfield network individually. Each Hopfield network that is being trained has 1681 nodes and is a fully connected recurrent neural network. The resultant weight matrix was of 1681x1681. When training using 15 networks on 400 41x41 QR codes each, we get the 15 1681x1681 weight matrices corresponding to the 15 networks. These 15 matrixes can be used to train any QR code[31,32,33]

IV.RESULTS

We tested our system for with distinct sorts of noise including Gaussian and salt and pepper noise.

For Gaussian noise, the system had denoised the codes effectively, signifying its viability on an enough normal sort of noise.

Such QR codes with Gaussian noise of variance=0.5 were totally denoised by our network. The denoised QR code coordinates precisely the equivalent with the first one.



Fig 5: Denoised QR

Such QR codes with a corner damaged by high measures of salt and pepper noise for likewise totally denoised by our system.

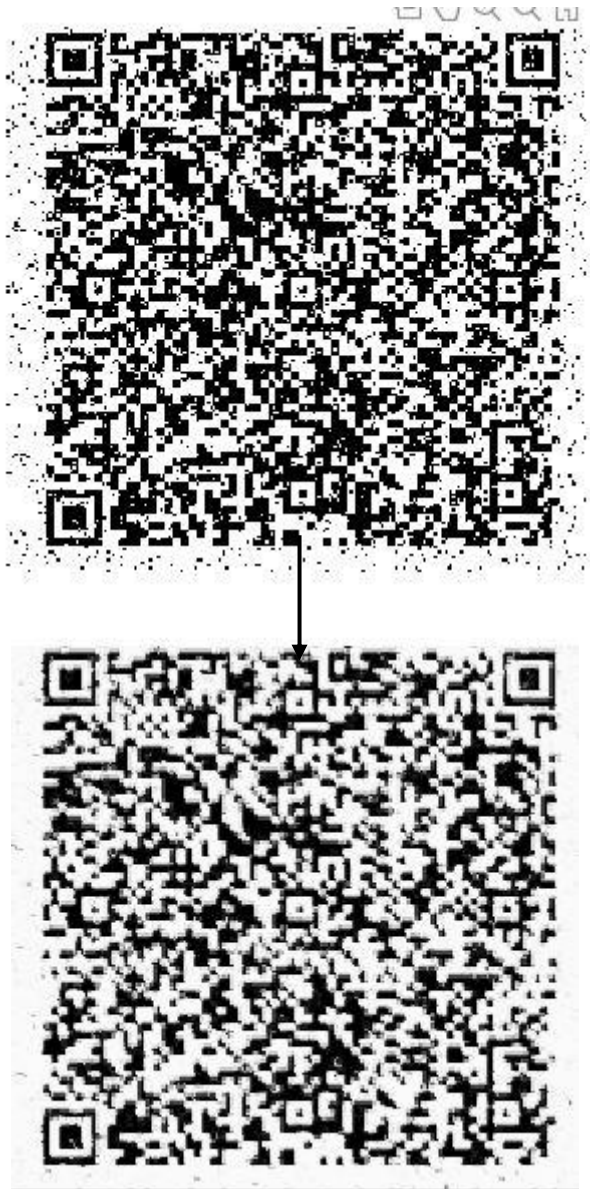


Fig 6: Denoised QR

The Hopfield arrange precisely denoised QR codes with fluctuating kinds of noise. It additionally effectively denoises and confirms QR codes with a high amount of noise localized in a few regions.

The capacity limit of QR codes for an arrangement of n organizes for our situation was $400 \times n$ where n is the quantity of networks utilized in parallel. It is a lot quicker than a single Hopfield arrange having a similar limit, as though our system has 1681 nodes and a limit of $400 \times n$, a single Hopfield system would have $1681 \times n$ nodes as the limit of a Hopfield organize scales straight. Such a network with $1681 \times n$ nodes would be much slower to consolidate, as it has a lot bigger weight grid of the request $(1681 \times n)^2$ terms while every one of our networks would just be just of the request of $(1681)^2$ terms. This would make the update quicker. Our algorithm would apportion less memory than a single Hopfield network of similar storage capacity. A single network with the same storage capacity would require a capacity of the request $(1681 \times n)^2$ terms. Our algorithm would take a lot lesser capacity of the request of $n \times (1681)^2$. This means that our algorithm leads to large gains in speed and storage requirements over usual Hopfield networks, making

them suitable for a wider variety of purposes.in different uses of Hopfield networks for increasing the capacity.

V. CONCLUSIONS

Denoising utilizing Hopfield systems gives another strategy to denoising QR codes. A lot of noise can be endured by our denoising technique as found in the outcomes. Our algorithm for distributing the QR codes in a few Hopfield organizes and choosing the right one helps increment the capacity limit of QR codes by the network subsequently making it conceivable to utilize it in vast frameworks for QR code recognition. It makes utilization of an abundance of deceptive minima's and the energy capacity of the network to choose the system containing the denoised QR code. Additionally, our strategy is speedier than putting away every one of the networks in a lot bigger strategy as we have various smaller network, which is kept running for not very many cycles. Just a single of them is kept running until assembly, in this way giving a huge speed advantage. It additionally reduces the capacity cost of the system, diminishing it by n times when contrasted with a single Hopfield organize. This technique can be utilized in different employments of Hopfield systems for expanding the limit.

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