# A Report on: Quantum Inspired Neural Networks for Signature Verification

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Design Project (EEE F376)

### Under the guidance of

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#### Abstract

In this report, Enhanced Quantum based Neural Network Learning paper is implemented for Signature Verification The proposed algorithm forms a neural network architecture constructively by adding the hidden layer neurons. The connection weight and threshold of the neurons are decided using the quantum computing concept. The quantum computing concept gives large subspace for selection of appropriate connection weights in evolutionary ways. Also, the threshold value is decided using the quantum computing concept. To uniquely identify the signatures, a total of 45 features are extracted from each signature of dataset BHSig260. The performance of the proposed algorithm is evaluated by rigorous training and testing with these signatures, and the results confirm its accuracy and effectiveness.

#### 1 Introduction

Human brain has the great ability to unravel and classify the complex patterns of the real world. Inspiring from the brain anatomy, artificial neural network was introduced in 1943. Human brain needs training specific to the kind of task involved. Analogously, artificial neural network also needs training algorithm. Many models have been proposed like back propagation, perceptron and recurrent network which represent working of the human brain. These models have been successfully applied in several fields like economics, defense, stock market, engineering, medical, computer network and many more. However, performance of neural network in these mentioned areas depends on many parameters like, quality of input data set, number of hidden layer neurons, threshold of neurons, connection weights, To enhance the approximation and generalization ability of classical artificial neural network (ANN), the principles of quantum computation are employed. However, as yet, there is little understanding of the essential components of artificial neural networks based on quantum theoretical concepts and techniques. The basal model and theory of quantum neural networks are in research. At present, there is not a set of perfect theory to direct the construction of model. Quantum computing concept was, firstly, introduced in classical computing. The significant work has been done by Han and Kim to solve the knapsack problem using the quantum computing concept with and without termination criteria. Here, qubit q is defined as a smallest unit of information which have better characteristic of the population diversity than other representations. Since qubits are linear superposition of states of probabilistic thus, with the help of Gaussian random generation it gives diversity to select the optimal value of parameters from large subspace.

A neural network algorithm has been proposed in which optimization of the learning parameters was carried out using quantum computing concept. Earlier an algorithm was proposed based on binary neural network learning algorithm in which the neural network architecture is formed constructively. In this algorithm, the connection weights are decided using the quantum computing concept. Further improvement is proposed in this paper by deciding the connection weights and threshold using the quantum computing concept. The neural network formed in this way is trained and tested on a signature dataset.

Application: Handwritten signatures are widely used to authenticate financial transactions and documents. Signature Verification is used to authenticate signatures, by capturing their unique features, to avoid forgery. Various

forms of biometric security systems exists such as fingerprint, iris, speech, heart sound and keystroke based recognition, all of which depend on the physical attributes of the users. But still, signature verification is one of the most popular attribute accepted by the public, as it: (1) is more comfortable, (2) is more economical and (3) requires less storage space. It is an automated method of verifying a signature with the actual authorized signature by capturing some of its unique features like, the shape of signature (i.e., static or off-line signature verification) or the parameters that can capture the unique features of how the authenticator signs his/her name in real-time. To make this task more efficient, an enhanced quantum-based neural network learning algorithm for signature verification is proposed.

## 2 Image Preprocessing

We don't want our algorithm to be affected by the selected dataset and thus we pre process the image so that no matter how we take an image of a signature, the proposed algorithm classify it correctly. Following are the pre processing steps:

- 1. Converting to Black and White: We convert the image to black and white so that the pen colour does not effect out feature extraction process. By doing so, the colour of the image is made uniform.
- 2. Noise Removal: The noise removal process is performed after converting all images in uniform i.e. black and white color. The signature images have noise due to two main sources: first, the background paper on which the signature is taken which may not be uniform of the same color. Secondly, the noise arises while scanning the paper having signatures. This noise will hinder the training and testing of signatures and hence must be removed. Median Filtering is used as a remedy here.

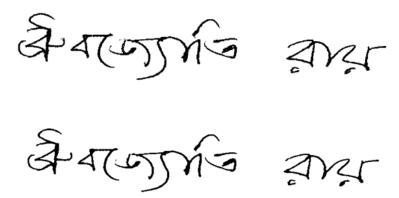


Figure 1: Top image is the original signal signature and bottom is after the median filtering

- 3. **Image Resizing:** Every image size is reduced to 128 X 128 pixels so that all the images have the uniform size.
- 4. **Image Thinning:** A signature impression may be made with pens of varying tips. However, the difference in tip size shouldn't be a factor to distinguish signatures. The thickness of every stroke in a signature is reduced to a width of a single pixel. The steps discussed above help to standardize a given signature image [2].

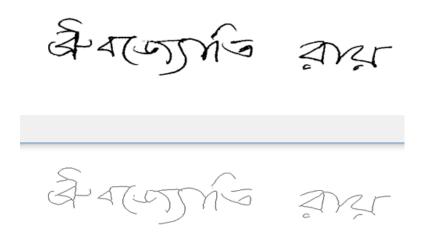


Figure 2: Top image is the original signal signature and bottom is after thinning

5. **Image Cropping:** Sometimes due to variable distance of camera from

the signature the paper content image is more. Thus to reduce that effect we crop image to exact size of signature.

### 3 Feature Extraction

The unique features are extracted from the pre processed x-y coordinate that are further given as input to QNN model for signature recognition.

- 1. **Angle of Signature:** It may happen that the same authenticator may use different elevation angles for every instant w.r.t origin in the x-y grid. Therefore, the angle of rotation must be standardized [3].
- 2. Centre of Mass Coordinates: Every person signs bit differently every time but the centre of mass remains approximately same as the width and the height vary relatively.
- 3. **No. of Loops:** Count the no. of loops in a signature as they are peculiar to particular signatures.



Figure 3: White Regions shows the loops

- 4. **Dense Rows and Columns:** This gives 30 feature values. Calculate the density of rows and columns and choose the highest 10 values for both rows and columns. Furthermore distances of each most dense row and column is calculated from the origin.
- 5. Density of 5 most dense patches: We took 9 X 9 square patches and calculated their densities and then chose the highest 11 densities.

## 4 Basic Concepts of QNN

In this section some basic necessary concepts are discussed in brief, which helps to illustrate the proposed algorithm. Preliminaries related to quantum computing is explained:

#### 4.1 Quantum Neural Network

This method forms a neural network architecture, which consists of four layers: an input layer, two hidden layers, and the output layer. The number of input nodes is equal to the number of attributes of the signature dataset. Let  $P_1 = (X_1^1, X_1^2, ..., X_1^{c1})$  denote the input samples, where  $c_1$  is the number of input samples and  $X_i^c = (x_i^1, x_i^2, ..., x_i^e)$  where e denotes the number of attributes in one instance of the input sample The number of input layer nodes is equal to e [4]. The number of neurons in the hidden layer is decided constructively. For  $i^{th}$  hidden layer neuron, the connection weights are denoted as follows:

$$W_i^{real} = (w_{i1}, w_{i2}, ..., w_{ie}) \tag{1}$$

In the proposed algorithm, these connection weights are decided using the quantum computing concept.

## 4.2 The Qubit Representation

Quantum bits, which differ from traditional bits, use probability to represent binary information. A characteristic of quantum bit representation is the ability to represent a linear superposition of "1" and "0" states probabilistically. A quantum bit individual containing a string of q quantum bits can be defined as:

$$\begin{pmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_q \\ \beta_1 & \beta_2 & \cdots & \beta_a \end{pmatrix}$$

where  $0 \le \alpha_i, \beta_i \le 1$ ,  $(\alpha_i)^2 + (\beta_i)^2 = 1$ , and i = 1, 2, ..., q,  $(\alpha_i)^2$  is the probability that the  $i^{th}$  quantum bit will be found in state "1" and  $(\beta_i)^2$  is the probability that the  $i^{th}$  quantum bit will be found in state "0." Since  $(\alpha_i)^2 + (\beta_i)^2 = 1$ ,

$$\langle \alpha_1 | \alpha_2 | \dots | \alpha_q \rangle$$
 (2)

The observation is a process that produces a binary string b from (1), which operates as follows. For a quantum bit individual with q quantum bits, generate a q random number vector  $r = [r_1, r_2, ...., r_q]$ , where  $0 \le r_i \le 1$ , i =

1,2,...,q; the corresponding bit in b takes "1" if  $r_i \leq (\alpha_i)^2$ , or "0" otherwise [5].

#### 4.3 Conversion from Quantum Bits to Real Value [1]

The algorithm which is proposed here works on classical computers, therefore conversion from quantum bits to real value is required. The weight matrix in terms of quantum bits  $W_j'$  is converted into a real value weight matrix  $W_j^{real}$ . Similarly the threshold value in terms of quantum bits  $\lambda_j'$  is converted into real value  $\lambda_j^{real}$ . This conversion process starts by taking random number matrices R, where  $R_j = [r_{j1}, r_{j2}, ..., r_{jk}]$ . Then, further mapping is done by using binary matrix  $S_j$  where  $S_j = [s_{j1}, s_{j2}, ..., s_{jk}]$  and Gaussian random number generator with mean value  $\mu$  and variance  $\sigma$ , which can be represented as  $N(\mu, \sigma)$ . The mapping between binary value to Gaussian number generator is done with the help of formula binary to decimal conversion. The value of matrix  $S_j$  is passed into bin2dec( $S_j$ ) formula to select value from Gaussian random generator [5]. The value of matrix  $S_j$  is generated as follows:

$$if(r_{ji} \le (\alpha_{ji})^2)$$
 then  $s_{ji} = 1$  else  $s_{ji} = 0$ .

#### 4.4 Qubit Updation

Evolutionary algorithms are applied to optimize the solution of varying parameters and its find out in several iteration by observing their fitness [6]. Therefore, to evolve tehe new value of weight matrix  $W_j^{real}$  Fitness function for weight  $W_j^{real}$  and real threshold  $\lambda_j^{real}$ , the quantum weights  $W_j'$  and quantum threshold  $\lambda_j'$  are updated using quantum update function which utilizes the fitness value, let us denote fitness by F and  $F^*$ . To update qubit, the required quantum gate is as follows:

- 0	als.	n na	
$s_{ji}^g$	$s_{ji}^*$	$F_g < F^*$	$\Delta \theta$
0	0	false	0
0	0	true	0
0	1	false	$-0.03 * \Pi$
0	1	true	0
1	0	false	$0.03 * \Pi$
1	0	true	0
1	1	false	0
1	1	true	0

$$U(\Delta \theta) = \begin{vmatrix} \cos \Delta \theta & -\sin \Delta \theta \\ \sin \Delta \theta & \cos \Delta \theta \end{vmatrix}$$

where  $\Delta\theta$  is called rotation angle.

#### 4.5 Boundary Parameters

In the proposed algorithm, the threshold  $Th_i^{real}$  of the neuron is evolved using the quantum computing concept and boundary parameters. Here, to select threshold, min\_net and max\_net parameters are introduced. These parameters are initialized as  $-\inf and\inf$  respectively. The following formulations show the calculation of boundary parameter.

$$\begin{split} (TBP)_t^{max} &= max(max\_net_A, max\_net_B); \\ (TBP)_t^{min} &= min(min\_net_A, min\_net_B); \end{split}$$

Thus, threshold in terms of these boundary parameter is formulated as follows:

$$Th_t^{real} = \begin{cases} (TBP)_t^{min} & if \quad Th_t^{real} < (TBP)_t^{min} \\ (TBP)_t & if \ (TBP)_t^{min} \le Th_t^{real} \le (TBP)_t^{max} \\ (TBP)_t^{max} & if \quad Th_t^{real} > (TBP)_t^{max} \end{cases}$$

## 5 Algorithm

The overall process is explained in the form of an algorithm:-

**Step1:** Take Input sample as  $(X_1^1, X_1^2, X_1^3, ...., X_1^{c_1})$  and  $(Y_1^1, Y_1^2, Y_1^3, ...., Y_1^{c_1})$  corresponding to each person. Take first neuron with the weights  $W_g^{quant} = (Q_{w1}, Q_{w2}, ...., Q_{we})$  where e is the number of attributes and g denotes the iteration number.

Step2: for 
$$g = 1$$
 to m  
Initialization of other parameters  $F^* = 0, S^* = 0$   
 $\max\_net_A = -\inf$   
 $\min\_net_A = \inf$ 

```
\max_{n} net_B = -\inf
\max_{B} - \inf
Implement Conversion Process of W_q^{quant}
for i = 1 to c_1
net_A(i) = \sum W_g^{real} x Y_1^i
\max_{n} net_B = \max(\max_{n} net_B, net_B(i))
\min_{n} t_B = \min(\min_{n} t_B, net_B(i))
Call Quantum Threshold Function (W_q^{real})
if(F_q \ge (c_1 + c_2))
Finish learning process
Assigned new dataset to class A as P_{l+1} and class B as (P-P_{l+1})
Repeat step1 and step2 for learning of class P_{l+1} and (P-P_{l+1})
else
Evaluate F_g, F^*, s_i^g, s_i^* and update quantum bits of weights by using
qubits updation weight updation.
F^* = max(F^*, F_q)
endif
if ((g==m) \text{ and } (F^* \leq (c_1 + c_2)))
Add new neuron for unlearnt sample
((c_1+c_2)-F^*) and finalize its weight by using
Step1 and Step2. For second neuron number of samples will
be ((c_1 + c_2) - F^*) not c_1 + c_2.
endif
g=g+1
endfor
Repeat the process for each person from step1 to step2
```

#### **Quantum Threshold Function**

```
Step1: Initialization of different parameters for t=1 to z z is a variable whose value is decided by the user by deciding the number of iterations for threshold updation Th_t Th_t = (q_i^{Th}) count1=0 count2=0 F_{Th}^* = 0 Implement Conversion Process of Th_t to generate real value. for i = to c_1
```

```
net_A(i) = \sum W_g \times X_1^i

if (net_A(i) \le Th_t^{real})
increase count 1 by 1
endif
endfor
for i = 1 to c_2
net_A(i) = \sum W_g \times Y_1^i
if (net_A(i) > Th_t^{real})
increase count by 1
endif
endfor
F_t = \text{count}1 + \text{count}2
F_{Th}^* = \max(F_{Th}^*, F_t)
update quantum bits for Th_{t+1} using
qubits updation and weight updation
Generate real value of Th_{t+1}
t=t+1
F_g = F_{Th}^*
endfor
return F_a
```

## 6 Experimental Results

The proposed algorithm has been implemented in two parts.

- 1. The first part includes processing of the signature image and extraction of features which are implemented in MATLAB.
- 2. The second part consists of training of neural network and then testing, which has been implemented in Java.

(Implementations are done on Intel i-5 4th generation processor).

The algorithm is tested on a standard online database of signatures: BH-Sig260

To train the proposed algorithm we have taken 8 signatures each of 37 people, with 45 extracted attributes per signature. Furthermore, to test the algorithm, 2 signatures (one forged and one real) each of 37 people were tested. The quantum-based neural network forms network structure constructively, which reduces unnecessary training of the system. The connection weights

are decided using the quantum computing concept. To find the proper separation between input classes, a quantum threshold with boundary parameter is also proposed. The threshold boundary parameter helps to find the optimal value of threshold with the help of min, max function. This enhanced quantum-based neural network learning algorithm proposed by Prof. Om Prakash [4], is employed successfully to classify offline signatures.

To judge the performance of the proposed, it is compared with ANN algorithm with respect to ANN for signature verification,

	ANN	QNN
Maximum Efficency	68%	71%
Computation Time	2 min	$\int 5 \min$

It is clear from the results that there is definite improvement in Classification with QNN and is mainly due to the two reasons. Firstly, the unique features that have been selected to characterize signature. Secondly, the classification of signature dataset uses the quantum computing concept provides exploration due to which the large search space is achieved to get optimal value. It is also observed that more the number of iterations for weight and threshold updation, more is the accuracy.

#### References

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# Appendix

#### Counting loops

```
mainnewton.m X main.m X data30.m X signature_preprocess.m X loops.m X +
     function loopcount = loops(image)
1
     ☐ %image = imread('C:\Users\Arjun Gupta\Downloads\4-2\QNN\BHSig260\Bengali\001\B-S-1-G-01.tif');
 2
       -%imshow(image)
 3
       image = medfilt2(image);
 4 -
 5
       %figure, imshow(image)
 6 -
       image1 = image;
 7 –
       image1 = im2bw(image1, 0.5);
 8 -
       image1 = imcomplement(image1);
 9 -
       image1 = imfill(image1, 'holes');
10 -
       image2 = image;
11 -
       image2 = im2bw(image2, 0.5);
12 -
       image2 = imcomplement(image2);
       imshow(image1-image2)
13 -
      loopcount = max(max(bwlabel(image2-image1)));
```

## Signature Preprocessing

```
mainnewton.m × main.m × data30.m × signature_preprocess.m × loops.m × +
        clear all
        clc
        srcFiles = dir('C:\Users\Arjun Gupta\Downloads\4-2\ONN\test1\*.tif'); % the folder in which ur images exists
        dense_col = zeros(length(srcFiles),5);
        dense_row = zeros(length(srcFiles),5);
features = zeros(length(srcFiles),13);
        output_count = 1;
        var_count = 1;
11 - for si = 1 : length(srcFiles)
          filename = strcat('C:\Users\Arjun Gupta\Downloads\4-2\QNN\test1\',srcFiles(si).name);
12 -
         I = imread(filename);
%I=imread('signature.png');
13 -
14
15 -
16
         figure, imshow(I);
17 -
18 -
19 -
         loopcount = loops(I);
         imshow(I)
         I = medfilt2(I); %removing noise
20
21 -
         I2=imresize(I,[128 ,128]);
22
         %figure, imshow(I2)
%figure,imshow(I2);
23
        %I3=rgb2gray(I2);
I3=im2double(I2);
25
        I3=im2bw(I3);
       %figure, imshow(I)
```

```
mainnewton.m × main.m × data30.m × signature_preprocess.m × loops.m × +
29
           %converting image to black and white
I3 = bwmorph(~I3, 'thin', inf);
I3=~I3;
 30
31 -
                                                                                  %thining the image
 32 -
 33 -
           figure, imshow(I3);
 34
35
           [rows cols] = size(I3);
 36 -
37 -
           top = 0;
bottom = 0;
left = 0;
right = 0;
 38 -
 39 -
40 -
41
 42
 43 -
44 -
45 -
           k=1;
          for i=1:128
for j=1:128
if(I3(i,j)==0)
 46 -
47 -
48 -
                            <u>u</u>(k)=i;
<u>v</u>(k)=j;
 49 -
                             k=k+1;
                            %I3(i,j)=1;
 50
 52 -
                end
 53 –
54 –
           end
           C=[u;v];%the curve of the signature
N=k-1;%the number of pixels in the signature
55 -
```

```
mainnewton.m × main.m × data30.m × signature_preprocess.m × loops.m × + 55 - N=k-1;%the number of pixels in the signature
56 -
57 -
        oub=sum(C(1,:))/N; the original x co-ordinate center of mass of the image ovb=sum(C(2,:))/N; the original y co-ordinate center of mass of the image
59
60
         $$$$$$$$$$$$$$$$$$$$$$$$$$$$
61
         moving the signature to the origin
62 -
       for i=1:N
63 -
          u(i)=u(i)-oub+1;
64 -
65 -
            v(i)=v(i)-ovb+1;
        -end
66
67 –
68
         % the new curve of the signature
        C=[u;v];
69 -
70 -
        ub=sum(C(1,:))/N;
         vb=sum(C(2,:))/N;
71 -
         ubSq=sum((C(1,:)-ub).^2)/N;
72 -
73
         vbSq=sum((C(2,:)-vb).^2)/N;
74 -
       for i=1:N
75 -
76 -
77
78 -
        uv(i)=u(i)*v(i);
        uvb=sum(uv)/N;
        M=[ubSq uvb;uvb vbSq];
       %calculating minimum igen value of the matrix
minIgen=min(abs(eig(M)));
80
81 -
       %the eigen vector
```

```
84 -
85
        theta(si) = (atan((-MI(1))/MI(2))*180)/pi;
86
87 -
88
89
90
91
92 -
93 -
94 -
95 -
96 -
97 -
        thetaRad=(theta*pi)/180;
        *****************
       %cropping the picture to exact size of the image of or i=1:rows
            for j=1:rows

for j=1:cols

if (I3(i,j)==0)

top = i;

break;
            end
end
98 -
99 -
100 -
101 -
             if(top~=0)
           break;
end
       end
102 -
103
104 -
105 -
106 -
      for i=rows:-1:1
            for j1=1:cols
if (I3(i,j1)==0)
107 -
108 -
109 -
                  bottom = i;
break;
           end
end
110 -
```

```
mainnewton.m X main.m X data30.m X signature_preprocess.m* X loops.m X + 110 - enc 111 - if (bottom:-e) 112 - break;
113 -
114 -
115
             -end
115 | for j=1:cols

116 - | for j=1:cols

117 - | for i=1:rows

118 - | if (13(i,

119 - | left

120 - | break

121 - | end
                             if (I3(i,j)==0)
                               left = j;
break;
122 -
123 -
124 -
                      if(left~=0)
                           break;
125 -
126 -
              -end
127
128 -
129 -
130 -
131 -
132 -
133 -
             for j=cols:-1:1
for i=1:rows
                         if (I3(i,j)==0)
right = j;
                          break;
end
134 -
135 -
136 -
137 -
138 -
          preak;
end
end
                      if(right~=0)
```

```
mainnewton.m x main.m x data30.m x signature preprocess.m x loops.m x +

139

46 *finiding 5 most dense rows and cols

141 - countz = zeros(1,cols) ;

142 - colz = 1;
 142 -
143 -
           for i=1:cols
 144 -
                  for j=1:rows
if(I3(j,i)==0)
 145 -
                         countz(1,colz) = countz(1,colz)+1;
end
 146 -
147 -
 148 -
149 -
                   colz=colz+1;
 150 -
             -end
 151
 152 -
            countz = countz./rows;
 153
 154 -
155 -
156
                    [max_num,Y]=max(countz(:));
%[X Y]=ind2sub(size(countz),max_num);
 157 -
158 -
                   dense_col(si,i) = Y;
countz(1,Y) = 0;
 159 -
160
161 - countz1 = zeros(1,rows) ;

162 - rowz = 1;

163 - for i=1:rows

164 - for derivatives
 165 -
166 -
                         if(I3(i,j)==0)
                               countz1(1,rowz) = countz1(1,rowz)+1;
 167 -
```

```
mainnewton.m X main.m X data30.m X signature_preprocess.m X loops.m X +
169 -
          rowz=rowz+1;
170 -
       end
171
172 -
      countz1 = countz1./cols;
173
174 - \frac{1}{2} for i = 1:21
175 -
           [max_num,Y]=max(countz1(:));
176
           %[X Y]=ind2sub(size(countz), max num);
177 -
          dense row(si,i) = Y;
L78 -
          countz1(1,Y) = 0;
      -end
179 -
180
181
       %storing all obtained features in a matrix
182
       features(si,1) = theta(si);
183 -
       features(si,2:3) = [oub,ovb];
184 -
185 -
       features(si,4) = loopcount;
186
       %features(si,5) = count;
       features(si,5:45) = [dense_col(si,:), dense_row(si,:)];
187 -
188
      I4 = I3(top:bottom, left:right);
189 -
190 -
      figure, imshow(I4);
```

#### JAVA Code

```
eclipse-workspace - sig_ver/str/sig_ver/functions.java - Eclipse

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```
1 package sig_ver;
 3 import java.util.Vector;
 5 public class interior node {
 6
 7
        int featur = 45;
 8
       double [] incomingedges = new double[featur];
9
         double value;
   double outgoingedge;
int class_classifying;
int number_within_class;
LO
11
12
      double alpha;
1.3
      double alphagreater;
1.5
       double alpha1[] = new double[featur];
16
        double alpha2[] = new double[featur];
L7
         double alpha3[] = new double[featur];
L8 }
19
```

```
eclipse-workspace - sig_ver/st/sig_ver/taking_input_ava - Eclipse

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| *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *
```

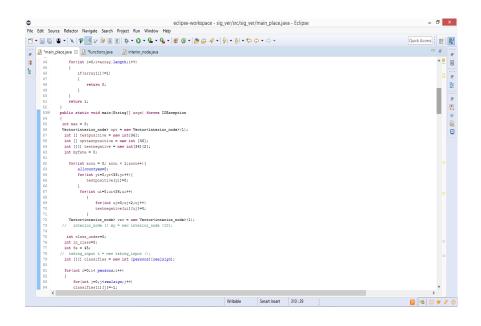
```
eclipse-workspace -sig_ver/str/sig_ver/taking_input_java -Eclipse

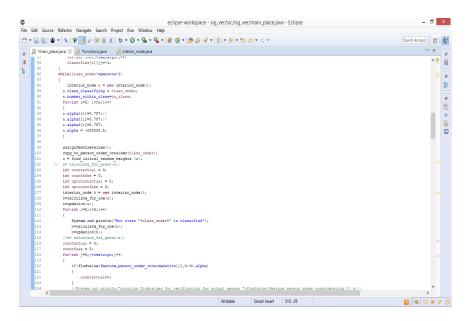
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| Countactual + countactual + countactual + contactual + contactual + countactual + co
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eclipse-workspace-sig yer/src/sig yer/src/
```

```
edipse-workspace-sig_ver/srx/sig_ver/main_place java - Edipse

File Edit Source Relactor Navigate Search Project Run Window Help

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```

