Hybrid Quantum–classical Systems for NISQ Devices with Fast Gates on EEG classification

1**Qin He,** 2**Rubin Wang,** 3**Xiaochuan Pan**

1,2,3**Affiliation: East China University of Science and Technology, Meilong 130**

**Email:** 1**asamiko@aliyun.com,** 2**rbwang@163.com,** 3**pxc@ecust.edu.cn**

# Abstract

# It is not until the advantage of quantum computing devices, the possibility to store more states than either 0 or 1 in one qubits, bring the wide variety of formation processing tasks that the computation power makes breakthrough in the new era of information process. The noisy intermediate-scale quantum (NISQ) devices are defined as the quantum computer for which general-purpose quantum error correction is not feasible and ineradicable hardware errors with modules of two-qubit operations of proper size in the classification problem of EEG signals. Meanwhile, the Gaussian boson sampling (GBS) has demonstrated to be capable of providing a highly-efficient approach to large-scale implementations limiting the fast gates operations. Furthermore, with improved Shor’s algorithm adopted, the hybrid algorithms are realized with available circuit depth in quantum phase estimation, optimizing through operation minimization, with the truth that Bayesian variance methods converge faster than the Bayesian inference methods. Last but not the least, EEG data is usually with noise and to thus to make sure of getting correct results, our model is based on NISQ devices and the correspondant results are analized on basis of noisy signals classified by the hybrid system composed of multi-qubit as the many-body entanglement and classical bits for measurement solved by the Shor’s algorithm and the improvement of annealing quantm on carry-save adder. On the othe hand, the Bose-einstein condensates, as the experiment well known for its possibility to create observable data of the entangled states, investigating the advantage of combining both quantum and classical bits operations based on many-particle entanglement.

# INTRODUCTION

# The EEG signal usually stands for the recorded electrical activities of brain with invasive electrodes, measuring the voltage fluctuations of the brain neurons. As the signal-to-noise rate of EEG data are usually high while the aim of the analysis of collected data are usually to detect some specific pattern driven by event-related potentials, investing EEG as potential fluctuations time locked on some event(e.g. stimulus onset) or brain waves oscilating differently on specific frequency domain. And thus we consider the simulation as the stochastic process computed on noisy intermediate-scale quantum devices and to classify the signal on basis of the QM principle with Schrodinger wave equation(SWE).

# Specifically, the time series recorded is termed as the state vector ѱ initialized in the Hilbert space Ԩ, evolving with time as a wave function or a probability amplitude function. Annotated in accordance with SWE:

# Where H is the Hamiltonian or the energy operator and is given as i where 2π is the Plank’s cconstant. Thus, the solution of the SWE, complex valued with the activation function represented by modulus square that localizes the position of the quantum oject in vector space and thus such pdf can be regarded as the wave packet, a partial differential equation dynamics denoting the particles defined by the force field, moving described the time-dependent single-dimension nonlinear SWE.

# Thus, to classify the data effitiently with the designed hybrid system variationally instead of inferenced by bayes method on each iteration, the signals are preprocessed before classification. Hilbert-Huang Transform is utilized for its advantage on non-stationary and nonlinear signal. Any complicated data set can be decomposed into a finite number of components, significantly smaller than other two methods and these components are of nearly orthogonal basis usually. To be specific, the first component carries the most oscillating (high-frequency) components which are always rejected to remove high-frequency components, for instance, random noise. Therefore, HHT is also frequently used on EEG data for HHT applying EMD is adaptive and highly efficient with the decomposition based on local characteristic time scale. The applicability of the concepts of energy, the Hamiltonian and regional, ‘smeared out’ content compares exactly located problems to particle and non-exactly located problems to wave functions.

# Specifically, to classify within error tolerance, after the EMD, we choose to use the Shor’s algorithm considering it into the optimization of the weighted network. As originally, shor’s algorithm is a BQP complex problem advantaging the average realiation of NISQ devices comining the quantum and classical computation, faster exponentially than the most efficient known classical factoring, it still is only ideal on large quantum computer cancelling the quantum-decoherence phenomena generally. After all, the current largest number factored by Shor’s algorithm is still only 35, larger computation can be only realized combining other algorithms, for instances, quantum annealing, modular carry-save addition and etc. We thus try to improve the efficiency through parameterizing the network separately on Hilbert and wavefunction space. Firstly, with parameterizing the Shor’s algorithm as the module of fast gates and conduct the inverse QFT on it later. On improved algorithm, the module size is changed with carry-save adder and quantum annealing separately. Furthermore, the 4 qubits regarding to QFT are dynamically updated with EEG, correcting the wavefunction. Reconstructed signal with the gaussian pulse approximating the EEG is fitted in each bin with the Shor’s algorithm, through fidelity. On each time window, the cost function is optimized with weights update through stochastic gradient descendent search and finally, we try to check if the phase estimated of the wavefunction can satisfy some general rules so that become the solution of some differential partial equation.

# In the following chapter, some mathematics and physics methodology will be introduced as well as analysis of the experiment results and discussion regarding to the current research prominent fields and future directions. In the second chapter, the methodology includes the EMD, EEG and some related metrices, Hybrid Quantum–classical Systems on basis of Shor’s algorithms, Boson Samplings, rabi fit and phase estimation with Gaussian pulse and fidelity; In the third chapter, more experiment detailed application and analysis are covered with regards to the simulation on the open data; in the forth chapter, discussion are made referencing more other references and some comparisions are conducted to give some heuristic conclusions. The future direction are also stated. Acknoewledge are mainly made to thank to the some related people and labs. Some demonstration and supplementary material can be found in the appendix.

# Methodology

## 2.1 Pre-process: Huang Hilbert Transform (HHT) after Intrinsic Mode Functions (IMF) and Empirical Mode Decomposition (EMD)

The Hilbert spectral analysis can be only conducted to compute the instantaneous frequency on time domain after the IMF and EMD. The decomposed parts of the original signal are sifted as following:

1.Detect all the extrema in the original data.

2.Connect all the local maxima as the upper envelope through interpolation with cubic spline.

3.Connect all the local minima as the lower envelope through interpolation with cubic spline similarly.

Then, denote the mean of upper and lower envelopes as m1 and the difference between the data and m1 as the first component h1 : X(t)–m1 = h1, which satisfies the requirements of IMF [13]:

a. The number of extrema and zero-crossings must either be equal or differ at by one in the whole data.

b. Mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero at any point. Identical to satisfy the symmetry and keep positivity for maximums and negativity to minimums.

In the next process, h1 is took as proto-IMF for calculating h11:

h1–m11 = h11, (1)

Repeat sifting up to k times until h1becomes an IMF: h1(k − 1)–m1k = h1k And formally assign h1k as the first IMF component of the data: c1 = h1k

Stop sifting until the following stoppage criteria is satisfied:

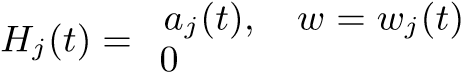
**S Number Criterion:** The S-number is defined as the number of consecutive siftings for which the number of zero-crossings and extrema are equal or at most differing by one. And when that number reaches the pre-given value, stop sifting. And when that number reaches the pre-given value, stop sifting.

3.Threshold Method: Set two threshold values as boundaries guaranteeing globally small fluctuations as well as avoiding large excursions.

4.Energy Difference Tracking: If the result of EMD is not an orthogonal basis of the original signal, the amount of energy will be different from the original energy and the components of EMD are usually physically meaningful, defined as dyadic filter bank. Finally, instantaneous energy and instantaneous frequency are calculated when the signal x(t) decomposed to:

x(t) = r(t)+Σkj=1cj(t) (2)

where cj(t) = Raj(t)e(−iθ(t)) = aj(t)cos(θ(t)) (\*) Then the instantaneous angle wj(t) = d(θj(t))/dt, where the θ(t) is instantaneous frequency. While, we can define the Hilbert Spectrum for c(t) as:



, otherwise

(3)

The Hilbert Spectrum of x(t) is accordingly:

H(w,t) = Σkj=1Hj(w,t) (4)

# EEG channels and metrics on different band

# 

This EEG data is downloaded from the open data of the Introduction to Artificial Neural Networks public domain data files.[…]. The data for computation in this paper is one from dataset a with 896 samples on time domain and 29 channels recorded. In addition, it is labeld with 1 and 0 differently according to its pattern annotated manually by phisicians into 8 features.(Two physicians give different labels separately. )

The sampling frequency of EEG data is 20kHz and each bin is set as 200 samples with duration as 0.0448 s.

|  |  |
| --- | --- |
| Specific bands Hz(coupled windows) | Spike samples per second, dense bin |
| Delta = [0.5, 3] | 4-35, 1 |
| Theta = [4,7] | 36-71, 1, 4 |
| Alpha = [8,12] | 72-108, 1, 4 |
| Mu = [7.5, 12.5] | 67-115, 1, 4 |
| SMR = [12.5, 15.5] | 116-142, 1,2,4 |
| Beta = [16, 31] | 143-285, 1,2,3,4 |
| Gamma = [32, 100] | 286-896, 1,2,3,4 |

PSTH is the histogram of the peristimulus spiketrains, where spike is detected as signal after fourier transform over threshold and train as the interval of continuous of spikes over some special threshold.

The alpha asymmetries were calculated using the following equations,

αf=αAF4−αAF3αAF3+αAF4 (5)

αt=αT8−αT7αT8+αT7 (6)

αa=αf+αt (7)

where αf,αt and αa represents the frontal alpha, temporal alpha, and alpha asymmetry respectively and αchannel represents the alpha power spectral density of the frontal and temporal EEG channels. Similarly, the frontal and temporal beta asymmetries were calculated using,

βf=βAF4−βAF3βAF3+βAF4 (8)

βt=βT8−βT7βT8+βT7 (9)

where βf, and βt represents the frontal and temporal beta asymmetries and βchannel represents the beta power spectral densities for the frontal and temporal EEG channels. Test are also conducted later for seeking whether it possible to discriminate EEG channels significantly.

# Hybrid Quantum–classical Systems

# As the Hamiltonian of the system is the metrics depending on both motion and location while the wavefunction is also usually relevant to time and spatial both and the EEG signal is considered as the stochastic process recorded as mentioned in introduction, it is nature to use the gradient descent search to update the parameters of Hamiltonian and wavefunction alternatively first. While ideally, after the pre-process of EMD, it is possible to establish differential equations that might give fixed optimized paramaters of wavefunction change with intrinsic modes of the Hamiltonian help to improve the efficiency of the computation. For a good algorithm thus need to solve quantum system considering the space of Hamiltonian and wavefunction both, it is natural to seek the method does phase estimation on the non-linear systems which refers to Shor’s algorithm. In the following chapters, it starts with the shor’s algorithm on total its as total bits of N = 15, qubits number a = 2 and counting numbers q= 3, later improves with Quantum Carry-Save Addition and quantum annealing.

## Shor’s algorithm

## As a factoring algorithm using Hamiltonian’s property, Shor’s algorithm use fast multiplication, making the interger-factoriation into bounded-error quantum polynomial time(BQP), i.e. the error probability of at most 1/3 is guaranteed for all instances in polynomial time. As this can be cut into two parts hybridly, the first classical part is to initialize the problem with a random number, a, among 1 and N. With the aim of finding the period r so that a^(x+T) mod N is equal to a^(x) mod N, changes to quantum part for the set of the period and the stop of the process is also finally checked by classical part as it is on the base of the measurement result of the quantum computer on classical bit.

## Algorithm:

## Pick a random number, a, among [1,N], where N stands for the

## Compute the gcd(a,N) denoted as d

## If d is not 1: finish;

## Otherwise, go to quantum period-finding process: find the natural r denoted as the period:

## f(x) = a^(x+r) mod N =a^(x) mod N = f(x+r)

## The r finding can be changed into: Find Q = 2^q among [N^2, 2\*N^2] implying that Q/r > N, where both input and output registers hold superpositions among [0,Q-1].

## Initialize the registers:

## 1/sqrt(Q)\*sum(range(Q)) =tensor product of (1/sqrt(2)\*(|xq0>+ |xq1>))

## Apply f(x) as a quantum function(in this paper is the C-U gate on q+n pubits in total and where q bits for input and n its for output), which Uf|x,0^q> = |x,f(x)>

## Apply Pauli X gate on the last bit of the C-U gate to make it registered at state |1>

## Apply the inverse QFT to these a bits.

## Measure the results of the q qubits and check if the {\displaystyle a^{r}\equiv 1{\bmod {N}}.}

## 2.3.2 Quantum Annealing

## As integer factorization problem solved by Shor’s algorithm is based on the idea of reducing the factorization problem to the order-finding problems, quantum annealing solve the factorization on the base of quantum adiabatic computing(QAC), combining Ising Hamiltonian and modified multiplication, making the computation does not rely on ad-hoc calculations and does not need to increase one extra bit.

## According to the adiabatic theorem, given slow enough evolution, the system state can evolve from ground state of the complex Hamiltonian avoid turning to any higher-level excitation state. And thus, the measured qubits are in a bounded degree of certainty.

## The time-dependent Hamiltonian H(t) evolves according to Schordinger equation (\*) here is the addition of the initital Hamiltonian and the final Hamiltonian:

## H(t) = (1-t/T)\*HB + t/T\*HP,

## Where HB is the initial Hamiltonian, ground state conveniently constructed as the summation of gates:

## HB = -sum(ϭx(i))

## with Pauli operator ϭx defines the x-basis. The Hamiltonian HP is the final Hamiltonian encoding the ground state as the solution to the prime factor finding of an, mapped to the final Ising Hamiltonian:

## HP = sum(hi\* ϭz(i)) + sum(Jij\* ϭz(i)\* ϭz(j))

## where HP gives the total energy of the system.

## Algorithm:

## Assume N = p\*q where p is at most 2 bits and q is at most 3 bits: p = (x1\*l)2 = x1\*2+1, q = (x2\*x3\*l)2 = x2\*2^2 + x3\*2+1, xi <{0,1}), because p and q are prime numbers.

## The objective function is set as:

## f(x1, x2, x3) = (N-p\*q)^2

## Reduce the 3-local term to 2-local term as follows: x1\*x2\*x3 = x4\*x3 + 2\*(x1\*x2-2\*x1\*x4-2\*x2\*x4+3\*x4) if x4 != x1\*x2: f(x1, x2, x3, x4)

## Use the positive of the coefficient of x1x2x3, to set the value for xi = (1-si)/2, i= 1,2,3,4

## Get the result of f(x1, x2,x3, x4)= 2\*g(s1,s2,s3,s4)

## 5. Up date The energy function: HP(ϭz(i), ϭz(j), ϭz(i), ϭz(j)) = g(s1,s2,s3,s4)

## The Ising function is to be optimized with the local fields: h’ =(ϭz(1) , ϭz(2) , ϭz(3) ,ϭz(4)) Couplings J = (ϭz(1) ,ϭz(2) , ϭz(3) ,ϭz(4))’ , where ϭz(1) = (0 ,z11,z12,z13), ϭz(2) = (0 ,0,z23，z24), ϭz(3) = (0 ,0,0,z34), ϭz(4) = (0 ,0,0,0)

## \*Transfer to multiplication table and finally get the solution

## 2.4 Gaussian boson sampling

As the most operations in quantum computations are normalized to be unitary, there is the Boson sampling constitutes the non-universal quantum computation introduced by A. Arkhipov and S. Aaronson after the work of L. troyansky and N. Tishby, among which, the photonic computation evaluating expectation values of permanents of matrices. However, it is actually well defined for any bosonic particles. Consider a multimode linear-opical circuit of N modes injected with M indistinguiable single photons, the photonic version of the boson sampling generates a sample form the porobaility distribution of single-photon measurements. Thus, by characterized non-unitarym the setup of boson sampling does not require any ancillas, adaptive measurements or entangling operations. Specifically, suppose the linear interferometer is described by an N\*N unitary matrix U, which performs a linear transformation of the creation (annihilation) operators a+ of the circuit’s input modes:

Here i(j) labels the input (output) modesm and bj denotes the annihilation operators of the output modes. On the other hand, the interferometer characterized by the unitary U naturally induces the transformation W of its input states. Moreover, there is a homomorphism etween the unitaries U and W, and the W transformation acts on the exponentially big Hilbert space: simple counting arguments show that the size of the Hilber space corresponding to a system of M indistinguishable photons distributed among N modes is given by the binomial coefficient.

The Gaussian input states is considered in photonic implementation as the quasiproability Wigner distribution function is a Gaussian one. And one has to generate two-mode entangled Gaussian states and apply a Haar-random unitary U to their ‘right halves’, while doing nothing to the others. Then the left halves are measured to find out which of the input states contained a photon before the application of U.

## Rabi fit and phase estimation with gaussian pulse

## As in improving the Shor’s algorithm, we resort to the annealing algorithm for Hamiltonian computation. As in the computation, the key is about the energy difference between two neiboring state, while out interest is kept to be between ground state and first state not to bringing further into higher energy states, considering our labels are binary only.

## On one hand, considering the raising and lowering operators of the two levels, the aim is to minimize the potential energy(classical Hamiltonian) constructed the cost function. Specifically, as we keep the peoblem simple as not considering commutators in the system(EEG signal is said to be non-spatical characterized leading to consider the bins of different channels recorded as non-commuting variables), in addition to the pertential term, the kinetic part, i.e. the non-commuting part dominated by the tunneling field, is added to the Hamiltonian with regards to the tunneling field mainly.(Less related to temperature compared to simulated annealing). Basically, for constant value of phase, one gets the path propotion to the sqare root of N power to the e. (In comparison, the one for thermal annealing is squared as the proportion to the N power of e.)

## On the other hand, to harness the quantum entanglement is the key to the quantum computer, since tunning is performed directly in a quantum computer.Back to the property of the wavefunction, the key point is still about the oscillator’s intrinsic property which take roles in the frequency of the whole system. Again, the neuron in the brain has the ability to fire spontaneously. Thus it is natural to use the vacuum rabi oscilation to fit the activities of the EEG, which is a damped oscillation of an initially excited atom coupled to an electromagnetic resonator where the problem can be alternatively solved as the atom interacts with a single-mode filed in optical cavity confined to one limited volume V. This according to Jaynes-Cummings model, can be modeled as the Hamiltonian in rotating wave approximation as:

## Where Pz is the paulli z spin operator for the two eigen states of exvitation and ground of the isolated two level system. The strength of the coupling between the dipole moment d of the two level system and the cavity mode with volume V and electric field polarized along the strength of the coupling between the dipole moment d of the two level system and the cavity mode with volume V and elevcctric field polarized along eps：

## 

## Thus, we have the energy eigenvalues and eigenstates for this model to be:

## 1/2)

## Where is the detuning, and the angle is defined as:

## ,

## Given the eigenstates of the system, the time evolution operator can be written down.

## We have the probability that the teo level system is in the excited state |g,n+1> as a function of time t is then:

## Where is identified as the Rabi frequency. Specifically, the non photon case gives the . Then, the probability that the two level system goes from its ground state to its excited state as a function of time t is:

## Note that a cavity that admits a single mode perfectly resonant with the energy difference between the two energy levels, the detuning vanishes, and becomes a squared sinoid with unit amplitude and period 2\*pi/g.

## Fidelity and confusion matrix

Fidelity is the function of probabilities of the final state composed by variablesX, Y, which has the probabilities of being in category [1,2,3,…n] as [p1, p2,…, pn], [q1, q2, …, qn].

F = ∑ ,

Confsion matrix: (describe Predict| Real)

Prob(])

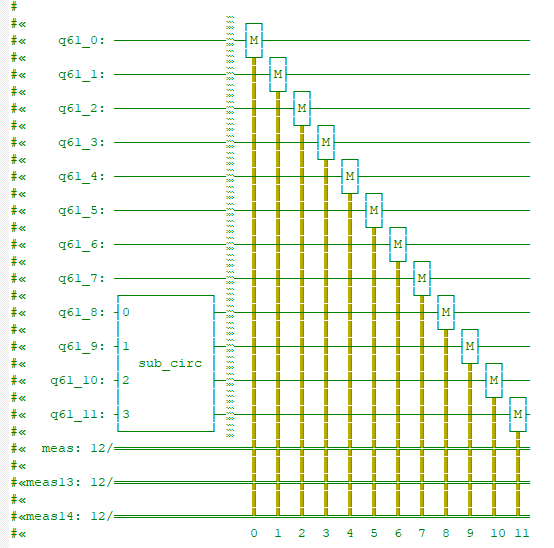
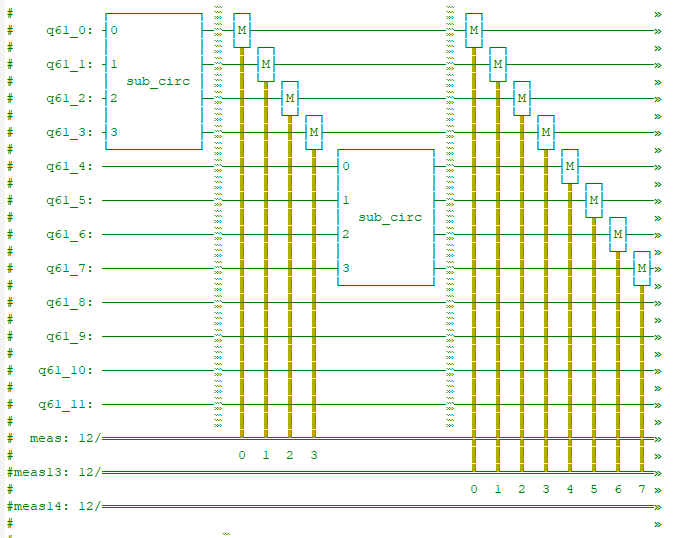
KL divergence: sum(P\*log(P/Q))

## Comparisons between single 5 qubits modle and 3 aggregated 5 qubit modle cicuit

## Circuit Graph for 5 qubits(python function in appendix)

## 

## Circuit Graph for 15 qubits(see python function in appendix):



Total algorithm:

1. Read in the EEG data from online data-base denote as dataset
2. Go through the pre-process:
3. Baseline remoe: Signal = Dataset – mean(dataset)
4. Decomposition into IMFs annotated as tsignal, and get instantaneous frequencies {InsFreq} and instantaneous phase {Insw} through Hilbert transformation in python
5. First precompute the phase with the first bin of the first channel as it is labeled as 1 and get the parameterized model with the first bin of the first bin of the fifth channel as it is labeled as 0. So our rabi experiments are calibrated with parameters for both excitation and ground states.
6. For each IMF sample in range(800),isignal[I,j], check the label given by two physicians whether the same:
7. If same, give it to the new label directly
8. Othterwise, use the gradient decendent search for the channels from it to next 4 as the training data for the label classification, taking label 1 for weight computation, denote tsignal[I,j:j+4] as temp:

B1. Initialixe the weights as the same as [1/4,1/4,1/4,1/4]

B2. Compute dw = temp\*(1-2\*label1[I,j]) and update wtemp = wtemp-dw

B3. Check the distance tance between prediction and original label with given tolerance tol: d = abs(1/(1+exp(wtemp\*signal)) – label1[I,j]),

B31:if d <tol：get the predicted binary label: target = np.array（1/(1+exp(wtemp\*temp))， dtype = int) and let it Go through the circ1, circ2 function, storing the process time dt1,dt2, count result: count1, count2,and fidelity :F1, F2:

B310. Take everytime the forth channel as test data while the first three as for training data only

B311.start timing, Order the target according to the weight asendingly into o(so that the most significant bits are at right sides)

Process the single 5 qubit cirbuit 3 times and np.pi assengent get the counts, store counts/shots in C,sum the counts for no larger than the right helf bits number: only take down if it’s good in more (than 1 time,

Compare the 5 qubits and 15 qubits results through fit and take the one with better confusion matrixand KL divergence

# Experiments and Results

# 3.1 Preprocess after EMD

# Amplitude v.s. time after baseline removement(original-mean(original))on all dimensions(896,29):

# Baseline removement shows the proceesed channels mainly lie near 0 and in addition to two channels(F3 and F4 in blue and orange), all other channels are relatively stationary signals. Thus, it can be implied that chances are that there are stimuli from outside or event-related spontaneous fires occurs around F3 and F4(Later, pi-pulse calibration is thus conducted aiming to estimate the drive phase.) And furthermore, there is also small normal like spikes trains on the T7 and T8 channels(purple and red separately). Thus in the following chapters, we focus on these four channels as our region of interest.

# 3.2 metrics on different band

# As according to the observation after pre-process, we choose F3, F4, T7 and T8 (accordingly, the 0th , 2nd , 7th , 11th EEG channel), time bins are for tracking trending of the EEG of each signal as well as for the set off of some specific event. However due to later, the computation of energy related quantities, we also perform the fourier transform to the original data and have their power related information on frequency domain, filtered on the 0-100 Hz, as Delta(0.5-3)Hz, Theta(4-7)Hz, Alpha(8-12)Hz, Mu(7.5-12.5)Hz, SMR(12.5-15.5)Hz, Beta(16-31)Hz and Gamma(32-100)Hz. And the power later is utilized for quantum annealing as well as the quantum forier transformation is also applied to simulation data for Shor’s algorithm although it is only used to decompose the 15 into 3 times 5 which is later the idea for the circuit design. Feature as the asymmetry, pi-pulse for excitation and ground state are utilized in the classification and prediction of the 8 labels.

# 3.2.1 PSTH(left colume for the first 0.5s while right colume for the second 0.5s)

# 

# 

# As we choose the analysis in one single channel, the total samples for one bin is 200(while the last bin has only 97 samples.), the figures above shows the total stimulis on 5 bins sperately on alpha band(first row) and delta band(seconde row). While the maximum is more than 100 in the alpha band while was reduced by more than half in delta(50). It can be suggested that signal fires more on alpha than delta frequency. And interestingly, for both two different channels, they both give fewest spikes at the last bin usually due to the off resonance. Differently, the alpha and scilations are relatively low significantly except for the fist and second bins while the signal on the delta and gives generally higher frequency for their sudden change into close to zero amount of the oscillation fires.

# 3.2.2 Spikes

# As the four channels gives quite similar distribution of the EEG signal on each band and even time bins. (Delta, theta, alpha, mu, SMR, beta and gamma band annotation from first row to the last shows the distribution of each channel. High ocillated signal mainly exists at first halves. On Delta band, almost all the four channels fo not detect significant spikes and on the alpha band, F4, T7 and T8 gives some spikes decay with 5 bins; On the alpha band, F3 gives more on 1,2,4th bin, F4 gives more on 3,4th while T7and T8 both give more on 1 and 4th. On the Mu and mainly the 3rd bin does not have spikes detected. For the SMR band, signals behave quite similar on the all 4 channels, spikes around 25 in a very short interval and reversely at next band, beta band, the spikes are generally on all the 4 bins for all 4 channels although there are some bursts extra for T7 channel around 50 on 4th bin. On the last band, gamma band, spikes are only detected at later half mainly and some burst like phenomenon can be found at the first bin around 200 samples for all 4 channels.

# As on the whole time domain, the four channels do gives similar spike distributions showing no significantly different behaviers, in accordance with the character of the EEG signals which usually do not reveal explicit spatial information of the brain activities.

# 

# 

# 3.2.3 Assymetry of Alpha and Beta

# The asymmetry of the alpha and beta are all negative, suggesting higher amplitude for the F4 and T8(right brain) compared with the F3 and T7(left brain), implying high asymmetry and most probably, the one of the semi-sphere of the the brain is after some stimulation(both the two halves are firing with positive non-trivial signal) or some activities governed by semi-sphere are under process.

# 

# The asymmetry locally on the frontal area is more significantly detected on the beta band and they are generally even distributed on beta band instead of only giving value on first and forth bins on Alpha band. As the highest value is on the 4th bin on alpha band, it become most negative on the first bins on beta band.

# 

# Since the asymmetry on the temporal seems to be smaller on both band, the value for temporal Alpha almost is as same as the ones on the frontal alpha band. On contrast, fewer asymmetry can be detected for temporal beta band than frontal and the most negative bins alocates on the thirds bins on beta bands.

# 

# Generally speaking, as the asymmetry is also only addition linearly for alpha and beta band on the frontal and temporal area, it can be showed that the alpha band shows stronger asymmetry but on short intervals only detected on first and fourth bins while the asymmetry are weaker ut evenly detected on beta band, giving the most negative detections on the second bins with broader span on time domain.

# Some related activities or disease leading to such asymmetry recorded will be discussed in the discussion chapter as well although the main task for this paper is to use the features to calssify.

# 3.2.4 Test and regression of ROIs

# The linearity for any single factor can refer to some mono-factor high interpretation of the whole matric. As the y values here are same, total asymmetry, skewer line can also stand for requiring fewer change in that single factor. Of course, although not shown here, the frontal and temporal asymmetry themselves are not linearly correlated guaranteeing their independence to each other as factors.

# 

# The alpha frontal(k ~8/7) shows fewer linearity than the temporal(k~2.5) alpha band on the asymmetry but with more robustity(nearly no outliers while for temporal alpha there is one significant outlier.)

# 

# The beta frontal(k~4/3) shows fewer linearity than the temporal(k~6/5) beta band on the asymmetry and worse robust as well. It is obvious that small asymmetry is of higher probability to be not correctly regressed for beta band as both on its frontal and temporal area, the outliers are both nontrivial. We can suppose the frontal alpha more illustrative property in the total asymmetry for band alpha and reversely temporal area to be more important in asymmetry computation on beta band EEG.

# 3.3 Pi-pulse calibration on first bin of T3 and related simulation of pi-pulse on excitation and ground state:

# 

# With the rabi experiment conducted, our pi-pulse(see appendix A) is calibrated on 0.75 scale of the Gaussian pulse with duration time as 120 which is the samples of each time bin, and after small time delay, the second measure is conducted as sweep process. And the ground state is exactly set for qubit 0 while excitation for qubit 1. It is easily shown to the public that the excitation happens due to the Gassian Pulse. And the first bin of the first test signal gives good fitness to oscilations with Gaussian

# 

# While it is also necessary to design the circuit being possible to get-Updated theta. The rabi experiment give us the largest value time approximating the time for excitation.

# After applying the

# 3.4 Computation results using Shor’s algorithm and Classification results

# 

# The original Shor’s algorithm here is applied for the defactorizing of 15 and it can be found that with the a set as 2, the qubit number required for the factorization r is also 2 and the period for the QFT is indeed f as can be found from the figure which means the U applied to all eigenstates [|3>,5>,|7>,|11>,13>] as 4\*([3,5,7,11,13]) mod 15 giving out [3, 5, 13, 13, 7] are still eigenstates. Thus, 4 is the correct period, in addition to satisfying the definition. However, the Shor’s algorithm here is not so efficient as the inevitable error of the quantum computer, we thus change to the Quantum Annealing which compute the problem through Hamiltonian through Ising model as following:

## Assume N = p\*q where p is at most 2 bits and q is at most 3 bits: p = (x1\*l)2 = x1\*2+1, q = (x2\*x3\*l)2 = x2\*2^2 + x3\*2+1, xi <{0,1}), because p and q are prime numbers.

## The objective function is set as:

## f(x1, x2, x3)

## = (N-p\*q)^2

## = [15-(x1\*2+1)\*(x3\*2^2 +x2\*2 +1 )] ^2

## =128\*x1\*x2\*x3-56\*1\*x2-48\*1\*x3+16\*x2\*x3-52\*x1-52\*x2-96\*x3+196

## Reduce the 3-local term to 2-local term as follows: x1\*x2\*x3 = x4\*x3 + 2\*(x1\*x2-2\*x1\*x4-2\*x2\*x4+3\*x4) if x4 != x1\*x2,:

## f(x1, x2, x3, x4)

## =128\*(x4\*x3+2\*(x1\*x2-2\*x1\*x4-2\*x2\*x4+3\*x4))-56\*x1\*x2-48\*x1\*x3+16\*x2\*x3-52\*x1-52\*x2-96\*x3+196

## =200\*x1\*x2-48\*x1\*x3-512\*x1\*x4+16\*x2\*x3-512\*x2\*x4+128\*x3\*x4-52\*x1-52\*x2-96\*x3+768\*x4+196

## Use the positive of the coefficient of x1x2x3, to set the value for xi = (1-si)/2, i= 1,2,3,4

## Get the result of f(x1, x2,x3, x4)

## =200\*(1-s1)/2\*(1-s2)/2-48\*(1-s1)/2\*(1-s3)/2-512\*(1-s1)/2\*(1-s4)/2+16\*(1-s2)/2\*(1-s3)/2-512\*(1-s2)/2\*(1-s4)/2+128\*(1-s3)/2\*(1-s4)/2-52\*(1-s1)/2-52\*(1-s2)/2-96\*(1-s3)/2+768\*(1-s4)/2+196

## =116\*s1 + 100\*s2 + 24\*s3 -160\*s4 +50\*s1\*s2 -12\*s1\*s3 -128\*s1\*s4 + 4\*s2\*s3 +4\*s2\*s3 -128\*s2\*s4 + 32\*s3\*s4 +298

## = 2\*g(s1,s2,s3,s4)

## 5. Up date The energy function: HP(ϭz(i), ϭz(j), ϭz(i), ϭz(j)) = g(s1,s2,s3,s4) = 58\* ϭz(1)+ 50\*ϭz(2) + 12\*ϭz(3) – 80\* ϭz(4) +25\*ϭz(1)\*ϭz(2)-6 \*) + 80\* ϭz(4) +25\*ϭz(1)ϭz(2) -\*6\*ϭz(1) \* ϭz(3)-64\* ϭz(1) \* ϭz(4)+ 2\*ϭz(2) \* ϭz(3)-64\* ϭz(2) \* ϭz(4) +16\*ϭz(3) \* ϭz(4)+149\*I

## The Ising function is to be optimized with the local fields: h’ =(ϭz(1) , ϭz(2) , ϭz(3) ,ϭz(4)) = (58, 50, 12, -80) ,

## Couplings J = (ϭz(1) ,ϭz(2) , ϭz(3) ,ϭz(4))’ , where ϭz(1) = (0 ,25,-6,-64), ϭz(2) = (0 ,0,2,-64), ϭz(3) = (0 ,0,0,16), ϭz(4) = (0 ,0,0,0)

## \*Note that here the multiplication can also be achieved through multiplication table:

## Table : Multiplication table for 5 × 3 = 15 in binary.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | 2^4 | 2^3 | 2^2 | 2^1 | 2^0 |
| P |  |  |  | 1 | 1 |
| Q |  |  | 1 | q | 1 |
|  |  |  | 1 | 1 |  |
|  |  |  | q | q |  |
|  |  | 1 | 1 |  |  |
| carries | C2 | C1 |  |  |  |
|  | 0 | 1 | 1 | 1 | 1 |

## This change the redundant computation into solving the two euqations:

## 1+q+2\*q+2+2\*c1-c2=3

## C2+1 =1

## After the simplification process,we get:

## 3\*q +2\*c1 =2，

## C2= 0

## Because q,c1 can be only from {0,1}, q = 0, c1=1

## Finally, 15 = 5\*3

## And take the precompute of 1 annotated first channel’s fist bin counting result(left resutls), the sum of MSB sum countings for more than half, and the

## The countings with 3\*(4+1) aggregated circuitite

## Left is the counting with traditiional aggregated

## 

## :As the result of the classification accuracy for the training frequency.

# Conclusions

# With the VQE single circuit, training(training to testing ratio as 3:1 ) results perform better with Rabi qubit 1 and the test results perform better than training results for this time with more data fitted.This might goes to the over fitting reason.

# 

# Test True positive for the last samples go bad maybe because of overfit as well, True negatives go down fast generally and goes down to 0.5 for almost all the qubits after 20 samples. Test negatives also got large as according to my intuition, the Test false positives go down also fastly.

# 

# The confusion matrix is also in accordance with some current articles about hardware efficient circuit as the circuit mght not as efficient as it thought to be with error but with error correction well studied, after the mitigation, quantum computer can be close to ideal machine leachine.

# As mentioned before, the asymmetry of the signal although might not help with classify directly but it is one important information for EEG, as the results of the experiments to be the asymmetry on higher value at right brain, this can refer to some active activities governed by right brain. For instance, music, art, create and etc. Vice versa, for left higher amplitude situation, some activities like computation and deduction might be conducted and generally, outliers might infere to some disease like schizophrenia and dyslexia and some anormal handedness

Hilbert transform is chosen to be the method for getting spectrum either with instantaneous frequency and energy due to its advantage in distinguishing different modes of non-linear or non-stationary signal. It has already been commonly applied on biomedical applications, neuroscience, epidemiology, chemistry and chemical engineering, financial applications, image processing , atmospheric turbulence and etc. Especially with seizure EEG data, it is combined with different classification, detection and prediction methods on clinical EEG data . Compared with other two commonly used transform: Fourier, Wavelet transform. Hilbert transform is adaptive method instead of a priori basis and it is based on differentiation calculation locally based on frequency domain, giving certainty thus instead of uncertainty brought by convolution (globally with Fourier transform and regionally with Wavelet transform). And it is the empirical method well known for the performance on feature extraction with non-stationary and non-linear data feature extraction. Since EEG signal analysis

# encounter high sensitivity to noise especially those with deep stimulation, Hilbert transform with IMFs help to make the further calculation of instantaneous energy and instantaneous frequency much predictable and thus give out higher accuracy and robust. Our IMFs shows distinguishable properties of different module after sifting stooped by energy criteria. And get the kinetic energy calculate the kinetic energy and either likelihood or likelihood-free parameter on basis of instantaneous energy. According to the final examination of accuracy based on accumulative sensitivity (true positivity), specificity (true negativity), positive prediction (positive prediction rate), miss rate (false positive prediction), false discovery rate(false prediction rate) and accuracy. The approximate energy conserving properties which is the critical factor guaranteeing the time-reversibility and volume preserving of the numerical integrator, leapfrog integrator in our paper is iterated and tempered in relatively low number of steps due to limited computing power with the working laptop (MacBook Pro). This might is the reason leading to some uselessness of some examine quantities, for instance, miss rate and false discovery rate. With more leapfrog steps or maybe adaptive leapfrog stepsize, the algorithm might most probably go with more interpretive accuracy examination and even faster convergence. Furthermore, the energy function which is not calculated with intractable likelihood free gradient but with evidence-lower-bound Bayes inference either using truncated rejection sampling or self-normalized importance sampling might also improve the accuracy with examination on step-wise scale. Bauer and Mnih has also raised one algorithm evaluating the target density using an exponential moving average to estimate the normalizing algorithm truncating the process trying to raise the efficiency of the algorithm.

# More data with event related fire might be interesting as well.

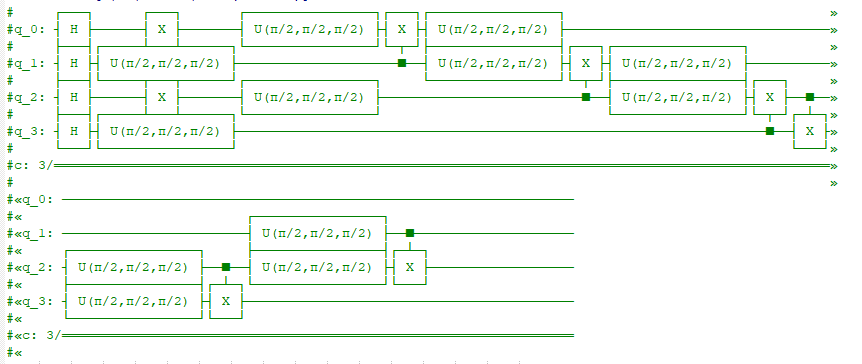
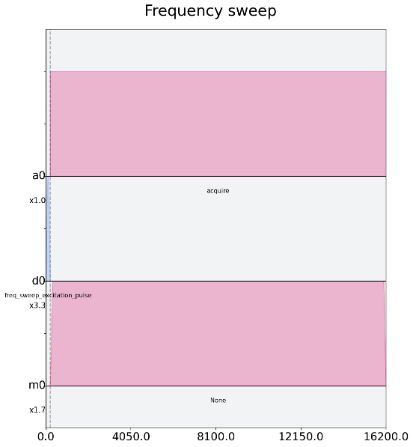
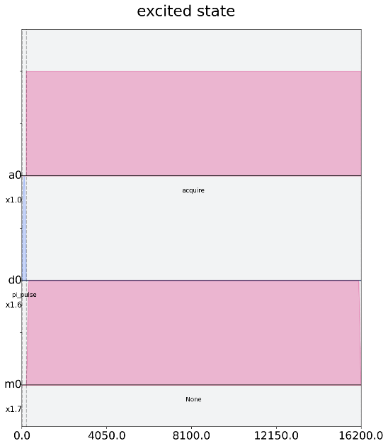
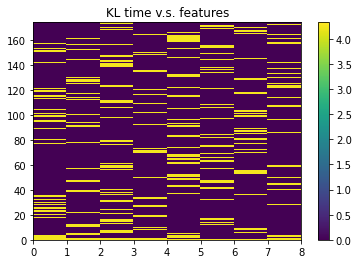
# Acknoeledgements

# Thanks to the professors in UK and especially in Oxford as well as the professors in East China University of Sience and Technology. .

# References

# References

Appendix:

****