

# Quantum Neural Network based surface EMG signal filtering for control of Robotic Hand

Vaibhav S. Gandhi and Thomas-Martin McGinnity

**Abstract**— A filtering methodology inspired by the principles of quantum mechanics and incorporating the well-known Schrodinger wave equation is investigated for the first time for filtering EMG signals. This architecture, referred to as a Recurrent Quantum Neural Network (RQNN) can characterize a non-stationary stochastic signal as time varying wave packets. An unsupervised learning rule allows the RQNN to capture the statistical behaviour of the input signal and facilitates estimation of an EMG signal embedded in noise with unknown characteristics. Results from a number of benchmark tests show that simple signals such as DC, staircase DC and sinusoidal signals embedded with a high level of noise can be accurately filtered. Particle swarm optimization is employed to select RQNN model parameters for filtering simple signals. In this paper, we present the RQNN filtering procedure, using heuristically selected parameters, to be applied to a new thirteen class EMG based finger movement detection system, for emulation in a Shadow Robotics robot hand. It is shown that the RQNN EMG filtering improves the classification performance compared to using only the raw EMG signals, across multiple feature extraction approaches and subjects. Effective control of the robot hand is demonstrated.

**Index Terms**— electromyogram (EMG), Recurrent Quantum Neural Network (RQNN), filtering.

## I. INTRODUCTION

THE detection of surface Electromyographic (sEMG) signals is becoming an increasing requirement in biomedical applications. However, sEMG signals that originate in the muscles are frequently contaminated by noise. Noise or artifacts may be generated by different sources, such as movement of electrodes during signal acquisition, hardware employed for signal amplification, etc. If the type of noise present in a signal is known *a priori* then appropriate filtering techniques may be employed. However, in many practical applications the nature of the noise is unknown. Under such circumstances, filtering methods that can be applied with little or no *a priori* knowledge about the signal or the embedded noise are required. There has been decades of research, however, improved methodologies are still needed, to enable robustness and adaptivity. The filtering methodology discussed in this paper is one such concept that is being investigated for the first time for EMG signal filtering. This EMG signal preprocessing approach

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utilizes concepts from quantum mechanics (QM) and neural network theory within a framework referred to as Recurrent Quantum Neural Network (RQNN) [1, 2]. Various groups have shown EMG-based control of prosthesis with greater movement dexterity using different combinations of extracted features and classification methods [3-6]. However, if an appropriate filtering method, such as the one discussed in this paper can be introduced prior to extracting features, then the performance of the classifier can be improved simply by using the enhanced input signal.

Since EMG signals are considered a realization of a random or stochastic process [7], a stochastic filter can be designed based on probabilistic measures. Bucy in [8] states that every solution to a stochastic filtering problem involves the computation of a time varying probability density function (*pdf*) on the state space of the observed system. In the architecture of the RQNN, the Schrodinger wave equation (SWE) [9] plays a central role so as to enable online estimation of a time varying *pdf* in estimating and removing noise from the EMG signal.

In quantum terminology, the state is represented by  $\psi$  (a vector in the Hilbert space  $\mathcal{H}$ ) and referred to as a wave function or a probability amplitude function. The time evolution of this state vector  $\psi$  is according to the SWE and is represented as,

$$i\hbar \frac{\partial \psi(x, t)}{\partial t} = H\psi(x, t) \quad (1)$$

Here  $H$  is the Hamiltonian or the energy operator and is given as  $i\hbar \frac{\partial}{\partial t}$  where  $2\pi\hbar$  (i.e.  $h$ ) is Plank's constant<sup>1</sup> [10]. Here  $\psi(x, t)$  is the wave function associated with the quantum object at space-time point  $(x, t)$ .

Fig. 1 shows a basic architecture of the RQNN model discussed in this paper. Here a one-dimensional array of neurons mediates a spatio-temporal field with a unified quantum activation function in the form of a Gaussian that aggregates the *pdf* information from the observed noisy input signal. The solution of the SWE (which is complex valued and whose modulus squared is the *pdf* that localizes the position of the quantum object in the vector space) gives

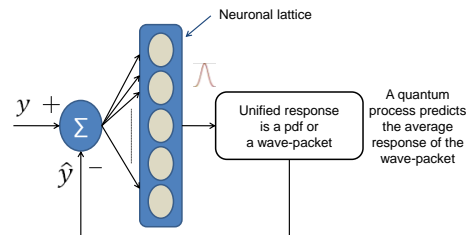


Fig. 1. Conceptual framework of the RQNN model

<sup>1</sup> The Plank's constant is an atomic-scale constant that denotes the size of the quanta in quantum mechanics. The atomic units are a scale of measurement in which the units of energy and time are defined so that the value of the reduced Planck constant is exactly one.

ues the activation function. The time-dependent single dimension nonlinear SWE can be considered a partial differential equation describing the dynamics of the wave packet (modulus-square of this wave is the *pdf*) in the presence of a potential field (or function). The potential field is the force field in which the particles defined by the wave function are forced to move [11]. Thus the RQNN model is based on the concept that a quantum object mediates the collective response of a neural lattice (a spatial structure of an array of neurons where each neuron is a simple computational unit as shown in Fig. 1 and explained in detail in section II) [12, 13]. The neurons within this model are stimulated directly from the raw input signal and the learning rule for the weight update process utilizes a de-learning scheme. Similar filtering techniques have also been investigated for robot control [14], eye tracking [12] and stock market prediction [15] applications.

The remainder of the paper is organized into nine sections. Section II describes the theoretical concepts of the RQNN model. Section III describes the RQNN signal filtering approach. Section IV and V discuss the datasets and the methodology for EMG filtering with the RQNN model respectively. Section VI details the feature extraction (FE) and classification methodology utilized in this work. The parameter selection approach for the RQNN model is discussed in Section VII. Section VIII presents the results of applying the approach for EMG filtering while section IX discusses the application for the shadow robot hand control. Section X concludes the paper.

## II. A CONCEPTUAL RQNN FRAMEWORK

Dawes [16, 17] proposed a novel parametric avalanche stochastic filter using the concept of the time varying *pdf* proposed by Bucy in [8]. This work was improved by Behera et al. [12, 13, 18] using Maximum Likelihood Estimation (MLE) instead of an inverse filter in the feedback loop. Further, Ivancevic in [15] provided an analytical analysis of the non-linear Schrodinger equation (NLSE) and used the closed-form solution for the concerned application. The basic approach of RQNN is that it does not make any assumption about the nature and shape of the noise embedded in the signal to be filtered. Therefore, such an approach is suitable for signals such as the EMG, within which the characteristics of the embedded noise are not known.

Conceptually, the RQNN model is basically a one dimensional array of neurons (cf. Fig. 1) whose receptive fields are initially excited by the signal input  $y$  reaching each neuron through the synaptic connections. The neural lattice responds to the stimulus by actuating a feedback signal  $\hat{y}$  back to the input. The time evolution of this average behavior  $\psi$  is described by the SWE [9]:

$$i\hbar \frac{\partial \psi(x,t)}{\partial t} = -\frac{\hbar^2}{2m} \nabla^2 \psi(x,t) + V(x,t) \psi(x,t) \quad (2)$$

where  $\psi(x,t)$  represents the quantum state,  $\nabla$  is the Laplacian operator and  $V(x,t)$  is the potential energy.

The potential energy  $V(x)$  acts as a force under which the quantum state  $\psi$  evolves according to (2). As  $V(x)$  sets up the evolution path of the wave function, any desired response can be obtained by properly modulating the potential energy.

A similar RQNN approach for stochastic filtering [12, 13, 18] is able to reduce noise, but its stability is highly

sensitive to model parameters, owing to which, in case of imperfect tuning, the system may fail to track the signal and its output may saturate to unrealistic values. In the architecture used in this paper (cf. Fig. 2) (and in our previous work on EEG filtering [2]), the spatial neurons are excited by the input signal  $y(t)$ . The difference between the output of the spatial neuronal network and the *pdf* feedback  $|\psi(x,t)|^2$  is weighted by a weight vector  $W(x)$  to get the potential  $V(x)$ . The model can thus be seen as a Gaussian Mixture Model (GMM) estimator of the potential energy with fixed centers and variances, and only the weights being variable, thereby making the system less prone to instability. The weights can be trained using any learning rule.

The parameters of the RQNN model have been selected using the particle-swarm optimization (PSO) [19-21] technique for filtering simple signals such as DC and staircase DC used to validate the method. However, there are several parameters to tune from and hence applying any optimization technique without the knowledge of the multi-dimensional search space for filtering the complex signals such as the EMG can be time-consuming. Therefore, in the work presented in this paper, the parameters of the RQNN model are heuristically selected for filtering the EMG signals of different subjects. An ideal approach, however, would be to obtain subject-specific choice of parameters by using optimization techniques such as the one discussed in [1]. This would guarantee optimal performance, but as said, it may also be time-consuming.

## III. RQNN SIGNAL FILTERING

This section describes the RQNN architecture shown in Fig. 2. The basic assumption in this architecture is that the average behavior of a neural lattice that estimates the signal is a time varying *pdf* which is mediated by a quantum object placed in the potential field  $V(x,t)$  and modulated by the input signal so as to transfer accurate information about the *pdf*. The SWE is used to recurrently track this *pdf*. It is well-known that the square of the modulus of the  $\psi$  function, the solution of the wave equation in (2), is also a *pdf*. The potential energy is calculated as:

$$V(x) = \zeta W(x,t) \phi(x,t) \quad (3)$$

where

$$\phi(x,t) = e^{-\frac{-(y(t)-x)^2}{2\sigma^2}} - |\psi(x,t)|^2 \quad (4)$$

where  $y(t)$  is the input signal,  $W(x,t)$  represents the time varying synaptic weights,  $\zeta$  represents the scaling factor to actuate the spatial potential energy  $V(x,t)$  and  $\sigma$  is the variance of the neurons in the lattice (taken here as unity). The potential energy modulates the non-linear SWE described by equation (2). The filtered estimate is calculated using MLE as

$$\hat{y}(t) = E[|\psi(x,t)|^2] = \int x |\psi(x,t)|^2 dx \quad (5)$$

where  $x$  represents the different possible values which may

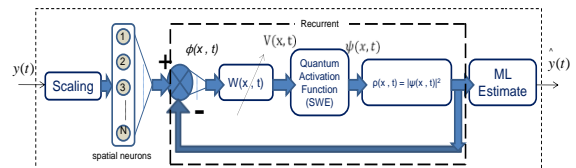


Fig. 2. Signal estimation using the RQNN model

be taken up by the random process  $y$ . Another interpretation of the variable  $x$  can be as the discrete version in quantum space with the resolution within the discrete space referred to as  $\delta x$  (taken as 0.1 in the present work) (cf. Table 1). Thus all possible values of  $x$  construct the number of spatial neurons  $N$  for the RQNN model.

The weights  $W(x, t)$  of the RQNN are updated based on the filtered estimation, which subsequently establishes a new potential  $V(x, t)$  for the next time evolution. The synaptic weights evolve in such a manner so as to drive the  $\psi$  function to represent the exact information of the *pdf* of the filtered signal  $\hat{y}(t)$ . The weights are updated using the following learning rule

$$\frac{\partial W(x, t)}{\partial t} = -\beta_a W(x, t) + \beta \phi(x, t)(1 + v(t)^2) \quad (6)$$

where  $\beta$  is the learning rate, and  $\beta_a$  is the de-learning rate. De-learning is used to forget the previous information, as the input signal is not stationary, rather quasi-stationary in nature. In addition, de-learning prevents unbounded increase in the values of the synaptic weights  $W$  (see the first right hand side term in the above equation with negative sign) and does not let the system become unstable. The variable  $v(t)$  in the second term is the difference between the noisy input signal and the estimated filtered signal, thereby representing the embedded noise as,

$$v(t) = y(t) - \hat{y}(t) \quad (7)$$

If the statistical mean of the noise is zero, then this error correcting signal  $v(t)$  has little effect on the weights and it is the actual signal content in the input  $y(t)$  that influences the movement of the wave packet along the desired direction, which in effect helps achieve the goal of the signal filtering.

#### IV. DATASETS

The EMG data used in this analysis was collected at the Intelligent Systems Research Center, University of Ulster. 3M Ag/AgCl circular monitoring electrodes with hypoallergenic, acrylic adhesive, typically used for short term applications are used in the present work. The diameter of these electrodes is 3 cm and thickness is 0.8 cm. Seven EMG channels (cf. Fig. 3) were recorded in unipolar mode with a sampling frequency of 512 Hz and high pass-filtered from 5 Hz. Seven subjects, all normally healthy adults, were recruited. Six of the seven subjects were male while one was female. The subjects varied in the age group 23 - 47. All subjects contributed three runs each for the training phase and one run for the evaluation phase except subject S01 and S05 who contributed one run in each phase. Each run consisted of 65 trials. There were 5 repetitions for each of the 13 classes, thereby resulting in 65 trials for each run. Each class represents an individual finger movement (open and close, resulting in 10 classes) and a complete fist open, close and rest position (remaining 3 classes) as shown in Fig. 4. The dataset is obtained using a cue-based paradigm, as shown in Fig. 5, which displays the thirteen classes. The trial started at second 0 with a blank screen. At second 2, a short warning beep (1 kHz, 70 ms) was given. The cue was presented on the screen from second 3 to 8 in the form of a darkened color of the finger movement required from the subject.

A dark blue color indicated flexion of the corresponding finger(s) while a dark red color indicated extension of the

corresponding finger(s) movement. In addition to this, an arrow pointing inward or outward was also displayed along with the corresponding text written beneath the figure (cf. Fig. 4) so as to help visualize the task. The subjects, as per the display cue, were required to perform the specific finger(s) movement(s). The order in which the cues (trials) were presented to the user was generated randomly. In addition, the time between any two trials was also randomized in a range of 0.5 to 2.5 s. Randomness of presenting time of the heterogeneous cue raises the concentration power of the subjects; this is thought to be the main cause of the consistency in performance in similar investigations [22]. In the evaluation phase, feedback to the subjects was given in the form of a number representing the requested cue/class and a number representing the actual finger(s) detection (class) by the classifier. If both the numbers matched, the target for that particular trial was said to have been achieved.

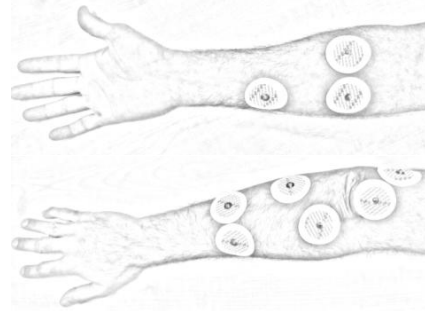


Fig. 3: Position of EMG electrodes on the lower arm (front and back) (7 Channels, Ground and Reference)

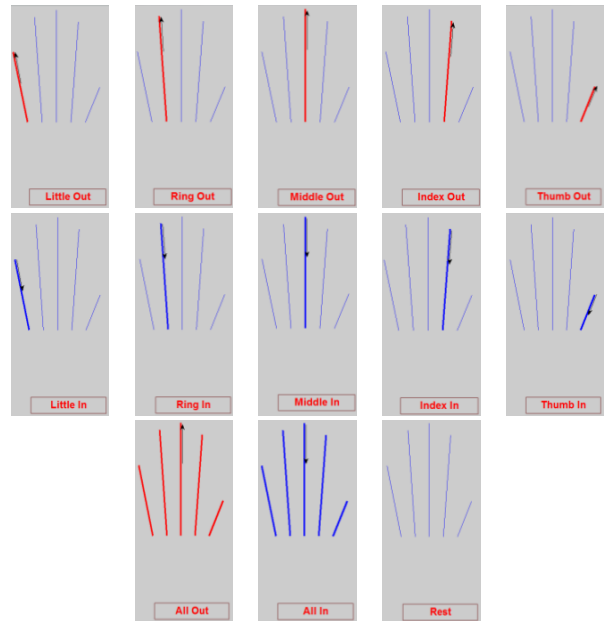


Fig. 4. Display of 13 classes indicating task to be performed

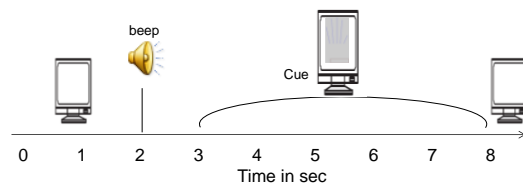


Fig. 5. Training scheme of the paradigm

## V. EMG FILTERING WITH RQNN

Fig. 6 shows the RQNN model as a component within the complete system. The raw EMG signal from each channel is fed one sample at a time and an enhanced signal is obtained as a result of the RQNN filtering process. The raw EMG is first scaled in the range 0-2 (so that fewer neurons can capture the input signal) before it is fed to the RQNN model. The range 0-2 is arbitrary and may also be taken -1 to +1. During the offline classifier training process, all the trials from a particular channel of the EMG are available. Therefore, the complete EMG is scaled by using the maximum of the amplitude value from that specific channel. During the evaluation process, the EMG signal is approximately scaled in the range of 0-2 by using the maximum of the amplitude value obtained from the offline training data of that specific channel. The net effect is that the input signal during the evaluation stage is also maintained approximately in the region of 0-2 and this enables the tracking of the sample using a reduced range of the movement of the wave packet as well as a smaller number of spatial neurons. In the present case, the number of spatial neurons along the x-axis is kept as  $61^2$  to cover the input signal range up to 3 (because at the evaluation stage the signal may vary beyond the value of 2). If scaling of the input signal is not implemented, then the number of neurons required to cover the input signal range will be larger thereby leading to increased computational expense.

## VI. FEATURE EXTRACTION AND CLASSIFICATION

The next task, after the RQNN filtering process, is to obtain the features from the enhanced EMG signal. In the present case, several feature extraction (FE) approaches have been assessed - Hjorth [23], band power, burg autoregressive (AR) [24], yule AR and Short Time Fourier Transform (STFT) [25]. These features are fed as an input to train the offline classifier, which in this case is the Linear Discriminant Analysis (LDA) classifier. Once the offline

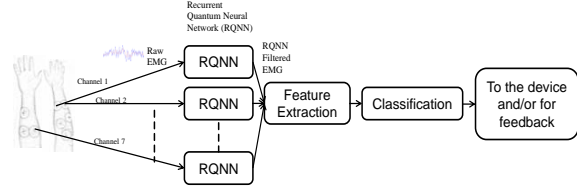


Fig. 6. RQNN model framework for EMG signal enhancement

analysis is complete and the classifier is trained, the parameters and weight vector are stored for use with the classifier to identify the unlabeled EMG data during the online analysis. In order to capture the dynamic property of the continuous EMG signal, the weight updation process of the RQNN filter is continuous (to enhance the EMG signal) during both the offline and the online stages while the classifier parameters are tuned offline and then kept fixed for the online classification process.

For the frequency based FE methods i.e., band power, burg AR, STFT and yule AR, the range of the frequency bands may vary from one subject to the other. Therefore, the band of frequencies suitable for each subject is obtained offline (from within the range from 5 Hz to 150 Hz) after trial and error over the data at the training stage.

## VII. RQNN PARAMETER SELECTION

This section discusses the possible ways of selecting the RQNN model parameters. The parameters of the RQNN that may be kept fixed are explained in Table 1. These parameters may be obtained heuristically but after suitable trial and experimentation over a small set of training data. The variable parameters of the RQNN are explained in Table 2. These parameters may be selected through optimization techniques such as PSO, genetic algorithm (GA) or an inner-outer cross-validation technique as the one discussed in [1] for a 2-channel EEG filtering application. A PSO approach has been implemented in this paper for

TABLE 1  
RQNN PARAMETERS THAT MAY BE OBTAINED HEURISTICALLY

Parameter	Explanation	Value
$N$	Number of centres along the spatial axis of the RQNN model. This can be considered as if some quantum object (i.e., each neuron in the form of a window) in the neuronal lattice is looking at the spatial neural network and accepting the input signal sample.	60
$ITER$	Number of iterative steps that are required for the response of the SWE to reach a steady state for a given computational sampling instant.	10
$\delta t$	The SWE equation is converted to the finite difference form with time steps $\delta t$ .	0.001
$\delta x$	The spatial axis is divided into $N$ mesh points (here 60) so that $x$ is represented as $x_j = j\delta x$ where $j$ varies from $-\frac{N}{2}$ to $+\frac{N}{2}$ . As $\delta x$ was fixed as 0.1, it covers the spatial axis range from -3 to +3.	0.1

TABLE 2  
RQNN PARAMETERS THAT MAY BE OBTAINED HEURISTICALLY OR USING OPTIMIZATION TECHNIQUES

Parameter	Explanation
$\beta$	Learning parameter and is thus necessary to update the synaptic weight vector $W$ .
$m$	Mass of the quantum object and is associated with self-excitation of the SWE.
$\zeta$	Scaling factor to actuate the spatial potential field $V(x)$ and thus causes input excitation (since it appears as a multiplicand in the SWE). The value of $\zeta$ can be kept negative or positive.
$\beta_d$	De-learning parameter and is used to forget the previous information. De-learning is used to prevent unbounded increase of the values of the synaptic weights $W(x, t)$ .

<sup>2</sup> If the range of the neuronal lattice is -2 to +2, then with a spacing of 0.1 between each neuron, the total number of neurons covering the range will be -2, -1.9, -1.8 ... -0.1, 0, +0.1, ... 1.9, 2 i.e. 41. However, to incorporate the behaviour of the signal during the unknown evaluation stage, the range has been extended to cover the range up to +3 by using 61 neurons.

selecting the RQNN parameters to filter simple example signals such as DC, staircase DC and sinusoidal signals. This is discussed in the next section. However, as discussed in [1], utilizing optimization techniques such as PSO or GA

for selecting the RQNN parameters for a 2 channel EEG is computationally expensive. This is because the RQNN model has several parameters (cf. Table 1 and Table 2) that should be varied in agreement with the frequency bands at the FE stage to suit each channel of an individual subject's physiological signal. The EMG based control system presented in this paper requires a 7-channel EMG filtering. Thus, a large multi-dimensional search space may be required for parameter selection, which will be even more computationally expensive than the one for the 2-channel EEG application discussed in [1]. Therefore, a heuristic approach is used to obtain the RQNN parameters for the subject-specific 7-channel EMG filtering discussed in this paper.

## VIII. RESULTS AND DISCUSSION

### A. Simple example signals

To validate the RQNN technique for filtering complex EMG signals, we first applied it to filter simple example signals in the form of DC, staircase DC and sinusoidal signals that have been embedded with a known amount of noise [1]. A DC signal of fixed amplitude (2, 5, 8 and 10) was embedded with 0 dB noise; the staircase DC with amplitude varying from 0 to 2 was embedded with 20 dB noise; and the sinusoidal signal of amplitude 3 was embedded with 20 dB noise. The parameters of the RQNN model (cf. Table 2) were obtained by using the PSO technique [19, 20]. A video showing the movement of the wavepacket for DC filtering is available at [26]. The root-mean-square error (RMSE) in filtering the DC signal of amplitude 2 with the proposed RQNN as well as with the Kalman filter [27] is shown in Table 3 (partially reproduced from [13]) and demonstrates that the RQNN performs better than the Kalman filter. Fig. 7 shows filtering of the staircase DC signal using the RQNN approach. It can thus be stated that the RQNN is able to capture effectively the statistical behaviour of the input signal and appropriately track the true signal despite the presence of noise.

### B. EMG signal filtering

The effect of filtering can be ascertained through the conventional performance quantifiers such as classification accuracy (CA) (i.e., the percentage of correct classifications) and kappa<sup>3</sup> value. Fig. 8 displays the CA plot using the LDA classifier while using different sets of features with the raw EMG and the RQNN filtered EMG on the evaluation dataset for the subject S1. Table 4 and Table 5 displays the peak CA while Table 6 and Table 7 displays the maximum of kappa values for the training and the evaluation datasets respectively for all seven subjects. The average improvement with the RQNN technique across all seven subjects in the evaluation stage is approx. 4% in CA ( $p < 2.5756e-007^4$ ) and more than 0.04 in kappa values ( $p < 1.4979e-007$ ) when compared with the unfiltered EMG by using the similar feature extraction approaches and classifier. As there are 13 classes to be identified, the chance accuracy is only 7.69% and therefore the CA enhancement of approx. 4% using the RQNN model is noteworthy. The

<sup>3</sup> Kappa is a measure of agreement between two estimators and since it considers chance agreement, it is regarded as a more robust measure in comparison to accuracy [29].

<sup>4</sup> Two-way Analysis of Variance (ANOVA2) test is performed with the results of the training and the evaluation stages for the RQNN filtered and the raw EMG approach.

TABLE 3  
PERFORMANCE COMPARISON FOR DC SIGNAL OF AMPLITUDE 2

SNR (signal-to-noise ratio)	Kalman filter RMSE	Proposed RQNN RMSE
20 dB	0.015	0.0004228
6 dB	0.037	0.0012071
0 dB	0.090	0.0017837

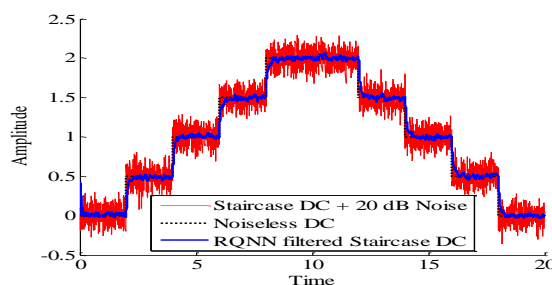


Fig. 7. Staircase DC signal filtering

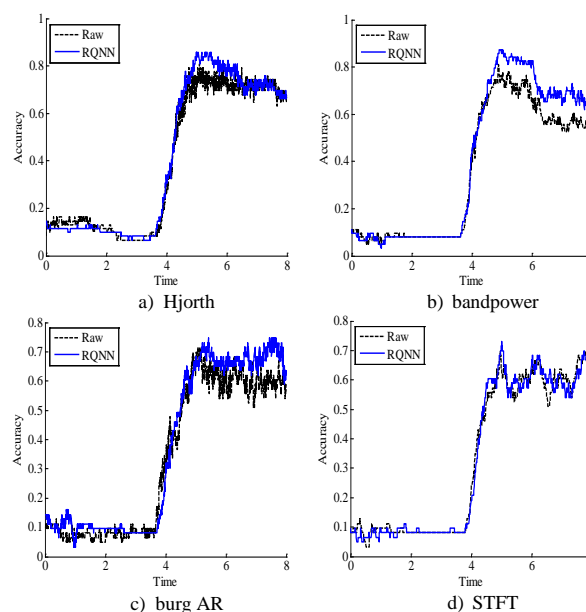


Fig. 8. CA plot (evaluation) for Subject S01 (with different features)

average enhancement in the value of CA (evaluation stage) for each FE approach namely Hjorth, bandpower, burg AR, STFT and yule AR is 3.39, 3.99, 4.46, 4.2 and 2.85 respectively. Thus, there is an increase in the system's performance using the RQNN model across all the FE approaches. Further, the maximum enhancement in the value of CA (evaluation stage) for each FE approach namely Hjorth, bandpower, burg AR, STFT and yule AR is 7.7, 7.7, 11.11, 6.15 and 12.11 respectively. Thus, if the parameters of the RQNN model are obtained specific to a subject and/or FE methodology, the CA may be enhanced significantly even furthermore for every FE approach and all the subjects. This can also be said from the fact that the current set of heuristically selected RQNN model parameters has shown negative performance for only two cases amongst the thirty-five combinations with seven subjects and five FE methods. Future work would therefore focus on selecting the parameters of the RQNN by using optimization techniques, preferably computationally less intensive approaches.

It can therefore be concluded from these results that the RQNN improves the average performance for almost all the

subjects (evaluation stage) along with using different feature extraction approaches when compared with the unfiltered EMG. The results thus show that without prior knowledge of the type of the noise characteristics present in the EMG, the RQNN can be utilized to enhance EMG signal separability and that the quantum approach based filtering method can be used as a signal preprocessing method. A very important feature of the RQNN methodology is that a single incoming sample (particle) is viewed as a wave-packet which evolves as per the potential field (or function) under the influence of the SWE (cf. video at [26]).

## IX. ROBOTIC HAND

The shadow dexterous hand (cf. Fig. 9) is a humanoid robot hand system developed by the Shadow Robot Company in London [28]. The hand is very similar to an average male human hand, and is designed to reproduce a range of movements comparable to the degrees of freedom of a human hand. The fingers of this humanoid robot hand are expected to mimic the classifier outcome from the system presented in Fig. 6 i.e., follow the subject's finger movements as detected by the classifier during the online stage. The classifier is set up from the data collected during the training stage, wherein, the user has performed the finger movements as directed from the computer screen (cf. Fig. 4

TABLE 4  
PEAK CA WITH DIFFERENT MODELS (TRAINING)

Sr. No.	Subj.	RQNN					RAW				
		Hjorth	BP	BurgAR	STFT	yuleAR	Hjorth	BP	BurgAR	STFT	yuleAR
1	S1	98.46	98.46	98.46	93.84	100.00	98.46	96.92	96.92	90.77	100.00
2	S2	90.25	85.64	67.69	62.05	86.15	92.30	86.66	66.66	63.08	86.66
3	S3	84.02	85.56	72.16	70.61	63.40	80.41	85.05	64.43	62.37	63.91
4	S4	74.87	76.41	65.64	52.82	62.56	78.97	73.33	55.38	50.77	62.05
5	S5	96.92	93.84	87.69	90.77	92.30	93.84	92.30	86.15	76.92	86.15
6	S6	87.18	81.53	67.17	59.48	71.28	87.17	81.53	58.97	64.10	77.94
7	S7	88.72	77.44	74.87	76.41	85.12	93.33	82.56	75.38	69.74	83.58
Average		88.63	85.55	76.24	72.28	80.12	89.21	85.48	71.98	68.25	80.04

TABLE 5  
PEAK CA WITH DIFFERENT MODELS (EVALUATION)

Sr. No.	Subj.	RQNN					RAW				
		Hjorth	BP	BurgAR	STFT	yuleAR	Hjorth	BP	BurgAR	STFT	yuleAR
1	S1	87.30	87.30	74.60	73.01	85.71	80.64	80.95	71.42	69.84	79.36
2	S2	72.30	67.69	58.46	50.77	73.84	69.23	64.61	58.46	47.69	75.38
3	S3	60.00	80.00	66.15	53.84	53.84	52.30	72.30	64.61	47.69	53.84
4	S4	60.00	61.53	44.61	35.38	44.61	55.38	53.85	38.46	33.84	41.54
5	S5	52.38	50.79	44.44	50.79	58.73	47.62	47.62	33.33	46.03	46.62
6	S6	80.00	84.61	60.00	64.61	63.07	78.46	84.61	55.38	60.00	63.07
7	S7	75.38	64.61	63.07	63.07	81.53	80.00	64.61	58.46	56.92	81.53
Average		69.62	70.93	58.76	55.92	65.90	66.23	66.94	54.30	51.72	63.05

TABLE 6  
MAX. OF KAPPA WITH DIFFERENT MODELS (TRAINING)

Sr. No.	Subj.	RQNN					RAW				
		Hjorth	BP	BurgAR	STFT	yuleAR	Hjorth	BP	BurgAR	STFT	yuleAR
1	S1	0.98	0.98	0.98	0.93	1.00	0.98	0.97	0.97	0.90	1.00
2	S2	0.89	0.84	0.65	0.59	0.85	0.91	0.85	0.64	0.60	0.86
3	S3	0.83	0.84	0.70	0.68	0.60	0.78	0.83	0.61	0.59	0.60
4	S4	0.73	0.74	0.63	0.49	0.59	0.77	0.71	0.52	0.47	0.59
5	S5	0.97	0.93	0.87	0.90	0.92	0.83	0.91	0.85	0.75	0.85
6	S6	0.86	0.80	0.64	0.56	0.69	0.86	0.80	0.55	0.61	0.76
7	S7	0.78	0.76	0.73	0.74	0.84	0.92	0.81	0.73	0.67	0.82
Average		0.86	0.84	0.74	0.70	0.78	0.86	0.84	0.70	0.66	0.78

TABLE 7  
MAX. OF KAPPA WITH DIFFERENT MODELS (EVALUATION)

Sr. No.	Subj.	RQNN					RAW				
		Hjorth	BP	BurgAR	STFT	yuleAR	Hjorth	BP	BurgAR	STFT	yuleAR
1	S1	0.86	0.86	0.72	0.70	0.84	0.79	0.79	0.69	0.67	0.78
2	S2	0.70	0.65	0.55	0.47	0.72	0.67	0.62	0.55	0.43	0.73
3	S3	0.57	0.78	0.63	0.50	0.50	0.48	0.70	0.61	0.43	0.50
4	S4	0.57	0.58	0.40	0.30	0.40	0.52	0.50	0.33	0.28	0.37
5	S5	0.48	0.47	0.40	0.47	0.55	0.43	0.43	0.27	0.41	0.43
6	S6	0.78	0.83	0.57	0.62	0.60	0.76	0.83	0.51	0.56	0.60
7	S7	0.73	0.61	0.60	0.60	0.80	0.78	0.61	0.55	0.53	0.80
Average		0.67	0.68	0.55	0.52	0.63	0.63	0.64	0.50	0.47	0.60



Fig. 9. Shadow dexterous hand

and Fig. 5). The parameters of the classifier are thus set up offline, in accordance with the subjects and the different feature extraction methods selected, as discussed in section VI. After setting up the classifier from the training dataset, the evaluation phase begins. Here the task involves finger movement by the subject, RQNN filtering of the EMG, feature extraction, classification and finally a classifier output command which is sent to the shadow dexterous hand through universal datagram protocol (UDP). The shadow hand is expected to emulate the classifier outcome shown in Fig. 6, which ideally represents the detection of the actual finger movement by the subject. Thus, in essence, future research will extend the work to control the shadow dexterous hand through the EMG signals of the subject(s). The future work would also involve mounting the tactile sensors on the robotic fingers so that tasks such as grasping, object manipulation etc. can be accomplished using similar signal processing, feature extraction and classification methodologies.

## X. CONCLUSION

The RQNN was evaluated with case-studies of simple signals and the results show that the RQNN is significantly better than the Kalman filter while filtering a DC signal added with different noise levels. The learning architecture and the associated unsupervised learning algorithm of the RQNN take into account of the complex nature of the EMG signal. The basic approach of the RQNN ensures that the statistical behavior of the input signal is suitably transferred to the wave packet associated with the response of the quantum dynamics of the network. At every computational sampling instant, the EMG signal is encoded as a wave packet which can be interpreted as the *pdf* of the signal at that instant. The CA and the kappa values obtained from the RQNN enhanced EMG signal show a realistic improvement during the evaluation stages across multiple subjects as well as different feature extraction approaches. This performance enhancement (through the RQNN model) can further be improved by utilizing appropriate subject specific RQNN parameters obtained using cross-validation and/or suitable optimization techniques as discussed in [1].

The noteworthy feature of the proposed scheme is that without introducing complexity at the FE or the classification stages, the performance can be significantly improved simply by enhancing the EMG signal at the preprocessing stage. The end application of this scheme is to enhance the performance while controlling the humanoid dexterous hand through EMG. Future work will involve tasks such as grasping, manipulation and control while using advanced perception using fingertip sensors.

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