Quaternion Neural Network with Temporal Feedback Calculation: Application to Cardiac Vector Velocity during Myocardial Infarction

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***Abstract*—Quaternion neural networks have been shown to be useful in image and signal processing applications. Herein, we propose a novel architecture of a neural unit model characterized by its ability of encoding 3-dimensional past information and that facilitates the learning of velocity patterns. We evaluate the implementation of the network in a study of the cardiac vector velocity and its usefulness in early detection of patients with anterior myocardial infarction. Experimental results show an improvement of the performance in terms of convergence speed and precision when comparing with traditional methods. Furthermore, the network shows successful results in measuring the velocity reduction that is usually observed in vectorcardiogram signals in the presence of myocardial damage. Through a linear discriminant analysis, a pair of 100% / 98% of sensitivity / specificity is met with only two velocity parameters. We conclude that this method is a very promising development for future computational tools devoted to early diagnosis of heart diseases.**

***Resumen*— Las redes neuronales cuaterniónicas han mostrado ser de gran utilidad en aplicaciones de procesamiento de señales e imágenes. En este trabajo, proponemos una arquitectura novedosa para el modelo de una unidad neuronal caracterizada por su capacidad de codificar información tridimensional temporal que facilita el aprendizaje de patrones de velocidad. Evaluamos la implementación de la red en un estudio de la velocidad del vector cardíaco y su utilidad en la detección temprana de pacientes con infarto anterior de miocardio. Los resultados experimentales muestran una mejora del rendimiento en términos de precisión y velocidad de convergencia cuando se compara con redes tradicionales. Adicionalmente, la red muestra resultados exitosos en la medición de la ralentización del vector que se observa habitualmente en las señales vectorcardiográficas en presencia de daños miocárdicos. Mediante un análisis discriminante lineal, se alcanza un par de sensibilidad / especificidad del 100% / 98% con sólo dos parámetros de velocidad. Concluimos que este método es un desarrollo prometedor para futuras herramientas computacionales dedicadas al diagnóstico temprano de enfermedades cardíacas.**

I. INTRODUCTION

Quaternion algebra was discovered by Hamilton in 1843 and it has been extensively used in modern mathematics and physics [1]–[3]. Quaternion neural networks had originally been proposed in the mid-1990 with an architecture similar to classical multilayered networks but with quaternary units [4]. Since then, many applications have been shown ranging from control systems, such us tracking operations, to image and signal processing, such as affine transformations [5]–[8].

We have recently developed several quaternion markers of myocardial infarction (MI) which are capable of computing angular velocity during both ventricular loops of depolarization and repolarization [9]. This method has turned out to be efficient and robust against noise but it requires a temporal averaging of patterns that may produce a low-pass effect with a possible loss of information. An accurate detection is required to avoid unnecessarily treating subjects who did not suffer a MI and to quickly begin treatment of patients with early infarction. A MI is an irreversible process. A delayed diagnosis causes a progressive muscle degeneration, increasing the cardiac death risk. It is of crucial importance to develop noninvasive markers that detect early MI as this is the major cause of death in the world [10]. The gold standard for MI diagnosis is actually the study of significant rises of plasma troponin levels but unfortunately it is only possible to be performed between 12 and 24 hours after the damage. Electrocardiogram (ECG) studies complement the diagnosis along with clinical judgment but acceptable values of accuracy are not yet reached either in the enzymatic or in the computational methods [11]. Our quaternion markers have proved to be promising solutions for reaching high values of sensitivity and specificity when combined with linear velocity indices.

In this work, we propose a quaternion neural network with temporal feedback calculation (QNNT) characterized by the ability of encoding past information that facilitates the learning of velocity functions. Also, we show a direct application to the learning of linear and angular cardiac velocity patterns and its usefulness to differentiate between patients during healing stage of anterior myocardial infarction and healthy subjects with very high accuracy.

II. MATERIALS AND METHODS

A. Dataset

We have proposed two study populations: healthy subjects and patients with anterior myocardial infarction. All the recordings have been extracted from the Physikalisch-Technische Bundesanstalt (PTB) database which have been acquired at the Department of Cardiology of University Clinic Benjamin Franklin in Berlin, Germany [12], [13]. The database included 290 subjects. We have selected all the patients with anterior MI (N=46) whose ECG and vectorcardiogram (VCG) recordings were made until 7 days after injury. An equivalent number of healthy volunteers was randomly selected in order to achieve 50% of prevalence rate. Ages ranged from 17 to 86 years with a mean of 52; 23% of the subjects were female. Each record includes 15 simultaneously measured signals: the conventional 12 ECG leads together with the 3 Frank VCG leads. Each signal were digitized at 1kHz.

B. Quaternion algebra

Quaternions are hypercomplex numbers that constitute a non-commutative field ($\mathbb{H}$). They are very useful in the study of rotations in three-dimensional space. Moreover, they are very efficient in terms of uncertainty propagation and computing time by comparison with traditional methods such as Euler matrices [3]. Each quaternion (1) has a real unit (associated with an amount of rotation) and three imaginary units (associated with the rotation axis) that satisfy the Hamilton rule ($\boldsymbol{i}^2 = \boldsymbol{j}^2 = \boldsymbol{k}^2 = \boldsymbol{ijk} = -1$).

$$q_t = a_1 + a_2\boldsymbol{i} + a_3\boldsymbol{j} + a_4\boldsymbol{k} \quad , \quad a_{1\ldots4} \in \mathbb{R} \tag{1}$$

Similarly, q_t can be written in terms of a rotation angle α from a point P_t to another point P_{t+1} in the three-dimensional space:

$$q_t = cos\left(\frac{\alpha}{2}\right) + \vec{\mathbf{u}}.sin\left(\frac{\alpha}{2}\right) \tag{2}$$

where $\vec{\mathbf{u}}$ represents the rotation axis. Both trigonometric functions can easily be obtained from dot and cross products between P_t and P_{t+1}.

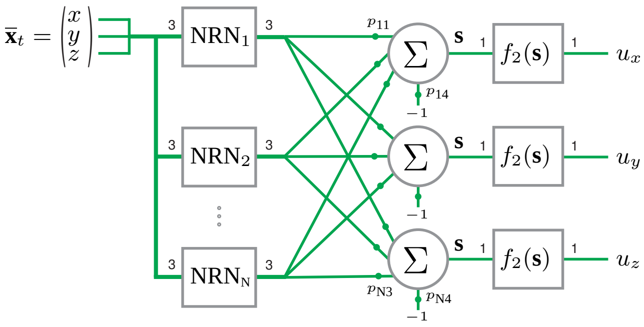
Then, if we take every point in a given three-dimensional loop we can compute a sequence of quaternions and thereby obtain the instantaneous angular velocity by solving the Poisson equation [14]:

$$\dot{q}_t = \frac{1}{2}.\vec{\omega}_t.q_t \tag{3}$$

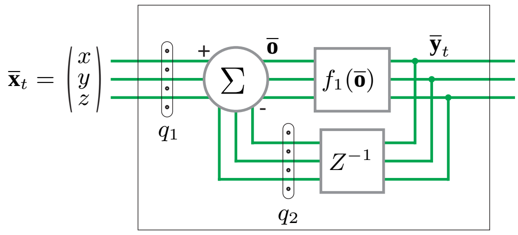
Finally, the quaternion product can be useful in the geometric interpretation. The mapping $\rho_q(x) := qxq^{-1}$ in $\mathbb{H}$ defines a rotation of a real vector x (purely imaginary quaternion) about the axis of q. Quaternion inverse can be expressed in terms of its conjugate and its norm: $q^{-1} = \overline{q}/\|q\|^2$.

C. Quaternion neural network with temporal feedback calculation (QNNT)

In Fig. 1a we show the proposed network architecture along with the neural unit model in Fig. 1b. The weights q of each neuron in the input layer are quaternions and both inputs and outputs are three dimensional vectors (purely imaginary quaternions). At the input of the activation function we have the difference of the current point rotated by the quaternion q_1 from the output of the neuron at the previous point rotated by the quaternion q_2 (Fig. 1b).



(a) Neural network



(b) Quaternion neuron model (NRN) with temporal feedback

Fig. 1: (a) Proposed neural network (QNNT). In each connection the number of branches involved has been indicated; (b) Quaternion neuron with temporal feedback calculation model. $\overline{\mathbf{x}}_t$ = represents the point of the 3D space at the instant t. $q_{1-2} \in \mathbb{H}$. f_1 is a split-type activation function (Eq. 5). Z^{-1} implies a temporal displacement.

$$\overline{\mathbf{o}} = \frac{q_1 \overline{\mathbf{x}}_t \overline{q_1}}{\|q_1\|^2} - \frac{q_2 \overline{\mathbf{y}}_{t-1} \overline{q_2}}{\|q_2\|^2} \tag{4}$$

The activation function is defined in a split-type form through a hyperbolic tangent.

$$f_1(\overline{\mathbf{o}}) = tanh(\mathbf{o}_i)\boldsymbol{i} + tanh(\mathbf{o}_j)\boldsymbol{j} + tanh(\mathbf{o}_k)\boldsymbol{k} \tag{5}$$

In the output layer (Fig. 1a) there are three conventional neurons with real weights p. The geometric interpretation of each output bears a relation to the velocity patterns learned in each xy, yz and zx plane. The neural network is trained with a back propagation algorithm with the Summed Squared Error (SSE) as the cost function. It is determined by the differences between the desired output u_d and the output of the network u (in each plane). The weights q and p of the connections are updated by the gradient descent method:

$$\delta_s = f_2'(\mathbf{s})(u_d - u) \tag{6}$$

$$\delta_o = f_1'(\mathbf{o})\omega\delta_s \tag{7}$$

$$p_t = p_{t-1} + \Delta p \ , \ \Delta p = \eta\delta_s\overline{\mathbf{y}}_t \tag{8}$$

$$q_t^* = (\overline{\mathbf{x}}_t \bullet \delta_o; \overline{\mathbf{x}}_t \times \delta_o) \tag{9}$$

$$q_t = q_{t-1} + \Delta q \ , \ \Delta q = \eta q_t^* \tag{10}$$

where $f_2(\mathbf{s}) = tanh(\beta\mathbf{s})$ and η is the learning coefficient.

D. Application on cardiac vector loops

Myocardial tissue damage constantly changes the conduction velocity. We have previously shown that these changes can be measured from VCG signals [9]. Thus, a suitable combination of parameters may be able to early detect the occurrence of MI. In Fig. 2, we show a T-wave loop constructed by using XYZ signals. Typical patterns of both angular and linear velocities are also shown. These patterns have large magnitude peaks which are severely affected in the presence of MI, considerably reducing their value. The highest peaks of the angular velocity signal, that usually appear in the next 50 ms after the T-wave peak, could be associated with the fast rotations occurring in the cardiac vector at the end of transmural repolarization.

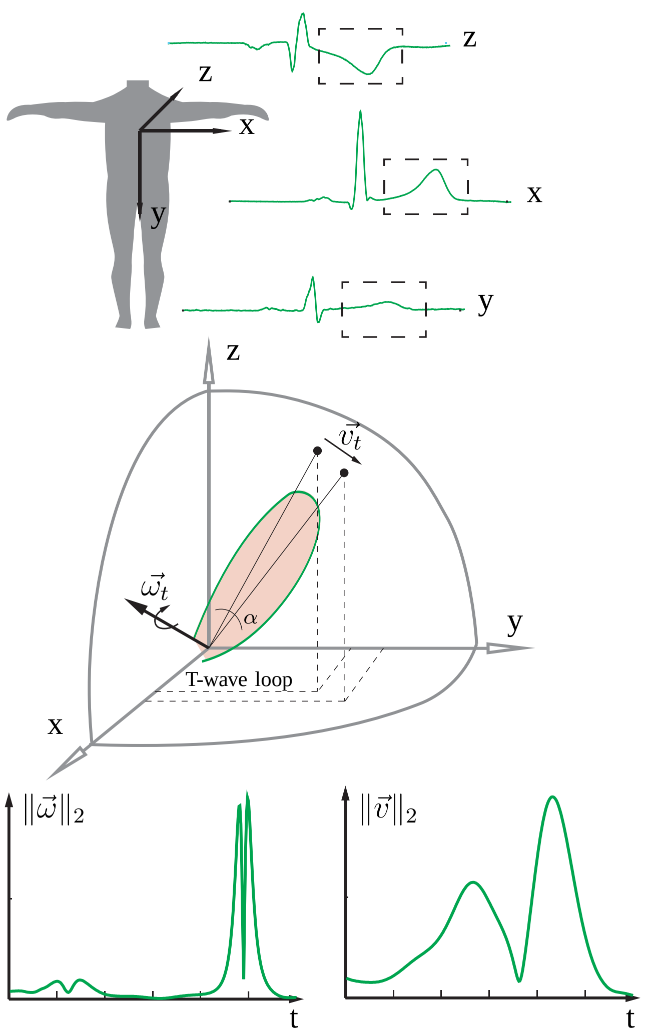


Fig. 2: Top panel: Typical VCG signals from a heartbeat. Middle panel: Constructed loop through the selected T-waves in each lead (x, y, z). Lower panel: 2-norm of both angular and linear velocities in complete T-wave signal.

In the present work, the VCG signals are selected from the populations of healthy subjects and patients during healing stage of anterior MI. Then, a bidirectional high-pass filter (0.5Hz, Butterworth) is applied for baseline wander correction. High frequency noises are reduced by applying a bidirectional low-pass filter (20 Hz, Butterworth, T-wave).

In order to show the improved ability of our QNNT on the learning of velocity functions we have evaluated its performance by computing both linear and angular velocities patterns of T-wave loop in each coordinate plane. The patterns are scaled to 1 for learning process and then re-scaled to the original magnitude. The angular velocity is obtained from Equation 3 while the linear velocity is obtained by direct differentiation of the VCG signal. For the purpose of ensuring a fair comparison, we have also studied the traditional Multilayer Perceptron (MP) with back propagation algorithm, whose architecture is described in [15]. It should be noted that, in order to make a valid computational comparison, the number of weights in both methods were the same. That is, the neurons of the QNNT are 10 whereas 22 units were used in the MP (a total of 111 weights).

For the statistical analysis we have selected the maximum velocities: ω_x^M, ω_y^M, ω_z^M, v_x^M,v_y^M,v_z^M. Using a two-sided Wilcoxon signed rank test, each statistical significance is obtained. Possible cross correlation between parameters is evaluated by computing the correlation coefficient. Finally, we can select a subset of parameters and apply a linear discriminant analysis in order to classify both study groups.

III. RESULTS

In Figure 3a, we show an example of a velocity learning in a window of 50 ms defined about the second half of the T-wave immediately after the peak (where maximum angular deflections are located in normal ECGs [9], [16]). The graphs have been obtained after 150 iterations in both methods. It can be seen that the fitting of the QNNT has better accuracy than traditional MP network. In Figure 3b, the mean error and standard deviation (30 trials) corresponding to the learning of the prior T-wave are shown.

Following with the application described above (Section II-D), maximum linear and angular velocities in each coordinate plane have been obtained as follows: Ten consecutive beats have taken from each VCG recording. Thus, the network has fed with each pattern and the number of iterations has increased with each pattern from 1 to 10. Lastly, the maximum obtained for each signal has been selected. ω_y^M and v_y^M showed highest statistical significance: $p < 10^{-13}$ and $p < 10^{-10}$ respectively. Consequently, the linear discriminant analysis has been carried out with these two parameters:

$$Q_{INDEX} = -17.0\ \omega_y^M + 1.2\ v_y^M \tag{11}$$

Finally, the Q_{INDEX} has been evaluated in the complete dataset. Herein, we show the confusion matrices for both methods (See Tables IA and IB) and the statistical comparison of MI diagnosis accuracy between QNNT and a MP network with back propagation learning (See Table IC). The former has -17 and 1.2 as discriminant coefficients (Q_{INDEX}) while the latter has -8 and 0.1. All values have been obtained by seeking to minimize the p value of the Wilcoxon test. AUC refers to Area Under the ROC curve. It can be seen that QNNT reaches higher values of sensitivity and specificity. Furthermore, the MP method has failed to classify 4 controls and 4 patients while QNNT missed only one control.

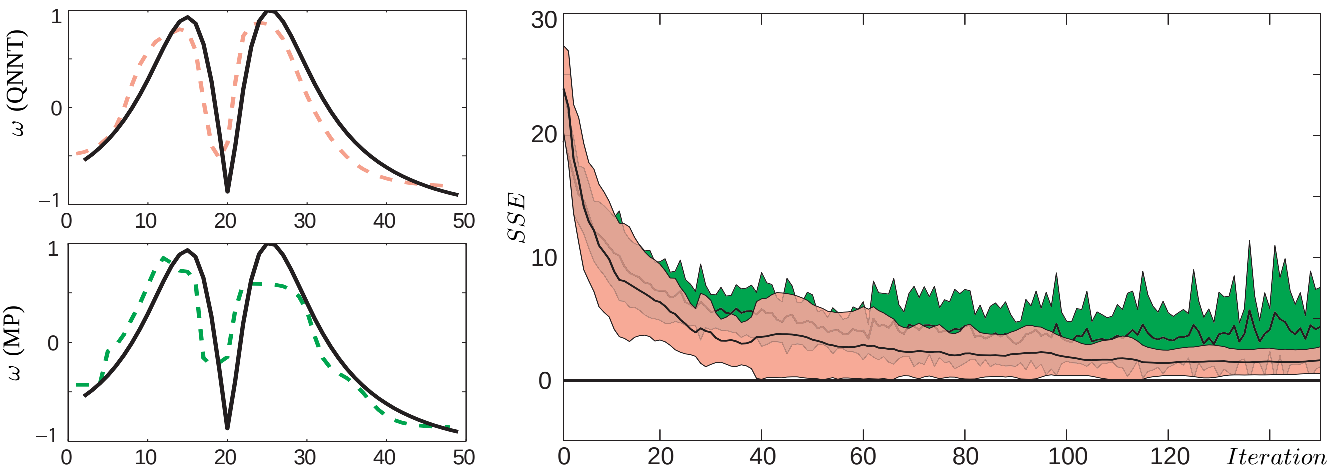


Fig. 3: Example of angular velocity learning. Left panels show the fitting achieved by both QNNT and traditional MP network with back propagation learning. Right panel plots summed squared error for each iteration in mean and standard deviation. Red graphs corresponds to QNNT and it shows lower values than traditional network (green graph). A total of 30 trials has been carried out to obtain the statistical results.

TABLE I
MI DIAGNOSIS ACCURACY (HEALTHY VS. ANTERIOR MI PATIENTS) FOR QNNT AND A MP NETWORK WITH BACK PROPAGATION LEARNING.

$N_{MI} = 46$, $N_{Healthy} = 46$		Predicted	
		MI	**Healthy**
Actual	**MI**	46	0
	Healthy	1	45

(A) QNNT CONFUSION MATRIX

$N_{MI} = 46$, $N_{Healthy} = 46$		Predicted	
		MI	**Healthy**
Actual	**MI**	42	2
	Healthy	4	42

(B) MP CONFUSION MATRIX

Network	**Sensitivity**	**Specificity**	**AUC**
QNNT	100	98	99.8
MP	92	92	98.0

(C) ACCURACY COMPARISON

IV. DISCUSSION

We have presented a novel neural unit model characterized by its ability of encoding 3-dimensional past information and that facilitates the learning of velocity patterns. Following the results shown in Fig. 3, the performance of QNNT in terms of convergence speed and precision seems to be an improvement when comparing with MP networks with back propagation learning [15]. The QNNT initial weights has been randomly set. The learning coefficient as well as the slope of the activation function have been optimally selected for a single signal and then all the processes used the same values. Traditional MP algorithm had to use lower values to ensure convergence.

Several quaternion neural networks have been presented previously and most of them use split-type functions [5], [17], [18]. However, some authors have reported that functions with local analyticity are more suitable for the activation in updating the neuron states [7], [19]. Further investigations are needed to evaluate this possible improvement.

As for the problem of early MI detection, the network shown successful results in measuring the velocity reduction that has been previously observed in VCG signals in the presence of myocardial damage [9], [20]. Furthermore, through the linear discriminant analysis very high values of sensitivity and specificity were met with only two parameters in the discriminant function. Future work will involve other MI locations and other non-cardiac pathologies that usually reduce accuracy of the computational methods.

V. CONCLUSION

The quaternion neural network with temporal feedback calculation has been shown to be highly efficient in the learning of velocity patterns. The experimental results show that its use in the computation of cardiac vector velocity parameters may be an important tool in the early diagnosis of myocardial infarction.

ACKNOWLEDGMENT

This work was supported by CONICET, under project PIP #112-20130100552CO, Argentina.

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