Algorithm for Classification of EEG Signals in Astronauts

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***Abstract*—An algorithm is presented for filtering and classification of electroencephalographic (EEG) signals, based on extended Kalman filters and dynamic neural networks. The EEG signals acquisition process is complicated since they have a lot of white noise and because the amplitude and frequency of the different rhythms are in a very small range. The astronaut's brain, when subjected to a microgravity environment, changes its physiology. It is important to analyze these changes because we can analyze: biomechanics, psychological issues, intracranial pressure and using a brain machine interface, among others. The filtering and sorting algorithm are designed based on extended Kalman filters and neural networks. These algorithms are used primarily because of their ease to remove white noise and detect small changes of the different types of rhythms present in EEG signals. Since the presence of EEG rhythms is unknown, an estimator and an observer are designed based on neural networks for the appropriate classification of signals. The neural network algorithm can be adapted to the extended Kalman filter and get one feedback system. The algorithm is used to make more robust the Kalman filter. This algorithm has been able to effectively classify EEG rhythms and which are of interest for biomechanical analysis, and brain machine interface. This algorithm is tested using a database. However, the same proposed algorithm can be used on astronauts in microgravity environments.**

Keywords–Neural Network; Astronauts; EEG Signals.

I. INTRODUCTION

Our brains are changing all the time. Nerves are rearranging themselves and the connections between the nerve cells are reforming as the brain memorizes new information, stores the old and continuously adapts to new situations [1]. New experiences, learning, physiological changes, sleep disturbance and fatigue are among the most influential factors. Sometimes, especially after an accident or a cerebral stroke, the recover power of brain tissue is simply mind-boggling: the remaining healthy tissue can take over the functions of damaged areas. The weightlessness in orbit is also a big change for brains. Not only are there changes in blood circulation and other physical conditions, but the way that cognitive functions of daily life are managed also alter the brain dramatically. Adapting to the multitudinous effects that gravity has on the human body and the way the brain deals with them is perhaps the greatest demand that the nervous system has to face in outer-space. The increased load on the cognitive capacity is accompanied by a multitude of stresses on the brain [2].

A. Extended Filter Kalman

The Kalman filter is an algorithm that is based on the model state space of a system to estimate the future state and future output filtering optimally the output signal, depending on the delay of the samples to be introduced, the filter of the parameter estimator can be used or the filter can be used in the function. In both cases the noise can be eliminated, these equations are widely used because they include statistical probabilities since it takes into account the randomness of both the signal and the noise. Unlike other types of filters that do not require a specific cutting frequency Kalman is based on the characteristic of the noise filter thus allowing across the frequency spectrum [3].

B. Brain Computer Interface (BCI)

BCI systems today are considered a tool with enormous potential for establishing communication alternatives to restore motor functions. There are different types of EEG potentials, which can be classified according to different factors. Brain rhythms can be classified depending on frequency bandwidth and have been designated a Greek letter. [4].

- Delta Rhythm (δ): They are typically between 0.5 and 3.5 Hz and has amplitudes of 20 to 200 μV.
- Theta Rhythm (θ): It occurs in the band of 4 to 7 Hz with amplitudes ranging from 20 to 100 μV.
- Alpha rhythm (α): The alpha rhythm is mainly manifested in the frequency band from 8 to 13 Hz with amplitudes ranging from 20 to 60 μV.
- Mu Rhythm (μ): It manifests in the range of 8-13 Hz and its amplitude is less than 50 μV.
- Beta Rhythm (β): It is an irregular rhythm, with frequencies between 13 and 30 Hz. Its approximate amplitude is between 2 and 20 μV.
- Gamma Rhythm (γ): This rhythm at higher frequencies to 30 Hz and amplitudes manifests between 5 and 10 μV [5].

II. METHODOLOGY

The first step is to obtain EEG signals from different database to show the proposed algorithm. The databases we used were: a database of a group of researchers from different institutions of the European Union [6], Ecole Polytechnique Federale de Lausanne [7] and Graz University of Technology [8].

A. Equation numbers

The electroencephalography study is complicated to perform because the patient must be at rest, the study has a lot of noise and can be confused with any noise rhythm of the EEG signal. For that reason apply extended Kalman filters as they are appropriate filters to eliminate noise caused by the system. Consider the equation of state and output of a non-stationary system with noise form:

$$\begin{array}{c} x(k+1) = A\,(k)\,x\,(k) + B\,(k)\,u\,(k) + \upsilon\,(k) \\ y\,(k) = C\,(k)\,x\,(k) + \omega\,(x)\,, \end{array} \tag{1}$$

Where matrices $A(k)$, $B(k)$ and $C(k)$ are deterministic and are generally variants variables in linear systems with time, $\upsilon\,(k)$ and $\omega\,(x)$ are stochastic processes and noise measurement system respectively, which are considered white noise average.

For the classification of signals, we use dynamic neural networks, unaware of how it will end EEG signal acquired have to estimate and observe the different rhythms, dynamic neural networks are suitable for this procedure. The neural network algorithm can be adapted to the extended Kalman filter and get one feedback system, the algorithm with 2 hidden layers is used to make more robust the Kalman filter. This algorithm has been able to effectively classify rhythm signals and which are the rates of interest.

The design idea can be illustrated observers to invariant systems in the time:

$$\begin{array}{c} \dot{x} = Ax + Bu \\ y = Cx, \end{array} \tag{2}$$

A linear observer is designed in the same way as the original system with an additional pending input from the difference between the actual values and the estimated values of the output vector:

$$\dot{\hat{x}} = A\hat{x} + Bu + L\,(C\hat{x} - y)\,, \tag{3}$$

Where $\hat{x}_t$ is an estimate of the state vector of the system $L \in \Re^{nxl}$ and is an input matrix. Of course, the vector state observer $\hat{x}$ is available to generate the control action using auxiliary system dynamics.

$$\begin{array}{c} \frac{d\hat{x}_t}{dt} = A\hat{x}_t + W_{1,t}\sigma\,(\hat{x}_t) + W_{2,t}\varphi\,(\hat{x}_t)\,u_t + K_1 e_t + K_2 e_t \\ \hat{y}_t = C\hat{x}_t \end{array} \tag{4}$$

Where $\hat{x}_t$ is the state vector representing the neuronal observer estimates brain signals; $\hat{y}_t$ is the output of the neural network corresponding to the differential value of the estimated rate of rhythm signals: μ and β rhythm; A, K_1 y K_2 are the constants appropriate matrices which fit during training, to enhance the process of approximation of the neural network dimensions; $\sigma()$ and $\varphi()$ are vector fields are compounds with standard sigmoid functions; C is assumed that the matrix output previously known; parameters $W_{1,t}$ and $W_{2,t}$ are the weights are adjusted to ensure a good approximation of the neural network to the uncertain nonlinear function. The first is that the adjustment of feedback and the second is related to the effect of the entry in the state estimation process whose time evolution is determined by a special procedure of learning online. The data set available are the rhythms acquired from the BCI, i.e., $y = x$. In this way and in this particular case $C = (1, 0, , 0)$.

III. RESULTS

In this section, we present the EEG signals obtained from each of the databases. These images also reflect the different rates. In Figure 1, we show for the database Europe Union in Figure 2. The database Ecole Polytechnique Federale de Lausanne in Figure 3. the Graz University of Technology.

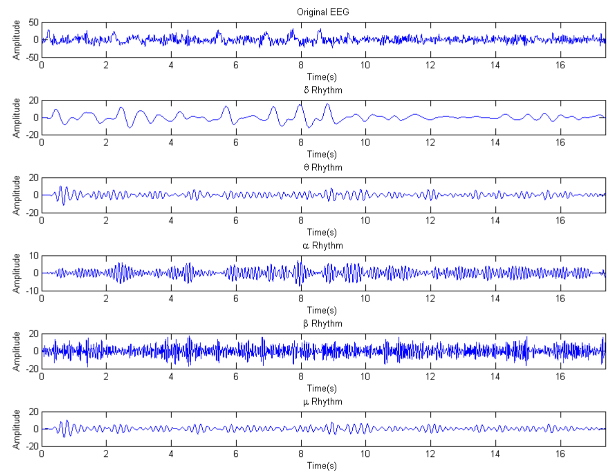

Figure 1. Database of EEG signal, database of the European Union.

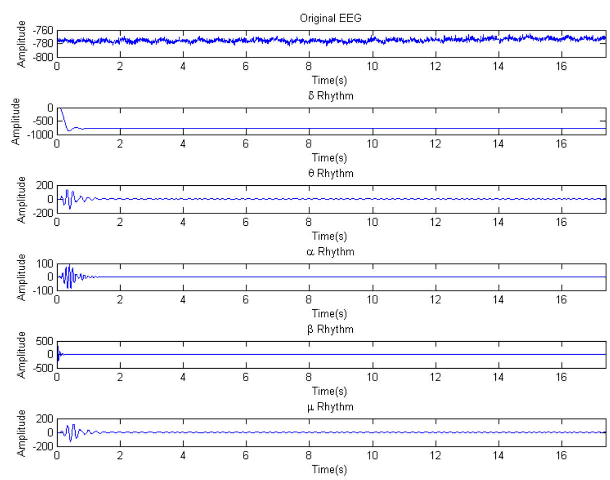

Figure 2. Database of EEG signal, database of the Ecole Polytechnique Federale de Lausanne.

After obtaining signals from the database, we applied the extended Kalman filter to the signal to filter and obtain the rhythm wish, Figure 4 and Figure 5 shows the output of the Kalman filter for rhythms μ and β of first database respectively.

Figure 6 and Figure 7 shows the output of the Kalman filter for rhythms μ and β second database respectively.

Figure 8 and Figure 9 shows the output of the Kalman filter for rhythms μ and β of the third database respectively. Since we have the output of the extended Kalman filter, apply the neural network. The neural network learns from the original network. Specifically, the network learns this is the right pace, we resubmitted another signal type of neural network will

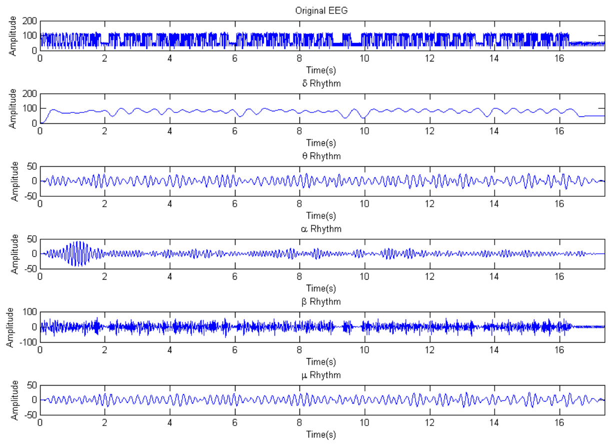

Figure 3. Database of EEG signal, database of the Graz University of Technology.

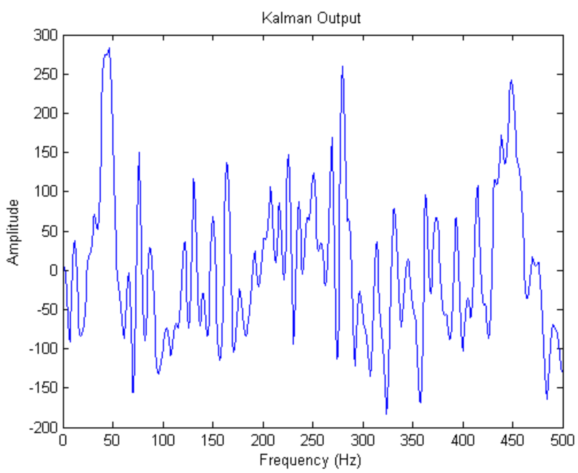

Figure 4. Output extended Kalman filter for μ rhythm, database of the European Union.

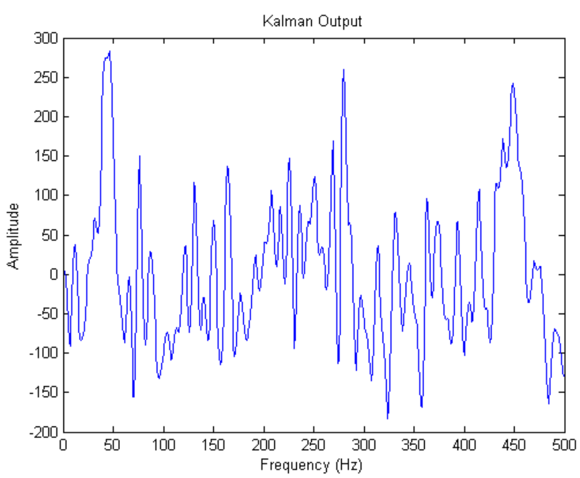

Figure 5. Output extended Kalman filter for β rhythm, database of the European Union.

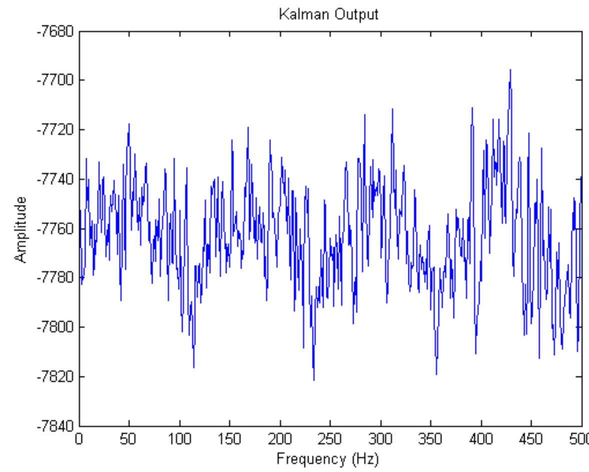

Figure 6. Output extended Kalman filter for μ rhythm, database of the Ecole Polytechnique Federale de Lausanne.

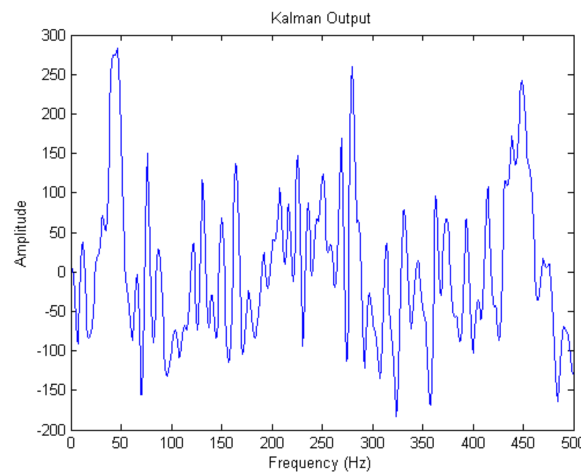

Figure 7. Output extended Kalman filter for β rhythm, database of the Ecole Polytechnique Federale de Lausanne.

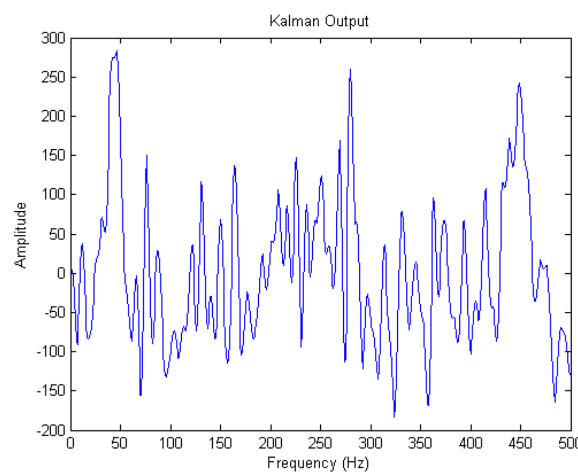

Figure 8. Output extended Kalman filter for μ rhythm, database of the Graz University of Technology.

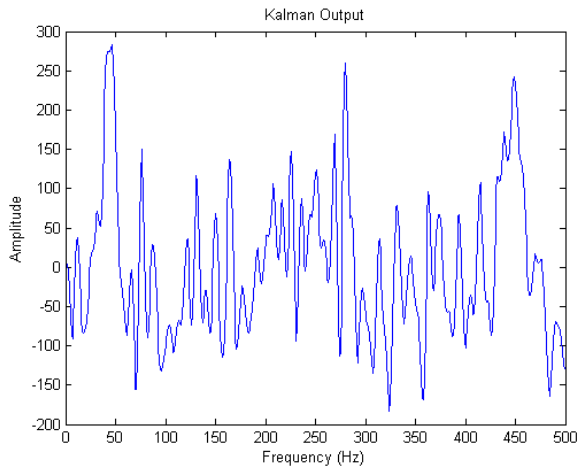

Figure 9. Output extended Kalman filter for β rhythm, database of the Graz University of Technology.

take it as another EEG signal. This is the behaviour that we expect as a first test for our classification signals. Because the implementation of the neural network is in matlab takes a long time for the amount of data. In Figure 10 and Figure 11, we show the application of the neural network μ rate signal and β respectively.

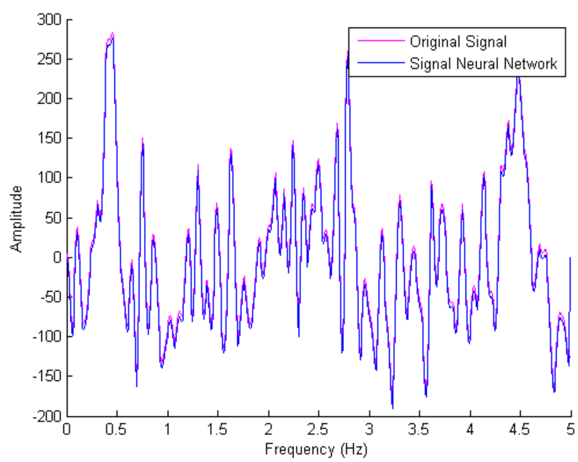

Figure 10. Output neural network for μ rhythm, database of the European Union.

Figure 12 and Figure 13 shows the output of the neural network for the rhythm μ and β of second database respectively. Figure 14 and Figure 15 shows the output of the neural network for the rhythm μ and β of third database respectively.

IV. Discussion.

When we obtain the signal from Extended Kalman Filter, enters the EEG signal to the system Dynamic Neural Networks. The application of dynamic neural network to μ rhythm. In the figures of the neural network estimation signal (red) is shown, the estimate is appropriate and that would

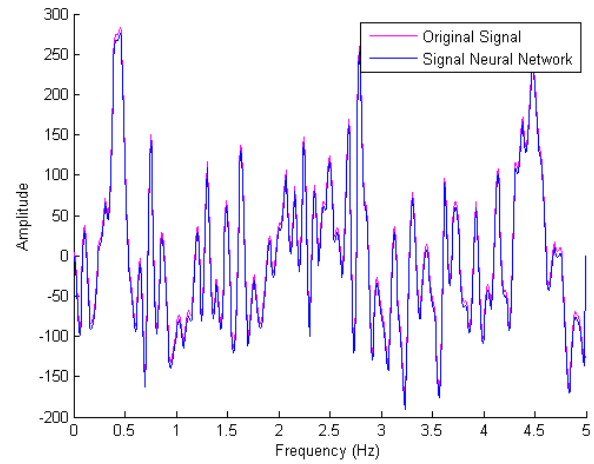

Figure 11. Output neural network for β rhythm, database of the European Union.

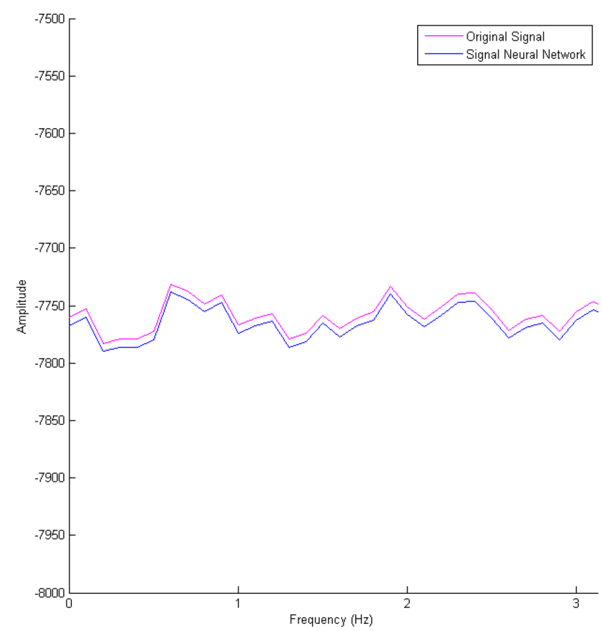

Figure 12. Output neural network for μ rhythm, database of the Ecole Polytechnique Federale de Lausanne.

classify the correct signal for the movement of the limbs. The same applies to the β rhythm

The algorithm applied model helped us to estimate the parameters of the neural network, by means of the error matrix K provides us with the estimate of the neural network. The lower the K matrix best estimate of the neural network. Another important parameter is to calculate the matrix of the weights W. The weights are given us the speed with which estimates the network, this data is important because it also indicates the computational cost of the algorithm.

V. Conclusion

The proposed algorithm is able to identify EEG signals in the first instance removing noise that provides acquisition

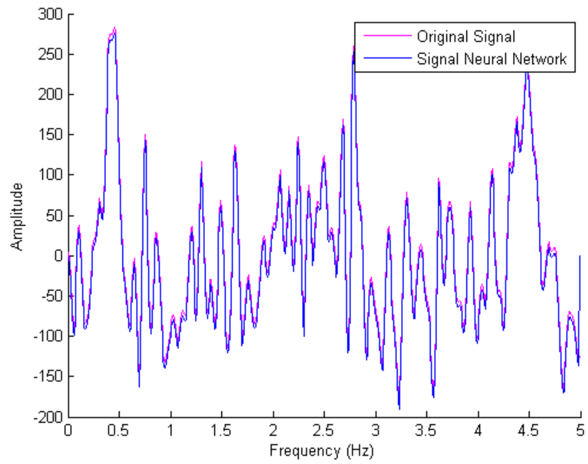

Figure 13. Output neural network for β rhythm, database of the Ecole Polytechnique Federale de Lausanne.

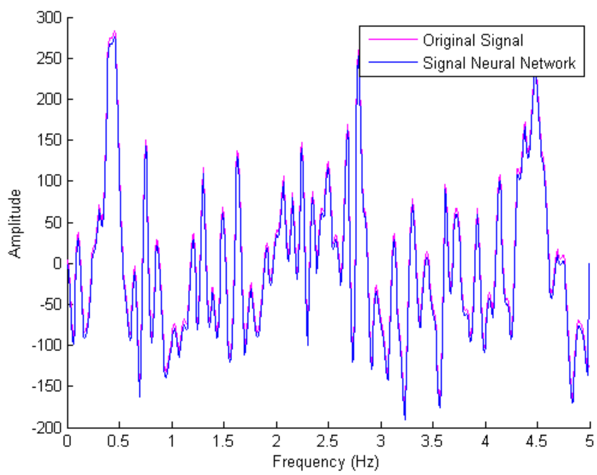

Figure 14. Output neural network for μ rhythm, database of the Graz University of Technology.

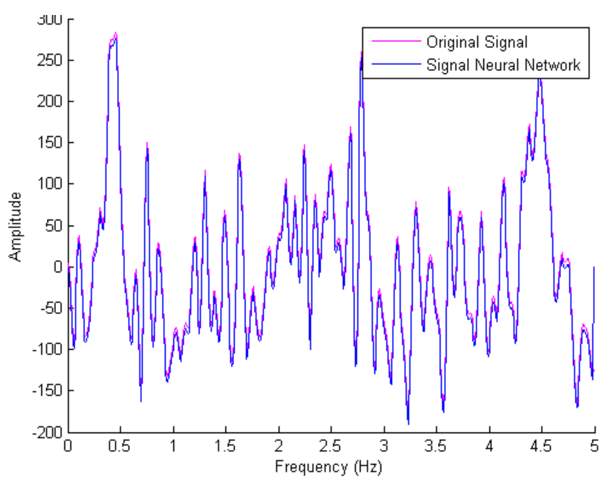

Figure 15. Output neural network for β rhythm, database of the Graz University of Technology.

system which guarantees that we can get the rhythm we want. The other part of the algorithm is the observer of the neural network, which showed us that it is able to learn the correct signal (required rhythm). This system could be used in microgravity environments for astronauts and who wish to acquire EEG signals where system noise is more common.

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