

# Missing Samples Estimation of Synthetic ECG Signals by FCM-based Adaptive Neuro-Fuzzy Inference System (FCMANFIS)

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## Research Article

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# Abstract

This paper presents an estimation of missed samples recovery of Synthetic electrocardiography (ECG) signals by an ANFIS (Adaptive neuro-fuzzy inference system) method after designing the ANFIS model using FCM (Fuzzy C Means) clustering method. In MATLAB's standard library for ANFIS, only least-square-estimation and the back-propagation algorithms are used for tuning membership functions and generation of fis (fuzzy inference system) file, but at current work, we have used the FCM method that shows better results.

Root mean square error (difference of the reference input and the generated data by ANFIS) for the three synthetic data cases are:

a. Train data: RMSE =  $1.7112e-5$

b. Test data: RMSE =  $5.184e-3$

c. All data: RMSE =  $2.2663e-34$

## 1. Background

Missing samples recovery [1] is a known problem that was addressed in some contexts such as:

-audio restoration [2, 3],

-image completion [4, 5],

-data recovery in electricity distribution systems [6],

-biomedical applications [7,8].

This paper is organized as follows. In Section 3 a model for the ECG signal generation and formulation the problem of missing samples recovery in this context is proposed. In Section 4 the proposed estimation procedure for the recovery of the missing samples demonstrated. Comparative simulation results on synthetic ECG data [11] are presented in Section 4.2.

ANFIS is a fuzzy logic method for function approximation and control of various engineering fields such as biomedical engineering systems; AC and DC motor control and power plant control and even social engineering problems [12,13].

The proposed estimation scheme presents generation of missed samples recovery of ECG signals by a fuzzy method called ANFIS (Adaptive neuro-fuzzy inference system). In this study FCM used as a method to tune fuzzy system parameters (membership functions).

## 2 Anfis Concept And Design

ANN has strong learning capabilities. Fuzzy logic has ability of interpretability. The true scheme of the two method is a hybrid neural/fuzzy system, which uses the merits of both systems, ANFIS. The general ANFIS structure is presented in this section. The ANFIS model with one input and one output variable and five layers is shown at Figs. 1a,1b.

The functions of the various layers are given in the form of an algorithm as described in [9]. The structure contains the same components as fis (fuzzy inference system), except for the NN block. The ANFIS structure is regularly adjusted by least-square-estimation and back-propagation algorithms.

### **3. Anfis Learning Methods**

For a given data set, different ANFIS models can be constructed using three different identification methods such as grid partitioning, subtractive clustering method and fuzzy C-means clustering [9]. In the present paper, the FCM method is used to find the premise

membership functions for the ANFIS model.

Considering that the training data will be given from patient ECG signal, the online method of receiving the data will not be useful. Instead offline data from healthy people will be used to train ANFIS. Offline training methods are:

I. Grid Partitioning:

II. Subtractive clustering:

III. Fuzzy C -Means (FCM):

Methods one and two are investigated in our earlier work [10]. FCM method was used and compared with other methods in this paper. FCM convergence speed is very faster than other two previous methods.

FCM was introduced by Bezdek [14] is a clustering method in which each data point belongs to two or more clusters. FCM is an algorithm, that wants to find cluster centers based on minimization of an objective function. This function is the summation of squares distances between each data points and the cluster center.

### **3.1 ANFIS controller design by FCM method and comparison with other methods**

Because FCM method is not available in MATLAB toolboxes, we have used a script developed by Dr. Kalami[1] to realize FCM. As before Input and output data pairs used as train and test data for generating the ANFSI model (fis) to be used in generating the estimated data.

The generated fis file is used in a MATLAB script to generate the missed signal ECG data with FCM method. FCM method has been simulated and input parameters and output results are shown at figures 2-7.

## **4. Synthetic Data Generated At Matlab Environment (The Proposed Method)**

The ECG data is generated by a script taken from Quiroz and et al. work [11]. The main .m file has two parts. First part is used to generate 12 lead ideal noise-free ECG signals. At this noiseless state, we can obtain RR intervals with a simple algorithm for recognition of the signal maximums. For second state i.e. noisy ECG signal, we should use complex algorithms. The latter state also consists of 12 leads.

### **4.1 ANFIS learning methods:**

The training data is collected from artificial 12 lead ECG signals (50 percent of data) and fuzzy 'fis' file is used to simulate the remained 50 percent to test the generated ECG data by ANFIS.

The ANFIS method used at this article is used for generation of the missed ECG signal offline but it can be used in applications that needs real-time and online estimation of missed signal.

The offline methods that investigated are:

- Grid Partitioning
- Subtractive Clustering
- FCM
- GA

And the online methods that can be investigated later are:

- CANFIS (Co-Active ANFIS)
- DENFIS (Dynamic Evolving Neural Fuzzy Inference System)

### **4.2 Design of FCM based ANFIS:**

With ANFIS, we can estimate any missed signal from 12 lead ECG signals with a good accuracy.

First the following 12 lead ECG are generated by the MATLAB script [11]:

lead\_I, lead\_II, lead\_III, lead\_aVL, lead\_aVL, lead\_aVL, lead\_V1, lead\_V2, lead\_V3, lead\_V4, lead\_V5, lead\_V6

The V3 signal omitted from the data. Then by FCM method for ANFIS with following parameters as input the lost signal (V3) has been reconstructed:

Number of clusters: 10

Maximum repetition rate: 100

Minimum improvement error:  $1e-5$

Maximum no. of epocs: 100

Error Goal: 0

Initial Step Size:0.01

Step Size Decrease Rate: 0.9

Step Size Increase Rate: 1.1

The train and test signals and ALL data is shown at figures 5,6 and 7.

Rms error for the three cases are:

- a. Train data, RMSE =  $1.7112e-5$
- b. Test data, RMSE =  $5.184e-3$
- c. All data (train and test), RMSE =  $2.2663e-3$

## 5. Results And Discussion

In this section we test and evaluate the performance of the proposed fuzzy method on synthetic ECG data. Test signals were generated synthetically by a MATLAB script from [15], consisting of 12 ECG signals for twelve ECG leads. The V3 ECG test signals were zeroed in 50 percent position of data so as to simulate lost samples, where the size of the lost sample interval was 50 percent of consecutive samples. Then the generated data is fed to another script that uses a fis file generated previously that its output is reconstructed (lost) ECG signal i.e. the V3 signal.

## 6. Conclusion

In the context of missing samples recovery of ECG signals, we proposed a fuzzy approximation model (ANFIS) to generate the lost signal among input ECG stream data which was empirically shown to be

more suitable due to its fuzzy and Neural characteristics. Additionally, we proposed an appropriate estimation procedure according to the ANFIS model, which is comprised of two phases, model parameters estimation by FCM clustering, followed by the missing samples estimation and generation based on the ANFIS model. In comparison to previously published works, our model and estimation procedure yield more accurate results and better recovered ECG signals.

Also this study shows the capability of AI methods for modelling biomedical engineering problems containing ECG signals based on input output data, which were published in literature, for this purpose, the FCM-ANFIS method was developed for modelling and function approximation.

The next step will be to use the proposed method for real ECG data instead of synthetic data.

## 7. Methods

In MATLAB's standard library for ANFIS, only least-square-estimation and the back-propagation algorithms are used for tuning membership functions and generation of fis (fuzzy inference system) file, but at this work the Fuzzy C Means (FCM) method is used for tuning purpose. FCM is an algorithm, that wants to find cluster centers based on minimization of an objective function. This function is the summation of squares distances between each data points and the cluster center. FCM convergence speed is very faster than other two Grid Partitioning and Subtractive clustering methods.

At first the data from input and output data from a PID controlled heart rate controller generated and they are used in a MATLAB code for FCM, then fuzzy inference system (fis) file then applied to another code that uses FCM for tuning parameters of membership functions. The new fis file applied to the MATALB anfis function to generate the V3 missed signal (may be one of twelve synthetic ecg signals).

## Declarations

- **Ethical Approval and Consent to participate**

No applicable.

- **CONSENT FOR PUBLICATION**

No applicable.

- **Availability of data and materials**

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

- **Competing interests**

The authors declare that they have no competing interests.

- **Funding**

No applicable.

- **Authors' contributions**

AD developed and implemented the whole concepts of the algorithm presented within this manuscript, NJ provided refinements and performed data acquisition and generation as well as further supplemental programming, FN and KM provided further technical knowledge and support. All authors read and approved the final manuscript.

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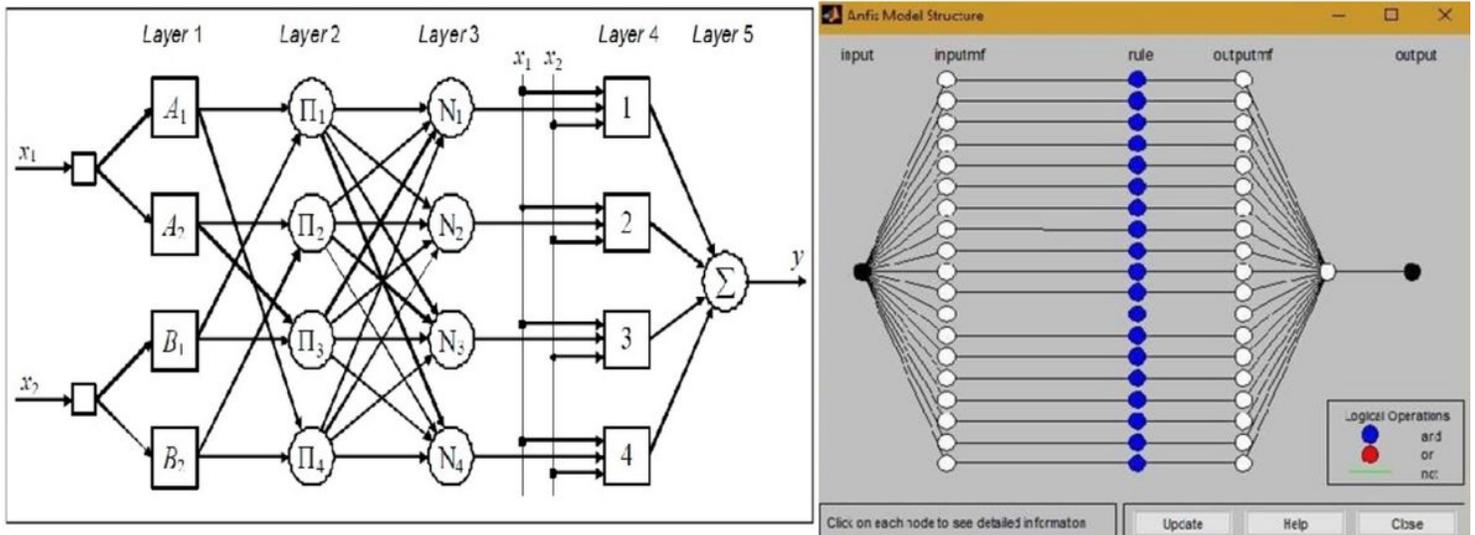
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## Figures



**Figure 1**

1a: ANFIS model with one input and one output showing the ANN architecture

1b: ANFIS layers with two inputs and one output with 5 layers

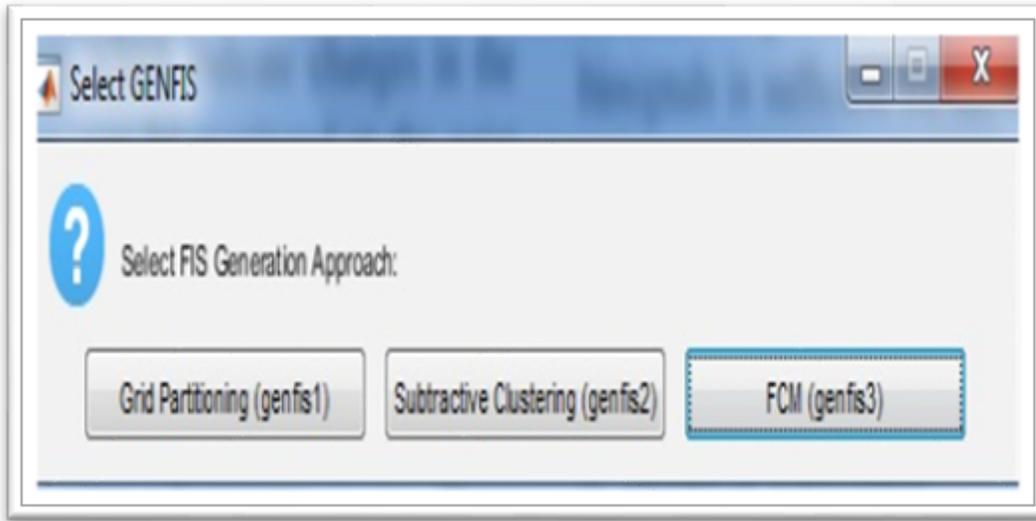


Figure 2

Number of clusters

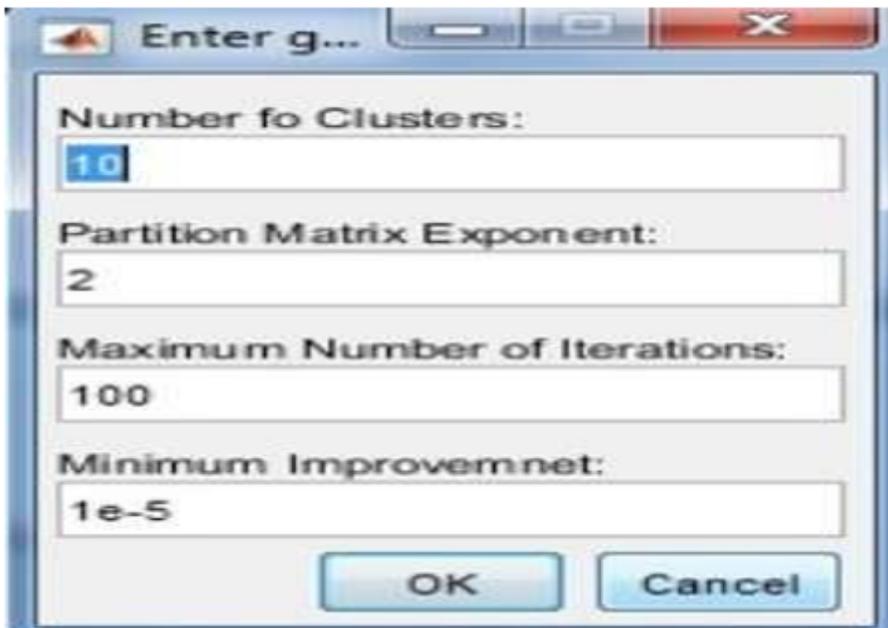
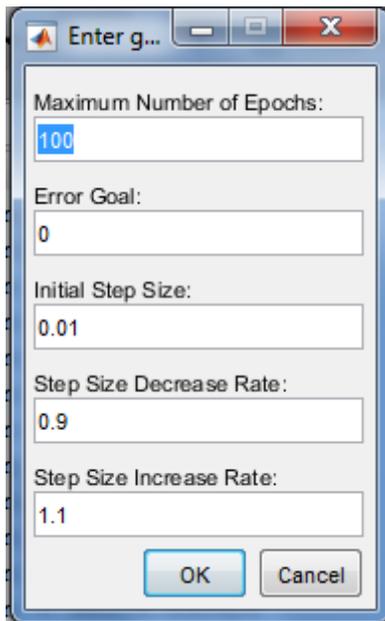


Figure 3

FIS generation method selection



**Figure 4**

Number of Epochs and Error goal

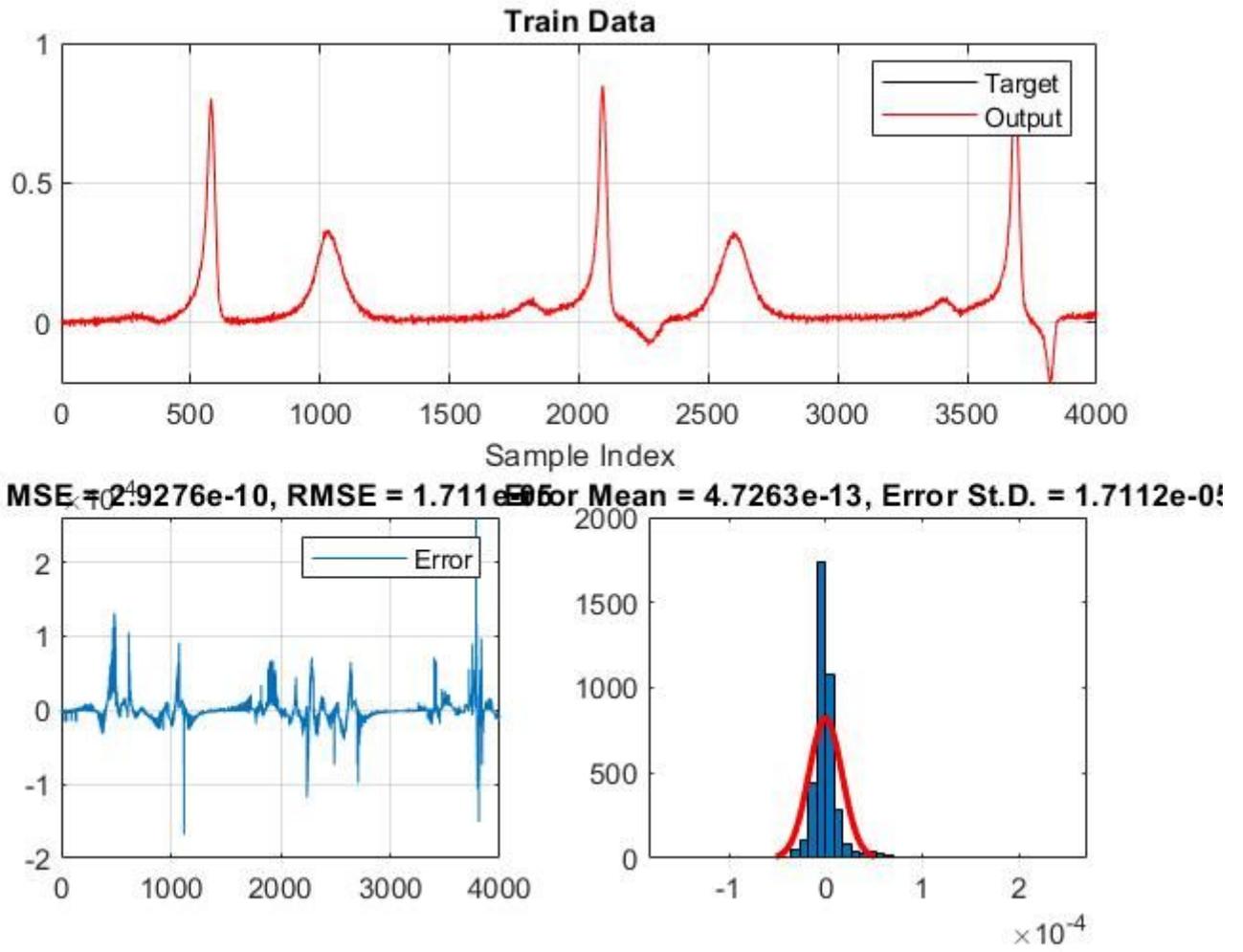
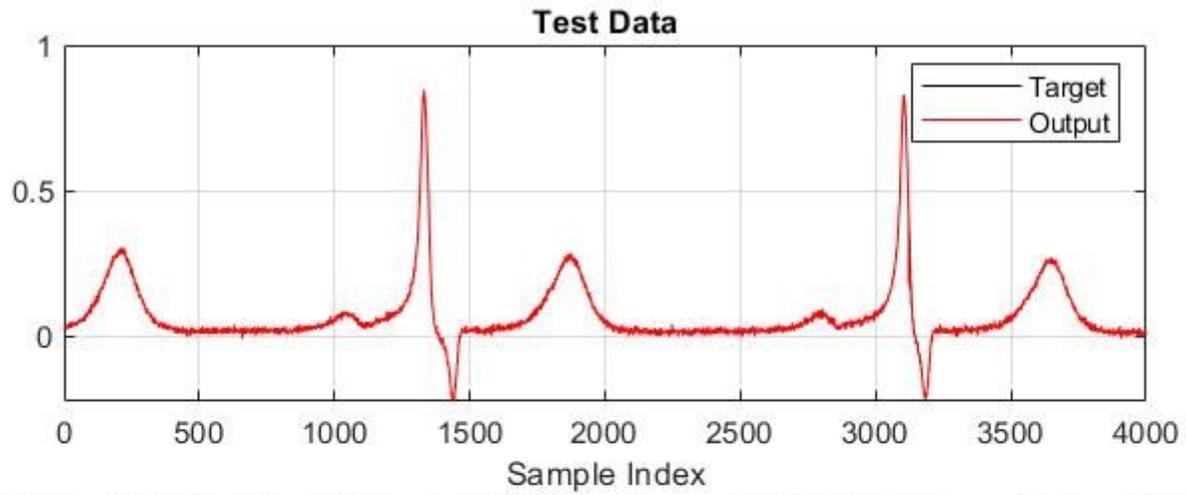
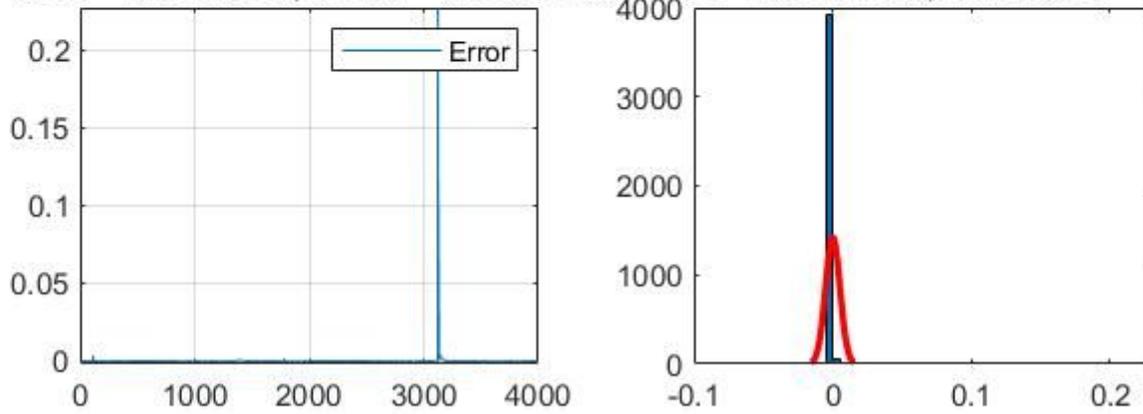


Figure 5

Train data ,RMSE =1.7112e-5

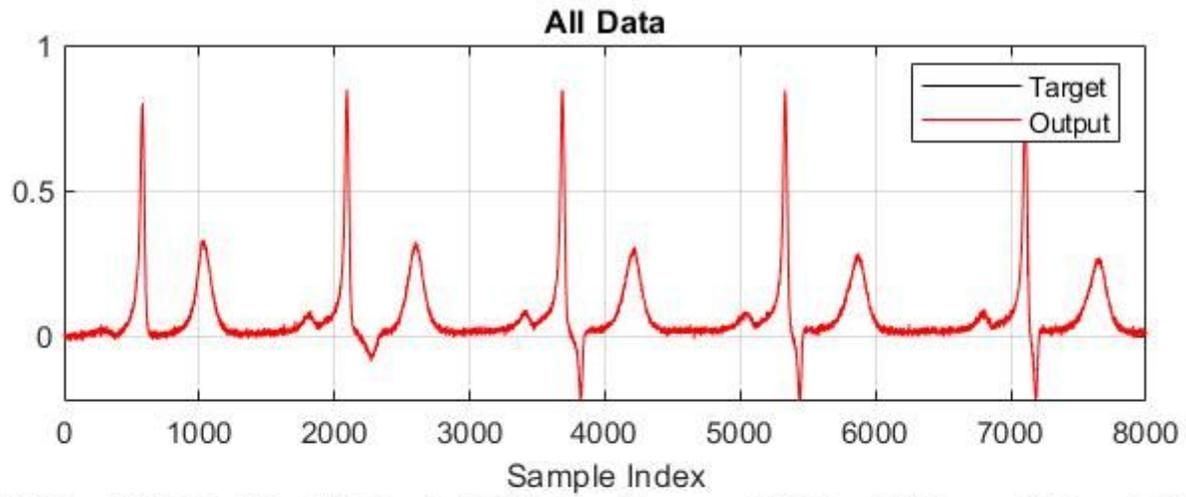


**MSE = 2.6909e-05, RMSE = 0.005184, Error Mean = 0.00019931, Error St.D. = 0.005184**



**Figure 6**

Test data ,RMSE = 5.184e-3



**MSE = 5.1396e-06, RMSE = 0.0022667, Error Mean = 6.5064e-05, Error St.D. = 0.0022663**

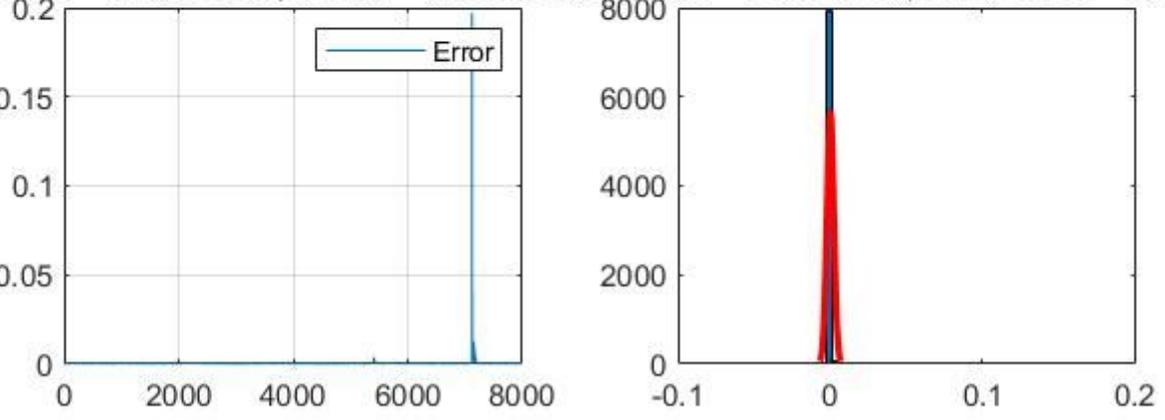


Figure 7

All data, RMSE = 2.2663e-3