Predicting Electrocardiogram and Arterial Blood Pressure Waveforms with Different Echo State Network Architectures

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ABSTRACT

Alarm fatigue caused by false alarms and alerts is an extremely important issue for medical staff in Intensive Care Units. The ability to predict and classify ECG and ABP patient waveforms can potentially help the staff and hospital systems better classify a patient's waveforms and subsequent alarms. This project approaches this problem by evaluating the effectiveness of different Echo State Network (ESN) architectures at predicting ECG and ABP waveforms. Several architectures and metrics are evaluated showing similar performance between parallel ESN architectures and integrated architectures. The results also suggest potentially greater benefit of larger integrated reservoirs at predicting ECG waveforms and the adaptability of such models across individuals. Although there are limitations to this analysis, the work presented here offers a unique way of understanding and predicting a patient's waveforms and provides suggestions for further extensions of this research.

1. INTRODUCTION and MOTIVATION

Intensive Care Units (ICUs) are designed to handle the most physiologically fragile patients in the hospital [12]. As a result, ICUs utilize a wide spectrum of machines, technologies, and tests to help its medical staff better understand and care for patients. However, the wide array of stand-alone machines often collect data and produce alarms and alerts independently, leaving the difficult integration tasks up to the medical staff. Time sensitive decisions, identifying non-critical alarms, are just some of the problems faced by ICU medical staffs. Studies have shown that staffs in ICUs face an extraordinary amount of alarms each day, some as much as 1,000 alarms a day, most of which are non-actionable or not necessary for patient care [7, 17]. Excess amounts of non-critical alarms can lead to alarm fatigue which can adversely affect patient care [4, 5, 11]. While there is ongoing research to effectively minimize false alarms, such as allowing nurses to adjust alarm thresholds, much work is still needed to better classify and develop systems that are less error prone to false alarms [5, 10]. One of the main challenges that arise is the development of algorithms robust enough to understand, integrate, and predict multiple physiological waveforms from patient data that can better classify and interpret alarms.

The recent release of clinical ICU patient data makes it possible to develop better models and support tools to aid medical workers in understanding and filtering the abundance of information and alarms they are exposed to [14]. This publically available database, MIMIC II (Multiparameter Intelligent Monitoring in Intensive Care II), has already been analyzed and used in several ways, for example to develop decision support systems to better categorize and classify mortality rates in the ICU [2, 3, 6, 14, 15]. Furthermore, a study has previously used this data and an expert review panel to reclassify five common ICU alarms into true alarms and false alarms. They developed an algorithm that classified alarms based on both electrocardiogram (ECG) and arterial blood pressure (ABP) waveforms immediately prior to the machine generated alarms. When tested, the algorithm suppressed approximately 59.7% of the false alarms [1]. While their algorithm is focused on classification, this project aims to complement their work by developing a neural network that can predict an individual's waveform. An effective predictive model can help medical staff better anticipate a patient's condition as well as the occurrence of false alarms.

The purpose of this project is to use recurrent neural network models to predict an individual's waveform. These networks will be learning to predict an individual's ECG and ABP waveform data, which can potentially help prioritize alarms as well as predict life-threatening situations in the ICU. This project uses the clinical ICU patient data previously discussed to develop, train, and test various Echo State Network (ESN) architectures at predicting a patient's ECG and ABP. ESNs were chosen for this project because they have been previously shown to accurately predict chaotic time series without the need to train the specific internal representations of the system [9, 16]. These advantages make ESNs very attractive for predicting ECG and ABP time series which are both chaotic and difficult to learn. The rest of this paper describes the data, approach taken, evaluations, discussion of the results, and suggestions for future work.

2. DATA SOURCE

The data used for this project comes from the Multi-Parameter Intelligent Monitoring for Intensive Care II (MIMIC II) database which is publically available [13, 14, 15]. The complete database currently contains data from approximately 33,000 patients collected over 7 years (beginning in 2001) from Boston's Beth Israel Deaconess Medical Centers, and combines both clinical and physiological data. The adult patient ages ranged from 18 to over 90 years (mean 68 years), and were collected from 48 medical, surgical, and coronary intensive care beds. Each patient record typically contains data from two electrocardiogram (ECG) leads, arterial blood pressure (ABP) and pulmonary arterial pressure (PAP) stored at 125Hz over time intervals that can range between a few hours to a few days, a sample of the raw data is shown in Figure 1. The ECG was originally sampled at 500Hz but was compressed to 125Hz while still preserving the peaks [1]. The resulting database is quite large (over 3TB). This project focuses on the data from the ECG II and ABP data from six randomly select patients. ECG II data was selected because it appeared to be more available from a cursory look at the patient records. ABP was selected because of its relationship to ECG in the interpretation and classification of alarms [1].

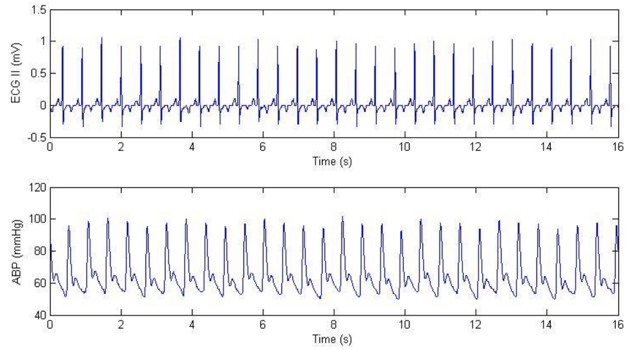

Figure 1: Samples of standard ECG II and ABP waveforms. This data was from patient a41278.

3. METHOD

This project evaluates the performance of three different types of ESN architectures at predicting two related physiological waveforms. There are many parameters and conditions associated with a basic ESN, such as reservoir size, activation rule, learning rates, etc. Some preliminary analysis was done to identify reasonable ranges of interesting parameters. The following sections first describe the data and preprocessing of the data. Next, a basic ESN architecture, was implemented, tested, and applied to both ECG and ABP waveforms which help fix some network parameters, such as activation and learning rules. These parameters were then used to build three different types of ESNs which were evaluated on predictive performance.

3.1 Data Processing

Although the data was publically available, a specialized WFDB (WaveForm DataBase) software package was required to download, interpret, and format the data [13]. Cygwin was used to connect directly to the server to download and format the data. Unfortunately, this process was done manually because of the complex nature of the data and some limitations of Cygwin. The downloaded data was converted to comma separable version files which were readable in Matlab.

Some basic preprocessing was needed to make the magnitudes for the two waveforms comparable. A simple smoothing function, that averaged the data points in a 5-time step moving window, was applied to both the ECG and ABP data. This window size was effective at smoothing the waveform while maintaining the important features of the waves. The ABP data was also normalized to fall within the values 0 and 1. The ECG was vertically shifted up by the minimal value so it would be within the same range as the ABP data. These transformations were done to make the two waveforms more comparable and similar in magnitude while maintaining unique features.

3.2 Building and Testing a Basic ESN

A standard ESN, Figure 2, was first built, in Matlab, adopted from Jaeger and Tong's previous work [9, 16]. This standard architecture has four sets of unique weights: W_{in_hidden} were randomly assigned fully connected weights between the input node to the reservoir nodes, W_{hidden} were sparsely connected, randomly assigned recurrent weights between the reservoir nodes, W_{hidden_out} were randomly assigned fully connected weights from the reservoir nodes to the output node, and W_{in_out} were randomly assigned weights from the input node to the output node. Note that this architecture does not have connections from the output nodes back to the hidden nodes. This was done to reduce the model complexity and to align more fully with some of the models previously discussed. Weights were initially assigned

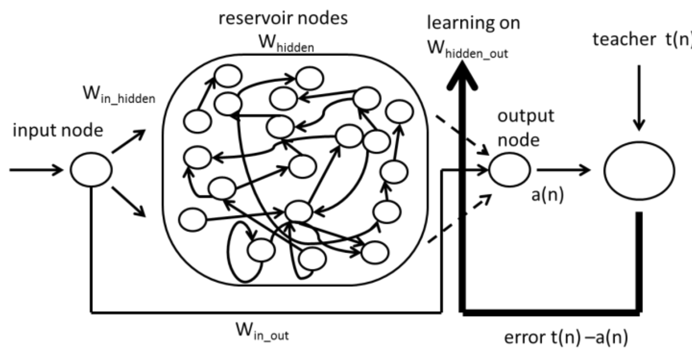

Figure 2: Basic ESN with learning only on W_{hidden_out} (dashed arrows).

random values between -0.5 and 0.5. Similar to previous work, approximately 20% of the possible connections in the reservoir had non-zero weights and scaled with a spectral radius of 0.98, using equation 1:

$$W_{hidden} = \frac{\alpha W'_{hidden}}{|\lambda_{max}|}$$

where α is the spectral radius, W'_{hidden} is the weight matrix for the reservoir prior to transformation, and λ_{max} is the maximum eigenvalue of W'_{hidden} [16].

The activation for the hidden nodes, A_{hidden}, and output nodes, A_{out}, is:

$$A_{hidden}(t) = tanh\left(W_{in\_hidden}\left(A_{in}(t)\right) + W_{hidden}\left(A_{hidden}(t-1)\right)\right)$$

$$A_{out}(t) = W_{in\_out}\left(A_{in}(t)\right) + W_{hidden\_out}\left(A_{hidden}(t)\right)$$

The learning rule and training only applied to the connections between the hidden nodes and the output nodes; all other weights remained unchanged through initialization, training, and testing. Although several learning techniques to train these weights were tried, such as linear regression, simplified error back propagation, and other learning functions, a simple learning rule that incrementally changed the weight based on the product of the learning rate and the training error, was shown to be both effective and fast. To prevent excessive oscillations in weights, a minimal error threshold was applied such that weights would not change if the absolute value of the error was less than 0.0001 (determined empirically).

The basic ESN was first tested with a trivial simulated sine wave. The data was divided into training data (2,000 time-steps) and testing data (1,000 time-steps). The ESN, with 600 reservoir nodes and a learning rate of n = 0.0001, was initialized by passing all the data through the reservoir once to let the internal transients of the system dissipate. Next the training data was introduced to the network and the hidden-to-output weights were allowed to learn. The purpose of this project was to develop a model that could predict a waveform; hence the teacher signal was the input signal 100 time-steps to the right (100 time-steps in the future). This trivial example verified the basic workings of this network. Mean Square Error (MSE) was used to evaluate this and subsequent test predictions:

$$MSE = {}^{1}/_{N} \sum_{n=1}^{N} \left(t(n) - a(n)\right)^2$$

where N is the total number to time-steps in the test prediction, t(n) is the actual teacher value at time-step n, and a(n) is the output predicted value at time-step n.

This trivial but useful prediction demonstration resulted in a low MSE_{test} of 0.025 (run results in the Appendix).

3.3 Refining ESN Parameters

It was next necessary to identify some useful ESN parameter ranges for the ECG and ABP waveform data. Identifying which parameters to set and the ranges of interest made the comparisons of different ESN architectures more appropriate. Two separate ESNs with similar architectures to the ESN mentioned above were used to predict ECG and ABP waveforms 625 time-steps into the future. Different combinations of reservoir sizes and learning rates were tried because of their influence on how the waveforms were represented, decomposed, and learned by the system.

A cursory assessment was first completed with the ECG data, varying the number of hidden nodes (100, 500, 750, and 1000) and the learning rates (0.01, 0.001, and 0.0001). The data was divided into initializing (1-5,000 time-steps), training (5,001-8,000 time-steps), and testing segments (8,001-10,000 time-steps). The data was tested 10 times for each combination. As shown in Table 1, reservoirs with nodes ranging between 100 and 750 and learning rates ranging from 0.001 and 0.0001 had on average better performance, prompting additional investigation.

Table 1: ECG MSE test results (standard deviations)

MSE test	100	500	750	1000
0.01	3.78e42 (6.55e42)	7.83e7 (1.26e8)	4.1e13 (7.1e13)	4.6e76 (8.0e76)
0.001	0.026 (0.023)	18.39 (31.07)	1.42 (2.32)	1.6e6 (2.7e6)
0.0001	0.013 (0.0018)	0.02 (0.0029)	0.043 (0.031)	0.11 (0.14)

Reservoir size and learning rate ranges were further investigated with higher fidelity. The network ran ten more times with randomly initialized weights with new combinations of reservoir sizes (100, 200, 300, 400, 500, 600, and 700) and learning rates (0.001, 0.0005, and 0.0001). The results suggested that learning rates of 0.0001 and reservoir sizes of 500 or less than 300 tended to have better performance. Although both reservoir size and learning rate

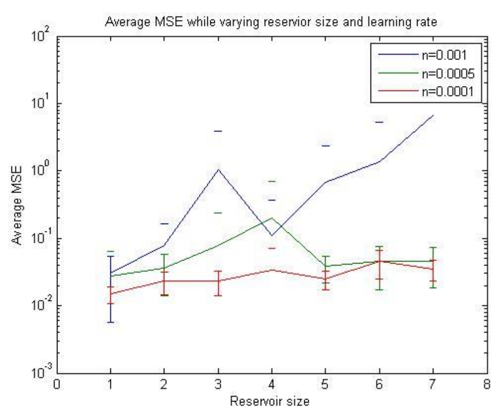

Figure 3: Lowering learning rates tend to reduce the average ECG MSE (error bars/marks show one standard deviation from the mean). Results without a lower error bar indicate significantly larger differences only meaningful in the positive direction.

affected performance, the latter had much more influence on the results, as shown by the overlapping error marks in Figure 3. As a result, a learning rate of 0.0001 and a reservoir size of 500 were used for the ECG components of the test ESN architectures. A reservoir size of 500 was chosen because it had slightly less variability compared to sizes of 300 nodes or less.

A similar analysis, done using ABP data, suggested a learning rate of 0.0001 and a reservoir size of 400 for the ABP components of the test ESN architectures.

3.4 ESN Architecture Designs

Three ESN architectures were designed to predict ECG and ABP waveforms using the previously discussed reservoir sizes and learning rates. The first ESN, ESN1 in Figure 4, served as a control for the experiment, and was essentially two ESNs running in parallel with no connections between the networks.

The second architecture, ESN2 in Figure 5, was similar to the first architecture, having two separate reservoirs whose sizes were set by the initial findings previously discussed. However, the nodes in both reservoirs were connected to each of the output nodes. While the learning rates did not change, these weights were updated independently. The learning of the hidden to output weights were specific to the error generated by the corresponding waveform. For example, only the error between the predicted and actual ECG waveforms was used to update the W_{hidden_out} connect to the ECG output node. Both reservoirs were initialized synchronously with their corresponding waveform. It was interesting to investigate if the predictions of one reservoir could benefit from the other reservoir with this architecture. Furthermore, it was interesting to determine if having two separate reservoirs would make the overall network more robust to limitations associated with the randomly assigned weights.

The third architecture, ESN3 in Figure 6, comprised of one large reservoir with two input and two output nodes. This architecture was

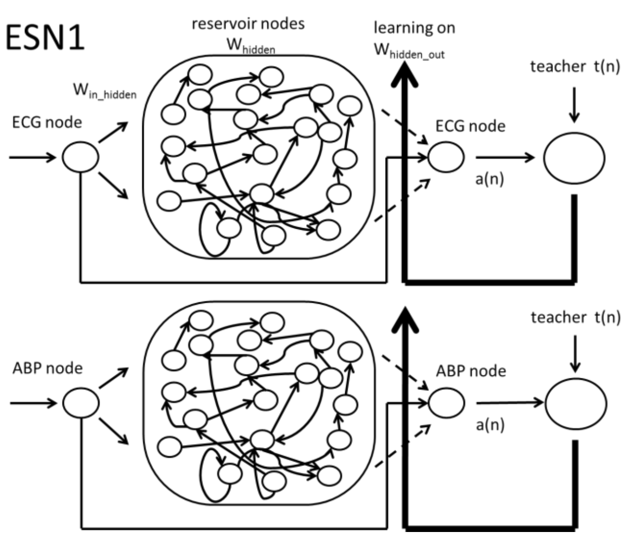

Figure 4: Echo State Network architecture 1 (ESN1).

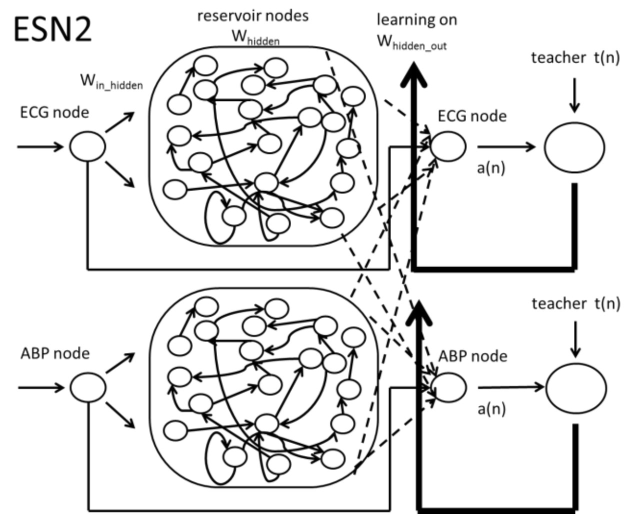

Figure 5: Echo State Network architecture 2 (ESN2).

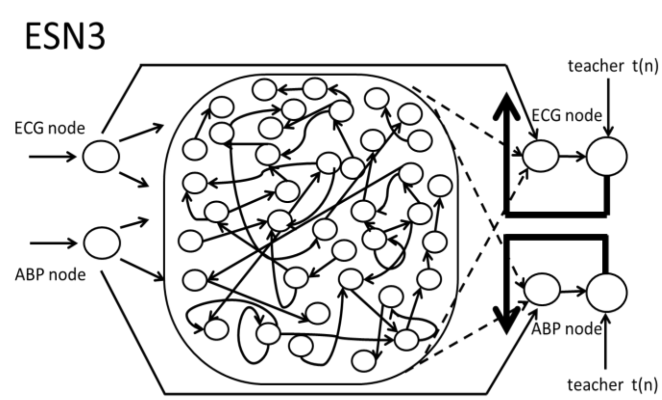

Figure 6: Echo State Network architecture 3 (ESN3).

chosen to investigate how single reservoir systems compared to multiple reservoir systems when predicting multiple related waveforms. It was interesting to test if initializing and training one reservoir with two related waveforms could lead to better performance. To be consistent with ESN1 and ESN2, both the inputs and outputs were fully connected to the hidden nodes but inputs were only connected to their corresponding output waveform node. The other network parameters, such as spectral radius, W_{hidden} sparsity, were consistent with ESN1 and ESN2. This ensured that the analysis would primarily focus on differences resulting from the network architecture. Nevertheless, a single reservoir system can perform differently based on its size. As a result, ESN3 with reservoirs of 800 and 700 nodes were also investigated. ESN3 was initialized with both waveforms, and similar to ESN2, the fully connected weights from the hidden to each output node were different and were trained based on the error associated with their corresponding predicted waveforms.

The performance of these three architectures was assessed on MSE, equation 1, and the maximum prediction error (max error) between the performance and the actual waveform for both ECG and ABP data. A 10,000 time-step sample from patient record a41278 was used for this analysis. The data was divided into initializing (1-5,000), training (5,001-8,000), and testing segments (8,001-10,000). Initialization, training, and testing with all the networks followed the sample protocol. After testing, the ECG and ABP MSE and max error were evaluated using one-way ANOVA. This was used to determine if there were statistically significant differences between the ECG and ABP MSE and max error for the different architecture types (ESN1, ESN2, ESN3-900, ESN3-800, ESN3-700). Based on these results, randomly sampled data from five individuals (a41325, a40416, a40076, a40432, and a41563) were used to evaluate the consistency and performance of one of the higher performing networks.

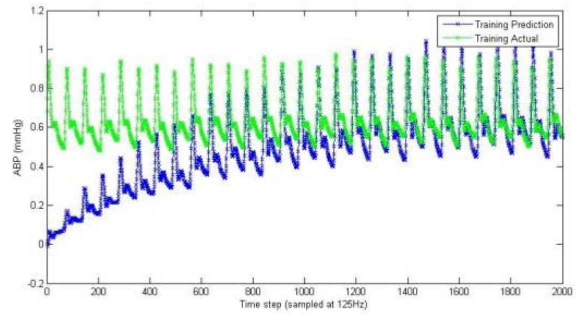

Figure 7: Sample ABP training run.

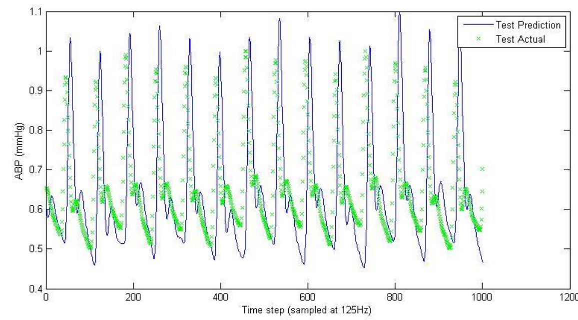

Figure 8: Sample ABP test prediction.

4. RESULTS

Each ESN architecture ran thirty times with randomly initialized weights. The networks were evaluated on their prediction/test MSE and the maximum error values for both ECG and ABP waveforms. Figures 7 and 8 show data from a training and testing ESN1 run. In Figure 7, the ESN1 was able to learn and adjust to match the phase and magnitude of an ABP waveform as well as have decent predictive performance. Additional, sample results from ESN1, ESN2, and ESN3-900 are included in the Appendix.

The boxplots in Figures 9 and 10 show the

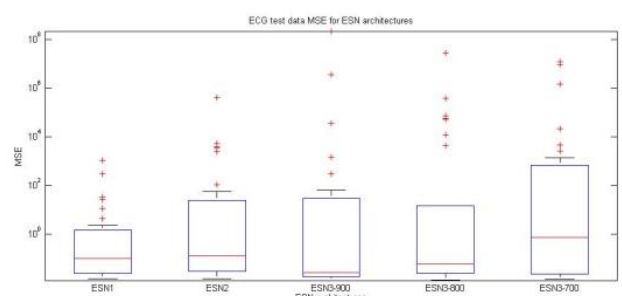

Figure 9: Boxplot of ECG test MSE for the different ESN architectures.

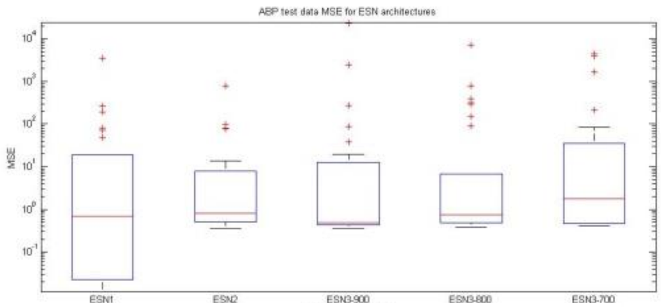

Figure 10: Boxplot of ABP test MSE for the different ESN architectures.

MSE from both the ECG and ABP results binned by architecture type. The outliers were most likely caused by poor randomly initialized weights. These outliers (results greater than three standard deviations from the mean) were removed, approximately five per factor level, for the remainder of the analysis. Similar boxplots for the maximum error results were produced and included in the Appendix.

Next the Kolmogorov-Smirnov (KS) test was used to test both the ECG and ABP MSE results for normality. Although the KS values for the ECG and ABP distributions were 0.5 and 0.53 respectively, parametric statistical tests could still be applicable considering the sample size.

One-way ANOVAs were used to evaluate the MSE and max error of the predictions. The factors levels were the different architectures (ESN1, ESN2, ESN3-900, ESN3-800, and ESN3-700). Table 2 shows the F-values and the corresponding probability values of both the MSE and max errors for the different waveforms.

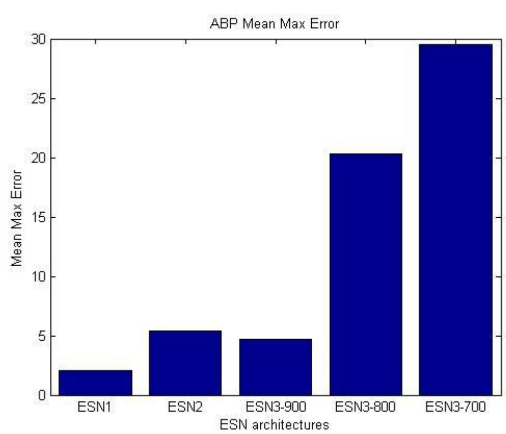

Figure 11: Marginal significance most likely driven by ESN3-800 and ESN3-700.

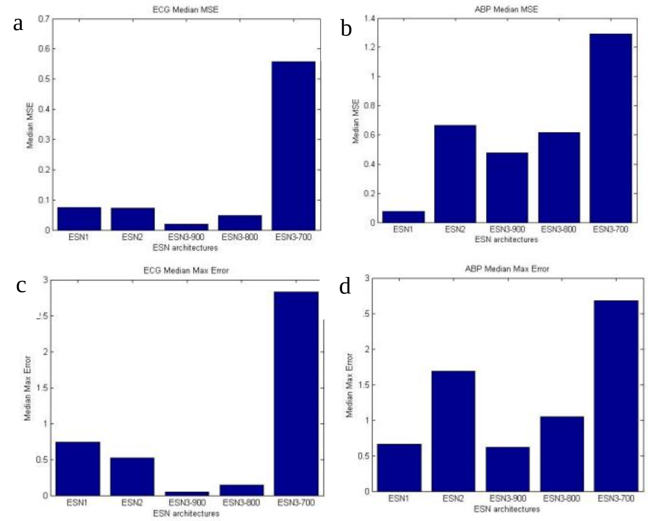

Figure 12: Median results for a) ECG MSE, b) ABP MSE, c) ECG max error, and d) ABP max error.

Table 2: ANOVA results

F-value (p-value)	ECG	ABP
MSE	1.48 (0.21)	1.19 (0.32)
Max Error	1.65 (0.17)	2.22 (0.071)

The results from the ABP max error analysis were marginally significant (p-value = 0.071), while the other evaluations were less significant. The ABP max error significance was most likely driven by the poor performance from ESN3-800 and ESN3-700 as shown in Figure 11. The ANOVA tests used factor level means for statistical comparisons which showed little statistical differences. However, there are interesting trends to note from the median metric values, Figure 12. ESN3-900 tended to predict ECG waveforms slightly better than ESN1 and ESN2. However, ESN3's performance decreased quickly with less hidden nodes. This may be due to the inability of the reservoir to correctly learn the two waveforms. In general, ESN1 gave a much better prediction for the ABP waveform, although ESN3-900 had comparable performance in terms of ABP max error predictions. These results showed that there was no significant difference in the architectures at predicting two related waveforms together. There may also be increases in performance when combining waveforms in a single reservoir that is

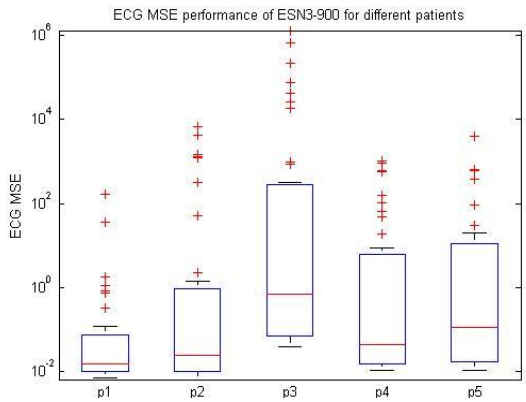

Figure 13: ECG MSE results for ESN3-900 tested with five randomly selected patients.

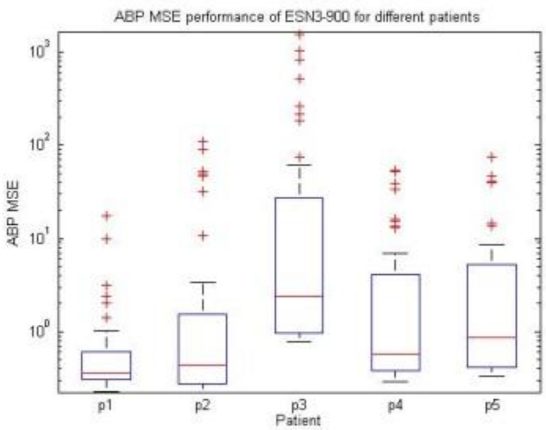

Figure 14: ABP MSE results for ESN3-900 tested with five randomly selected patients.

approximately similar in size to the two individual reservoirs. This showed the potential benefits of combining reservoirs to predict different but related waveforms.

Lastly, ESN3-900 was tested and compared using randomly sampled data from five individuals. ESN3-900 was chosen because its performance was similar to the basic ESN1 architecture and it was easier and faster to implement. The results showed that the ECG and ABP, Figure 13 and 14, performance across subjects were fairly similar, with the exception of patient 3. Though further work is needed, these results suggest that this architecture may be robust enough to be applied to different patients with little customization.

The next section will discuss these results in more detail as well as the limitations, improvements, recommendations, and further extensions and questions that can be investigated.

5. DISCUSSION

The ability to predict and classify the ECG and ABP waveforms of patients is extremely important for the medical staff in Intensive Care Units. This project approached this problem by evaluating the effectiveness of different Echo State Network (ESN) architectures at predicting ECG and ABP waveforms. The results showed that there was little significant difference in performance when predicting ECG and ABP waveforms using the different ESN architectures. However, ESN3 showed potential benefits of using one large reservoir, especially when predicting the ECG waveform. ESN3 was also test with different individuals with comparable results.

5.1 ECG versus ABP

The ESN architectures in general tended to have much better performance predicting ECG compared to ABP. This might be because the ECG waveforms have higher frequencies then the ABP waveforms. The loosely coupled subsystems in the reservoir might resonate or echo at higher frequencies better compared to lower frequencies. Furthermore, the ability of one larger reservoir to predict the waveforms was dramatically worsened as the size of the reservoir decreased. As the reservoir size decreased, the performance degradation was much more apparent with ABP then with ECG. This might also suggest that any coupling of ECG and ABP waveforms is biased toward the faster waveforms. This is an area that will require further investigation.

5.2 ESN3 Adaptability

Furthermore, analysis of ESN3-900 with five different individuals showed that this network architecture could be adaptable to different subjects. Without changing the parameters of the model, ESN3-900 resulted in similar performance for four of the five randomly selected patients. Having a model that can be applied to different patients with little or no tailoring is attractive, and can be very beneficial in developing a predictive system for hospitals.

5.3 Two versus One Reservoir

Although this project was in some sense exploratory, it does highlight some potential advantages of having one large reservoir for learning and predicting two related waveforms. The performance of ESN3-900 was comparable to ESN1 and ESN3, and was easier to implement. This analysis hints at interactions between how these waveforms are learned and stored in the reservoir. This could be investigated further and in more detail, perhaps starting with simpler, less chaotic waveforms. There are many questions to ask: for example, could initializing two reservoirs separately and then combining and reinitializing them lead to more robust internal subsystems in the reservoir? These and other queries can help further the understanding of Echo State Networks and make them more applicable for engineering and other applications.

5.4 Limitations

There are limitations associated with this project, some of which were already discussed. It would always be helpful to collect more data, test more patients, and try different combinations of waveforms (not just the ECG II and ABP waveforms). Furthermore, the parameters for each network (besides the learning rates and reservoir sizes) could be optimized more individually. This would greatly increase the number of factors to control for but with more time, a detailed factor level analysis of the network parameters would be very insightful. Data transformations of the results might also provide more normalized data. However, more research is needed to understand what these transformations mean intuitively for the results before they should be applied.

5.5 Alarm Classification

A model that can predict ECG and ABP waveforms can naturally be extended to classify waveforms and predict alarms. A model that can forecast the accuracy of ECG alarms or classify false alarms based on predicted waveforms will be extremely beneficial to medical staff, especially those in the ICU. There are several types of alarms in the ICU, each with unique waveform patterns, and this work can be extended to investigate the differences between predicted waveforms during a false alarm and a true alarm. Models that can extrapolate what a patient's waveforms will be like even a few seconds after an alarm can help medical staff and hospital systems better understand and classify alarms, with the ultimate goal of reducing false alarms, alarm fatigue, and improving patient care.

6. CONCLUSION

Alarm fatigue caused by bedside machines is a serious issue in Intensive Care Units. Part of this problem is the inability of these machines to predict and classify a patient's ECG and ABP waveforms. This study evaluated different Echo State Network architectures for predicting ECG and ABP waveforms. The results showed that a large ESN reservoir architecture, ESN3-900, that combines both waveforms had a similar performance to separate smaller reservoirs. ECG was generally predicted more accurately suggesting that the ESN with combined waveforms tended to learn the higher frequency waveform better. Furthermore, results showed the potential benefits for applying a large ESN reservoir for different individuals, which could be very helpful for hospital systems. This paper also discussed limitations of this project, as well as suggestions for future works, especially to investigate the one versus two reservoir interactions and applications for predictive alarm classifications.

7. ACKNOWLEDGEMENTS

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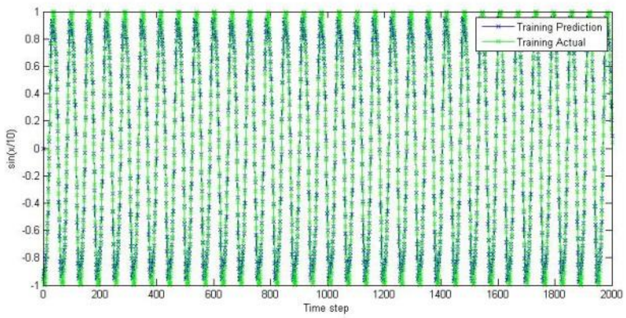
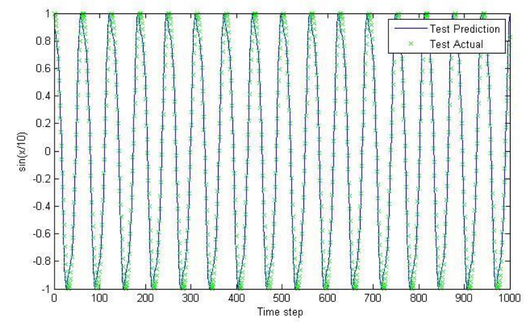
APPENDIX

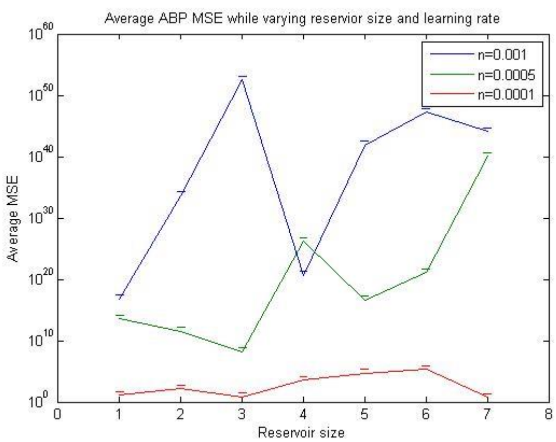
Results from sine wave predictions

This trivial example generated very low training MSE (0.0213) and test MSE (0.0250).
The parameters in this model could be optimized further, however because this was just to show a proof of concept, the parameters were not further optimized.



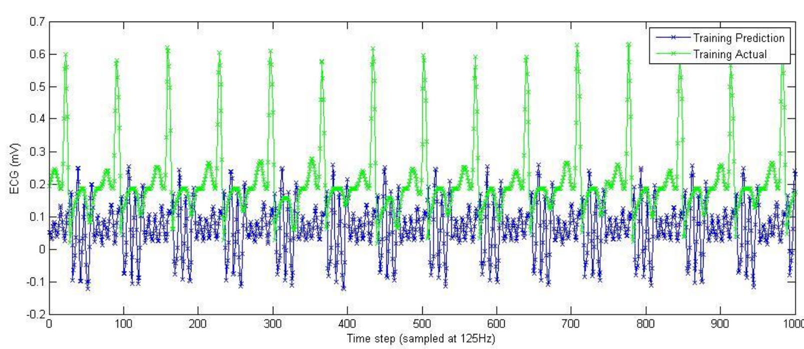


Results from testing ABP MSE for different combinations of reservoir size and learning rates

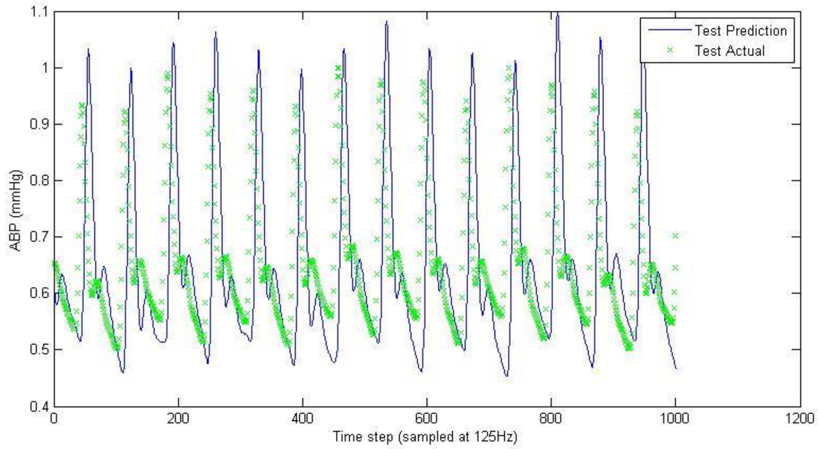


Sample test results from ESN1, ESN2, and ESN3-900 (please note that these results were selected at random and do not reflect the best performing runs)

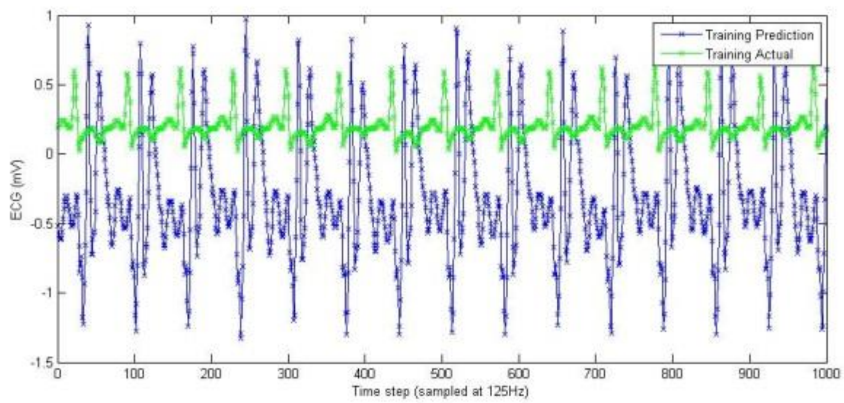
ECG_ESN1



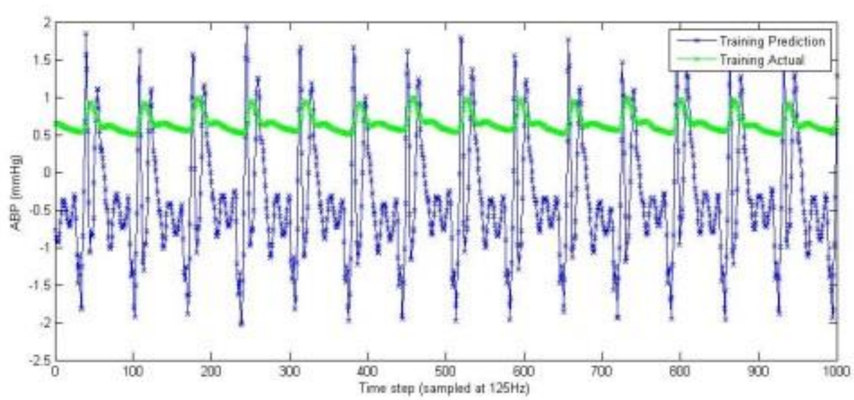
ABP_ESN1



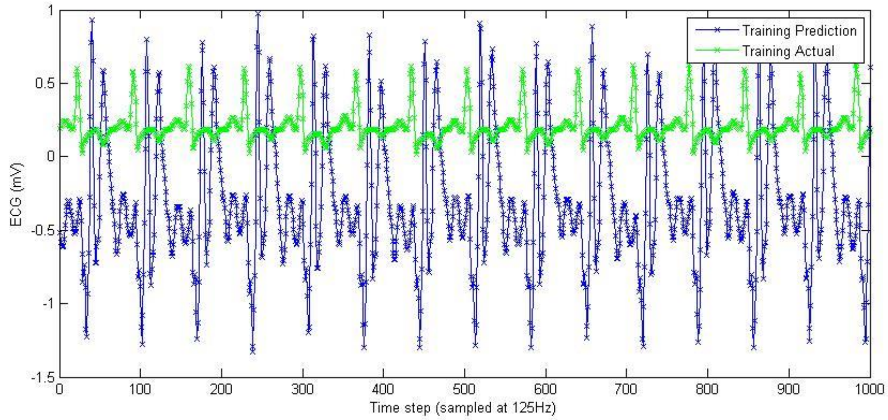
ECG_ESN2



ABP_ESN2



ECG_ESN3



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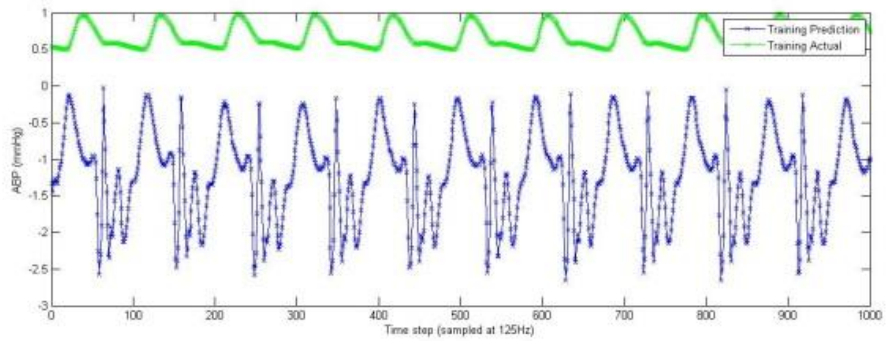
ABP_ESN3



Boxplot for ECG and ABP max error results binned by ESN architecture type