

## A Novel Deep Learning Strategy for Classifying Different Attack Patterns for Deep Brain Implants

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# A Novel Deep Learning Strategy for Classifying Different Attack Patterns for Deep Brain Implants

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**Abstract**—Deep brain stimulators, a widely used and comprehensively acknowledged restorative methodology, is a type of implantable medical device which uses electrical stimulation to treat neurological disorders. These devices are widely used to treat diseases such as Parkinson, movement disorder, epilepsy, and psychiatric disorders. Security in such devices plays a vital role since it can directly affect the mental, emotional, and physical state of human bodies. In worse case situations, it can even lead to patient's death. An adversary can inhibit the normal functionality by introducing fake stimulation inside the human brain. Nonetheless, the adversary can impair the motor functions, alter impulse control, induce pain or even modify the emotional pattern of the patient. This paper presents a deep learning methodology to predict different attack patterns in deep brain stimulators. The proposed work uses long short term memory, a type of recurrent network for forecasting and predicting rest tremor velocity (a type of characteristic observed to evaluate the intensity of the neurological diseases). The effect of deep brain stimulation was tested on Parkinson tremor patients. The proposed methodology was able to detect different types of the emulated attack patterns efficiently.

**Keywords:** security, implantable medical devices, deep brain stimulators, machine learning, deep learning

## I. INTRODUCTION

For a few decades now the electrical stimulation has been utilized to tweak the sensory and neurological system in human beings [1]. The principal reports of Deep Brain Stimulation, being utilized to treat Parkinsons Disease at Professor Benabid's facility, were distributed in 1993 despite the fact that the group had performed initial experiments in 1987 [2]. In 2002, Deep Brain Stimulators (DBS) were granted endorsement by the US Food and Drug Administration (FDA) for the treatment of Parkinson's ailment [3]. Thereafter, DBS, which utilizes a pacemaker-like gadget to convey consistent electrical stimulation inside the cerebrum, has been utilized to treat more than 100,000 individuals around the world with Parkinsons Disease and tremor. The worldwide DBS market was estimated to be around USD 618.6 million in 2014 and is expected to grow at a compound annual growth rate of over 17.0% over the next years [4]. Worldwide DBS market is expected to achieve USD 1,592.9 million by 2020, as per a review by Grand View Research, Inc [5].

Current DBS frameworks incorporate a quadripolar electrode embedded into the human cerebrum, inline expansions either running behind or embedded inside the ear, and an inside

heartbeat generator (IPG) embedded either on top of or inside the region above the chest as shown in Figure I. The patient is given a controller to turn the device on or off. Some IPGs can likewise be customized to permit the patient to change the voltage inside set points of confinement. Needless to say DBS has led to enhancements and personal life satisfaction in patient's with Parkinson disease. It has also shown tremendous efficacy for patients with movement disorders. It has been estimated that there are over 180,000 individuals in the United States below 70 years of age with Parkinson Disease [11]. Moreover, depression influences more than 18 million individuals in the United States alone [9]. Notwithstanding psychiatric disorders, DBS has additionally been proposed as a potential treatment for hypertension, obesity and dietary issues. Nonetheless, it is also being used for neurological pains and headaches [7]. Medtronic65 and Advanced Neurologic Frameworks are some of the types of frameworks which are utilized as a part of DBS.

**Security**  
A novel innovation brings with it a set of issues especially related to security. This requires training of doctors, medical attendants, and patients to learn how to deal with these unpredictable security issues in such gadgets. The ability to control the gadget, and generate stimulation, allows us to perform randomized, blinded, hybrid trials to assess the efficacy of the device [8]. With practical imaging and fundamental science systems recognizing discrete regions of the cerebrum associated with various neurological and psychiatric conditions, security to such vulnerable device plays a major role. Researchers have demonstrated that they could forge an erratic signal with radio frequency electromagnetic waves in order to hack the implants inside the body. Theoretically, a false signal, like the one they created, could inhibit required stimulation or induce unnecessary shocks in human brain [10].

The methodology proposed in this paper brain tunes DBS with the help of its own replica i.e. a biologically neural inspired model, to develop an efficient, robust and secure solution. The proposed work i.e. deep learning strategy, is inspired from biological neural networks i.e. human brain. The biological neural network comprises of interconnected neurons utilized to trade messages between one another. The interconnections have weights that can be tuned with respect to experience, thus making neural networks fit for learning [28]. The objective here is not to make practical models of the hu-

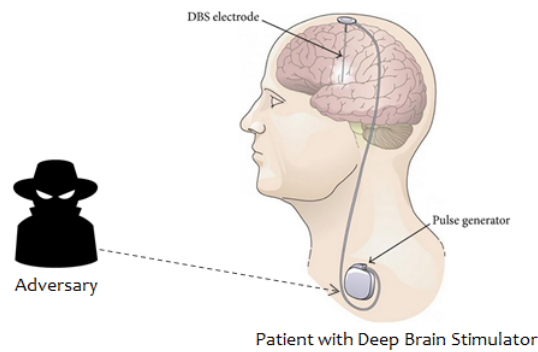


Fig. 1. Threat Model: Adversary inhibit the implanted Deep Brain Stimulators inorder to generate fake stimulations

man brain, but rather to create robust and effective information structures that we can use to model difficult problems.

This paper presents techniques to emulate attack patterns and propose deep learning strategy to classify different attack patterns for deep brain implants. The outline of the paper is as follows: Section II presents the related work on the security of implantable medical devices. Section III provides an insight on the network and attack model. Section IV presents the details on the proposed model. The section also gives the motivation for the proposed problem. Results of the proposed work is shown in Section V. Section VI concludes the paper and presents scope for future work.

## II. RELATED WORK AND BACKGROUND

Wireless Implantable Medical Devices (IMDs) have wireless capability of transmitting information. This capability provides room for the attackers to eavesdrop the information, compromise the patient's data with the intent to physically harm them by reprogramming the implanted devices [14]. For instance, an intruder can listen to an IMD's radio transmissions and can frequently learn private data with insignificant effort from his side. Such an attack can access to the data acquisition of an oscilloscope, programming radio, directional receiving wires, and other listening gears of the medical devices. A few reviews have considered such an attack of listening stealthily or eavesdropping to steal patients' information [17], [18], [23]. Besides this, another type of attack can be introduced in wireless medical devices where in the intruder has the capability to create radio transmissions tended to the IMD, or to replay recorded operations. A study performed by [23] shows that with a programmable radio, one can control an implanted defibrillator by replaying messages, thereby incapacitating modified treatments. Alternatively, it can also convey amessage to stun planned to initiate a deadly heart attack. Insulin pumps used to monitor glucose for the diabetic patients works on an open loop methodology i.e. they require patients to change the pump setting [16]. Modifying the pump settingS showed a threat vulnerability which proved to be a crucial concern for the patients. Work presented in [17] has shown comparable control over an insulin pump, including the

capacity to stop insulin or infuse enormous dosage. Another way is to dismantle the framework to control the device operation. By assessing the Java-based program provided with his own particular insulin pump, analyst Jerome Radcliffe was able to figure out the insulin pump's structure, uncovering that the pump neglected to preserve the medical information it transmitted [19]. Moreover, there may be a situation which is much more coordinated where the attacker can be both near the patient and the device programmer. Even during the setting or modifying of the IMD code for security, software/hardware engineer or health care professional can install a malign code to give excess dosage in case of medical devices. IMDs should address the above mentioned threat vulnerabilities to ensure safety, security, availability and privacy for the patients. Thus, these medical devices should be secure to capture any sort of threat that can be injurious for the health of the patients.

There are a number of diverse solutions which address the security issues in wireless IMDs [28]. Bio-metric based approaches access the unique physiological characteristics of the human body and provide authentication. Though the mechanism is secure and lightweight, the scheme lacks to accommodate the changes of bio-metric with respect to time. Distance based approaches estimate the physical distance between the IMD and the caregiver by utilizing the transmitted and received transmission in proximity through piezoelectric elements [20], Diffie Hellam protocol [21], and near field communication [22]. The scheme fails since the attacker can make a physical connection with the patient by approaching in near proximity, thus leading to weak authentication. Key management protocols are used for providing authentication to the authorised users using symmetric [23], public key [24] and physiological [25] signals for the generation of keys. Key management protocols are less reliable and incur extra waiting time for the authentication. Additionally, anomaly detection mechanism such as deep learning [28] and support vector machines [27], [29] have been used for determining the dosage pattern for the insulin pump security. External device methodologies employ extra devices to be worn to provide authentication such as IMDGaurd [34], MedMon [35], Cloaker [36] and IMDShield [37]. These methodologies not only require extra gadget to be carried besides the wireless medical device, but also consume battery life of the medical device. Additionally, the adversary can come close to the patient and disrupt the functionality of the device. Besides this, there are a diverse set of the conventional schemes utilized for overcoming attacks in wireless medical devices [30]- [33]. Several other papers (e.g., [ [38]- [40]]) studied related security issues to such gadgets.

This paper presents a fast and efficient model for improving the security issues in deep brain stimulators with the help of human inspired model, viz deep learning strategy. More specifically, it plans to achieve the following research objectives:

- Design and train a Long Short Term Memory (LSTM) classifier to predict consecutive deep brain stimulation pattern.

- Emulate different types of attack patterns and classify them in deep brain implants, i.e., determine or classify the type of attack strategy that can be used by the attacker. More specifically, a prediction mechanism is developed by emulating different attack patterns that can be utilized by the attacker.

III. NETWORK AND ATTACK MODEL

A. Adversary Model

Neural implants such as Deep Brain Stimulators (DBS) are intended to stimulate certain regions of the brain for the treatment of various chronic diseases. DBSs are implanted to treat diseases such as Parkinsons disease, chronic pain, and other therapeutic conditions such as tremors, movement disorders, and psychiatric treatment. In the near future, DBSs hold the potential to be ubiquitous, mechanically fit, thereby addressing more extensive clinical needs [11]. As this happens addressing brain implants security turns out to be a key challenge. For instance, patients may endeavor to self-endorse raised states of mind or expanded initiation in the cerebrum, or programmers may endeavor to program the stimulation treatment. However these perfectly valid actions may breach the integrity property of the device. Moreover, the attacker can damage the brain cells or can cause diverse neural pathways by inserting the mind with arbitrary stimulation signals. On the other hand, attacker may remotely keep the gadget from working as designed to diminish availability property. Besides that, the risk escalates if the patient is receiving treatment on more sensitive condition such as depression.

B. Problem Statement

The primary goal of deep brain stimulators is to superimpose a stimulation pattern over the patient’s chronic pain pattern and to establish a correct stimulation waveform with the help of specified stimulation parameters such as amplitude, pulse width, effective or ineffective stimulation etc. Figure 2 shows a typical continuous stimulation waveform given to DBS.

When an external reader attempts to connect with an IMD,

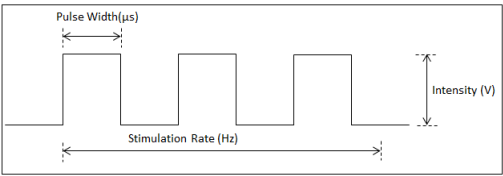


Fig. 2. Stimulation Waveform in DBS

authentication followed by communication between the IMD and the reader is made. In such cases, the attacker can modify the stimulation pattern in order to introduce acute stimulation pattern inside the human brain. The attacker can introduce different types of stimulation parameters to disrupt the normal functionality of the DBS. This paper emulates different types of attack strategies by changing the patterns of pulse width,

stimulation rate, intensity etc. It then studies the pattern of rest tremor velocity (a type of characteristic observed to evaluate the intensity of the neurological diseases) based on the pattern of introduced attack strategies.

IV. PROPOSED WORK

A. Motivation

Biological systems have caught the attention of scientific community in diverse fields such as computer science, mechanical, agriculture, energy etc [26]. One basic question which arises: What can we learn from what we observe in the nature? Bio-inspired systems refer to applying concepts from biology domain regarding body and brain operation to practical problems in other domains such as security and intrusion prevention. Biologically inspired approaches seem promising and are considered stronger in comparison to any other system. It can be observed that, in contrast to the existing models which require regular updating, replacement, nourishing, bio-inspired models maintain themselves and even learn during changing conditions. Therefore, engineers and scientists of diverse domains are engaging themselves in investigating innovative design architectures to resolve different challenges. In the near future we may even create machines that repair themselves, like the way skin recuperates over an injury. The future of engineering lies in the development of flexible, self-healing bio-inspired models.

B. Recurrent Neural Network

Deep learning, a type of biologically inspired model, is a special branch of machine learning used to understand the inbuilt patterns in the information. Deep learning comprises of neural network training which conditions the available data by calibrating the weights and input data with the help of an activation function. This paper uses recurrent neural network which permits the information to persist. With recurrent neural network, the input data is passed into a cell, which besides outputting the activation function, passes the output as a feedback to the cell. Long Short Term Memory (LSTM) network is a type of recurrent neural network which stores the information for longer period of time. LSTM, with the help of Keep Gate or Forget Gate, decides which data to keep, or remove from the recurring data. Those gates either block or pass on the information received based on its strength. This action, similar to neural networks, is done by filtering with their own sets of weights. Those weights, like the weights that modulate input and hidden states, are adjusted via the recurrent networks learning process. That is, the cells learn when to allow data to enter, leave or be deleted through the iterative process of making guesses, backpropagating error, and adjusting weights via gradient descent.

Figure 3 shows the schematic diagram of a simple recurrent neural network and LSTM neural network. LSTMs memory cells give different roles to addition and multiplication in the transformation of input. The central plus sign (additional node) helps them preserve a constant error when it must be back-propagated at depth. Instead of determining the subsequent cell

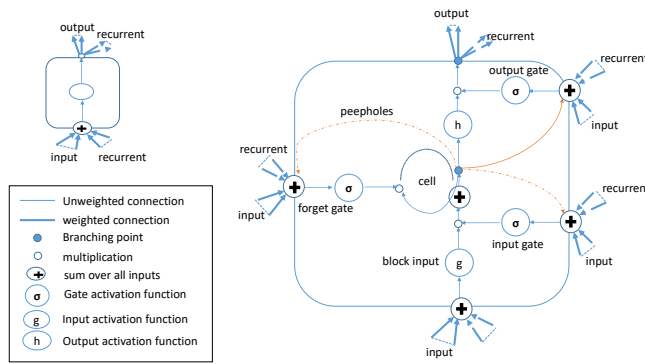


Fig. 3. Detailed Schematic of Simple Recurrent Neural Network and Long Short Term Memory Neural Network (Reproduced from [42])

state by multiplying its current state with new input, they add the two. Different sets of weights filter the input data for input, output and forgetting gates. The forget gate is represented as a linear identity function, because if the gate is open, the current state of the memory cell is simply multiplied by one, to propagate forward one more time step.

### C. LSTM for Parkinson Disease

This paper has two contributions. First, we design and train a LSTM classifier to predict consecutive deep brain stimulation patterns for all the patients. Secondly, we emulate and predict different types of attack patterns in deep brain implants for individual patients. By doing so we can determine the type of attack strategy that can be used by the attacker. More specifically, a prediction mechanism is developed by emulating different attack patterns to change brain stimulation parameters which can be utilized by the attacker for deep brain implants.

1) *Multivariate LSTM Forecast Model for all Patients:* The essential objective of programming the neurostimulators is to superimpose the stimulation or paraesthesia design over the patient to set up the right stimulation waveform. Every patient requires a unique stimulation pattern to help control their pain. The classification task involves predicting the genuine or fake stimulation of deep brain stimulators from the data obtained from Physionet [43]. To evaluate the performance of the proposed approach, experiments were ran on following 10 features. A typical brain stimulator has following parameters which are used to control individual pain [44]:

- *Stimulation Target:* Parkinson's disease which receives chronic high frequency electrical deep brain stimulation (DBS) in one of three targets viz: the ventro-intermediate nucleus of the thalamus, the internal Globus pallidus, or the subthalamic nucleus.
- *Stimulation Rate:* Frequency (Hz) of effective stimulation ( $> 100$  Hz).
- *Intensity:* It is experienced by the patient as the strength of the paraesthesia, measured in volts (V). It can be set from 0 to 10.5 V, depending on the patients needs.
- *Pulse Width:* A measure in microseconds ( $\mu s$ ) of the duration of a pulse. In general, the wider the pulse

width, the larger the tissue area being stimulated, and the stronger the sensation of paraesthesia. For neuro-stimulation, the pulse width is normally set at  $180 \mu s$ .

- *Mode:* Various stimulation alternatives can be utilized to enhance comfort, increment battery life, and modify the stimulation design. For instance: the continuous mode conveys continuous electrical stimulation to the chosen nerves over a drawn out timeframe on 24 hour basis. After the patient gets accustomed to the vibe of stimulation, the cycling mode is generally modified in light of the fact that it might fundamentally expand battery life, while regulating pain. The cycling mode consequently invigorates for indicated ON and OFF duty cycle e.g., 30 seconds ON and 30 seconds OFF.
- *Electrode selection:* This includes bipolar or unipolar stimulation.
- *Patient information:* 16 subjects with Parkinson's disease in the age group of 37-68 are studied.
- *Code:* Two conditions of deep brain stimulators are studied viz with medication (11) and without medication (10).
- *Rest Tremor Velocity (RTV):* It is defined as the tremor which occurs when the muscles are not being voluntarily moved. The recordings in this database are of RTV in the index finger.

Figure 4 shows the plot with 10 subplots of Parkinson tremor data for each stimulation parameter. The Parkinson tremor dataset from Physionet is used to frame a forecasting problem where, given the stimulation conditions and RTV for a time period  $T$ , we forecast the stimulation condition and RTV at  $T + \delta T$ . For this study,  $T$  and  $\delta T$  are set to 1 second. The training makes the classifier learn the consecutive stimulation pattern.

In this study, as seen in Figure 4, we can analyze the pattern of deep brain stimulation. Here, we frame the supervised learning problem as predicting the RTV at the current second ( $t$ ) given the RTV measurement and DBS parameters conditions at the prior time step. The training is made on 8760 samples and validated on 164638 samples. Also, the features are normalized to fed into the network. Finally, the stimulation parameters inputs (X) are reshaped into the 3D format expected by LSTMs, namely [samples, timesteps, features]. The LSTM is defined with 50 neurons in the first hidden layer and 1 neuron in the output layer for predicting RTV. The input shape is of 1 time step with 9 features. We used mean absolute error loss function and the efficient Adam version of stochastic gradient descent. The model is fitted for 50 training epochs with a batch size of 72. For this study we calculate the loss between the actual stimulation parameter and the predicated consecutive stimulation parameter as shown in Figure 8.

2) *Predicting the Rest Tremor Velocity by Emulating Different Attack Pattern:* Adversary can apply different attack strategies as explained in Section V in order to change the behaviour of the patient using DBS. In order to study the effect of deep brain stimulation on amplitude and frequency characteristics of rest tremor in Parkinsons disease [41], dif-



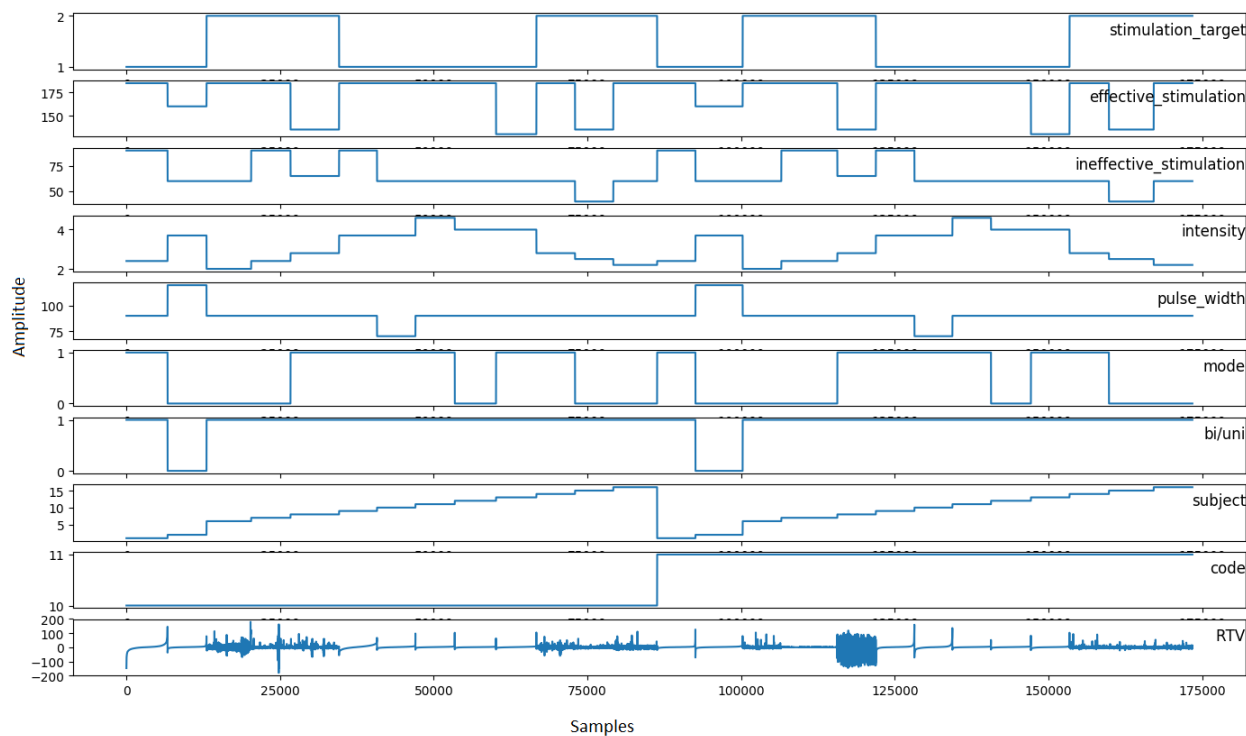


Fig. 4. Line Plots of Parkinson Tremor Stimulation Pattern for Different Subjects

ferent attack strategy was carried out. RTV generally has a frequency of about 46 Hz for controlled neurological patients. It is considered as the main characteristic to be measured for DBS implanted patients. Besides this, in [41], authors have studied four more tremor characteristics. These are:

- *Amplitude*: It is defined as the root mean square of the RTV signal. The increase in the RTV amplitude is considered as the sign of abnormality. For each patient, for our study, we computed the amplitude for next 100 steps (i.e. RTV for nearly 1 min).
- *Amplitude Fluctuations*: It is defined as the variability of the RTV amplitude. Increasing scores indicate that tremor amplitude is fluctuating over time and is considered as a sign of abnormality.
- *Spectral Concentrations*: It is measured by the concentration of power in a narrow frequency range which is set as 100 for our study. Decreasing scores are sign of abnormality.
- *Median Frequency*: Median RTV is calculated for every 100 samples (1 min). Decreasing values are sign of abnormality.

For this study, besides RTV, we also calculated aforementioned tremor characteristics to feed in the LSTM for training and predicting purposes. Once the attack is classified, a warning is given to the patient about the attack to check the settings

of the brain stimulation and change accordingly.

For this study, the data is transformed and loaded from the CSV file to the array that feeds in the LSTM. The Keras LSTM layers take the **numpy** array of 3 dimensions ( $N, W, F$ ) where  $N$  is the number of training sequences,  $W$  is the sequence length and  $F$  is the number of features of each sequence. For this paper,  $W$ (read window size) is set as 50 which allows the network to get glimpses into the shape of the RTV at each sequence. This process enable us to build up a pattern of the sequences based on the prior window received. The sequences themselves are sliding windows and hence shift by 1 each time, causing a constant overlap with the prior windows. We used 1 input layer (consisting of a sequence of size 50) which feeds into an LSTM layer with 50 neurons, that in turn feeds into another LSTM layer with 100 neurons which then feeds into a fully connected normal layer of 1 neuron with a linear activation function. These steps will be used to give the prediction of the next time step. We used 1 training epoch with this LSTM. With this 1 epoch, an LSTM will cycle through all the sequence windows in the training set once. At each time step, we then pop the oldest entry out of the rear of the window and append the prediction for the next time step to the front of the window, in essence shifting the window along so that it slowly builds itself with predictions, until the window is full of only predicted values. In our case, as our

window is of size 50 this would occur after 50 time steps. We then keep this up indefinitely, predicting the next time step on the predictions of the previous time steps, to see an emerging trend. We limited our prediction sequence to 50 future time steps and then shifting the initiation window by 50 each time, in effect creating many independent sequence predictions of 50 time steps.

## V. PERFORMANCE EVALUATION

The hardware used for the training phase was nvidia GPU card and Windows 7 operating system with nvidia Cuda 7.5 as the general software architecture. For data preparation, training, and evaluating deep neural networks, the Keras [48] framework with Theano [49] backend was used. The section presents the data analysis of Parkinsons disease patients and the results for the proposed work. It presents the study of Parkinsons disease patients with and without the stimulation.

### A. Data Analysis and Insights from Physionet Data

Among all the features, Rest Tremor Velocity (RTV) is the most important feature for evaluating the Parkinson tremor intensity. It is considered as the first sign of neurological disorder. RTV value is negligible or close to zero for normal individuals and controlled Parkinson disease patients. Figure 5 shows the frequency of RTV values for patient 'G' from the physionet dataset. It is observed that the RTV is generally close to zero when the DBS is controlled with genuine stimulations.

The RTV for a Parkinson disease patient is shown in

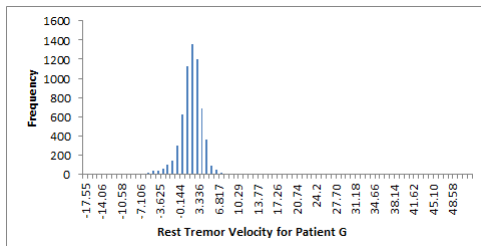


Fig. 5. Patient G Rest Tremor Velocity Analysis: With stimulation on and medication on, RTV is close to zero (No attack)

Figure 6 on various conditions viz.: stimulation on, medication on; stimulation on, medication off; and stimulation off and medication off. It can be inferred from the figure that after the DBS implantation, the RTV is controlled and the value is mostly close to zero as compared to other conditions.

### B. Adversary Attack Strategies

The adversary can employ different types of attack strategies [45] in deep brain stimulators. We have emulated different attack strategies by changing the learnt stimulation pattern from study 1. The different attack strategies are:

- *Spike (Single Acute Spike Attack)*: Spike attack strategy, as shown in Figure 7(a), are multiple data points with a much greater expected rate of change. These pattern can be caused by multiple acute intensity pulses targeted to the patient.

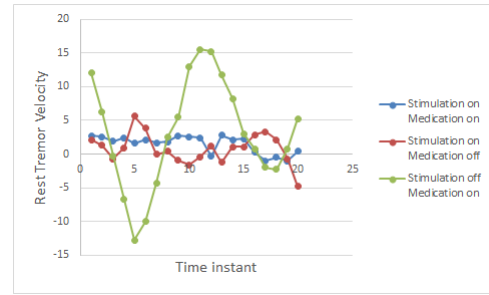


Fig. 6. Rest Tremor Velocity of a Parkinson Disease Patient g2 for 20 sec (stimulator implanted in the Globus pallidus)

- *Outlier (Multiple Overdose Attack Strategy)*: Outlier attack strategy produces discontinuous acute stimulation which produces the rest tremor velocity pattern shown in Figure 7(b). It can be caused by high intensified pulse at discontinuous stimulation rate.
- *Stuck At Attack Strategy*: Stuck-at attack strategy, as shown in Figure 7(c) also make RTV experience zero variation for unexpected lengths of time, which can be caused by increased pulse width for a definite amount of time.
- *Incremental (Increasing Attack Strategy)*: RTV pattern shows a increasing trend with the increased stimulation rate, as shown in Figure 7(d).
- *Chronic (Incremental Decremental Attack Strategy)*: Chronic attack strategy looks similar to incremental attack strategy with the continuous form of increase and decrease in the RTV pattern, as shown in Figure 7(e).
- *Noise (Arbitrary Attack Strategy)*: Noise faults make RTV values experience unexpectedly high variation, which can be due to hardware failure caused by the adversary (See Figure 7(f)).
- *Unusual Attack Strategy*: The unusual attack pattern can be caused by the adversary by arbitrary changing the intensity, pulse width, stimulation rate and intensity of the DBS. Here, the RTV pattern shows an arbitrary form.

The observable pattern of these attacks can be pictorially represented in Figure 7:

### C. Performance Metrics

The following performance evaluation metrics are used to validate the proposed work.

- **Training Loss**: It is the average loss during the epoch between real RTV and predicted RTV.
- **Validation Loss**: It is the average loss after the end of the epoch.
- **Training Duration**: Amount of time required to learn and train the classifier for different attack strategies.

### D. Results

For study 1, we calculate the Root Mean Squared Error (RMSE) to find the error between the predicted and actual value of RTV. Figure 8 plot shows the train and test loss during

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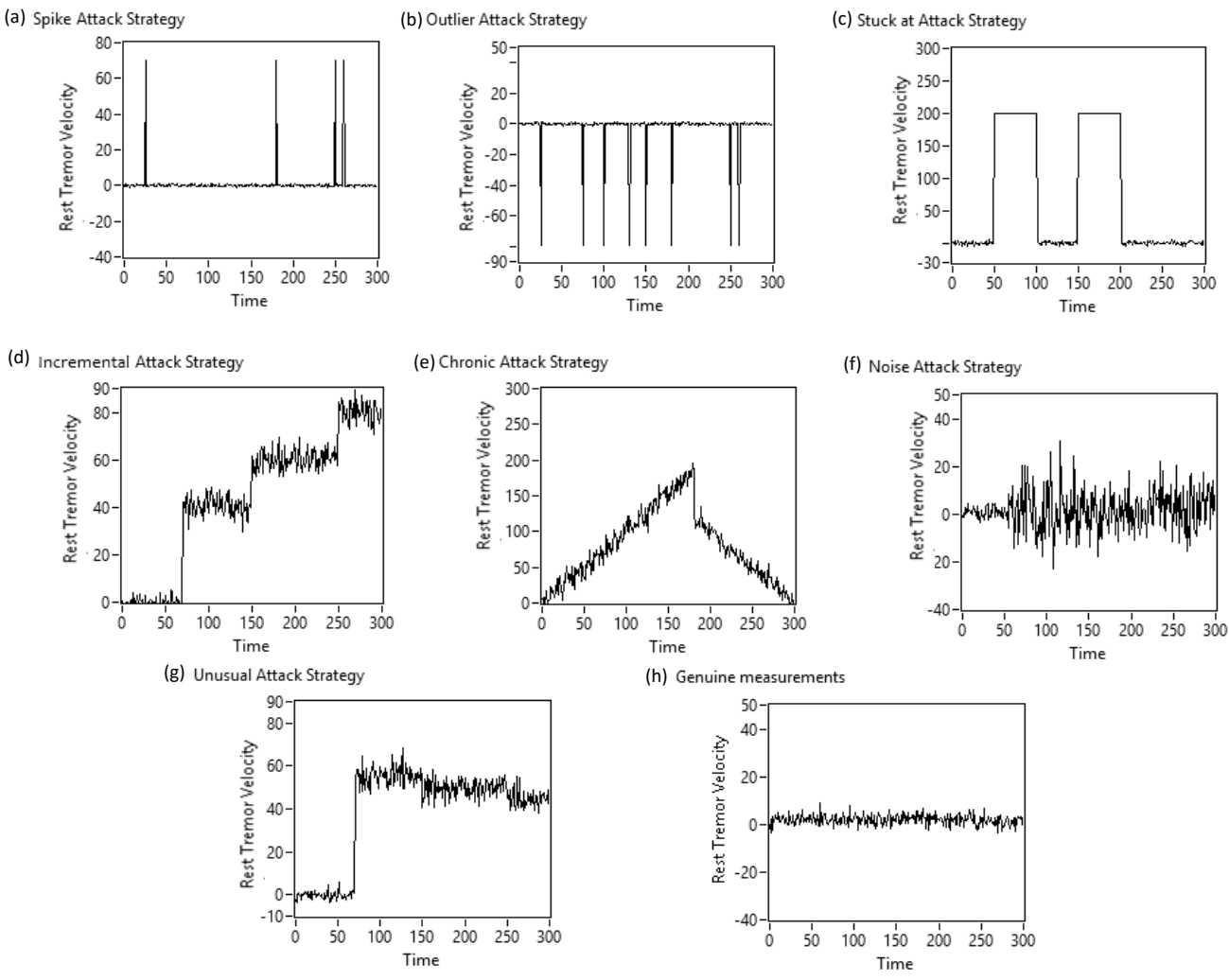


Fig. 7. Emulating Different Attack Strategies in Deep Brain Implants: The emulated pattern is made by changing the deep brain parameters such as stimulation rate, intensity, pulse width, mode etc. RTV is the observable pattern or outcome of simulations.

training. As seen from figure, the loss between the predicted and actual data is minimal. Also, the model achieved RMSE as 0.095.

For study 2 (introducing attack strategies), we predict RTV and calculate amplitude, amplitude fluctuations, spectral concentrations and median frequency to feed them as features to LSTM. LSTM detects abnormality in the RTV, by observing the signals of amplitude, amplitude fluctuations, spectral concentrations and median frequency, (which is calculated by observing next 100 time steps). LSTM is used here to predict the next epoch (50 steps forward). Figure 9 shows the predicted and true attack RTV data values 50 time step ahead at each step in time for 700 steps. It can be inferred from the figures that inspite the emulated attack strategy, LSTM is able to predict the genuine RTV values after introducing attack patterns in the network. Table I shows the training loss, validation loss and training duration for different types of attack strategy for deep brain implants. It can be seen for con-

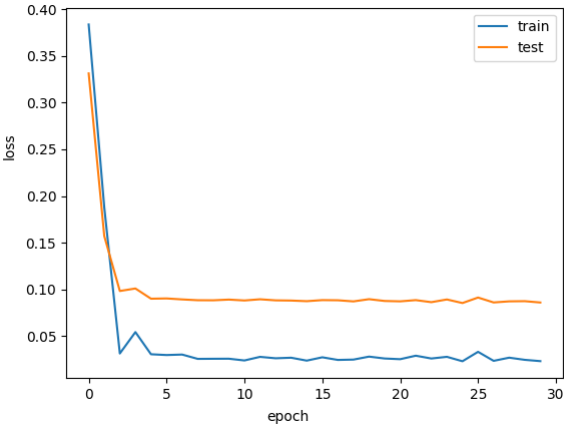


Fig. 8. Loss Plot of the Actual Stimulation Parameter and the Predicated Consecutive Stimulation Parameter



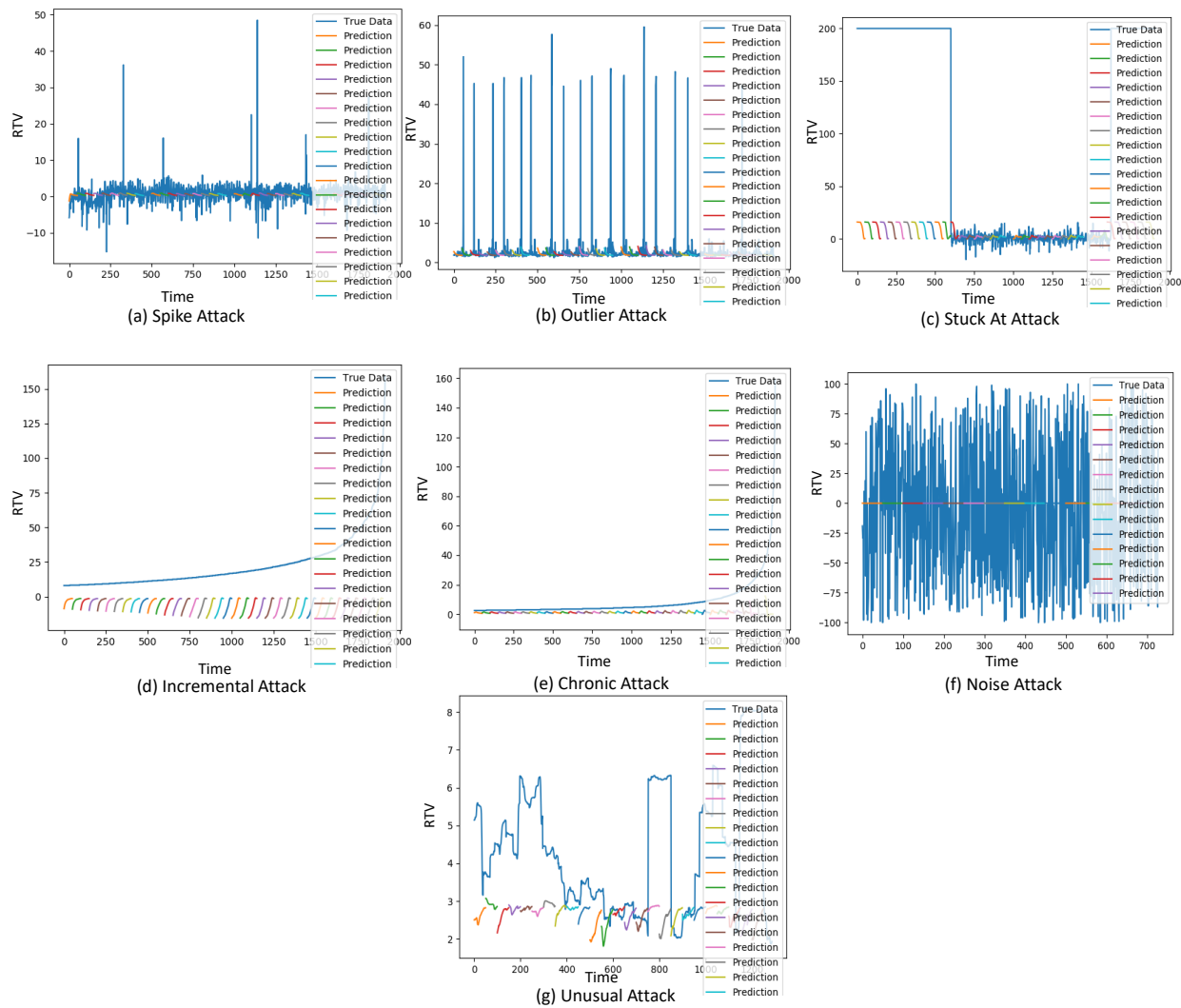


Fig. 9. Emulating Different Attack Strategy in Deep Brain Implants: epochs = 1, window size = 50, sequence shift = 50

tinuous and single pulse attack patterns such as spike, outlier, incremental, chronic, the loss values were less in comparison to the discontinuous and arbitrary attack patterns(stuck-at and noise). Stuck-at and noise attack pattern showed the maximum loss values since they require more training as the pattern is hard to be predicted. As seen from the results, the classifier

disease patient is warned about the attack and notified to change the current stimulation parameters set. In other words, whenever the predicted RTV and the true RTV exhibited a difference, a flag was raised and consecutive iterations was studied to predict the emulated attack.

## VI. CONCLUSIONS

Deep brain stimulators (DBS), a type of wireless implantable medical device, treats neurological disorders by giving stimulations inside the patients brain. DBS have progressively benefited patients, yet they have posed in parallel certain security implications. Security for such devices is important since they can directly affect the mental and physical orientation of patients. This paper utilizes Long Short Term Memory, a type of recurrent neural network, to predict and forecast the pattern of DBS. Rest Tremor Velocity (RTV) is examined to study the intensity of neurological disorders. For this, we studied and examined RTV values to design and train the neural network. Various attack patterns were introduced

TABLE I  
PERFORMANCE EVALUATION FOR DEEP BRAIN IMPLANTS

Attack	Training-Loss	Validation-loss	Training Duration
Spike Attack	56.87	239.48	84.28
Outlier Attack	60.47	43.67	81.9 7
Stuck at Attack	13120.94	27.24	199.77
Incremental Attack	22.67	176.65	80.101
Chronic Attack	122.66	3.36	79.49
Noise Attack	2839.15	3473.6162	80.07
Unusual Attack	388.07	44.65	79.86

was able to classify the emulated attack strategies in the deep brain implants. As soon as the attack is detected, the Parkinson

in the DBS framework to emulate and classify different attack strategies. The results show that the model was able to classify different attack patterns in the DBS with smaller loss values and minimal training time.

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REFERENCES

[1] Long, D.M., 1977. Electrical stimulation of the nervous system for pain control. *Electroencephalography and clinical neurophysiology*. Supplement, (34), pp.343-348.

[2] The Parkinson's Appeal for Deep Brain Stimulation, "History of deep brain stimulation".

[3] Gardner, J., 2013. A history of deep brain stimulation: Technological innovation and the role of clinical assessment tools. *Social studies of science*, 43(5), pp.707-728.

[4] Market Research Report, 2015. "Deep Brain Stimulators (DBS) Market Analysis By Application (Pain Management, Epilepsy, Essential Tremor, Obsessive Compulsive Disorder, Depression, Dystonia, Parkinsons Disease) And Segment Forecasts To 2020".

[5] Grand View Research, 2015. "Deep Brain Stimulators Market Worth \$1.6 Billion By 2020".

[6] Dorsey, E., Constantinescu, R., Thompson, J.P., Biglan, K.M., Holloway, R.G., Kieburtz, K., Marshall, F.J., Ravina, B.M., Schifitto, G., Siderowf, A. and Tanner, C.M., 2007. Projected number of people with Parkinson disease in the most populous nations, 2005 through 2030. *Neurology*, 68(5), pp.384-386.

[7] Leone, M., Franzini, A., Felisati, G., Mea, E., Curone, M., Tullo, V., Broggi, G. and Bussone, G., 2005. Deep brain stimulation and cluster headache. *Neurological Sciences*, 26, pp.s138-s138.

[8] Keller, M.B., 2004. Issues in treatment-resistant depression. *The Journal of clinical psychiatry*, 66, pp.5-12.

[9] Schwab, J.M. and Hamani, C., 2008. The history and future of deep brain stimulation. *Neurotherapeutics*, 5(1), pp.3-13.

[10] Archimedes, <https://www.youtube.com/watch?v=Fmflaz06ig>, 2017.

[11] Denning, T., Matsuoka, Y. and Kohno, T., 2009. Neurosecurity: security and privacy for neural devices. *Neurosurgical Focus*, 27(1), p.E7.

[12] Rathore, H., 2016. Artificial Neural Network. In *Mapping Biological Systems to Network Systems* (pp. 79-96). Springer International Publishing.

[13] Rathore, H., Mohamed, A., Al-Ali, A., Du, X. and Guizani, M., 2017, June. A review of security challenges, attacks and resolutions for wireless medical devices. In *Wireless Communications and Mobile Computing Conference (IWCMC)*, 2017 13th International (pp. 1495-1501). IEEE.

[14] Ankarali, Z.E., Abbasi, Q.H., Demir, A.F., Serpedin, E., Qaraqe, K. and Arslan, H., 2014, November. A comparative review on the wireless implantable medical devices privacy and security. In *Wireless Mobile Communication and Healthcare (Mobihealth)*, 2014 EAI 4th International Conference on (pp. 246-249). IEEE.

[15] Halperin, D., Heydt-Benjamin, T.S., Ransford, B., Clark, S.S., Defend, B., Morgan, W., Fu, K., Kohno, T. and Maisel, W.H., 2008, May. Pacemakers and implantable cardiac defibrillators: Software radio attacks and zero-power defenses. In *2008 IEEE Symposium on Security and Privacy* (sp 2008) (pp. 129-142). IEEE.

[16] Burleson, W., Clark, S.S., Ransford, B. and Fu, K., 2012, June. Design challenges for secure implantable medical devices. In *Proceedings of the 49th Annual Design Automation Conference* (pp. 12-17). ACM.

[17] Li, C., Raghunathan, A. and Jha, N.K., 2011, June. Hijacking an insulin pump: Security attacks and defenses for a diabetes therapy system. In *e-Health Networking Applications and Services (Healthcom)*, 2011 13th IEEE International Conference on (pp. 150-156). IEEE.

[18] Paul, N., Kohno, T. and Klonoff, D.C., 2011. A review of the security of insulin pump infusion systems. *Journal of diabetes science and technology*, 5(6), pp.1557-1562.

[19] Radcliffe, J., 2011, August. Hacking medical devices for fun and insulin: Breaking the human SCADA system. In *Black Hat Conference presentation slides* (Vol. 2011).

[20] Halperin, D., Heydt-Benjamin, T.S., Ransford, B., Clark, S.S., Defend, B., Morgan, W., Fu, K., Kohno, T. and Maisel, W.H. "Pacemakers and implantable cardiac defibrillators: Software radio attacks and zero-power defenses". In *Security and Privacy, 2008. SP 2008. IEEE Symposium on* (pp. 129-142). IEEE, 2008.

[21] Rasmussen, K.B., Castelluccia, C., Heydt-Benjamin, T.S. and Capkun, S. "Proximity-based access control for implantable medical devices". In *Proceedings of the 16th ACM conference on Computer and communications security* (pp. 410-419). ACM, 2009.

[22] Kim, B., Yu, J. and Kim, H. "In-vivo nfc: Remote monitoring of implanted medical devices with improved privacy". In *Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems* (pp. 327-328). ACM, 2012.

[23] Halperin, D., Heydt-Benjamin, T.S., Ransford, B., Clark, S.S., Defend, B., Morgan, W., Fu, K., Kohno, T. and Maisel, W.H. "Pacemakers and implantable cardiac defibrillators: Software radio attacks and zero-power defenses". In *IEEE Symposium on Security and Privacy* (sp 2008) (pp. 129-142). IEEE, 2008.

[24] Singh, K. and Muthukkumarasamy, V., "Authenticated key establishment protocols for a home health care system". In *Intelligent Sensors, Sensor Networks and Information, 2007. ISSNIP 2007. 3rd International Conference on* (pp. 353-358). IEEE, 2007.

[25] Zheng, G., Fang, G., Shankaran, R., Orgun, M.A. and Dutkiewicz, E. "An ECG-based secret data sharing scheme supporting emergency treatment of implantable medical devices". In *Wireless Personal Multimedia Communications (WPMC), 2014 International Symposium on* (pp. 624-628). IEEE, 2014.

[26] Rathore, H., 2016. Bio-inspired Approaches in Various Engineering Domain. In *Mapping Biological Systems to Network Systems* (pp. 177-194). Springer International Publishing.

[27] X. Hei, X. Du, S. Lin, I. Lee, and O. Sokolsky, "Patient Infusion Pattern based Access Control Schemes for Wireless Insulin Pump System," *IEEE Transactions on Parallel and Distributed Computing*, Vol.26, no. 11, pp. 3108-3121, 2015.

[28] H. Rathore, A. Al-Ali, A. Mohamed, X. Du and M. Guizani, "DLRT: Deep Learning Approach for Reliable Diabetic Treatment", in *Proc IEEE Globecom*, 2017.

[29] X. Hei, X. Du, S. Lin, and I. Lee, "PIPAC: Patient Infusion Pattern based Access Control Scheme for Wireless Insulin Pump System", in *Proc. of IEEE INFOCOM*, 2013.

[30] X. Hei, and X. Du, "Biometric-based Two-level Secure Access Control for Implantable Medical Devices during Emergency", in *Proc. of IEEE INFOCOM*, 2011.

[31] X. Du, Y. Xiao, M. Guizani, and H. H. Chen, "An Effective Key Management Scheme for Heterogeneous Sensor Networks", *Ad Hoc Networks, Elsevier*, Vol. 5, no 1, pp 2434, 2007.

[32] X. Hei, X. Du, J. Wu, and F. Hu, "Defending Resource Depletion Attacks on Implantable Medical Devices," in *Proc. IEEE GLOBECOM*, 2010.

[33] X. Du, M. Guizani, Y. Xiao and H. H. Chen, "A Routing-Driven Elliptic Curve Cryptography based Key Management Scheme for Heterogeneous Sensor Networks", *IEEE Transactions on Wireless Communications*, Vol. 8, No. 3, pp. 1223 - 1229, 2009.

[34] F. Xu, Z. Qin, C.C. Tan, B. Wang, and Q. Li, "IMDGuard: Securing implantable medical devices with the external wearable guardian". In *Proc. IEEE INFOCOM*, pp. 1862-1870, 2011.

[35] M. Zhang, A. Raghunathan, and N.K. Jha, "MedMon: Securing medical devices through wireless monitoring and anomaly detection". *IEEE Transactions on Biomedical circuits and Systems*, Vol. 7, no. 6, pp. 871-881, 2013.

[36] T. Denning, K. Fu, and T. Kohno, "Absence Makes the Heart Grow Fonder: New Directions for Implantable Medical Device Security". In *HotSec*, 2008.

[37] Gollakota, S., Hassanieh, H., Ransford, B., Katabi, D. and Fu, K. "They can hear your heartbeats: non-invasive security for implantable medical devices". *ACM SIGCOMM Computer Communication Review*, 41(4), pp. 2-13, 2011.

[38] Y. Xiao, V. Rayi, B. Sun, X. Du, F. Hu, and M. Galloway, A Survey of Key Management Schemes in Wireless Sensor Networks, *Journal of Computer Communications*, Vol. 30, Issue 11-12, pp. 2314-2341, Sept. 2007.

- [39] X. Du, M. Guizani, Y. Xiao, and H. H. Chen, Secure and Efficient Time Synchronization in Heterogeneous Sensor Networks, *IEEE Transactions on Vehicular Technology*, Vol. 57, Issue 4, pp. 2387-2394, July 2008.
- [40] X. Du and H. H. Chen, Security in Wireless Sensor Networks, *IEEE Wireless Communications Magazine*, Vol. 15, Issue 4, pp. 60-66, Aug. 2008.
- [41] Beuter, A., Titcombe, M.S., Richer, F., Gross, C., Guehl, D., 2001. Effect of deep brain stimulation on amplitude and frequency characteristics of rest tremor in Parkinson's disease. *Thalamus and Related Systems*, Volume 1 (3): 203211 (published by Elsevier Science).
- [42] <https://deeplearning4j.org/lstm.html> [accessed on 18/10/2017]
- [43] <https://physionet.org/physiobank/database/tremordb/>
- [44] <http://www.functionalneurosurgery.net/programmingofneurostimulationdevices.htm> [accessed on 10 May, 2017]
- [45] Rathore, H., Badarla, V. and Shit, S., 2016. Consensus-aware sociopsychological trust model for wireless sensor networks. *ACM Transactions on sensor networks (TOSN)*, 12(3), p.21.
- [46] Heida, T., Wentink, E.C. and Marani, E., 2013. Power spectral density analysis of physiological, rest and action tremor in Parkinsons disease patients treated with deep brain stimulation. *Journal of neuroengineering and rehabilitation*, 10(1), p.70.
- [47] <http://www.jakob-aungiers.com/articles/a/LSTM-Neural-Network-for-Time-Series-Prediction>
- [48] F. Chollet, "Keras: Theano-based deep learning library". Code: <https://github.com/fchollet>. Documentation: <http://keras.io>, 2015.
- [49] The Theano Development. "A Python framework for fast computation of mathematical expressions". arXiv preprint arXiv:1605.02688, 2016.



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