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Essential Tremor Severity Classification using a Multi-layer Perceptron and the TETRAS Scale*

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***Abstract*—Essential tremor (ET) is the most prevalent type of movement disorder responsible for inducing tremor in an individual's limbs. Various scales, such as the Fahn-Tolosa-Marin (FTM) tremor rating scale and The Essential Tremor Rating Assessment Scale (TETRAS), have been developed and used by physicians to classify the severity of ET. While the FTM scale is highly utilized in ET severity diagnosis, it relies on subjective assessments of the tremor. TETRAS, on the other hand, provides a more quantitative analysis of ET severity by ranking the severity of the tremor based on tremor magnitude. However, TETRAS requires a trained professional (such as a neurologist) to be present, and even in such cases, physicians use TETRAS as a metric baseline to visually approximate the severity of the tremor. In this pilot study, a deep neural network (DNN)-based scale is developed to accurately classify ET severity without the presence of trained experts. To validate the developed DNN-based ET classification scale, a preliminary experiment is performed on a single healthy participant during a leg extension exercise. Tremor was artificially induced at the knee using a motorized lower-limb exoskeleton. To enable near real-time ET classification and to enable rapid DNN response, the DNN assessed the severity of ET every 0.5 seconds; utilizing the previous 0.5 seconds of knee-angle data for DNN training and ET severity classification. The results of the preliminary experiment showed that the DNN achieved a training accuracy of 94.80% and a validation accuracy of 95.18%. Additionally, the DNN achieved a training accuracy of 93.63% and a validation accuracy of 94.05% using computer generated knee-angle measurements.**

I. Introduction

Essential tremor (ET) is the most common type of movement disorder that causes tremor, characterized by rhythmic and involuntary shaking of an individual's limbs during task specific actions [1–3]. The diagnosis of ET severity often relies on subjective methods, such as simple clinical observation, standardized rating scales, or the subjective assessment of drawn figures [4]. One of the earliest and most commonly used scales for classifying the severity of ET is the Fahn-Tolosa-Marin (FTM) tremor rating scale, which establishes a metric baseline for physicians to visually approximate the severity of ET [5]. Yet, despite the wide use of FTM in tremor severity diagnosis, FTM spans a smaller range of tremor amplitudes, potentially resulting in a ceiling effect in studies involving more severe ET [6]. A more contemporary ET classification scale is The Essential Tremor Rating Assessment Scale (TETRAS), which addresses the limitation of the FTM scale by allowing physicians to visually approximate the severity of ET across a broader spectrum of tremor amplitudes [7–9]. Another approach to classify ET severity involves having a participant draw spirals on a paper and rating the tremor based on the individual's ability to draw a perfect spiral [4], [10], [11]. Despite their common usage, these ET severity classifiers are highly subjective and inconsistent due to the potential for clinician bias and misdiagnosis. In fact, the misdiagnosis rate has been reported to range between 37%-50% [12], [13]. Consequently, limitations of existing tremor rating scales, such as the FTM and TETRAS, are that they require the expertise of a clinician and still result in poor tremor classification. An open problem is the development of a quantifiable, accurate, and repeatable tremor classification scale that can be implemented without trained expertise.

Quantitative classification of ET requires wearable sensors that can be used to measure the motion of the affected limbs. The use of wearable sensors, such as inertial measurement units and gyroscopes, have allowed quantitative measurements of ET by converting task specific motion into time-series based signals [14–19]. These quantitative measurements allow the use of statistics, machine learning, and, due to tremors being quasi-sinusoidal movements, power spectral techniques to aid the diagnosis of ET severity and to help differentiate between Parkinsonian tremor and ET [20–26]. Additionally, electromyography (EMG) sensors can monitor the nerve's stimulation of the muscle to detect tremor activity [27].

Driven by advancements in Artificial Intellegence (AI), the widespread adoption of neural networks (NNs) for classifying and assessing tremors is evident in the work of numerous researchers [25], [26], [28–32]. These NN-based classifiers employ a variety of NN architectures, including convolutional NNs, artificial NNs, and long short term memory to identify and diagnose various tremors. Most notably, these classifiers utilize affordable and readily available wearable sensors (i.e., accelerometers from smartphones) to collect time-series data for training and classifying tremors with NNs, highlighting the validity and extensive research into the use of wearable sensors and machine learning techniques for tremor classification and its potential application to daily life. Moreover, the implementation of AI-driven ET diagnostics can enhance teleoperative approaches in ET diagnosis by enabling individuals with ET to receive treatment and ET diagnosis from the comfort of their

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homes. However, despite extensive research, there is currently no DNN-based approach capable of rapid diagnosis (i.e., 0.5 second increments) of ET severity using TETRAS to the best of the authors' knowledge. In this pilot study, a multi-layer perceptron, that is trained using 0.5 second incremented time series signals obtained from simulations and experiments, is developed to accurately and objectively classify the severity of ET. Moreover, by eliminating subjectivity in the diagnosis of ET severity, the outcomes of this study will improve the classification of individuals with ET before developing one's treatment plans. Notably, the proposed DNN classifier excels in its ability to classify in real-time, delivering assessments every 0.5 second. Unlike previous classification methods that analyze tremor severity during post-processing, this rapid approach offers near real-time insights into the variability of tremor during treatments that may require constant monitoring of the severity of tremor [33]. To elaborate, rapid severity diagnosis of ET will provide clinicians with an increased understanding of the temporal pattern of ET in the context of daily life and activities [33]. Furthermore, near real-time tremor classification capabilities can have extensive applications; for instance, real-time tremor classification can serve as a tool to facilitate novel anti-tremor medications and tremor suppression treatments, and can serve as a categorical factor during a statistical analysis, all of which may need continuous ET severity diagnosis.

II. Material and Methods

A. Participants

A single able body subject (23 year old male) participated in this pilot study. Prior to participation, written informed consent was obtained from the participant, as approved by the institutional review board at Auburn University (protocol #23-100 MR 2303).

B. Tremor analysis

ET severity can be classified based on the tremor's frequency and amplitude. In most cases, the tremor frequency for ET occurs at a frequency band between 4-12 Hz, with more intense ET typically exhibiting a lower frequency band of 4-8 Hz [34–36]. TETRAS, a scale used to assess the severity of ET based on tremor amplitude, assigns higher scores to tremors with greater amplitudes to indicate a more severe tremor. Specifically, TETRAS comprises of nine items, each rated individually from 0 to 4, with 0 indicating no tremor and 4 indicating the most severe tremor. These nine items include head tremor, face tremor, voice tremor, lower limb tremor, and handwriting induced tremor, among others. In this work, a DNN classifier will be trained to classify ET using only the lower limb metric of TETRAS. Table I outlines the amplitudes employed by TETRAS to classify the severity of lower limb tremor. Although TETRAS provides a comprehensive evaluation of ET severity based on tremor amplitude, it lacks a distinct evaluation of tremor frequency across different ET severities. Therefore, ET frequencies were assigned using findings from [34]. It is important to note that TETRAS characterizes patients with ET only; therefore, the scale does not assess drug induced tremor, rest tremor, or Parkinsonian Tremor.

Table I
TETRAS Scale for Lower Limb ET

Rating	Lower Limb Tremor Amplitude*
0	none
1	< 0.5 cm
2	$0.5- < 1$ cm
3	$1- < 5$ cm
4	≥ 5 cm

This table depicts the metric measurements of lower limb ET amplitude for different severities.
*The lower limb ET amplitude is measured bilaterally through heel-shin movement. Scoring is based on the difference between the highest and lowest amplitude during the entire tremor cycle.

C. Signal Generation for Simulation

A data set composed of 25,000 leg extension signals was generated to train the DNN classifier. Since the pilot study focuses on lower limb ET during leg extensions, each signal represents knee angle measurements between the vertical axis and the shank of the leg, as illustrated in Fig. 1. These signals are sinusoidal with a frequency of 0.2 Hz and maximum/minimum angles of 70 degrees and 0 degrees, respectively. To ensure rapid DNN response and to mimic the sampling frequency of the exoskeleton testbed, each signal had a sampling frequency of 200 Hz over a 0.5 second interval, resulting in a total of 101 samples per signal. Additionally, an auxiliary ET signal was incorporated into the aforementioned signals to simulate ET during leg extensions. The ET signals followed a sinusoidal trajectory, and are scaled based on the severity criteria outlined in Table I. To account for the frequencies associated with different ET severities, ET signals with greater amplitudes (indicating more severe ET) were given lower frequencies, consistent with the findings in [34]. The generated signals, denoted as $\phi \in \mathbb{R}^{101}$, are defined as

$$\phi_i = (35 - 35\cos(P + 0.4\pi t_i)) + \sin^{-1}\left(\frac{A\sin(2\pi\sigma t_i)}{2L}\right),$$

where ϕ_i is the i^{th} element of ϕ, $i \in \mathbb{Z}$ takes values from 0 to 100 such that $i \in [0, 100]$, $t_i = 0.005i$ is the time index that ranges from 0 and 0.5 seconds, $P \in \mathbb{R}_{\geq 0}$ is the phase of the signal which has a value randomly selected from 0 to 2π such that $P \in [0, 2\pi]$, $A \in \mathbb{R}$ is the amplitude associated with the ET signal, randomly selected based on the criteria in TETRAS, $\sigma \in \mathbb{R}$ denotes the frequency of the ET signal, selected based on the randomly selected tremor amplitude, and $L \in \mathbb{R}$ is the length of the leg. Subsequently, the signals were labeled based on the severity of the tremor to represent the true tremor classification.

D. Experimental Testbed

The lower limb exoskeleton used in this pilot study was an Ekso Bionics Indego exoskeleton as depicted in Fig. 1. Adjustments were made to the lower-limb exoskeleton to

Figure 1. Exoskeleton testbed used to simulate tremor and to measure the knee joint angle (θ in the image).

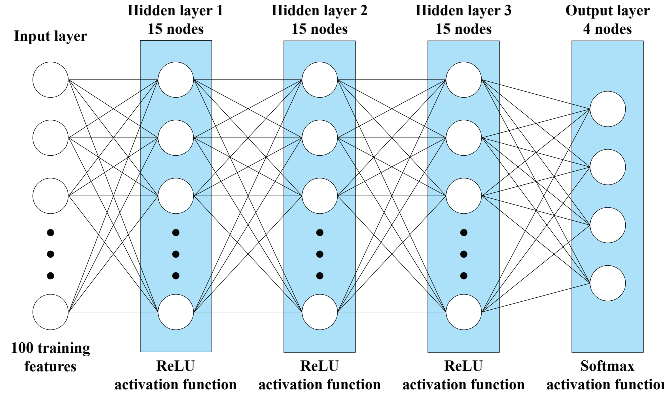

Figure 2. The structure of the DNN consists of three hidden layers, each with 15 nodes and employing rectified linear (ReLU) activation functions. These layers are connected sequentially to the output layer, which consists of four nodes, each employing a softmax activation function. Each node in the output layer represents the severity of ET.

guarantee user comfort and to facilitate pure rotation about the knees. Optical encoders, positioned at both knees, are capable of measuring the angular displacements between the vertical axis and the shanks of both legs, as illustrated for the left leg in Fig. 1 as θ.

E. Experimental Protocol

The participant was asked to extend their left knee to near full extension over a duration of approximately 2.5 seconds and to flex their knee back to the initial position over another duration of approximately 2.5 seconds for a knee extension and flexion frequency of 0.2 Hz. The total experimental run time was 200 seconds, which led to approximately 40 leg extension repetitions. To simulate a tremor, a sinusoidal input with an amplitude and frequency obtained from the TETRAS scale and [34] was injected into the motor at the knee. An optical encoder measured the angle of the knee during the knee extension and flexion movements and captured the knee angle measurements at 200 Hz. While the encoder captured the knee movements, the motor inputs intended to simulate tremor where simultaneously recorded. Similar to the generated simulation signals, the encoder measurements were separated into 0.5 second intervals in real-time for a total of 101 samples per training feature. The encoder measurements were then used to train and test the DNN classifier.

F. Neural Network Structure and Training

Fig. 2 depicts the DNN architecture used to classify ET in this pilot study. The DNN structure is a multi-layer perceptron consisting of three sequentially connected hidden layers that take 101 knee angle measurements as the inputs. Weights and biases are implemented at each layer of the DNN, where the outputs of each of the hidden layers are fed through a rectified linear activation function. Each hidden layer contained 15 neurons, a ReLU activation function, and was connected to the next layer. To compute the confidence and classify the severity of ET, the outputs of the output-layer vector had 4 elements that were fed into a softmax activation function. The DNN $f : \mathbb{R}^{101} \to \mathbb{R}^4$ can be defined as

$$f = \sigma_4 \left(W_4 \sigma_3 \left(W_3 \sigma_2 \left(W_2 \sigma_1 \left(W_1 x + b_1 \right) + b_2 \right) + b_3 \right) + b_4 \right)$$

where $\sigma_4 : \mathbb{R}^4 \to \mathbb{R}^4$ is the activation function associated with the output layer, $W_4 \in \mathbb{R}^{4\times15}$ are the output layer weights, $b_4 \in \mathbb{R}^4$ are the output layer biases, $W_3, W_2 \in \mathbb{R}^{15\times15}$ are the hidden layer weights, $b_3, b_2 \in \mathbb{R}^{15}$ are the hidden layer biases, $\sigma_3, \sigma_2, \sigma_1 : \mathbb{R}^{15} \to \mathbb{R}^{15}$ are the hidden layer activation functions, $W_1 \in \mathbb{R}^{15\times101}$ is the input layer weights, $b_1 \in \mathbb{R}^{15}$ is the input layer biases, and $x \in \mathbb{R}^{101}$ is a vector of inputs of the DNN and represents the knee angle measurements. The value of each element in the output layer ranges from 0 to 1 and corresponds to the severity of the ET. To be specific, the first element of the vector indicates level 0-1 ET severity while the final element indicates level 4 ET severity according to TETRAS. The element with the greatest value indicates the estimated severity of the ET. Categorical cross-entropy was selected as the loss function for the DNN, and the Adam optimizer algorithm was used to train the DNN. A total of 300 epochs and a batch size of 101 was selected to train the DNN using the simulation data. For the experimental data, a batch size of 70 was used, instead. To monitor the performance and prevent over-fitting, the data was randomly split where 75% of the training data was used to train the DNN, while the remaining 25% of the data was used to validate the DNN.

III. Evaluation of the Deep Neural Network

As previously mentioned, the purpose of this pilot study is to classify the severity of ET in near real-time using a multi-layer perceptron. Results using the simulation and experimental data to train the DNN classifier are detailed below.

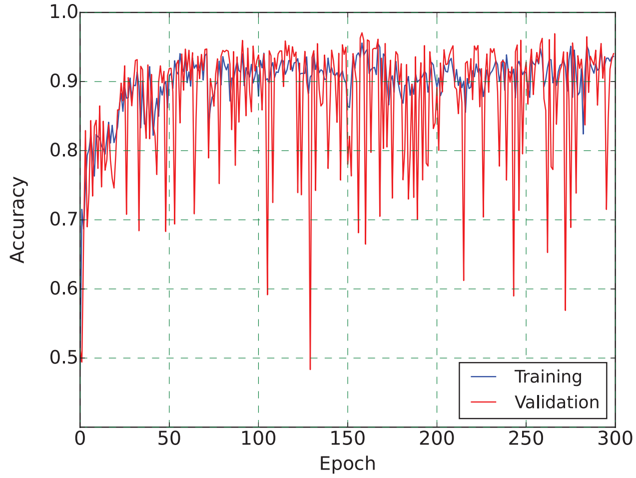

Figure 3. Simulation DNN Model Performance: this figure depicts the training and validation accuracy of the DNN for each training epoch. The DNN model achieved a 93.63% training accuracy and a 94.05% validation accuracy. The blue line indicates the training accuracy per training epoch and the red line indicates the validation accuracy per training epoch.

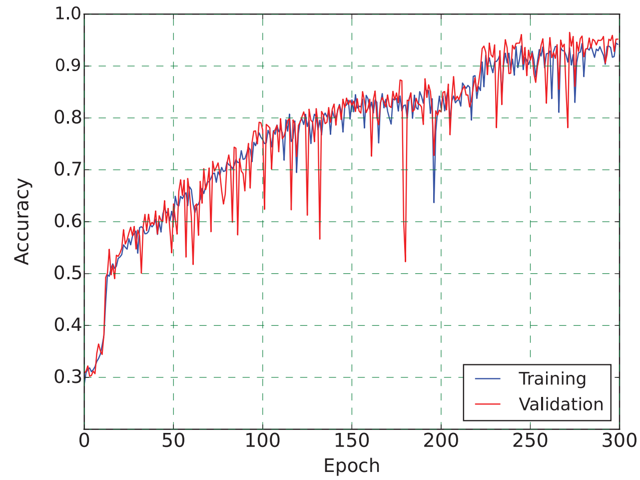

Figure 4. Experimental DNN Model Performance: this figure depicts the training and validation accuracy of the DNN for each training epoch. The DNN model achieved a 94.80% training accuracy and a 95.18% validation accuracy. The blue line indicates the training accuracy per training epoch and the red line indicates the validation accuracy per training epoch.

A. Simulation Results

Knee angle measurements that were created and ranked using the criteria obtained from TETRAS was used to train the DNN. Fig. 3 depicts the training and validation accuracy of the DNN trained using simulation data per training epoch. After 300 training iterations, the model achieved a 93.63% training accuracy and a 94.05% validation accuracy.

B. Experiment Results

To validate the effectiveness of implementing a DNN to classify the severity of ET, shank-angle measurements were taken from an encoder located at the left knee of the exoskeleton testbed. An artificial tremor was injected into the left knee motor of the exoskeleton and ranked using TETRAS. Fig. 4 depicts the training and validation accuracy of the DNN trained using experimental data per training epoch. After 300 training iterations, the model achieved a 94.80% training accuracy and a 95.18% validation accuracy.

IV. Discussion

The proposed DNN classifier, which was trained using experimental data from a single able bodied subject, has proven effective in classifying ET severity, with simulation results indicating a 93.63% training accuracy and experimental results showing 94.80% accuracy. Although the proposed TETRAS-based classifier demonstrates good training and validation accuracies, data obtained from a single test subject may limit the generalizability of the DNN, impeding its classification ability for a broader population. Hence, to enhance the DNN's generalizability and to cater to a wider demographic, a more diverse training data set will be created in the future by including data from additional participants, particularly those diagnosed with lower limb ET. Moreover, since the DNN was trained using a simulated and experimental data sets, combining the computer generated signals with the encoder measurements could further diversify the data set, further enhancing the generalizability of the DNN classifier. Additionally, employing different DNN training methodologies and architectures, such as implementing a dropout layer in the DNN, could help improve the generalizability of the DNN. These approaches aim to improve the model's effectiveness throughout a broader population.

It should be mentioned that the DNN exhibited better performance (i.e., training accuracy and validation) when the experimentally recorded signals were used to train the DNN. Despite potential noise and biases introduced by sensor measurements, this improvement in performance may be credited to the data-processing techniques applied to the sensor data prior to inputting it into the DNN. In actuality, research has indicated that a DNN's performance is influenced by the characteristics of the signals used for training [37], [38]. Consequently, the DNN may have demonstrated improved performance due to the application of a zero order hold on the knee encoder which, in turn, introduced discretized sensor data to the input of the DNN.

It's important to note that while tremors are characterized as sinusoidal oscillations in this pilot study, research suggests that ET signals exhibit asymmetric, quasi-sinusoidal patterns [11], [39]. This asymmetry can be attributed to various factors in the leg, such as differing joint stiffness across the joint space and the viscoelastic effects of the leg. This can be addressed by leveraging the generalizability of DNNs as the quasi-sinusoidal features may be captured in the experimental data. Moreover, the use of 0.5 second increments might not provide sufficient time for the asymmetric tremor behavior to be expressed within the signal, which may result in a more sinusoidal pattern for each training feature. Nonetheless, future efforts will incorporate the varying parameters of the leg as inputs, such as joint stiffness, enhancing the categorical performance of the DNN.

V. Conclusion

This study marks the initial phase in the creation of an AI driven tremor classification system capable of diagnosing the severity of ET continuously without the presence of a physician, furthering the implementation of remote in ET diagnosis and treatment. Specifically, this study demonstrates the feasibility of continuously identifying the severity of lower limb tremors in near real-time succession (i.e., 0.5 second increments) when using encoder measurements and computer generated signals as inputs to the DNN. Moreover, TETRAS was utilized to establish a metric benchmark for creating accurate training labels and data, facilitating effective DNN training. Given an ample amount of training data, this rapid response in diagnosing the severity of ET holds promise for advancing the classification and treatment of ET by eliminating clinician bias and providing clinicians a temporal understanding of an individuals ET. Beyond computer generated signals, This study demonstrates the DNN's effectiveness in classifying the severity of lower limb ET using signals obtained from an exoskeleton encoder. Future work will extend the results to classify additional items included in TETRAS such as upper limb tremor, and additional experiments will be performed using participants with ET.

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