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MusTENG: A Wearable Triboelectric Nanogenerator for Personalized Rehabilitation of Children with Cerebral Palsy

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Abstract

Cerebral palsy (CP) is a cognitive disorder in which a child's brain cannot send direct messages to the muscles of a body resulting in impaired motor functions. It is the most common childhood disability that affects up to 3.6 of 1000 kids in the United States. Health professionals currently provide a standard physical therapy plan that has proven to not significantly help. They lack the ability to distinguish the severity level and what is happening at the anatomy of a cerebral palsy patient. This leads to two main problems: without detailed information on which muscles are underperforming, children with cerebral palsy are not getting the most optimal exercises. The second challenge is that there is no method for tracking a child's progress because visual improvement can take months to even years.
This project's system presents a novel approach using a wearable Triboelectric Nano sensor that converts movement from a microscopic level into electricity. The sensors are utilized on the leg, where it gets readings from the three main muscles: quadriceps, hamstrings, calves. An autoencoder neural network machine learning algorithm is run on the data of a simulated cerebral palsy patient and compared to a patient without a disability to determine the severity and location of the spasticity. To test the accuracy of the system a series of comprehensive experiments were run where the sensors readings were compared to muscle tension. Ultimately this system achieved a greater than 83% accuracy in determining muscle spasticity in all 3 leg muscles. To test the applicability of the system, walk testing was conducted where the system was successfully able to give a complete analysis of a simulated Cerebral Palsy patient. With the accurate analysis, personalized exercises are given through a game to ensure the patient's motor functions are improved faster than standard physical therapy.

Keywords: Cerebral Palsy, Triboelectric Nanogenerator, Nanotechnology, Wearable Sensor

1. Introduction

Cerebral palsy is a group of movement-based disorders that primarily appears in childhood. It is caused by abnormal brain development or brain damage in which parts of the brain that work on the body's mobility, posture, and balance underperform. The core of the problem is that a child with CP's brain that controls the basic motor functions of a child sends mixed and delayed signals affecting the way a child moves. About 3.6 of 1000 children develop some type of cerebral palsy in early childhood making cerebral palsy the most common disorder among children.

A child with CP can face numerous symptoms including weak muscles, muscle tension, and tremors. Around ⅓ of all CP patients face severe symptoms such as seizures and lack of thought and reasoning. There are five main types of cerebral palsy: spastic, mixed, athetoid, hypotonic, and finally ataxic. Among all cases 77% are spastic otherwise known as hypertonic cerebral palsy. Spastic cerebral palsy is

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caused by damage to the brains motor cortex and pyramidal tracts which relays signals to the muscles. That specifically causes the muscles of a child to experience a problem known as hypertension, which is when the muscles are extremely tight and have a overload of tension. Some of the common symptoms of spastic cerebral palsy include abnormal walking, involuntary movements, contractures, and stiffness. There is no cure for cerebral palsy, but with the right treatment which can include physical therapy, medicine, and surgery a child can reach a near normal adult life. Physical therapy has proven to be one of the most effective sources of treatment for CP patients as it helps strengthen muscles and joints, reinforcing the patient's stability and positioning. Spasticity can be reduced by performing exercises regularly.

1.1. Challenges with Physical Therapy

Even though physical therapy is at the forefront of treatment for CP patients, it has a couple of main pain points. The first is the classification of the problem, because physical therapists use a basic evaluation method to determine which muscles need to be worked on and with what exercises. The problem with this method is that professionals lack data to corroborate their visual analysis, which can lead to misclassification and ineffective treatment. For CP patients it is vital to find the exact muscles that are under-forming and by how much to make sure exercises are not over-strain and counterproductive. The second problem with the current physical therapy for CP is there is no method for tracking progress and improvement which prevents the patient and professional from knowing if the treatment is truly helping and which exercises are helping the most. All these problems come from the inability to track muscle spasticity in a CP patient. The third problem with current physical therapy treatment for CP patients is therapist variation. A therapist often can have differing opinions to other therapists based on their individual analysis. Leading to incorrect and inconsistent exercise regimes and patterns for CP patients. Finally, the fourth problem with current physical therapy is the substantial cost. Year round for a child with cerebral palsy the family must pay up to $20,000. This is simply not sustainable for all families especially for kids with the disorder in 3rd world or developing countries. The high and increasing cost of physical therapy is preventing kids and adults with challenges such as CP right now from getting the care they need and deserve.

1.2. Existing Technologies

There are a variety of products available for improving the current process of treatment for children with Cerebral Palsy. Many of them track a CP patient's gait movements such as X sense, which is currently being used in very high-end therapy centers around the world. X sense gives the unique advantage of tracking the way a CP patient walks. It uses a 3D imaging system to model and analyze a child's gait (walking pattern). Another commonly used device or system used for treatment is the Opto-electronic system. Similarly, to the X sense system it tracks the gait or movement of a child with cerebral palsy. However instead of using a motion sensor approach it uses 12 precise cameras and machine learning. Some other commonly used medical devices to treat CP patients include devices like apple watches which track heart rate and steps.

1.3. Challenges with Existing Technology

Currently, there are limited solutions for evidence-based analysis of CP patients and the fundamental problem of gathering quantifiable muscle spasticity data for improvement of rehabilitation is unsolved

a. The current systems available for CP patients such as Xsense and Optoelectronic lack the ability to track a patient's muscle tension and spasticity.
b. All current technology is highly expensive and infeasible for many CP patients.
c. All the current and upcoming technology is focused on tracking how a patient walks which is not getting at the core of the problem caused by Cerebral Palsy which is the increased muscle tension.

Table 1: Limitations of existing technologies in quantifying muscle spasticity

Technology	Observation	Challenges
Opto-electronic system (Macintosh, A., et. al. 2021)	Detailed gait analysis of a CP patients using high resolution cameras and machine learning	Very expensive and not feasibly applicable to all CP patients daily. Also lacks the ability to track muscle tension
Activity Sensors (Sharan, D., el. al. 2016).	Activity trackers used movement patterns and gather data such as steps, and heart rate.	Does not directly target rehabilitation for CP patients due to the lack of data on muscle spasticity and tension.
Xsense (https://www.xsens.com/)	Xsense is a product to track a full body gait movement. Modeling system to recreate movements in a 3D platform.	Lacks the ability to track muscle tension and provide quantifiable data on the CP patient. Also does not provide direct biofeedback to patients to improve rehabilitation.

1.4. Objectives

The objective of the project is to develop a complete system for evidence-based analysis of a Cerebral Palsy patient using a custom-made sensor and machine learning algorithms. Furthermore, the project's overarching goal is to make the physical therapy process for children with CP more quantitative rather than qualitative. More specific objectives pertaining to the project include high accuracy rates in determining spasticity, a reliable physical therapy game, and a low cost yet highly reliable triboelectric sensor.

1.5. Hypothesis

The proposed system for improving CP therapy will achieve a greater than 80% accuracy in determining spasticity in the 3 major leg muscles. The sensor will reliably be able to convert muscle movements into electricity, which will be used for data. The proposed solution will create a closed loop system for physical therapy that can measure the spasticity in all 3 leg muscles at the same time and collect data that can be used to improve physical therapy.

2. Materials and Methods

Based on the research the problem that needed to be solved was determining personalized muscle spasticity data in patients with Cerebral Palsy. As seen in the previous section there's no cost-effective technology that can solve the problem today. Also, based on scientific literature personalized data and a biofeedback loop has been demonstrated to show improvement in CP patients.

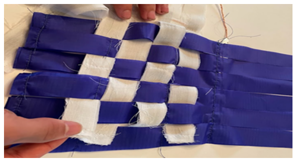
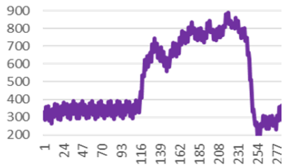
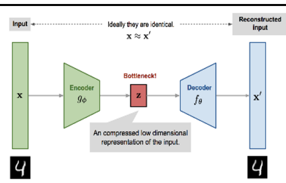
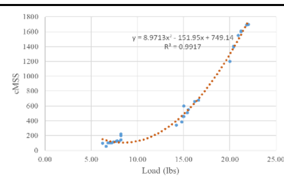
To tackle this rather large problem, the solution (method) was broken into four main parts. First, was to design a wearable custom Triboelectric Nanogenerator. This sensor is worn by the patient, and it generates continuous readings of muscle movement. Second, is data collection using the sensor for normal muscle movement and spastic movements. Third, is train an 1D convolutional autoencoder neural network and establish a baseline through the data. Finally fourth, the sensor values of a simulated CP patient will be compared to the baseline where the algorithm will produce a personalized muscle spasticity score.

To bring the entire solution together, the solution applies the sensor ability by simulating different types of CP patients, analyzing the individual muscles, developing a targeted exercise plan, and finally incorporating it all into an interactive game.

3. Sensor Development

The triboelectric effect is a type of contact electrification in which certain materials become electrically charged after coming into contact with another different material and are then separated. A triboelectric nanogenerator (TENG) is an energy harvesting device that converts the external mechanical energy into electricity by a conjunction of triboelectric effect and electrostatic induction. A triboelectric nanogenerator (Zhang, et. al., 2021) works in 3 primary steps. First is the initial

Table 2. Steps required for total solutions

Method	Visual	Description
Step1		Develop a custom wearable Triboelectric nanogenerator sensor. This sensor is low cost and has high sensitivity. Test it on various muscle groups. *Note: A custom sensor was developed since large, wearables, muscle sensors were not available. EMG sensors were evaluated as well.*
Step2		Collect the MusTENG sensor specific spasticity readings. Reduce noise with Notch filter Test on isolated thigh muscle to ensure sensor works effectively
Step3		Train an Autoencoder neural network. Establish a threshold for baseline conditions. Calculate anomalies beyond the threshold. Evaluate optimum threshold best results Source: https://lilianweng.github.io/posts/2018-08-12-vae/
Step4		The Area under the curve of the anomalies (MSE) between the actual and predicted values has a direct correlation with the muscle spasticity

generating layer which harnesses the electrons. Then the collecting layer with positive charge attempts to gain electrons. Where finally the trapping layer detects the transfer of electrons between the generating and collecting layers. In all regular Triboelectric nanogenerators there is some object or material that is charging the initial material and leading to the transfer of electrons such as the acrylic plate in the picture above. In free standing triboelectric layer based nanogenerators there is no acrylic plate causing the initial transfer in electrons.

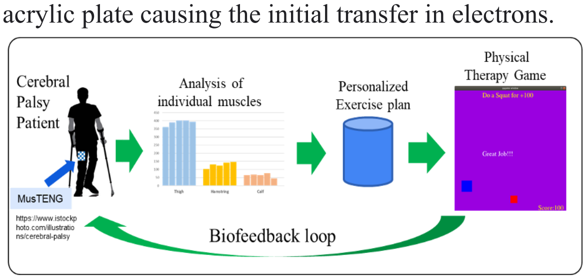


Figure 1. Solution Overview shows the different components of the projects and how those come together. With MusTENG sensor the project creates a Biofeedback loop (Pavlenko, V., 2022) for improved physical therapy of patients with CP

What is generating the electrons is the pure movement in the sensor. Free standing triboelectric nanogenerators allow the ability to track and gather energy from any arbitrary moving object. The charge transfer is also close to a 100% efficiency meaning any movement will cause all the possible electrons to transfer leading to extremely precise and accurate results while working with small movements.

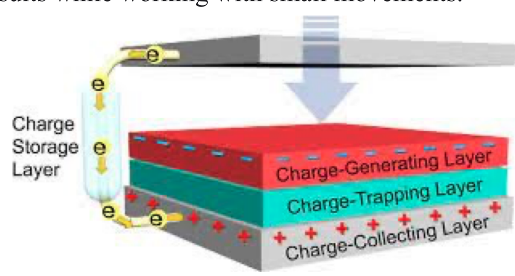


Figure 2. Representative components of a triboelectric nanogenerator (TENG) https://www.nature.com/articles/s41427-019-0176-0

3.1 Triboelectric charge testing

An initial sensor was built using a 2-inch by 2-inch piece of Nylon and Polyester fabric. The charge trapping layer was a silver fabric. To evaluate whether the sensor would work, two standard tests for TENGs were run, the vertical displacement and lateral displacement tests.

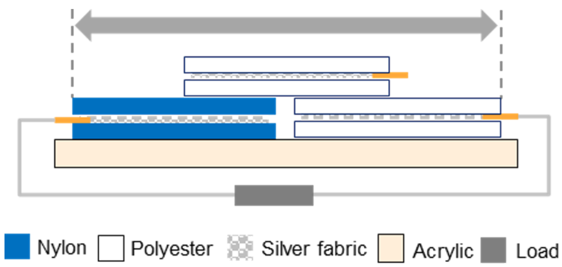


Figure 3. Lateral displacement test to evaluate triboelectric charge of different fabrics

For this test a vertical displacement of acrylic was moved over the sensor triggering the electrons to be transferred at different rates through the piezoelectric sensor. The results above came from an oscilloscope where the transfer of electrons was captured through the voltage.

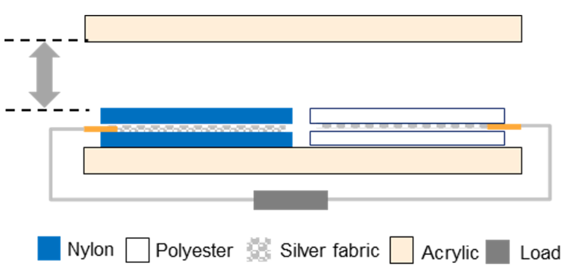


Figure 4. Vertical displacement test to evaluate triboelectric charge of different fabrics

For the lateral movement test the acrylic glass was moved laterally along the sensor and the electrons transfer was picked up and the results are shown above.

3.2 Fabric and Form-Factor Selection

To design a highly sensitive and high response sensor, different fabrics of polyester and nylon were tested with. 5 different combinations of fabrics were tried, and the best was selected. Then using strips of the best fabric, mesh patterns of different widths were tested. Again, optimizing for the highest range of sensor reading. Through this test the combination of 65% polyester and 100% nylon provided the best results. The best results directly correlated to the greatest range of sensor output, because that means there will be a noticeable difference between smaller changes in pressure, movement, and deformation of the sensor. The combination that yielded the best results had a sensor range of 468. The results are surprising, because logically the purest combination of polyester and nylon should provide the best results, but an interesting error occurred where the lower end of the range was substantially higher than the other fabrics due to the amount of noise the combination of 100% polyester and 100% nylon picked up.

Fabric Sensors	Poly Type	Nylon Type	Range
	90% polyester, 10% spandex	47% Rayon, 43% Nylon, 10% Spandex	128
	100% Polyester	82% Nylon, 18% Spandex	231
	60% Cotton 40% Polyester	90% Nylon 10% Spandex	320
	65% Polyester 35% Cotton	100% Nylon (interwoven threads)	468
	100% Polyester	100% Nylon	390

Figure 5. Fabric selection based on quantitative results from vertical and lateral displacement tests

Sensor Mesh	Strip size	Reading
	1½ inch width	Sensor output: 300 - 732
	1 inch width	Sensor output: 300 – 812
	½ inch width	Sensor output: 300 – 562

Figure 6. Sensor mesh size selection based on sensor output results

Once the type of fabric that yielded the best results was determined a series of 3 different lengths and widths were tested in a mesh format to again see the best sensor out of the data. The optimal results came from the 1inch wide by inch long squares. This provided the best results because it had the right ratio of amount of silver to collect energy as well as a strong mesh.

3.3 Sensor Fabrication

The following picture gives an overview of the sensor fabrication process. The sensor was built using Nylon and Polyester fabric strips that were later weaved into a mesh. Each strip is made up to either polyester or nylon fabric. The fabric sandwiches a silver fabric that acts as a conductor. At the end of the strip is a small copper wire to enable electrical flow.

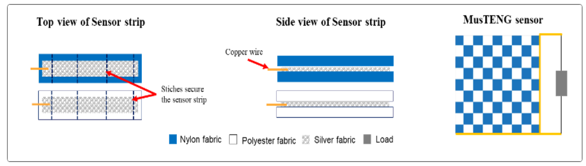
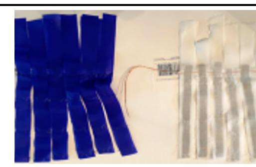
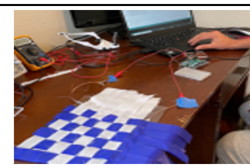


Figure 7. Design and components of MusTENG sensor and how the sensor is developed

Table 3: Sensor fabrication method

Method	Visual
Step 1: The nylon fabric and polyester fabric are cut into strips (1 inch wide and 8 inches long). The silver fiber fabric is cut into strips (1 inch wide and 6 inches long). The silver fiber fabric strip is layered onto the center of the nylon fabric strip using a sewing machine.	
Step 2: A lead wire is run through the nylon silver strips and the polyester silver strips and acts as a conductor. Then the two fabrics are woven together such that the nylon and polyester strips follow an in-out pattern.	
Step 3: The final woven triboelectric nanogenerator sensor (MusTENG) is developed by sowing the ends so that the sensor has structure. Finally, the ends are hooked up to an Arduino for collecting live reading	

3.4 Sensor Response

To test sensor sensitivity the sensor was moved with a lateral displacement using a mechanical force ranging from 0-20 hertz. This determined the sensor's peak value and the relationship between lateral displacement and the sensor output.

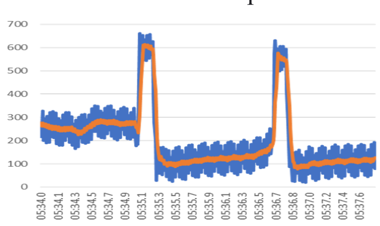


Figure 8. Notch filter usage to remove extraneous noise from sensor readings

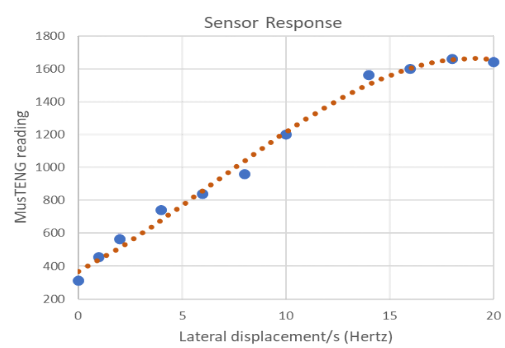


Figure 9. Sensor sensitivity based on lateral displacement test with varying mechanical force

One of the initial challenges with the sensor was its sensitivity to extraneous motion, sounds, and forces. It made the data unreliable as it would pick up the voltage of these extraneous noises. To prevent this from happening a notch filter was applied to the Arduino code. The premise of the notch filter is that it works as an opposite of a low pass filter. It removes the outliers of a data set by looking for unrealistic peaks where the sensor values are >50 hertz and removes them allowing for consistent and reliable data.

4. Phase 1 Testing: Isolating Muscle Tension

The purpose of this test is to see if the MusTENG sensor has a direct relationship with muscle tension/spasticity through the isolation of the muscle contraction. Before doing movements and different motions while the sensor is attached to the leg it is vitally important to see the sensor's response to pure muscle movement. Literature and previously conducted tests show that the amount a muscle moves while contracting is directly proportional to the actual muscle's tension. So, to conduct a test where the MusTENG's response to muscle tension can be observed without the effect of other movement or noise a simple test was conducted. The premise of the test was to contract and release the thigh muscle without any leg movement while different loads of tension were applied to the leg. If the results data shows a significant increase as the load of tension is increased the MusTENG sensor is truly getting the muscle deformation movement readings.

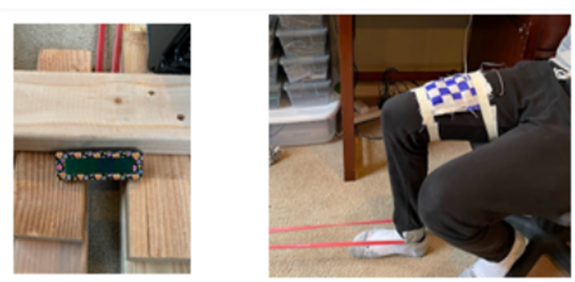


Figure 10. Apparatus for isolated muscle test

The Following graphs show observed results and the sensor readings. The red band with the lowest load or 6-8 lbs shows small peaks of sensor readings at the muscle contracts when the load is applied. As the load increased peaks of data were longer and more sustained. At the highest level of load the sensor pickups all the muscle activities of the smaller muscles of the thigh.

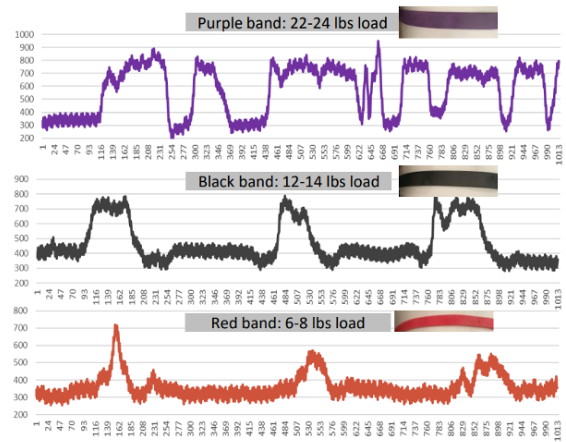


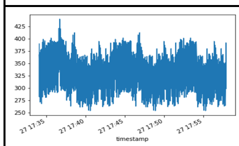
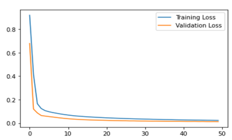
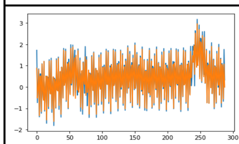
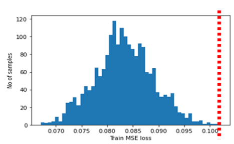
Figure 11. Sensor readings for different loads, ranging from 6lbs to 24lbs, on the isolated thigh muscle test

4.1 Calculation CMSS (Computed Muscle Spasticity Score)

Although the raw data has a correlation to tension and muscle spasticity an algorithm must be run on the data in order to compare when no added load was on the leg to different loads of tension. Comparing a simulated spastic child to a non spastic child. This enables the ability to determine the severity of cerebral palsy and muscle spasticity in any patient. This muscle spasticity score is the core of the solution because it is a method of representing the severity of a patient's cerebral palsy and spasticity. To create the cMSS score the algorithm goes through a multi-step process. First it trains the baseline data which is not shown above but it is the data when no load is added onto the leg. It trains over that set of data for 50 epochs or entire run throughs of the data until it fully learns the data. Once the data is fully learned it attempts to predict the data using its training it predicts through the whole data set and calculates the validation loss or error between each predicted point and actual point. The following table shows the steps to train an autoencoder neural network.

The largest error is then set as the threshold for anomalies. So, any error greater than the threshold curated through the prediction would be considered an anomaly. Then an anomalous data set is taken into the algorithm for example the purple band data above with 22-24lbs of load. This is also the data for a simulated spastic cerebral palsy patient.

Table 4. Method to train autoencoder Neural Network

Training Autoencoder Neural Network	Steps to train autoencoder
	Baseline data is collected from the sensor with the leg under no tension. Then an Autoencoder neural network is trained
	Autoencoder is composed of 7 layers and over 9500 parameters. Training and validation loss shows model training over 50 epochs
	The plot above shows training data and model-predicted data
	Threshold = Max MSE loss. It is the worst the model has performed in reconstructing the sample

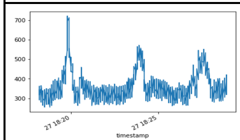
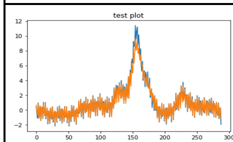
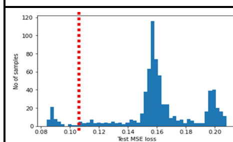
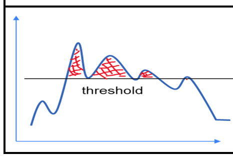
Using the same model trained model for the baseline data it compares the two data sets of a simulated CP patient with the purple band data above to baseline set by a non-spastic child. Then the errors or (MSE) values are calculated by finding the difference in a predicted value which is the base line and the purple band data which is much higher.

Any errors or MSE values over the threshold set previously with the training data are accumulated. This represents the area of error over the threshold and has proven to have a very strong relationship with muscle spasticity as explored later. The following tables shows the steps involved in calculating the cMSS.

5. Phase 2 Testing and Results

The purpose of phase 2 testing is to develop a relationship between added load on the leg to the cMSS or muscle spasticity values. This testing also will determine the accuracy and precision of the MusTENG sensor and the cMSS calculations.

Table 5. Method to calculate muscle spasticity score

Compare Test Data and calculate cMSS	Steps involved
	Now use data collected for muscle spasticity as Test input data
	Use the trained model to reconstruct the test data sample
	Calculate MSE loss. All the data points beyond the Threshold are considered anomalies.
	**cMSS** is the sum of MSE for all anomalies. It represents the Area under the curve of anomalous data

For thigh calf and hamstring-based testing a baseline was set by conducting an extraction of the thigh muscle without any added load. Then to simulate a CP patient spastic muscles pounds of load were added to the leg to simulate creating muscle tension. To conduct the test, a simple supination and pronation of the leg was performed with different movements that focused on each specific muscle group. It allowed me to conduct a basic yet reliable extraction and contraction of the right muscle. The tests were designed based on Modified Ashworth scale. The images below show how the thigh was extracted and contracted. The band that adds tension to the muscles can also be seen.

After conducting a total of 30 tests a strong relationship was developed between the added load in pounds to the calculated cMSS score or muscle spasticity. This means that the MusTENG sensor can distinguish the muscle movement of any level of a spastic muscle to a non spastic muscle with extreme precision. Furthermore, it is able to do it for each main muscle group on the leg being the thigh, hamstring, and calf. The following curves show the quadratic relationship that was developed after 30 tests with varying loads added to the leg. As more tension or load is added on to the leg the sensor and algorithm is able to not only determine it but precisely quantify the increase in muscle spasticity.

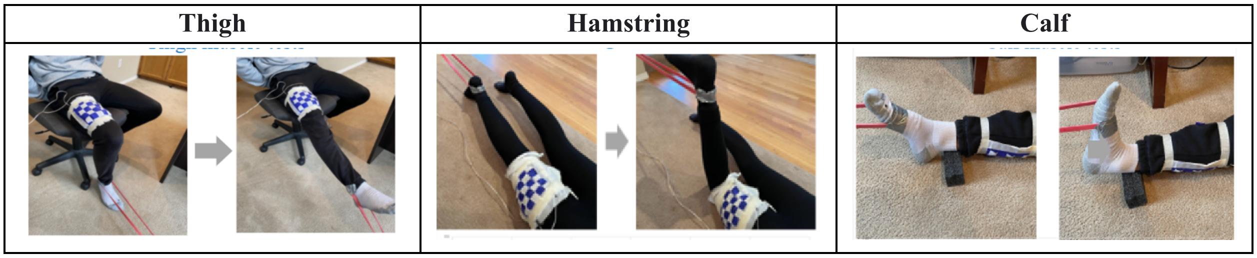


Figure 12. Muscle movement test for Thigh, Hamstring, and Calf muscl

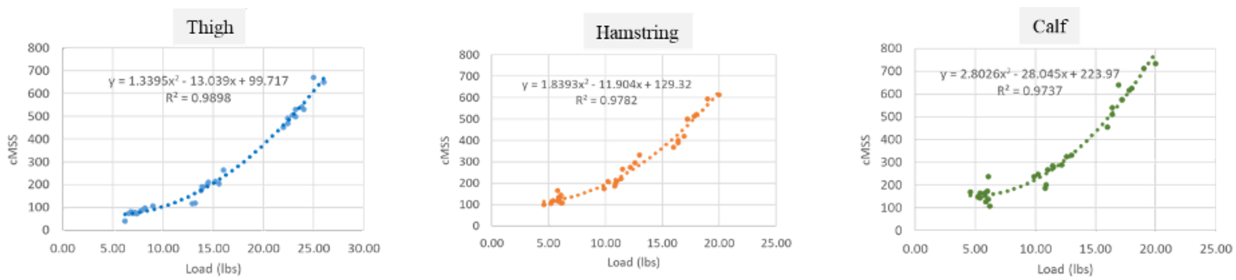


Figure 13. Muscle spasticity response curves for different muscle groups tested

5.1 Results: Precision and Accuracy of cMSS and MusTENG sensor

A total of 75 tests on the thigh, 40 on the hamstring, and 55 on the calf were run to determine the precision and accuracy of the sensor and algorithm. The tests were conducted at a variety of varying loads and a cMSS score was generated for each test. Each score was compared to the muscle spasticity curves equation shown above and an error of <5% was considered a successful reading.

Using that 5% threshold as a success the algorithm sensor and whole system was able to achieve a final 91% accuracy for thigh-based testing. 84% accuracy for hamstring-based testing, and finally 89% accuracy for calf based testing. These results enable the ability to track any CP patient's spasticity with the MusTENG sensor.

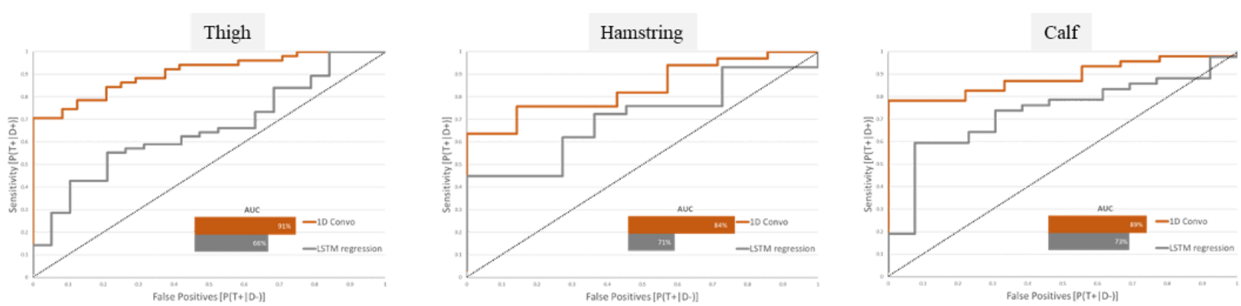


Figure 14. ROC curves of test results for different muscle groups tested

To optimize results the algorithm was changed from an LSTM regression to a 1D convolutional autoencoder. In addition, the calculated spasticity score was changed from a mean MSE + 3 sigma method to an AUC calculation. This provided a major benefit because instead of the algorithm purely looking at the peak of the data set it finds the area of the anomalies or difference between a spastic and non spastic child's readings. This makes the algorithm encompass the whole muscle contraction and release rather than just the point of greatest results.

6. Phase 3: Walk Testing - Muscle Cohesiveness

The purpose is to observe how all the muscles of a CP patient work together while walking in order to develop a deeper understanding and generate extremely valuable data of the spasticity of each muscle at the same time.

6.1 Baseline

CP patients in most cases have three main walk patterns or gaits: true equinus, jump gait, and crouch gait. To establish a baseline that would be used for the rest of walk testing and to determine cMSS the researcher walked five steps without any load or rig. The raw MusTENG data from the sensor is trained upon and established as the baseline in the autoencoder neural network. For all the tests, the researcher walked a total of 5 steps down the hall with the rig and the added load. Then the average cMSS score calculated between the 5 steps. Furthermore, the researcher did 4 more trials and got 5 average cMSS or muscle spasticity readings for the thigh, hamstring, and calf for the true equinus walk.

6.2 Walk 1: True Equinus

The true equinus gait is when the knee is fully extended and restricted to extremely limited movement. To simulate this gait on a non-CP patient the researcher devised a rig using two simple wooden planks. The wooden planks extend up the leg on both sides and restrict the knee from bending. This all simulates a true equinus walk. A picture of the rig can be seen on the right. The researcher also added 10 pounds of load to the leg to increase the muscle tension as done previously to simulate a CP patient.

These results below show that for the simulated true equinus walk where 10 pounds of load were added to the leg the thigh had a very high cMSS or spasticity. The hamstring faced a moderate level of spasticity, and finally the calf experienced a low cMSS.

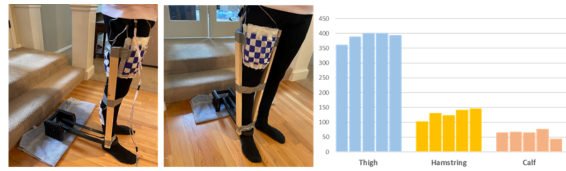


Figure 15. Apparatus and results for True Equinus walk testing

6.3 Walk 2: Jump Gait

The true equinus gait is when an anterior pelvic tilt, excessive knee, and hip flexion are caused by an excessive angle between the foot and leg. To simulate this walk, gait a wooden rig was designed that ensures a constant 115-degree angle between the foot and leg is maintained while walking. A picture of the rig can be seen below. Ten pounds of load was added to the leg to increase the muscle tension as done previously to simulate a CP patient.

These results blow show that for the simulated jump gait walk where 10 pounds of load were added to the leg the thigh had a very low cMSS or spasticity. However, the hamstring faced a high level of spasticity, and finally the calf also experienced an extremely high level of spasticity.

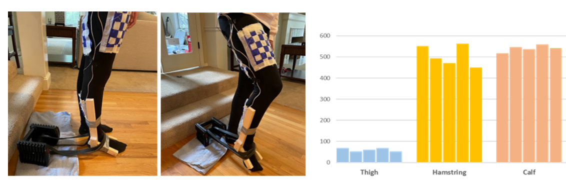


Figure 16. Apparatus and results for Jump gait walk testing

6.4 Walk 3 Crouch Gait

The crouch gait is when a child has excessive ankle dorsiflexion from an unnatural reduced angle between the foot and leg. To simulate this gait, a wooden rig was designed that ensures a constant 80-degree angle between the foot and leg is maintained while walking. A picture of the rig can be seen below. Ten pounds of load was added to the leg to increase the muscle tension as done previously to simulate a CP patient.

These results blow show the spasticity for the simulated crouch gait walk where 10 pounds of load were added to the leg. The thigh had a moderate cMSS or spasticity. The hamstring faced a low level of spasticity, and finally the calf experienced an extremely high level of spasticity.

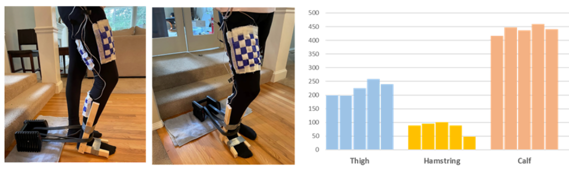


Figure 17. Apparatus and results of Crouch gait walk testing

These results give an in-depth analysis of each muscle's performance while walking, and show how different walk patterns affect different muscles in quite diverse ways and substantial improvement for CP based PT.

7. Physical Therapy Game

Based on the results in phase 3 a CP patient can simply walk with the MusTENG sensors on their thigh, calf, and hamstring and get an in-depth analysis on their spasticity levels. From there the data can be sent to experts where a personalized exercise plan can be given to the child. That personalized exercise plan now is input into a software game system.

The exercise plan is converted from exercises into a list of shapes that represent the exercises. Then the game drops a shape and begins collecting data from the exercises targeted muscle. For example, in a squat the game data collected comes from the thigh sensor. When the block reaches the bottom of the screen the data set is sent to the algorithm where the cMSS value of the patient is calculated. If the targeted muscle experiences a certain amount of tension measured by the cMSS values, it is considered a success. That cMSS threshold value is determined based on if the cMSS value has a 20% increase to the initialization quantity.

If the threshold cMSS is reached the game rewards a certain number of points and drops the next shape (exercise). The game ends when all the exercises are completed correctly.

The idea behind that is for children to be properly exercising their muscles they need to be experiencing a greater spasticity for a small period which is the basis behind all exercises. This ensures exercises are done properly and for the right muscle group. The game also provides the ability to observe how the muscles perform while doing different exercises and can give an even more in-depth analysis on how their muscles respond to exercises. The best part about the game is that it makes physical therapy more engaging especially for children with cerebral palsy.

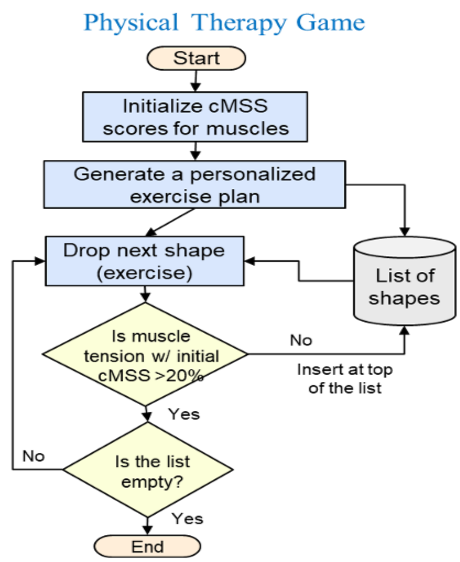


Figure 18. Flow chart for physical therapy game

8. Discussion: Improvement Analysis

Through this project a major leap was achieved in the data-based analysis of a CP patient. Currently in practice a method known as the Ashwood scale is used for determining a CP patient’s severity level. After the therapist analysis the scale is used to determine the severity of the patients CP from a 1-4 scale. With this project the Ashwood scale was reimagined and designed through a wearable sensor and machine learning algorithms. Which provides specific data down to decimal places of a CP patient's muscle spasticity. Improving the analysis of CP patients increased muscle tension from a basic classification to an in-depth quantifiable number. This project even goes a step further and can analyze how the muscles work together while walking. This data of how each muscle is affected differently is vitally important for CP patients because without it they are blindly exercising their different muscles without any data showing that they are doing the right exercises or making progress.

Cost Improvement: Cerebral palsy is a lifelong disorder that requires long-term care and treatment. In 2003, the center of disease control estimated that the lifelong cost for individuals with CP was approximately $1M in additional to normal living costs. CP patients expect to spend up to $20K in physical therapy costs annually.

Recent studies have shown that structured home-based exercise programs can help improve abilities of children with CP. The low cost MusTENG sensor enables CP patients to collect quantifiable data that physical therapists use and optimized exercise programs. Furthermore, the game that was developed using the custom MusTENG's ability can eventually make physical therapy at home the new standard. Even if the project can reduce 2 PT visits, a patient will save $8K/year and deliver tremendous value

9. Conclusion

This project was able to meet all the Engineering goals and design criteria. It was able to show that the MusTENG wearable sensor that was designed can accurately detect muscle spasticity conditions. It was able to achieve an accuracy of 91% on the Thigh, 84% on hamstring and 89% on calf muscle groups. After reading through literature, talking to Physical Therapists, and clinicians there is a understanding that lack of quantified and personalized data is the missing link in creating new systems and standard of care for CP patients. With the MusTENG sensor physical therapists can get adequate data about the muscle spasticity of the patient and recommend the right exercise and routines. But even further rehabilitation is driven by repetitive practice and is boring for kids. So, the game will help motivate the kids, but also enable tailored responses from the game to exercise the correct muscles of the patient.

Overall, the MusTENG provides several unique and important benefits to current physical therapy. It enables the ability to track progress, determine the most beneficial exercises, reduce physical therapy cost, and determine muscle cohesiveness. Once this sensor and system is implemented into the real world it will revolutionize the basis of physical therapy for children with cerebral palsy. In the future, this project can be improved in several areas. The following are key next steps for the project are:

- Improving the accuracy of the Muscle spasticity score algorithm
- Evaluate MusTENG sensor on different patients with CP and validate results
- Work with exoskeleton companies (Biomotum), and gaming companies (Microsoft) and incorporate the MusTENG sensor in their designs
- Evaluate other applications of this sensor beyond CP, potentially in sports injury and rehabilitation

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