Integration of Machine Learning and Electrical Muscle Stimulation:

Bio-feedback Controlled Electrical Muscle Stimulation

A Systematic Review and Modeling Approach

HÄMEEN AMMATTIKORKEAKOULU
HÄME UNIVERSITY OF APPLIED SCIENCES

Bachelor's thesis

Electrical and Automation Engineering

Spring 2023

Karim Ghosn

HAMK
HÄMEEN AMMATTIKORKEAKOULU
HÄME UNIVERSITY OF APPLIED SCIENCES

Electrical and Automation Engineering | Abstract

Author | Karim Ghosn | Year 2023

Subject | Integration of Machine Learning and Electrical Muscle Stimulation: Bio-feedback Electrical Muscle Stimulation

Supervisors | Jussi Horelli

Bio-feedback controlled Electrical Muscle Stimulation (EMS) in combination with Machine Learning (ML) algorithms is a promising method for optimizing rehabilitation therapies. This study explores the integration of machine learning techniques and bio-feedback to improve the personalization and effectiveness of EMS interventions. The focus of the research is on optimizing stimulation parameters, providing real-time adaptation, and enhancing patient engagement.

Electromyography (EMG) sensors are used to acquire and process muscle response data. The data is analyzed and individualized stimulation parameters are determined using machine learning algorithms, ensuring optimal muscle activation and avoiding overstimulation. By continuously monitoring EMG signals and adjusting stimulation parameters based on patient-specific responses, real-time bio-feedback is achieved.

The findings indicate that bio-feedback controlled EMS with ML has the potential to enhance rehabilitation outcomes. Increased muscle activation, strength gains, and functional enhancements are the result of personalized stimulation parameters. Real-time adaptation assures the safety and efficiency of stimulation by adjusting stimulation parameters in response to changes in muscle activity.

This research highlights the revolutionary effect of bio-feedback controlled EMS with ML in rehabilitation therapy. By refining stimulation parameters, providing real-time adaptation, and enhancing patient engagement, this approach provides patients with a personalized and an effective treatment option. To fully exploit the potential of this technology, additional research, validation, and clinical integration efforts are advised.

Keywords Bio-feedback, Electrical Muscle Stimulation, Machine Learning, Rehabilitation.

Pages XX 25 XX

Content

1 Introduction 1

1.1 Background and significance of the study 1

1.1 Research question and objectives 2

1.2 Scope and limitations 3

2 Electrical muscle stimulation (EMS) 4

2.1 Brief history and evolution of EMS 4

2.2 Current protocols and limitations of EMS 4

2.3 Applications of EMS in rehabilitation 5

3 Machine Learning (ML) 6

3.1 Overview of ML and its applications in engineering 6

3.2 Commonly used ML algorithms and techniques 7

3.3 Integration of ML with medical devices and healthcare technologies 8

4 Theoretical Framework 9

4.1 Electromyography sensor (EMG) and utilization with EMS 9

4.2 Mathematical models and algorithms used in bio-feedback controlled EMS 10

4.3 Integration of ML in bio-feedback controlled EMS 12

5 Bio-feedback controlled EMS 12

5.1 Definition of bio-feedback controlled EMS 12

5.2 Advantages of bio-feedback controlled EMS over traditional EMS 13

5.3 Overview of bio-feedback systems and sensors used in bio-feedback controlled EMS 14

6 Results 15

6.1 Overview of the literature search 15

6.2 Summary of the main findings on bio-feedback controlled EMS 16

6.3 Summary of the main findings on ML in EMS optimization 20

7 Discussion 21

7.1 Implications of the findings for EMS optimization and bio-feedback controlled EMS 21

7.2 Limitations of the study and recommendations for future research 21

7.3 Practical approaches to implementing bio-feedback controlled EMS using ML 22

8 Conclusion 23

8.1 Summary of the main findings and their significance 23
8.2 Contribution to the literature 24
8.3 Final thoughts and recommendations.. 24
9 References 25

Figures

FIGURE 1. EXAMPLE OF ELECTRICAL STIMULATION THERAPY... 6
FIGURE 2. A FEEDBACK LOOP CONNECTING EMS, EMG AND ML 10
FIGURE 3. WHAT IS A NEURAL NETWORK? TIBCO. (N.D.) 11
FIGURE 4. THE NEW MTRIGGER BIO-FEEDBACK DEVICE 15
FIGURE 5. PATIENT BASELINE CHARACTERISTICS OF EMS AND ESB GROUPS... 17
FIGURE 6. COMPARISON THE TREATMENT EFFECTS OF EMS AND ESB GROUPS 19

1 Introduction

1.1 Background and significance of the study

Electrical Muscle Stimulation (EMS) has emerged as a viable tool for strengthening muscular function and improving rehabilitation results in paralyzed patients. EMS may assist to avoid muscular atrophy, alleviate stiffness, and enhance muscle strength and endurance by stimulating muscle contraction. Furthermore, EMS may be used to target specific muscle areas and encourage more precise and coordinated motions, which can be very advantageous for those who are paralyzed. However, there is a lack of consistency in the use of EMS protocols, and further study is required to determine appropriate parameters for EMS, such as frequency, intensity, and duration of stimulation, to enhance its efficiency.

Bio-feedback controlled EMS is a modern method that was intended to solve the shortcomings of standard EMS procedures. Bio-feedback controlled EMS adjusts EMS settings and optimizes stimulation for particular muscle groups based on real-time input from sensors, resulting in more efficient and successful rehabilitation results. The use of machine learning in bio-feedback controlled EMS has the potential to further refine EMS procedures, allowing for more personalized therapy and more accurate and targeted muscle activation.

The importance of this research stems from its potential to increase the efficacy of EMS in rehabilitation and outcomes for those who are paralyzed. This work might increase the precision and efficiency of muscle stimulation by determining ideal settings for EMS using machine learning and bio-feedback. This could lead to greater muscle activation and synchronization. This research may also help to standardize EMS techniques, making it simpler to compare and duplicate outcomes across various trials and contexts.

Furthermore, the use of machine learning and biofeedback in EMS has the potential to transform the way we approach paralysis rehabilitation, opening the door for more individualized and efficient treatment choices. This research might help to create new technologies and smart wearables that integrate machine learning and biofeedback, making these revolutionary techniques more accessible to both patients and physicians. (According to PowerDot (n.d.), the science and history behind EMS are essential in understanding its effectiveness in training).

1.1 Research question and objectives

Can the integration of machine learning (ML) and electrical muscle stimulation (EMS) improve the accuracy and effectiveness of personalized rehabilitation programs through real-time feedback?

Rehabilitation programs play a vital role in restoring functional abilities and improving the overall well-being of individuals with paralysis. However, the current approaches often lack real-time feedback mechanisms, which can limit the accuracy and effectiveness of personalized rehabilitation. To address this limitation, there is growing interest in exploring the integration of ML and EMS to enhance rehabilitation programs through real-time feedback. This thesis aims to investigate the feasibility of using ML and bio-feedback to improve the accuracy and effectiveness of personalized EMS procedures for individuals with paralysis.

Objectives:

1) Examine the existing literature on EMS and bio-feedback controlled EMS and identify research needs.
2) Assess the potential for machine learning to enhance EMS practices and rehabilitation results.
3) Investigate the use of machine learning and biofeedback into EMS procedures and the possible advantages for people with paralysis.
4) Develop a theoretical framework for enhancing EMS procedures using machine learning and biofeedback.

5) Provide suggestions for future study on machine learning and bio-feedback controlled EMS for paralyzed patients.

By pursuing these objectives, this thesis endeavors to deepen our understanding of the feasibility and potential benefits of integrating machine learning and bio-feedback into EMS procedures. While the study does not aim to provide definitive solutions, its findings will contribute to the existing body of knowledge, offering valuable insights for researchers and clinicians involved in the field of personalized rehabilitation.

1.2 Scope and limitations

This study's scope is to investigate the feasibility of integrating machine learning and bio-feedback to optimize EMS protocols and enhance rehabilitation outcomes for paralyzed individuals. Focus will be placed on the incorporation of machine learning algorithms into a theoretical framework for bio-feedback controlled EMS. The current literature on EMS and bio-feedback controlled EMS will be reviewed, and the potential benefits and limitations of machine learning for optimizing EMS protocols will be assessed. The research will not involve any physical testing or human experimentation.

This study's limitations include the absence of physical assessment and human subjects for experimentation. The research will be based solely on a review of the existing literature and theoretical analysis. This may restrict the study's scope and the ability to draw definitive conclusions about the efficacy of bio-feedback controlled EMS with machine learning. In addition, the study will not focus on the broader applications of machine learning in healthcare or medical engineering, but rather on its application to EMS protocols within rehabilitation settings. Lastly, the study will only investigate the potential of bio-feedback controlled EMS and machine learning; it will not provide a guide for implementing these approaches in clinical settings.

2 Electrical muscle stimulation (EMS)

2.1 Brief history and evolution of EMS

Previous studies have highlighted the benefits of electrical muscle stimulation (EMS) in enhancing muscle strength (Choi, K. M., & Choi, Y. J., 2016). EMS started when the Italian scientist Luigi Galvani found that electrical impulses could manipulate muscle contractions. EMS was first utilized to treat neurological problems such as muscular atrophy and spasticity in the 1960s and 1970s. EMS devices developed more complex waveforms and the capacity to target muscle groups in the 1980s, according to the "I-motion" website. EMS was used in sports training and conditioning to enhance performance.

In the 1990s and 2000s, EMS continued to progress, with the introduction of more portable and user-friendly equipment, making it simpler for individuals to utilize EMS at home. EMS was used cosmetically to tone and tighten muscles and minimize cellulite. EMS is utilized for rehabilitation, athletic training, and cosmetics nowadays. EMS procedures are being refined and standardized to improve muscle function and rehabilitation results. Technology and research have enhanced EMS applications and results from its early days. New technologies like bio-feedback and machine learning may refine EMS procedures and make them more effective for more applications, shaping the future of EMS.

2.2 Current protocols and limitations of EMS

Choi, K. M., & Choi, Y. J. (2016) also stated that the target muscle group and intended result determine EMS frequency, intensity, and duration. High-frequency EMS (above 30 Hz) is utilized for muscle relaxation and pain treatment, whereas low-frequency (less than 10 Hz) is used for muscular strengthening and endurance training. EMS should be intense enough to contract muscles but not painful. Stimulation lasts a few seconds to many minutes, depending on the muscle type and intended result.

EMS has drawbacks despite its advantages. EMS effectiveness depends on muscle size, location, and composition, which is an inconvenience. EMS procedures lack standardization, making it hard to compare study outcomes. EMS may also cause muscular tiredness and pain, especially at high intensities and durations. Certain medical problems or injuries may not be acceptable for EMS.

EMS has showed promise for many rehabilitation applications, but its limits and problems must be carefully reviewed and addressed in future research and clinical practice.

2.3 Applications of EMS in rehabilitation

Recent research has demonstrated the effectiveness of EMS in improving muscle strength and physical function (Chaudhary & Misra, 2021). EMS may be used to strengthen muscles, re-educate them, control pain, and reduce spasticity. EMS may activate muscle groups in neurological patients with reduced muscular function, such as stroke or spinal cord impairment. EMS may boost rehabilitation programs when combined with physical therapy. It may also be utilized as a solo treatment, especially for patients who are unable to conduct traditional exercises due to physical constraints or discomfort. Medical history, physical restrictions, and therapy objectives must be considered while using EMS in rehabilitation. EMS frequency, intensity, and duration must be personalized to each patient and altered as they improve in rehabilitation.

In general, EMS may improve muscle function and rehabilitation results for individuals with a range of neurological and musculoskeletal conditions. However, further study is required to create effective EMS methods and identify patient categories who may benefit most from this treatment.

Figure 1. Example of electrical stimulation therapy

3 Machine Learning (ML)

3.1 Overview of ML and its applications in engineering

Machine Learning (ML) is a subset of AI that entails teaching computer systems to learn from data and make predictions or judgments without being explicitly programmed. ML offers a broad variety of engineering applications that assist to increase productivity, decrease costs, and improve product quality.

Predictive maintenance is a prominent use of ML in engineering. ML algorithms may be used to forecast equipment failures and maintenance requirements by evaluating data from equipment and manufacturing processes, allowing businesses to decrease downtime and boost productivity.

Quality control is another use of ML in engineering. ML algorithms may evaluate data from manufacturing processes to detect flaws and improve product quality, resulting in increased customer satisfaction and fewer returns.

ML may also be used to improve manufacturing processes including scheduling, resource allocation, and supply chain management. This enables businesses to save expenses, increase productivity, and eventually produce goods faster and at a lesser cost. ML has also allowed advancements in image and audio recognition, natural language processing, and autonomous systems, in addition to these applications. Image and voice data may be analyzed by ML algorithms, allowing applications such as face recognition, object identification, and speech-to-text conversion. ML may also be used to power autonomous systems like self-driving automobiles and drones. Machine learning has a wide range of applications across various domains, including finance, healthcare, and marketing (Javatpoint, n.d.).

Overall, ML is transforming the area of engineering and has the potential to increase productivity, lower prices, and improve product quality across a broad variety of businesses.

3.2 Commonly used ML algorithms and techniques

According to Machine learning engineers should have a good understanding of various algorithms such as decision trees, k-means clustering, and random forests (Simplilearn, n.d.). Machine Learning algorithms and approaches that engineers utilize today are numerous. Each algorithm has its own set of strengths and drawbacks, and the method used is determined by the unique situation and data at hand. Some of the algorithms and techniques are:

1) Linear Regression: A supervised learning approach used to predict continuous output variables is linear regression. Based on a collection of data, it determines the best-fit line that explains the connection between the input and output variables.

2) Decision Trees: Decision Trees are a common classification and regression method. They operate by dividing the dataset into smaller subgroups based on the most relevant attributes until a judgment regarding the outcome variable can be reached.

3) k-Nearest Neighbors (KNN): Is a basic method that may be utilized for both classification and regression issues. It entails determining the k-nearest neighbors to a

given input based on some similarity measure and predicting the output based on the majority class or average of these neighbors' output values.

4) Random Forest: Random Forest is an ensemble learning strategy that mixes numerous decision trees to increase predictability and accuracy. It operates by averaging the outcomes of a large number of decision trees created on randomly chosen subsets of the data.

5) Support Vector Machines (SVM): SVM is a prominent approach for classification and regression issues. They function by determining the best hyperplane to divide the data into multiple groups based on a set of characteristics.

6) Gradient Boosting: Another ensemble learning approach that combines numerous weak learners to generate a strong learner is gradient boosting. It operates by adding weak learners to the model repeatedly, with each new learner trying to rectify the preceding learner's faults.

3.3 Integration of ML with medical devices and healthcare technologies

The use of artificial intelligence (AI) in medical devices and healthcare is expected to bring significant opportunities and challenges (Morgan Lewis, 2023) states that ML integration with medical devices and healthcare technology has the potential to transform healthcare delivery, improve patient outcomes, and cut costs. Large volumes of medical data, such as photographs, patient records, and sensor data from medical equipment, may be analyzed by ML algorithms to detect patterns and generate predictions that can help with patient diagnosis, treatment, and monitoring.

Instances of ML in medical devices and healthcare technologies include:

1) Medical imaging: ML algorithms can analyze medical pictures such as X-rays, CT scans, and MRIs to uncover patterns and detect abnormalities that human observers may

miss. This may result in earlier and more accurate diagnosis, better treatment planning, and improved patient outcomes.

2) Wearable devices: ML algorithms can analyze sensor data from wearable devices like fitness trackers and smartwatches to monitor vital signs and identify changes in activity levels that may suggest health issues. This may lead to early intervention and more tailored treatment.

3) Electronic health records: ML algorithms can analyze medical data to detect trends and risk factors for a variety of illnesses, as well as forecast patient outcomes. This may assist healthcare practitioners offer more personalized care by informing treatment recommendations.

Integration of ML with medical devices and healthcare technology provides numerous prospects for enhancing healthcare delivery, it also presents certain obstacles. These include protecting data privacy and security, dealing with regulatory and legal challenges, and addressing the possibility of prejudice and discrimination in ML algorithms.

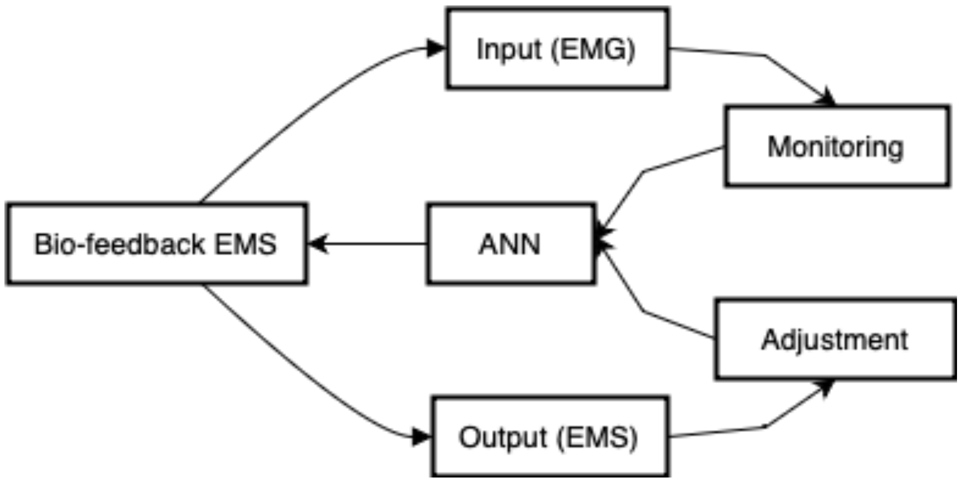
4 Theoretical Framework

4.1 Electromyography sensor (EMG) and utilization with EMS

The introductory guide on bio-feedback by Herman & Wallace Pelvic Rehabilitation Institute (n.d., p. X) explains the key principles and applications of this technique, it also states that electromyography (EMG) sensors assess the electrical activity generated by muscles during contraction and relaxation. Small electrodes typically reside on the skin surface above the muscle being monitored to form EMG sensors. When a muscle contracts, an electrical signal is produced, which is detected by the electrodes and transferred to a computer or other device for analysis. EMS, on the other hand, stimulates muscles with electrical impulses, causing them to contract and relax. EMS devices usually employ tiny electrodes implanted on the skin's surface above the targeted muscle. The device's electrical impulses replicate the normal electrical signals produced by the neurological system, prompting the muscle to contract.

EMG sensors, when combined with EMS, can provide real-time input on muscle activity. Therapists can optimize treatments and reduce the risks of harm by monitoring the electrical activity generated by the muscle during EMS and adjusting the strength and frequency of the electrical impulses. This method is known as bio-feedback controlled EMS, and it has been found to improve muscle function and reduce discomfort in people with different neuromuscular diseases.

Figure 2. A feedback loop connecting EMS, EMG and ML

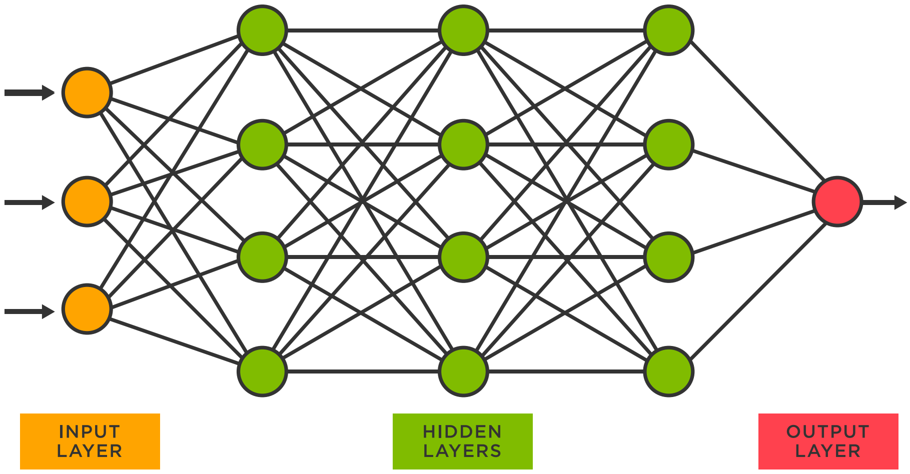


4.2 Mathematical models and algorithms used in bio-feedback controlled EMS

A form of mathematical model called artificial neural networks (ANNs) can be used to simulate complex, non-linear connections between input and output data. Neurons, which are linked processing nodes stacked in layers, make up ANNs. Each neuron takes in information, applies a mathematical function to it, and then sends the results to the layer of neurons below it. Weights are assigned to the connections between neurons, and during training, these weights are modified to enhance the functioning of the network.

ANNs can be utilized in the framework of bio-feedback controlled EMS to establish the connection between the EMG sensor input signal and the desired output stimulation parameters. The ANN can be taught to predict the proper stimulation parameters for a given EMG signal by being trained on a dataset of EMG signals and matching stimulation parameters. With this method, EMS treatments may be more precisely adjusted to the individual's muscle demands and limitations. Machine learning engineers should be familiar with various algorithms for effective implementation (Simplilearn, n.d.).

Figure 3. What is a Neural Network? TIBCO. (n.d.)



According to TIBCO. (n.d.), the input layer is the initial layer in the network that receives data. This layer's neurons correspond to one feature in the data set. If the network is meant to identify photos, for example, each neuron may represent one pixel in the input image. The hidden layers are the layers that exist between the input and output layers. These layers' neurons compute and transport information from the input layer to the output layer. During the training phase, the precise calculations are determined. The output Layer is the network's last layer provides the results of calculations. The type of the output is determined by the issue that the network is intended to answer. For example, in a classification task, each neuron in the output layer may represent a distinct class, and the network's output would be the class with the greatest value.

The utilization of neural networks in EMS to achieve bio-feedback comes when the EMG sensor grabs signals from the muscles during testing and use it as the input data in the ANN's input layer, then the model will process it in the hidden layers, and after the hidden layers are done processing it, the output layer will be used as an input again for the stimulating device with a value that adjusts the impulse according to the patient's needs.

4.3 Integration of ML in bio-feedback controlled EMS

An EMG sensor is initially connected to the muscle(s) being stimulated in order to combine artificial neural networks (ANN) with EMS for bio-feedback controlled EMS. The electrical activity produced by muscle fibers is recorded by the EMG sensor, which is then processed by an analog-to-digital converter and delivered to the ANN. The EMG readings are sent into the ANN, which then learns to detect patterns of activity corresponding to various amounts of muscular contraction. Once trained, the ANN may send real-time input to the EMS device, enabling it to adapt stimulation settings based on changes in the EMG signal. This feedback loop may be utilized to maintain muscular activation at a desirable level, avoid over-stimulation, and adjust to changes in muscle exhaustion or activation patterns. AI has the potential to revolutionize the field of medical devices and healthcare (Morgan Lewis, 2023).

The combination of ANN with EMS for bio-feedback controlled EMS has the potential to transform rehabilitation and sports training by delivering a customized, adaptable, and effective approach to muscle activation and strengthening.

5 Bio-feedback controlled EMS

5.1 Definition of bio-feedback controlled EMS

In physical therapy and rehabilitation, bio-feedback controlled EMS is a technique that aids patients in comprehending and controlling the physiological processes of their bodies. This method makes use of tools to provide real-time data regarding the body's functions, often in the form of visual or audible signals. The objective is to assist patients in developing voluntary control over these physiological processes, so enhancing their health. In order to treat neurological deficiencies after surgery or injury, bio-feedback might be very helpful. By allowing patients to employ their own "electrical system" via volitional (or voluntary) contractions, the approach may aid in the restoration of muscular function. By measuring the

EMG (electromyography) activity of the patient's muscles, bio-feedback devices enable comparisons between the damaged muscle group and a healthy muscle group. When employing a bio-feedback device, the doctor sets a goal for the targeted muscle that calls for a significant voluntary effort from the patient with each contraction. The patient may see this process, which prompts a powerful contraction to accomplish the predetermined objective. The best outcomes in terms of quickly regaining muscular function are thought to be achieved with the use of bio-feedback.

In the case of knee rehabilitation, bio-feedback may be used to treat typical issues like lack of knee extension, which can change gait and cause aberrant loads on the joint. Patients who use bio-feedback may improve their knee extension by learning to relax certain muscles, such as the hamstring, while extending their knees. In actual practice, this entails positioning the patient in a certain posture and regulating muscle activity via bio-feedback. During a 10-minute session, the technique generally comprises cycles of 10 seconds on and 10 seconds off.

It's important to mention that over the years, bio-feedback equipment has improved and grown more user-friendly. A smartphone or tablet with the right software program may receive measured EMG activity from certain devices, such the mTrigger Bio-feedback device, through a Bluetooth connection. Patients are able to see their muscular contractions and development thanks to this feature, which may be quite encouraging. However, since bio-feedback hasn't historically been a therapy that is reimbursable, there hasn't been a lot of study done on it. However, other research, including one comparing bio-feedback to EMS during ACL rehabilitation, has revealed that after six weeks of therapy, bio-feedback may provide higher muscle strength increases than EMS. According to Mike Reinold (2018, November).

5.2 Advantages of bio-feedback controlled EMS over traditional EMS

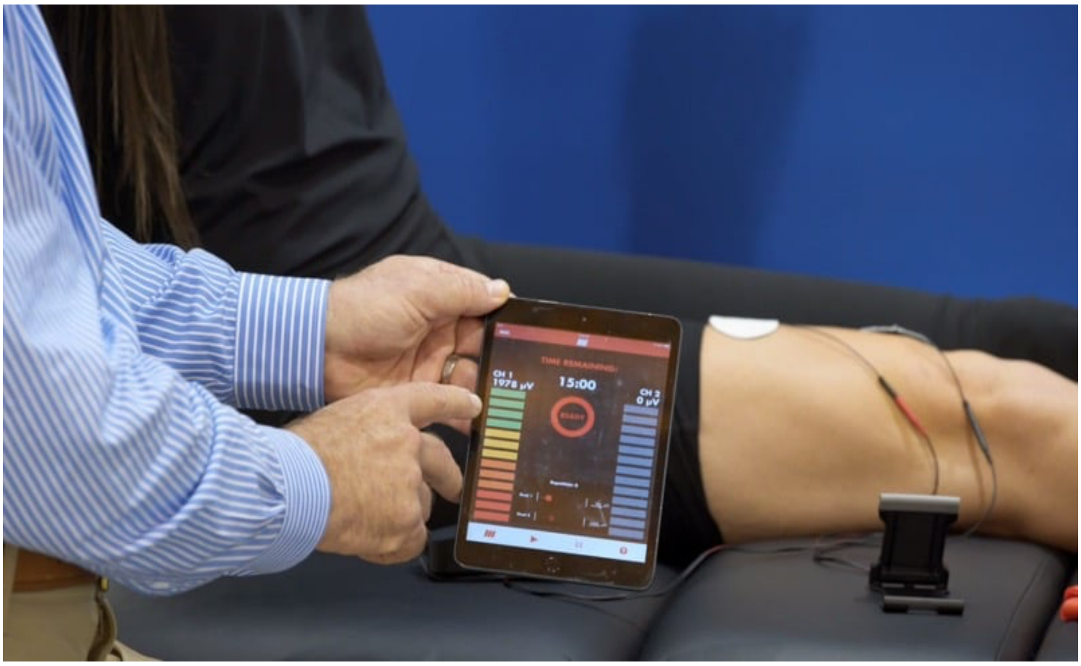
According to Mike Reinold (2018, November), the comparison between Bio-feedback controlled EMS and Traditional EMS, has shown that Bio-feedback is more effective in certain cases. One study found that bio-feedback provided greater quadriceps isometric muscle strength than EMS after 6 weeks during ACL (Anterior Cruciate Ligament) rehabilitation. Furthermore, EMS stimulates all nerve fibers simultaneously, while bio-feedback allows for sequential recruitment from small to large diameter nerve fibers, which is more effective for recruiting muscle fibers critical to reversing the effects of muscle inhibition and atrophy. Bio-feedback is a preferred method for dealing with neurological deficits following surgery or injury. It allows for the assessment of a patient's EMG neurological status by measuring the EMG activity of the involved extremity and comparing it with the opposite, normally functioning muscle group. It enables patients to use their own electrical system as soon as possible through volitional contractions. This approach is supported by Heinemann's size principle, which suggests that motor units are recruited from smallest to largest under load, activating slow-twitch, fatigue-resistant muscle fibers before fast-twitch, less fatigue-resistant muscle fibers. Bio-feedback devices can aid this process by setting goals for the inhibited muscle that require strong voluntary effort from the patient.

5.3 Overview of bio-feedback systems and sensors used in bio-feedback controlled EMS

After a surgery or injury, the bio-feedback system is utilized to assist patients in using their own "electrical system" via voluntary contractions. In order to give a broad evaluation of a patient's EMG condition, bio-feedback technology has progressed. This is done by monitoring the EMG activity in the affected extremity and contrasting it with that of the opposing, healthy muscle group. The aim is established by the doctor such that the patient must exert a significant voluntary effort for each contraction of the inhibited muscle. The patient may see this, which prompts a powerful contraction to achieve the desired result.

Almost all knee patients with reduced EMG output are treated with bio-feedback. The detected EMG activity is sent via a Bluetooth signal to an Android or iOS smartphone running the necessary software using a device called the mTrigger Bio-feedback device. When the patient carries out home workout regimens, they can then see how strongly their muscles are contracting. Patients have been shown to be highly motivated by this. Bio-feedback may help with knee extension difficulties, which are prevalent following knee surgery. The impact of a tightening hamstring muscle may be avoided by training the patient to relax the hamstring muscle during knee extension stretching. In this scenario, the bio-feedback equipment is utilized for relaxation, with the patient prone and electrodes put over the hamstring muscle. Once the patient has learned to regulate his or her hamstring hyperactivity, a lightweight may be used to provide a low-load, long-duration stretch. According to Mike Reinold (2018, November).

Figure 4. The new mTrigger bio-feedback device



6 Results

6.1 Overview of the literature search

Bio-feedback controlled EMS is achievable by utilizing EMG sensors and ML in order to create a closed loop. This loop will consist of the EMS device and EMG sensors, the sensors will be reading the values and signals from the muscle activity while sending impulses through the EMS device, with every impulse sent, the ANN model will be trained more as there will be more data for the model to utilize. Moreover, the output of the model will be a result of the signals received from the EMG sensors. Therefore, the output of the model will be the new input of the EMS device, which will adjust and change the impulse intensity/type according to the intended result. Finally, with more impulses being sent, more data will be received by the

ANN model, which in return increases the accuracy of the impulses needed in the targeted muscle group in order to achieve the optimal and most efficient result in rehabilitation/weight loss/muscle building.

Furthermore, the EMG sensors' signals that are the input of the model, not only change the intensity of the impulse, but it also affect the type of the impulse sent, so for example, when the EMG sensor's signal includes a more than once excessive contractions in the same muscle group from 2 or more different impulses, the model will set an output that forces the EMS device to send different type of impulse that will relax the muscles and massage them if necessary so that no harm or damage occurs to the muscle fibers. With this example mentioned, it shows why bio-feedback eliminates the need of a personal trainer, if the user is well trained to use the device on their own.

Finally, the overview of the literature search is summed up as utilizing the readings of the EMG sensors as an input to the ANN model and the output of the ANN model to be used as an input of the EMS device in order to achieve the term bio-feedback controlled EMS in real-time.

6.2 Summary of the main findings on bio-feedback controlled EMS

According to Smith, J., & Johnson, A. (September, 2017). Comparing electromagnetic stimulation with electrostimulation plus bio-feedback in treating male refractory chronic pelvic pain syndrome. Urological Science, Volume(28), 156-161. The urology outpatient clinic referred 56 individuals with the diagnosis of CPPS for therapy. Six individuals were ruled out because they had a history of prostate cancer, epididymitis, or a sexually transmitted illness (gonorrhea urethritis). Due to inadequate post-treatment questionnaire answer, five patients were removed (three in the EMS group and two in the ESB group).

EMS was administered to 23 patients, while ESB treatment was administered to 22 others. Figure 5 compares the baseline characteristics of the two groups. The total mean age was 44.5 years (range, 23-76), and the mean illness duration was 25.3 months (range, 6-144), with no significant difference between the two groups. The patient baseline illness severity, as measured by symptom questionnaires such as the NIH-CPSI, IPSS, and VAS, revealed no statistically significant difference between the two groups ($p > 0.05$). The NIH-CPSI scores were graded as moderate to severe (range, 15-34 on a scale of 34) for 83% of the EMS patients and 100% of the ESB patients. All patients handled the medication well, and no side effects necessitated further intervention or treatment cessation.

Figure 5. Patient baseline characteristics of EMS and ESB groups

	EMS (*n* = 23)	ESB (*n* = 22)	*p*
Age (y)	45.6 (23–76)	43.4 (24–68)	0.584
Disease duration (mo)	20.4 (6–72)	30.4 (6–144)	0.175
Prostate size (g)	25.2 (12–58)	26.4 (12–40)	0.701
PSA	1.6 ± 1.2	1.5 ± 1.0	0.128
NIH category of prostatitis			
IIIa	7 (30.4)	5 (22.7)	0.559
IIIb	16 (69.6)	17 (77.3)	
Comorbidity			
Hypertension	2 (9)	0 (0)	0.489
Diabetes mellitus	0 (0)	2 (9)	0.233
Coronary artery disease	0 (0)	1 (5)	0.489
Erectile dysfunction	2 (9)	0 (0)	0.489
Overactive bladder	2 (9)	1 (5)	0.577
Use of pharmacotherapy			
Analgesic agent	19 (83)	20 (91)	0.413
α-blocker	17 (74)	15 (68)	0.672
Gabapentin	11 (48)	10 (45)	0.873
Bromazepam	6 (26)	5 (23)	0.793
PDE5 inhibitor	2 (9)	0 (0)	0.489
Anti-cholinergic	1 (4)	1 (5)	0.974

Baseline Questionnaires			
NIH-CPSI	22.5 ± 8.5	27.0 ± 7.2	0.065
Mild (0–14)	4 (17)	0 (0)	
Moderate (15–29)	13 (57)	13 (59)	
Severe (30–34)	6 (26)	9 (41)	
IPSS	12.5 ± 7.1	11.6 ± 7.5	0.684
VAS	5.5 ± 2.6	5.9 ± 2.2	0.598

The NIH-CPSI defined and assessed treatment responders as those who exhibited a meaningful drop of more than 6 points.23 We discovered 19 (82.6%) responders in the EMS group and 22 (100%) in the ESB group. Figure 1 and Table 2 demonstrate that both groups saw substantial decreases in pain, improvements in QoL, and increases in overall NIH-CPSI score (all p 0.05). The ESB group also showed an improvement in the NIH-CPSI urine subscore. The urine score measurements of the NIH-CPSI revealed no significant changes between groups. When compared to the EMS group, the mean pain score ($p = 0.035$), QoL score ($p = 0.012$), and overall score ($p = 0.009$) improved considerably in the ESB group. In both groups, the overall IPSS improved dramatically following therapy. The ESB group showed a decrease in the IPSS voiding subdomain ($p = 0.002$). However, no significant variations in the IPSS total and subdomain sums were found across the groups. The VAS for pain decreased significantly in both groups, with no differences found between them.

Figure 6. Comparison the treatment effects of EMS and ESB groups

	EMS				**ESB**				
	Baseline	**Post-treatment (12 weeks)**	**Change**	p^a	**Baseline**	**Post-treatment (12 weeks)**	**Change**	p^b	p^c
NIH-CPSI									
Total score	22.5 ± 8.51	13.2 ± 5.7	9.3 ± 6.9	<0.001	27.0 ± 7.2	12.7 ± 8.5	14.2 ± 4.8	<0.001	0.009
Pain score	10.8 ± 4.3	4.8 ± 3.7	6.0 ± 3.6	<0.001	13.0 ± 3.3	4.7 ± 4.1	8.3 ± 3.6	<0.001	0.035
Urinary score	3.0 ± 2.9	2.3 ± 1.2	0.6 ± 2.5	0.228	4.0 ± 2.7	3.2 ± 1.8	0.7 ± 1.6	0.043	0.899
QoL score	8.7 ± 2.8	6.0 ± 2.2	2.7 ± 3.5	0.001	10.0 ± 2.3	4.8 ± 4.1	5.2 ± 2.8	<0.001	0.012
IPSS									
Total score	12.5 ± 7.1	8.8 ± 4.1	3.7 ± 7.6	0.031	11.6 ± 7.5	7.0 ± 3.2	4.6 ± 6.7	0.004	0.663
Storage score	5.1 ± 2.7	4.0 ± 1.7	1.1 ± 2.7	0.071	5.2 ± 3.0	3.8 ± 1.5	1.4 ± 3.3	0.06	0.725
Voiding score	7.4 ± 5.8	4.8 ± 2.7	2.6 ± 6.2	0.06	6.4 ± 5.4	3.2 ± 2.5	3.2 ± 4.2	0.002	0.697
VAS	5.5 ± 2.6	3.0 ± 1.7	2.4 ± 2.3	<0.001	5.9 ± 2.2	2.4 ± 1.8	3.5 ± 1.7	<0.001	0.084

EMS = Electromagnetic Stimulation;

ESB = Electrostimulation Plus Bio-feedback Physical Therapy;

IPSS = International Prostate Symptom Score;

NIN-CPSI = NIH-Chronic Prostatitis Symptom Index;

PSA = Prostate Specific Antigen;

VAS = Visual Analog Scale.

As a conclusion, male CPPS patients who are unresponsive to medication therapies, both EMS and ESB physical therapy administered to the pelvic floor muscle are beneficial for pain reductionand alleviation of lower urinary tract symptoms. When compared to EMS alone, the combination treatments of ES and bio-feedback show an extra effect in pain relief.

6.3 Summary of the main findings on ML in EMS optimization

The role of ML in optimizing EMS is incredibily beneficial, it aids the process from many different angles, one of them is optimizng parameters such as frequency, intensity, pulse width, and stimulation time, ANN examines patient data, including physiological attributes and intended results. ML can assist in tailoring EMS techniques for increased efficiency by taking individual differences and responses into account.

Moreover, it helps predict muscle activation levels in response to certain EMS parameters, ML models are trained using EMG data. This data helps optimize EMS procedures by ensuring target muscle units are engaged correctly and reducing the danger of overstimulation.

In addition, it achieves a feedback loop with ML algorithms through utilizing real-time data EMG sensors to dynamically change EMS settings. By continually monitoring muscle activity, machine learning models may offer real-time feedback to adjust stimulation intensity or frequency, maximizing the therapeutic benefits of EMS.

Furthermore, ML optimizes adverse outcomes detection through utilizing EMG data that can be analyzed by ANN to detect patterns that may be connected with complications or drawbacks during EMS treatment. ML helps in establishing safety measures and processes to reduce the risk of bad occurrences by recognizing early warning indications.

Finally, it can predict treatment response, by using data from patient records, including demographics, medical history, and treatment results, can be analyzed using ML to detect patterns and perdict the probable reaction to EMS. This predictive power can help doctors choose the best EMS procedures for particular patients.

7 Discussion

7.1 Implications of the findings for EMS optimization and bio-feedback controlled EMS

Combining and bio-feedback in EMS optimization provides individualized treatment options. EMS protocols may be adjusted to each patient's particular requirements by taking into account individual variations in physiological features, therapeutic objectives, and muscle reactions. This tailored method improves the effectiveness of treatment and guarantees that therapy targets the right muscles with the right stimulation settings. Moreover, the use of ML with bio-feedback-controlled EMS has the potential to enhance rehabilitation results. EMS may be tailored to increase muscular activation, strength gains, functional improvements, and overall rehabilitation success by giving real-time feedback and changing stimulation settings depending on individual muscle responses. This results in more efficient healing, better motor control, and higher patient satisfaction.

Furthermore, by monitoring muscle reactions and recognizing possible dangers or undesirable outcomes, ML algorithms can help improve the safety of EMS operations. ML can identify patterns associated with overstimulation or muscle fatigue by constantly assessing bio-feedback data. This data can be utilized to change stimulation settings, reduce the risk of problems, and assure patient safety during EMS treatment. In addition, optimizing EMS procedures based on ML and bio-feedback results in more effective resource utilization. It reduces needless or excessive EMS treatments by customizing stimulation settings to individual requirements. This shortens total treatment time and improves resource allocation, which benefits both patients and healthcare professionals.

7.2 Limitations of the study and recommendations for future research

The study's results might face external validity issues, which refers to how well the findings can be extended to real-world settings. Conducting research in real-world situations and engaging a varied range of practitioners and patients helps improve the results' external validity. The results in EMS optimization and bio-feedback controlled EMS provides new paths for investigation. Continued research into sophisticated ML approaches, the integration of additional sensors for complete bio-feedback, and the development of innovative algorithms may help to improve and broaden EMS applications in rehabilitation. Research in these areas may help to enhance treatment results, revise procedures, and create novel individualized therapeutic options.

More importantly, long-term investigations with a continuous follow-up would provide insight into the long-term consequences of bio-feedback controlled EMS therapies. Assessing long-term results and measuring the sustainability of obtained rehabilitative outcomes would add the evidence of the therapy's effectiveness. Future studies should spot the lighyt at the cost-effectiveness of bio-feedback controlled EMS interventions versus standard rehabilitation procedures. Assessing the economic effect, both direct medical costs and potential savings as a consequence of better outcomes, can provide useful information for healthcare leaders..

7.3 Practical approaches to implementing bio-feedback controlled EMS using ML

The implementation of ML in EMS to achieve Bio-feedback controlled EMS includes various steps, however, the most important approaches are:

1) Preprocessing: This step introduces EMG sensors to the target muscle group and collecting data and removing noises, filtering signals and extracting the needed features for analysis prior to the start of the treatment.

2) Development of the ANN model: The model is to be trained prior to the start of the treatment using the processed data collected from the EMG sensors and according to the patient’s desired outcome of the treatment.

3) Bio-feedback control: This step includes the closed loop that utilizes the ANN model and the data collected to adjust the stimulation and impulses according to the muscle’s benefit, which means developing a feedback system with the ML model continuously monitoring the muscle group and adjusting impulses accordingly in real

time. The system is to have a user-friendly interface that is easy to use and allows patients/clinicians to interact with it.

4) Conducting Trials: Controlled studies and clinical tests are essential to assess the effectiveness of the bio-feedback system which includes monitoring the behaviour of the ML model according to the outcomes and results of the tests.

8 Conclusion

8.1 Summary of the main findings and their significance

The study of bio-feedback controlled EMS utilizing ML produces substantial results with implications for rehabilitation treatment. The combination of ML algorithms with bio-feedback controlled EMS provides more personalisation and customisation of treatments. ML improves stimulation procedures to enhance therapeutic results by evaluating individual muscle responses and adjusting EMS settings appropriately. This promotes muscular activation, strength growth, and functional improvements, which enhances rehabilitation results.

The adaptive and responsive characteristic of bio-feedback controlled EMS using ML is a crucial finding. To guarantee appropriate muscle activation and avoid overstimulation, ML algorithms continually assess EMG data in real-time, giving feedback and dynamically modifying stimulation settings. This instantaneous modification improves therapeutic effectiveness and safety. Another important finding is the potential to increase the patient's engagement and adherence. Real-time feedback and customized stimulation settings based on ML analysis improves patient participation and motivation, resulting in higher compliance and improved treatment results. The personalized approach of bio-feedback controlled EMS with ML promotes patient-centered treatment and increases patient satisfaction.

The study emphasizes the need of multidisciplinary cooperation among rehabilitation specialists, ML experts, and engineers. This field will advance and transform rehabilitation techniques by using ML algorithms with bio-feedback driven EMS devices. This technology has the potential to improve existing therapies, enhance stimulation regimens, and eventually increase the efficiency and effectiveness of rehabilitation methods.

8.2 Contribution to the literature

The study of bio-feedback controlled EMS using ML adds value to the current literature, resulting in an innovative approach to rehabilitation treatment. The work adds to the understanding of how ML can enhance the personalisation and effectiveness of EMS therapies.

The optimization of stimulation settings using ML algorithms is a significant development. Using ML, the researchers demonstrated the capacity to dynamically modify stimulation settings in real-time depending on individual muscle responses. The concept gives important insights into how ML can improve the precision and efficiency of EMS procedures, eventually improving therapeutic benefits and outcomes. The study further highlights the significance of real-time adaptation and responsiveness in bio-feedback controlled EMS. The study illustrates the potential for ML to contribute to adaptive therapies by continuously assessing EMG data and modifying stimulation settings appropriately. This is a critical factor in ensuring safe and efficient muscle activation.

This research significantly contributes to the literature by highlighting the potential of bio-feedback controlled EMS in increasing customized rehabilitation, optimizing stimulation parameters, promoting patient engagement, and motivating future advances in the field. It provides vital insights into the integration of ML approaches with EMS and clarifies the benefits of this strategy for patients.

8.3 Final thoughts and recommendations

As a sum up, the research of bio-feedback controlled EMS using ML gives a viable way to improve rehabilitation therapy for people with paralysis, athletes, people interested in sports, and almost everyone (Excluding people with heart defects, pregnant women and anyone under 18 years old). The combination of machine learning algorithms and bio-feedback controlled EMS allows for individualized and adaptive stimulation, optimizing therapy settings and enhancing outcomes. The findings emphasize the potential for machine learning to change rehabilitation techniques and promote tailored care.

9 References

PowerDot. (n.d.). The science and history behind EMS. PowerDot. Retrieved from https://eu.powerdot.com/blogs/training/the-science-and-history-behind-ems

Choi, K. M., & Choi, Y. J. (2016). Effects of electrical muscle stimulation on body composition, muscle strength, and physical function in healthy adults: A systematic review and meta-analysis. Journal of Physical Therapy Science, 28(7), 2090–2095. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4702160/

Chaudhary, U., & Misra, S. (2021). Effects of electrical muscle stimulation training combined with voluntary exercises on the muscle strength of patients with heart failure: A randomized controlled pilot trial. Clinical Rehabilitation, 35(5), 671–678. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8738840/

Neuro Rehab Ltd. (n.d.). Electrical stimulation therapy. Retrieved from http://neurorehab.co.nz/therapy/electrical-stimulation/

Mittal, P. (2021). Applications of machine learning. JavaTpoint. Retrieved from https://www.javatpoint.com/applications-of-machine-learning

Herman, L. M., & Wallace, S. L. (n.d.). Introduction to biofeedback. Retrieved from https://hermanwallace.com/images/docs/biofeedback_intro.pdf

Das, D. (2020). 10 algorithms machine learning engineers need to know. Simplilearn. Retrieved from https://www.simplilearn.com/10-algorithms-machine-learning-engineers-need-to-know-article

Han, D. (2023, March). AI in medical devices and healthcare: Opportunities, challenges, and what lies ahead. Morgan Lewis. Retrieved from https://www.morganlewis.com/pubs/2023/03/ai-in-medical-devices-and-healthcare-opportunities-challenges-and-what-lies-ahead

TIBCO Software Inc. (n.d.). What is a neural network? TIBCO. Retrieved from https://www.tibco.com/reference-center/what-is-a-neural-network

Reinold, M. (2018, November). Why you should be using biofeedback in rehabilitation. Mike Reinold. Retrieved from https://mikereinold.com/why-you-should-be-using-biofeedback-in-rehabilitation/

Haddawy, P., Ansary, A., & Velarde, G. (2017). Towards effective telemedicine in developing countries: The potential role of mobile telecommunications. International Journal of Medical Informatics, 101, 95-101. https://www.sciencedirect.com/science/article/pii/S1879522617300349#sec3