Evaluating the Viability of Neural Networks for Analysing Electromyography Data in Home Rehabilitation: Estimating Foot Progression Angle

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Keywords: Electromyography, Neural Network, Deep Learning, Rehabilitation, Intramedullary Nailing, Femur Shaft Fracture, Foot Progression Angle.

Abstract: Intramedullary (IM) nailing is a widely accepted treatment for femoral shaft fractures due to its good healing rate and rapid return to full weight bearing. However, a significant number of patients experience impairments years after treatment. One possible cause is a malrotation of the femur, resulting in altered foot progression angles (FPAs), which can lead to changes in gait or persistent pain. To gain a better understanding of compensation mechanisms and improve rehabilitation strategies, a continuous surface electromyography (EMG) measurement system worn on vastus lateralis (VL) and vastus medialis (VM) is proposed. To test the feasibility of this approach, a study is conducted with healthy participants (N=10) simulating different FPA. The EMG signal was recorded and analysed using a convolutional neural network (CNN). The feasibility study showed promising results, as the CNN could on average achieve a validation accuracy of 74% in classifying FPAs as normal, inward (-15°), or outward (+15°). These results show the potential of using EMG measurements from VL and VM to monitor changes in FPA during rehabilitation. This approach offers the opportunity to increase our understanding of compensatory mechanisms and improve rehabilitation outcomes following malrotation caused by IM nailing.

1 INTRODUCTION

The established gold standard for the treatment of femoral shaft fractures is the use of an intramedullary (IM) nail. The widespread adoption of this method is attributed to its compelling properties, including a high likelihood of fracture union (99%) (Mavrogenis et al., 2016), a low risk of infection (El Moumni et al., 2012) and a rapid weight bearing (Rommens & Hessmann, 2015). However, potential risks include implant failure (Mavrogenis et al., 2016) or non-union of the fractured femur (El Moumni et al., 2012).

Despite the relatively low risk associated with IM nailing, approximately 20% of patients subjected to this procedure suffer from long-term residual impairments. These complications can include pain, hip ossification, altered gait patterns or restricted mobility in hip and knee (El Moumni et al., 2012; Hamahashi et al., 2019). The cause of these complications remains a topic of ongoing debate. Surgical factors, including the risk of injuring surrounding muscle tissue, nerve supply or articular cartilage may contribute (El Moumni et al., 2012). Another potential factor could be, that there is no direct visibility of the femur during surgery making it difficult to precisely restore rotation and length of the fractured femur and thus increasing the risk of malrotation or malpositioning (Jaarsma & van Kampen, 2004). Such misalignments are defined as deviations greater than 5° in the frontal or sagittal plane, 15° in the axial plane, and 2 cm in length (Ricci et al., 2008). The incidence of such deviations varies between 22.7% to 28% across studies (Jaarsma & van Kampen, 2004; Papachristos, 2019; Rommens & Hessmann, 2015).

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Siegel, F., Buj, C., Merfort, R., Hein, A. and Aschwege, F.
Evaluating the Viability of Neural Networks for Analysing Electromyography Data in Home Rehabilitation: Estimating Foot Progression Angle.
DOI: 10.5220/0012385100003657

In *Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2024) - Volume 2*, pages 132-141
ISBN: 978-989-758-688-0; ISSN: 2184-4305

Irrespective of an identified cause, long-term residual impairments pose a substantial burden to the affected patient. Effective rehabilitation, essential for moderating or even resolving these consequences, depends on accurate identification of limitations. After hospitalization, as patients transition to a home-based care, monitoring is mostly based on subjective self-assessments, which tend to be inaccurate and can reduce the quality of rehabilitation (Toogood et al., 2016).

Previous research by Siegel et al. (2023) suggests the use of wearable home devices as a strategy to improve the accuracy of rehabilitation monitoring, allowing the identification of long-term residual impairments, thereby providing a basis for the treating specialist to take adapted countermeasures. In addition, a continuous monitoring system could detect possible malrotation and monitor any changes during rehabilitation (Siegel et al., 2023). Research by Jaarsma et al. (2004) showed that, on average, patients are capable of compensating for approximately 71% of a given malrotation. However, an enhanced understanding of malrotation mechanisms could provide further insight into the compensation strategies and enable clinicians to help patients cope by training targeted supporting muscles. This is relevant, as some studies show a high likelihood for malrotation to be a major source of pain (Dagneaux et al., 2018).

To gain insight into malrotation, compensation mechanisms and coping strategies, it is necessary to continuously measure foot progression angle (FPA). In a previous paper, the concept of employing a wearable device, positioned above the knee, equipped with electromyography (EMG) sensors to measure the FPA, was introduced (Siegel et al., 2023).

An EMG measurement records biopotentials when an electrochemical stimulus triggers muscle fibre (Al-Ayyad et al., 2023). The possibility of using EMG measurements to draw conclusions about FPA is based on the premise that alterations in movement are accompanied by a corresponding change in the measurable EMG signal (Akuzawa et al., 2017). In addition, Benedetti el al., 2003 found that altered muscle contractions, quantifiable through EMG measurements, may account for a compensation mechanism (Benedetti et al., 2003).

In order to detect these alterations in muscle activity, a surface EMG measurement should ideally record the electrical activity of uniformly active motor units within one muscle. However, the resulting EMG signal is subject to many influences, including fatigue, quantity of active motor units, firing rates, firing amplitudes, superposition from surrounding muscles, low-pass characteristics of surrounding tissue, sensor properties and extraneous signals such as ambient noise. This complexity makes it difficult to reliably classify EMG recordings using basic filter algorithms or feature extraction methodologies. As a possible answer to this challenge, deep learning has proven to be a successful tool (Faust et al., 2018). Especially the usage of convolutional neural networks (CNNs) has been proven reliable (Olsson et al., 2019; Yang et al., 2019; Zia Ur Rehman et al., 2018). CNNs are particularly suitable for detecting patterns in one-dimensional or multi-dimensional data due to a high degree of invariance to translation, scaling, skewing or distortion. This is possible because each neuron receives its input from a local receptive field from the previous layer. Thus, the position of features becomes less important as long as they maintain their relative position to each other (Al-Jabery,Khalid et al., 2020), enabling a classification of variant time series (Zhao et al., 2017). I.e. Bakircioğlu and Öskurt (2020) used a CNN to classify EMG recordings of movements made while gripping six different objects and achieved 95.9% accuracy. Olsson et al. (2019) used a CNN, classifying 16 independent states of the hand recorded using an EMG system and achieved 78.7% accuracy.

1.1 Aim of this Study

The aim of this study is to evaluate the potential utility of EMG sensors in improving the reliability of monitoring FPAs during home-based rehabilitation, a crucial aspect considering the FPA contributes significantly in long-term outcome following femoral shaft fracture treatment.

As of now, EMG measurements have been successfully used in numerous rehabilitation applications, such as:

- In neuromuscular rehabilitation, EMG measurements can be used to quantitatively assess spasticity as well as monitor treatment progress (Campanini et al., 2020).
- In post-stroke rehabilitation, EMG measurements can be used to monitor the healing process (Simpson et al., 2011) or to control an exoskeleton aimed to reactivate paralysed limbs (Nam et al., 2022).
- In orthopaedic rehabilitation, EMG measurements can be used to evaluate muscle function, to detect abnormalities or to manage pain-inducing syndromes during sessions with specialists (Barton et al., 2013; Benedetti et al., 2003).

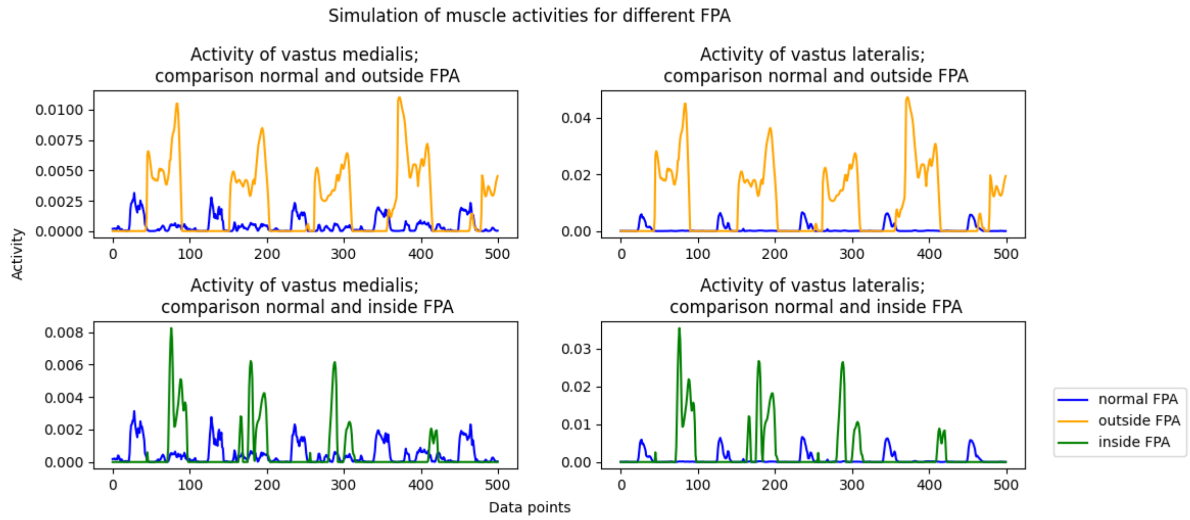

Figure 1: Presentation of simulation results, generated with Anybody software. Simulated muscle activity during normal gait and gait with an intentional alteration (approximately 15° inside or outside) of foot progression angle is displayed. The overview is shown for vastus medialis and vastus lateralis.

However, until now, EMG measurements have not been used to monitor a patient's activity or malrotation in a home environment.

There are already sensor systems measuring FPAs, such as inertial measurement units (IMUs) or pressure sensors, but these have limitations such as inaccurate results indoors or a dependency on the footwear (Siegel et al., 2023). An EMG system, worn on the leg, could potentially overcome these limitations while increasing data availability, and is therefore being tested in this study.

Since this study is intended to provide a first overview of the usability of EMG measurements for FPA monitoring, it was decided to conduct the tests on a healthy cohort rather than on patients. The study will evaluate the following hypotheses:

<u>Hypothesis A:</u> A CNN can classify FPAs of unknown steps for a single proband, after training on EMG data obtained from the same proband.

If a CNN is capable do discriminate EMG signals from different FPAs within a single proband, this knowledge holds potential to monitor changes in FPAs during rehabilitation. However, this is limited, since the proband would need to simulate different FPAs in order to train such neural network. In practical clinical scenarios, this data aggregation may not be feasible, due to the recently treated femur shaft fracture. Therefore, it is important to investigate, whether a neural network can be trained using data from diverse patients and enabling it to classify EMG signal for different FPAs without prior subject specific training. To test this the following hypotheses is formulated:

<u>Hypothesis B:</u> A CNN can classify FPAs for an unknown proband, after training on EMG data obtained only different probands.

To test hypotheses A and B, EMG signals of several probands simulating different FPAs are recorded and analysed using a CNN.

2 MATERIAL AND METHODS

For the acquisition of EMG data across different FPAs, ten volunteers were recruited. Exclusion criteria were adhesive tape and silver allergy, implanted electrical devices and known deformities of the lower limb. The gender distribution was 50% male to 50% female with a mean age of 36.5 years (±14.3 years).

2.1 Sensor Placement

To ensure optimal sensor placement, aligned to answer the hypotheses, literature was reviewed to find potential correlations between lower limb muscle activity and FPA. A simulation was used to verify the results. Mohammad and Elsais (2020) investigated the correlation between EMG signal amplitude and hip rotation in male runners. They found such a relationship for Vastus Lateralis (VL), Vastus Medius (VM) and Gluteus Maximus. As the overall goal, outlined in earlier work (Siegel et al., 2023), is to wear a sensor array positioned above the knee, the electrical activity of VL and VM are promising muscles for conclusions to be drawn about FPAs.

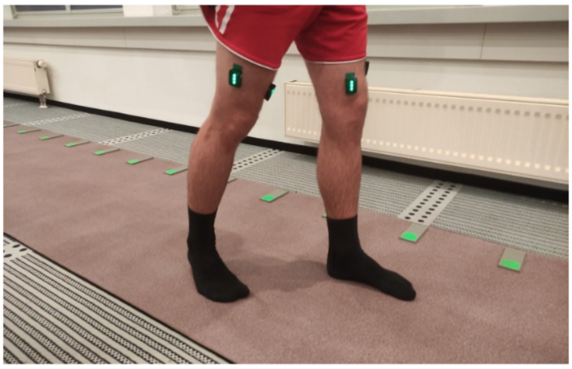

Figure 2: Exemplary image from the study displaying placement of EMG sensors on VL and VM. The GaitRite mat, used for FPA verification, is also visible.

To further confirm that change in FPA induces change in muscle activity for VL and VM, a simulation was performed in collaboration with university hospital in Aachen, Germany. A volunteer was fitted with a MTw Awinda motion tracker system (Paulich et al., 2018) and walks with different FPAs were conducted. The FPA was varied between 15° inward, normal and 15° outward. To derive muscle activity from the collected data, the AnyBody Modelling System (Paul & Doweidar, 2023) was used in combination with the AnyBody Managed Model Repository. This approach allows an inverse dynamics analysis to be performed, based on a third-order polynomial muscle recruitment criterion, which produces a simulation of the electrical activity in the lower limb muscles during walks. The results are shown in figure 1. This figure displays muscle activity during gait with normal FPA compared to gait with an inward or outward FPA. The simulated activity is shown for VM and VL. It is immediately noticeable, that the shape of the curves for normal and modified FPA are distinctly different. To quantify these observations, the integral of the curves was calculated (python library: numpy.trapz (Harris et al., 2020)), displayed in table 1. The results show variation in the area under the curve for normal FPAs compared to modified FPAs. The differences are particularly significant for outside FPAs in comparison to inside FPAs. The simulation supports the choice of using VL and VM as EMG measurement points to detect differences in FPA.

In conclusion it was decided to place the EMG sensors on VL and VM. The European recommendations for sensors and sensor placement for EMG (Hermens et al., n.d.) was used as a guide to ensure optimal placement of the sensors on VL and VM, minimising superposing of signals by surrounding muscles. To further improve signal quality, the skin was shaved and cleaned prior to sensor placement. An example of placed sensors is given in figure 2.

Table 1: To quantify figure 1, the area under the plotted curves is calculated using the trapezoid method (python library: numpy.trapz) and the results are shown in this table.

	Vastus Medius	Vastus Lateralis
Area: Normal FPA	0.958	1.151
Area: Inside FPA	0.817	3.502
Area: Outside FPA	3.711	15.901

2.2 Signal Acquisition

The EMG signal was recorded using the Delsys Trigno-Wireless-Biofeedback System (Delsys, n.d.). This system consists of a base station that wirelessly collects data from individual sensors. Each sensor is capable of collecting data at a frequency of 4 kHz with a bandwidth of 20-450 Hz and an input range of 11 mV.

For the purpose of supervised learning, it is necessary to label EMG data recordings. Consequently, a GaitRite mat was used to record the FPAs. The mat is manufactured by CIR Systems represents a gold standard in gait analysis. 36 864 pressure sensors evenly distributed of over a length of 914 cm allows steps to be recorded and a gait profile to be created. This profile includes the FPA for each step executed. A section of the mat can be seen in the figure 2.

In order to conduct this study, each proband had to perform a total of 45 walks along the entire length of the GaitRite. 15 normal walks, 15 walks with outward FPAs and 15 walks with inward FPAs. For each simulated malrotation, the participants were asked to change their FPA by -15° inward or +15° outward. Prior to the study, foot positions were trained using the GaitRite mat. During the study any steps deviating by more than ±8° from proposed FPA were removed from the dataset. Only one foot was varied during the different walks. The side to be varied was freely chosen by the proband, the choice remained consistent throughout the study. A metronome was used to ensure uniform walking speed during different walks. In order to merge EMG data with GaitRite data, software was developed to record both systems simultaneously. Both data streams were synchronised by an output signal generated by the GaitRite system.

2.2.1 Data Preprocessing

Data preprocessing is performed according to a general data preparation paradigm (Al-Jabery et al., 2020). During the study, walks across the GaitRite mat were recorded alongside the corresponding EMG signals, resulting in 15 datasets per class (inward, outward and normal FPA). However, this quantity proved insufficient to train a supervised deep learning algorithm (Alwosheel et al., 2018). To increase the size of each class, the walks are divided into individual steps. For this purpose, software was developed that extracts individual steps based on EMG peak detection and assigns them to the appropriate FPA class. This results in a dataset for each proband containing the EMG signal for VL and VM and the corresponding FPA for each step.

To extract non-stationary properties from the EMG signal, time windowing is performed (Zha et al., 2021). Initially, the EMG signal of one step spans over a duration of one second. This can be contracted, since VL and VM are only active for approximately 20% to 25% of the time during one gait cycle (Róisín Howard, 2017). The average duration of a gait cycle is around one second (Murray et al., 1964), enabling the EMG signal be to contracted to a duration of 250 ms. As data was collected at 4 kHz, the EMG signal is truncated to a time window of 1000 data points (250ms). The next step is a high and low pass filtering (Morbidoni et al., 2019), already conducted by the sensor. To filter motion artifacts, a low-pass filter with a cutoff frequency of 20 Hz is used. A high-pass filter with a cutoff frequency of 450 Hz is applied, as not much additional information is available above this frequency (Bakircioğlu & Özkurt, 2020). This is followed by a rectification of the data, enhancing the chances of successful training of deep learning algorithms (Li et al., 2011). Next, a Fast Fourier Transformation (FFT) is performed creating additional input features and enhancing information density (Yang et al., 2019). Finally, data is normalised using the peak-dynamic method, requiring each data point to be divided by the maximum value. While this method results in a loss of information regarding the degree of muscle activation, it enhances the comparability between probands.

Table 2: This table displays the distribution of steps generated in this study across different subjects and FPAs, showing the class sizes used to train the neural network.

	Prob 1	Prob 2	Prob 3	Prob 4	Prob 5	Prob 6	Prob 7	Prob 8	Prob 9	Prob 10	Total
Normal FPA	62	66	64	74	73	72	74	54	75	49	663
Inward FPA	69	84	85	75	68	68	80	71	71	73	744
Outward FPA	76	88	80	74	72	73	73	61	67	75	739
Total	207	238	229	223	213	213	227	186	213	197	2146

In Conclusion, a matrix is generated containing both a time series and a frequency series, for each labelled step and each sensor. Combining the measurements for VL and VM results in a matrix of

Table 3: This table shows the structure of the CNN used. The optimizer *adam* and *sparse categorical crossentropy* were used for training.

Layer	Modules	Configurations	Layer	Modules	Configurations
/	Input	n_steps*1000*4*1	9	Flatten	
1	Convolution	Filters=256 Kernel=4*2, Padding=same Activation=ReLu (α=0.02)	10	Dense	Units=40 Activation=ReLu (α=0.005)
2	Dropout	0.1	11	Dropout	0.1
3	Convolution	Filters=80 Kernel=4*2, Padding=same Activation=ReLu (α=0.02)	12	Dense	Units=90 Activation=ReLu (α=0.005)
4	Dropout	0.1	13	Dropout	0.1
5	Convolution	Filters=40 Kernel=4*2, Padding=same Activation=ReLu (α=0.02)	14	Dense	Units=27 Activation=ReLu (α=0.005)
6	Dropout	0.1	15	Dropout	0.1
7	Max Pooling	Pool size=3*2 Strides=2, Padding=same	16	Dense	Units=9 Activation=ReLu (α=0.005)
8	Dropout	0.1	17	Dense	Units=3 Activation=softmax

Table 4: Representation of the accuracy achieved for individual subjects using a CNN for classifying the classes normal, inside and outside FPAs. The network was trained and evaluated three times. The average accuracy and the corresponding standard deviation are also presented.

	Prob 1	Prob 2	Prob3	Prob 4	Prob 5	Prob 6	Prob 7	Prob 8	Prob 9	Prob 10	Average	STD
1. Iteration	64.3%	60.4%	60.9%	82.2%	88.4%	83.7%	79.2%	79.1%	71.8%	90.0%	76.0%	10.5%
2. Iteration	66.7%	56.9%	54.2%	68.9%	80.0%	81.4%	82.0%	76.1%	79.5%	90.0%	73.6%	11.0%
3. Iteration	66.7%	56.3%	58.0%	75.6%	75.2%	83.0%	79.2%	72.2%	74.4%	88.3%	72.9%	9.6%
Average	65.9%	57.9%	57.7%	75.6%	81.2%	82.7%	80.1%	75.8%	75.2%	89.4%	74.2%	10.4%

four features with 1000 data points times the number of steps. In this study, a total of 186-238 steps were recorded, per participant. Resulting in 2146 steps available to train the CNN, see table 2. This is a relatively modest dataset size for the application of deep learning (Alwosheel et al., 2018), but the purpose of this study is to provide an initial insight in the possibility of determining FPAs using EMG measurements in conjunction with deep learning evaluations and therefore declared acceptable for this feasibility study.

2.2.2 Used Network

The structure of the CNN used is shown in the table 3. The network is built using TensorFlow (Martín Abadi et al., 2015) and Keras (Chollet & others, 2015) libraries in Python. To obtain reliable results, each run was performed three times and the average validation accuracy is taken as the result.

3 RESULTS

In the following the results gained from the analysis of the study data are presented in relation to the tested hypothesis.

3.1 Results for Testing Hypothesis A

H: *A CNN can classify FPAs of unknown steps for a single proband, after training on EMG data obtained from the same proband.*

To test this hypothesis, data from the gait study obtained by each proband individually was used to train the CNN. The labelled data was combined, randomly mixed and 85% was used for training and the remaining 15% served as validation data. To

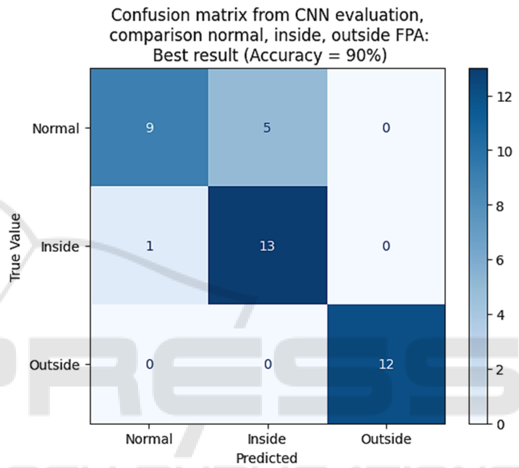

Figure 3: Confusion matrix, showing the result for the best prediction. The predicted value is shown against the true value.

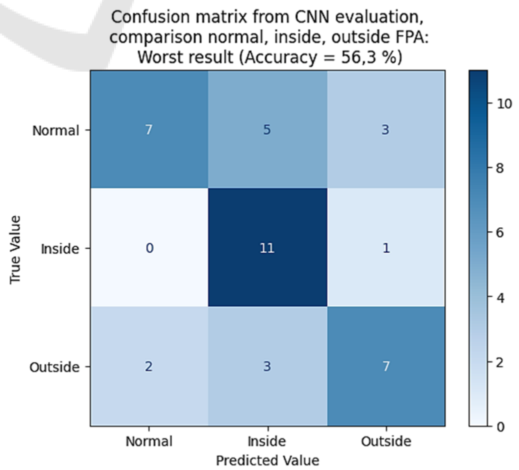

Figure 4: Confusion matrix, showing the result for the least successful prediction. The predicted value is shown against the true value.

Table 5: Presentation of the interproband validation accuracy achieved using a CNN to classify the classes normal, inside and outside FPAs. Shown is the average validation accuracy.

	Prob 1	Prob 2	Prob 3	Prob 4	Prob 5	Prob 6	Prob 7	Prob 8	Prob 9	Prob 10	Average
Validation accuracy	44.6%	36.4%	39.7%	38.4%	34.0%	43.3%	37.3%	42.3%	39.7%	46.8%	40.3%

ensure a reliable conclusion, each training iteration was performed three times. The results are presented in table 4.

Steps are classified into three classes (normal, internal and external rotated FPAs) with an average classification accuracy of 74.2% (±10.4%). This performance exceeds chance level of $33.\overline{3}\%$. Additionally, a confusion matrix is displayed, for the most successful and the least successful classification, see figure 3.

The result suggests that a CNN can learn and discriminate features within the EMG signal allowing conclusions to be drawn about FPAs. However, the high variance of 10.4% indicates inconsistency in the quality of features identified by the CNN between probands.

3.2 Results for Testing Hypothesis B

H: *A CNN can classify FPAs for an unknown proband, after training on EMG data obtained from different probands.*

To test this hypothesis, datasets from all probands excluding one for validation were combined and used to train a CNN. This process was repeated, ensuring each proband's data was tested against the combined majority. The results are shown in table 5. It can be seen that a CNN, trained on a whole population, can distinguish validation steps an average accuracy of 40% across inward, outward and normal FPAs. The results indicate a limited reliability for a classification of unknown EMG data recorded from different FPAs.

4 DISCUSSION

In this study, each class (normal, inside and outside FPA) contains 1326-1488 trails (for VL and VM combined), which, in the context of deep learning, accounts for a relatively small dataset (Alwosheel et al., 2018). However, when working with EMG measurements, the availability of data is limited by the number of times a person can repeat a specific movement. This limitation restricts the size of available datasets, which needs to be considered when working with deep neural networks. Nevertheless, researchers have shown that small datasets can be used successfully, i.e. Grag et al. (2021) used three classes of EMG recordings and a total of 1575 trails while achieving an accuracy of 85.44%.

The inclusion of 10 probands, as in this study, is in line with the approach of other researchers, when experimenting with EMG data. I.e. Rehman et al. (2018) collected data from seven healthy probands and Bakircioğlu and Öskurt (2020) had five probands enrolled in their study.

4.1 Discussion of Hypothesis A

H: *A CNN can classify FPAs of unknown steps for a single proband, after training on EMG data obtained from the same proband.*

This study has shown a CNN can learn features from EMG recordings of VL and VM to distinguish between outward, inward and normal FPAs with an average success rate of 74.2%. The standard deviation of 10.4% reflects the high variance of the EMG signal, which has also been reported by other researchers (Rane et al., 2019). The variability of the EMG signal can be attributed to its inherent nature, which is non-stationary, non-linear, stochastic, and unpredictable (Geng et al., 2016). At the same time, the characteristics of the sensor play a role, as the signal varies depending on the position relative to the muscle and the quality of the contact with the skin. In addition, the signal is prone to noise, including instrument noise, ambient noise, motion artefacts, and signal instability (Reaz et al., 2006).

The result of this part of the study is in line with results of other studies, i.e. Tryon et al. (2021) achieved an accuracy of 74.7% in discriminating EMG signals into three classes related to elbow flexion while holding different weights.

It is important to note, when dealing with hand gestures using a CNN, results tend to be significantly better. For instance, Lee at al. (2020) achieved an accuracy of 94% when discriminating between ten gesture classes. The differences in performance may be due to the availability of distinct movements, whereas this study focuses on detecting small changes in movement sequences, which are easily masked by the noise of the EMG signal.

An improvement in results could be achieved by using CNNs in combination with other deep learning algorithms. For example, by connecting CNNs to bidirectional LSTM networks. Karnam et al. (2022) were able to improve the accuracy of classifying EMG recordings of hand gestures by up to 18.7% compared to state-of-the-art models.

Another way to improve the accuracy of the CNN is using transfer learning. This involves pre-training the network on subjects with comparable data recorded from other subjects followed by training on target data. Soroushmojdehi et al. (2022) showed that this methodology can improve the accuracy of a CNN, when predicting hand movements based on EMG data, up to 10%.

4.2 Discussion of Hypothesis B

H: *A CNN can classify FPAs for an unknown proband, after training on EMG data obtained from different probands.*

The result of this hypothesis testing shows an average accuracy of 40.3%, barely surpassing chance level (33.33%). A major contributing factor is the high interpatient variability. This high variability has already been reported by Anders et al. (2019), who demonstrated substantial interindividual variability and Guidetti et al. (1996) found significant variation between subjects.

Furthermore, the interpatient comparison results are consistent with findings in existing literature. In this study, three classes of FPAs were classified with up to 46.8% validation accuracy, see table 4. This performance is comparable to that of Castellini's team, who achieved an accuracy of 51.7% for three classes in an interpatient evaluation (Castellini et al., 2009).

One way to improve the results could be to use the normal gait pattern of a subject under investigation as calibration followed by detecting changes in FPAs with the help of a trained CNN. Cano et al. (2022) showed, that the accuracy of predicting high blood pressure in unknown subjects could be increased by up to 30% this way.

5 CONCLUSIONS

The aim of this study was to provide initial insights into the potential utility of EMG sensors in improving the reliability of FPA monitoring during home rehabilitation. It has been demonstrated that EMG measurements, evaluated by a CNN trained on an individual proband, can be used to classify between inward, outward and normal FPAs with an average validation accuracy of 70.4%. In conclusion, while the results show that such a system is not yet ready for use as a medical device, they highlight the potential and need for further research into this approach.

The major goal for the future is to develop a user-friendly measuring device capable of precisely detecting changes in FPA, providing essential data for the recovery process. The next steps on this path include minimising the variance between different patients. The use of an EMG sensor array is one possible solution for this, as it allows the determination of the sensor with the optimal signal quality, thus reducing the need for precise sensor placement. In addition, increasing the size of the data set is a critical factor. The possibility to integrate more steps could significantly increase the accuracy of a neural network. other optimisation approaches include combining different deep learning algorithms and testing the usability of transfer learning.

To the best of our knowledge, this study represents the first instance of utilizing EMG measurements in combination with CNNs to provide insight into FPA.

ACKNOWLEDGEMENTS

This work is founded by the German Federal Ministry of Education and Research (BMBF) (FKZ: 01IS21085) and is part of the ITEA Secure-e-Health project.

REFERENCES

Akuzawa, H., Imai, A., Iizuka, S., Matsunaga, N., & Kaneoka, K. (2017). The influence of foot position on lower leg muscle activity during a heel raise exercise measured with fine-wire and surface EMG. *Physical Therapy in Sport*, *28*, 23–28. https://doi.org/10.1016/j.ptsp.2017.08.077

Al-Ayyad, M., Owida, H. A., De Fazio, R., Al-Naami, B., & Visconti, P. (2023). Electromyography Monitoring Systems in Rehabilitation: A Review of Clinical Applications, Wearable Devices and Signal Acquisition Methodologies. *Electronics*, *12*(7), 1520. https://doi.org/10.3390/electronics12071520

Al-Jabery,Khalid, Obafemi-Ajayi, Tayo, Olbricht, Gayla, & Wunsch, Donald. (2020). *Computational learning approaches to data analytics in biomedical applications*. Academic press.

Alwosheel, A., Van Cranenburgh, S., & Chorus, C. G. (2018). Is your dataset big enough? Sample size requirements when using artificial neural networks for discrete choice analysis. *Journal of Choice Modelling*, *28*, 167–182. https://doi.org/10.1016/j.jocm.2018.07.002

Anders, J. P. V., Smith, C. M., Keller, J. L., Hill, E. C., Housh, T. J., Schmidt, R. J., & Johnson, G. O. (2019). Inter- and Intra-Individual Differences in EMG and MMG during Maximal, Bilateral, Dynamic Leg Extensions. *Sports*, *7*(7), 175. https://doi.org/10.3390/sports7070175

Bakircioğlu, K., & Özkurt, N. (2020). Classification of Emg Signals Using Convolution Neural Network. *International Journal of Applied Mathematics Electronics and Computers*, *8*(4), 115–119. https://doi.org/10.18100/ijamec.795227

Barton, C. J., Lack, S., Malliaras, P., & Morrissey, D. (2013). Gluteal muscle activity and patellofemoral pain syndrome: A systematic review. *British Journal of Sports Medicine*, *47*(4), 207–214. https://doi.org/10.1136/bjsports-2012-090953

Benedetti, M. G., Catani, F., Bilotta, T. W., Marcacci, M., Mariani, E., & Giannini, S. (2003). Muscle activation pattern and gait biomechanics after total knee replacement. *Clinical Biomechanics*, *18*(9), 871–876. https://doi.org/10.1016/S0268-0033(03)00146-3

Campanini, I., Disselhorst-Klug, C., Rymer, W. Z., & Merletti, R. (2020). Surface EMG in Clinical Assessment and Neurorehabilitation: Barriers Limiting Its Use. *Frontiers in Neurology*, *11*, 934. https://doi.org/10.3389/fneur.2020.00934

Cano, J., Fácila, L., Gracia-Baena, J. M., Zangróniz, R., Alcaraz, R., & Rieta, J. J. (2022). The Relevance of Calibration in Machine Learning-Based Hypertension Risk Assessment Combining Photoplethysmography and Electrocardiography. *Biosensors*, *12*(5), 289. https://doi.org/10.3390/bios12050289

Castellini, C., Fiorilla, A. E., & Sandini, G. (2009). Multi-subject/daily-life activity EMG-based control of mechanical hands. *Journal of NeuroEngineering and Rehabilitation*, *6*(1), 41. https://doi.org/10.1186/1743-0003-6-41

Chollet, F. & others. (2015). *Keras*. https://keras.io

Dagneaux, L., Allal, R., Pithioux, M., Chabrand, P., Ollivier, M., & Argenson, J.-N. (2018). Femoral malrotation from diaphyseal fractures results in changes in patellofemoral alignment and higher patellofemoral stress from a finite element model study. *The Knee*, *25*(5), 807–813. https://doi.org/10.1016/j.knee.2018.06.008

Delsys. (n.d.). *Trigno Wireless Biofeedback System*. https://www.delsys.com/downloads/USERSGUIDE/trigno/wireless-biofeedback-system.pdf

El Moumni, M., Voogd, E. H., Ten Duis, H. J., & Wendt, K. W. (2012). Long-term functional outcome following intramedullary nailing of femoral shaft fractures. *Injury*, *43*(7), 1154–1158. https://doi.org/10.1016/j.injury.2012.03.011

Faust, O., Hagiwara, Y., Hong, T. J., Lih, O. S., & Acharya, U. R. (2018). Deep learning for healthcare applications based on physiological signals: A review. *Computer Methods and Programs in Biomedicine*, *161*, 1–13. https://doi.org/10.1016/j.cmpb.2018.04.005

Garg, N., Balafrej, I., Beilliard, Y., Drouin, D., Alibart, F., & Rouat, J. (2021). Signals to Spikes for Neuromorphic Regulated Reservoir Computing and EMG Hand Gesture Recognition. *International Conference on Neuromorphic Systems 2021*, 1–8. https://doi.org/10.1145/3477145.3477267

Geng, W., Du, Y., Jin, W., Wei, W., Hu, Y., & Li, J. (2016). Gesture recognition by instantaneous surface EMG images. *Scientific Reports*, *6*(1), 36571. https://doi.org/10.1038/srep36571

Guidetti, L., Rivellini, G., & Figura, F. (1996). EMG patterns during running: Intra- and inter-individual variability. *Journal of Electromyography and Kinesiology*, *6*(1), 37–48. https://doi.org/10.1016/1050-6411(95)00015-1

Hamahashi, K., Uchiyama, Y., Kobayashi, Y., Ebihara, G., Ukai, T., & Watanabe, M. (2019). Clinical outcomes of intramedullary nailing of femoral shaft fractures with third fragments: A retrospective analysis of risk factors for delayed union. *Trauma Surgery & Acute Care Open*, *4*(1), e000203. https://doi.org/10.1136/tsaco-2018-000203

Harris, C. R., Millman, K. J., Walt, S. J. van der, Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., Kerkwijk, M. H. van, Brett, M., Haldane, A., Río, J. F. del, Wiebe, M., Peterson, P., … Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, *585*(7825), 357–362. https://doi.org/10.1038/s41586-020-2649-2

Hermens, Freriks, Merletti, Rau, Disselhorst-Klug, & Stegeman. (n.d.). *SENIAM (Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles) project*. http://www.seniam.org/

Jaarsma, R. L., Ongkiehong, B. F., Grüneberg, C., Verdonschot, N., Duysens, J., & van Kampen, A. (2004). Compensation for rotational malalignment after intramedullary nailing for femoral shaft fractures. *Injury*, *35*(12), 1270–1278. https://doi.org/10.1016/j.injury.2004.01.016

Jaarsma, R. L., & van Kampen, A. (2004). Rotational malalignment after fractures of the femur. *The Journal of Bone and Joint Surgery. British Volume*, *86-B*(8), 1100–1104. https://doi.org/10.1302/0301-620X.86B8.15663

Karnam, N. K., Dubey, S. R., Turlapaty, A. C., & Gokaraju, B. (2022). EMGHandNet: A hybrid CNN and Bi-LSTM architecture for hand activity classification using surface EMG signals. *Biocybernetics and Biomedical Engineering*, *42*(1), 325–340. https://doi.org/10.1016/j.bbe.2022.02.005

Lee, S., Sung, M., & Choi, Y. (2020). Wearable fabric sensor for controlling myoelectric hand prosthesis via classification of foot postures. *Smart Materials and Structures*, *29*(3), 035004. https://doi.org/10.1088/1361-665X/ab6690

Li, G., Li, Y., Yu, L., & Geng, Y. (2011). Conditioning and Sampling Issues of EMG Signals in Motion Recognition of Multifunctional Myoelectric Prostheses. *Annals of Biomedical Engineering*, *39*(6), 1779–1787. https://doi.org/10.1007/s10439-011-0265-x

Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey

Irving, Michael Isard, Jia, Y., Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, … Xiaoqiang Zheng. (2015). *TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems*. https://www.tensorflow.org/

Mavrogenis, A. F., Panagopoulos, G. N., Megaloikonomos, P. D., Igoumenou, V. G., Galanopoulos, I., Vottis, C. T., Karabinas, P., Koulouvaris, P., Kontogeorgakos, V. A., Vlamis, J., & Papagelopoulos, P. J. (2016). Complications After Hip Nailing for Fractures. *Orthopedics*, *39*(1). https://doi.org/10.3928/01477447-20151222-11

Mohammad, W. S., & Elsais, W. M. (2020). Association Between Hip Rotation and Activation of the Quadriceps and Gluteus Maximus in Male Runners. *Orthopaedic Journal of Sports Medicine*, *8*(11), 232596712096280. https://doi.org/10.1177/2325967120962802

Morbidoni, C., Cucchiarelli, A., Fioretti, S., & Di Nardo, F. (2019). A Deep Learning Approach to EMG-Based Classification of Gait Phases during Level Ground Walking. *Electronics*, *8*(8), 894. https://doi.org/10.3390/electronics8080894

Murray, M. P., Drought, A. B., & Kory, R. C. (1964). Walking Patterns Of Normal Men. *The Journal of Bone and Joint Surgery. American Volume*, *46*, 335–360.

Nam, C., Rong, W., Li, W., Cheung, C., Ngai, W., Cheung, T., Pang, M., Li, L., Hu, J., Wai, H., & Hu, X. (2022). An Exoneuromusculoskeleton for Self-Help Upper Limb Rehabilitation After Stroke. *Soft Robotics*, *9*(1), 14–35. https://doi.org/10.1089/soro.2020.0090

Olsson, A. E., Sager, P., Andersson, E., Björkman, A., Malešević, N., & Antfolk, C. (2019). Extraction of Multi-Labelled Movement Information from the Raw HD-sEMG Image with Time-Domain Depth. *Scientific Reports*, *9*(1), 7244. https://doi.org/10.1038/s41598-019-43676-8

Papachristos, I. V. (2019). Complications of Femoral Intramedullary Nailing: What should the Surgeon Remember? . . *EC*, 7.

Paul, G., & Doweidar, M. H. (Eds.). (2023). *Digital human modeling and medicine: The digital twin*. Academic Press, an imprint of Elsevier.

Paulich, M., Schepers, M., Rudigkeit, N., & Bellusci, G. (2018). *Xsens MTw Awinda: Miniature Wireless Inertial-Magnetic Motion Tracker for Highly Accurate 3D Kinematic Applications*. https://doi.org/10.13140/RG.2.2.23576.49929

Rane, L., Ding, Z., McGregor, A. H., & Bull, A. M. J. (2019). Deep Learning for Musculoskeletal Force Prediction. *Annals of Biomedical Engineering*, *47*(3), 778–789. https://doi.org/10.1007/s10439-018-02190-0

Reaz, M. B. I., Hussain, M. S., & Mohd-Yasin, F. (2006). Techniques of EMG signal analysis: Detection, processing, classification and applications. *Biological Procedures Online*, *8*(1), 11–35. https://doi.org/10.1251/bpo115

Ricci, W. M., Schwappach, J., Tucker, M., Coupe, K., Brandt, A., Sanders, R., & Leighton, R. (2008). Trochanteric versus Piriformis Entry Portal for the Treatment of Femoral Shaft Fractures. *Journal of Orthopaedic Trauma*, *22*, S9–S13. https://doi.org/10.1097/01.bot.0000248472.53154.14

Róisín Howard. (2017). *The application of data analysis methods for surface electromyography in shot putting and sprinting*. https://doi.org/10.13140/RG.2.2.15907.04640

Rommens, P. M., & Hessmann, M. H. (Eds.). (2015). *Intramedullary Nailing*. Springer London. https://doi.org/10.1007/978-1-4471-6612-2

Siegel, F., Buj, C., Schwanbeck, R., Petersik, A., Hoffmann, U., Kemper, J., Hildebrand, F., Kobbe, P., Eschweiler, J., Greven, J., Merfort, R., Freimann, C., Schwaiger, A., & Aschwege, F. (2023). Concept for General Improvements in the Treatment of Femoral Shaft Fractures with an Intramedullary Nail: *Proceedings of the 16th International Joint Conference on Biomedical Engineering Systems and Technologies*, 360–367. https://doi.org/10.5220/0011679100003414

Simpson, K. M., Munro, B. J., & Steele, J. R. (2011). Backpack load affects lower limb muscle activity patterns of female hikers during prolonged load carriage. *Journal of Electromyography and Kinesiology*, *21*(5), 782–788. https://doi.org/10.1016/j.jelekin.2011.05.012

Soroushmojdehi, R., Javadzadeh, S., Pedrocchi, A., & Gandolla, M. (2022). Transfer learning in hand movement intention detection based on surface electromyography signals. *Frontiers in Neuroscience*, *16*, 977328. https://doi.org/10.3389/fnins.2022.977328

Toogood, P. A., Abdel, M. P., Spear, J. A., Cook, S. M., Cook, D. J., & Taunton, M. J. (2016). The monitoring of activity at home after total hip arthroplasty. *The Bone & Joint Journal*, *98-B*(11), 1450–1454. https://doi.org/10.1302/0301-620X.98B11.BJJ-2016-0194.R1

Tryon, J., & Trejos, A. L. (2021). Evaluating Convolutional Neural Networks as a Method of EEG–EMG Fusion. *Frontiers in Neurorobotics*, *15*, 692183. https://doi.org/10.3389/fnbot.2021.692183

Yang, W., Yang, D., Liu, Y., & Liu, H. (2019). EMG Pattern Recognition Using Convolutional Neural Network with Different Scale Signal/Spectra Input. *International Journal of Humanoid Robotics*, *16*(04), 1950013. https://doi.org/10.1142/S0219843619500130

Zha, X., Wehbe, L., Sclabassi, R. J., Mace, Z., Liang, Y. V., Yu, A., Leonardo, J., Cheng, B. C., Hillman, T. A., Chen, D. A., & Riviere, C. N. (2021). A Deep Learning Model for Automated Classification of Intraoperative Continuous EMG. *IEEE Transactions on Medical Robotics and Bionics*, *3*(1), 44–52. https://doi.org/10.1109/TMRB.2020.3048255

Zhao, B., Lu, H., Chen, S., Liu, J., & Wu, D. (2017). Convolutional neural networks for time series classification. *Journal of Systems Engineering and Electronics*, *28*(1), 162–169. https://doi.org/10.21629/JSEE.2017.01.18

Zia Ur Rehman, M., Waris, A., Gilani, S., Jochumsen, M., Niazi, I., Jamil, M., Farina, D., & Kamavuako, E. (2018). Multiday EMG-Based Classification of Hand Motions with Deep Learning Techniques. *Sensors*, *18*(8), 2497. https://doi.org/10.3390/s18082497