Comparative Analysis of Force Myography and Electromyography Signals in Isokinetic Ankle and Knee Joint Motion

Charlotte Marquardt*[‡], Gunther Kurz[†], Miha Dežman*, Thorsten Stein[†] and Tamim Asfour*[‡]

Abstract—Exoskeletons aim to enhance mobility by integrating muscle-level biomechanics and by addressing limitations like personalized control, with sensing methods such as electromyography (EMG) and force myography (FMG) to provide biofeedback. Previous comparative analyses of EMG and FMG were focused on specific classification and regression tasks without accounting for the full range of motion (RoM) of the human joints. This paper presents a descriptive analysis of both FMG and EMG signals of eight leg muscles obtained in a user study with ten participants, comparing both signals and their variations across the complete RoM of the ankle and knee joints during isokinetic motion at four different joint angular velocities. Results indicate that FMG signals exhibit higher repeatability in maximum amplitude and the corresponding joint angle, though they show higher variability in the signals full width at half maximum. While EMG features are influenced by changes in angular velocities, FMG signals appeared to be more susceptible to cross-talk caused by opposing muscle activities. This analysis contributes to a better understanding of the relationship between FMG and EMG and their potential applications in the control of assistive wearable technologies.

I. INTRODUCTION

Wearable robotic systems such as exoskeletons are created to aid or enhance mobility. While the primary focus of these devices has been on joint biomechanics, there is a growing interest in integrating muscle-level biomechanics for more effective interaction with the user's musculoskeletal system. Incorporating muscle-level biomechanics into the design and control of exoskeletons has the potential to address current limitations, such as the lack of personalized control. This includes the manual adjustment of control parameters for each user and monitoring user fatigue or energy expenditure [1]. Research on muscle biomechanics offers valuable data and insights for understanding human movements and joint function, thereby enhancing the effectiveness of exoskeleton control [2].

Muscle contraction is influenced by the frequency of electrical action potentials. The central nervous system activates slow muscle fibers at low frequencies and fast muscle fibers at high frequencies. Engaging more motor units, especially fast ones, during movement leads to greater force and more dynamic contractions [3]. Electromyography (EMG) gives the quantitative and objective recording of muscle function

*High Performance Humanoid Technologies Lab, Institute for Anthropomatics and Robotics, Karlsruhe Institute of Technology (KIT), Germany [†]BioMotion Center, Institute of Sports and Sports Sciences, Karlsruhe Institute of Technology (KIT), Germany during a contraction and thus the recording of muscle activity [4]–[6]. Additionally, this facilitates the detection of changes in contraction patterns due to fatigue during prolonged exertion. Changes in EMG signals can generally be utilized to control the exoskeleton in various applications [7], [8]. Force myography (FMG) detects mechanical changes associated with muscle contraction rather than electrical effects. It measures the normal forces resulting from changes in muscle volume during contraction, which is related to the muscle activity [9], [10].

To integrate muscle biomechanics into the control of exoskeletons, sensors and methods are required to acquire or approximate biosignals. Non-invasive technologies such as EMG or FMG offer the potential to measure muscle activity and integrate this information into control [1], [11]. The quality of the EMG signal is influenced by factors such as the positioning of the electrodes, tissue properties, physiological cross talk, and changes in the distance between the muscle and the electrodes due to muscle movement [12], [13]. Therefore, the recording of EMG signals involves precise preparation for data acquisition and extensive signal post-processing. On the other hand, FMG does not necessitate direct skin contact or as precise sensor placement and complex post-processing as EMG [9], [10].

Various research studies have been conducted on the performance of FMG and EMG in upper limb motion control applications. The findings suggest that FMG offers greater accuracy and repeatability compared to EMG, as well as higher stability over time, in both offline and online usability tests, particularly when there is a time gap between training and testing [9], [14]–[17]. This makes FMG more suitable



Fig. 1: Schematic demonstration of the experimental setup and process of data acquisition, feature extraction, and analysis.

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[‡] Corresponding authors: {charlotte.marquardt,asfour}@kit.edu

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for assistive exoskeleton applications for daily activities, as it does not require users to undergo retraining after frequent use. In contrast, EMG is better suited for rehabilitation applications where continuous monitoring of muscle activity is required [14]. And while an EMG signal can indicate the onset of contraction, an FMG signal is better suited for identifying the end of contraction [18]. Overall, FMG-based methods appear to be more effective for classification and regression control in daily exoskeleton use and are preferred by users [15]. This makes FMG a promising yet less explored technology for the control of wearable systems.

Recent studies [16], [19]–[23] indicate that combining FMG and EMG sensing enhances muscle activity analysis. This integration can benefit from their complementary strengths for a more thorough assessment of muscle function. While most co-located, sensing devices are used in forearm or hand motion recognition, Wang et al. [23] introduced a dual-mode wearable system for monitoring lower-extremity muscular activity. It utilizes a multi-channel pressure sensing matrix to map FMG in a single muscle while simultaneously capturing electrophysiological signals with a custom EMG module. Experimental results indicate that this system effectively captures both the activation and structural changes in the tibialis anterior and gastrocnemius medialis muscle. Both sensor modalities demonstrate high stability and repeatability during walking, and the measured data of muscle activity complements each other during certain gait phases, enhancing gait phase recognition accuracy.

In our previous research, we investigated the application of FMG for exoskeletons, utilizing barometric pressurebased FMG units [10] and compared it to EMG regarding its positioning. Our current work diverges from previous studies by providing a comprehensive descriptive analysis of both FMG and EMG signals gathered concurrently and collocated. This study explores the similarities and variations in signal amplitude, occurrence of maximum amplitude, and variability between these two signal modalities throughout the full range of motion (RoM) of the ankle and knee joints in isokinetic sagittal motion. By examining these parameters, we aim to enhance our understanding of the relationships between FMG and EMG signals and their dependence on joint angle and joint velocity. The findings from this analysis not only contribute to the existing knowledge of FMG and EMG but pave the way for future research focused on optimizing exoskeleton performance through customized design options and control mechanisms.

II. METHODS

This section outlines the sensor setup and the user study used for data acquisition, followed by the signal processing and feature extraction, and concluded by the analysis methods as indicated in Fig. 1.

A. Sensor Setup

The sensor unit for FMG, as explained in [10], detects the normal force resulting from alterations in the volume and stiffness of the human muscle beneath the cuff during leg movement. It contains five barometric pressure sensors on a single printed circuit board (PCB), all housed under a silicon dome. Changes in pressure identified by these sensors signify changes in the forces exerted on the silicon dome.

The muscle activity of rectus femoris (RF), biceps femoris (BF), semitendinosus (ST), vastus medialis (VM), vastus lateralis (VL), gastrocnemius medialis (GM), gastrocnemius lateralis (GL) and tibialis anterior (TA) was measured using eight FMG units and eight EMG electrode pairs placed at specific anatomical locations, as indicated in Fig. 2. The



Fig. 2: EMG (white electrodes) and FMG (black straps) sensor positions on the back (a) and front (b) of the left leg.

placement of the sensors was determined based on recommendations from SENIAM [24] and real-time feedback from the EMG sensor. Each EMG electrode pair was positioned directly above and below the FMG sensor unit, leaving a distance of about 20 mm between the electrodes, along the muscle to ensure common measurement points. In addition, the respective angular position θ_J of the joints were recorded via the IsoMed 2000 device (Fig. 3).

B. User Study

The user study was conducted in a controlled laboratory setting using an IsoMed 2000 device. This device offers an integrated mode enabling isokinetic motion of one joint at a time in the sagittal plane (Fig. 3). In isokinetic motion, the velocity of limb movement remains constant even as muscle forces vary. Additionally, it provides a direct on-axis measurement of the true joint torque.

For this study, we analyzed ten healthy adults, their characteristics are detailed in Table I. The experimental protocol received approval from the Ethics Committee of the

TABLE I: Participant Information

Age (y)	Thigh length (cm)	Max. thigh circ. (cm)
26.8 ± 3.2	44.0 ± 1.72	53.5 ± 4.28
Height (cm)	Shank length (cm)	Max. shank circ. (cm)
175.2 ± 6.78	42.0 ± 1.96	35.7 ± 1.44

Values represent the mean and standard deviations.

Karlsruhe Institute of Technology (KIT) as part of the JuBot project. All participants provided written informed consent before participating in the experiment, and all methods were conducted in accordance with the Declaration of Helsinki.

The experiment was conducted with participants seated on the IsoMed device, secured with their left leg on a foot or shank support. This enabled pure sagittal motion of the ankle or knee joint respectively (Fig. 3). Each participant had a familiarization period of up to 10 min with the IsoMed device. During this time, the alignment of the device's rotation axis with the sagittal joint axis of rotation was manually optimized using an integrated laser pointer. Additionally, the mechanical end stops of the device were adjusted to align with each user's maximum RoM within their anatomical limits. Following this, the participants performed two tasks in a random order:

- *Ankle*: The ankle joint was initially positioned at maximum dorsiflexion. The participant then performed five swing motions (Fig. 3a), including both dorsiflexion and plantarflexion, within their maximum active RoM. The five swing motions were repeated at four different angular velocities v_i : 30°/s, 60°/s, 90°/s, and 120°/s.
- *Knee*: The knee joint was first set to maximum extension for initialization. The participant then performed five swing motions (see Fig. 3b), including flexion and extension, within their maximum active RoM. These motions were executed at four different angular velocities v_i : 60°/s, 90°/s, 120°/s, and 150°/s.



Fig. 3: Participant set-up on the IsoMed 2000 device for ankle motion (a) and knee motion (b) and the corresponding definition of the joint angle θ_I .

The five swing motions of each joint were repeated three times for each velocity. For calibration, FMG was initialized before accessing the IsoMed device. This was done by standing upright and relaxing on both feet for approximately 10 seconds. Calibration measurements of the joint angle were conducted at each initial position $\theta_J = 0^\circ$ as marked in Fig. 3.

C. Signal Processing

To process the EMG signals, a band-pass filter with a frequency range of 20 Hz to 500 Hz was applied, followed by rectification and a low-pass filter set at 6 Hz. All filters used were fourth-order zero-phase Butterworth filters. Outliers in the EMG signals were identified using a Hampel filter and

replaced with linearly interpolated values derived from the neighboring non-outlier values. The baseline offset of the FMG was removed using the mean values obtained from the calibration measurements, no filter was applied to this signal.

The FMG sensor units have a maximum sampling rate of 200 Hz, while the EMG signals were sampled at 2000 Hz. To align and concatenate all the datasets, each dataset was linearly interpolated to achieve an equidistant number of data points. This process resulted in the down-sampling of the EMG data to match the FMG data. Both signals were normalized according to the minimum and maximum values measured for each participant and muscle after filtering.

The segmentation of each complete motion including flexion and extension of the knee joint and dorsi- and plantarflexion of the ankle joint was performed based on the joint angle and thus corresponding change in motion direction.

D. Analysis Methods

The analysis focused on the complete time-series signals during each swing motion, as well as specific features namely the peak amplitude and its corresponding joint angle, as well as the full width at half maximum (FWHM) (Fig. 4). The



Fig. 4: Signal features analyzed in each complete swing motion over the full RoM.

peak amplitude is a distinct feature to evaluate the amount of muscular activity measured, the corresponding joint angle provides information on the amplitude distribution within the RoM and the FWHM indicates the the range of joint angles during which a muscle is active.

The variations of each feature were evaluated based on the coefficient of variation (CV), calculated for each feature over all swing motions of each participant and over all participants. The CV also known as relative or normalized standard deviation, is a standardized measure of signal variability. A lower CV corresponds to a lower variation and thus a higher repeatability of the signal. The variation analysis was conducted on the data of all four angular velocity recordings for each joint.

In a manner similar to the primary flexor and extensor muscles involved in the movement of each joint, the analysis of ankle joint motion focused on the TA (dorsiflexion), GM (plantarflexion), and GL (plantarflexion). For the knee joint motion analysis, the muscles examined included the RF (extension), VM (extension), VL (extension), BF (flexion), and ST (flexion). It's important to note that the effects of biarticular muscles, which influence the movements of multiple joints simultaneously, were not considered in this analysis.



Fig. 5: **Muscle signals**. Mean and standard deviation of the EMG and FMG signals over all participants. Each muscle is displayed separately for (a)-(c) ankle and (d)-(h) knee motion. Each graph includes all four velocities (v_1 : solid, v_2 : dashed, v_3 : dash-dotted, v_4 : dotted) of each EMG (orange) and FMG (blue) signal.

III. RESULTS

This chapter presents the results from the comparison between EMG and FMG signals after segmentation of all measurements to each complete swing motion, with a particular emphasis on three essential features: the maximum amplitude, the corresponding joint angle, and the FWHM, also considering each feature's variability. Figure 5 displays the mean and standard deviation of the normalized EMG and FMG signals over one complete swing motion and across all participants. Each muscle is presented separately for both ankle and knee movements, and each graph includes data for all four angular velocities of the EMG and FMG signals. The transition between motion directions is emphasized in the middle of one swing motion by a



Fig. 6: **Peak signal amplitude**. Mean and standard deviation of the maximum signal amplitude for ankle (a) & (c) and knee (b) & (d) joint displayed for each motion direction. Muscle groups are categorized by the four velocities (from v_1 left to v_4 right) and by EMG (square) and FMG (circle).

vertical line. In most muscles, the EMG signal exhibits a single prominent peak, whereas the FMG signal tendentially shows two peaks, one peak per motion direction. Notably, one of these FMG peaks is generally more pronounced than the other. In the muscles contributing to knee motion, most dominantly in BF, ST, RF and VM, the muscles tend to show contrasting activity behavior between EMG and FMG. On the other hand, the TA and the VM muscle display no peak and thus consistent activation in EMG during the complete swing motion. Furthermore, the signal FMG shows a notable drop in its signal amplitude in the middle of the swing motion, coinciding with periods in which the angular velocity of the joint is zero and the direction of motion changes. This effect is not prominently observed in the EMG data. Furthermore, the EMG activation pattern appears to shift to the left with increasing velocity. In contrast, the FMG signal maintains a consistent activation pattern across all velocities.

The mean and standard deviation of the normalized maximum amplitude observed during flexion and extension in the knee joint and plantar- and dorsiflexion in the ankle joint is shown in Fig. 6. In both joints and both, EMG and FMG signals, it can be observed that the amplitude displays a contrasting behavior in its height between the flexor and extensor muscles in both motion directions. While the BF and ST muscle show a higher activity in the FMG signal during flexion of the knee joint, the opposite can be observed for the RF, VL and VM muscle. However, an opposing effect is displayed in the EMG signal. Generally, the effect is more prominent in the knee joint than in the ankle joint and the TA displays no such effect at all. Again, the FMG signal displays a higher consistency regarding the height of the maximum amplitude than the EMG signal throughout the four angular velocities.

Figure 7 shows the mean and standard deviation of the occurrence of the maximum amplitude during flexion and extension in the knee joint and plantar- and dorsiflexion in the ankle joint, dependent on the corresponding joint angle. The FMG signal demonstrates a higher consistency in the joint angle at which the maximum amplitude occurs, while the EMG has a higher dependency on the angular velocity at which the signal was obtained. It is especially notable in the EMG signal during knee joint motion that the flexor and extensor muscles (e.g. BF and ST compared with RF and VL) display a contrasting shift of the maximum amplitude within the RoM with increasing angular velocity. This shift is more pronounced in the flexion than in the extension of the knee joint. In the ankle joint this effect is less notable though still present.

Variability was evaluated on the basis of the CV of the maximum signal amplitude and the FWHM (Figs. 8 and 9) in each muscle as the mean and standard deviation over all ten participants. The FMG generally demonstrates a lower CV for the peak signal amplitude compared to the EMG, both in terms of its mean and standard deviation. Only the TA and GL muscle demonstrate higher mean variation in FMG than in EMG at $120^{\circ}/s$, RF muscle at both $120^{\circ}/s$ and $150^{\circ}/s$. The highest variation can be observed in the EMG signal of

the GM muscle in the ankle joint motion at $60^{\circ}/s$ and the BF muscle in the knee joint motion at $120^{\circ}/s$. In contrast, the variation in the FWHM is higher for the FMG than for the EMG signal not only in its mean but also its standard deviation throughout all muscles and angular velocities. The greatest variation can be observed in the TA muscle for the FMG at $30^{\circ}/s$ during ankle joint motion and in the ST muscle at $120^{\circ}/s$ in the knee joint motion, whereas the EMG signal does not show one muscle standing out specifically.



Fig. 7: **Joint angle at peak amplitude**. Mean and standard deviation of the joint angles at the maximum signal amplitude for ankle (a)-(b) and knee (c)-(d) joint displayed for each motion direction. Muscle groups are categorized by the four velocities (from v_1 at the top to v_4 at the bottom) and by EMG (square) and FMG (circle).



Fig. 8: **Coefficient of variation (ankle)**. Mean and standard deviation of the CV of (a) the maximum signal amplitude and (b) the FWHM of each EMG (orange, left) and FMG (blue, right) signal of each swing motion over all participants for the ankle joint.

IV. DISCUSSION

The evaluation of both FMG and EMG signals during isokinetic motion focused on maximum amplitude, the corresponding joint angle, and the FWHM. The first and last features were specifically examined for their variability. This evaluation explored the similarities and differences between these two signals throughout the RoM of the ankle and knee joints of ten participants.

Higher variations in the mean value of the maximum amplitude and the corresponding joint angle in the EMG signal (e.g. in the muscles BF and ST in Figs. 6d and 7d) suggest that EMG is more dependent on the angular velocity than FMG. The shift in the EMG signal amplitude with increasing angular velocity shown in Fig. 5 indicates a dependency on the joint angle. This observation supports the findings of Hahn et al. [25], who discovered that the excitation of all lower limb muscles measured by EMG changes based on knee flexion angles. This is also evident in the high mean values recorded for only the first angular velocity, as illustrated in Fig. 6. Notably, this includes the GL muscle during dorsiflexion, the RF and VL muscles during extension, and the BF and ST muscles during flexion, shifting them towards the opposing motion direction. On the other hand, the FMG signal exhibits a visible drop in amplitude during the transition between motion directions, as shown in Fig. 5. This occurs when the angular velocity is momentarily zero, indicating that the FMG signal is sensitive to sudden changes in angular velocity suggesting that joint acceleration has a larger influence on FMG. This supports the idea that a combination of both sensing methods could be beneficial not only in motion recognition but also in estimating kinematic and kinetic joint data.

The EMG signals show only one prominent peak during the swing motion, as displayed in Fig. 5. In contrast, the FMG signals exhibit two distinct peaks (e.g. RF, VL, and VM), corresponding to each direction of motion or a peak where no muscle activity was expected (e.g. TA) in Fig. 5. Whereas this effect is generally, more pronounced in the knee joint compared to the ankle joint, it is most drastic in the TA muscle. Since the TA muscle acts as a flexor of the ankle



Fig. 9: **Coefficient of variation (knee)**. Mean and standard deviation of the CV of (a) the maximum signal amplitude and (b) the FWHM of each EMG (orange, left) and FMG (blue, right) signal of each swing motion over all participants for the knee joint.

joint, its peak amplitude during plantarflexion should not be as prominent. A possible explanation for this is the crosstalk produced by the muscles that are covered by the strap attaching one or more FMG sensor units to the leg. Changes in shape and volume from the antagonistic muscle can affect the pressure signals measured from the agonistic muscle, either due to its muscle being activated in parallel or due to the passive motion of the leg. The soft tissue may function as a damper with its stiffness dependent on the subject or motion [26], affecting the transfer of forces between the agonistic and antagonistic muscles within the straps. Since the lower leg generally has less soft tissue than the upper leg, and the shinbone is situated close to the surface, the crosstalk observed in the TA muscle could be more pronounced. In the future, the effect based on passive motion could be studied and potentially excluded by measuring the FMG signal obtained by leg motion while the participant is in a relaxed state. Additionally, it is important for the design of an exoskeleton to consider the sensitivity of FMG sensors to cross-talk. When these FMG sensors are integrated into the cuffs of an exoskeleton, they should be designed to be as decoupled from one another as possible.

The analysis of the EMG signals from both the TA and VM muscles reveals a generally low signal amplitude, as depicted in Fig. 5, with a slightly lesser effect observed in the VM muscle. Enhanced noise can obscure significant maxima, leading to the filtering of insufficiently pronounced peaks and complicating data interpretation. The stochastic nature of EMG signals, characterized by rapid fluctuations, contributes to challenges in post-processing, potentially resulting in undetected outliers and reduced normalization quality. Furthermore, peaks in muscle activation may occur at varying stages of the swing motion for each participant, which could lead to cancellation when calculating the mean across participants. Addressing these limitations is essential for advancing our understanding of muscle activation patterns and improving the efficacy of wearable robotic systems in clinical and rehabilitative contexts.

The signals from EMG and FMG exhibit nearly opposite behaviors with respect to their signal amplitude. This phenomenon can be observed during a complete swing motion, where the normalized maximum amplitude occurs in contrasting phases/directions of the motion, which is especially prominent in the knee joint motion. This distinction may account for the improved performance of classification methods in [19]–[23] that combine both EMG and FMG signals, as their differing features and variability provide a complementary advantage for feature-based, data-driven machine learning approaches.

The EMG signals exhibit greater variability in the activation patterns between the participants compared to the FMG signals. Specifically, the FMG signals demonstrate enhanced repeatability in terms of maximum amplitude across multiple participants, aligning with the observations reported in previous studies [16], [17]. In contrast, the duration of muscle activity, as measured by FWHM, shows greater consistency in the EMG signals, as evidenced by their lower CV. This discrepancy suggests that while FMG signals may provide more reliable peak amplitude readings, the EMG signals offer a more stable representation of the duration of muscle activation. However, no general trend regarding variations within any angular velocity can be extracted from either EMG or FMG in the peak amplitude and the FWHM.

However, it is important to note that a limited number of participants exhibited a small subset of muscles with either a markedly elevated or non-existent CV. For instance, the VM muscle in two participants displayed such outlier behavior. In particular, these outliers did not correlate with any identifiable characteristics of the participants, suggesting that external factors may play a role in these variations. One plausible explanation for this phenomenon is sensor misalignment or interference caused by the attachment of participants to the IsoMed device. The necessity for precise positioning of the IsoMed actuation levers to avoid interference with the EMG and FMG electrode locations may have inadvertently introduced variability in the signal quality. This highlights the importance of ensuring optimal electrode placement and minimizing external influences to enhance the reliability of EMG and FMG readings.

The study's findings are based on a relatively small sample size of ten participants, which may limit the statistical power necessary for rigorous hypothesis-driven analysis. Consequently, we advise that these results be interpreted as preliminary indicators that warrant further investigation. It would be beneficial to explore these findings in subsequent research with a larger and more diverse participant group to enhance the validity and generalization of the conclusions drawn. Such efforts would contribute significantly to advancing our understanding of the topic.

Although the data presented in this paper provide valuable information on both EMG and FMG, the untapped potential remains to be explored. A more in-depth examination of each specific motion direction, focusing on both agonistic and antagonistic muscles, could yield additional information. Furthermore, a closer analysis of the FWHM alongside the corresponding joint angles may reveal relevant details about the range of motion detectable by the muscular signals of each sensing method and the extent to which they can be measured. The results of this paper offer strong potential for deeper exploration, especially in highlighting the benefits and limitations of FMG compared to EMG.

V. CONCLUSION

The evaluation of FMG and EMG signals during isokinetic motion reveals that FMG signals demonstrate higher repeatability in maximum amplitude and corresponding joint angle both within and across participants compared to EMG signals, which show more consistent muscle activity duration. Although high repeatability supports the generalization of control methods for different users of wearable robots, signals with higher variability can contribute to the personalization of control, allowing for the adaptation of the controller to satisfy the particular requirements of individual users. While EMG signals appear to be more affected by angular velocity, FMG signals seem more sensitive to sudden changes in angular velocity. The contrasting and augmenting behavior of EMG and FMG signals, particularly in signal amplitude during motion phases, suggest that combining these signals enhances their performance in application due to their complementary features and indicates their potential for comprehensive motion recognition and joint data estimation. Future research could focus on exploring these complementary strengths to develop more effective control systems for wearable robotics, while also addressing FMG's sensitivity to cross-talk and EMG's normalization challenges. Furthermore, the results underscore FMG as a promising method for the integration of biofeedback in the control of wearable robotic technologies.

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