Journal of Physical Education and Sport ® (JPES), Vol. 24 (issue 4), Art 98, pp. 855 - 863, April 2024
online ISSN: 2247 - 806X; p-ISSN: 2247 – 8051; ISSN - L = 2247 - 8051 © JPES

Original Article

Analyzing optimal muscle dynamics during handstands: a comprehensive investigation of skilled gymnasts

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Published online: April 30, 2024
(Accepted for publication April 15, 2024
DOI:10.7752/jpes.2024.04098

Abstract:
This study aimed to evaluate the muscle dynamics involved in single and double-arm handstands performed by five skilled gymnasts, with a mean age of 23.6 ± 1.94 years. Myoware Muscle Sensor (AT-04-001) (MMS) signals were collected from three key upper limb muscles: Wrist Flexor (WF), Triceps Brachii (TB), and Lateral Deltoid (LD), all on the dominant side of the body. To facilitate data collection and processing, Internet of Things (IoT) programs were employed, utilizing Arduino IDE and Python 3.10.0 applications to connect the NodeMCU (ESP8266) via server and client code. The NodeMCU's display frequency range was set at 0–1024 Hz, with a Baud (Bd) rate of 9600 in Arduino, which is a crucial parameter for visualizing the data accurately. It continuously reads the serial and plotter monitor signals from the MMS through the A0 pin. The processed data was transmitted wirelessly by the NodeMCU, displayed on a monitor, and recorded for analysis. Participants executed three trials of their maximum handstand performance on the floor; the gymnasts peak level of 15 seconds performance was used for analysis (i.e., the middle time of the best trial; e.g., maximum performance was 45 seconds in this 16–30sec used). The observed muscle stimulation range was from a minimum of 109617 Hz to a maximum of 151292 Hz. Overall, one-arm handstands (52.79%) demonstrated better muscle activation than double-arm handstands (47.21%). The analysis revealed a statistically significant positive Correlation (r) and Probability (p) between the WF and LD ($r = 0.870$, $p = 0.001$). However, no significant correlations were observed between the WF and the TB ($r = 0.507$, $p = 0.134$) or the TB and the LD ($r = 0.491$, $p = 0.150$). To conclude, despite comparable inter-muscle contributions, the study suggests a significant association between WF and LD. Future research can build on these findings, exploring additional muscle groups and refining training protocols for performance optimization and injury prevention. This study encourages broader investigations, including more muscles in the upper and lower body, with advanced research laboratories and larger sample sizes.
Key Words: - Gymnastics, Handstands Balance, Internet of Things, Myoware Muscle Sensor, Python, Sports Biomechanics.

Introduction

The pursuit of optimal performance in gymnastics demands a clear understanding of the muscle dynamics involved in various activities. Among these, handstands represent a top of skill and strength, requiring specific coordination of muscle groups (Kochanowicz et al., 2018). This study explored the realm of optimal muscle dynamics during single and double-arm handstands, with a particular focus on the wrist flexors (WF), triceps brachii (TB), and lateral deltoids (LD) (De Bock, 2012). The exploration of these specific muscle groups is essential for separating the complexities of handstand performance and informing targeted training strategies.
Background and Significance: Gymnastics, as an art form and sport, epitomizes the fusion of grace, strength, and precision. Within this intricate discipline, the handstand stands as a testament to the pinnacle of athletic achievement, demanding not only extraordinary physical prowess but also an acute understanding of biomechanics. The ability to maintain a stable handstand position is a hallmark of gymnastic excellence, requiring a delicate interplay of muscle groups to achieve and sustain balance.

Fundamental to the mastery of handstands are the wrist flexors, triceps brachii, and lateral deltoids, whose coordinated efforts provide the foundation for stability and control. While previous research has shed light on the importance of these muscle groups in handstand performance, the nuances of their activation during

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different handstand variations remain relatively unexplored (Kinoshita, K et al., 2022). This gap in knowledge presents an opportunity to delve deeper into the biomechanical intricacies of handstands and uncover insights that could revolutionize training methodologies and performance optimization strategies (Kokarev, B et al.,2023).

Building upon existing literature, this study aims to investigate the dynamic interplay of muscle activations during single and double-arm handstands. By leveraging advanced technologies such as Muscle Monitoring Systems (MMS) and the Internet of Things (IoT), we seek to unravel the complexities of muscle dynamics with unparalleled precision and depth. Through meticulous data collection and analysis, we endeavor to not only enhance our understanding of handstand biomechanics but also contribute to the broader discourse on athletic performance and injury prevention.

In this introduction, we outline the significance of handstand performance in gymnastics, emphasize the importance of wrist flexors, triceps brachii, and lateral deltoids, and highlight the need for further research to elucidate the differences in muscle activation between single and double-arm handstands (Blenkinsop, G. M. et al., 2016; Kochanowicz, A et al., 2019; Nahi, Z. M et al., 2023). By bridging the gap between theoretical knowledge and practical application, this study aims to advance our understanding of gymnastic excellence and pave the way for more informed training practices in the pursuit of optimal performance.

To achieve a comprehensive understanding, our methodology integrates advanced technologies that push the boundaries of traditional biomechanical research (Ajithkumar et al., 2022). Muscle Monitoring Systems (MMS) emerge as essential tools in our data acquisition strategy, offering precise and real-time readings of muscle activity (Kochanowicz et al., 2015; Sobera et al., 2019). The integration of the Internet of Things (IoT) amplifies the sophistication of our approach, facilitating seamless communication and data transfer between myoware muscle sensors and the analytical framework.

Within this technological ecosystem, the NodeMCU serves as the central hub, seamlessly connecting with the Arduino IDE and Python, enabling synchronized data acquisition and processing (Parihar, 2019). The NodeMCU, a programmable microcontroller, orchestrates the transmission and analysis of signals from the MMS. The synergy between the Arduino IDE and Python 3.10.0 applications enables the interpretation of signals, unravelling insights into muscle movements in gymnastic routines (Kojima et al., 2021; Vladimir et al., 2014; Kumar P. et al., 2023). This study, rooted in biomechanics and cutting-edge technology, seeks not only to clarify the mechanics of muscle activations but also to contribute to the broader understanding of athletic performance (Prassas, S. G. 1988; Kumar, F. A. et al., 2022). By separating the relationship between the WF, TB, and LD muscles during single and double-arm handstands, we aim to provide insights that extend beyond the limits of gymnastics (Kochanowicz. A et al., 2018; Forminte, V. N. et al., 2022; Conde, T. F. et al., 2022). The implications of this research may extend various fields, influencing training methodologies, and injury prevention strategies, and contributing to the evolving discourse on the biomechanics of dynamic gymnastic performances. At the core, this exploration of muscle activations during handstands represents an integration of the physical unit displayed by professional gymnasts and the technological accuracy afforded by MMS and the IoT (Zou, X. 2020; Schwartz, M. 2016).

Material & methods

Participant Selection and Characteristics

The study involved five skilled gymnasts with a mean age of 23.6 ± 1.94 years. Each participant performed both single and double-arm handstands, Data were completely gathered from the dominant side of the body (determined by the participant's preferred writing hand), This approach minimized variability in limb dominance, crucial for a focused exploration of muscle dynamics to provide a comprehensive dataset for analysis. The eligibility criteria for participants included the following: i) All gymnasts commenced their training journey between the ages of ten and eleven; ii) Each participant engaged in a minimum of 24 hours of training per week; iii) Skilled gymnasts were considered eligible if they were able to maintain a faultless handstand on the floor for fifteen seconds. All participants gave informed consent before their participation.

Instrumentation and Muscle Signal Recording

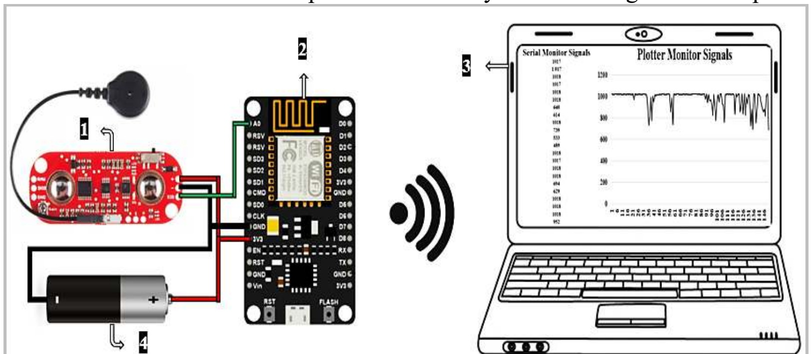
The participant's skin underwent preparation for MMS/EMG evaluation following the guidelines established by the SENIAM organization, which included scrubbing, cleansing with alcohol, and, if required, shaving. The placement of surface electrodes at the motor points of the muscles followed by SENIAM guidelines (Hermens, H. J. et al., 1999). Myoware Muscle Sensors which were positioned properly in the upper limbs, MMS recorded signals from three key muscles – wrist flexor, triceps brachii, and lateral deltoid. This instrumentation aimed to capture muscle activation patterns during handstand performance (Kochanowicz. A et al., 2018).

Implementation of IoT Technology

In the conducted research, NodeMCU and MMS (EMG) sensor were employed to comprehensively explore muscle activity (Zou, X. 2020). The NodeMCU, serving as a Wi-Fi-enabled microcontroller and functioning as the Central Processing Unit (CPU), facilitated wireless communication. Paired with the MMS, featuring power, ground, and signal pins labelled +, -, and SIG, respectively, the NodeMCU and MMS were powered by a 5V battery to provide the required voltage for the components. This setup was designed to capture and interpret the electrical pulses generated by muscle contractions. In this wiring setup played a vital role in this process, the "+" pin of the MMS was connected to the 3.3V pin of the NodeMCU to ensure a stable power supply. Simultaneously, the "-" pin of the MMS was linked to the ground (GND) pin of the NodeMCU. The SIG pin of the MMS was connected to the A0 pin of the NodeMCU. Both the positive and negative ends of the 5V battery were connected to the 3.3V pin and GND pin of the NodeMCU for a consistent power supply. The SIG pin of the MMS, linked to the A0 pin of the NodeMCU, enabled the microcontroller to capture the muscle activity data recorded by the MMS (Schwartz, M. 2016). The integration of IoT Technology is shown in the Fig 1.

Amplifying Technological Sophistication:

Using the IoT programs, the study employed Arduino IDE and Python to connect with the NodeMCU. This integration facilitated a unified connection between the muscle sensors and data processing systems, elevating the sophistication of the overall methodology. *NodeMCU Connectivity:* The Arduino IDE and Python were used to connect with the NodeMCU by server and client code to execute a sequence of actions for effective data acquisition and processing. *Display Frequency Range:* The NodeMCU's display frequency range was 0–1024 Hz, determining the visual representation of the Bd 9600 value in Arduino IDE. These accurate control display parameters enhanced the quality of data visualization. *Serial and Plotter Monitoring:* Continuous monitoring of MMS signals through the A0 pin, enabled by NodeMCU, provided real-time response. This monitoring mechanism ensured the accurate capture of muscle dynamics during handstand performance



1. Myoware Muscle Sensor (AT-04-001), 2. NodeMCU (ESP8266), 3. Monitor, 4. Battery (5V).

The methodology applied in this research, integrates electrical components, with a properly planned and executed process. The interconnection of all components was carried out with accuracy, ensuring a proper evaluation of power requirements. The systematic approach employed in gathering and generating high-quality and reliable data reflects a commitment to obtaining impactful insights and drawing conclusive findings. The careful design and execution of the methodology highlight the dedication to achieving thorough and reliable results in the exploration of muscle activity.

Results

Execution of Handstand Trials:

Participants executed three trials of their maximum handstand performance on the floor; the gymnast's peak level of 15 seconds performance was used for analysis (i.e., the middle time of the best trial; e.g., maximum performance was 45 seconds in this 16–30sec used) (Kochanowicz. A et al., 2018). *Muscle Stimulation Range:* The observed muscle stimulation range from a minimum of 109617 Hz to a maximum of 151292 Hz, was accurately documented. This detailed range provided insights into the variability and intensity of muscle activation during handstand performance. The mean and standard deviation for all 3 muscles data shown in Table 1.

Table 1. Mean and standard deviation for all 3 muscles

Muscles	OAHS	DAHS
	$\bar{x} \pm \sigma$	$\bar{x} \pm \sigma$
WF	134648.80 ± 5689.01	118918.40 ± 7728.49
TB	139891.60 ± 13023.10	129614.40 ± 11650.35
LD	148464.80 ± 3495.96	130354.20 ± 10447.50

Mean ($\bar{x}$) and Standard Deviation (σ)

The presented data provides a detailed picture of the Mean ($\bar{x}$) and Standard Deviation (σ) values for muscle stimulation frequencies (in Hertz) in both One-Arm (OA) and Double-Arm (DA) handstands across three key muscle groups: Wrist Flexor (OAWF, DAWF), Triceps Brachii (OATB, DATB), and Lateral Deltoid (OALD, DALD). During one arm handstand: OAWF shows a $\bar{x}$ stimulation frequency of 134648.8 Hz with a σ of 5689.01 Hz. OATB demonstrates a $\bar{x}$ frequency of 139891.6 Hz, accompanied by a σ of 13023.10 Hz. OALD shows a $\bar{x}$ stimulation frequency of 148464.8 Hz, with a σ of 3495.96 Hz. During the Double arm handstand: DAWF records a $\bar{x}$ frequency of 118918.4 Hz and a σ of 7728.49 Hz. DATB displays a $\bar{x}$ stimulation frequency of 129614.4 Hz, along with a σ of 11650.35 Hz. DALD has a $\bar{x}$ frequency of 130354.2 Hz, with a σ of 10447.50 Hz. A graphical representation of the mean and standard is shown in Fig 2. Comparing the two handstand variations, the data suggests a degree of variability in muscle activation during double-arm handstands, evident in the slightly lower mean frequencies and higher standard deviations.

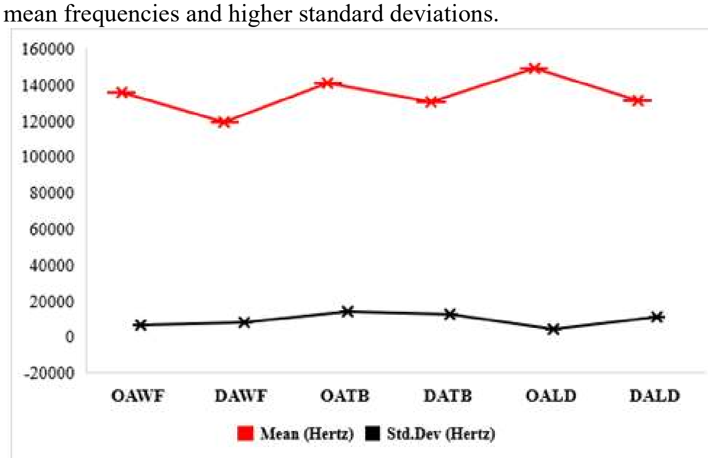


Fig. 2 Graphical representations of mean and standard deviation for all 3 muscles. Abbreviations: OAWF – one arm wrist flexor, DAWF – double arm wrist flexor, OATB – one arm triceps brachii, DATB – double arm triceps brachii, OALD – one arm lateral deltoid, DALD - double arm lateral deltoid

In the complicated realm of gymnastic performance, the muscle activation percentages during one-arm and double-arm handstands provide exact insights into the dynamic relationship of important muscle groups (Kochanowicz. A et al., 2018). Percentages of selected muscle activations are shown in Table 2. All muscle amplitude ratios were calculated as follows; General Eq:

$$One\ arm\ handstand\ Muscle\ I\ (\%) = \frac{Muscle\ "1"}{Total\ muscle} \times 100$$
$$Double\ arm\ handstand\ Muscle\ I\ (\%) = \frac{Muscle\ "1"}{Total\ muscle} \times 100$$

Example (for wrist flexors-WF):

$$One\ arm\ handstand\ WF\ Muscle\ (\%) = \frac{WF}{WF+TB+LD} \times 100$$
$$Double\ arm\ handstand\ WF\ Muscle\ (\%) = \frac{WF}{WF+TB+LD} \times 100$$

This equation expresses the percentage of muscle activity for the wrist flexors in the specific handstand position. Numerator (WF): Represents the muscle activity of the wrist flexors. The denominator (WF + TB + LD): Represents the total muscle activity of wrist flexors, triceps brachii, and lateral deltoid combined. Percentage Calculation: The ratio of WF activity to the total muscle activity is then multiplied by 100 to express the result as a percentage. This formula essentially normalizes the wrist flexor muscle activity by considering it in the context of the total muscle activity of the wrist flexors, triceps brachii, and lateral deltoid during the handstand.

Table 2. Percentages of selected muscle activations

	WF	**TB**	**LD**
OAHS	31.83%	33.07%	35.10%
DAHS	31.39%	34.21%	34.40%

Table 2. During the one-arm handstand (OAHS), the WF 31.83%, TB 33.07%, and LD 35.10% contribute respectively, to the overall muscle activation. These percentages underscore the pivotal role of the LD in providing shoulder stability, while the TB and WF play significant roles in supporting the body's weight and maintaining balance. In the double-arm handstand (DAHS) variation, the WF 31.39%, TB 34.21%, and LD

34.40% contribute respectively, the TB displays a slightly higher activation. In both handstand variations, the WF, TB, and LD play essential roles in maintaining the balance and stability required for the handstand position. The LD consistently demonstrates the highest activation, indicating its pivotal role in providing shoulder stability during handstands. The TB, responsible for elbow extension, shows comparable activation levels in both variations, emphasizing its consistent contribution to overall stability. The differences in muscle activation percentages between single and double-arm handstands are shown in Fig 3 and Table 3 shows a correlation between all 3 muscles

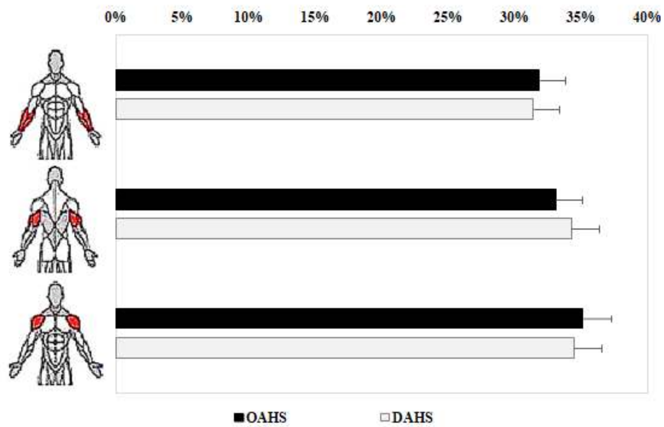


Fig. 3 Graphical interpretations of Percentage for selected muscle activations. Abbreviations: OAHS – one arm handstands, DAHS – double arm handstands.

Pearson Correlation Analysis

Table 3, Pearson Correlation Analysis between all 3 muscles

		WF	TB	LD
WF	r	1	.507	.870*
	p		.134	.001
TB	r	.507	1	.491
	p	.134		.150
LD	r	.870*	.491	1
	p	.001	.150	

**Pearson Correlation was significant at the 0.05 level (2-tailed).*

The analysis revealed a statistically significant positive correlation between the Wrist Flexor and Lateral Deltoid (r = 0.870, p = 0.001). However, no significant correlations were observed between the Wrist Flexor and Triceps Brachii (r = 0.507, p = 0.134) or between Triceps Brachii and Lateral Deltoid (r = 0.491, p = 0.150). These findings suggest that there was a significant association between the Wrist Flexor and the Lateral Deltoid and no significant between other muscles.

Muscle Activation Percentage

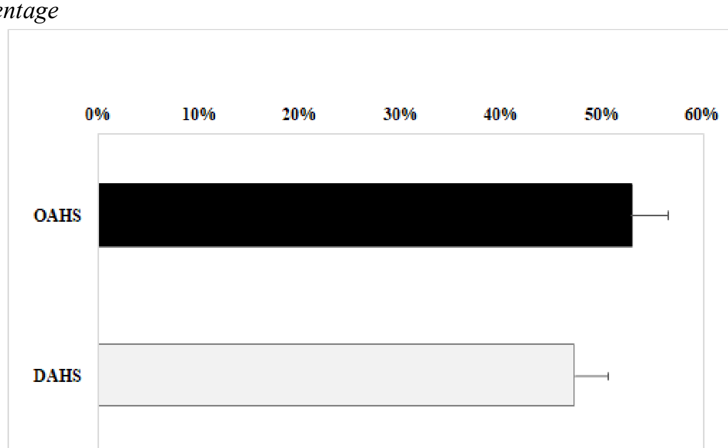


Fig. 4 Comparative analysis of One and Double-Arm Handstands

The Comparative Analysis of Single and Double-Arm Handstands graph is shown in Fig 4. A comparative analysis revealed that one-arm handstands demonstrated higher muscle activation (52.79%) when compared to double-arm handstands (47.21%). This division formed the basis for exploring the specific challenges posed by handstand variations. Fig 5, shows data collection during OAHS and DAHS, and Fig 6, shows the muscle frequencies during OAHS and DAHS for a gymnast.

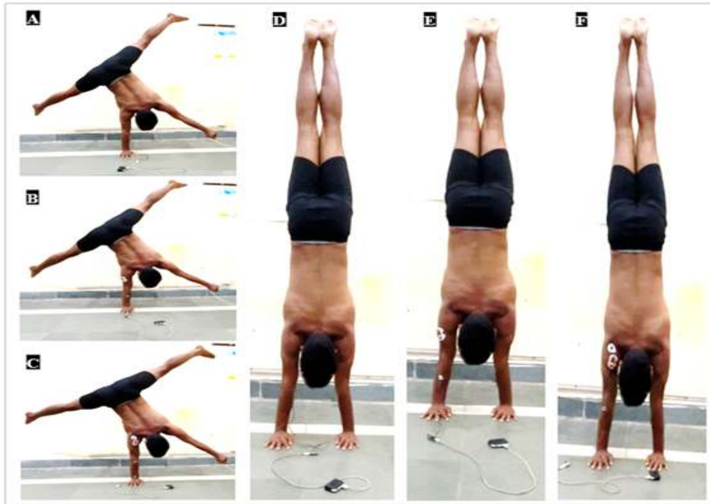


Fig. 5 Data collection during OAHS and DAHS for a gymnast ((a) OAWF, b) OATB, c) OALD, d) DAWF, e) DATB, f) DALD)

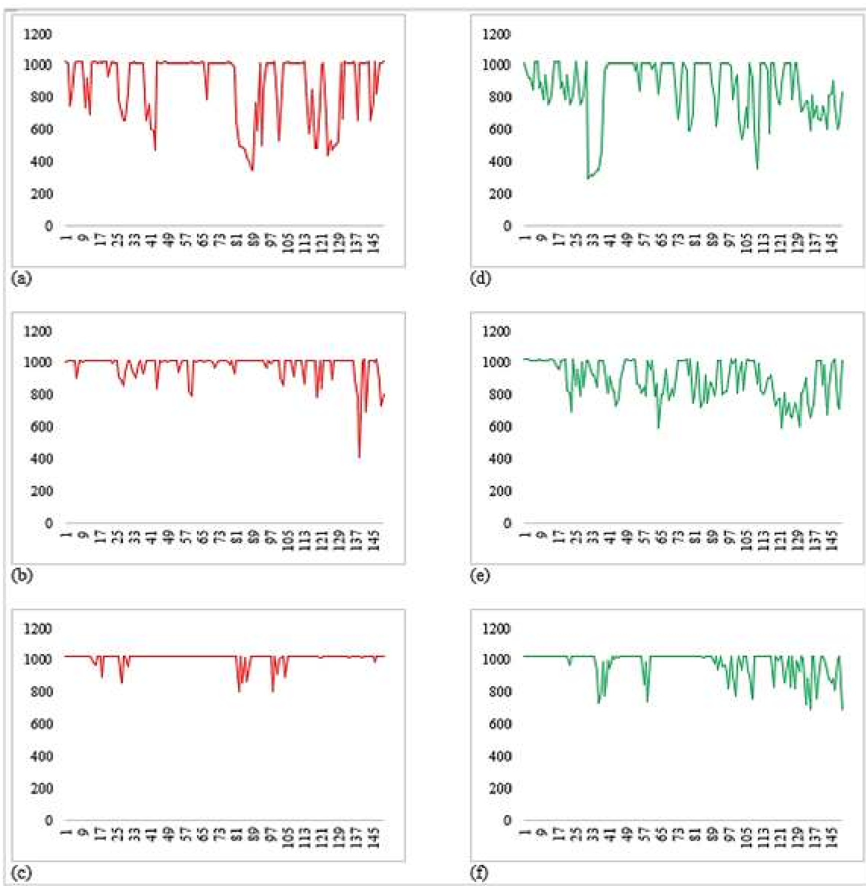


Fig. 6 Muscle Frequencies during OAHS and DAHS for a gymnast ((a) OAWF, b) OATB, c) OALD, d) DAWF, e) DATB, f) DALD)

The single gymnast muscle activation outline shows that there was a clear variation between OAHS and DAHS in all given muscles.

Discussion

The findings of this study offer an exact perspective on the opted muscle dynamics during Single and double-arm handstands among skilled gymnasts. The research aimed to investigate the complexities of muscle activation patterns, particularly focusing on the WF, TB, and LD muscles. The integration of advanced technologies, including MMS, the IoT, and the NodeMCU, enabled real-time data acquisition and analysis, providing a comprehensive understanding of muscle dynamics in handstand performance. The observed range of muscle stimulation, spanning from a minimum of 109617 Hz to a maximum of 151292 Hz, reflects the relationship of muscles during the execution of handstands. Remarkably, the study revealed a minor yet significant difference in muscle activation between the two handstand variations. One-arm handstand demonstrated a higher level of muscle activation (52.79%) compared to double arm handstand (47.21%). This discrepancy in muscle engagement suggests a distinct relationship between muscle activity and the type of handstand performed.

These findings align with previous research emphasizing the importance of specific muscle activation in achieving and maintaining handstand positions. highlighted the significance of targeted muscle recruitment, especially in the TB and WF muscles, for sustaining inverted postures (Calderón-Díaz, M. et al., 2021; Rohleder, J., & Vogt, T. 2018). The current study builds upon these insights by not only verifying the importance of these muscles but also expanding the investigation to include the lateral deltoid, offering a more comprehensive view of upper limb muscle dynamics. Moreover, the utilization of MMS adds a layer of precision to the study (Gautier, G. et al., 2009). In a similar context, the reliability and accuracy of MMS for capturing muscle activity in dynamic movements (Kochanowicz. A et al., 2018; Nahi, Z. M. et al., 2023). The real-time nature of the data acquisition, facilitated by the IoT and NodeMCU, enhances the ecological validity of the study, capturing the dynamic nature of muscle engagement during actual gymnastic performances (Kochanowicz, A. et al., 2017).
The observed difference in muscle activation between one-arm and double-arm handstands increases interesting questions about the role of imbalance and distribution of load in gymnastic skills (Matuska, S. et al., 2020). Previous research explored the impact of asymmetry in gymnastics and found that it could influence performance outcomes (Malíř, R. et al., 2023; Sobera, M. et al., 2007; Uzunov, V. 2008; Felici, F. 2006). The current study extends this conversation highlighting specific muscle activation differences related to handstand variations, providing valuable insights for coaches and athletes aiming to optimize training and skill development (Grabowiecki, M. et al., 2021). The implications of these findings extend beyond the realm of gymnastics training. Understanding the opted muscle dynamics in single and double-arm handstands provides valuable insights into biomechanical principles that can inform rehabilitation practices for upper extremity injuries and enhance performance in various gymnastic activities.

Conclusion

The exploration of muscle dynamics in single and double-arm handstands provides invaluable understandings into the complex biomechanics fundamental these challenging gymnastic exercises. Through the utilization of advanced technologies such as IoT programs and Myoware Muscle Sensor (MMS), this study has achieved a deeper understanding of the muscle activation patterns crucial for achieving and maintaining handstand positions. The real-time data acquisition and processing capabilities afforded by these technologies have added a layer of sophistication to biomechanical analyses, enabling accurate measurement and interpretation of muscle activity during dynamic movements. Our findings highlight the interconnected nature of the wrist flexors (WF), triceps brachii (TB), and lateral deltoids (LD) during handstand performances. Specifically, we observed significant relations between the wrist flexor and lateral deltoid muscles, indicating their coordinated efforts in maintaining stability and control during handstands.

While no significant relations were found between other muscle groups, the understandings gained from this study lay the groundwork for further exploration into the role of additional muscle groups in handstand biomechanics. Beyond the realm of gymnastics, the implications of this research extend to sports science and rehabilitation. By explaining the specific muscle activation patterns involved in handstand performance, this study provides valuable information for coaches, athletes, and rehabilitation professionals seeking to optimize training protocols and reduce the risk of injuries. The identification of key muscle groups and their functional relationships informs targeted training strategies aimed at enhancing performance and preventing musculoskeletal imbalances. As we explore deeper into the complexities of handstand biomechanics, future research activities can build upon these foundations, exploring additional muscle groups and refining analytical techniques to further enhance our understanding of gymnastic excellence. By including interdisciplinary approaches and leveraging cutting-edge technologies, we can continue to push the boundaries of biomechanical research, ultimately advancing the fields of sports science and rehabilitation while empowering athletes to reach their full potential.

Acknowledgment

Authors would like to express deepest gratitude to Mr. Varthya Srikanth from Central University of Haryana for his enthusiastic support in connecting the IoT Integration, his expertise and resources have significantly enhanced the connectivity and data acquisition process, and we express our sincere thanks to the participants of this research, their willingness to engage with IoT devices and systems has been pivotal in generating actual data that contributes to the depth and relevance of our findings, their cooperation has been invaluable, and a special thanks to Mr. Amit from Central University of Haryana for his enthusiastic participation.

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