REGAIN K.Exo: Rehabilitation and Gait Assistance through Innovative Knee Exoskeleton

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***Abstract* – This study presents the development and implementation of the REGAIN K.Exo system, a single-leg exoskeleton designed to enhance rehabilitation and gait assistance for post-stroke recovery. The system combines sensor fusion, machine learning algorithms, and motorized assistance to deliver a comprehensive solution for improving mobility. Equipped with accelerometers and gyroscopes on the thigh and shin, the system calculates joint angles to classify gait phases and predict recovery times using random forest algorithms. A motor integrated into the shin section provides an auto-assist mode, dynamically adjusting torque to support user movement safely and effectively. A dedicated webpage interface visualizes gait metrics, predicts recovery, and offers a curated list of rehabilitation exercises to promote adherence to therapy. Targeting chronic stroke patients with functional ambulation categories (FAC) 2–5, the REGAIN K.Exo system operates on level ground within predefined angle limits for safety. By integrating wearable technology, motorized support, and interactive digital tools, this research advances the accessibility and effectiveness of home-based rehabilitation while addressing critical gaps in traditional clinic-based therapies.**

***Keywords* – Rehabilitation robotics, Gait analysis, Robot-Assisted Gait Training (RAGT), Machine learning in rehabilitation, Knee exoskeleton, Chronic stroke rehabilitation, Auto-assist motor technology, Wearable sensor technology**

I. INTRODUCTION

Human gait, the repetitive sequence of movements essential for walking, serves as a foundation for mobility and independence. Disruptions in gait due to neurological, orthopedic, or age-related conditions can severely affect quality of life, necessitating targeted rehabilitation strategies (Wright et al., 2021). The analysis of gait, which involves examining movement patterns during walking, plays a pivotal role in these strategies. It allows clinicians to monitor recovery, customize therapeutic interventions, and reduce the risk of complications like falls (Perry & Burnfield, 2010; Tao et al., 2012). A critical aspect of gait analysis is gait classification, which segments the gait cycle into discrete phases such as heel strike and toe-off. These classifications are integral to understanding the biomechanics of walking and have informed the development of assistive technologies such as robotic prostheses and orthoses, which aim to restore mobility for individuals with gait impairments (Gregg et al., 2014).

Traditional gait analysis methods relied on laboratory-based systems like motion capture cameras and force plates, offering high accuracy but at significant cost and requiring specialized facilities. Advances in technology have shifted focus toward wearable sensors, including inertial measurement units (IMUs), accelerometers, gyroscopes, and force-sensitive resistors (FSRs). These devices provide a more portable and cost-effective alternative, enabling real-time gait analysis in clinical and everyday environments (Tao et al., 2012).

Despite their potential, wearable sensors face several challenges that limit their widespread adoption. Sensor accuracy remains a significant hurdle, as wearable devices are prone to drift, noise, and sensitivity to environmental factors such as temperature and humidity (Behboodi et al., 2015). Furthermore, the calibration and precise placement of these devices often require significant expertise, and their durability is limited due to wear and tear, battery constraints, and placement inconsistencies during prolonged use. The integration of multiple sensors further complicates system design, as each sensor typically requires individual adjustments, increasing setup time and introducing risks of data synchronization errors (Lim et al., 2017; Behboodi et al., 2015).

Robotic-assisted gait training (RAGT) builds on these advances by integrating wearable sensors and algorithms into devices that enhance ambulation, balance, and mobility in individuals recovering from conditions such as stroke. Devices like robotic knee orthoses, combined with task-specific training, have demonstrated improvements in gait speed, endurance, and functional independence (Wong et al., 2012; Iida et al., 2017). However, the high costs and professional supervision requirements associated with these systems restrict their accessibility. Home-based rehabilitation programs incorporating wearable robotic devices and physiotherapy have shown promise in overcoming these barriers, delivering sustained improvements in walking distance, balance, and overall mobility (Wright et al., 2021). Continued innovation in algorithms and wearable technologies will be crucial to making gait analysis and rehabilitation systems more effective, accessible, and widely applicable.

The study aims to develop REGAIN K.Exo, a single-leg exoskeleton system tailored for chronic stroke patients classified within Functional Ambulation Categories(FAC) 2 to 5. The system will integrate accelerometer and gyroscope sensors positioned on the thigh and shin to calculate joint angles for the thigh, knee, and shin. A complementary filter will be applied to the raw data to minimize noise and enhance reliability. The data collected from the lower limb will support a machine learning framework that employs a random forest classifier to detect gait phases. Additionally, a random forest regression model will predict recovery time based on the maximum knee flexion.

The scope of the project is limited to level-ground walking for chronic stroke patients, with the exoskeleton operating within predefined angle limits to ensure user safety. The exclusion of a database and the focus on a single-leg system prioritize accessibility and practicality. By combining wearable sensors, motorized assistance, and an intuitive web interface, the proposed solution aims to improve mobility outcomes while making advanced rehabilitation technologies more accessible.

The inclusion of a webpage interface providing rehabilitation exercises is inspired by the findings of Housley et al. (2018), who demonstrated that telerehabilitation and home-based robotic interventions can increase access to cost-effective rehabilitation services. These interventions are particularly valuable for patients in rural or underserved areas where frequent clinic visits may not be feasible. By enabling therapy to occur in the home environment, such systems improve adherence to rehabilitation protocols, as patients can integrate exercises into their daily routines. This approach aligns with the goals of the proposed project, as the integrated webpage will not only display gait metrics but also offer a curated list of rehabilitation exercises to encourage active engagement and sustained mobility improvements.

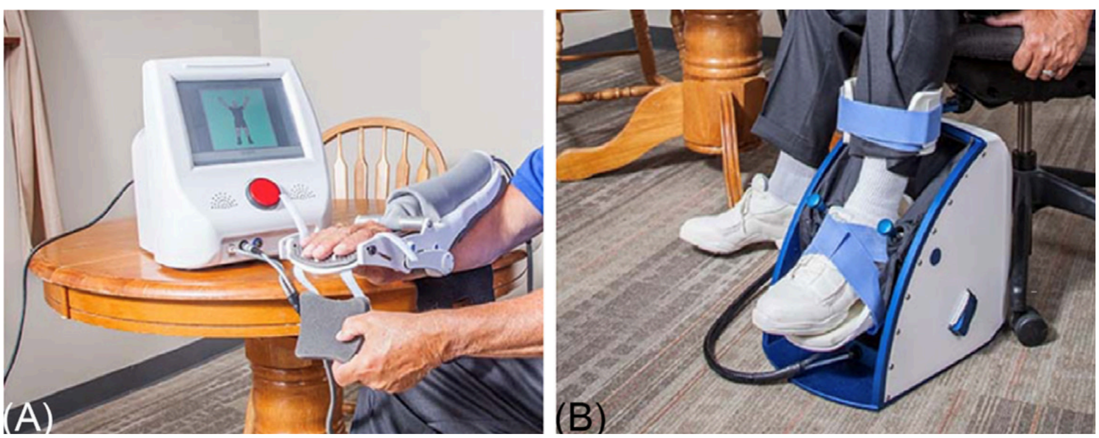

Figure 1. Hand and Foot Mentor air muscle assemblies

The placement of sensors in the proposed exoskeleton is based on the methodology used by Chereshnev (2020), who positioned inertial sensors on the thigh, shin, and foot to collect comprehensive gait data. Specifically, focusing on the thigh and shin for sensor placement allows the system to capture critical joint angles necessary for both gait phase detection and rehabilitation analysis. This alignment with prior research ensures that the system benefits from validated sensor configurations while enhancing its applicability to gait analysis.

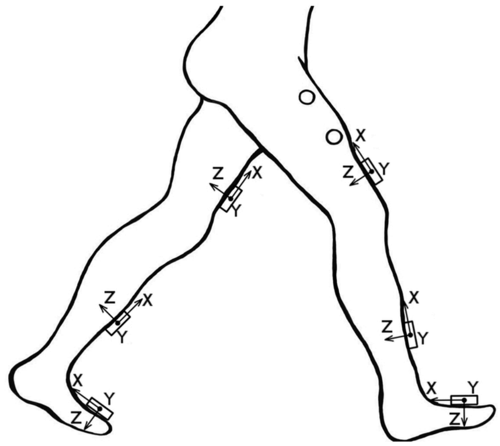

Figure 2. Location of Sensors. EMG sensor are shown as circles while boxes represent inertial sensors

The motor design in the proposed system draws from the work of Shaari et al. (2015), who analyzed the torque requirements for lifting a user's limb. By employing their formula, the proposed exoskeleton's motor is calibrated to provide a controlled boost of 20–50% to the wearer's movements. This range ensures that the motor delivers sufficient assistance to reduce user exertion while maintaining natural movement dynamics. The integration of an auto-assist mode further builds on this principle, dynamically adjusting the torque output based on real-time gait phase data, enhancing the user's safety and experience during rehabilitation.

$m_1 = mass\ of\ actuator\ at\ hip\ joint$
$m_2 = mass\ of\ thigh$
$m_3 = mass\ of\ actuator\ at\ knee\ joint$
$m_4 = mass\ of\ shank$
$m_5 = mass\ of\ actuator\ at\ ankle\ joint$
$m_6 = mass\ of\ foot$
$m_{L1} = mass\ of\ thigh\ link$
$m_{L2} = mass\ of\ shank\ link$
$m_{L3} = mass\ of\ ankle\ link$
$l_1 = length\ of\ thigh$
$l_2 = length\ of\ shank$
$l_3 = length\ of\ foot$
$T_1 = torque\ required\ at\ hip\ joint$
$T_2 = torque\ required\ at\ knee\ joint$
$T_3 = torque\ required\ at\ ankle\ joint$

$$\boldsymbol{T_2} = sin\theta\left[(m_4 + m_{L2})g\left(\frac{l_2}{2}\right)\right] + sin\theta[+m_5 g(l_2)] + sin\theta[+m_6 g(l_2)]$$

$$+cos\theta\left[(m_6 + m_{L3})g\left(\frac{l_3}{2}\right)\right]$$

Figure 3. Torque Requirements for Knee Joint

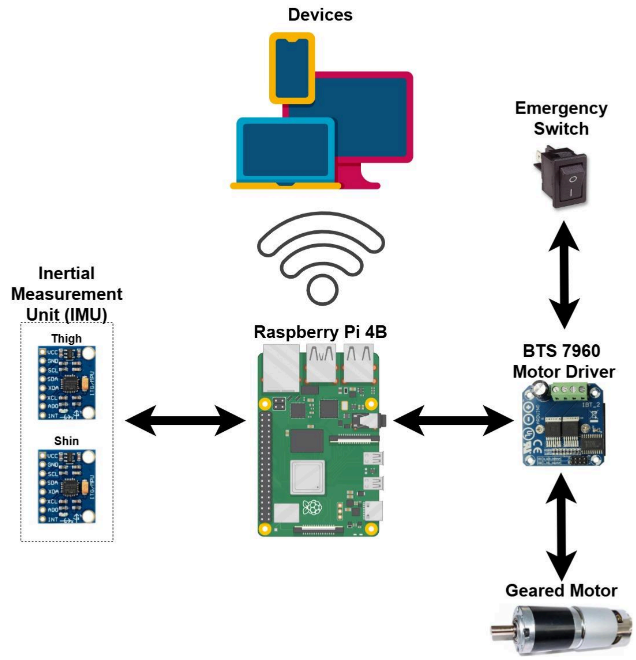

Figure 4. Theoretical Framework

Figure 4 shows the theoretical framework. The design incorporates Inertial Measurement Units (IMUs) positioned on the thigh and shin to capture precise orientation and motion data. These sensors are interfaced with the Raspberry Pi 4B, which functions as the primary processing unit, managing data acquisition and control operations. The Raspberry Pi transmits control signals to the BTS 7960 motor driver, which regulates the operation of the geared motor, facilitating motion. An emergency switch is integrated into the framework to provide a manual override mechanism, ensuring operational safety. Furthermore, the Raspberry Pi enables wireless communication with external devices, including laptops, smartphones, and desktop computers, facilitating real-time monitoring and control. This framework demonstrates a solid integration of sensor data processing, motor control, and user interaction mechanisms, contributing to a reliable and efficient system design.

The development of a knee exoskeleton system offers significant benefits to various stakeholders. For chronic stroke patients, the system enhances mobility, independence, and quality of life through precise movement recognition and predictive recovery models, making rehabilitation more effective. Physiotherapists and medical professionals benefit from reduced workloads and improved treatment precision, allowing them to focus on specialized care rather than repetitive tasks. Healthcare institutions stand to gain from integrating innovative technologies into rehabilitation practices, improving infrastructure, and promoting inclusive health services. This project also fosters broader social benefits by increasing recovery rates and accessibility for individuals with mobility challenges. Additionally, future researchers will benefit from the project’s advanced capabilities and the valuable dataset generated during testing and implementation.

This data enables further analysis, algorithm refinement, and new approaches to enhance patient recovery outcomes, advancing the field of rehabilitation science and promoting continual innovation in healthcare practices worldwide.

II. MATERIALS AND METHODS

This part explains the methods used to arrive at the results of your study. This part should answer the following: a) the participants/ research subjects, study population, sampling plan and the number b) the research design c) the methods/ test used or methods of data collection d) data analysis procedure

A. *Methods for Hardware Development*

Circuit Development:

For this project, the REGAIN K.Exo system utilized a Raspberry Pi 4 Model B as its primary computational and communication hub. The Raspberry Pi was programmed using Python, with Flask employed for backend operations to facilitate communication between the exoskeleton and the web application. Essential hardware components included the MPU-6050 IMUs for motion tracking, the BTS7960 motor driver for actuator control, and geared DC motors for knee movement assistance.

Casing and Other Parts:

Comfort, cost, functionality and safety were all considered in developing the device. However, due to technological constraints, The design became bulky as presented below.

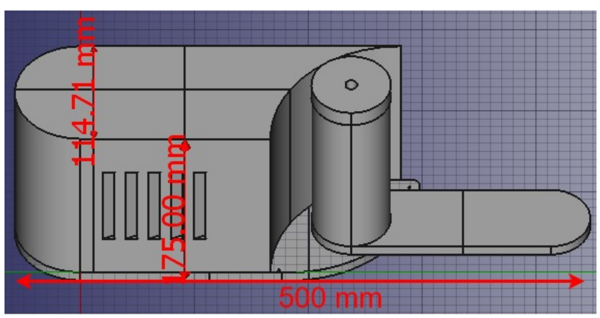

Figure 5. Theoretical Framework

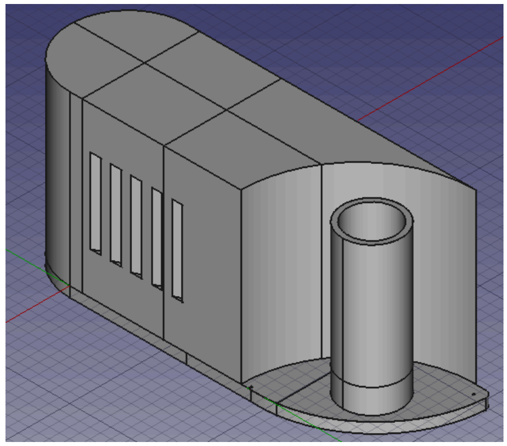

Figure 6. Thigh and Main Housing

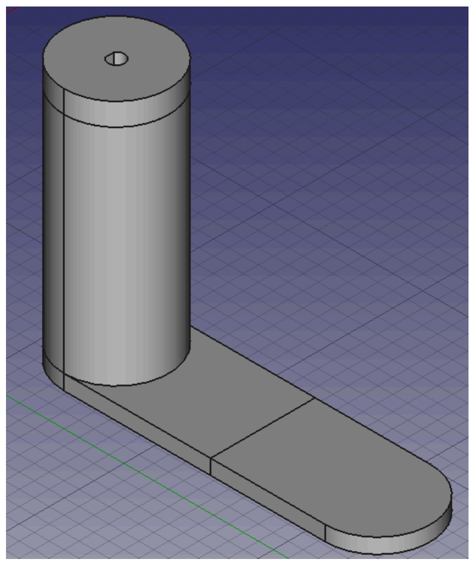

Figure 7. Shin Part

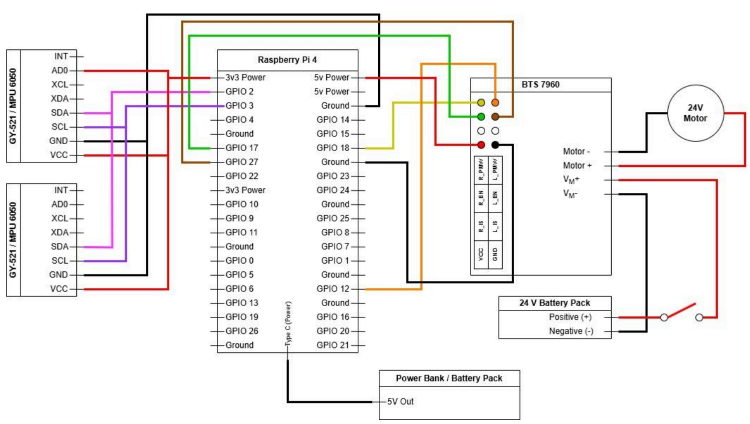

Figure 8. Wiring Diagram

Figure 5 shows the 3D design of the device which was used in 3D printing using polycarbonate filament which allows the device to become cheaper while maintaining durability and lightness. Breaking down each part, Figure 6 shows the main housing of the microcontroller, motor driver, motor mounting, and one IMU for thigh angle detection. Figure 7 shows the shin part of the device, which is not fully detailed as its only main function is to detect shin angle and be driven by the motor to assist the user during activities.

Despite the large size, the device offers a modular design which allows easier modification in the future when smaller parts can be developed.

B. *Methods for Software Development*

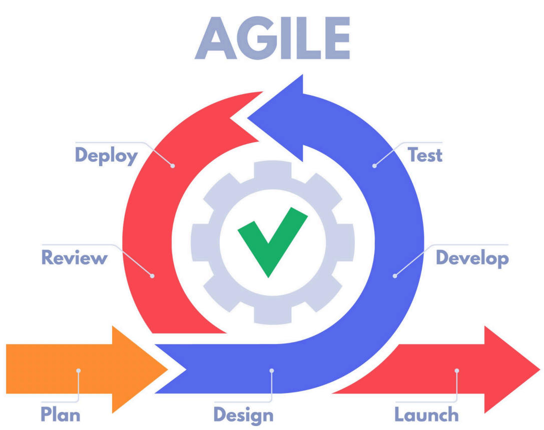

Figure 9. Agile Development Method

The Agile software development paradigm is repetitive, flexible, and is user-friendly that is appropriate for the development of the REGAIN K.Exo system. Agile emphasizes constant feedback, enabling prompt adjustments in response to evolving user needs and project requirements. Agile's repeated cycles, known as sprints, facilitate regular reassessment and moderate improvements, bringing the project closer to optimal performance and usability with each iteration. As Gabriel (2021) emphasizes, the development of intelligent technical systems, which combine software and hardware, requires careful management of interdisciplinary difficulties. Agile methods address these challenges by allowing for the creation of prototypes and gathering stakeholder feedback at each sequence, ensuring that the REGAIN K.Exo system aligns with user requirements and technological advancements.

Planning:

Requirements are gathered from physiotherapists, potential users, and studies on gait rehabilitation. Interviews and consultations define software and hardware needs, ensuring the system aligns with user expectations and project feasibility.

Design:

A design for the web application and knee exoskeleton is created based on gathered requirements. Wireframes, mockups, and 3D models are developed to plan layout, flow, and hardware placement, with diagrams detailing hardware-software interactions.

Development:

In this phase, system coding and construction occur iteratively using Agile methodology. The knee exoskeleton is assembled, the web application is developed, and machine learning models are trained with movement data, including gait patterns. Iterative adjustments ensure the system meets requirements and incorporates feedback effectively.

Testing:

The testing phase assesses defects and quality using unit, integration, and system tests for hardware and software. User acceptance testing (UAT) with physiotherapists and users ensures functionality and usability. Agile enables continuous refinement for a seamless user experience.

Deployment:

During the deployment phase, the REGAIN K.Exo system is introduced in a controlled real-world setting, allowing users to integrate it into their routines. The process is monitored to gather feedback, address issues, and validate performance, ensuring it supports gait recovery and movement assistance effectively before wider release.

Review:

The review phase analyzes feedback and data from deployment, assessing performance, usability, and effectiveness. Developers and stakeholders identify strengths and areas for improvement, refining the system through repeated adjustments to ensure it evolves based on real-world experiences and meets user needs.

Launch:

In the launch phase, the REGAIN K.Exo system is released for widespread use after stakeholder approval. User training and detailed manuals ensure effective setup, operation, and adjustment. The phase concludes with a final evaluation to confirm real-world performance.

C. *Methods for Project Testing*

Trial and Error was used to understand the project further for possible improvements during hardware and software testing. The prototype was initiated when the whole system was complete.

Circuit Testing:

A simple multimeter was used to check if connections within the circuit were functioning properly.

Other Component Testing:

Specifications and datasheets of each component were checked to know if each part is compatible with each other. Each component was also tested with Raspberry Pi through sample programs provided by the datasheets.

Software Testing:

Each part of the software was tested separately, including the machine learning models and the web application. Before integration, the machine learning models were evaluated using user inputs and random values to assess their accuracy.

System Testing:

After slowly integrating and testing each part of the software and hardware together, system testing was conducted. Interaction between the web application and the device was checked for errors and additional modifications.

Process Flow

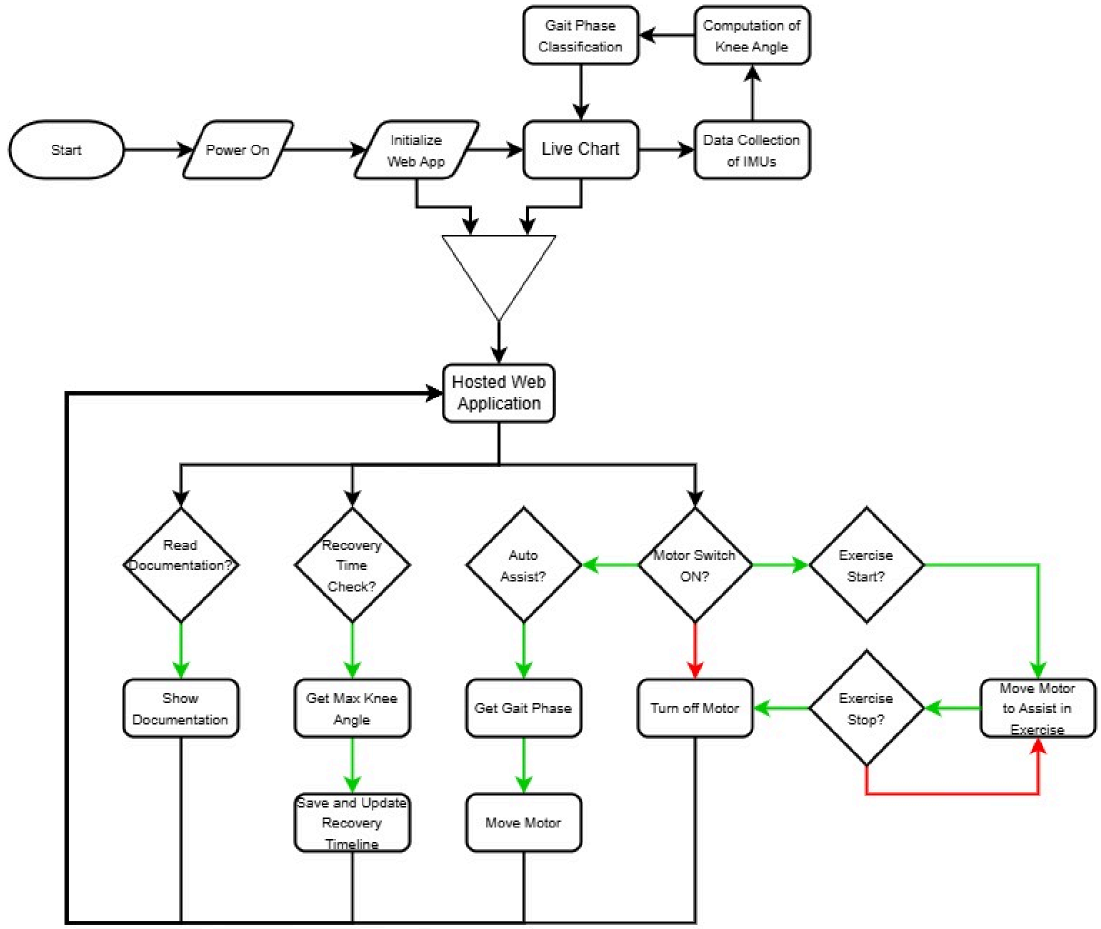

Figure 10. REGAIN Main Process Flow

The main process flow of the REGAIN system is shown in Figure . On start, power will be switched on to initialize the web application and start real time collection of IMUs for gait classification. The web application will then allow the user to interact with the device as it serves as its interface. Users will be allowed to choose between reading the documentation, checking their recovery time, enabling auto assist, and starting exercises. Reading Documentation shows the paper of how the device was created and how it operates. Checking recovery time provides detailed directions on how to get the max knee angle to get an estimation of recovery time. Auto assist allows the device to help the user with walking by predicting gait phase to move the motor in coordination. Starting an exercise will move the motor to perform exercises which will assist and instruct the user in movement while giving the user freedom to stop the exercise at any time. However, functionalities involving the motor need to have the physical switch on the battery turned on. As a safety measure, a power switch is implemented in case any emergency or error happens to force stop the motor by cutting off its power supply.

III. RESULTS AND DISCUSSION

This section presents the outcomes of the K.Exo system, focusing on its usability, performance, and integration of machine learning features. The results are categorized into key components, including user acceptance testing with a physical therapist, interactions between the device, web application, and actions, predictive recovery time analysis using Random Forest Regression, and gait phase classification through machine learning. Each component highlights the device's capability to provide personalized and effective rehabilitation solutions for post-stroke patients.

3.1 Demonstration of the K.Exo to a Physical Therapist

Figure 11. Demonstration of the K.Exo to Physical Therapist

As part of the user acceptance testing (UAT) process, the K.Exo device was demonstrated to a licensed physical therapist (PT) prior to its application with actual post-stroke patients. The demonstration aimed to ensure the PT's familiarity with the product, enabling them to guide patients effectively during consultations. The session included a simulated use case to showcase the device’s core functionalities, such as guiding rehabilitation exercises, and tracking progress. The PT was also given an opportunity for hands-on interaction to assess the device's usability and applicability in real-world scenarios. Feedback was gathered to identify any potential adjustments needed for seamless integration into therapy routines. This step ensured that the physical therapist could confidently explain and demonstrate the device to chronic stroke patients, allowing them to better understand and utilize the product during their rehabilitation process.

3.2 Device and Wearer View, Web Application View, and Actions

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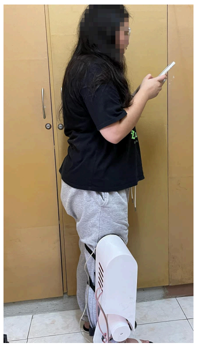
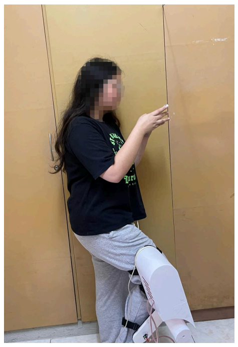
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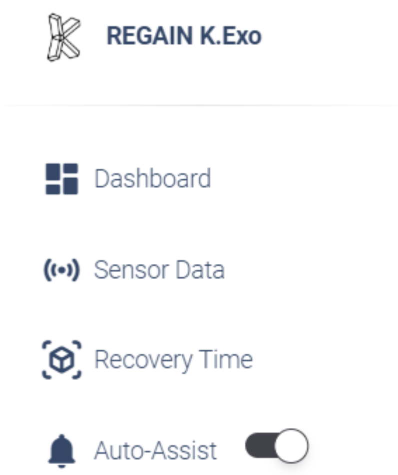

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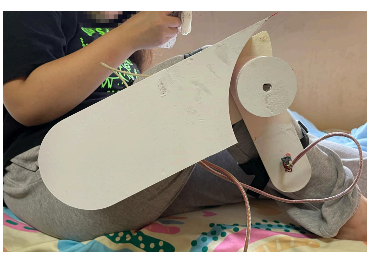
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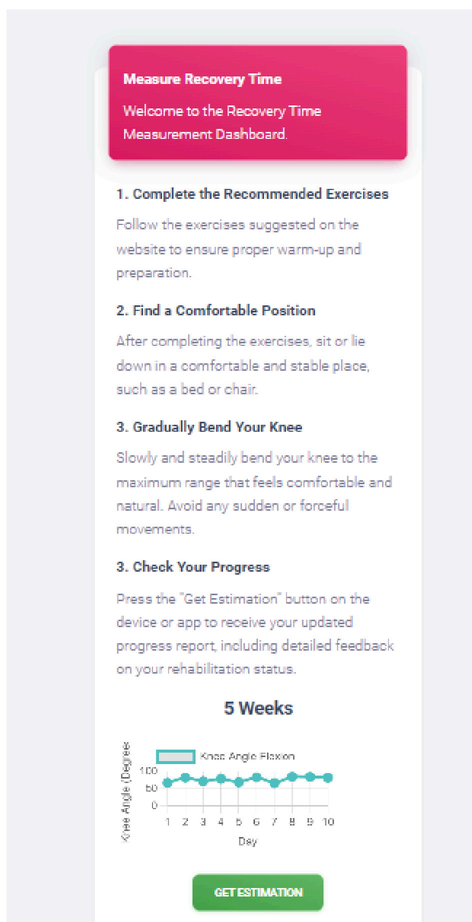

</td><td>Recovery Time</td></tr>
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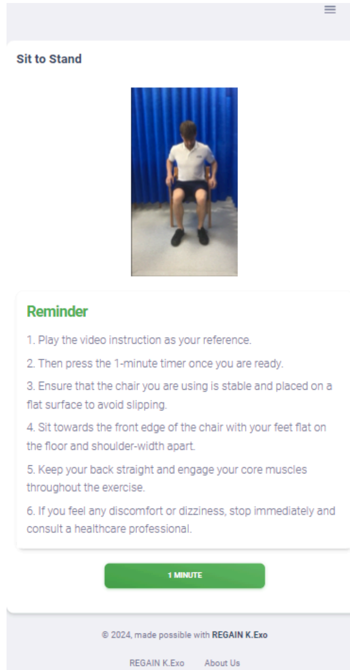
<td>
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<td>Exercise: Sit to Stand</td>
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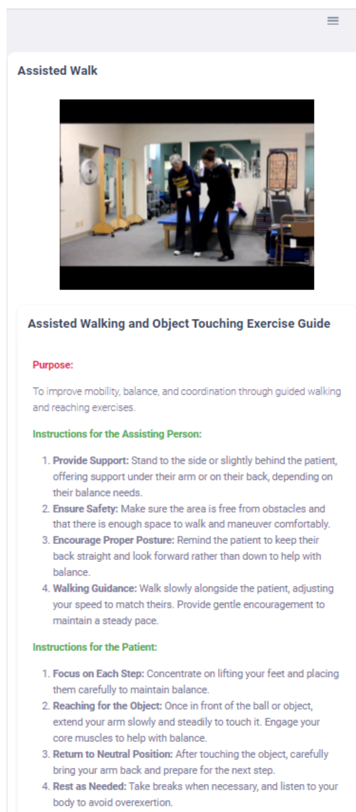
<td>
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<td>Exercise: Assisted Walking</td>
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Table 1. Interaction Between Device, User, and Web Application

Table 1 shows how the user interacts with the device with the use of the web application with certain actions. These components work together to deliver an ordered and effective rehabilitation experience for post-stroke patients.

From the Device and Wearer View, the K.Exo provides direct, user-friendly features such as an Auto-Assist Mode, which automatically adjust the motor speed automatically based on the user's needs. It also includes a Recovery Time Display that offers real-time feedback on progress, enabling users to monitor their recovery metrics easily. Additionally, the device incorporates a random forest classifier for gait phase classification, which helps assess the patient's walking mechanics and stages of gait recovery. The device supports guided exercises, including Sit-to-Stand, which enhances lower body strength and joint stability, and Assisted Walking, which aids in gait improvement and confidence building during ambulation.

The Web Application View complements the device by providing a platform for detailed data visualization and analysis, focusing on two key features: a random forest classifier for gait phase classification and a random forest regression model for recovery time analytics. While the estimated recovery time offers valuable insights, it is subject to verification by a physical therapist to ensure accuracy and alignment with the patient's rehabilitation progress. These features enable therapists to make data-driven adjustments to the rehabilitation program, ensuring a more adaptive and responsive recovery process.

The Actions column bridges the hardware and software components by outlining specific tasks facilitated by the K.Exo. These actions include Auto-Assist, which adjusts the device's support level dynamically, Recovery Time Measurement to track and analyze recovery efficiency, and targeted exercises like Sit-to-Stand and Assisted Walking. Each action is designed to guide patients through their recovery journey, gradually increasing their independence and mobility.

3.3 Predictive Analysis of Recovery Time Using Random Forest Regression

A key component of this study was the development of a machine learning model to predict patient recovery time using data collected from the **K.Exo** rehabilitation system, as shown in Table 1, Recovery Time. The Random Forest Regression model was chosen due to its validity and ability to handle non-linear relationships, which are common in physiological datasets.

The dataset used in this study comprised two primary variables such as the maximum knee flexion (in degrees) and the observed recovery time (in weeks). Data was collected over two weeks of patient sessions with the **K.Exo** device. The dataset was split into training (80%) and testing (20%) sets to train and validate the model.

The trained Random Forest model demonstrated high accuracy, as reflected in its performance metrics. The **Mean Squared Error (MSE)** was 1.76, indicating minimal prediction error, while the **R-squared (R^2)** value of 0.93 showed that the model could explain 93% of the variance in recovery times. These results validate the model's ability to predict recovery time effectively and reliably.

The workflow for prediction integrates orderly into the **K.Exo** system. Data from the past 14 days of knee angle measurements is collected, and the maximum knee flexion is extracted as input for the model. The model then predicts the recovery time, rounding the output to the nearest week. For instance, given a maximum knee flexion of 85 degrees, the model predicted a recovery time of 6 weeks, which aligns with observed clinical trends.

The integration of this predictive feature into the **K.Exo** system offers multiple benefits. Firstly, the high accuracy of the model, indicated by its low MSE and high R^2, ensures precise monitoring of recovery progress. Accordingly, it enables personalized therapy plans by tailoring recovery timelines to individual patient data, optimizing therapy outcomes. Finally, it serves as a valuable tool for clinicians, providing data-driven insights that support adjustments to rehabilitation strategies.

The Random Forest Regression model's performance demonstrates its ability to handle the variability and complexity inherent in biomechanical recovery data. Its implementation in the **K.Exo** system highlights the potential of combining robotics and machine learning to enhance rehabilitation monitoring and outcomes. Through transforming raw data into actionable insights, the **K.Exo** system exemplifies how innovative technology can bridge the gap between rehabilitation robotics and personalized patient care.

3.4 Gait Phase Classification Using Machine Learning

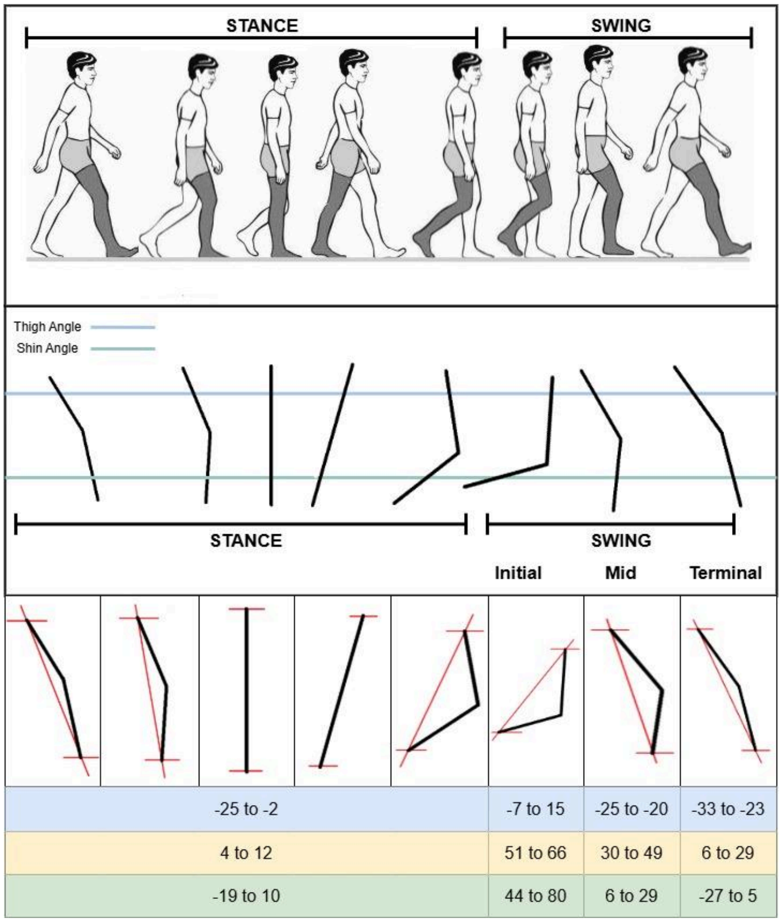

Figure 13. Breakdown of Gait Phases for IMUs and Gait Phase Classifier ML Model

The figure shown above shows how each gait phase is broken down for effective IMU placements and deeper understanding of how human gait patterns can be processed with the use of IMUs. As the stance phase comprises subtle changes in the knee angle, it has been classified together for simplicity. However, the swing phase involves significant movements in each angle, requiring the classification to retain each sub-category. To calculate for the knee angle, Triangle Angle Theorem and Exterior Angle Theorem where used as the IMUs get their values relative to the ground. This allows the Theorems to be implemented to find the knee angle.

IV. CONCLUSION and RECOMMENDATIONS

A. *Conclusion*

The proponents successfully designed and developed the REGAIN K.Exo system, a knee exoskeleton capable of providing rehabilitation and gait assistance for post-stroke recovery. The system integrates features such as motion detection, real-time adjustment, and a responsive web application. For motion detection, the system effectively classifies gait phases using IMUs and machine learning algorithms. Real time gait classification enables the exoskeleton to adapt to users' movements during therapy, ensuring precise assistance. Additionally, the web application allows seamless user interaction for managing rehabilitation sessions and monitoring progress.

The REGAIN K.Exo system was rigorously tested to ensure accuracy and reliability. Gait phase detection was validated through multiple trials, achieving consistent recognition of motion patterns. The system demonstrated its ability to support users in walking and performing rehabilitation exercises, showing improvements in gait speed and balance. Factors such as sensor placement and calibration were observed to influence accuracy, highlighting areas for refinement.

Lastly, the deployment phase included user feedback to validate system functionality and usability in real-world settings. The results confirmed the system's potential for reducing dependency on professional supervision while promoting independent recovery. With its innovative features and user-centered design, the REGAIN K.Exo system contributes to advancing affordable and accessible rehabilitation solutions, particularly for underserved communities.

B. *Recommendations*

The proponents suggest that modifications with the system can be done by students and researchers in the near future, especially Engineering, Computer Engineering, and Computer Science students. As a system for human gait classification with the use of IMUs have been developed by the project, the proponents would like to recommend the following:

1. Future researchers can change the design to make it more compact and lightweight.
2. Future researchers can use additional sensors such as Electromyography (EMG) to further increase accuracy of movement prediction.
3. Using a smaller and lighter motor while retaining required torque can significantly reduce the weight and size of the device.
4. Additional datasets can further improve accuracy of gait phase recognition.

5. Use of multiple filters and changing the IMUs can help in reducing drift and noise.

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