Data Assessment Methods for Monitoring in Seamless At-Home Hand Rehabilitation

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To be able to perform everyday tasks, a continuous hand rehabilitation process is required for patients with hand impairment after facing a condition such as a stroke. Concerning this matter, the smart Frehabilitation toolkit was developed by a team of the University of Twente (UT) researchers. The toolkit consists of a smart toothbrush, a coffee cup, a computer mouse, and a placemat, and allows for seamless integration of the hand therapy into patients' everyday activities. In this research, I propose to mainly focus on developing algorithms for smart toothbrush data processing. Based on this development, I aim to pave the way for utilizing the algorithm across the majority of devices within the Freehabilitation toolkit, considering the similarity of their sensor systems. I target to assess such factors as the increment in daily training duration, adherence to the daily routine, consistency, and frequency of daily sessions. This would enable further analysis of the patient's usage of the Freehabilitation toolkit.

Additional Key Words and Phrases: Rehabilitation, Interactive tools, Data processing algorithm, Device tracking, Hand impairment, ADL

1 INTRODUCTION

The majority of stroke survivors and individuals dealing with other neurological or musculoskeletal conditions experience intense challenges in motor hand functionality [2, 3]. The hand's functionality is affected by reduced strength, poor coordination, and limited range of motion. This leads to a severe negative impact on their Activities of Daily Living (ADLs) such as simple actions like eating, managing basic hygiene, and dressing [2, 7, 9, 14]. By using the Barthel ADL scale Clive E. Skilbeck et al.[14] perform a quantitative study of post-stroke effects on their patients. However, even the highest score doesn't necessarily imply full recovery, it merely reflects a level of independence without attendant care. This allows thinking how fragile patients' condition is without proper constant therapy. Meaning their functional abilities may deteriorate or decline, once they are discharged to their homes and left on their own. In addition to this, the healthcare system faces challenges in sustaining rehabilitation therapy for such patients. As a result, rehabilitation is often shifted to the home environment, where they are expected to continue their therapy with decreased support or independently. This process is discussed in greater detail in the work by Miquel Angel Mas and Marco Inzitari [8].

Another complication is that the independence placed on patients often fails due to the lack of motivation from patients, as even simple home tasks may now become significant obstacles[11, 12]. Clinicians usually prescribe about 30 minutes/day of exercises for the patients. Research shows that patients tend to neglect the recommendation of a doctor over time and spend less time on the exercises [11, 16]. Researchers have been trying to develop strategies to address the significant challenge patients face in adapting rehabilitation therapy to their daily routines and maintaining consistency. In this research, I focus on a Frehabilitation toolkit, which was developed by a team of the UT researchers[4, 15]. The Frehabilitation toolkit integrates seamless rehabilitation into daily life by using the devices during the ADL. Previous research has shown that clinicians and patients are positive about making the training part of their daily routines which would make it easier to continue with rehabilitation [4, 15].

The Freehabilitation toolkit consists of several devices, such as a smart toothbrush, a coffee cup, a computer mouse, and a place mat. The toolkit allows for training certain grips and hand and wrist movements and can be adjusted for the difficulty level of the training to the patient's abilities. Previous research has made significant progress in the design and physical implementation of the devices. Provided with feedback from clinicians and patients the design has undergone multiple modifications. At present, the Freehabilitation toolkit has already been integrated into patients' homes. With this research, I intend to create methods for processing data collected specifically from the smart toothbrush, with the final goal of facilitating the other devices as well.

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2 PROBLEM STATEMENT

As of the final phase of validation of the Freehabilitation toolkit, the researchers need to determine whether the patients are using the devices. If so, it needs to be determined how and when the device is being used in an unsupervised home environment, so the focus of researchers has shifted to the data-collecting phase. Therefore, in this research, I will be developing algorithms for processing the data gathered from the usage of the device. Mainly, I am focusing on the data collected from the smart toothbrush. Consequently, I seek to provide the suggestions for further integration of the developed algorithm for other devices within the toolkit, considering the similarity of the sensor systems. The algorithm of this research would enable researchers to perform an experimental analysis on a group of patients and provide them with valuable quantitative data. Data collected from sensors, embedded within the product, will be analyzed to evaluate various metrics, including the duration and frequency of product usage, frequency and consistency of training sessions, number of repetitions per session, and finally, the patient's ability to move the device according to the suggestion. In the future, this will allow for the assessment of the patient's adherence to the usage of the device and their usage patterns.

2.1 Research question

The problem statement described above leads to the following research questions:
How can algorithm be developed to effectively process sensor data from a smart toothbrush rehabilitation device to evaluate patient adherence?
And the following sub-questions:

(1) What triggers can be observed to determine the start of the new session, and the end of a usage session?

(2) What algorithm can be developed to evaluate usage patterns, and the patient's adherence to the device's operating guidance?
(3) How can developed algorithm be integrated into other devices within the Freehabilitation toolkit?

3 RELATED WORK

In this section, I will look into studies that will provide a broader understanding of computational and analytical techniques for processing data from the gyroscope and accelerometer sensors, which are embedded within rehabilitation devices. Given the fact that the toothbrush is a novel device, it is convenient to look into more general devices that process data for rehabilitation purposes. Specifically, research that details algorithms for processing IMU sensor[1] can provide valuable insights. It is important to highlight that research in hand rehabilitation involving IMUs is currently limited to more complex sensor arrays. For instance, Rick A. Hyde et al. [5] propose mathematical models for estimating the position and orientation of the upper limb using a sensor array. Fundamentally, the paper proposes relevant filters for the resulting IMU data and addresses the challenges of developing them. However, since the Freehabilitation toolkit devices support only a single IMU sensor or a combination of individual sensors of such kind, only the general aspects of their model can be considered.

Broadening the scope of IMU data processing, some algorithms and general design guidelines for them have already been established. For example, Ahmad Jalal et al. [6] detail in designing a machine learning algorithm for general-purpose logging of day-to-day activities. In addition, their work defines a general algorithmic architecture and a pre-processing stage. More importantly, the paper discusses signal analysis techniques that are likely relevant for the majority of IMU-based devices. Having such guidelines as a starting point, it should be possible to develop more specialized algorithms for the smart toothbrush, even if not using machine learning but more traditional signal analysis techniques.

4 HARDWARE AND SOFTWARE

In order to develop and test the algorithms, a toothbrush from the Freehabilitation toolkit of the UT was used, which can be seen in Figure 1. More specifically, for the purposes of this research, the 3-axis gyroscope and accelerometer are used as sensors, as logged by the proprietary Freehabiliation Logger circuit. All described algorithms are implemented using Python 3.13. Furthermore, the NumPy 2.2 and SciPy 1.15 libraries are used for performing computations and taking statistical measures, while MatPlotLib was used for plotting and inspecting the resulting data. All implementations of the algorithms can be found in this GitLab repository.

5 METHODOLOGY

5.1 Procedure

In this section, I outline an approach to algorithm design by dividing it into components of a single session and analyzing the patient's adherence to therapy exercises over time. Additionally, I discuss existing metrics and identify those that are most appropriate for the creation of the algorithm.

Fig. 1. Smart toothbrush from the Frehabilitation toolkit.

5.1.1 Single usage session. For the purpose of obtaining the usage overview data over time, first, I will examine a single usage session. To gain meaningful insights into user behavior generic metrics as such can be observed: length of session, user rotation of the brush. These metrics help identify trends in usage frequency, accuracy, and session length, offering a broad perspective on engagement over time. I develop the algorithm for processing single sessions that is described in the subsequent sections.

5.1.2 Multiple sessions. To proceed with the algorithm, I aggregate the session data collected within a single day. It is important to emphasize that first, this research focuses on developing an algorithm for a single session. This approach enables the aggregation of the results from individual sessions and later inclusion of additional metrics to finalize the evaluation of the multiple sessions, such as the average number of sessions in total, amount of sessions per day, and other related measures. Further details on these aspects are provided in subsequent sections.

5.2 Data recording

To design the algorithm, I first need to gather related data as a foundation. Specifically, this section focuses on the procedure for a single usage session, as the data from multiple sessions is simply an aggregation of individual session data. At first, I performed a data-collection session, during which specific movements were performed, including picking the toothbrush, holding it, and rotating it. Similar data collection sessions were carried out over multiple days and preserved for subsequent application of the algorithm over time. After acquiring multiple individual samples for each corresponding movement, the next step involved examining the structure of the captured data.

Before describing the data format, it is useful to provide a brief explanation of how the smart toothbrush operates. The toothbrush is turned on or turned off with a single button press. This targets the answer to the first sub-question (1) of this research. Therefore,

[1] Sensors which measure acceleration and orientation (usually a combination of a gyroscope and accelerometer)

a button press dictates the start and the end of the session for the smart toothbrush, eliminating the need for implementing tracking mechanisms. Each session is saved as a CSV format file containing the following data columns:

- UNIX timestamp (in seconds),
- Current brush angle,
- Current brush head speed,
- 3-axis instantaneous acceleration,
- 3-axis instantaneous rotational velocity.

Furthermore, the CSV files are logged with a name describing the time (year, month, day, hour, minute, second) that the recording started, which can be parsed using a regular expression.

One limitation presented by the logger is that of time reporting accuracy. This data requires additional pre-processing in order to suit the research objectives. The toothbrush reports to the second, while up to 10 events can be logged within one second (with the logger running at a fixed rate of 10Hz). In terms, it is impossible to distinguish the exact moment within the second an event occurred. As the logger writes at a fixed rate, I can interpolate events within one time slot by spacing them equally within the second. This pre-processing mechanism is exemplified in Figure 2 Another challenge

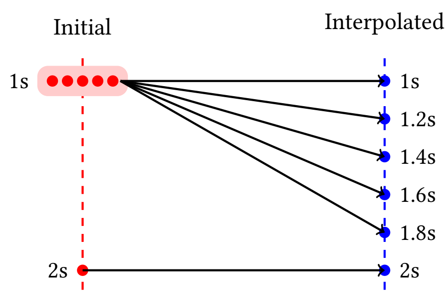

Fig. 2. Diagram of sub-second interpolation mechanism.

observed is the relatively low logging frequency of 10Hz. Usually, the logging frequency of similar devices is much higher, which also would be advantageous in this context as it would provide more data points, thereby improving algorithm precision.

5.3 Data processing

In this section, I present the methods for processing toothbrush usage data. I will focus on addressing the second research sub-question (2) in this and the following sections. The primary focus is on implementing an algorithm, which performs analysis of individual session data. By consequently aggregating results across multiple sessions, I aim to extract meaningful insights into patient's usage patterns and adherence trends over time.

To obtain the identified trends, I concentrate on the angle of the brush and the extent to which the user follows the recommended rotation. For each session, I propose introducing a score (from 0 to 100), which quantifies the patient's performance while following the suggested rotation. The explicit computation of the score will be shown later in this paper. The scoring approach allows to assess both consistency over time - the score stays stable over multiple days - and the improvement of the patient, indicated by the increase of the score over time. To derive the score, it is first necessary to derive the angular position of the toothbrush during motion. To achieve this, I investigated three methods and selected the most suitable for the research objectives:

5.3.1 Naive Integration. Firstly, in order to gain insight into the usage of the toothbrush, a way to extract its angular position must be found. Given the access to gyroscope data, specifically angular velocity, it is logical to compute the angle of interest by integrating it.

5.3.2 Complementary Filter. Previous studies [10, 13] also indicate the advantage of sensor fusion over simple integration. More specifically, sensor fusion involves utilizing data from multiple sensors simultaneously, which in the case of this research means adding accelerometer data to mitigate gyroscope bias drift errors.

5.3.3 Kalman filter. Going one step ahead of the Complementary filter, the Kalman filter involves a more complex implementation of filtering. However, a more intricate method does not always mean the most appropriate choice for every application. In this context, I will explain why the Kalman filter would be more useful for this system than Naive Integration and the Complementary filter in the results section.

5.4 Signal Alignment

In this section, I focus on another part of the algorithm. As I mentioned previously, a score representing the accuracy of brushing is assigned to each session. This can be done by comparing a reference signal, the current rotation of the toothbrush head, with the actual tilt of the entire device. Before this can be done, I must account for a delay between the reference and measured signals, as other factors (such as human response time) intervene. Following that, I can apply any given scoring algorithm as a function of the two aligned signals. Traditionally, finding the delay between two correlated signals can be done using the cross-correlation function, by taking the argument maximum of the function:

$$delay = \arg\max((f \star g)(t))$$

5.5 Angle comparison methods

In order to compare the suggested and measured angles various methods can be applied. For this research, I have reviewed several possible metrics for angle comparison, including:

- Root mean square error (RMSE),
- Sliding window with mean absolute error (MAE),
- Derivative matching,
- Pearson correlation.

5.5.1 RMSE. One of the key metrics considered is the *Root Mean Square Error* (RMSE), which measures the average difference between two signals by calculating the squared differences between corresponding values, averaging them, and then taking the square root of the result. In simple terms, this metric provides an overall measure of how much a patient's movement deviates from the reference signal. Thus, RMSE is particularly useful in evaluating the accuracy of the movement.

5.5.2 Sliding window with MAE. Another metric considered for this research is the *Sliding window with Mean Absolute Error* (MAE), which involves breaking the signals into smaller segments, or windows, for comparison. Unlike RMSE, MAE compares the absolute error between the signals without squaring the differences, making it less sensitive to large fluctuations caused by noise and advantageous in noisy environments, such as in this research. The sliding window technique is focused on local signal patterns. Windows with low error values are flagged as periods with "successful movement".

5.5.3 Derivate matching. The purpose of this research necessitates searching for other metrics, which give more focus on analyzing the trends of the two signals. One of these metrics to observe is the *Derivative matching* (5.5), which compares the derivatives (changes in position) of the two signals and emphasizes similar patterns in the movements. The derivative matching assesses whether the patient follows the correct trajectory of change, which is the information that I am interested in, and as has been discussed can be more important than matching every position exactly.

5.5.4 Pearson Correlation. The final metric that I have explored and ultimately selected is *Pearson Correlation*, which despite its simplicity, proved to be the most suitable. The motivation for this selection will be explained in subsequent sections. Pearson Correlation is one of the most widely used statistical metrics for measuring the linear relationship between two continuous variables. The outcome of this calculation is a value between 0 and 1, where 0 indicates no linear relationship and 1 stands for perfect linear correlation.

5.6 Scoring algorithm

5.6.1 Scoring a single session. To convert the correlation values into scores, I mapped the correlation range to a score scale ranging from 0 to 100. But, this linear mapping approach results in awarding higher scores for poor performance, making it less effective at capturing performance differences. To address this issue, I applied a sigmoid function to map the correlation values to scores, as illustrated in Figure 3. The final computation of the single session score comprises the following metrics:

- *Correlation value* gives a general insight into how well the patient follows the suggested rotation.
- *Session length* provides additional data about session duration. Longer sessions (more specifically the closer the session duration to 1 minute) contribute to a higher score.
- *RMSE* describes the accuracy of the patient's movements. Higher RMSE contributes to lower score.

5.6.2 Aggregating scores across multiple sessions. To finalize the scoring algorithm, single session scores as well as other metrics must be aggregated into a final score which can be used to assess the patient's situation. Similar to the previous score, this can be expressed by means of a weighted average, comprised of three key metrics:

- *Mean session score* is the key metric utilized, as it gives insight into the success of each session that the patient undertakes. As the score is already normalized, a simple mean of all session scores already provides a good indication of the user's consistency.
- *Mean daily session count* is another important metric, as a patient is expected to perform 2 sessions on a day-to-day basis. Thus, a higher score should be assigned to 2 daily, even spaced-out sessions (for example, in the morning and afternoon).
- *Daily session count standard deviation* further augments the above, as a patient should be consistent in their usage of the toothbrush. By measuring the standard deviation of their daily sessions, and assigning a higher score for a measurement of 0, I encourage the user to use the device at a similar rate.

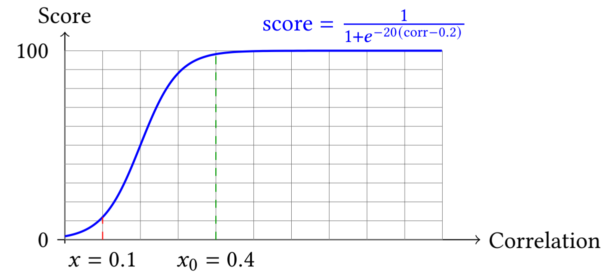

Fig. 3. Sigmoid function mapping the correlation values to scores.

6 RESULTS

In this section, I summarize the methods selected and provide the reasoning for their implementation.

6.1 Data Processing

6.1.1 Naive Integration. To begin, Naive Integration provides smooth, rapid changes, but accumulates error over time (also called drift), which can easily be seen in the example of Figure 4.
The limitations of obtaining a clear signal solely through integrating the gyroscope data have been described in previous studies, such as the work by Ilaria Pasciuto et al. [10], and work by Angelo Maria Sabatini [13]. They also indicate that while naive integration is effective for short time frames (within around 20 seconds), it is less reliable in longer periods. It is particularly relevant in this case, as the usual tooth-brushing session lasts at least 1.5 minutes.

6.1.2 Complementary filter. To meet the objectives of this research, I improved simple integration by implementing the Complementary Filter. This filter combines outputs from both the gyroscope and accelerometer. The Complementary Filter balances the two by relying on the gyroscope for rapid and precise updates while using the accelerometer to correct for drift, as it provides absolute orientation relative to gravity, even if noisy. I implemented a Complementary Filter that achieves this balance by applying a lighted combination using a tuning parameter α:

$$\theta = \alpha \cdot \text{gyro\_angle} + (1 - \alpha) \cdot \text{acc\_angle}$$

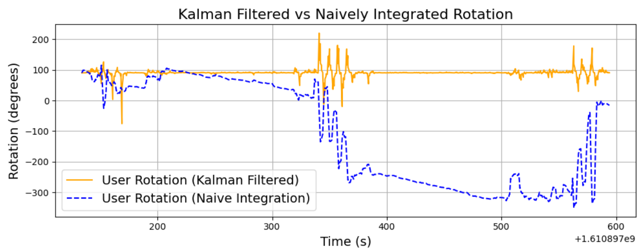

Fig. 4. Measured angle signal using naive integration as compared to the Kalman filter.

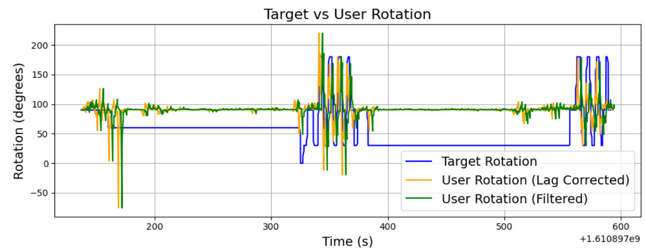

Fig. 5. Original filtered rotation signal as compared to the lag-corrected signal.

This way long-term stability can be ensured, which is essential for monitoring the toothbrush's motion during brushing, as the brush undergoes continuous movement and rotation.

6.1.3 Kalman filter. Nonetheless, I also explored whether more precise methods could be identified for this research. Unlike the Complementary filter, which uses fixed gains, the **Kalman filter** updates its gains based on each iteration to handle the noise and measurement variability. The primary advantage of the Kalman filter lies in its ability to adapt to dynamically changing systems, by continuously adjusting the final estimated value based on changing sensor conditions. The advantages, along with a comprehensive explanation of Kalman filtering, are detailed in the book by S. Grewal et al. [1].

To conclude, the **Kalman filter** provides smoother and more precise predictions in environments with high noise levels. This characteristic is important for the system as the toothbrush device generates noisy and fluctuating measurements due to factors such as the vibration of the toothbrush and the patient's hand tremors. Finally, as illustrated in Figure 4, this filtering approach produces a clear and steady signal when the user operates the brush (rotating it as instructed), making it a critical factor in its selection.

6.2 Signal Alignment

For the signal alignment, the delay between the reference and measured signals was found by taking the argument maximum of the cross-correlation function. As seen in Figure 5, this approach accounts for the generally fixed delay that the user exhibits during use. Furthermore, this approach is preferable over other techniques such as Dynamic Time Warping (or DTW). This is because these methods are often too permissive, allowing the users to misuse the device and still appear as if they are correctly using it. Additionally, a dynamic approach would allow the user's consistency to fluctuate greatly, disincentivizing them from keeping a steady usage pace.

6.3 Angle comparison

6.3.1 RMSE. The RMSE method is effective at detecting significant deviations, which is beneficial in applications such as toothbrush motion tracking, where random noise is present during usage. However, RMSE metric has certain limitations, it is not well-suited for temporal trend matching, which is the main target of this study. Therefore, while the metric is useful for understanding overall accuracy, it is preferable to complement it with other metrics that provide insights into trend matching. Such a combination of RMSE and another metric will be discussed later in this section.

6.3.2 Sliding Window with MAE. The Sliding Window with MAE approach can provide a clearer picture of the alignment of the signals and offer insights into specific segments of the performed task. Although, the main challenge with this method is selecting an appropriate window size. The choice of the window size is critical: if the window is too large, it may miss local patterns, if it is too small, it becomes overly sensitive to noise. Additionally, the difference in each session's conditions complicates the task of determining the optimal window size. Given these facts, I have decided against using the Sliding window with MAE as a primary metric for this algorithm.

Two of the previously described metrics are well-suited for assessing the magnitude of differences between signals and, subsequently, evaluating the accuracy of the user's movements. This type of information is valuable as it provides insights into the precision of the motion. However, it is important to clarify that the primary interest of this research lies not in measuring magnitudes but rather in detecting the attempt of the movement. Nevertheless, some degree of accuracy estimation remains beneficial for gaining additional information. Therefore, a trend-matching algorithm that can effectively compare two signals to determine whether they follow similar patterns over time is required. Once this is established, I further improve it by adding a metric to assess the magnitude of differences.

6.3.3 Derivative Matching. Although Derivative Matching is a trend matching metric, it is very sensitive and less forgiving if the patient has difficulty performing or synchronizing the movements, and will be later indicated with a low score. Moreover, if the signals are noisy, the calculated derivative might not portray the true movement pattern, especially when the small tremors or vibrations cause minor rapid and inconsistent changes in the signal. This way, derivative matching could be harder to apply without introducing errors.

6.3.4 Pearson Correlation. Unlike more complex methods, such as Derivative Matching, Pearson Correlation is not as precise and less sensitive to noise and minor imperfections in the signal. Pearson Corelation focuses on tracking if the rotations in the signals are similar in magnitude, regardless of small deviations. As a result, it provides a clear indication of "good quality" movement, even in the presence of unavoidable noise. This makes it especially useful for this study, allowing to track whether the patient is following the intended movement, even if their performance is affected by neurological impairments.

In conclusion, I have determined that implementing the **Pearson Corelation** metric in combination with the **RMSE** metric is the most suitable for the intended purpose. Pearson Corelation provides trend matching between signals, while RMSE offers an understanding of the magnitude difference between signals. This combined approach allows for a broader scope of data, leading to more precise and, therefore, fairer scores. The methodology for assigning these scores will be discussed in the next section.

6.4 Scoring algorithm

6.4.1 Single session. During the data collection session, the highest average correlation value observed during session recordings was approximately 0.4. It is important to note that this data was collected from individuals without any hand impairments. Consequently, I established 0.4 as the bound for correlation in this scoring system, thus limiting the correlation value to the range of 0 to 0.4. However, this limit can be altered in the future if necessary.
For the computation of the single session score, each metric is normalized and assigned the weights according to its priority, which are computed based on collected data samples (currently assigned weights for metrics are: 0.6 for correlation, and 0.2 for RSME and session length). The block diagram in Figure 6 describes the complete single session score computation.

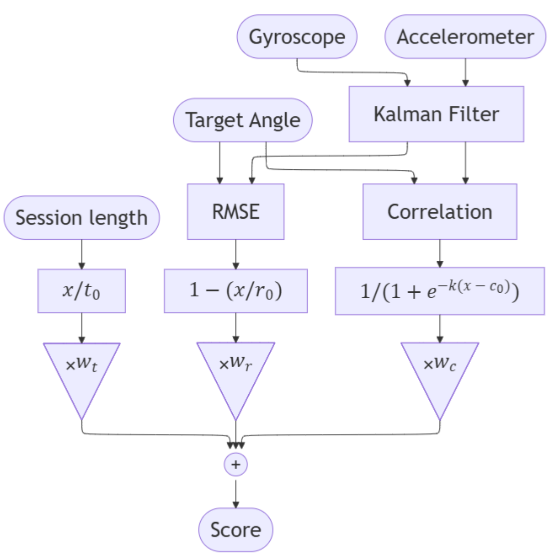

Fig. 6. Block diagram of single session score computation.

6.5 Multiple sessions

Finally, when aggregating results from a single session, I incorporate three additional metrics for computation of the ultimate score, as referenced in (5.6.2). I assign a higher weight to the mean session score, and evenly distribute the remainder to the daily session count metrics (with current weights of 0.5, 0.25 and 0.25 respectively). In this way, I obtain a score portraying both the habits of the patient through time, as well as their individual session progress.

7 OTHER DEVICES

While the above details implementing an algorithm for the smart toothbrush, there are 3 other devices in the Freehabilitation toolkit: a coffee cup (together with a placemat), a cooking spatula, and a computer mouse. Additionally, with this section, I want to answer the last research sub-question (3). Since all devices feature the same logger hardware, the filtering approach will remain unchanged. Yet, when it comes to individual sessions, some changes have to be made for each individual device:

- *Coffee cup*: For the coffee cup, the individual session score can be computed by measuring when the user picks up the device and puts it down. This can be done by measuring the filtered acceleration and finding moments that exceed a given threshold. These pick-up and put-down moments can then delimit a session, giving a session duration. The score can also be improved by computing it in conjunction with the data from the placemat, with a higher score being awarded for smaller placement error. Finally, the cup also features sensors that measure the user's grabbing force, which could also be factored into the score.
- *Cooking spatula*: The cooking spatula can follow the same pattern as the coffee cup, measuring its velocity in order to detect pick-up and put-down moments. In addition, the filtered rotation can be considered in order to check how much the user is attempting to rotate their hand.
- *Computer mouse*: As with the coffee cup and cooking spatula, usage sessions can be detected from the (horizontal) velocity of the mouse. Additionally, the mouse records clicks, which could be factored into the individual session score.

Furthermore, the overall architecture of scoring individual sessions, and aggregating them into an overall score is also applicable. When aggregating, it would be applicable to change the target number of daily sessions, as some activities may be carried out more often.

8 DISCUSSION

In this section, I provide perspectives on expanding the implementation of the algorithm and discuss potential directions for future research based on the findings of this work. First, it is important to acknowledge that while this algorithm performs well in "modeled" settings, including edge-case scenario samples, these samples are conducted with data from physically unaffected individuals. This highlights a key limitation: the lack of diverse and real-world data. Moreover, achieving a perfect correlation value of 1 is unrealistic due to various external factors, such as human variability, background noise, and other influences. This inherent limitation further emphasizes the importance of validating the algorithm with real-world data to ensure its adaptability.
The primary goal of this research is to offer a foundational tool that other researchers can build upon to conduct large-scale tests

involving patients. These tests would serve two main purposes: (1) to evaluate whether the algorithm performs effectively in real-life settings, and (2) to observe how patients interact with and utilize the tool. Insights gained from these studies would allow specialists to refine or improve the algorithm.

Additionally, to broaden the algorithm's scope and precision, future efforts could explore training AI models to analyze patient usage data. However, implementing a machine learning approach would require a considerably large dataset to properly train the model and ensure reliable performance.

Ultimately, this study aims to lay the groundwork for further innovation, paving the way for the effective integration of seamless Frehabilitation set tools in rehabilitation technologies.

9 CONCLUSION

As seamless devices to assist with activities of daily living (ADL) for hand-impaired patients continue to be integrated into their homes, it becomes crucial to establish effective methods for monitoring their adherence to routines and device usage. This study contributes to this goal by collecting smart toothbrush data and developing a robust assessment algorithm. Notably, this algorithm is among the first tailored specifically for rehabilitation devices, combining the Kalman filtering technique, aligning delays between signals through the argument maximum of the cross-correlation function, and utilizing Pearson Correlation with the RMSE metric for thorough signal comparison. Additionally, assigning scores to the sessions as a motivational tool, encouraging patients to maintain consistency and achieve better performance. Future research in this domain could focus on utilizing real-world data collected from patients' homes to evaluate the reliability of these methods or to explore machine-learning approaches for further advancements.

REFERENCES

[1] Mohinder S. Grewal and Angus P. Andrews. 2014. *Kalman filtering: Theory and Practice with MATLAB.* John Wiley & Sons.

[2] Osman H. Gündüz and Canan Şanal Toprak. 2019. *Hand Function in Stroke.* Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-17000-4_9

[3] R. Langton Hewer. 1990. Rehabilitation After Stroke. *QJM: An International Journal of Medicine* 76, 1 (07 1990), 659–674. https://doi.org/10.1093/oxfordjournals.qjmed.a068473 arXiv:https://academic.oup.com/qjmed/article-pdf/76/1/659/4615949/76-1-659.pdf

[4] Quirien Hover, Armağan Karahanoğlu, Kostas Nizamis, Anke Kottink, Johan Rietman, and Juliet Haarman. 2023. Development of interactive hand rehabilitation tools based on activities of daily living. In *Proceedings of the Seventeenth International Conference on Tangible, Embedded, and Embodied Interaction.* 1–9.

[5] Rick A. Hyde, Laurence P. Ketteringham, Simon A. Neild, and Rosie J. S. Jones. 2008. Estimation of Upper-Limb Orientation Based on Accelerometer and Gyroscope Measurements. *IEEE Transactions on Biomedical Engineering* 55, 2 (2008), 746–754. https://doi.org/10.1109/TBME.2007.912647

[6] Ahmad Jalal, Majid Ali Khan Quaid, Sheikh Badar ud din Tahir, and Kibum Kim. 2020. A study of accelerometer and gyroscope measurements in physical life-log activities detection systems. *Sensors* 20, 22 (2020), 6670.

[7] Jayme S. Knutson, Mary Y. Harley, Terri Z. Hisel, and John Chae. 2007. Improving Hand Function in Stroke Survivors: A Pilot Study of Contralaterally Controlled Functional Electric Stimulation in Chronic Hemiplegia. *Archives of Physical Medicine and Rehabilitation* 88, 4 (2007), 513–520. https://doi.org/10.1016/j.apmr.2007.01.003

[8] M. Àngel Mas and Marco Inzitari. 2015. A critical review of Early Supported Discharge for stroke patients: from evidence to implementation into practice. *International Journal of stroke* 10, 1 (2015), 7–12.

[9] Louise Meijering, Christa S. Nanninga, and Ant T. Lettinga. 2016. Home-making after stroke. A qualitative study among Dutch stroke survivors. *Health & Place* 37 (2016), 35–42. https://doi.org/10.1016/j.healthplace.2015.11.006

[10] Ilaria Pasciuto, Gabriele Ligorio, Elena Bergamini, Giuseppe Vannozzi, Angelo M. Sabatini, and Aurelio Cappozzo. 2015. How angular velocity features and different gyroscope noise types interact and determine orientation estimation accuracy. *Sensors* 15, 9 (2015), 23983–24001.

[11] Jolita Rapolienė, Erika Endzelytė, Indrė Jasevičienė, and Raimondas Savickas. 2018. Stroke patients motivation influence on the effectiveness of occupational therapy. *Rehabilitation research and practice* 2018, 1 (2018), 9367942.

[12] Maude Rittman, Christopher Faircloth, Craig Boylstein, Jaber F. Gubrium, Christine Williams, Marieke Van Puymbroeck, and Charles Ellis. 2004. The experience of time in the transition from hospital to home following stroke. *Journal of Rehabilitation Research & Development* 41 (2004).

[13] Angelo M. Sabatini. 2011. Estimating three-dimensional orientation of human body parts by inertial/magnetic sensing. *Sensors* 11, 2 (2011), 1489–1525.

[14] Clive E. Skilbeck, Derick T. Wade, R. Langton Hewer, and Victorine A. Wood. 1983. Recovery after stroke. *Journal of Neurology, Neurosurgery & Psychiatry* 46, 1 (1983), 5–8.

[15] Floor Stefess, Kostas Nizamis, Juliet Haarman, and Armağan Karahanoğlu. 2022. Gr! pp: Integrating Activities of Daily Living into Hand Rehabilitation. In *Proceedings of the Sixteenth International Conference on Tangible, Embedded, and Embodied Interaction.* 1–6.

[16] Miguel A. Teruel, Víctor López-Jaquero, Miguel A. Sánchez-Cifo, Elena Navarro, and Pascual González. 2020. Improving Motivation in Wrist Rehabilitation Therapies. In *Ambient Intelligence – Software and Applications –,10th International Symposium on Ambient Intelligence*, Paulo Novais, Jaime Lloret, Pablo Chamoso, Davide Carneiro, Elena Navarro, and Sigeru Omatu (Eds.). Springer International Publishing, Cham, 199–206.

A APPENDIX A

During the writing phase of this research, the author utilized OpenAI's ChatGPT 4.0 version[2] to improve the formulation of certain sentences and the Grammarly[3] web extension to refine clarity and grammatical correctness. The author takes full responsibility for the content of the paper.

[2] https://chatgpt.com/

[3] https://app.grammarly.com/