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Design and Control Soft Pneumatic Actuators (SPAs) with Embedded Flexion Sensor for Finger Therapy in Post-Stroke Patients

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ABSTRACT : *Stroke is one of the leading causes of disability worldwide. One way to minimize post-stroke disability is through rehabilitation therapy, such as Range of Motion (ROM) physical movement therapy, which targets joints affected by paralysis due to post-stroke muscle weakness. This therapy aims to maintain or restore joint mobility and increase muscle mass. However, finger therapy devices available in the market are still limited. In this research, a therapy glove based on soft pneumatic actuators was developed to assist in finger flexion and extension movements. Finger muscle strength is classified into three levels—weak, moderate, and normal—using a Machine Learning method with the K-Means algorithm. The results showed that the actuator's bending angle could reach up to 101 degrees with a maximum air pressure input of 5 Psi. In the experiments, the muscle strength scale was measured using 80% of the data, comprising 70% mean equations and 10% Machine Learning, yielding adc values of 1070 for the weak level, 1267 for the moderate level, and 1597 for the normal level..*

KEYWORDS *Stroke rehabilitation, Range of Motion (ROM), , soft pneumatic actuators, flexion and extension, Machine Learning, K-Means algorithm, muscle strength classification, post-stroke therapy.*

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I. INTRODUCTION

Stroke remains one of the leading causes of disability globally, leaving millions of individuals with impaired motor function, particularly in the hands and fingers. Post-stroke rehabilitation therapy is essential for minimizing the long-term impact of stroke-induced disabilities. Among the various rehabilitation techniques, Range of Motion (ROM) exercises are crucial for maintaining and restoring mobility in joints affected by muscle weakness. These exercises help prevent joint stiffness, increase muscle mass, and aid in the recovery of motor function [1]. The demand for rehabilitation therapies, particularly those targeting fine motor skills such as finger movement, is increasing due to the rise in the number of stroke survivors. However, there is a significant gap in the availability of effective and accessible finger rehabilitation tools, especially for patients who need to continue therapy independently at home [2].

In recent years, the use of soft pneumatic actuators (SPAs) has gained attention as a promising solution for assisting post-stroke patients in performing rehabilitation exercises [3]. SPAs offer several advantages, including flexibility, adaptability, and lightweight design, which makes them more comfortable for patients compared to traditional rigid exoskeletons [4]. Moreover, the integration of embedded sensors, such as flexion sensors, allows real-time monitoring and precise control of finger movements, enabling more personalized therapy [5]. With the advent of Machine Learning techniques, these sensors can collect data on muscle performance and classify it into different strength levels—weak, moderate, and normal—based on algorithms like K-Means [6][7]. This automated classification enhances the rehabilitation process by adapting to each patient's specific needs and improving recovery outcomes.

Initial experiments with the SPA device have demonstrated that it can achieve a flexion angle of up to 101 degrees at a maximum air pressure of 5 Psi, indicating its potential for facilitating finger movements. The system was able to classify muscle strength levels based on adc values, with measurements showing 1070 for weak, 1267 for moderate, and 1597 for normal strength. These results are promising, as they provide objective metrics to track patient progress and adjust therapy accordingly. However, further refinement is needed to enhance the precision of the device. During Machine Learning trials, the error rate in classifying muscle strength varied from 0% to 13.9%, with the lowest error rate occurring when the predicted data closely matched the experimental values. The higher error rates were likely caused by the variation in data between older averages and new data, as well as challenges in mapping adc values from 256 to 4095.

To address these issues, future developments will focus on improving the system's mapping algorithm and refining sensor accuracy. Additionally, enhancing the data storage capacity of the device will allow it to track patient progress over time, providing more comprehensive rehabilitation solutions. By optimizing these components, the SPA device holds great potential to revolutionize stroke rehabilitation therapy by offering a more accessible, adaptable, and personalized treatment option for patients.

II. METHODS

The development of the soft pneumatic actuator (SPA) system for post-stroke rehabilitation involved several key phases: the design and fabrication of the actuator, integration of the flex sensor, implementation of a control system, and data collection using Machine Learning algorithms for muscle strength classification. The following sections outline the methodology used in the study.

2.1 Design and Fabrication of the Soft Pneumatic Actuator (SPA)

The SPA was designed to support flexion and extension movements of the fingers, essential for post-stroke rehabilitation therapy. The actuator was constructed from silicone rubber, which provides flexibility and the ability to inflate and deflate for controlled movement. The actuator measured 10,6 cm in length , 1,8 cm in width and 1,3 cm in thickness, optimized for comfortable use on a patient's hand[7] **Fig 2.1** .

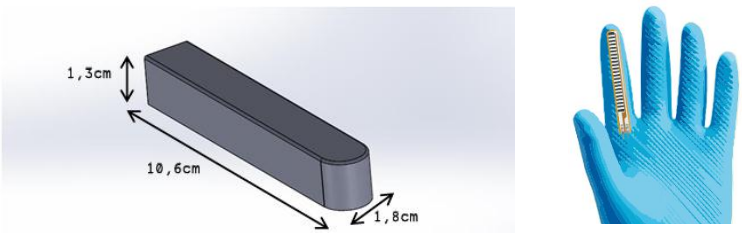

Fig 2.1. soft pneumatic actuator Glove

The actuator was connected to an air pump capable of providing a maximum pressure of 5 psi. At pressures above 5 psi, the actuator was found to be at risk of overinflation and potential rupture, limiting its operational range to safe air pressures for consistent actuation.
The flexion achieved by the actuator was measured in degrees of bending. Initial tests showed that the actuator could reach a maximum bending angle of 130 degrees under optimal conditions [8]. This degree of bending was deemed sufficient for supporting rehabilitation exercises focused on finger movement.

2.2 Integration of Flex Sensor and Muscle Strength Monitoring

A flex sensor was embedded into the actuator to track the bending angle in real time and monitor muscle strength **Fig 2.1** . The sensor detected changes in the actuator's curvature, sending the data to a microcontroller for analysis. This sensor provided real-time feedback to the control system, which was essential for accurately measuring the effectiveness of each movement[9][10].
Muscle strength was classified into three levels—weak, moderate, and normal—using data collected from the flex sensor. Each strength level was associated with an analog-to-digital converter (adc) value. Weak muscle strength corresponded to an adc value of 1070, moderate strength to 1267, and normal strength to 1597, based on the centroid values calculated during the experiment.

2.3 Machine Learning Implementation for Muscle Strength Classification

To enhance the precision of muscle strength classification, a K-Means clustering algorithm was used. Machine Learning was implemented to analyze data from the flex sensor and classify muscle strength based on predefined adc thresholds[11][12]. The dataset used in this study was split, with 10% of the data used for Machine Learning-based classification and 70% for mean equation-based calculations. The remaining data was reserved for validation and testing.

During the Machine Learning trials, the error rate was calculated to assess the performance of the classification algorithm. The lowest error rate achieved was 0%, while the highest error rate was 13.9%. The variation in error rates was attributed to the differences between older averaged data and new data, as well as difficulties in mapping adc values from 256 to 4095 during classification. This highlighted the need for further refinement of the mapping algorithm to reduce classification errors and improve accuracy.

Table 2.1. K-Means clustering algorit

Algorithm : K-means clustering algorithm to classify muscle strength

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Input: Sensor data (Flex Sensor), number of clusters k: 3
Output: Clustered muscle strength  (weak, moderate ,Normal)
1. Initialize K (number of clusters = 3 for weak, moderate ,Normal)
2. Select 3 random centroids from the dataset as initial centroids
3. Repeat until convergence:
  a. Read ADC value from the flex sensor (input = ADC_value)
  b. Assign ADC_value to the nearest centroid:
    for each ADC_value:
      Find the nearest centroid C_j
      Assign ADC_value to cluster j
  c. Update centroids:
    for each cluster j:
      C_j = average of all ADC_values in cluster j
  d. Check if centroids have changed significantly:
    if not changed:
      stop the loop
4. Output final clusters and centroids with labels:
  - Weak: Centroid C_1
  - Moderate: Centroid C_2
  - Normal: Centroid C_3
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III. RESULTS AND DISCUSSION

A gradual testing approach is required in this research to make sure that all of the tool's components can function as intended. The tools and systems that were tested are included in the results and discussion of the testing method. The purpose of this testing is to measure, evaluate, and determine the degree of success of the tools and systems.

3.1 *Flex sensor test results*

The testing of the flex sensor involved measuring the degree of bending or flexibility and recording its output values. The results indicated that as the bending angle of the sensor increased, the corresponding ADC value also rose significantly. This relationship suggests that the flex sensor can effectively detect and quantify movements, which is crucial for applications such as rehabilitation therapy, where tracking the progress of muscle strength and joint flexibility is essential **Table 3.1**.

Table 3.1. *Flex sensor test results*

Trial	Sensor (degrees)	ADC From sensor
1	0	1839
2	10	1680
3	20	1552
4	30	1423
5	40	1335
6	50	1296
7	60	1243
8	70	1183
9	80	976
10	90	887

Furthermore, understanding the correlation between the bending angle and ADC readings can aid in refining the calibration of the sensor. By establishing a precise mapping between the degrees of flexion and their respective ADC values, we can enhance the accuracy of muscle strength assessments. This improvement is vital for ensuring that patients receive appropriate feedback during therapy, thus facilitating a more effective rehabilitation process. As the technology continues to evolve, integrating such sensors into therapeutic devices can lead to significant advancements in patient care and recovery outcomes.

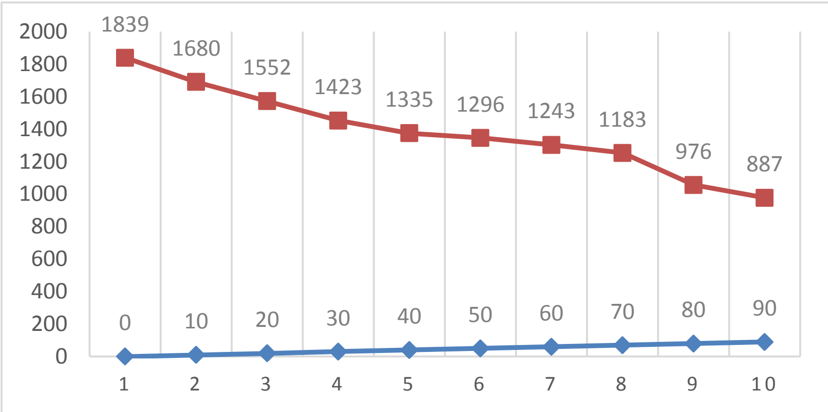

Fig 3.1. comparison graph of the test results obtained using a protractor and a flex sensor

Figure 3.1 illustrates a comparison graph of the test results obtained using a protractor and a flex sensor. The graph reveals a clear upward trend, indicating that as the angle of bending increases, the ADC value recorded by the flex sensor also rises correspondingly. This correlation highlights the sensor's capability to accurately track and quantify the degree of flexion, making it a valuable tool for assessing movement in rehabilitation settings. Such findings are consistent with previous studies that have demonstrated the effectiveness of flex sensors in capturing real-time data on joint angles and movement patterns.

Moreover, the alignment of results from both the protractor and the flex sensor underscores the reliability of the flex sensor as an alternative measurement tool. While traditional methods like protractors provide precise measurements, the flexibility and ease of use of the flex sensor can enhance patient engagement during therapy sessions. This dual approach not only validates the readings but also opens avenues for integrating advanced data analytics into rehabilitation practices, enabling healthcare professionals to monitor patient progress with greater accuracy. As technology continues to advance, the adoption of such innovative measurement techniques is likely to play a crucial role in improving therapeutic outcomes.

3.2 Machine Learning Testing Result

This test is conducted using the A-RES test, also known as the muscle strength test for the fingers, to assess the patient's muscle strength level following a stroke. The data collected from the flex sensor yields ADC values that are critical for analyzing muscle performance. Subsequently, a machine learning process is employed to classify the muscle strength levels based on these ADC readings. This automated approach allows for a more efficient and objective assessment compared to traditional methods. A comparison is then made between the machine learning results and manual calculations, illustrating the potential benefits of integrating technology into rehabilitation practices.

Table 3.2 presents a detailed comparison between the results obtained through machine learning and those derived from manual equations. This comparative analysis highlights the accuracy and reliability of the machine learning model in evaluating muscle strength levels. By validating the machine learning outputs against manual calculations, the study underscores the importance of utilizing advanced analytical methods in clinical settings. Such innovations not only enhance the assessment process but also improve patient outcomes by facilitating timely and accurate evaluations of muscle recovery. As rehabilitation technology advances, these findings may pave the way for more personalized treatment plans and better monitoring of patient progress.

Table 3.2 . Machine Learning Testing Result

No	Keterangan	*Machine learning Output (ADC)*	*equation calculation results*	*Error*(%)
1.	Weak	1062	1062,6	0,047
2.	Weak	871	974	5,75
3.	Normal	1607	1607	0
4.	Weak	873	974,3	9,17
5.	Normal	1551	1579	1,7
6.	Moderate	1297	1297,5	0,03
7.	Normal	1539	1547	0,5
8.	Weak	974	1029,5	13,9
9.	Normal	1578	1547	2
10.	Normal	1595	1595	0
11.	Moderate	1257	1278,3	1,66
12.	Moderate	1236	1251,5	1,23
13.	Weak	1162	1092	10,5
14.	Weak	928	889,4	4,3
15.	Moderate	1308	1320	0,9
16.	Moderate	1306	1306,9	0,06
17.	Normal	1638	1616,4	1,3
18.	Normal	1662	1640,3	1,3
19.	Weak	965	1001,1	3,6
20.	Moderate	1425	1426,8	0,12

Table 3.2 presents a comprehensive comparison between the output values obtained through machine learning techniques and the results derived from traditional equation calculations in assessing muscle strength levels of patients post-stroke. The table categorizes muscle strength into three levels: Weak, Moderate, and Normal. Each entry includes the ADC (Analog-to-Digital Converter) values measured for the corresponding muscle strength level, the results from equation calculations, and the percentage error between the two methods.

From the conducted tests, the mean ADC values were found to be 1070 for the Weak level, 1267 for the Moderate level, and 1597 for the Normal level. The findings reveal that most ADC values align closely with the equation calculation results, demonstrating a high degree of accuracy in the machine learning outputs. The error percentages range from 0% to 13.9%, with several instances of negligible error, indicating that the machine learning model effectively replicates or closely approximates the traditional calculation methods. For example, the output for "Normal" muscle strength with an ADC value of 1607 matches perfectly with the equation result, resulting in a 0% error, while another instance of "Weak" muscle strength presents a higher error of 13.9%, highlighting potential variability in the assessment process. These results emphasize the potential for machine learning to enhance the accuracy and reliability of muscle strength evaluations in clinical settings, offering an innovative approach to rehabilitation assessment.

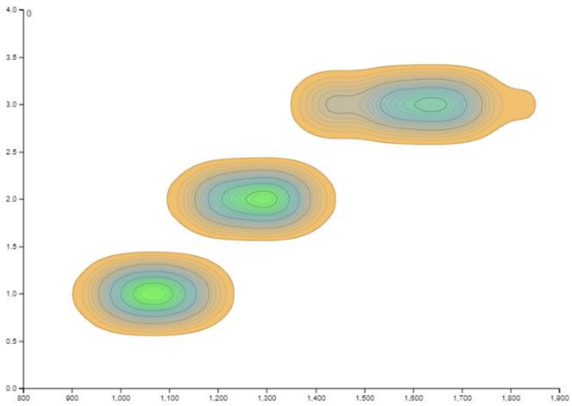

Fig 3.1. muscle strength scale graph using K-means

From Figure 3.1 and the mean calculations, the centroid values for muscle strength classifications have been established: an ADC value of 1070 corresponds to the Weak level, 1267 to the Moderate level, and 1597 to the Normal level. These centroid values act as crucial reference points for distinguishing between the varying degrees of muscle strength in patients post-stroke.

Incorporating these centroids into the machine learning program facilitates the algorithm's ability to accurately classify muscle strength. By utilizing these predefined ADC thresholds, the program enhances its analytical performance, allowing it to process real-time data from the flex sensor more effectively. This integration significantly improves the algorithm's predictive accuracy, contributing to a more comprehensive assessment of muscle recovery and rehabilitation progress. As machine learning continues to evolve, such data-driven methodologies are expected to transform rehabilitation practices, offering more personalized and precise treatment options for patients

IV. CONCLUSION

The muscle strength scale design using a flex sensor and Machine Learning resulted in three strength levels: weak, moderate, and normal. From the experiment using 80% of the data, where 10% was processed through Machine Learning and 70% through mean equations, the centroid values were determined. The weak level had an adc value of 1070, the moderate level an adc value of 1267, and the normal level an adc value of 1597. In testing the bending degree of the soft pneumatic actuator, which measured 8.5 cm in length and 2 cm in thickness, it was found that the actuator could achieve a bending angle of 130 degrees under 5 psi of pressure. Beyond this pressure, the actuator became overinflated and risked bursting. The Machine Learning tests revealed an error rate ranging from 0% to 13.9%. The higher error rate was attributed to discrepancies between the old average data and new data, as well as challenges in mapping adc values from 256 to 4095 and vice versa.

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