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# Analysis of Skin Deformation Differences on the Upper Arm Between Active and Passive Movements During Elbow Flexion and Extension

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*Abstract*— **The motion ability of patients in the acute phase of stroke is difficult to define with existing indexes such as the Brunnstrom stage. Hence, for designing a novel evaluation index for stroke rehabilitation in the acute phase, we focused on the differences between the skin deformations in active and passive movements. Skin deformation reflects the activities of body tissues that are related to motion ability. We measured skin deformations on the upper arm in active and passive movements during elbow flexion and extension and extracted features from these deformations. For practical rehabilitation applications, we developed a novel flexible distance sensor array to reduce the time needed for attaching sensors to patients. Using principal component analysis (PCA), the skin deformation could be decomposed into joint movements and activeness of movements as the first two components (PC1 and PC2). The joint angle and PC1 exhibited a high correlation, and the standard deviation (SD) of PC2 indicated a significant difference in the types of movements. From the above results, we concluded that the SD ratio between PC2 and PC1 may be used to evaluate motion ability considering the inherent biomechanical characteristics.**

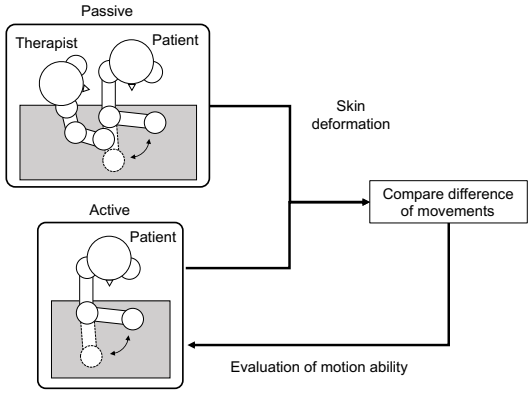


Fig. 1: Assumed rehabilitation scheme.

## I. Introduction

Intervention to patients in the acute phase after stroke onset influences the positive effects of motion ability recovery [1]. The motion ability of the patient in the acute phase is difficult to define with existing indexes such as the Brunnstrom stage (Brs [2]), as these indexes are determined via discrete evaluations of whether the patient can perform a certain motion. Thus, if we could develop a novel index for the continuous ability recovery of patients (in the acute phase), we could improve the recovery process based on the index.

To design the abovementioned novel evaluation index, we focused on skin deformation. Skin deformation measurements are similar to mechanomyogram and force myogram [3]–[5] measurements and reflect the activities of body tissues (muscles, bones, and tendons) related to motion ability. One interesting aspect is that such types of skin deformation can be observed during active and passive movements [6]. Skin deformation reflects not only the voluntary activities of body tissues but also the inherent biomechanical characteristics. The index for continuous ability recovery can be extracted while considering individual differences in skin deformation using biomechanical characteristics. As a therapist often teaches a motion to a patient using passive movements, it is unnecessary to perform any additional operations for indexing during rehabilitation. The rehabilitation scheme that we assumed is shown in Fig. 1. A therapist passively moves the arm of the patient. Next, the patient moves his/her arm (active movement). The therapist could compare the features of both movements and evaluate his/her current motion ability.

For designing the novel index for rehabilitation evaluation as described above, we analyzed the skin deformation differences between active and passive movements. This study investigated the skin deformation on the upper arm with a developed flexible distance sensor array during elbow flexion-extension in active and passive movements involving healthy participants. When a person performs single-axis motions, the features of these movements can be decomposed into joint movements and activeness of movements. We assumed that muscle bulge is the sum of muscle deformations caused by joint movements and muscle contractions caused by voluntary movements (activeness of movements). The active movements contain both muscle deformation and muscle contractions. To extract these features, we used principal component analysis (PCA). Using PCA, the skin deformation was compressed into a two-dimensional feature with the first two components (PC1 and PC2). We determined the differences between both movements in the principal component space. The first principal feature was mainly related to the joint movements, and the second one could be related to the activeness of the movements.

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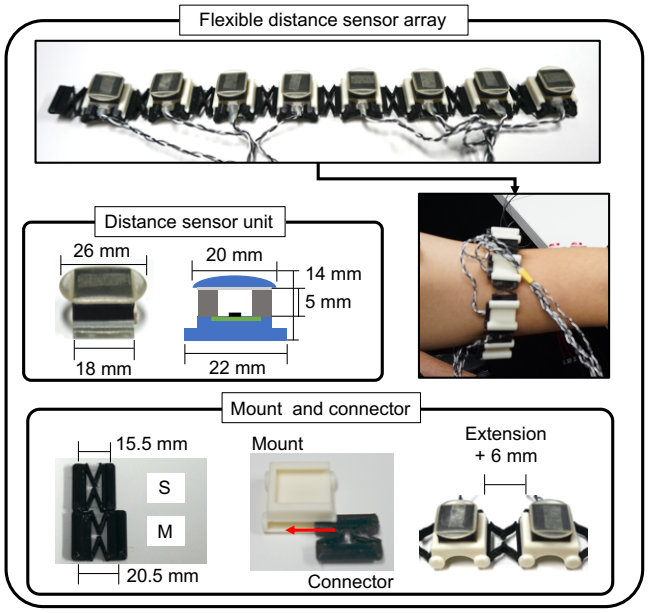



Fig. 2: Structure of flexible distance sensor array.

## II. Methods

### A. Measurement of Skin Deformation

In our previous study [7], we developed a distance sensor array to measure skin deformation on the upper arm. This array is fabricated from a rigid material to measure deformation stably and has a size adjustment mechanism for adapting to different arms sizes. However, fine adjustment of the array takes a long time. During a preliminary attempt to measure the skin deformation, therapists pointed out time becomes a burden on the patient and therapist.

In this study, we developed a novel flexible distance sensor array. As shown in Fig. 2, this flexible array consists of distance sensor units, mounts, and flexible connectors. The distance sensor unit that converts deformation to voltage was developed in one of our previous studies [8]. In this study, we used eight units. As the skins of some patients are sensitive to friction compared to healthy persons, an ellipsoidal contact plate was used to reduce the pressure on the skin. The mount is fabricated from a rigid material, and it has two holes for inserting the flexible connectors. The connector is made from thermoplastic polyurethane (TPU), which is a flexible material. To insert the cylindrical connector into the holes of the mount, each mount is connected. The extension of the connector is approximately 6 mm. Using the extension, the size of the array is adjusted to match the arm size of the user.

Owing to the different arm sizes of users, we fabricated flexible connectors of various sizes. By replacing the connector, the array can be used on arms with various sizes. Considering the size variations, we used connectors of two sizes (S and M) in this study. The lengths of S and M between the cylindrical connectors were 15.5 and 20.5 mm, respectively. If the appropriate connector size is determined in advance, the array can be attached to the arm in approximately one minute. We chose the sizes to ensure that users did not feel excessive pressure and the array did not shift during movements. As a guide for size selection, the S connector was used for arm circumferences of 25 to 26.8 cm, and the M connector was used for arm circumferences of 28.5 to 29.2 cm, in this study.

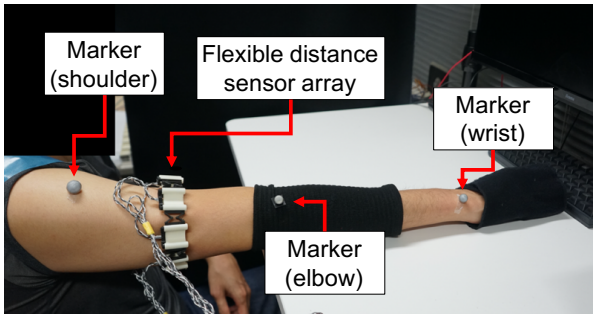



Fig. 3: Measurement setup used for the experiments.

### B. Comparing Features in Active and Passive Movements

The skin deformation measured with the flexible distance sensor array was presented as an eight-dimensional feature (outputs of eight units). To extract the features from the overall skin deformation, we use PCA to compress the deformation data.

After compression using PCA, the correlation coefficient (CC) and standard deviation (SD) were used to analyze the relationship between the features and movements. For example, a component related to joint movement can be used to determine the CC between joint movements and each principal component. If the CC is high, the component is related to joint movements. If the CC is low, the component is not/weakly related to joint movements.

We hypothesized that when the activeness of movements increases, the muscle contractions caused by voluntary movements increase. Thus, the active movement deviates from the passive movement. If this deviation shows a similar tendency independent of the array users in the PCA space, we can design the evaluation index by quantifying the deviation along a certain direction. We intend to investigate the correctness of the above hypothesis and the extent of the deviation.

## III. Experiments

To confirm the difference in skin deformation between active and passive movements, we performed skin deformation measurement experiments.

### A. Setup

Fig. 3 shows the setup used for the experiment. In this experiment, we focused on elbow flexion and extension on a table, involving simple single-axis motions. These motions can be performed by patients facing difficulties in performing anti-gravity movements. The array was set on the maximum

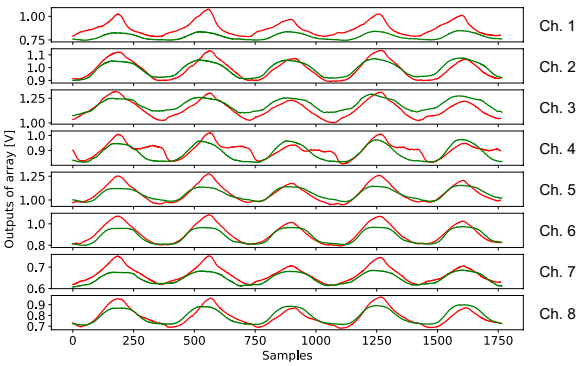
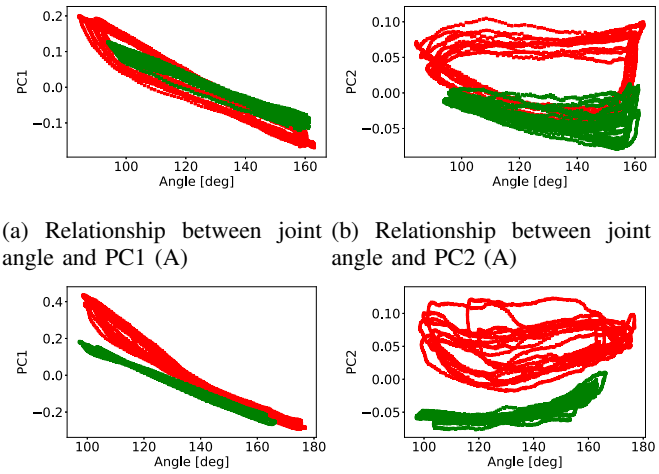



Fig. 4: Example of the measured skin deformation at 40 bpm (participant D). Red line represents active movement and green line represents passive movement.




(a) Relationship between joint angle and PC1 (A)

(b) Relationship between joint angle and PC2 (A)

(c) Relationship between joint angle and PC1 (D)

(d) Relationship between joint angle and PC2 (D)

Fig. 5: Relationships between angle and PC1/PC2. Red dot represents active movements and green dot represents passive movements. Upper row contains data of participant A, and lower row contains data of participant D.

bulge of the biceps brachii when participants flexed their arms. The signals from the array were acquired with an A/D converter (USB-6218, National Instruments). To compare skin deformation and joint movements, we also recorded the joint angles with a motion capture system (v120 Duo, Optitrack). The elbow joint angle was calculated from three makers attached to the wrist, elbow, and shoulder. The signals from the array and the motion capture data were measured at 120 Hz. By inputting the trigger signal of the motion capture system to the A/D converter, the start times of both data recordings were synchronized.

The participants sat in a chair placed in front of a table and placed their elbows near the edge of the table. By changing the height of the table, the elbow and shoulder positions of the participants were adjusted at almost the same height. If the height differs significantly, then the motions would include elbow flexion/extension and unintentional internal/external shoulder rotations. The participants were instructed to maintain constant elbow and shoulder positions as much as possible. To reduce the friction between the skin and table, the participants wore a support on the elbow, and a cloth was placed under their hands.

### *B. Conditions*

We performed the experiments with five healthy participants A to E (four males in their 20s and one female in her 40s, all the participants are right-handed). The experimental protocol of this study was approved by the research ethics board of Nara Institute of Science and Technology. Informed consent was obtained from the participants before participation in the experiments.

We collected the data for active and passive movements. In the active movements, the participants flexed and extended their elbows by themselves on the table. In the passive movements, an experimenter held their forearms and moved them to flex and extend their elbows, as in the active movement. In the passive movements case, the participants were asked to relax as much as possible. The motion range of passive movements is smaller than that of active movements (the maximum difference was approximately 20 degrees).

The motion speed was controlled by three metronome speeds: 20, 30, and 40 beats per minute (bpm). For each speed, we collected the data for one minute. The numbers of flexions and extensions were 10, 15, and 20, respectively.

We used data pertaining to continuous stable 30 s from the measurements conducted for 60 s in each trial. Because there was a sudden outlier value, we used data of two continuous stable 15 s for one person's one trial. Fig. 4 shows an example of the measured array data (eight channels) in both movements. The red and green lines represent data for active and passive movements, respectively; ch. 1 is set on the biceps brachii, and the order of the channels is clockwise from the shoulder side. In both movements, continuous deformations can be observed. Compared to passive movements, the active movement data indicate varieties of deformations.

The PCA matrix was calculated using the data recorded under all conditions (two movements and three motion speeds) for each participant. We analyzed the data of the first and second components, as the sum of contribution rates for the first two components (PC1 and PC2) was 0.95 or higher in all participants.

## IV. Results and Discussion

Fig. 5 shows the relationship between the PCA-compressed features and the joint angles at a speed of 40 bpm for two participants (A and D). The red and green dots represent the data of active and passive movements, respectively. The differences in the movements could be found from the relationship between the joint angles and PC2. Compared to active movements, the deviation of the data for passive movements was small.

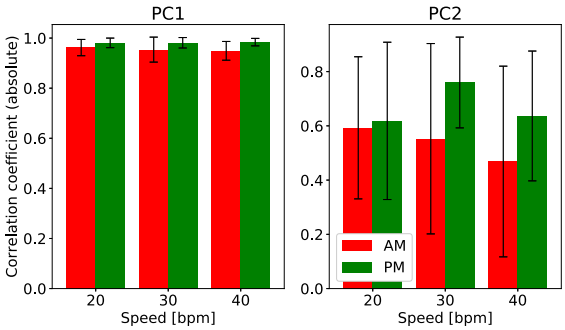



Fig. 6: Correlation coefficient between joint angle and PC1/PC2. AM denotes active movement, and PM denotes passive movement.

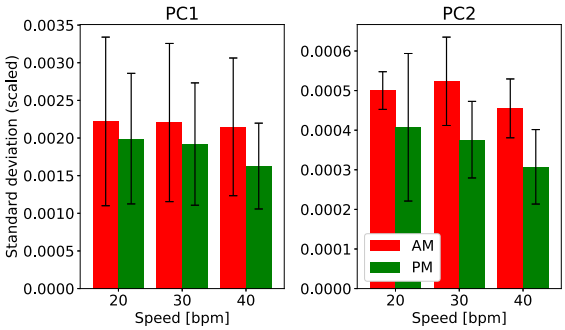



Fig. 7: Standard deviation of PC1 and PC2. The SD data were scaled using the joint angle range. AM represents active movement, and PM represents passive movement.

Fig. 6 shows the CC (absolute value) between joint angles, and PC1 and PC2. The mean of CC in all movements and speeds was 0.97 for PC1 and 0.60 for PC2. In PC1, the SD of the CC was small for all participants. These results prove that PC1 is mainly related to joint movements.

Fig. 7 shows the SD of each component. To remove the difference in motion range, the SD data were scaled using the joint angle range under each condition. To confirm the SD differences, we performed an analysis of variance with two types of movements and three speeds. In PC1, movements and speeds have interaction ($F(2,8) = 8.843, p < 0.01$). The simple main effect between speeds and passive movement showed a significant difference ($F(2,16) = 5.679, p < 0.05$) and that between movements and a speed of 40 bpm showed a significant difference ($F(1,12) = 9.563, p < 0.01$). According to the results obtained using Ryan's method [9], 40 bpm showed a significant difference ($p < 0.05$) compared to the other two speeds in passive movements. Considering that PC1 is highly correlated with the joint angle, the speed of the movement affected the difference in the joint movement.

In PC2, movements and speeds showed no interaction ($F(2,8) = 0.368, p > 0.1$), and the main effect indicated significant differences in the speeds and movements

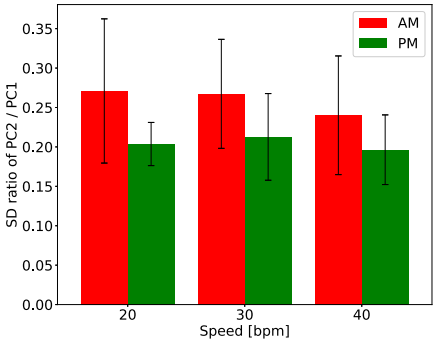



Fig. 8: Ratio of standard deviation between PC2 and PC1. AM denotes active movement, and PM denotes passive movement.

($F(2,8) = 5.415, p < 0.05$) and ($F(1,4) = 9.561, p < 0.05$). The results obtained using Ryan's method indicated no significant difference between each speed. In PC2, although speed effects were evident, the differences in the features reflected the differences in the types of movements. These results proved that differences between active and passive movements are found in PC2.

Fig. 8 shows the SD ratio between PC2 and PC1. The ratio of active movements is higher than that of the passive movements. In these experiments, we used a motion capture system to measure joint angles. However, it is difficult to use a motion capture system during actual rehabilitation as the setup needs time and occlusion of the markers will happen. Using the ratio, we could normalize the activeness of movements by considering the SD of PC1, which is highly related to joint movement. Further, we could evaluate motion ability and provide feedback through comparisons with a baseline for passive movements. The SD ratio at 30 bpm shows significant differences ($p < 0.05$) between active and passive movements based on the paired t-test. This indicates that controlling the movement speed is one of the important factors influencing stable observations of the activeness of movements.

In the previous studies, an electromyogram (EMG) had been used to observe the motion ability [10], [11]. Because the signal of the EMG is generated by voluntary muscle contraction, the EMG could not obtain during passive movement. Observation of active movements from a baseline of passive movement is an advantage and uniqueness of the proposed index based on skin deformation.

In short, the key finding of this study is that the difference in the skin deformations between active and passive movements can serve as an index of the motion ability of users. The activeness of movements can be determined from skin deformation without additional steps in the current rehabilitation procedure.

## V. Conclusions

In this study, we analyzed the skin deformation on the upper arm in active and passive movements during elbow flexion and extension. For practical rehabilitation applications, we developed a novel flexible distance sensor array to reduce the time needed for attaching sensors to patients. From the experimental results, we confirmed that the differences in the skin deformations during active and passive movements could be observed in the PC space. PC1 is mainly related to joint movements, and PC2 is related to the types of movements. Using PCA-compressed features, such as the SD ratio between PC2 and PC1, we could obtain an evaluation index that reflects the motion ability of patients considering the inherent biomechanical characteristics.

In the future, we will try to apply this method on actual patients to analyze the differences between healthy persons and patients. We intend to establish relationships between the proposed and existing indexes.

## Acknowledgment

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