Estimating wrist joint angle with limited skin deformation information

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Abstract
Ascertaining a person’s motion intentions through muscle activity is important for controlling various assistive devices for people with disabilities. Several techniques have been proposed for estimating the extent of intended joint angle motion using skin deformation information derived from muscle contractions. The objective of this study is to verify our signal processing procedure for estimating intended wrist joint angle with skin deformation information in able-bodied subjects and subjects with an upper-limb amputation. Skin deformation was measured with a tactile sensor consisting of 48 distance sensors over a large measurement area. The root-mean-square error (RMSE) of the measured and estimated angles are evaluated offline using multiple linear regression in one individual with an upper-limb amputation and five able-bodied participants. In all tests, subjects undertook a wrist flexion and extension task guided by visual feedback, measured in real time. Sensors are selected in descending order of the standard deviation of each sensor’s value. Strong relationships occur between the position and displacement of the area of greatest skin deformation and the intended wrist joint angle in all subjects. The minimum RMSE was 8.19° for the individual with an upper-limb amputation using 48 sensors as input, and 2.24° for able-bodied individuals using 16 sensors. One-way repeated-measures analysis of variance showed that at least 16 sensors are needed to reliably record skin deformation. Skin deformation analyzed with multiple linear regression is a plausible means of estimating intended wrist joint angle in persons with an upper-limb amputation. Even when a limited number of sensors (≥16) are used, continuous joint angle can be estimated reliably. These findings will inform the design of assistive devices that must noninvasively determine muscle activity.

Keywords: Assistive device, Joint angle estimation, Multiple linear regression, Skin deformation

1. Introduction
Biosignal processing has focused in recent years on developing assistive and rehabilitation devices for people with disabilities. In robotics, biosignal control methods have been developed for wearable devices such as exoskeletons, orthoses, and prostheses to improve the quality of daily life for disabled people. Biosignals are a promising source of information for detecting motion intention and understanding muscle activity, even when measured by noninvasive means.
Biosignals used to detect a person’s intentions can detect what motion is intended or how it will be performed. Powered prostheses have long been studied as biosignal-controlled assistive devices (Childress, 1985).

There are two main noninvasive techniques for extracting motion intention from biosignals (Lobo-Prat et al., 2004). One relies on the classification of biosignal motion patterns, for example, using brain signals for hand motion recognition (Agashe et al., 2015). Less invasive means of measuring biosignal patterns can also be used, for example, on the surface of the skin. Motion pattern recognition using a surface electromyogram (sEMG) is highly accurate in able-bodied subjects and persons with an upper-limb amputation (Kato et al., 2006). The second technique uses proportional estimation of the extent of motion such as joint torque (Ziai et al., 2011) or joint angle (Jiang et al., 2012). sEMG measures the electric potential of many different muscles, and may require multiple electrodes to estimate the extent of motion of one joint (Celadon et al., 2016). There is a great deal of interest in minimizing the number of electrodes used, to make the technique more practical (Kumar et al., 2013). Electric potentials, whether from the brain or sEMG, tend to have a low signal-to-noise ratio that impairs the estimation of the intended motion (Luca et al., 2010), and their use requires a complex model for numeric calculation (Wang et al., 2002). In kinetic calculations, the relationship between muscle exertion tension (the moment around the joint) and the intended angle is nonlinear (Zajac, 1989). In addition, errors may accumulate when calculating joint angles from angular acceleration by time integration (Koike et al., 2995). To overcome this problem, ultrasound can be used to measure the mechanical muscle deformation caused by muscle contraction; ultrasound has thus been used to estimate the intended angle of finger joints (Castellini et al., 2012) and wrist joints from the cross-sectional area of muscles in the residual limb measured with a compact ultrasonic sensor mounted in the socket of the prosthesis (Tsutsui et al., 2005). The use of ultrasound is critically dependent on the quality of contact between the skin and sensor; poor contact increases estimation errors. Measuring changes in skin deformation is thought to be less influenced by contact quality, and a prosthetic hand can reportedly be opened and closed by skin deformation at a single point using one distance sensor (Yoshikawa et al., 2015). The best results for people with upper-limb amputations are achieved by locating the sensor where the change in skin deformation is greatest. There is substantial interest in using skin deformation measured over a large area by high-resolution tactile sensors to control intended hand and wrist activity (Koiva et al., 2015) and gestures (Radmand et al., 2016, Li et al., 2008). By applying a strain gauge to the stump tip, the change in the extent of skin deformation in response to rotation of the bone within the stump can be used to control the extent of hand motion (Cho et al., 2016). However, these techniques do not capture the muscle contraction corresponding to the subject’s intended motion, as the sensors are located where there is a large change.

To overcome the limitations of these techniques, it is necessary to achieve continuous control of the joint angle from a biosignal that is directly related to the user’s intended motion. We have proposed a method using longitudinal skin deformation along the forearm, derived from contraction of the agonist muscles of wrist extension, to allow continuous estimation of wrist joint angle. In previous work, we used a bespoke distance sensor module for non-contact sensing of skin deformation to confirm that skin deformation derived from the wrist agonist muscles corresponded to changes in the joint angle in an almost linear relationship (Kato et al., 2015). Our distance sensor module was constructed with 12 sensors arranged longitudinally on the forearm over approximately 60 mm. Our device uses a linear regression algorithm, modeled offline, to calculate the functional relationship between skin deformation and intended wrist joint angle. The main reason for errors in the estimated joint angle was individual variation in the ideal location for measuring skin deformation. Considering our former result, using skin deformation as a source that can directly respond to a person’s intended joint motion could be considered useful for amputees who cannot show their intended motion as actual limb movement. In addition, people with an upper-limb amputation report that adjusting the wrist angle is an important degree of freedom of the forearm when reaching for an object (Polatiuk et al., 2007). Hence, installing the measurement device in the socket of the prosthesis and using of the minimum number of sensors increases the practicality and user-friendliness of a powered prosthetic hand in everyday life.

In this study, we seek to explicitly determine the number of sensors required to measure skin deformation for wrist joint angle estimation by collecting data from many sensors. Further, we verify an applicability of the signal processing procedure tested in able-bodied subjects for a subject with an upper-limb amputation.

2. Methods

We aimed to establish the measurements method required for continuous wrist joint angle estimation in a person with
upper-limb amputation and able-bodied controls. We determined the number of sensors required to measure skin deformation within the prosthetic socket for practical use, by offline analysis of selecting a desired number of sensors from a large measurement area to estimate the intended wrist joint angle. In this experiment, we sought to establish the extent of differences in skin deformation between the subject with an upper-limb amputation and able-bodied controls, and evaluated the feasibility of estimating wrist joint angle by comparing measured and estimated angle using a limited number of sensors. Under an ideal experimental environment where the subject’s arm was placed on an arm rest and measurement is performed by a separately fixed sensor, we collected the data of the intended wrist joint angle and corresponding skin deformation.

2.1 Subjects

We recruited one person with an upper-limb amputation who had had his right forearm amputated 13.2 cm below the elbow 14 years previously; he was able to intentionally generate EMG signals for some phantom hand motions. We also recruited five healthy volunteers who had no history of neuromuscular disorder to act as controls. The five able-bodied volunteers comprised four men and one woman, whose mean age was 25.2 years (± standard deviation 0.75 years), mean height was 169.0 cm (± 6.7 cm), mean weight was 59.0 kg (± 8.7 kg), mean forearm length was 23.8 cm (± 2.1 cm) and mean maximum forearm circumference was 24.2 cm (± 2.1 cm).

2.2 Experimental setup

2.2.1 Skin deformation recordings

We manufactured a tactile sensor device comprising three Shokacubes (Touchence, Tokyo, Japan), which are soft tactile sensors that we used to measure three-dimensional deformation of the skin on the forearm. Each Shokacube consists of 16 distance sensors, each of which detects skin deformation using nitrile rubber as an exterior sponge in a manner widely adopted in the cosmetics market. The distribution of the forearm skin surface deformation was therefore measured by 48 distance sensors covering an area of 96 mm × 32 mm (Figure 1). Each Shokacube was connected in series to a personal computer through the recording microcontroller unit (Touchence, Tokyo, Japan). We positioned the tactile sensor device against the arm using a flexible joint that accommodated the positions of underlying muscles, which tend to vary between individuals depending on surgical amputation technique. We positioned the sensor on the skin around the belly of extensor carpi radialis brevis, an agonist of wrist extension that exhibits considerable skin deformation due to its large volume (Kaneushi et al., 1984) and cross-sectional area (Tani, 1989). Subjects placed their forearm on a rest according to the anatomical position of the muscle: the lateral epicondyle of the humerus—the origin of the extensor carpi radialis brevis—was placed on the proximal forearm rest and the styloid process of the ulna was placed on the distal rest (Figure 2).
Fig. 2 Experimental setup for the subject with upper-limb amputation: the tactile sensor device is on the residual side and the goniometer is on the unaffected side.

Fig. 3 Visual feedback of skin deformation and wrist joint angles against target angles in real time.

2.2.2 Wrist joint angle recordings
Wrist joint angle was recorded by a goniometer (SG150, Biometrics Ltd., Newport, UK) with a measurement precision of ± 2° connected to an eight-channel analog output amplifier (K800, Biometrics Ltd., Newport, UK) and a personal computer by means of a ArduinoUNO device (Arduino, Ivrea, Italy). The sampling rate for skin deformation and wrist joint angle was 0.05 s, with a 10-bit measurement resolution.

2.3 Experimental protocol
For each experiment, the subject sat in a standard chair adjusted to the height of the desk. We used the tactile sensor device to measure skin deformation and the goniometer to measure wrist joint angle. In our method, the wrist joint angle estimation was realized by associating the correspondence relationship between the intended wrist joint angle and the skin deformation. It is therefore, in able-bodied subjects, sensors were positioned on the dominant arm; in the subject with upper-limb amputation, we measured the intended wrist joint angle on the left, intact arm. For the measurement condition of the subject with amputation, we measured the wrist joint angle on the unaffected side because the subject did not have the wrist joint on the amputated side. We thus instructed him to extend his left wrist and right phantom wrist to the indicated angle at the same time. We gave visual feedback to allow the subject to adjust the measured wrist joint angle to the target angle. Visualization was executed by Siv3D, a C++ library (Figure 3). Each participant performed five trials. One trial included seven wrist extension and flexion movements. Before starting the actual measurement, subjects conducted five trials of experimental tasks for getting used to them. Target angles were set randomly from 0° to 60° in intervals of 10°. We set the minimum wrist joint angle at 0° and the maximum at 60° to match the normal range of motion of the wrist joint (Ryu et al., 1991). Regardless of the amount of angle change, one extension or flexion movement was performed in 4 seconds which synchronized to three beats of a metronome at 80 beats per minute. Therefore, the motion speed at each amount of angle change (10°, 20°, 30°, 40°, 50°, 60°) were calculated as 2.5°, 5°, 7.5°, 10°, 12.5°, 15° per second.

We gave each participant a detailed account of our experimental objectives, made it clear that they were entitled to stop the experiment at any point, and obtained informed consent. This experiment was approved by the Institutional Review board of Waseda University.

2.4 Data analysis
2.4.1 Multiple linear regression
We applied a linear model to derive the functional relationship between the intended wrist joint angle and skin deformation using data collected at 48 points. Figure 4 shows the whole data analysis flow. Our previous work suggested that this relationship was approximately linear (Kato et al., 2015). From the measurement data obtained from the tactile sensor device, we used multiple linear regression to determine the functional relationship as

\[
\theta_M = [a_1 \cdots a_{48}] \begin{bmatrix} z_1 \\ \vdots \\ z_{48} \end{bmatrix} + b,
\]  

(1)
Fig. 4 Data analysis flow from measurement of skin deformation to calculate RMSE. a) Measured skin deformation shown as a heat map at 60° of wrist joint angle. b) Sensor selection based on the analyses in descending order of standard. c) Calculate functional relationship between measured wrist joint angle and skin deformation to determine the coefficients using multiple linear regression. d) Calculate RMSE between measured and estimated wrist joint angle.

where $\theta_M$ is the measured wrist joint angle, $z_n$ ($n = 1, 2, \cdots, 48$) is the skin deformation measured at each of the 48 sensors as independent variables, and $a_n$ and $b$ are constant coefficients determined individually by using the least-squares method to minimize $Q_\ell$ by

$$Q_\ell = \| \theta_M - \theta_E \|^2,$$

(2)

where $\theta_M$ is the measured angle, $\theta_E$ is the estimated angle, and $Q_\ell$ is the difference between the estimated and measured joint angles as a dependent variable.

2.4.2 Training and test data collection

We examined the algorithm’s performance with the full number of sensors (48), and reduced numbers of sensors (40, 32, 24, 16, 8 and 1), where the sensors were selected using the standard deviation of their output values. From the total measured data from five trials for each subject, standard deviations were calculated for each of the 48 sensors. Sensors were selected for inclusion in subsequent analyses in descending order of standard deviation. After the selection of sensors in each subject, we also used multiple linear regression to determine the functional relationship with each number of sensors.

For the joint angle estimation, there were a training step and a test step using leave-one-out cross-validation. Subjects each took part in five trials and we divided four trials as a training data set and the rest one trial as a test data set. In training step, we calculated constant coefficients for the functional relationship using the training data set in each subject. The functional relationship was determined using measured wrist joint angle and skin deformation data with a variety of numbers of sensors (48, 40, 32, 24, 16, 8 and 1). In test step, we estimated the wrist joint angle using the test data set. Thus, the wrist joint angle was estimated five times in each subject by dividing measured five trials into four trials as training data set and rest of one trial as test data set. In this study, we did not estimate using the same functional relationship across subjects. The test data set comprised each trial of each subject. We therefore obtained five trials of the time-series of the estimated wrist joint angle for each number of sensors.

2.4.3 Statistical analysis

We calculated the root-mean-square error (RMSE) between the measured and estimated wrist joint angles as a performance index. RMSE was calculated as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n}(\theta_{Mi} - \theta_{Ei})^2/n},$$

(3)

where $n$ is the measurement time according to the sampling rate. The RMSE was calculated every 0.05 s to match the
Fig. 5 Skin deformation in all subjects when intended wrist joint angles were 0°, 30° and 60° in a) a subject with an upper-limb amputation, and b) to f) five able-bodied subjects.

Fig. 6 Time-series of estimated and measured wrist joint angles in a) a subject with an upper-limb amputation using 48 sensors as input, and b) able-bodied subjects using 48 sensors as input.

3. Results

3.1 Skin deformation versus wrist joint angle

We observed a qualitative change in skin deformation with changing wrist joint angles in the subject with an upper-limb amputation and in able-bodied subjects. We measured skin deformation at 48 points: the color distribution in the figures, visualized by linear interpolation of the displacement at each sensor position, shows the change in skin shape at intended wrist joint angles of 0°, 30° and 60° (Figure 5). The results from the subject with an upper-limb amputation showed that the position of the largest deformation moved from the wrist ($y = 0$) to the elbow ($y = 96$) as the wrist joint angle increased. In addition, the displacement increased with the wrist joint angle. In able-bodied subjects, there was...
Table 1: Root-mean-square error between measured and estimated wrist joint angle for each number of sensors.

| Subject       | Number of sensors |
|---------------|-------------------|
|               | 1     | 8     | 16    | 24    | 32    | 40    | 48    |
| Amputee       | 15.66 | 13.68 | 11.26 | 9.83  | 9.52  | 9.11  | 8.89  |
| Subject 1     | 19.91 | 10.81 | 7.07  | 5.96  | 5.53  | 5.12  | 4.99  |
| Subject 2     | 19.42 | 7.80  | 5.79  | 4.63  | 4.38  | 4.01  | 3.87  |
| Subject 3     | 14.11 | 7.21  | 3.63  | 3.55  | 3.49  | 3.45  | 3.45  |
| Subject 4     | 18.79 | 12.95 | 8.18  | 6.67  | 5.86  | 5.53  | 4.76  |
| Subject 5     | 17.08 | 11.26 | 8.67  | 7.81  | 7.35  | 6.96  | 6.66  |
| Mean          | 17.49 | 10.60 | 7.43  | 6.41  | 6.02  | 5.70  | 5.44  |

Fig. 7 Root-mean-square error for each number of sensors in a) a subject with an upper-limb amputation and b) the mean of five able-bodied subjects. *p < 0.05.

prominent change in skin deformation; although the trends in the position and displacement of the maximum deformation were the same in the subject with an upper-limb amputation, the location of the areas of maximum deformation and change in skin shape were different in each subject. These results suggest that skin deformation can be observed reliably in able-bodied persons and those with an upper-limb amputation.

3.2 Accuracy of wrist joint angle estimation

We also validated the feasibility of the proposed method of estimating wrist joint angle from skin deformation with a limited number of sensors. Figure 6 shows the results with 48 sensors for one trial in the subject with an upper-limb amputation and for the able-bodied controls. The minimum error in all trials was 8.19° for the subject with an upper-limb amputation using 48 sensors (Figure 6a), and 2.24° for the third able-bodied subject using 48 sensors (Figure 6b). Estimation was particularly accurate when the angle changed, rather than when it remained stable. There was no appreciable difference in the variance of motion speed. In this experiment, motion speed changed according to the variation of the target angle. Table 1 summarizes the estimation quality results using different numbers of sensors.

Performance initially increased with more sensors. Figure 6 shows a box plot for the number of sensors for the subject with an upper-limb amputation (Figure 7a) and able-bodied controls (Figure 7b). However, performance for the subject with upper-limb amputation plateaued at $n \geq 16$ and for the able-bodied controls at $n \geq 24$. For fewer than 16 sensors, the RMSE was significantly larger than when more sensors were used ($p < 0.05$), but performance was not significantly different for more sensors.

4. Discussion

4.1 Skin deformation versus wrist joint angle

The position of the greatest displacement (represented by the red area in Figure 5) was different in each subject, but
we confirmed there was a common trend. The position of muscles in the residual limb of people with an upper-limb amputation depends on the surgical technique used; in our subject, the area of maximal deformation was on the anterior surface of the residual limb. In able-bodied subjects, the areas of maximal deformation were nearer the elbow, which would be expected when anatomy is normal. From Figure 5, those could divide into two groups according to their deformation trends. First group was observed in subject with upper-limb amputation, subject 1 and 4 that the maximum deformation area was positioned at the center of the measurement area. On the other hand, in second group, the maximum deformation area in subject 2, 3 and 5 was observed at the left end of the measurement area, that is, at the position near elbow joint. Figure 8 shows an actual sensor position as representative example of each group from a) the subject with upper-limb amputation and from b) the able-bodied subject as subject 4. Sensor placement was slightly different on those two groups. The sensor was placed above the elbow joint in first group (Figure 8a) and the sensor was located closer to the wrist joint than the elbow joint in second group (Figure 8b). It is therefore, the placement of the deformation caused by the muscle contraction was measured above the elbow joint. This corresponds to the anatomical belly of extensor carpi radialis brevis which is the target muscle of this paper.

Ours is the first study to have observed changes in skin deformation on the residual limb surface according to the intended joint motion in a person with an upper-limb amputation. When he imagined extending his phantom wrist, the extensor carpi radialis brevis contracted, resulting in deformation of the skin. We measured skin deformation while the other upper limb joint degrees of freedom (such as elbow flexion and wrist pronation and dorsiflexion) and the origin of the extensor carpi radialis brevis on the lateral epicondyle of the humerus were fixed. Consequently, other forearm muscles would likely not have influenced skin deformation in our study.

4.2 Accuracy of wrist joint angle estimation

We also evaluated the feasibility of using RSME to estimate wrist joint angle using skin deformation for different numbers of sensors. The minimum RMSE in one trial in the subject with an upper-limb amputation was 8.19°, compared with 2.24° in able-bodied controls, which are broadly comparable with sEMG (4.98°) (Sawaguchi et al., 2011) and ultrasound (9.6°) (Tsutsui et al., 2005) techniques. Furthermore, the RMSE with one sensor was high in all subjects, corroborating existing evidence that one distance sensor cannot accurately estimate joint position (Yoshikawa et al., 2015). The RMSE with one sensor (15.7°) in the subject with an upper-limb amputation was smaller than that of able-bodied controls (17.5°). This difference could be explained by reduced muscle contraction, and hence skin deformation: after amputation, contraction is mainly isometric and suturing the muscle tip to other muscles or bones in the stump may result in less overlying skin deformation.

We also found that RMSE fell as the number of sensors increased. We established the minimum number of sensors inside the prosthesis socket required to estimate the intended joint angle. From our offline analysis, sensors were selected given the standard deviation of their values; at least 16 sensors were required in the subject with an upper-limb amputation, and 24 in the able-bodied subjects. The sensors, selected in descending order of standard deviation in each subject, were matched the changed area of the skin surface according to the angle change show in Figure 5. According to the wrist joint angle change, the skin deformation area was changed in each subject as we mentioned in section 4.1 and those were
corresponded to the anatomical belly of the target muscle. It is therefore, we can use only the skin deformation data around the muscle belly with 16 as minimum number of sensors. In this experiment, we did not change any condition such as other joint motion. Collected skin deformation was only corresponded to the wrist joint motion and it caused RMSE fell as the number of sensor increased. Considering the other muscles located around the target muscle in the forearm for other joint motion, it could become a disturbance of the wrist joint angle estimation. In order to reduce RMSE to be estimated using the skin deformation measured with the prosthetic socket, the measurement area could be previously decided based on the large area measurement with 48 sensors.

5. Conclusion

We conclude that limited skin deformation information can reflect the intended joint angle of able-bodied individuals and a person with an upper-limb amputation. Our findings confirm that skin deformation can be used to estimate the intended joint angle for persons with an upper-limb amputation with relatively few sensors.

In this study, we measured the skin deformation in the ideal experimental environment that the subject’s arm was placed on an arm rest and measurement is performed by a separately fixed sensor. In daily life, however, skin surface deformation normally reflects the contraction of other muscle groups, and can be used to recognize patterns of motion (Radmand et al., 2016). Further research will be needed to collect skin deformation data with dynamic movements of other joints if the technique is to be used in clinical practice. For more understanding of the relationship between the skin deformation and the muscle contraction, following conditions can be considered. The condition of the elbow joint angle could influence greatly the deformation of the skin we are measuring. Agonist muscle for elbow flexion is located next to our target muscle and it also has large volume. By clarifying the effect of the other joint angle, we can improve our estimation algorithm stronger that is not affected by other joints and it is possible to reduce an incorrect motion of the prosthetic hand. For practical use, the number of the sensor should be reduced as much as possible as we claimed in this paper. We thus determine the exact position of the sensor according to the deformation of the muscle inside of the body that causes deformation of the skin surface at above the elbow joint. Actual deformation of the muscle which affect the amount and the pattern of the skin deformation can be examined based on medical images such as ultrasound imaging or computed tomography. In able-bodied subject as their anatomical muscle location are not significantly different in subject, the measurement place can be determined generally based on previously analyzed medical image. However, in subject with upper-limb amputation with wide variety of the muscle location, it is necessary to specify the deformation position of the muscle by ultrasound image beforehand for each subject. A series of processing method using skin deformation based on medical image analysis can be used to control not only the prosthesis or an exoskeleton, but also various assistive device for people with disabilities.

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