Active muscle stiffness sensor based on piezoelectric resonance for muscle contraction estimation

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ABSTRACT

In this paper, we present the development of a voluntary muscle contraction sensing system that provides motion information of body for computing human body forces for physical human–robot interactions (pHRI). A resonance-based active-muscle stiffness sensor (aMSS) using piezoelectric probes was built and tested to measure stiffness changes in muscles. The sensor is evaluated by comparing the results with those of a force sensor and surface electromyography in terms of accuracy and by assessing the response time test under isometric conditions. Experimental results pertaining to flexor carpi radialis (FCR) contractions are presented to show the feasibility and performance levels of the developed sensing system when sensing muscle contractions. Two notable advantages over sEMG-based sensing are that the proposed sensing method is far less sensitive to skin contact conditions and that it can measure muscle contractions through one’s clothes. Being capable of body force estimations noninvasively, the proposed sensing method is attractive in the field of exoskeleton robots or human-augmentation systems.

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1. Introduction

Estimating a human’s motion intention is a challenging issue in the study of physical human–robot interactions (pHRI) [1,2]. Research on the topic of pHRIs is important for helping limb amputees and the elderly with the intuitive use of assistive prostheses to aid them in enhancing their physical strength. The estimation of motion intention is classified into three steps: information sensing (information exchange or muscle activation dynamics), intention extraction (intention understanding or muscle contraction mechanics) and device control [3,4]. A reliable signal which accurately reflects the motion intention allows the other steps to be completed effectively. Surface electromyography (sEMG) is the most widely used muscle activation sensor for an intention-related signal, but the electrical measurement method is limited in that it is sensitive to skin tissue impedance as caused by moisture and the electrical conductivity between the skin and the electrode. Therefore, researchers study mechanical property changes of biological actuator skeletal muscles, which play a major role in the control of force and motion in humans [5]. The muscle activation shrinks the muscle’s length and expands its cross-sectional area while the muscle’s stiffness is also increased [6]. Muscle elastography sensors [7], muscle stretch sensors [8], and muscle pressure sensors [9], were developed, but the other sensors were limited in spatial resolution and sensor size. Strain–stress based stiffness sensors, muscle myokinematic (MK) muscle expansion sensors [10,11], and muscle stiffness sensors [12,13], have also been developed, but they require a continually vertical contact direction.

This study introduces a new type of a muscle stiffness sensor based on a resonance signal change. The associated muscle tissue stiffness changes can be measured by monitoring the change in the resonance frequency against induced external resonance oscillation [14–16]. This resonance frequency-based stiffness measurement method has been studied for tactile sensors [14–19]. Kleesattel and Gladwell discussed the contact-impedance problem of a resonance sensor [20], and Malinauskas and Barry used a Doppler ultrasound system to measure the properties of human tissues noninvasively [21]. A resonance sensor with a piezoelectric transducer (PZT) was developed to measure material stiffness [15] and was applied as a tactile sensor [17,18] to detect contact with materials. Krishna and Rajanna proposed a tactile sensor that consisted of a PZT array and tested its responses to external forces [14]. Jalkanen et al. used a resonance sensor to detect cancer tissues and developed a corresponding mathematical model [16]. Inaba et al. measured muscle stiffness in dogs [22,23]. These studies analyzed frequency shifts to distinguish different objects based on their stiffness under static conditions.

This paper proposes an active muscle stiffness sensor (aMSS) that measures muscle activation using a piezoelectric resonance probe. We also propose two analysis methods based on a frequency shift [17] as well as the newly proposed amplitude change for real-time continuous measurements. The linearity and response time of
the developed sensor were tested against reference joint force sensors for its ability to measure muscle activations. Additionally, we tested the measurement abilities of the sensor to muscle stiffness in indirect contact over clothes.

2. Materials and methods

2.1. Principles

In general, the resonance frequency of a mechanical system depends on its stiffness and mass properties [14]. When an oscillating probe is in contact with connective tissues (mainly muscle under the skin layer), the combined resonance frequency and stiffness are \( f_0 \) and \( k_0 \), respectively. The resonance frequency \( f_0 \) is determined by the mechanical properties of both the probe and the tissue when in contact. The stiffness of the underlying tissue (mainly skeletal muscle) can be altered by muscle contractions, which influences the changes in the resonance properties. As the tissue becomes stiffer \( (k_0 + \Delta k) \), the resonance frequency \( (f_0 + \Delta f) \) and the resonance amplitude \( (A_0) \) decreases \( (A_0 - \Delta A) \), as shown in Fig. 1. Thus, we can infer the stiffness change by measuring the resonance frequency shift or the signal amplitude change. There have been several studies [14–20] that measured stiffness changes of soft tissues by measuring the frequency shift of resonance signals.

In this study, we used a piezoelectric probe (PZTs) as an oscillating probe. Because PZTs have both electrical and mechanical characteristics, we must analyze the response by considering the mechanical properties and the electrical impedance. The frequency shift \( (\Delta f) \) of the PZT in contact \( (1) \) is related to the impedance of the object [15],

\[
\Delta f = -\frac{\sqrt{Y/\rho}}{2\pi l} \times \frac{m_0 - (k/\omega)}{Z_{PZT}} \tag{1}
\]

where \( Y, \rho, \) and \( Z_{PZT} \) are the Young’s modulus, density, length and impedance of the PZT, and where \( \omega, m \) and \( k \) are the oscillation frequencies, the mass and the stiffness of the muscle-containing tissues, respectively.

The signal amplitude \( (|\Delta S|) \) of the resonating PZT is related to the impedance of the overall system. The PZT resonance-based analysis technique has been studied for use in smart structures to monitor structural health and to detect damage [25–27]. From previous studies [25], the PZT impedance \( (Z_{PZT}) \) and the muscle impedance \( (Z_{muscle}) \) are modeled as shown in (2) and (3), and the overall impedance \( (Z_{Overall}) \) can be expressed as \( (4) \), where \( w, h, \varepsilon \) and \( d \) are the width, height, dielectric constant and piezoelectric constant of the PZT, respectively, and where \( c \) is the damping of the muscle tissues [25]. The \( Z_{Overall} \) decreases as the stiffness changes and as the resonance frequency shift becomes larger.

\[
Z_{PZT} = \frac{m_0 \sqrt{\rho/\varepsilon_y} \times \omega Y}{\omega Y} \tag{2}
\]

\[
Z_{muscle} = c + j \left(\frac{m_0 - (k/\omega)}{\omega Y} \right) \tag{3}
\]

\[
|\Delta S| \propto Z_{Overall} = \frac{1}{\omega (\rho/\varepsilon_y) \times \omega Y (Z_{PZT} + Z_{muscle}) \times d^2 Y} \tag{4}
\]

To verify the induced frequency shift \( (1) \) and the amplitude change \( (4) \) of the signal, the equations are simulated with actual values by changing the stiffness in the range of muscle tissue [33]. This study uses piezo stack actuators in the longitudinal mode, and the figures of the PZT properties are sourced from commercial piezoelectric transducers (PST150/5 × 5/7 by Piezomechanic, DE). The simulation results are shown in Fig. 2. The x-axis in the figure represents the range of typical muscle stiffness; within the area, the resonance frequency of the PZT increases and the signal amplitude decreases approximately linearly as the muscle stiffness increases.

2.2. Sensor design

The aMSS measures muscle contractions based on the changes in the resonance signal, which are generated from the PZT. The aMSS consists of two main parts: the resonating PZT probe and the resonance circuit (Fig. 3). The probe was designed by combining a driving PZT and a pickup PZT. The driving PZT (PST 150/5 × 5/7 by Piezomechanic, DE) induces mechanical oscillation, and the pickup PZT (PST 150/2 × 3/5 by Piezomechanic, DE) measures the oscillation. The size of the pickup PZT (2 mm × 3 mm × 5 mm) is smaller than that of the driving PZT (5 mm × 5 mm × 7 mm) to reduce noise effects. The contact tip is designed by considering the contact area between the sensor and the skin. A wide contact area has an advantage with respect to the resolution, and the area should remain

![Fig. 1. Concept diagram to explain the resonance frequency shifts and the amplitude changes caused by a stiffness change. The frequency becomes higher and the amplitude becomes smaller as the muscle becomes stiffer (as indicated by the direction of the arrow).](image1)

![Fig. 2. Evaluation of a mathematical model using actual values. The frequency shift \( (\Delta f) \) increases proportionally and the amplitude change \( (|\Delta S|) \) increases upon a change in the stiffness.](image2)

![Fig. 3. Schematic of the aMSS. The resonating PZT probe consists of a driving and a pickup PZT. The resonance circuit supports the resonance of the probe using a filter, an amplifier and phase shift components.](image3)
constant to account for skin deformations. A hemispheric tip with a diameter of 8 mm is selected. The chosen contact depth between the muscle and the skin tissue is 2 mm as determined by trial and error. Fig. 4 shows an assembled sensor with each component identified. To maintain the contact depth, the tip protrudes 2 mm below the sensor frame. The size of the assembled sensor is 20 mm × 20 mm × 12 mm.

The resonance circuit produces a periodic signal for the PZT probe. The resonance circuit consists of an amplifier, a filter and a phase compensator. The raw signal from the pickup PZT has insufficient power to drive the PZT. Therefore, the raw signal must be amplified for continuous resonance. The raw signal is amplified with a gain of two and is filtered using a band-pass filter ($\Omega_{cut}\$: 100–150 kHz) to extract only the resonance frequency component ($f_r$: 115 kHz). The phases of both the raw signal and the generating signal should be the same to induce resonance, but the amplifier and filter distort the signal phase. Thus, the distortion in the phase is compensated for with a phase-shift circuit. The phase-compensated signal drives the PZT input and resonates at an amplitude of 500 mV.

Two types of the signal features can be used for the muscle contraction measurements: the frequency shift ($S_f$) and the amplitude change ($S_a$).

- $S_f$: resonance frequency.
- $S_a$: resonance amplitude.

As shown in Fig. 5, the signal for the frequency measurement should be a digitized signal to reflect only the frequency regardless of the amplitude changes. The bias of the resonance signal shifts from 0 to 2.5 V, and the shifted signal is amplified by a gain of several hundred. We can then obtain the signal for the frequency measurement, as shown by the dashed line. A direct measurement of the signal amplitude is difficult due to its high frequency. The resonance signal is modified to express only the amplitude regardless of the frequency shift using a half-wave rectifier and a low-pass filter ($\omega_{cut}$: 15 kHz), as shown by the dashed line. The rectified signal is amplified approximately 10 times. The high amplification increases the signal resolution. The signal for the amplitude measurement is proportional to the resonating signal amplitude without the high-frequency ripples.

In general, as the object becomes stiffer, the frequency of the resonance signal becomes higher but the amplitude of the signal decreases, as illustrated in Fig. 5. To express the resonance feature changes in a positive direction, $S_f$ is defined as the resonance frequency increase, and $S_a$ is defined as the resonance amplitude decrease, as respectively expressed by Eqs. (5) and (6).

$$S_f = \Delta S_f = (S_{f,0} + \Delta S_f) - S_{f,0}$$  
$$S_a = \Delta S_a = S_{a,0} - (S_{a,0} - \Delta S_a)$$  

$S_f$ is determined by the frequency shift ($\Delta S_f$) between the current frequency ($S_{f,0} + \Delta S_f$) and the initial frequency in a relaxed state ($S_{f,0}$). Similarly, $S_a$ is determined by the amplitude change ($\Delta S_a$) from the value in a relaxed state ($S_{a,0}$). Current amplitude values are expressed as $S_{a,0} - \Delta S_a$ to indicate an amplitude change ($\Delta S_a$) in a positive direction.

2.3. Verification

$S_f$ and $S_a$ are compared using the stiffness measurement device, an indentation device [28], which can measure distance and force. The tissue phantoms are molded from silicone (DSE 7310, DLE 40 by DongYang Silicone Co. Ltd.) with a radius of 110 mm and a height of 55 mm. Five different stiffness phantoms are used, and the stiffness of the phantoms is adjusted by changing the portion of the silicone hardener (50%, 60%, 70%, 80% and 90%). Fig. 6 shows the results of the tests with the tissue. The indentation device [29] measures the Young’s modulus (kPa) based on the Hertz–Sneddon model. The results show that $S_f$ and $S_a$ become proportionally higher in relation to the material stiffness in the soft, medium and hard phantom models. These results indicate that the sensor signals reflect the stiffness change and that the sensor is able to measure the muscle contraction, as the stiffness of the phantom model and skeletal muscle are within the same range.

Fig. 4. The components of the aMSS include a resonating PZT probe, a sensor frame and a contact tip.

Fig. 5. Ideal aMSS output signals for the resonance signal and the conversion signals for the frequency ($S_f$) and the amplitude measurement ($S_a$).

Fig. 6. The frequency shift and amplitude change of the PZT transducer due to stiffness changes of the contacting material; the gray rectangular represents the region of typical muscle properties; $S_f$ and $S_a$ are the frequency shift and amplitude change, respectively.
3. Experiments

3.1. Muscle stiffness

Stiffness is the resistance of an elastic body to deformation by an applied force along a given degree of freedom (DOF) when a set of loading points and boundary conditions are prescribed on the elastic body. It is an extensive material property. The stiffness can be described generally with the stress–strain correlation. The physical properties of the muscle change during muscle contraction. The contraction shrinks the muscle length, expanding the cross-sectional area. The muscle stiffness also increases due to the contraction [6]. To analyze the correlation between the contraction force and the stiffness of a muscle, a preliminary experimental study was conducted. As a contraction sensor, surface electromyography (sEMG) was used. The sEMG amplitude is not directly proportional to the muscle contraction force, but under an isometric condition, it can be considered to be linear [4]. A subject holds weights vertically on his hands in a fixed pose to generate forces of 1 to 50 N, and the signal is measured at the belly of the biceps brachii for 5 s. The stiffness is measured with a durometer (KR-14A, KORI, JP), and the level of contraction is estimated with a commercial sEMG system (Bagnoli-16, Delsys, USA). The durometer works based on the stress–strain correlation. The sEMG is rectified and filtered with a 10 Hz low-pass filter to estimate the muscle contraction.

The data collected during the acquisition period are averaged and compared by normalization with their maximum amplitude. The stiffness and the sEMG signal amplitude increase linearly with the weight. The muscle contraction increases nonlinearly with the stiffness change. In previous studies, a polynomial [24] model is used, but we can also model this exponentially from the stress–strain properties of muscle. Fig. 7 shows that the muscle contraction can be measured through the stiffness change with this exponential correlation.

3.2. Experimental setup

Fifteen healthy subjects (35.2 ± 12.6 years) with no overt signs of neuromuscular disease volunteered to participate in the present study and signed an informed consent form. This study was conducted according to the protocol approved by the Institutional Review Board of the KAIST. All testing was conducted on a single day.

The sensor performances were evaluated by comparing the muscle contraction measurements in terms of accuracy and speed. A force sensor and sEMG were used for the comparison of each performance. The target muscle is the flexor carpi radialis (FCR), one of the major muscles responsible for wrist flexion. It is located near the skin surface. Thus, the FCR is suitable for measuring muscle contractions. The muscle is measured in the isometric condition, which contracts muscles without appreciable joint movement or muscle length changes. A test device was designed and implemented to maintain the isometric wrist flexion; this device is described in Fig. 8. The forearm, wrist and elbow are affixed to the device. The upper arm is kept in a vertical position relative to the forearm to induce the isometric contraction of the FCR. The force sensor is located in the palm of the hand to measure the wrist flexion force. The sensor is located on the belly of the FCR, and the sEMG is also located on the belly, immediately adjacent to the sensor.

The contraction level of the FCR is estimated with a linear function based on the wrist flexion force. Although the relationship between the muscle contraction and the flexion force is not exactly linear due to muscle length changes; linear models are often used, and they provide a reasonable description of the relationship under many isometric conditions [30]. The quantification of contraction level is based on a reference measurement, maximal voluntary contraction (MVC), which is measured before each individual test.

4. Results and discussion

4.1. Accuracy

The accuracy of the aMSS is analyzed by generating various level contraction forces based on each subject’s MVC values. Fig. 9 shows one case of the aMSS, sEMG, and the muscle contraction from force signals at 30% MVC. During repeated contraction and relaxation tests, each signal followed the force sensor well. Both $S_0$ and $S_f$ increase with the contraction, which means that the signals are highly correlated with the contraction level. Compared

Fig. 7. Relationship between muscle stiffness and muscle contraction.

Fig. 8. Experimental setup: the aMSS, force sensor.

Fig. 9. Sensor signal change time flow with sEMG and force sensor according to contraction force change.
with the force sensor, the fluctuation of the sEMG signal is much higher.

The contraction levels are compared with $S_x$ and $S_y$ as described in Fig. 10. The relationship between the force and stiffness of the muscle is modeled in exponential form, from the previous chapter. The simulation results, Fig. 10(c) and (d), also increase exponentially with the muscle contraction level and both conditional results are in the same range. We can consider the differences between the experimental results and simulation results largely two. One is using inaccurate parameters which are from literatures instead of individual parameters. The other is environment factors. The contact condition could affect the model parameters. The muscle contractions ($F$) are fit by an exponential function of the sensor signals (7) where $S_x$ denotes both $S_a$ and $S_f$.

$$F = A_x \times \exp(B_x \times S_x) \quad (7)$$

Table 1 shows the individual coefficients $A_x$ and $B_x$ of the equation based on (7) and the correlation coefficient ($R^2$) for each subject. The unit of $A_x$ is newton (N) for force, and $B_x$ is dimensionless unit. The $A_x$ and $B_x$ values are distributed individually, but the contraction levels are in the same range with a high correlation $(0.93 \pm 0.04)$ between the fitted sensor signals and the contraction levels. The exponential correlation is identical to the correlation between the muscle contraction and the muscle stiffness change shown in Fig. 10, indicating that $S_a$ and $S_f$ suitably reflect the muscle stiffness again. These results mean that muscle contractions can be measured from the exponentially fitted sensor signals. The correlation coefficient of $S_a$ $(0.94 \pm 0.03)$ was high, as was that of $S_f$ $(0.91 \pm 0.05)$.

Fig. 11 shows a Bland–Altman plot between the measured force and the estimated force from $S_a$ and $S_f$, respectively. The x-axis denotes the average between the two data points at the unit of MVC level (%), and the y-axis represents the difference between the data. The central dashed–dotted line is the mean ($\mu$) of the difference, and dotted lines are the region containing 95% of the data. Both graphs show that most of the $S_a$ and $S_f$ data are included in the region of 5% error. These results mean that the aMSS can function as a muscle contraction sensor capable of both accurate correlations and performance levels.

### 4.2. Response time

The response time is also important when sensing muscle contractions because it is related to the electro-mechanical delay. If

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Individual muscle contraction measurements and correlation coefficients.</th>
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<tbody>
<tr>
<td></td>
<td><strong>Amplitude change</strong></td>
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<tr>
<td></td>
<td>Coefficients</td>
</tr>
<tr>
<td></td>
<td>$A_{ao}$</td>
</tr>
<tr>
<td>$S_1$ (M, 21)</td>
<td>0.738</td>
</tr>
<tr>
<td>$S_2$ (M, 24)</td>
<td>0.931</td>
</tr>
<tr>
<td>$S_3$ (M, 24)</td>
<td>0.395</td>
</tr>
<tr>
<td>$S_4$ (M, 25)</td>
<td>1.005</td>
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<tr>
<td>$S_5$ (M, 26)</td>
<td>0.786</td>
</tr>
<tr>
<td>$S_6$ (M, 27)</td>
<td>0.172</td>
</tr>
<tr>
<td>$S_7$ (M, 31)</td>
<td>0.411</td>
</tr>
<tr>
<td>$S_8$ (M, 32)</td>
<td>0.744</td>
</tr>
<tr>
<td>$S_f$ (F, 24)</td>
<td>0.344</td>
</tr>
<tr>
<td>$S_{10}$ (F, 50)</td>
<td>0.288</td>
</tr>
<tr>
<td>$S_{11}$ (F, 60)</td>
<td>0.332</td>
</tr>
<tr>
<td>$S_{12}$ (F, 52)</td>
<td>0.204</td>
</tr>
<tr>
<td>$S_{13}$ (F, 54)</td>
<td>0.341</td>
</tr>
<tr>
<td>$S_{14}$ (F, 55)</td>
<td>0.480</td>
</tr>
<tr>
<td>$S_{15}$ (F, 24)</td>
<td>0.236</td>
</tr>
<tr>
<td><strong>Summary</strong></td>
<td></td>
</tr>
</tbody>
</table>
the sensor measures the muscle contraction signal more rapidly than generated force, it is possible to estimate the motion from the signal. In general, the response time is tested by means of various frequency tests, but muscle is difficult to control. Therefore, the response time of the sensor was evaluated by the activation onset time, the time at which the muscle changes from a relaxed state to a contracted state [31]. The onset time determinant method of the sEMG signal is widely used and utilizes threshold-based estimation methods, such as the baseline amplitude characteristics, mean and standard deviation [32]. Defining the exact onset time is difficult due to signal fluctuations and noise. Thus, researchers use the multiplied σ measure to determine the onset time. In this paper, we defined a threshold (DT) that is based on the mean (μ) and two standard deviations (2σ), as shown in (8). The aMSS and force signals are analyzed by the same method.

\[ DT = \mu + 2.0 \times \sigma \]  

(8)

The onset times of Sa and Sf, the contraction force and the sEMG were averaged from the previous results, as shown in Fig. 12. The sensor performance was analyzed by comparing the delays between the onset times of the other signals with that of the sEMG signal, showing that the onset time of the sEMG signal (tEMG) was faster than those of the other signals. Table 2 presents the time delays. The delay between the force and the sEMG signals (Δtforce-EMG) was 69.1 ± 27.5 ms. The delay from Sa (ΔtS0-EMG) was 55.4 ± 26.1 ms, while the delay from Sf (ΔtSf-EMG) was 55.3 ± 25.3 ms; both were shorter than the delay of the force. These results show that Sa and Sf measure muscle contractions with a faster response than the force sensor. This can be conceived in terms of the measurement information difference. The force sensor measures the result of muscle, tendon, and bone based kinematic motion, but the aMSS measures the mechanical properties of the muscle tissues. This difference leads to the time delay.

4.3. Measurement over clothes

One advantage of the sensor over the sEMG method is that it can measure muscle contractions through clothing. The sensor was used to measure muscle contractions through clothing, as shown in Fig. 13. The sensor in this case is attached to a thin single-layer cotton shirt over the skin. Eight subjects who also participated in the previous test were recruited as well for this test. The subjects were tested twice. During the first test, the muscle contractions were measured by the sensor when directly in contact with the skin, identical to the previous test. In the second test, the subjects wore their shirts, and the sensor was placed over the clothing. Although both sets of data were collected at different times, the data were measured under the same condition after sufficient rest. The effect of the clothing is analyzed by Sa and Sf under dynamic conditions.

The amplitude of the reduction in the signal obtained through the clothing may result from the properties of the clothing. The stiffness and mass of the clothing may affect the stiffness change measurement. The clothing reduces the stiffness change, but the muscle stiffness change can still be measured. The reduction ratio of the signal amplitude depends on the properties of the contact clothes. Although the changed ratio is reduced, the muscle con-

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**Table 2**

<table>
<thead>
<tr>
<th>Signal types</th>
<th>Onset time interval (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resonance amplitude (Sa)</td>
<td>55.4 ± 26.1</td>
</tr>
<tr>
<td>Resonance frequency (Sf)</td>
<td>55.3 ± 25.3</td>
</tr>
<tr>
<td>Force</td>
<td>69.1 ± 27.5</td>
</tr>
</tbody>
</table>

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Fig. 11. Bland–Altman plot (a) force–Sa and (b) force–Sf.

Fig. 12. aMSS, sEMG and force sensor signals for a comparison of muscle contraction times. Contraction starts are shown with dashed–dotted lines. The vertical lines are the detected activation moments of each signal with the threshold-based method.

Fig. 13. Experimental setup for the measurement over clothes.
traction can be measured conveniently using the sensor without the participant taking off his clothes. Fig. 14 shows the changes in $S_x$ and $S_y$ according to the muscle contraction level under both conditions. Each signal change in the indirect contact condition is smaller than those when in direct contact. This reduction can be considered by considering the properties of clothes and the changed contact area due to the clothes. However, the signal changes during the clothed condition were also correlated with the force level, indicating that we can measure the muscle contraction level over clothes using the aMSS.

5. Conclusion

This research introduces a new type of a muscle contraction sensor that can be used to extract the motion intention of a user noninvasively, which is one of the greatest challenges in physical human–robot applications such as exoskeleton robots. This research also proposes the measurement of the signal amplitude change as well as the frequency shift measurement. Each measurement method was mathematically analyzed based on the electro-mechanical impedance, which is a characteristic of piezoelectric transducers. The developed sensor was validated using silicone tissue phantoms with different stiffness levels. The sensor measured the muscle contractions based on resonance signals, which are highly correlated with the stiffness of the muscle. The response time of the developed sensor is faster than that of the force sensor, meaning that the aMSS can be used as an estimation sensor. The sensor was able to measure the muscle contraction through clothing, which is an advantage for a motion estimation sensor. This result means that the aMSS can be used as a muscle contraction sensor due to its fast response. The proposed sensor and its application method can be used in pHRI applications by measuring the muscle contraction level, which is a key component when estimating motion intentions. This information, with a musculoskeletal model that takes into account the geometric factors, will allow us to assist or enhance the movement of humans by controlling interaction devices such as exoskeletons.

The output signals are highly correlated with muscle contractions; however, there is some variation. One possible source of this variation is the thickness of the skin tissue. If the effect of the skin tissue thickness becomes too large, the relationship between the skin and muscle must then be treated as a multilayer viscoelastic problem. Another challenging issue of the piezoelectric-based sensor is thermal drift, which may also be limitation of other sensors. This limitation needs to be improved by further analysis for more accurate measurements.

This paper focused on information sensing in a pHRI process. Therefore, a mechanical contraction sensor was developed and used to analyze the performance of the muscle directly to find the correlation between muscle and the developed sensor. Although the mechanical sensing of muscle contractions is slower than the electrical input, sEMG, it is fast enough to estimate motions. Additionally, the sensing method is convenient for situations that require the sensor to be attached because it can measure the muscle properties through clothes. Study of intention extraction and device control steps is required to use this sensor in pHRI applications. Developments of physiological- and physical-based models between stiffness changes and limb motions considering other mechanical properties as well as tendons are required. A combination of bio-signal sensors could improve the estimation of joint motion by reducing the inherent limitations of each type.

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References


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