sEMG-Triggered Fast Assistance Strategy for a Pneumatic Back Support Exoskeleton

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Abstract—To prevent lower back pain (LBP) in the industrial workplace, various powered back support exoskeletons (BSEs) have been developed. However, conventional kinematics-triggered assistance (KA) strategies induce latency, degrading assistance efficiency. Therefore, we proposed and experimentally evaluated a surface electromyography (sEMG)-triggered assistance (EA) strategy. Nine healthy subjects participated in the lifting experiments: 1) external loads test, 2) extra latency test, and 3) repetitive lifting test. In the external loads test, subject performed lifting with four different external loads (0 kg, 7.5 kg, 15 kg, and 22.5 kg). The assistance was triggered earlier by EA compared to KA from 114 ms to 202 ms, 163 ms to 269 ms for squat and stoop lifting respectively, as external loads increased from 0 kg to 22.5 kg. In the extra latency test, the effects of extra latency (manual switch, 0 ms, 100 ms and 200 ms) in EA on muscle activities were investigated. Muscle activities were minimized in the fast assistance (0 ms and 100 ms) condition and increased with extra latency. In the repetitive lifting test, the EA strategy significantly reduced L1 muscle fatigue by 70.4% in stoop lifting, compared to KA strategy. Based on the experimental results, we concluded that fast assistance triggered by sEMG improved assistance efficiency in BSE and was particularly beneficial in heavy external loads situations. The proposed assistive strategy can be used to prevent LBP by reducing back muscle fatigue and is easily applicable to various industrial exoskeleton applications.

Index Terms—Electromyography, human-robot interaction, pneumatic actuators, wearable robots.

I. INTRODUCTION

Despite the trend of automation in the industrial workplace, many workers are still exposed to work-related musculoskeletal disorders (WMSDs) because of tasks requiring human precision and adaptability [1]. Lower back pain (LBP) is common in WMSDs, and not only degrades individuals’ quality of life but also causes a substantial economic burden [2], [3]. Therefore, studies on back support exoskeletons (BSEs) have been actively conducted to prevent LBP. Over 30 BSEs have been developed in the last five years [4].

BSEs provide assistive torque to users in tasks that induce significant burdens on the lumbar spine during flexion and lifting. BSEs are divided into passive and active types depending on the presence of a powered actuator. Passive type BSEs, including PLAD, Laevy V2 (InteSpring, Netherlands), BackX (SuitX, USA), HeroWear Apex (HeroWear, USA), LiftSuit (Auxivo AG, Switzerland), SPEXOR and VT-Lowe’s Exoskeleton use energy-storing components such as mechanical springs and elastic bands, to store energy during flexion and return it during lifting [5]–[11].

However, passive types hinder movements such as walking or sitting. For example, passive BSEs adversely affected gait pattern parameters, such as step width and gait variability [12]. Some passive BSEs can adjust their stiffness by manually adjusting the stiffness or replacing the elastic bands. However, manual adjustment degrades practicality specifically when the user is handling loads or in a dynamic environment where tasks and loads change frequently. Moreover, passive BSEs cannot meet assistance torque requirements, which sharply increase at the beginning of lifting [13]. Because high peak loading is reported as a contributor to LBP [14], providing additional assistance torque for lifting is necessary to prevent LBP.

Therefore, various active BSEs including Muscle suit (Inno-phys, Japan), HAL Lumbar Support (Cyberdyne, Japan), ATOUN model Y, Robo-Mate and H-WEXv2, have been developed [15]–[21]. Active BSEs require compliant actuators, such as a series elastic actuator (SEA) or a pneumatic actuator, for the safe and natural interaction between user and exoskeleton. However, the compliant elements lead to slow actuation responses. For example, a pneumatic-driven BSE can achieve approximately 80 Nm of maximum torque, but approximately 100 ms of rising time was required due to the inherent compressibility of air [21]. Because the required biological joint torque is at a maximum at the beginning of lifting [13], the slow response might degrade assistance efficiency. Manual switch-based assistance triggering, which is adopted in a commercial pneumatic back support exoskeleton, is one possible solution to address the slow response. Before initiating the movement, the user manipulates a mouthpiece...
Fig. 1. (a) An overall description and mechanical structure of a pneumatic back support exoskeleton (BSE) are shown. Pre-gelled Ag/AgCl electrodes were attached to detect muscle activation onset. (b) A schematic diagram of electrical system for measurement, control and data communication.

or a jaw switch to trigger the lifting assistance, and the user can start lifting with assistance. However, although manual switch-based methods are simple and robust, minimizing the cognitive burden on users is crucial for accepting these assistive exoskeletons in the workplace. Therefore, a fast and intuitive lifting detection strategy is required for active BSEs.

A previous study proposed lifting detection based on the hip joint angle’s kinematics changes [22]. Promising results in reducing back muscle activities by more than 30% were shown. However, the user must generate a detectable kinematics change before assistance is triggered. Moreover, the lifting speed affects the assistance onset timing detected using the kinematics-based method. The slower the lifting speed, the more delayed the assistance onset timing. This delay can degrade the assistance efficiency, especially when handling heavy external loads, because the heavier the external load, the more difficult it is to generate kinematics changes [23]. Therefore, we developed a lifting detection method based on muscle activation onset detection using surface electromyography (sEMG) signals to enable intuitive and fast assistance onset triggering. Since sEMG signals can be detected earlier than muscle forces due to the electromechanical delay (EMD) [24], sEMG-triggered assistance can compensate for the slow response by providing fast assistance compared to mechanical sensor-triggered assistance.

It has been claimed that fast assistance utilizing sEMG is beneficial compared to mechanical sensor-triggered assistance [25], but this claim has not been sufficiently explored yet. In a previous study, fast motion intention detection utilizing sEMG for an upper limb exoskeleton was developed [26]. Upper limb movement intention based on sEMG was detected earlier than kinematics onset by 88 ms to 134 ms, but the effect of early detection on the assistance was not evaluated. In another study, an sEMG-based controller for an ankle assistive device improved human-exoskeleton synchronization and reduced muscle activity compared to torque sensor-based controller [27]. Another study, which investigated the assistance efficiency with respect to extra assistance latency for an elbow assistive device [28], showed that the minimum latency did not always guarantee the best performance in terms of muscle activity and task completion time. It was concluded that optimal assistance latency, including actuator and signal processing, corresponds to human EMD. Therefore, as there have been limited results and several contradictory conclusions regarding the optimal latency, it is necessary to experimentally verify the effectiveness of sEMG-triggered fast assistance for individual target applications.

This study aims to experimentally evaluate the effect of fast lifting assistance in BSE applications. For the evaluation, we developed an sEMG-triggered lifting assistance (EA) strategy and compared it with a conventional kinematics-triggered assistance (KA) strategy. We then conducted three experiments to evaluate the effectiveness of the proposed strategy. In the first experiment, we compared the effect of the two assistive strategies on back muscle fatigue. In the second experiment, we introduced extra latencies from the muscle activation onset timing to observe the effect of assistance latency on back muscle activity. In the third experiment, the effect of external loads on each assistive strategy was evaluated.

II. MATERIALS AND METHODS

A. Pneumatic Back Support Exoskeleton (BSE)

The BSE prototype developed in a previous study was improved and used in this study [21]. The overview and mechanical structure of the BSE are presented in Fig. 1-(a). The BSE has a pair of pneumatic cylinders at the mechanical hip joints. Linear actuation of a pneumatic cylinder provides extension torque. The detailed mechanism of the BSE is described in [21]. The commercial thoracic lumbar sacral orthosis (TLSO) was replaced with a hip brace to allow natural spine flexion. Additionally, to measure the exoskeleton trunk inclination angle, an inertial measurement unit (IMU) (EBIMU-9DOF, E2BOX Inc., Korea) was attached to the pneumatic actuation pack. For lifting assistance triggering and analysis, we fabricated a custom multi-channel sEMG measurement unit and embedded it on the BSE. An ADC was used for biopotential measurement (ADS1299, Texas Instrument, USA), with a maximum 8-channel and 1 kHz of sampling rate. The sEMG data were transferred to the central MCU (myRIO) via UART communication. Pre-gelled Ag/AgCl electrodes were attached to the muscles. This study, squat and stoop
lifting, which are representative lifting techniques in daily life, were focused on. Among the various muscles activated during lifting, the gluteus maximus (GM) and biceps femoris (BF), which are hip extensor muscles, were selected as detection muscles for squat and stoop lifting, respectively. A schematic diagram of the electrical system is shown in Fig. 1-(b). The controller generated real-time torque commands based on the measured sensor data (i.e., IMU, pressure sensor, encoder and sEMG). Custom LabVIEW (National Instruments, USA) software was developed for control, data measurement, and recording. The controller operated at a frequency of 100 Hz.

B. Muscle Activation Onset Detection Algorithm

To detect muscle activation onset quickly and accurately, we applied the Teager-Kaiser Energy Operator (TKEO). Previous studies found that, compared to the simple threshold-based method, TKEO processing on sEMG enables fast detection by increasing the signal-to-noise ratio (SNR) [29], [30]. Moreover, TKEO induces negligible latency, making it suitable for real-time muscle activation onset detection.

The sEMG signal was band-pass filtered using a second-order Butterworth filter with 20 Hz and 450 Hz cut-off frequencies. Then, TKEO-processing was applied to the filtered sEMG as follows:

$$\Psi(n) = s^2(n) - s(n+1)s(n-1)$$

Here, \(\Psi(n)\) and s(n) are the TKEO-processed and band-pass filtered sEMG values at the nth sampling time (n), respectively. The TKEO induces a one-sample time delay in real-time operation. The threshold for the TKEO-processed sEMG was obtained as follows:

$$\eta_{ikeo} = \mu + \sigma J$$

Here, \(\mu\) and \(\sigma\) are the mean and standard deviation of the TKEO-processed sEMG during non-activated state. J is a multiplier that can be arbitrarily selected. Since the baseline noise level was very low, J was set at 15 based on the previous study’s suggestion [31]. When the rectified TKEO-processed sEMG value exceeds the threshold \(\eta_{ikeo}\), the muscle is considered to be activated.

C. Finite-State Machine (FSM) Based Assistive Strategy

The controller architecture is shown in Fig. 2. First, the FSM estimates the current state. Assistive torque was only provided in the lifting state and was set to zero (i.e., transparency control) for other states. The desired torque profile (\(\tau_{des}\)) for lifting state is generated and the assistive torque is converted to the desired pressure (\(P_{des}\)) through the actuator inverse model. Then, the actual pneumatic pressure (\(P_{act}\)) for the actuator is controlled by a closed-loop pressure controller in a pneumatic regulator. Finally, the assistive torque is provided to the human-exoskeleton system (\(\tau_{act}\)).

The state transition criteria are described as follows and are also summarized in Table I:

1. Others to Flexion (T01): State 0 (Others) is defined as any movement that is not directly related to lifting, for example, walking, sitting, and upright posture. During State 0, the actuator exhibits transparency to avoid hindering movements.

2. Flexion (T1): State 1 (Flexion) is defined as trunk and hip flexion movement to reach an external load on the ground. Therefore, only when the average of both hip joint angles (\(\theta_{h,m}\)), the difference between both hip joint angles (\(\theta_{h,d}\)), and the trunk angle (\(\theta_t\)) were below certain thresholds (\(\eta_1, \eta_2\), and \(\eta_3\) respectively) was the state classified as State 1. State 1 is distinguished...
TABLE I
DESCRIPTIONS OF TRANSITION BETWEEN STATES
OF FINITE-STATE MACHINE

| Transition | Description                                                                 | Condition                                      |
|------------|-----------------------------------------------------------------------------|------------------------------------------------|
| T01        | Trunk and both hip joints starts to flex simultaneously                      | \( \theta_{h,m} < \eta_1 \) and \( \theta_{h,a} < \eta_2 \) and \( \theta_1 < \eta_3 \) |
| T12        | Maximum hip flexion occurs to grasp the external load                         | \( \theta_{h,m} < \eta_4 \) and \( \theta_{h,m} < \eta_5 \) |
| T23,emg    | Muscle activation onset is detected                                           | \( |\Psi(n)| > \eta_{keo} \)                        |
| T23,kin    | Kinematic onset is detected                                                  | \( \dot{\theta}_{h,m} > \eta_6 \)              |
| Tn0 \((n=1,2,3)\) | Trunk and both hip joints are extended to upright posture                      | \( \theta_{h,m} > \eta_7 \) and \( \theta_1 > \eta_8 \) |

Fig. 3. Kinematic and sEMG data during repetitive liftings. (a) The averaged hip joint angle, (b) raw sEMG signal of BF muscle, (c) TKEO-processed BF sEMG signal, and (d) estimated state from FSM are shown. The threshold value for the TKEO-processed sEMG is shown in (c) as a blue solid line. In (d), state estimated by sEMG and kinematics-based detection are shown by the red solid line and black dashed line, respectively. Lifting state onset timings for the sEMG and kinematics-based detection are shown in (a), (b) and (c) as red and black dashed lines, respectively.

D. Desired Torque Profile Generation

In all states except the lifting state, the exoskeleton maintained a transparent mode. Since the actual pressure of the pneumatic cylinder was maintained at 0 in the transparent mode, resistance torque came only from friction force of the pneumatic cylinder. In the assistive mode, the desired torque was calculated based on the trunk inclination angle \([32]\) to provide assistance during the lifting state (State 3). The desired torque profile is as follows:

\[
\tau_{des} = \begin{cases} 
M \sin \theta_t, & S = 3, t \geq t_{ext} \\
0, & \text{otherwise}
\end{cases}
\]

\( \tau_{des} \) is the desired torque and \( M \) is the torque magnitude gain normalized to the user’s body weight \((Nm/kg)\). \( \theta_t \) is the trunk inclination angle, \( S \) is the current state, \( t \) is the time elapsed from lifting onset and \( t_{ext} \) is the extra latency to modulate the assistance timing.

III. EXPERIMENTAL EVALUATION

A. Experimental Setup

Nine healthy male subjects (age of 23.1±2.1 years; height of 171±3.6 cm; weight of 68.7±4.5 kg) who had no history of LBP volunteered for the experiments. An instruction and practice sessions for squat and stoop lifting were provided to each subject prior to the main experiments. Position of the feet was set based on self-preference and was maintained throughout the experiment. The external load dimensions were 49×35×19 cm.

sEMG electrodes were attached at the right side of L1 vertebral level of longissimus thoracis (L1), L5 vertebral level of multifidus muscles (L5), biceps femoris (BF), gluteus maximus (GM), vastus lateralis (VL) according to SENIAM guidelines [33], as shown in Fig. 4-(b) and (c). Note that L1, L5, and VL muscle data were used only for analysis whereas BF and GM muscle data were used for exoskeleton control and analysis. The sEMG data were sampled at 1 kHz. All sEMG sensors were attached after skin preparation using alcohol swabs. During the experiment, the subjects were asked to report lifting detection errors to the experimenter. All the experimental condition orders were randomized.

from State 0 in that it can assist flexion; however, since only lifting assistance was focused on in this study, we maintained transparency in State 1.

2) Flexion to Grasping (T12): After sufficient hip joint flexion \( (\theta_{h,m} < \eta_4) \), the maximum hip joint flexion \( (\dot{\theta}_{h,m} < \eta_5) \) and grasping of the external load occur in State 2 (Grasping).

3) Grasping to Lifting (T23,emg): State 3 (Lifting) is detected when the TKEO-processed sEMG \( (\Psi(n)) \) of GM and BF muscles exceed thresholds \( (\eta_{keo}) \) for squat and stoop lifting, respectively. The EA was provided based on sEMG-based lifting detection.

4) Grasping to Lifting (T23,kin): State 3 (Lifting) is detected by kinematics change, when the hip joint angular velocity \( (\dot{\theta}_{h,m}) \) exceeds a certain threshold \( (\eta_6) \). KA was provided based on the kinematics-based lifting detection.

5) State n to Others (Tn0) \((n=1,2,3)\): If the averaged hip joint angle and trunk angle reach certain threshold \( (\eta_7, \eta_8) \) the states (State 1, 2, 3) are initialized to State 0 (Others).
Fig. 4. Experimental setup. (a) Real-time visual and auditory feedback on lifting frequency were provided to the subjects. (b) sEMG electrodes were attached to the back muscles (L1 and L5), and (c) leg muscles (BF, GM, and VL).

The experimental protocol was approved by the Institutional Review Board of Korea Advanced Institute of Science and Technology (KAIST) (KH2016-62, approved on 8/1/2019). Written informed consent and assent were obtained from each participant.

B. Experimental Protocol

1) External Loads Test: The effect of external loads on detection latency was evaluated. Subjects performed lifting using two techniques (squat and stoop) with four weights (0 kg, 7.5 kg, 15 kg, and 22.5 kg) with EA, resulting in eight experimental conditions. Five self-paced liftings were performed for each condition, and a 5 min break was provided between each condition to prevent muscle fatigue. The assistive torque magnitude parameter was set at a constant \( M = 0.6 \text{ Nm/kg} \) and the external load was 15 kg.

2) Extra Latency Test: The effect of extra latency on muscle activity was evaluated. A manual switch was also used for comparison. During the grasping state, subjects could trigger the assistance manually by pressing the switch installed on the external load. Subjects performed lifting using two techniques (squat and stoop) with four extra latencies \( t_{\text{extra}} = \) manual switch, 0 ms, 100 ms, 200 ms) with EA, resulting in eight experimental conditions. 

3) Repetitive Lifting Test: Muscle fatigue during repetitive lifting was estimated and compared. Subjects performed lifting using two techniques (squat and stoop) with two assistive strategies (KA and EA), resulting in four experimental conditions. The lifting frequency was maintained constant (12 liftings per minute) for 3 min for each condition. Subjects were provided with visual and auditory cues (metronome) for the lifting frequency as shown in Fig. 4-(a). A 20 min break was provided to recover from fatigue between each condition. The assistive torque magnitude parameter for KA was greater than for EA to maintain the same mechanical work for both assistive strategies. The external load was 15 kg.

C. Data Analysis

The experimental data were analyzed by defining the performance metrics and statistical analysis was conducted (SPSS Statistics 26, IBM, USA). The normality and sphericity of the data were checked with the Shapiro-Wilk test and Mauchly’s test, respectively. Paired t-tests and one-way repeated-measures ANOVA with LSD post-hoc analysis were performed. If normality is not satisfied, Wilcoxon signed-rank tests were conducted. If sphericity is not satisfied, the Greenhouse-Geisser correction was used. The significance level was 0.05.

1) Muscle Activity: In the extra latency test, muscle activities during each lifting were estimated using the integrated sEMG (iEMG), as follows [22]:

\[
Y_n = \Delta t \sum_{i=1}^{N} X_i
\]

\( Y_n \), \( \Delta t \), and \( N \) are the iEMG of the \( n \)th lifting state, sampling time, and the number of samples in each lifting state, respectively. The \( i \)th raw sEMG sample was rectified, second-order Butterworth low-pass filtered with a 2.7 Hz cutoff frequency, and normalized by the maximum amplitude to obtain \( X_i \). The iEMG values for each muscle were averaged for all conditions. Finally, for statistical analysis, the iEMG values for all subjects were averaged for each conditions. One-way repeated-measures ANOVA was used.

2) Muscle Fatigue: Mean frequency of the sEMG power spectrum (MNF) is a widely accepted index for muscle fatigue, not only for static contraction but also for dynamic contraction as long as the range of motion is consistent [34]. Since a decreasing trend in the power spectrum of sEMG is observed as muscle fatigue occurs, a reduction in MNF was utilized to estimate muscle fatigue.

The MNF values of each lifting were grouped in epochs; these consisted of four liftings. The grouped MNF values of each muscle during first and last epoch were averaged.
Table II
Summary of Results for Three Experiments (Mean±SD)

| External load (kg) | Latency (ms) | iEMG (%Max. v) |
|-------------------|--------------|----------------|
|                   | squat        | stoop          |                |
| 0                 | 114±52.1     | 163±76.1       |
| 7.5               | 125±57.3     | 159±67.8       |
| 15                | 176±70.2     | 194±65.8       |
| 22.5              | 202±72.1     | 269±192        |

| Extra latency (ms) | mnS | BP | GM | VL | L1 | L5 | GF | GM | VL | L1 | L5 | GF | GM | VL |
|-------------------|-----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| manual switch     | 48.1±22.5 | 48.1±93.3 | 44.7±11.8 | 42.8±73.5 | 50.4±13.7 | 47.5±20.6 | 42.7±17.5 | 56.2±11.4 | 42.2±73.5 | 32.2±13.5 |
| 0                 | 37.0±18.4 | 36.1±11.6 | 37.5±11.0 | 37.5±9.81 | 41.2±14.3 | 36.8±17.8 | 37.3±14.6 | 44.8±12.6 | 35.1±9.01 | 26.6±6.71 |
| 100               | 39.3±23.4 | 35.3±13.5 | 41.1±16.2 | 37.4±6.90 | 45.7±15.9 | 44.8±18.0 | 37.8±14.2 | 48.7±13.7 | 36.0±9.64 | 25.2±6.38 |
| 200               | 44.0±22.5 | 41.8±8.94 | 41.4±16.7 | 35.5±9.12 | 49.6±20.7 | 51.5±20.8 | 44.2±15.7 | 53.7±22.3 | 37.2±11.3 | 33.2±13.5 |

| Assistance method | MNF reduction ratio (%) |
|-------------------|-------------------------|
| KA                | L1 | L5 | BP | GM | VL | L1 | L5 | GF | GM | VL | L1 | L5 | GF | GM | VL |
|                  | 5.23±5.80 | 6.32±7.03 | 0.334±1.00 | 2.74±4.31 | 4.13±3.16 | 6.33±5.66 | 6.62±7.59 | 0.957±2.36 | 2.14±4.40 | 5.21±5.75 |
| EA                | 4.50±5.60 | 3.29±5.34 | 2.27±4.19 | 2.88±4.25 | 2.00±3.05 | 1.88±2.69 | 7.95±9.44 | 1.67±1.73 | 1.19±1.79 | 4.21±2.68 |

Fig. 5. MNF of back muscle during repetitive liftings for one representative subject. First and last epochs are shown as blue and red regions. $f_{m,i}$ and $f_{m,f}$ represent averaged MNF of the first and last epochs, respectively.

An example of MNF trajectory during repetitive lifting is shown in Fig. 5. $f_{m,i}$ and $f_{m,f}$ are the averaged MNF of the first and last epochs, respectively. Finally, the MNF reduction ratio ($r$), which represents muscle fatigue, was defined as follows:

$$r = \frac{\Delta f_m}{f_{m,i}} \times 100\%$$  (5)

$\Delta f_m$ is the difference between $f_{m,i}$ and $f_{m,f}$. The MNF reduction ratios of each muscle were averaged across all subjects for statistical analysis.

3) Latency: In the external loads test, the latency ($\delta$) was defined as the time difference between onset timings of the kinematics and sEMG-based detections, as follows [26]:

$$\delta = t_{kin} - t_{emg}$$  (6)

Positive latency implies that lifting is detected earlier by sEMG-based detection than by kinematics-based detection. One-way repeated-measures ANOVA was used for each external loads condition.

IV. RESULTS

This section presents three experimental results for latency, muscle activity, and muscle fatigue. All detection errors reported by subjects were excluded from the analysis. The detection accuracies of KA and EA were 92.6% and 96.2%, respectively; and there was no statistically significant difference (paired-t test, $p>0.05$). The results are summarized in Table II. As the external load increases, the detection latency increase, as shown in Fig. 6. In the 15 kg and 22.5 kg squat lifting conditions, the detection latency significantly increased compared with the 0 kg condition ($p = 0.013, 0.0069$), by 54.4% and 77.2%, respectively. Also, in the 22.5 kg squat lifting condition, the latency significantly increased compared with the 7.5 kg and 15 kg conditions ($p = 0.015, 0.013$), by 61.6% and 14.8%, respectively. In the 22.5 kg stoop lifting condition, latency significantly increased compared with the 0 kg and 7.5 kg conditions ($p = 0.012, 0.040$), by 65.0% and 27.5%, respectively. No statistically significant difference was observed in other pairs.

An example of the assistive torque profiles for a single subject according to the extra latency conditions is shown.
In the 0 ms stoop lifting conditions for the BF muscle, the iEMG significantly decreased compared with the manual switch condition by 23.1% and 18.3%, respectively. For the L5 muscle, in the 0 ms and 100 ms squat lifting conditions, the muscle activity increases, except for the muscle activities were observed for all conditions. As the extra latency increases, the muscle activity increases, except for the VM muscle. For the stoop lifting, the MNF reduction ratio was significantly reduced under fast assistance compared with the KA condition, only for the GM muscle. For the L1 muscle, in the stoop lifting, the MNF reduction ratio was presented in Fig. 7-(b). Although the greatest mechanical work was delivered to user. For the squat lifting, the work was 0.91 J/kg, 0.84 J/kg, 0.80 J/kg and 0.66 J/kg for the manual switch, 0 ms, 100 ms and 200 ms of extra latency conditions, respectively. For the stoop lifting, the work was 0.86 J/kg, 0.82 J/kg, 0.70 J/kg and 0.64 J/kg for manual switch, 0 ms, 100 ms and 200 ms of extra latency conditions, respectively. The work was the greatest at the manual switch condition, and significantly decreased as the extra latency increased as shown in Fig. 7-(b). The iEMG of each muscle averaged across all subjects for each condition was averaged across all subjects shown in (a). The mean (±SD) normalized mechanical work averaged across all subjects for extra latency conditions are presented in (b). The mechanical work significantly decreased with extra latency (*p < 0.05).

The torque profiles were normalized by lifting cycle. As the assistance is delayed, less mechanical work was delivered to user. For the squat lifting, the work was 0.91 J/kg, 0.84 J/kg, 0.80 J/kg and 0.66 J/kg for the manual switch, 0 ms, 100 ms and 200 ms of extra latency conditions, respectively. For the stoop lifting, the work was 0.86 J/kg, 0.82 J/kg, 0.70 J/kg and 0.64 J/kg for manual switch, 0 ms, 100 ms and 200 ms of extra latency conditions, respectively. The work was the greatest at the manual switch condition, and significantly decreased as the extra latency increased as shown in Fig. 7-(b). The iEMG of each muscle averaged across all subjects for each condition was presented in (a). The mean (±SD) normalized mechanical work averaged across all subjects for extra latency conditions are presented in (b). The mechanical work significantly decreased with extra latency (*p < 0.05).

The iEMG values significantly reduced under fast assistance compared with the manual switch condition (*p = 0.0004, 0.0011), by 23.1% and 18.3%, respectively. For the L5 muscle, in the 0 ms squat lifting conditions, the iEMG significantly decreased compared with the manual switch condition (*p = 0.0023, 0.0032), by 24.9% and 26.6%, respectively. In the 0 ms stoop lifting conditions for the BF muscle, the iEMG significantly decreased compared with the manual switch condition (*p = 0.011), by 20.3%. For the VL muscle, in the 0 ms squat lifting conditions, the iEMG significantly decreased compared with the manual switch and 200ms conditions (*p = 0.010, 0.029), by 18.3% and 16.9%, respectively. No statistically significant difference was observed in other pairs.

An example of MNF reduction during repetitive lifting tests for a single subject is illustrated in Fig. 9-(a). The MNF values of each muscles decreased over the 36 liftings for each condition. The results considering all subjects are shown in Fig. 9-(b). Although the EA condition reduced the back muscle fatigue compared with the KA condition, only for the L1 muscle, in the stoop lifting, the MNF reduction ratio was significantly reduced (*p = 0.011) by 70.4%. No statistically significant difference was observed for the muscle activities during the first epoch as shown in Fig. 10. Since the torque parameter for KA was greater than the EA condition, the mechanical work differences were compensated. The work delivered for each condition was averaged across all subjects and shown in Fig. 11. No statistically significant difference was observed.
This study focused on developing and evaluating sEMG-triggered fast lifting assistance with a BSE. We developed an assistive strategy using sEMG and conducted three lifting experiments. The proposed strategy was evaluated in terms of latency, muscle activity, and muscle fatigue.

A. External Loads Effects on Latency

In the external loads test, the latency significantly increased for both squat and stoop lifting as the external load increased. This is because heavier external loads reduce lifting speed [35], which induce delay on kinematics-based lifting detection onset timing. However, no statistically significant difference was observed in latency values between 0 kg and 7.5 kg conditions, and 7.5 kg and 15 kg conditions. This is probably because, depending on individual muscle strength, those conditions did not make a significant difference in lifting speed for some strong subjects. Since the experiments were conducted on healthy young adult males, statistical significance could be found if the experiment were to be conducted by recruiting more subjects including a broader range of ages and genders.

B. Extra Latency Effects on Muscle Activity

In the extra latency test, 0 ms or 100 ms conditions minimized muscle activity, whereas manual switch conditions maximized muscle activity for each muscle, except for the GM muscle. Statistical significances were observed in L1, L5, and VL for squat lifting, and BF for stoop lifting. Although the manual switch and 0 ms conditions delivered a similar amount of work, the muscle activity difference was greatest among other pairs. Therefore, too fast assistance such as manual switch, even if it delivers a greater amount of work, negatively affects assistance efficiency. For example, several subjects rarely lost balance at the manual switch and 0 ms conditions in stoop lifting. This is probably because the assistance induced early knee extension torque development before knee flexion torque development from the BF muscle, which decreased the knee joint stability [36]. The optimal assistance timing range is 0 ms to 100 ms of extra latency for both squat and stoop lifting. In the 15 kg of external load condition, 176 ms and 194 ms of latencies were observed for squat and stoop lifting respectively, EA is recommended rather than KA.

V. DISCUSSION

This study focused on developing and evaluating sEMG-triggered fast lifting assistance with a BSE. We developed an assistive strategy using sEMG and conducted three lifting experiments. The proposed strategy was evaluated in terms of latency, muscle activity, and muscle fatigue.

A. External Loads Effects on Latency

In the external loads test, the latency significantly increased for both squat and stoop lifting as the external load increased. This is because heavier external loads reduce lifting speed [35], which induce delay on kinematics-based lifting detection onset timing. However, no statistically significant difference was observed in latency values between 0 kg and 7.5 kg conditions, and 7.5 kg and 15 kg conditions. This is probably because, depending on individual muscle strength, those conditions did not make a significant difference in lifting speed for some strong subjects. Since the experiments were conducted on healthy young adult males, statistical significance could be found if the experiment were to be conducted by recruiting more subjects including a broader range of ages and genders.

B. Extra Latency Effects on Muscle Activity

In the extra latency test, 0 ms or 100 ms conditions minimized muscle activity, whereas manual switch conditions maximized muscle activity for each muscle, except for the GM muscle. Statistical significances were observed in L1, L5, and VL for squat lifting, and BF for stoop lifting. Although the manual switch and 0 ms conditions delivered a similar amount of work, the muscle activity difference was greatest among other pairs. Therefore, too fast assistance such as manual switch, even if it delivers a greater amount of work, negatively affects assistance efficiency. For example, several subjects rarely lost balance at the manual switch and 0 ms conditions in stoop lifting. This is probably because the assistance induced early knee extension torque development before knee flexion torque development from the BF muscle, which decreased the knee joint stability [36]. The optimal assistance timing range is 0 ms to 100 ms of extra latency for both squat and stoop lifting. In the 15 kg of external load condition, 176 ms and 194 ms of latencies were observed for squat and stoop lifting respectively, EA is recommended rather than KA.
Specifically, customized extra latency could be added from EA depending on the individual preference. In future work, it could be possible to find optimal assistance parameters such as assistance timing and magnitude by using the human-in-the-loop (HIL) optimization technique [37].

C. sEMG-Triggered Fast Assistance Effects on Muscle Fatigue

In the extra latency test, mechanical work decreased as extra latency increased, because the torque parameter \( M \) was maintained constant. Muscle activity increased as the work decreased. However, in the repetitive lifting test, the mechanical work was compensated by increasing the torque parameter \( M \) for KA. Consequently, no significant difference in muscle activities between KA and EA conditions was found. Nevertheless, muscle fatigue for the L1 muscle in stoop lifting significantly decreased in EA compared with the KA condition. This is probably because, for KA, no assistance is provided from muscle activation onset to kinematics onset which imposes greatest burden to user. Therefore, accumulated fatigue is greater in KA than in EA in repetitive lifting. Note that although the work was compensated for KA to observe the effect of only assistance timing, compensation is unfeasible in real-working scenario because the latency is not known in advance, and the actuator torque capacity is limited.

D. Comparison With Previous Works

The experimental results showed that the fast assistance (0 ms and 100 ms) is optimal assistance timing except for the manual switch based assistance. This is inconsistent with previous research on optimal assistance timing of an elbow exoskeleton [28]. This is probably because, no external load was presented in the study. Since the latency increases under external load conditions, the experimental results might be affected under external load conditions. Also, the actuator has a shorter response time than the pneumatic actuator in this study, which might be why the delayed assistance is optimal timing.

In a previous study of BSE using a conventional KA strategy [22], the latency increased as the lifting speed decreased, consistent with this study. The authors claimed that even if the latency was introduced, it did not significantly degrade assistance efficiency. This seems because the external load was 5 kg, which is relatively lower compared to this study, there was no significant effect on assistance efficiency. However, as shown in the experimental results, the EA will be more beneficial in heavier external loads regarding muscle activity and muscle fatigue because the assistance from KA will be delayed and deliver less mechanical work.

In the external load tests, greater mechanical work introduced less muscle activity, consistent with previous results [38]. The suggested accelerometer-based control strategy provided more work than the conventional trunk inclination-based control strategy and reduced back muscle activity. Therefore, mechanical work is important factor in muscle activity. However, as shown in the repetitive lifting test, fatigue was reduced in fast assistance conditions even under the same work conditions. Therefore, fast assistance is also crucial for muscle fatigue reduction.

E. Practicality and Robustness of the EA Strategy

Using sEMG sensors introduces additional inconveniences compared with using exoskeleton-embedded mechanical sensors. We minimized the inconvenience by developing a low-noise, multi-channel sEMG measurement unit that can be embedded in the BSE system. However, since the sEMG electrodes require attachment and replacement for long-term operation, some inconvenience is unavoidable. Therefore, studies have been conducted on stable long-term operation, such as improving stability with flexible microneedle array sEMG electrode [39], and tattoo-like sEMG patch [40], candidates for improving the practicality for future work. Also, when the external load is between 0 kg and 7.5 kg in squat lifting, the latency is close to 100 ms (114 ms and 125 ms). Therefore, KA might be acceptable for lightweight lifting for performance and practicality. However, in heavy weight lifting, EA is proposed to prevent LBP.

The robustness of sEMG-triggered lifting detection should be considered because the muscle fatigue, sweat and electrode position changes can affect sEMG signals. In repetitive lifting tests, less muscle fatigue in detection muscles (BF and GM) was observed compared with back muscles (L1 and L5). We selected one subject with the greatest muscle fatigue (7.18% of MNF reduction ratio) on the BF muscle during tests, less muscle fatigue in detection muscles (BF and GM) during the repetitive lifting test. For versatility and practicality, the sEMG electrodes can be embedded inside customized clothing for individual users after finding proper electrode positions [44], [45], to eliminate repositioning electrodes for daily use.

F. Limitations

This study has several limitations. The proposed EA strategy was evaluated for only squat and stoop lifting. For versatility
We expect that the proposed fast lifting assistance strategy can be applied to other BSEs to improve the assistance efficiency. Furthermore, the proposed strategy will be beneficial not only for BSEs but also for various industrial exoskeleton applications that handle heavy external loads.

VI. CONCLUSION

In this study, we developed an EA for BSE and systematically evaluated it in a set of lifting experiments. To the best of the authors’ knowledge, this is the first attempt to investigate the effectiveness of a fast assistance strategy of assistive exoskeleton interacting with external loads. This study reported several novel findings. First, the time difference between the onset timings for EA and KA strategies increased significantly with external loads. This implies that, the heavier the external loads, the more beneficial the proposed EA strategy is than the conventional KA strategy because greater latency degrades assistance performance. Second, we proposed an optimal extra assistance latency range of 0 ms to 100 ms, minimizing the muscle activity. Interestingly, although the manual switch provided the greatest work, the muscle activity was maximized, indicating that fast assistance is beneficial, but too fast assistance negatively affects the assistance performance. Third, we investigated the effects of only assistance timing. Although no significant difference was found in the muscle activities of KA and EA conditions in repetitive lifting tests, back muscle fatigue significantly decreased in EA with stoop lifting conditions. Therefore, fast assistance is crucial for assistance performance regarding muscle fatigue.

Fig. 12. Latency values of a single subject with muscle fatigue on the detection muscle (BF) during 36 liftings divided into three groups. The mean (±SD) latency values for each group in repetitive lifting tests. No significant difference between the latency values for each group was found (*p < 0.05).

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