Let Me Give You a Hand: Enhancing Human Grasp Force with a Soft Robotic Assistive Glove

Cem Suulker[1], *Student Member, IEEE,* Alexander Greenway[1], Sophie Skach[1], Ildar Farkhatdinov[2,1], Stuart Miller[3], and Kaspar Althoefer[1], *Senior Member, IEEE*

***Abstract*—Soft robotic gloves are designed to assist individuals with daily tasks that involve grasping. Such devices are however often hampered by an inability to generate enough force to enable them to perform the tasks for which they were designed. This study evaluates the grasping capabilities of a novel textile soft robotic glove, which has performance-enhancing integrated elastic band actuators. We conducted a user study with 20 participants to assess the assistive glove's effectiveness. Our novel evaluation method, using surface electromyography sensors to measure muscle activity, enabled us to determine the respective grasping force contributions of the assistive device and the user. Our findings indicate that the device provides consistent grasp assistance across a force range from 20 to 80 Newtons. Average assistance for the fingers was 15.8 Newtons, with a maximum of 33.3 Newtons, while for the thumb it averaged at 12.4 Newtons, with a maximum of 23.3 Newtons. The results were validated using Linear Mixed-Effects Models, demonstrating statistically significant findings with p values of below 0.01. A user satisfaction survey (QUEST 2.0) suggested high perceived value given its excellent rating of 4.53 out of 5. Overall, these results suggest that the device can make a significant difference, helping users when performing grasping tasks.**

***Index Terms*—Soft Robotic Glove; Wearable Robotics; Soft Robot Applications; Soft Actuators.**

I. INTRODUCTION

HUMANS depend heavily on their fingers for everyday tasks involving pinching or grasping different objects. However, neurodegenerative disorders such as strokes or Parkinson's disease can restrict dexterity [1]. Wearable robotic devices have been developed to assist with these tasks [2], achieving increasing success. Beyond mentioned disorders, hand-wearable robots can enhance human capabilities, such as lifting heavy objects (for example when moving furniture) and supporting industrial applications where mobility is essential.

Actuators can guide fingers into a grasp position and apply forces to the target object [3]. Recent advancements in soft robotics have emphasized soft actuators over rigid ones, improving user safety and comfort through soft materials [4]. Pneumatically driven elastomers and textile structures have proven reliable for achieving the necessary blocking force and finger bending for many daily tasks [5], [6]. These wearable soft robotic structures are evidently more convenient due to their lighter weight and safer nature compared to rigid links and rotary motors.

Existing literature offers established methods for evaluating hand-wearable assistive devices using user studies. For instance, the Jebsen Taylor hand function test assesses benefits through various manipulation tasks like writing and turning over cards [7]. The box and blocks test times participant actions with a single box manipulation task [8]. These tests are effective for groups with compromised manual dexterity but working with such groups present challenges, including ensuring the prototype's safety for fragile individuals and addressing complex ethical issues.

To avoid these challenges, researchers often work with healthy individuals, but this introduces complexities related to trust, as their natural dexterity can skew results by overriding or aiding the robotic device. This issue is particularly acute with soft robotic devices due to their high flexibility and low actuation force. Instead, Electromyography (EMG) sensing should be considered to quantify the assistance provided by the robotic device.

In relation to hand-worn robotic systems, surface EMG (sEMG) sensors are used to measure electrical signals generated by muscles during contraction, providing critical insights into muscle activity, aiding in biomechanical research [9], rehabilitation [10], the development of prosthetics [11] or assistive devices [12]. In these cases, EMG signals are mostly used to understand better user intention and help guiding the limbs. Some studies have used EMG signals to establish whether users are applying forces that may be overriding the robotic system [13]. However, given the significant variation in task intensities, using EMG signals to evaluate the overall effectiveness of a hand-worn device is unprecedented in the literature. The wealth of critical information it can however provide about the effectiveness of a robotic device is significant and for this reason is the central focus of this paper.

In this paper, we introduce an sEMG sensor-validated method to evaluate the effectiveness of a wearable assistive hand device. Using this novel method, we evaluate our soft robotic glove and demonstrate its effectiveness in aiding

---

Manuscript received: March, 26, Year; Revised June, 27, 2024; Accepted July, 10, 2024.

This paper was recommended for publication by Editor Pietro Valdastri upon evaluation of the Associate Editor and Reviewers' comments.

The work of Cem Suulker was supported by the Ministry of National Education of Turkey.

[1] Authors are with the Centre for Advanced Robotics @ Queen Mary, School of Engineering and Materials Science, Queen Mary University of London, United Kingdom, `c.suulker@qmul.ac.uk`

[2] The author is with the School of Biomedical Engineering and Imaging Sciences, King's College London, United Kingdom.

[3] The author is with the William Harvey Research Institute, Barts & The London School of Medicine & Dentistry, Queen Mary University of London, United Kingdom.

Digital Object Identifier (DOI): see top of this page.

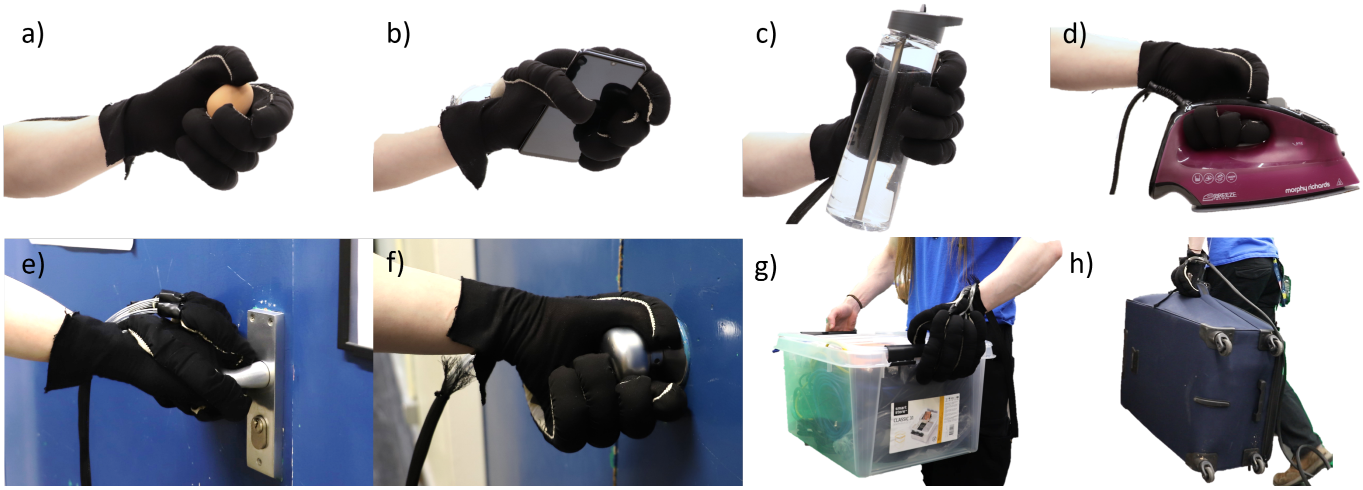

Fig. 1. The soft robotic glove prototype in the action of assisting the user in different weights of objects (a) 67 g, b) 192 g c) 818 g, d) 1.24 kg), opening door (e,f) and lifting heavy weight objects (g) 12.35 kg, h) 6.02 kg). The assistive device is so strong and efficient that, with 10 psi actuation pressure, it can lift and hold on to objects b, c, d, and h without a hand in it. Please refer to the multimedia attachment to see the assistive device in action.

grasping tasks. EMG signals are recorded as participants apply varying levels of grasp force to an object with an integrated force sensor, both with and without robotic assistance. The benefits of the assistive device are quantified using linear mixed-effects models (LMMs).

The key contributions of this paper are as follows:

- We introduce a novel assessment method that enables us to test the effectiveness of a hand-worn assistive device for both patients and healthy subjects, by determining the relative force contributions of the device and of the user.
- Using this method, we evaluate the performance of our soft robotic glove, with its integrated high force-capable ruffled actuators, demonstrating that the assistive device can indeed aid in grasping.
- We show that our soft robotic glove supports the hand, offering up to 33.3 N (Participant #5) of force for the fingers (mean score 15.8 N), and up to 23.3 N (Participant #13) of force to the thumb (mean score 12.4 N). These results are impressive when compared to other works in the literature, that focus on the power grasp — examples being [12], [13].
- We report that our soft robotic glove assists users in 66–100% of tasks requiring a 20 N power grasp force. This suggests that for most everyday activities, the assistive device does provide sufficient support [1].

II. MATERIALS

The materials used in this study include a wearable soft robotic assistive hand device, EMG sensing components, and a force sensor test rig.

A. The soft robotic assistive glove

The assistive device used in this study, as shown in Figure 3 a), is a soft robotic glove that was engineered for its ability to apply high forces to flex the hand [14]. When textile bending actuators placed on the dorsal side of the glove are inflated under pneumatic pressure, the fingers bend leading to closure of the hand. Finger extension, and as a result, hand opening, is achieved via another set of pneumatically driven actuators positioned directly below those that induce flexion.

The assistive device is made from textile materials, ensuring that it is lightweight and comfortable. The basic glove is made using four-way stretchable fabric (viscose jersey knit) so that the glove offers a snug fit irrespective of hand size — effectively a ’one-size-fits-all’ solution. Given that the feel of fabric on the skin is a familiar sensation, we anticipate that a textile-based assistive device will naturally be more agreeable to the end user. It is also extremely lightweight (between 50 and 80 g, depending on whether the integrated tubes are supported or need to be ”carried” by the user), which is a further bonus when considering that many users are likely to be frail and/or vulnerable.

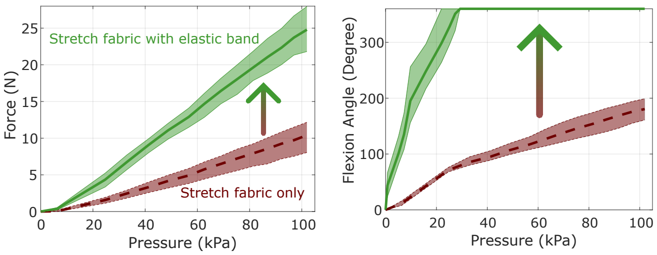

Fig. 2. The actuators selected for the assistive glove are optimized both in force and bending angle capabilities. Integration of elastic bands using the ”ruffles” method enhances the force (left) and bending angle (right) potential of the actuator. The data were gathered from three identical actuators, each undergoing five repetitions. The transparent area represents the range between the minimum and maximum boundaries.

The performance of the actuators that guide fingers into a flexion position is critical in this study, as they directly affect grasp success. For this reason, we chose high-force-capable elastic band integrated fabric actuators [14]. Due to their exceptional force-enhancing and lightweight design, this choice of actuators ensured both high comfort and performance efficiency. The selection criteria for the actuator material included the following:

- The bottom layer should be non-stretch but compressible, so we opted for a **plain cotton weave** — a cheap and comfortable option.
- Although the top layer should be able to expand and guide the bending direction of the actuator, it should only stretch in the desired direction. For this layer, we therefore used **a cotton mix with elastane yarn integrated into the weft** of the fabric.
- The actuators were tailored utilizing a technique known as ruffles, in which two layers of fabric are combined, using **elastic bands**, such that there is more material on one side (the top side in this case).

Because of the additional material, the top side exhibits greater extension which in turn results in a higher blocking force potential (Figure 2). Four identical elastic band-enhanced actuators, each 16 cm long and 3 cm wide, were positioned on the dorsal side of the hand, from near the wrist to just above the nail area of each finger. The actuator for the thumb was made differently to reflect its natural spiral motion. The actuators are driven at around 69 kPa (10 psi) pneumatic pressure for this study, as this value is considered their nominal pressure value. The control system for the glove consists of a button interface, and an SMC ITV2050-212BL4 pneumatic pressure regulator. Communication between the two is facilitated by an Arduino Uno board. The final exoskeleton prototype can be seen 'in action' in Figure 1.

B. EMG sensing

To validate the assumption that the glove decreases the muscle effort that users themselves are required to apply, sEMG signals were acquired using two SKU:SEN0240 Analog EMG Sensors from OyMotion which transferred data to a Simulink model using a F28069M LaunchPad board. One EMG sensor was attached to the Flexor Pollicis Longus to detect signals from thumb activation, and the second to the Flexor Digitorum Profundus to detect signals from activation of the four fingers (Figure 3 c).

The EMG Signals were processed by applying a notch filter at 50 Hz to remove unwanted noise from the electrical systems, along with a high-pass filter at 20 Hz and a low-pass filter at 450 Hz as the majority of EMG signals fall within this range [15]. A moving root mean square (RMS) was then applied to rectify the data and a moving average from a 150 sample window length was taken to remove spiking noise, then recorded in MATLAB and analysed.

C. Power grasp test rig

From eating with utensils or writing with a pen to moving furniture or climbing, we use our finger muscles to grasp. A key element in our fine motor skills repertoire, grasping plays a crucial role in allowing us to maintain our independence and quality of life — an indispensable ability in relation to a wide range of activities and interactions with our environment. In view of this, we focused on testing the ability of our soft robotic glove to assist with power grasping.

The test rig is made from 3D-printed PLA material and has a grasp width of 10 cm. A ROBOTOUS RFT40-SA01 force sensor, which can measure force/torque along six axes at a resolution of 0.2 N, is integrated into the test rig so that grasping force can be recorded (Figure 3 b). The design of the test rig ensured that force readings in the x and y directions, as well as torque readings, were negligibly small, the key reading considered being that of the z-axis.

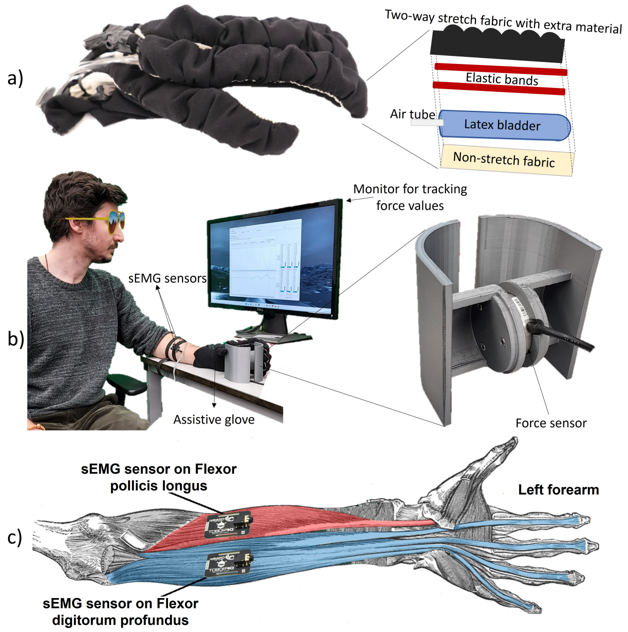

Fig. 3. a) On the left, the soft robotic glove. On the right, the elements of the actuators. b) On the left, a representation of the participant study. The participant's arm is resting on the desk, wearing the assistive device, holding the force sensor integrated object, and looking at the monitor to adjust the amount of force applied. On the right, the force sensor integrated object is shown on a bigger scale. c) sEMG sensors are placed for detecting muscle contraction for fingers to Flexor digitorum profundus (blue) and for thumb to Flexor pollicis longus (red).

III. METHODS

Participants were recruited and data was collected following ethics approval QMERC23.003 granted by Queen Mary's Ethics of Research Committee. Participants were also required to complete a consent form before the study.

A. Participant recruitment

A call-for-participants letter was circulated within Queen Mary University of London's Schools of Engineering and Material Science, and Electronic Engineering and Computer Science. It specifically requested participation from candidates who were over 18 with healthy hand muscles and normal or corrected to normal vision. No financial nor indeed any other incentives were offered. In total 20 participants committed to the study (n=20), of which 17 were male, 2 female, and 1 other/prefer not to say. 7 of them were between 18 and 25 years of age, and the other 13 in the 26–35 age range. All were right-handed.

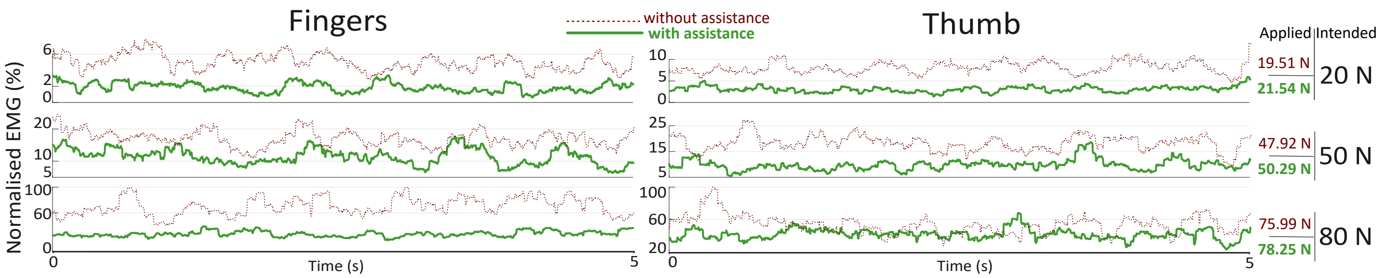

Fig. 4. Data from participant 10. The lines show the RMS EMG signals while the force sensor is grasped by applying the mentioned power grasp force value with assistance (green) and without assistance (red dotted). The mean applied forces for the trials are also given next to the graphs.

B. Experimental protocol

Each participant's arm was prepared for sEMG placement. With sensors attached, each participant was asked to position their arm on the table (Figure 3 b), grasp the test rig and exert a series of specific force values, which were set at 20-30-40-50-60-70-80 N. The lower range was set to 20 N as anything lower would require users to push against the glove to achieve that lower force value. The maximum force was set to 80 N as most activities do not require greater force. The arm was positioned naturally on the table to prevent participants from straining their wrist muscles. Additionally, participants were reminded to keep their wrists relaxed throughout the experiment. Via the integrated force sensor, each participant could see on a monitor how much force they were applying in real time, and could therefore adjust the exerted force accordingly. For each task, the glove was activated when the participant declared themselves ready, and deactivated once sufficient data had been collected. Rest periods, typically of between 1 and 2 minutes were allowed between each task. Each participant performed the task for each force value twice — once without, and once with the help of the glove. Half the participants started with the 'assisted' run-through (i.e. with glove), while the other half started with the 'unassisted' run-through.

C. Data analysis

For each force value, five-second intervals were recorded for analysis. Applied force values were recorded in 2 Hz and EMG signals were recorded in 1000 Hz. After taking a mean value, we stored EMG data for specific force values for all participants.

Data normalisation for each participant was performed using the maximum activation obtained during the most intense task (i.e., the 80 N task) — a method found to be highly reliable for comparisons between trials [16]. We then compared assisted and unassisted EMG signals for each participant, preferring the LMMs method as it gives accurate results when taking into account the multiple differences between the participants [17]. We also investigated whether the provided assistance changes for different intensity of tasks with LMMs.

D. Survey

The Quebec User Evaluation of Satisfaction with Assistive Technology (QUEST) 2.0 survey [18] is a comprehensive assessment tool designed to evaluate the quality and effectiveness of wearable assistive devices. It takes into consideration aspects such as user satisfaction, comfort, durability, and overall usability. Responses range from 1 — not satisfied at all, 2 — not very satisfied, 3 — more or less satisfied, 4 — quite satisfied, and 5 — very satisfied. Following the experimental work, each participant was asked to complete the survey.

IV. RESULTS

A. Results for a single participant

In this section, we focus solely on the data collected from participant #10, a choice made on the basis that this particular data set was deemed typical and representative of the group.

EMG signals for each force value are given in Figure 4. Red dotted lines show the participant's flexor digitorum profundus (left, labeled as 'Fingers'), and flexor pollicis longus (right, labeled as 'Thumb') muscle intensity during non-assisted task performance, while green lines show the same muscle's effort when performing the same task wearing the soft robotic assistive glove. The mean applied force for each task (here we present data for the 20, 50 and 80 N tasks — with and without assistance) is also shown in Figure 4. We note that the applied forces are quite close to their intended values, and also that the other force values, though not presented here, do follow a similar pattern.

In Figure 4, we see that the red line remains above the green line throughout, suggesting that the assistive glove provides consistent support across the tasks. Notably, in the 20 N tasks, the green line hovers just above the zero mark, demonstrating that for low grasp force tasks, the assistive device takes on almost all of the workload. Looking at the higher grasp strength tasks, we see that the muscle effort increases in both assisted and not-assisted scenarios. This suggests that the assistive device reduces the force required by the tasks, but cannot entirely mitigate participant force input. Looking at the thumb data for the 80 N grasp force tasks, we see that the lines get close to each other, even overlapping on occasion. If the mean of each line is taken, we note that the red dotted line still remains above the green line (53.76% MC red dotted, 41.63% MC green for 80 N). This may suggest a reduction in assistance in terms of ratio of red to green, but the assistance value in relation to maximum contraction (MC) is 12.13% MC which is the equivalent of about 17.1 N. These values are discussed in greater depth from a sample, rather than individual perspective in the following section.

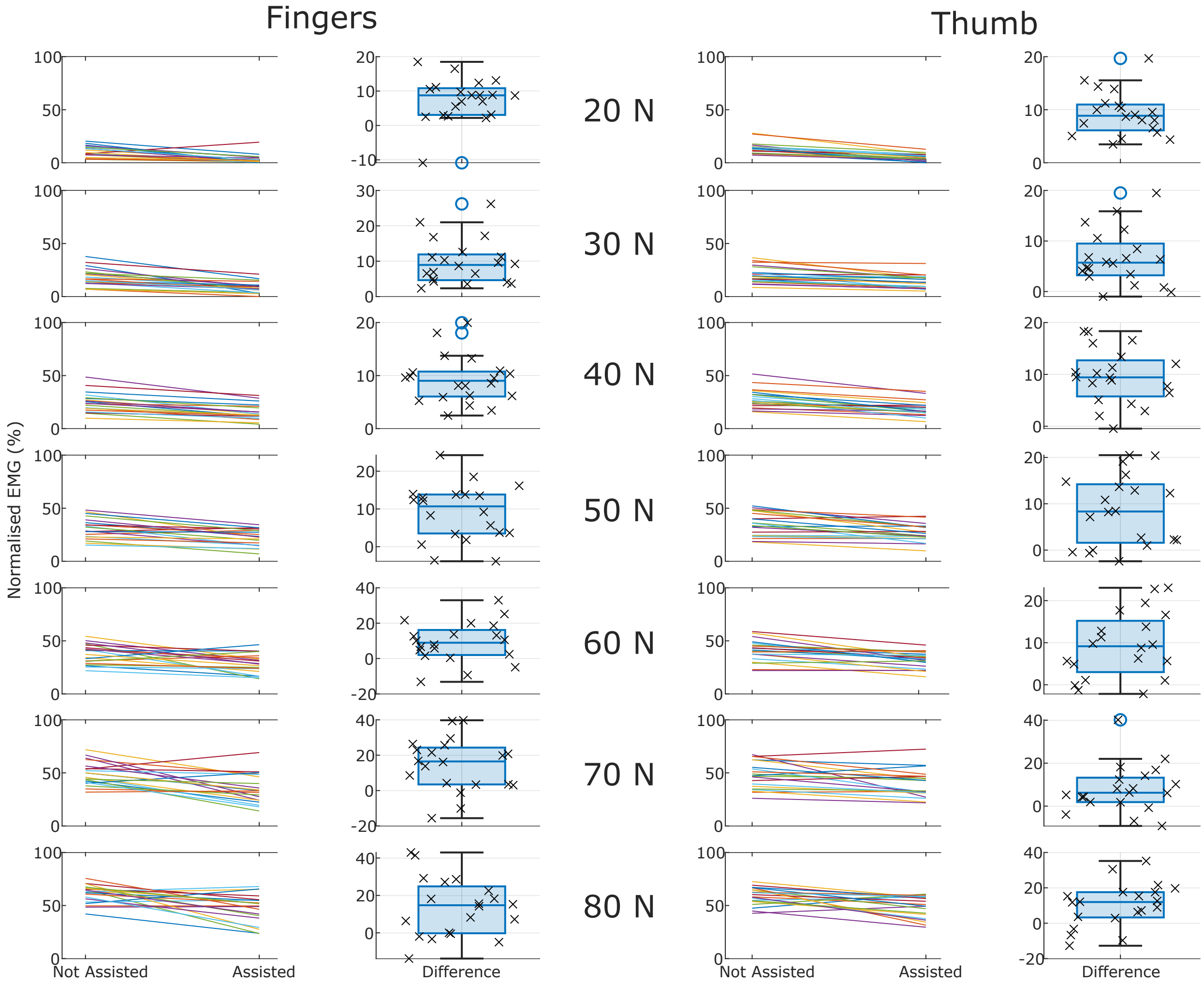

Fig. 5. The figure illustrates the alteration in normalised EMG signals upon the introduction of assistance. Each line represents individual data from a participant, and a negative slope indicates a reduction in EMG signals with the aid of the assistive glove. The box plots show the difference in the EMG signals between the not-assisted and the assisted cases. Also, all the data points are scattered on the box plot.

B. General Trends

To assess the impact of the glove, we examine the mean assistance provided to participants along with standard deviations, normalised for each participant with respect to the maximum contraction performed in the most intensive trial (see Figure 5, and Figure 6). The assistance is calculated by subtracting the RMS EMG signals measured with the assistive glove from those measured without the assistive glove. The mean assistance values for all (n=20) participants' fingers are as follows: 7.46% MC (Standard Deviation(SD)=6.27) for the 20 N task accounting for 70% of the task and providing the equivalent of 13.6 N of force, 9.84% MC (SD=6.33) for the 30 N task accounting for 53% of the task and providing the equivalent of 16.0 N, 9.22% MC (SD=4.51) for the 40 N task accounting for 37% of the task and providing the equivalent of 15.0 N, 9.02% MC (SD=7.43) for the 50 N task accounting for 29% of the task and providing the equivalent of 14.5 N, 9.01% MC (SD=11.46) for the 60 N task accounting for 24% of the task and providing the equivalent of 14.1 N, 14.41% MC (SD=14.89) for the 70 N task accounting for 29% of the task and providing the equivalent of 20.0 N, and 13.55% MC (SD=15.46) for the 80 N task accounting for 22% of the task and providing the equivalent of 17.3 N. Notably, the assistive glove appears to offer a consistent level of assistance across various task intensities, with a mean of 10.36% MC (SD=10.38) which corresponds to 15.8 N force. A more detailed presentation of the assistance provided by the device is given in Figure 5.

For the thumb, the assistance values are slightly lower than with the fingers. The mean assistance values for the thumb are as follows: 9.31% MC (SD=4.15) for the 20 N task accounting for 67% of the task and corresponding to 13.1 N of force, 6.61% MC (SD=5.42) for the 30 N task accounting for 32% of the task and corresponding to 9.7 N of force, 9.53% MC (SD=5.29) for the 40 N task accounting for 34% of the task and corresponding to 13.4 N of force, 8.45% MC (SD=7.57) for the 50 N task accounting for 24% of the task and corresponding to 12.0 N of force, 9.33% MC (SD=7.81) for the 60 N task accounting for 23% of the task and corresponding to 13.5 N of force, 7.96% MC

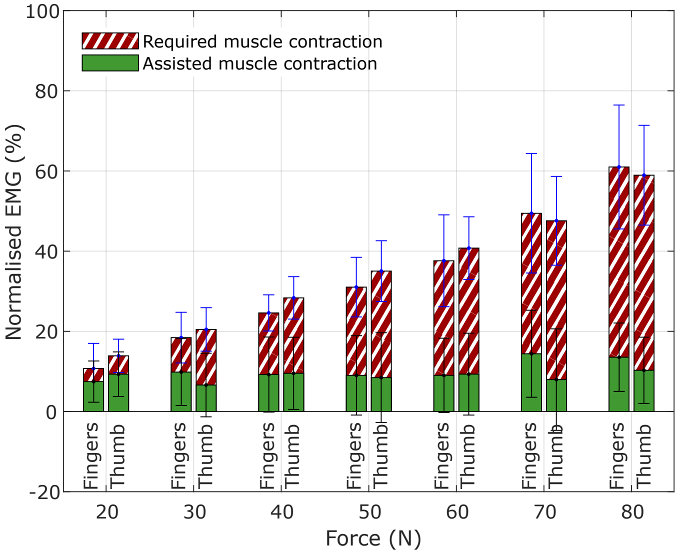

Fig. 6. Bar plot that shows how much muscle activity is needed for the tasks (red), and how much assistance is provided by the wearable robot (green).

(SD=11.08) for the 70 N task accounting for 17% of the task and corresponding to 11.5 N of force, and 10.29% MC (SD=12.45) for the 80 N task accounting for 17% of the task and corresponding to 13.6 N of force. Analysing these values, we see that the assistance remains consistent across the tasks, with an overall mean of 8.78% MC (SD=8.10) corresponding to 12.4 N of force. The differential between finger and thumb assistance can be explained by the number of actuators supporting each muscle group. For fingers there are four, and for the thumb, there is one.

The participants were able to grasp the test rig with a 96% degree of accuracy. The mean applied force values were 19.28, 30.54, 40.06, 50.09, 59.30, 68.27, 78.32 N for the assisted case, and 19.91, 29.45, 39.77, 49.49, 58.63, 68.75, 77.28 N for the non-assisted case. Their overall percentage errors were 4.6% and 3.5%, respectively. Given that these errors are relatively small, we assume that the effect they have on task comparison is also likely to be relatively small.

The findings show that for low-force grasping tasks, the soft robotic assistive glove can effectively provide the majority of the necessary force. In a 20 N power grasp, the assistive glove alleviates 70% of the workload from the fingers and 67% from the thumb, with instances in which the robotic device compensates for the entire workload (100%) for some participants. We note that when the hand is in a relaxed state, but on the test rig, and the glove is activated, it maintains a force of between 15 and 23 N (depending on hand size), which is indeed why we expected the results for the 20 N task to be more significant. We also observed that in a few instances the assistive device caused an increase, rather than a decrease, in muscle effort (Figure 5). The main reason behind the worse-than-expected result is that activating a wearable device usually increases EMG readings regardless of muscle effort [19] — a phenomenon brought about by the 'un-natural' haptic sensation that such devices engender. This creates a challenge for all studies involving exoskeletons and EMG sensing, the solution of which is critical to future progress in the field. To investigate this further, participants were also asked to fully relax their hand on the test rig, whereupon the assistive device was activated. In this way we were able to measure the signal increase caused purely by the activation of the device. For the finger flexion muscle group, we see a mean of 3.26% (SD=4.43) of MC change in EMG signals when the device is activated, and for the thumb 4.58% (SD=3.32) which correspond to 6.6 and 6.4 N of force respectively. For some participants, this value can be smaller than 0.01% MC suggesting that the change in EMG cannot be due to the static charge of the robotic system, but rather, due to the muscle contraction response of the participant to the activation of the assistive glove. We therefore suggest that the assistance provided by the robotic glove could potentially be approximately 6.5 N higher than the reported values. However, further analysis should be undertaken to scientifically validate this phenomenon, not only when the user's hand is passive, but also during activity.

C. Assistance Significance using Linear mixed-effects models

LMMs provide a statistical framework in the field of research and data analysis, offering distinct advantages over traditional t-tests, ultimately enhancing the accuracy of p values, and yielding more robust statistical results [17].

In LMMs, participants are treated as random effects — a recognition of the inherent variability between individuals in a study. By modeling this variability, LMMs provide a more accurate representation of the data's underlying structure, which can be complex due to individual differences, repeated measurements, or nested experimental designs. Consequently, LMMs yield p values that better reflect the true statistical significance of the effects being tested.

When considering the use of the assistive glove as a fixed effect, and participants as a random effect, we develop the following Equation 1, which gives us the effect of the assistance with respect to MC for different force tasks, along with p values. Another consideration is whether the reduction of EMG signals is consistent, or whether there is any correlation between the intensity of the task and the EMG reduction. This is analysed using Equation 2. Here, the Matlab "fitlme" function is used for the LMM analysis.

$$EMG \sim Baseline + Asst. + (Asst.|Pat.) \qquad (1)$$

The baseline in this equation is the default value (one). Assistance (Asst.) is either one or zero depending on whether the assistance is activated or not. Participant (Pat.) is the participant number (1,2,3,...,20). "$\sim$" represents a separation between dependent and independent variables. "$+$" indicates the addition of independent variables to the model. "$\times$" is used to output the interaction and correlation between the two main variables. The right-hand side of "$|$" are the random effects acting on the left-hand side. Calculations of p values using Equation 1 are given in Table I. These low p values suggest that the assistance values given for the tasks characterise the overall model well. For the fingers, assistance varies between 7.46% MC and 14.41% MC (13.6 and 20.0 N), a little higher

TABLE I
ASSISTANCE LEVEL WITH p VALUES USING EQUATION 1

	20 N	30 N	40 N	50 N	60 N	70 N	80 N
Assistance of fingers (% MC)	7.46	9.84	9.22	9.02	9.01	14.41	13.55
Force equivalent assistance (N)	13.6	16.0	14.9	14.5	14.1	20.0	17.3
p values for fingers	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0009	< 0.0001	0.0002
Assistance of thumb (% MC)	9.31	6.61	9.53	8.45	9.33	7.96	10.29
Force equivalent assistance (N)	13.1	9.7	13.4	12.0	13.5	11.5	13.6
p values for thumb	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0021	0.0005

than for the thumb (between 6.61 and 10.29% MC or 9.7 and 13.6 N). p values under the 0.05 threshold suggest that these findings are reasonably accurate and correct.

Assistance values from Table I also suggest that the assistance provided by the glove is stable across the different tasks. Using Equation 2 we can assess whether the assistance provided by the device is consistent in terms of % MC across the various grasp intensities. Intensity (Int) in this equation represents the force intensity (N) of the task (20,30,40,...,80). In terms of the relationship between assistance given and task intensity ($Assistance : Intensity$), the coefficients are 0.11 (p=0.08) for the fingers and 0.02 (p=0.65) for the thumb. As p values indicate that there is no significant relationship between the two it would appear that the glove provides consistent assistance, regardless of the force required for the task.

$$\begin{aligned} EMG \sim Baseline + Asst. \times Int. \\ + (Asst. \times Int. | Pat.) \end{aligned} \tag{2}$$

The discrepancy between the previously presented mean values and those derived from LMMs arises from the nuanced nature of LMMs. These models analyse and fit a line for each participant, capturing both individual trends and the overall pattern. While this approach enhances the depth of analysis, the resulting values tend to be lower than those obtained through mean analysis. This is because the final fitted model must accommodate the diverse responses of all, or most, participants, leading to more conservative estimates.

D. Survey analysis

The QUEST 2.0 survey results for our device are given in Figure 7.

Because the base glove was made from stretchable materials, it could be used by any participant, irrespective of their hand size. Indeed none had any significant issues in relation to fit, and the prototype was consequently assessed at 4.60/5 (SD=0.68) for the ”Dimensions” criterion. Another advantage of the stretchable fabric is noted in the ”Adjustability” assessment. As there are no adjusting mechanisms or bands, the prototype was assessed 4.70/5 (SD=0.57). The ’felt’ weight of the system, including the air tubes is around 70 g, which is considered light for an assistive wearable device. The ”Weight” rating from participants was 4.95/5 (SD=0.22). The ”Security” rating averaged 4.5/5 (SD=0.61) principally due to the device being soft and pneumatically actuated. However, it was noted that the inflation of the air chambers led to anxiety in some participants, as it resembled a balloon that potentially could burst with a resulting loud bang. ”Durability” of the device was assessed as 3.95/5 (0.69) which was the lowest score in the survey. Participants explained that the softness of the device made it seem fragile. On ”Simplicity” the device scored a perfect 5/5 (SD=0), confirming that participants found the device easy to wear and easy to use. Some participants also attributed this to the fact that the device resembled a ”normal everyday glove”. The ”Comfort” score was 4.25/5 (SD=0.91), again a result of the stretchable jersey fabric, reminiscent of everyday gloves. Lastly, in terms of ”Usefulness”, it scored 4.25/5 (SD=0.64) on account of its ability to be easily integrated into different use cases.

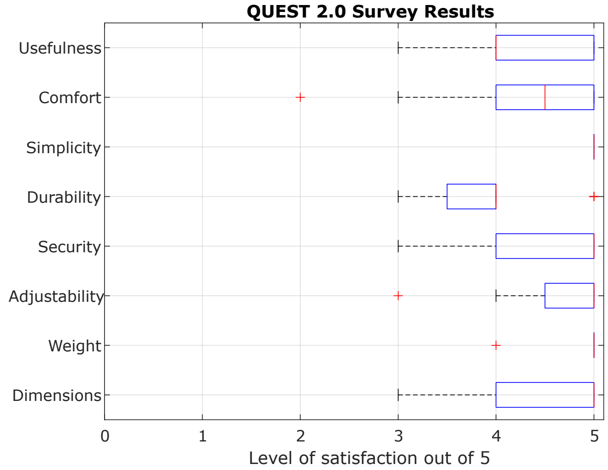

Fig. 7. Answers of participants to the QUEST 2.0 survey. The overall rating of the survey is 4.53/5 (SD=0.68).

V. CONCLUSIONS

Using the sEMG sensors showed that the glove provides mean assistance of 15.8 N (10.36% MC, SD=10.38) for the fingers and 12.4 N (8.78% MC, SD=8.10) for the thumb across all 20–80 N grasp tasks. Overall, Participant #5 experienced the most assistance, with a mean assistance value of 21.9 N (33.3 N for fingers and 10.6 N for the thumb). Although thumb assistance can reach up to 23.3 N (as in the case for Participant #13), it is generally found to be lower than finger assistance. Additionally, the user survey (QUEST 2.0) with a general score of 4.53/5 (SD = 0.68) shows that the glove is successful in terms of comfort, acceptability, and perceived assistance.

As this is an early stage prototype, there are clearly opportunities for development and refinement. A key problem with the glove was that the assistance provided to the thumb was somewhat less than that to the fingers. Another issue was that even though the assistance provided remained relatively constant as an absolute value, the percentage of help provided by the glove decreased as the grasp force increased. For a 20 N task, the glove provides around 68% of the task's force requirements, corresponding to approximately 13 N. However, for an 80 N task, it only provides around 20%, which corresponds to about 15 N. Although this may appear a disadvantage, it also highlights the consistency of the glove's assistive output.

In terms of design, our one-size-fits-all approach was effective, with the glove fitting all 20 participants. , Participant #9, however, experienced a loose fit due to their particularly small hand size (length 16 cm, width 7 cm). As a consequence, the assistance provided to this participant was less than that provided to others, and they were therefore marked as an outlier in Figure 5. From this, we conclude that by designing the base glove for smaller hands while using stretchy textiles, we ensure a good fit, ultimately enabling users to get the most out of the robotic device.

Some participants suggested reducing pressure on the lower two fingers, which are less used in grasping. Many participants provided positive feedback, describing the glove as "excellent," "useful," "definitely helps," and "surprisingly powerful." In the survey, participants rated the statement, "Wearing the assistive device while it is not activated was as comfortable as wearing a glove in daily life," with a 4.55 out of 5 (SD=0.60). This suggests the device is nearly as comfortable as a regular glove, highlighting the potential for unobtrusive, comfortable assistive robotic devices.

The minimum grasp force for the study was set at 20 N because the glove provides 13–20 N of power at its nominal operating pressure of 69 kPa. Reducing pressure to accommodate lower forces would have affected study consistency. The maximum grasp force was set at 80 N, a high power grasp force, which some participants found challenging without assistance.

Our EMG sensing validated assessment method offers key advantages, allowing us to evaluate assistive or rehabilitation devices using data from healthy participants, thus avoiding many ethical issues involved in working with medically impaired patients. This method serves as a preliminary assessment of the device, allowing for a more in-depth analysis on medically impaired patients in the future. This approach is indeed what we plan to pursue with our prototype moving forward.

ACKNOWLEDGMENT

The authors thank Mish Toszeghi, Thomas Christopher Mack, and Dilara Suulker for their valuable help. Huge thanks also to our reviewers for their constructive comments.

REFERENCES

[1] C. D. Takahashi, L. Der-Yeghiaian, V. Le, R. R. Motiwala, and S. C. Cramer, "Robot-based hand motor therapy after stroke," *Brain*, vol. 131, no. 2, pp. 425–437, 2008.

[2] Z. Jiryaei and A. S. Jafarpisheh, "The usefulness of assistive soft robotics in the rehabilitation of patients with hand impairment: A systematic review," *Journal of Bodywork and Movement Therapies*, 2024.

[3] M. Fontana, A. Dettori, F. Salsedo, and M. Bergamasco, "Mechanical design of a novel hand exoskeleton for accurate force displaying," in *2009 IEEE international conference on robotics and automation*, vol. 50, no. 6. IEEE, 2009, pp. 1704–1709.

[4] M. Zhu, S. Biswas, S. I. Dinulescu, N. Kastor, E. W. Hawkes, and Y. Visell, "Soft, wearable robotics and haptics: Technologies, trends, and emerging applications," *Proceedings of the IEEE*, 2022.

[5] C. Suulker, A. Hassan, S. Skach, and K. Althoefer, "A comparison of silicone and fabric inflatable actuators for soft hand exoskeletons," in *2022 IEEE 5th International Conference on Soft Robotics (RoboSoft)*. IEEE, 2022, pp. 735–740.

[6] A. F. Yilmaz, K. Ozlem, F. Khalilbayli, M. F. Celebi, F. Kalaoglu, A. T. Atalay, G. Ince, and O. Atalay, "Resistive self-sensing controllable fabric-based actuator: A novel approach to creating anisotropy," *Advanced Sensor Research*, p. 2300108, 2023.

[7] C. Correia, K. Nuckols, D. Wagner, Y. M. Zhou, M. Clarke, D. Orzel, R. Solinsky, S. Paganoni, and C. J. Walsh, "Improving grasp function after spinal cord injury with a soft robotic glove," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 6, pp. 1407–1415, 2020.

[8] V. Mathiowetz, G. Volland, N. Kashman, and K. Weber, "Adult norms for the box and block test of manual dexterity," *The American journal of occupational therapy*, vol. 39, no. 6, pp. 386–391, 1985.

[9] J. Taborri, J. Keogh, A. Kos, A. Santuz, A. Umek, C. Urbanczyk, E. van der Kruk, and S. Rossi, "Sport biomechanics applications using inertial, force, and emg sensors: A literature overview," *Applied bionics and biomechanics*, vol. 2020, 2020.

[10] M. A. Delph, S. A. Fischer, P. W. Gauthier, C. H. M. Luna, E. A. Clancy, and G. S. Fischer, "A soft robotic exomusculature glove with integrated semg sensing for hand rehabilitation," in *2013 IEEE 13th International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 2013, pp. 1–7.

[11] R. N. Khushaba, S. Kodagoda, M. Takruri, and G. Dissanayake, "Toward improved control of prosthetic fingers using surface electromyogram (emg) signals," *Expert Systems with Applications*, vol. 39, no. 12, pp. 10 731–10 738, 2012.

[12] Y. M. Zhou, D. Wagner, K. Nuckols, R. Heimgartner, C. Correia, M. Clarke, D. Orzel, C. O'Neill, R. Solinsky, S. Paganoni *et al.*, "Soft robotic glove with integrated sensing for intuitive grasping assistance post spinal cord injury," in *2019 International conference on robotics and automation (ICRA)*. IEEE, 2019, pp. 9059–9065.

[13] P. Polygerinos, K. C. Galloway, S. Sanan, M. Herman, and C. J. Walsh, "Emg controlled soft robotic glove for assistance during activities of daily living," in *2015 IEEE international conference on rehabilitation robotics (ICORR)*. IEEE, 2015, pp. 55–60.

[14] C. Suulker, S. Skach, and K. Althoefer, "Soft robotic fabric actuator with elastic bands for high force and bending performance in hand exoskeletons," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 10 621–10 627, 2022.

[15] C. J. De Luca, L. D. Gilmore, M. Kuznetsov, and S. H. Roy, "Filtering the surface emg signal: Movement artifact and baseline noise contamination," *Journal of biomechanics*, vol. 43, no. 8, pp. 1573–1579, 2010.

[16] M. Halaki and K. Ginn, "Normalization of emg signals: to normalize or not to normalize and what to normalize to," *Computational intelligence in electromyography analysis-a perspective on current applications and future challenges*, vol. 10, p. 49957, 2012.

[17] Z. Yu, M. Guindani, S. F. Grieco, L. Chen, T. C. Holmes, and X. Xu, "Beyond t test and anova: applications of mixed-effects models for more rigorous statistical analysis in neuroscience research," *Neuron*, vol. 110, no. 1, pp. 21–35, 2022.

[18] L. Demers, R. Weiss-Lambrou, and B. Ska, "The quebec user evaluation of satisfaction with assistive technology (quest 2.0): an overview and recent progress," *Technology and Disability*, vol. 14, no. 3, pp. 101–105, 2002.

[19] C. Fleischer and G. Hommel, "A human–exoskeleton interface utilizing electromyography," *IEEE Transactions on Robotics*, vol. 24, no. 4, pp. 872–882, 2008.