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An EMG-Controlled Hand Exoskeleton for Natural Pinching

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Spinal cord and other local injuries often lead to partial paralysis while the brain stays fully functional. When this partial paralysis occurs in the hand, these individuals are not able to execute daily activities on their own even if their arms are functional. To remedy this problem, a lightweight, low-profile orthotic exoskeleton has been designed to restore dexterity to paralyzed hands. The exoskeleton's movements are controlled by the user's available electromyography (EMG) signals. The device has two actuators controlling the index finger flexion that can be used to perform a pinching motion against a fixed thumb. Using this orthotic device, a new control technique was developed to allow for a natural reaching and pinching sequence by utilizing the natural residual muscle activation patterns. To design this controller, two actuator control algorithms were explored with a quadriplegic (C5/C6) subject and it was determined that a simple binary control algorithm allowed for faster interaction with objects over a variable control algorithm. The binary algorithm was then used as an enabling algorithm to activate the exoskeleton movements when the natural sequence of muscle activities found a pattern related to a pinch. This natural pinching technique has shown significant promise toward realistic neural control of wearable robotic devices to assist paralyzed individuals.

Keywords: hand, exoskeleton, orthotics, electromyography, spinal cord injury

1. Introduction

In the United States alone, there are over 11,000 new spinal cord injury cases every year [1]. Nearly half of these cases result in a loss of sensation or motion to the arms and hands. One realistic solution to this problem is the use of a functional electrical stimulation (FES) system to stimulate muscles that are no longer receiving signals from the central nervous system. While this solution shows promise, it still has significant technical barriers to overcome such as fast fatigue. In addition, even when it becomes available, FES is not applicable to those subjects who have inflicted local trauma to the muscles. To remedy this problem, a low-profile hand orthotic exoskeleton could provide assistive forces to the user's fingers.

Several hand orthotic exoskeletons have been constructed in the past [2–4]. These devices generally consist of rigid molded plastic as a basic support and hard metal hinges as the manipulation method. Grasping motions are achieved by mechanical actuation of the main hinge through gear or ratchet systems so that the device remains rigid when the actuator is not active. They are self-contained (all actuators are on board) but the entire mechanisms tend to be bulky and heavy.

Common controller inputs to the exoskeletons have been either voice or EMG signals [2, 3]. Voice activation systems use verbal commands such as "grasp" or "grip" to trigger the opening/closing of the actuated clasping mechanism in which the user's hand sits. Such systems allow for good control of objects during steady state operation, however, typical problems with voice recognition systems include background noise or false signals.

On the other hand, control strategies based on EMG signals could provide commands without suffering from the common voice recognition problems. For example, the electrical signal of the muscle activation from a working leg muscle could be amplified and used directly to control the actuators that control the finger movements. When the leg muscle was contracted beyond a threshold level, the fingers could be commanded to curl. When the leg muscle was relaxed below the same threshold, the fingers could be commanded to open. In a similar manner, EMG signals have also been used to control mechanical hardware [5–7] and simulations [8].

Most of the current work in this area uses EMG signals from muscles that are unrelated to the actual sequence of reaching and grasping movements. This technique successfully avoids the conflict between the movements to position to hand and to command the grasping movements. For example, if the right biceps signals were used to control the right hand grasping motion, the user's elbow motion used to reach for the object could trigger the exoskeleton to curl the fingers before the hand is positioned in the right place. However, by avoiding using related muscles, the control is unnatural and it is difficult for the users to adapt to this new mapping. Furthermore, when the muscles used for the control command are used for other activities (e.g., walking, etc.), the exoskeleton would open and close unnecessarily.

To address these issues, we constructed a low-profile and lightweight exoskeleton that allows a basic pinching motion using a natural sequence of muscle activation. The pinching motion between the index finger and the thumb provides the ability to perform a wide range of daily tasks such as picking up small objects, turning knobs, flipping switches, and opening bottles. We targeted the patient group with injuries in spinal column C5 and C6 (very common) that results in paralyzed hands while having some functions left in their shoulders, elbows, and/or wrists. We present results in extracting the residual muscle signals related to the actual reaching and pinching movements and utilizing them to trigger the correct pinching movements with the exoskeleton. Our results include data from a quadriplegic subject with C5/C6 injuries to determine the benefits of binary and variable algorithms.

2. Design of the Orthotic Exoskeleton

2.1. Mechanical Design

The human index finger has three joints and four degrees of freedom. From the distal end, the joints are: the DIP (distal interphalangeal), PIP (proximal interphalangeal), and MCP (metacarpophalangeal). The DIP and PIP joints have flexion/extension degree of freedom, while the MCP joint has both flexion/extension and abduction/adduction degrees of freedom. To enable a steady pinching motion to the fixed thumb, flexion and extension of all three joints are required. The flexion/extension of the DIP and PIP joints are coupled, but the DIP/PIP and MCP flexion/extension are independent. Active abduction/adduction movements are not used to allow the tip of the index finger to meet the thumb, but passive abduction/adduction movement is allowed so as to aid the finger in conforming to its target object.

To support such movements, we needed to provide (1) a coupled active degree of freedom for the DIP and PIP flexion/extension, (2) an active degree of freedom for the MCP flexion/extension, and (3) a passive degree of freedom for the MCP abduction/adduction. For both active degrees of freedom, we used pneumatic pistons (models 007 and 007-R from Bimba Manufacturing Company, Monee, IL) activating a cabling system. These pistons were connected to variable pressure pneumatic valves (model 4088x from Herion USA, Inc.). Our analysis showed that these movements could be accomplished by a linear actuation of 1 to 1.5 inches, depending on the hand size of the user, and the required 7 lbs of contact force could be accomplished by 10 lbs of linear force. We did not use artificial muscle actuators such as McKibben pneumatic muscles and shaped memory alloys, used in similar devices [4, 9–11], to keep the small profile while maintaining the required force and displacement.

Fig. 1. Our orthotic exoskeleton system. It is a low-profile lightweight exoskeleton that allows basic pinching motion using natural sequence of muscle activation. Pinching motion between the index finger and the thumb provides the ability to perform a wide range of daily tasks.

Figure 1 shows our orthotic exoskeleton system. The mechanical framework of the exoskeleton consisted of an aluminum anchoring plate mounted to the back of the hand and three aluminum bands, one for each of the finger bones. The aluminum bands were designed to be adjustable for different finger sizes. The flexion of the PIP and DIP joints was produced by steel cable running along the front of each finger band and through to the backside of the hand. These cables were pulled by a pneumatic cylinder acting in compression. The MCP flexion, on the other hand, was achieved by a linkage mechanism: a floating link was mounted between the finger band closest to the base plate and a second pneumatic actuator, acting in extension. When the extension pneumatic piston pushed this link mechanism forward (distal), the MCP joint resulted in flexion. To achieve smooth repeatable motion and the passive abduction/adduction motion, we added a flexible coupling between the base-plate and first finger band made from a canvas-like cloth material. The cloth was rigid in tension but was easily deformable along its length, which allowed for the device to maintain a set distance between the base plate and first finger band while not inhibiting flexion. Small springs were used at all three joints to extend them passively. When the finger was at rest, the springs kept the finger at full extension, and the pistons worked against the spring forces during flexion.

Figure 2 illustrates system components including all of the electronics and pneumatics which would be located in the user’s wheelchair or in an appropriate carrying case. The mechanical and electrical components

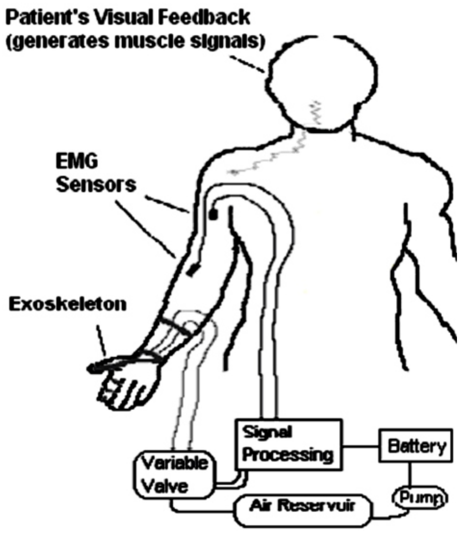

Fig. 2. The figure shows system components. The mechanical and electrical components of our system did not contain any sensors to establish the closed-loop system. Instead, the user judged the output and controlled their muscle contraction in a closed-loop format.

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2.2. EMG Signal Processing

Our exoskeleton is targeted for those with some residual EMG signals on their arm, even if it is not strong enough to move the joints. For this paper, we used the biceps as the example because quadriplegics with C5 and/or C6 injuries typically have good control of their biceps even though they are mostly unable to control their hands. Also biceps muscles are easily accessible from the skin surface, and it is intuitive to control the signals by moving the elbow.

The biceps EMG signal was recorded using a Delsys Bagnoli-8 system. The signal was amplified and digitized at 500Hz. The digitized EMG data was then rectified and smoothed using a Butterworth low-pass filter. This data was normalized using the maximum voluntary contraction (MVC) level of the user. This processed EMG signal was then used to control the pressure level in the pneumatic valves.

3. Actuator Control Algorithm

3.1. Binary Control Algorithm

To design the new natural control strategy, we first determined whether to control the actuator valves using binary or variable algorithm with a spinal cord injured individual. The binary control algorithm resembles the ones employed by [2]. This algorithm is called a binary controller because its output to the pneumatic valves was either off (0V) or on (10V). The output binary value was determined by the EMG signal: when it was above a specified EMG threshold value, the output was “on”, and when it was below, the output was “off”. We implemented a hysteresis in the valve triggering system to prevent the output oscillation. The mean threshold value was originally set to be at 55% MVC to turn on, and 45% MVC to turn off, but we adjusted it to the subject’s comfortable setting before each experiment.

While we tested for the validity of the binary versus variable control algorithm, we used the biceps signals from the side without the exoskeleton (contralateral biceps). When the bicep was contracted above the threshold value, both pneumatic pistons produced 120 psi at the same time. This resulted in the compression piston to flex the PIP and DIP joints and the extension piston to flex the MCP joint together in approximately 0.5 seconds. Once the full flexion was established, the exoskeleton maintained the same posture. When the EMG signal dropped below the threshold value, both valves turned off completely and the springs in each joint pulled the finger to full extension.

3.2. Variable Control Algorithm

While the binary control algorithm is simple to design and use, we compared its performance with a variable control algorithm that was designed to explore the benefit of continuous variable control of the pneumatic pressure. To accomplish this controller, a simple proportional controller was employed using the filtered EMG signal of the contralateral biceps. We set the minimum pressure level (20 psi) to be at 15% of the maximum muscle contraction level to avoid the twitching of the pneumatic system. Also, we set the maximum pressure level (120 psi) to be at 70% of the maximum muscle contraction level. As in the previous control algorithm, we adjusted these values to the subject’s comfortable setting before each experiment.

3.3. Experimental Protocol

We tested the efficiency and usability of binary and variable control algorithms on an individual with an upper spinal cord injury (quadriplegic). The individual was 19 years old, 6 years post-injury, with diffused C5/C6 injury. He was able to move both shoulders and the right elbow, had some control over his right wrist and the left elbow, and no control on his left wrist and both of his hands. We used his right biceps muscle to control the orthotic exoskeleton on his left hand as shown in **Fig.3**.

After placing the surface electrode on the subject’s right biceps and putting the exoskeleton on his left hand, we collected his EMG signals at rest and at MVC for 5 seconds. The mean of the filtered signals were used as 0 and 100% contraction levels. The on/off threshold was

Fig. 3. A spinal cord injured (C5/C6) individual using our orthotic exoskeleton to lift a roll of tape. He has no voluntary control over his hands.

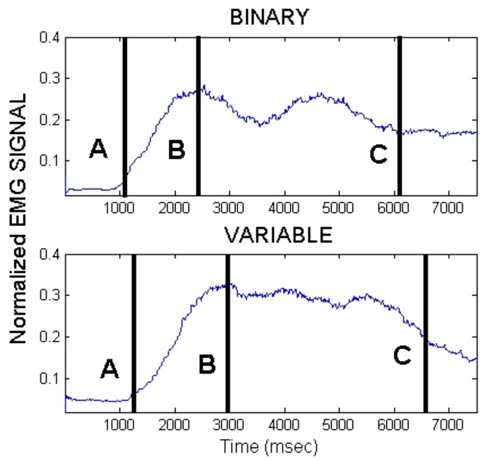

Fig. 4. Typical EMG signals recorded during reach/pinch/lift/place/release sequence for binary and variable control algorithms. Line A indicates initial contact, B indicates full closure, and C indicates final release.

set to 50% of his contraction level at first (which corresponded to an amplifier gain of 500) and we allowed the subject to adjust this level until he was comfortable with the threshold level. His final gain selection was at 200 (which corresponded to approximately 28% on and 18% off). We also calibrated the variable controller's range to be comfortable for the subject, and it was set to have the minimum pressure level at 15% of MVC and maximum pressure level at 40% of MVC.

We compared these two controllers by having the subject attempt a pinch grasp of six different objects spanning a range of size, weight, and compliance: a rubber ball, a plastic hockey puck, a roll of masking tape, an electric toothbrush, a deck of cards, and a Twinkie™. For all of these objects, we asked the subject to reach, pinch, lift, place, and release as fast as he could without failing the task. He repeated the reach/pinch/lift/place/release for 5-7 trials per object per control strategy. He was also instructed to not break the Twinkie™ in multiple pieces, requiring him to control his force level and pinch it delicately.

Table 1. The properties of objects used in the reach/pinch/lift/place/release task and their execution success rate for the quadriplegic individual. The rate was determined based on 5-7 trials.

Trial Object	Pinching Thickness (inches)	Weight (lbs)	Frequency of Grasping Success (minimum 5 trials) Binary	Variable
Roll of Tape	3/4	0.33	100%	100%
Rubber Ball	1	0.23	100%	100%
Plastic Hockey Puck	1	0.13	100%	100%
Twinkie™	1	0.09	50%	60%
Toothbrush	1 3/16	0.71	0%	0%
Deck of Cards	1/2	0.31	0%	0%

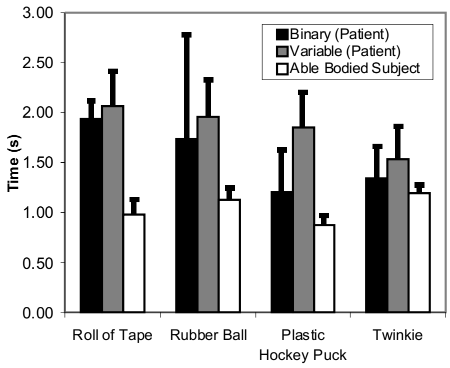

Fig. 5. The total time it took from the time the subjects were given a go signal to complete the reach/pinch/lift/place/release sequence. Black bar: binary control algorithm used for the quadriplegic individual. Grey bars: variable control algorithm used for the quadriplegic individual. White bars: normal reach/pinch/lift/place/release sequence executed by an able-bodied individual.

3.4. Results

Figure 4 shows typical EMG signals recorded during pinch/release for both actuator control algorithms. **Table 1** shows the success rate (i.e. whether the object was successfully lifted off the table) for each object. These results indicate that the exoskeleton was extremely effective (100% success rate) in pinching four out of six objects. An electric toothbrush and a packaged deck of cards were too slippery for the exoskeleton's metallic tip. **Fig.5** shows the average total time it took for both the quadriplegic and an able-bodied subjects from the initial go signal until the object was fully pinched (the toothbrush and the deck of cards were excluded from **Fig.5** because the disabled subject was never able to pinch these objects). The disabled subject executed the task slightly slower (on average by 0.44 seconds) but comparable to the able-bodied subject. There was a trend that the tasks were executed faster with the binary control algorithm, and it was statistically different for the hockey puck. There was a high correlation with the amount of time it took to pinch the object and the object weight (correlation coefficient: .89) while there was no significant correlation between the size of the object and the execution time (correlation coefficient: .57).

While the binary and variable control algorithms were proven to give similar results, we chose to use the binary algorithm for the natural control strategy described in the next section to allow faster execution of tasks.

4. Natural Pinching Technique

4.1. Methods

Ideally, the control signal would be a part of the natural reach and pinch movement rather than using the contralateral arm to control the pinching motion. If we could tap into the residual EMG signal of a muscle that used to control the index finger flexion and amplify it, it would make the most natural controller. However, most patients (including our subject) do not have detectable or usable amount of EMG signal on those muscles. The muscle that is most reliably available for the target population is the biceps muscle. Therefore, for the third control algorithm, we used the ipsilateral biceps (the arm with the exoskeleton) and used the signals that were part of the natural reach and pinch movements.

To understand the relationship between the biceps EMG signal and the timing of the pinch, we collected data from two able-bodied subjects while they reached and pinched a cylinder. The EMG signal was collected and filtered the same way as for the other algorithms. The cylinder was instrumented with a touch sensor to detect the exact contact timing. Subjects were asked to repeat this movement 60 times. Using these 60 movements, a clear trend between the pinching and the slope of the EMG signal was determined. As shown in **Fig.6**, the pinch occurred after the first peak and where a negative slope was observed for a few hundred milliseconds. The slope, S, at time sample T of the smoothed EMG function was calculated by

$$S(T) = \frac{\sum_{n=0}^{50} E(T-n)}{50} - \frac{\sum_{n=1}^{50} E(T+n)}{50} \quad . \; . \; . \; . \; . \; (1)$$

where $E(t)$ is the smoothed EMG signal at sample time T.

To use the data from the future EMG data, the slope calculation was delayed by 50 sample points (100msec). Due to this additional delay, we implement a 6th order low-pass Butterworth filter, which gives us the ability to use fewer coefficients without compromising on the quality of information about the pinching timing. Combining the faster low-pass filter and the slope trend detection in (1), the algorithm executed a pinch when $S(T)$ was negative 50 samples in a row. For subject 2, we added additional 80msec before executing the pinch. Once one pinch was detected, the algorithm terminated.

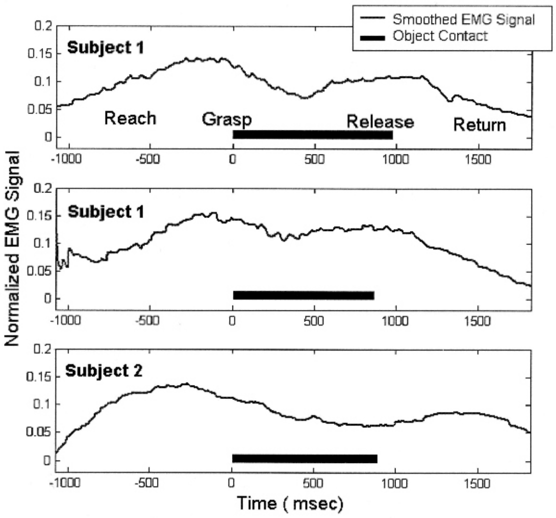

Fig. 6. Typical EMG signals recorded while two able-bodied subjects reached and pinched a cylinder. The thick line below represents the time that the hand was in contact with the object.

When the pinch was detected, we used the binary control algorithm to flex the MCP and curl the DIP and PIP at once. For this experiment, we did not train for release timing, and performance was judged based on correlation between EMG data and the actual pinch recorded by the touch sensor. We tested this algorithm using two sets of data: the original test data collected from two subjects (without wearing the exoskeleton) and new real-time data collected when two subjects made 20 reaches for an object located 40cm above and below the table height in addition the one on the table. For this real-time experiment, subjects had the exoskeleton on a mockup finger next to them to measure the timing difference between the actual and the exoskeleton pinches. We chose this method so that the accurate timing differences could be gathered (if the subjects wore the exoskeleton, the timing for the intended pinch would not be captured).

4.2. Results

4.2.1. Test Data

Out of the 120 reach/pinch test trials collected, the natural pinching algorithm detected pinching sequence on 117 trials correctly. The three failure trials occurred early in the experiment (3rd, 7th, and 14th trials). The average error between the predicted and real pinching timing was 0.31 seconds (SD = 0.32) for the first subject, and 0.28 seconds (SD = 0.30) for the second subject. The pinch was detected after the actual pinch for 67% of the trials. In reality, if the predicted pinches happened close to but before the desired pinches, it may not

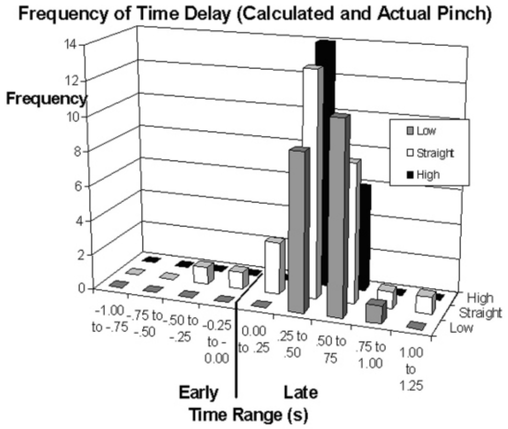

Fig. 7. The timing differences between the actual and exoskeleton pinches for three different objects placed at different heights. Most of the exoskeleton pinches were executed after the the actual pinch showing that it is an effective technique. The average delay was 0.45 seconds.

successfully pinch the object. We determined that if we added an additional 200msec delay before the pinch, all but three predicted pinches would occur after the desired pinch.

4.2.2. Real-Time Data

Figure 7 shows the timing differences between the actual and exoskeleton pinches for three different objects. One cylinder was placed 40cm above the table top (high), another was placed on the table (straight), and another was placed 40cm below the table top (low). Because the biceps are used in different ways to reach to objects at different heights, this test shows the robustness of our simple algorithm. Our results indicate that there was no significant difference in the results between the three levels of pinching when two subjects made 20 reaches for each object. Across all three experiments, the average delay of pinch timing was 0.45 seconds (0.53 seconds (SD = 0.16) for low, 0.39 seconds (SD = 0.29) for straight, and 0.43 seconds (SD = 0.15) for high). While we observed a longer delay between the desired and the actual pinch for the real-time experiment, the users described the difference to be hardly noticeable. There were 6 trials that the pinch was never detected and 7 false positive trials when the exoskeleton pinched before the subject started reaching for the object.

5. Discussion

Our exoskeleton system has shown to be effective in enabling pinching movements to those who lack hand mobility regardless of the control algorithms used. We met many of the mechanical design criteria that we specified. First, the device was constructed to be comfortable. The user showed no signs of having to adjust the exoskeleton to perform any of the desired motions. Second, our design kept minimal materials on the palmer side of the hand. The exoskeleton never interfered with the manipulated objects. In addition, the exoskeleton only weighed 6.67oz and kept a low profile on the hand.

We found that binary control algorithm allowed for faster interaction with objects, while variable control provided more success with deformable objects. To pick up the Twinkie™ without breaking it into many pieces required a well-calibrated light pinching force. To provide this light and controllable pinching force, the variable control algorithm proved to be more successful than the binary control. In a few trials on the variable control, the subject was able to bring the Twinkie™ to his mouth, release it into his mouth and eat it. The use of our device marked the spinal cord injured individual's first active control of the limb to lift a heavy object since his injury, an experience that he found to be exhilarating.

These contralateral arm algorithms may be used for non-repetitive pinching tasks that may require more intense user feedback. For example, a user who wants to pick up an object that may harm their fingers (heat or cold) can use the binary or variable control algorithms in order to provide instant feedback to the exoskeleton to release or decrease grip strength on the object. This method guarantees that as long as the user provides enough bicep signal feedback, the exoskeleton will react consistently.

While the variable control algorithm also had significant benefits, the binary control algorithm was used for the natural pinching technique for its speed. The advantage of having a natural pinching motion with an EMG signal from the ipsilateral biceps is that the user does not have to physically command the pinch through voice or unrelated muscle activation. We have shown that even with one muscle signal from the natural reaching sequence, a reliable and robust pinching motion can be produced with the exoskeleton. With the use of more residual muscles, the algorithm could because sophisticated enough to allow subjects to never "think" of pinching, similar to the way healthy individuals pinch objects.

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References:

[1] Christopher Reeve Paralysis Foundation. http://www.apacure.com.
[2] Benjuya, Nisim, and S. Kenny, "Myoelectric Hand Orthosis," Journal of Prosthetics and Orthotics, pp. 149-154, 1990.
[3] Slack, Mendal, and D. Berbrayer, "A Myoelectrically Controlled Wrist-Hand Orthosis for Brachial Plexus Injury: A Case Study," Journal of Prosthetics and Orthotics, pp. 171-174, 1992.
[4] J. B. Makaram, D. K. Dittmer et al., "The SMARTR Wrist-Hand Orthosis (WHO) for Quadriplegic Patients," Journal of Prosthetics and Orthotics, pp. 73-76, 1993.

[5] K. Kuribayashi, S. Shimizu, K. Okimura, and T. Taniguchi, "A discrimination system using neural networks for EMG-control prostheses-Integral type of emg signal processing," Proceedings of the 1993 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 1750-1755, 1993.

[6] K. Ito, T. Tsuji, A. Kato, and M. Ito, "EMG pattern classification for a prosthetic forarm with three degrees of freedom," IEEE International Workshop on Robot and Human Communication, pp. 69-74, 1992.

[7] R. F. Kirsh, and A. T. C. Au, "EMG-based motion intention detection for control of a shoulder neuroprosthesis," IEEE International Conference of the Engineering in Medicine and Biology Society, Vol.5, pp. 1944-1945, 1997.

[8] A. T. C. Au, T. C. Arthur, and R. F. Kirch, "EMG-based prediction of shoulder and elbow kinematics in able-bodied and spinarl cord injured individuals," IEEE Transactions on Rehabilitation Engineering, Vol.8., pp. 471-480, 2000.

[9] D. C. Johnson, and D. W. Repperger, "Development of a mobility assist for the paralyzed, amputee, and spastic patient," IEEE, pp. 67-70R, 1996.

[10] Y. Umetani, Y. Yamada et al., "'Skil Mate', wearable exoskeleton robot," IEEE, pp. 984-988, 1999.

[11] K. Kuribayashi, M. Takahashi et al., "An upper extremity prosthesis using SMA actuator," IEEE International Workshop on Robot and Human Communication, pp. 52-57, 1992.

[12] M. DiCicco, L. Lucas, and Y. Matsuoka, "Comparison of Two Control Strategies for a Muscle Controlled Orthotic Exoskeleton for the Hand," The Proceedings of the IEEE Intl. Conference on Robotics and Automation, pp. 1622-1627, 2004.

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Y. Matsuoka, "The Mechanisms in a Humanoid Robot Hand," Autonomous Robots, Vol.4, No.2, pp. 1-11, 1997.

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