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Neuromorphic vision and tactile fusion for upper limb prosthesis control

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***Abstract*— A major issue with upper limb prostheses is the disconnect between sensory information perceived by the user and the information perceived by the prosthesis. Advances in prosthetic technology introduced tactile information for monitoring grasping activity, but visual information, a vital component in the human sensory system, is still not fully utilized as a form of feedback to the prosthesis. For able-bodied individuals, many of the decisions for grasping or manipulating an object, such as hand orientation and aperture, are made based on visual information before contact with the object. We show that inclusion of neuromorphic visual information, combined with tactile feedback, improves the ability and efficiency of both able-bodied and amputee subjects to pick up and manipulate everyday objects. We discovered that combining both visual and tactile information in a real-time closed loop feedback strategy generally decreased the completion time of a task involving picking up and manipulating objects compared to using a single modality for feedback. While the full benefit of the combined feedback was partially obscured by experimental inaccuracies of the visual classification system, we demonstrate that this fusion of neuromorphic signals from visual and tactile sensors can provide valuable feedback to a prosthetic arm for enhancing real-time function and usability.**

I. INTRODUCTION

Upper limb prosthesis users face many challenges which originate from their prosthesis; however, surveys have found that while there was agreement that almost every aspect of prosthetic arms could be improved, there wasn't an overwhelming agreement on any single improvement that needed to be made [1]. Regardless, consumers prioritize enhanced functionality and improved socket comfort, as well as sensory feedback as future design considerations [2]. These consumer considerations are important for improving prostheses, given that upper limb prosthesis users have high device abandonment rates of 35-45% [3].

One active area of research that has proven useful is the incorporation of movement decoding from myoelectric (EMG) signals, which has continued to see improvements over the past several decades [4]. Pattern recognition and proportional control techniques have offered advanced functionality in terms of control over hand movements for prosthesis users [5]–[7]. Other advancements such as targeted muscle reinnervation (TMR) also enable enhanced control by leveraging muscles as biological amplifiers [5], [8]. Research efforts have also led to restoring sensations of touch [9], [10], texture [11], and even pain [12] in amputees.

Additional efforts have investigated incorporating other types of sensory information, such as vision. During natural limb movements, vision plays a key role in our reaching and grasping. While amputees rely on visual information for reach and grasp tasks, hand preshaping and alignment with the target object do not occur as quickly as for an intact hand. Previous researchers have incorporated visual information and a convolutional neural network (CNN) to classify objects based on their shape and orientation for automatically preshaping and rotating a prosthetic hand for grasping, which resulted in improved performance [13]. However, this method requires the user to provide an EMG command to take an image for processing and object classification, which may take several seconds. Researchers have also used a fusion of different sensors for improving prosthesis function, such as visual sensors and inertial measurement units (IMU) [14]. Another solution leverages contextual information from IMUs as well as grip force and hand aperture [15].

In this work, we present a sensor fusion of neuromorphic vision with tactile information as local feedback to a prosthesis for improving functionality in a grasping task. This neuromorphic approach is inspired by the behavior of the biological sensory systems that process the same kind of information. This biological basis aims to provide feedback that mimics the responses of sensory receptors in the nervous system, using active sensors to produce neuron-like spiking activity. Here, the neuromorphic vision sensor uses active local-level imaging to act like the retina to produce representations of the visual images. Similarly, the tactile sensor produces a spiking response to instances of tactile slip.

II. METHODS & EXPERIMENT

A. Neuromorphic Vision & Tactile Sensors

We mounted an embedded Dyanmic Vision Sensor (eDVS) (iniVation, Zurich) on the wrist (MC Wrist Rotator, Utah Arm, Salt Lake City) of a prosthetic hand (Fig. 1). The eDVS is neuromorphic in that it acts like the human retina and only transmits local pixel-level changes (Fig. 2(A)). This event-driven sensing enables extremely low-latency transfer of visual information, which has been used in applications such as autonomous robot locomotion [16]. Piezoresistive textile sensors were placed on the thumb, index, and middle fingers of a bebionic3 prosthetic hand (Ottobock, Duderstadt) to measure grip force (Fig. 1). The tactile sensors used in this experiment were previously developed and have been used for other prosthesis applications [17], [18]. In this paper, the

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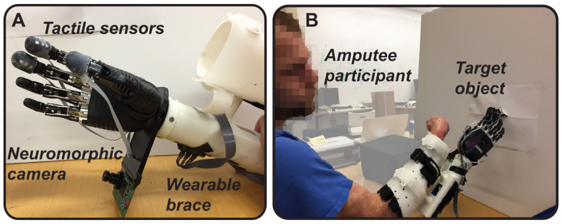

Fig. 1. (A) The neuromorphic camera is attached to the wrist and the tactile sensors are placed on the thumb, index, and middle fingers of the prosthetic hand. The wearable brace enables both amputee and able-bodied subjects to participate in the grasp task. (B) The participant wears the brace and controls the prosthesis to grab and move the target object.

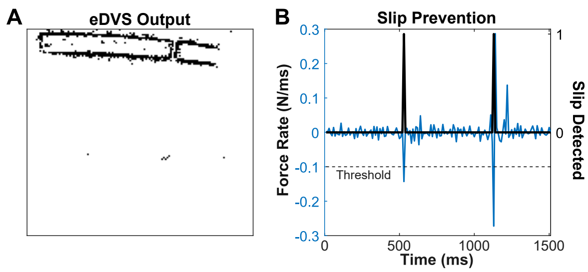

Fig. 2. (A) Sample image output from the eDVS neuromorphic camera viewing a block object with a 90°orientation. (B) Sample output of the neuromorphic slip prevention method that uses the rate of change of the grip force to detect and prevent slip.

tactile feedback from these fingertip sensors utilized the same slip prevention method as described in [18], where rapid changes in grip force resulted in corresponding increases in the prosthesis grip force to prevent additional object slip. This mimics the kind of signaling and grip force adjustment found in humans, and the output of this neuromorphic slip prevention method is shown in Fig. 2(B).

B. Object & Orientation Detection

The objects used were a cylinder, prism, and block, which require a power, tripod, and pinch grip, respectively (Fig. 3(A)). These objects were chosen from the Prosthetic Hand Assessment Measure (PHAM) [19]. A previously developed CNN was used for estimating object orientation from the eDVS signal [20]. The vision classifier was trained on the PHAM objects and object orientation was estimated by creating an axis of symmetry from the neuromorphic vision output. The grip type was selected by the classifier output, which utilized the axis-normal distance of the symmetry axis that is unique to each object type.

C. Experiment

The prosthetic hand and wrist were controlled using a custom control board (Infinite Biomedical Technologies, Baltimore). A Myo band (Thalmic Labs, Kitchener) was used to collect EMG signals (Fig. 3(B)). The hardware was integrated into a wearable brace with the neuromorphic camera and tactile sensors. A linear discriminant analysis (LDA) classifier [21] was used for predicting wrist and hand movements. A modified version of the Virtual Integration Environment (VIE) (JHU Applied Physics Laboratory, Laurel) was used to present visual cues for training the pattern recognition classifier. All sensor signals were processed

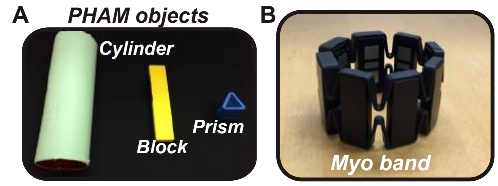

Fig. 3. (A) The PHAM objects used, from left to right, were the cylinder, block, and prism. (B) The Myo band is placed on the forearm of the subject to measure EMG activity.

through MATLAB 2017a (MathWorks, Natick) and prosthesis commands were sent using Bluetooth communication to the control board at a baud rate of 115,200 bits per second.

One amputee (right, transradial) and 2 able-bodied individuals participated in the experiment. The experiment was approved by the Johns Hopkins Institutional Review Boards, and written consent was given by all the participants. The prosthesis brace was worn over the Myo band electrodes placed on the right forearm. One of the three objects was placed in front of the participant. The participant was instructed to use the correct grasp based on the object presented to place that object in a bin approximately 20 cm away. Each object was presented at least 5 times in a random orientation of 0°, 45°, or 90°from the horizontal axis.

Each trial was repeated with no feedback to the prosthesis, only tactile feedback, only vision feedback, or both vision and tactile feedback. Both kinds of feedback are closed-loop and local to the prosthesis itself, rather than providing the user with additional information. When the tactile sensors detected slip, the prosthesis automatically adjusted grip force to compensate. For the visual feedback, object type and orientation were used to set grip and wrist rotation of the prosthesis at the start of each trial. The prosthesis would automatically close for 45 ms using the appropriate grip for the detected object. This partial closing makes it easier for the user to continue closing the prosthesis with that same grip. If an incorrect grip was used by the prosthesis, the user would have to open the hand fully and close the hand again using the correct grip. Once the grip and wrist rotation were set by the visual feedback, the user still retained control over the grip and wrist rotation and could override it if desired.

The trials were randomized and the participants were blind to the feedback type for each trial. The time to complete each trial were recorded as well as the number of errors, which were classified as the object falling, the wrong grip was used, or a time of 45 s was exceeded for a trial.

III. Results & Discussion

In order to see how the inclusion of two different feedback modalities affected task performance, we compared average task completion time and error rate. Fig. 4 and Table I show these measures respectively for each feedback type. Overall, completion time decreased with the use of tactile feedback alone and decreased even more with vision feedback alone. For the able-bodied participants, while trials with the combined feedback had longer times than trials that used vision feedback alone, both conditions showed significant decreases compared to the no feedback condition ($p<0.05$ and $p<0.01$, respectively). For the amputee participant, the

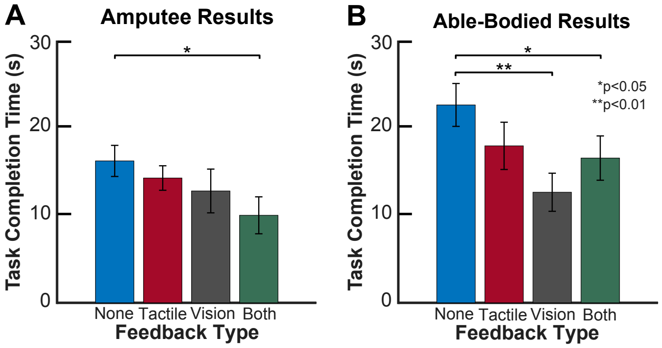

Fig. 4. Average movement completion time by feedback type for (A) amputee and (B) able-bodied participants. Error bars show standard error.

TABLE I

MOVEMENTS ERROR RATES BY FEEDBACK TYPE

Feedback Type	Object Falls	Wrong Grip	Timeout	Total Error Rate
Amputee				
None	8.7%	4.3%	2.2%	15.2%
Tactile	0.0%	6.3%	4.2%	10.4%
Vision	11.1%	5.6%	5.6%	22.2%
Both	16.7%	22.2%	0.0%	38.9%
Able-Body				
None	13.3%	20.0%	13.3%	46.7%
Tactile	6.7%	23.3%	16.7%	46.7%
Vision	8.0%	16.0%	4.0%	28.0%
Both	6.7%	23.3%	6.7%	36.7%

TABLE II

TASK COMPLETION TIME AND ERROR RATE BY VISION CLASSIFICATION

Classification	Completion Time (s)	Error Rate
Amputee		
Correct Object	9.2±1.6	25.0%
Incorrect Object	12.1±0.9	32.1%
Correct Orientation	10.0±1.6	12.5%
Incorrect Orientation	11.9±0.8	35.7%
Able-Body		
Correct Object	12.9±2.0	25.0%
Incorrect Object	13.8±1.5	37.5%
Correct Orientation	17.1±3.2	37.5%
Incorrect Orientation	13.9±2.0	30.8%

combined feedback resulted in the greatest decrease in average completion time ($p<0.05$). While this data comes from a limited set of participants, these results provide an initial indication of the utility of incorporating neuromorphic visual information, especially when combined with other feedback modalities.

Looking at the error rates in Table I, the able-bodied participants had overall higher error rates compared to the amputee participant, with a large portion of this error coming from the wrong grip being used. This may possibly reflect able-bodied participants' unfamiliarity with using a prosthesis and performing EMG pattern recognition compared to an amputee's experience. The able-bodied participants did, however, show decreased error rates with the inclusion of vision feedback while the amputee participant actually had higher error rates with vision feedback. These error rates increased even more for trials that used the combined feedback, in contrast to the pattern seen for completion time. While this may suggest that vision feedback is detrimental to the amputee's performance, it should be noted that the most common error, using the wrong grip, does not necessarily prevent the task from being completed, which is why some categories can have high error rates yet fast completion times.

However, since the trends in error rates are not consistent with the trends in average completion times, it is worth separating these times by trials with and without errors, shown in Fig. 5, to see how the error rate may be related to completion time. As expected, trials with an error generally had significantly longer average completion times than trials without an error. For trials without any errors, the amputee participant shows a trend similar to that of the completion times shown in Fig. 4. However, the able-bodied participants instead showed the fastest completion time for tactile feedback alone. While this could suggest that the vision feedback was actually slowing down able-bodied subjects, it is important to reiterate that with only two able-bodied participants, such generalizations should be avoided. In fact, one of the able-bodied participants actually showed the same trends in completion times seen in the amputee participant.

For the trials in which an error was recorded, average completion times across all subjects for trials that used vision feedback were lower than those without vision feedback. This may suggest that the presence of vision feedback to the prosthesis resulted in the best ability to compensate for errors when they occurred. This impact was even greater with the combination of vision and tactile feedback for the amputee participant, possibly indicating why using the combined feedback modalities resulted in the best average completion times despite the highest error rate.

This outcome is interesting considering the observed low accuracy of the visual detection system. Across all trials that utilized the neuromorphic vision feedback, object classification was correct on 35.2% of the trials, and orientation classification was within 15 degrees of the true object angle for only 26.4% of the trials. The low experimental accuracy of the visual detection algorithm seems to contradict its success in [20]. This may be due to differences in experimental setup or the kind of objects used, since these objects have multiple axes of symmetry and similiar shapes to each other that could confuse classification. To see how this might have affected performance, average task completion time and error rate are shown for correct and incorrect object type and orientation classification in Table II. For each category of classification aside from object orientation for able-bodied participants, completion time and error rate were

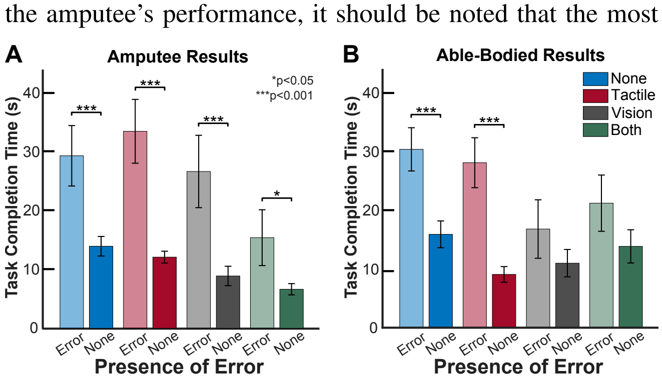

Fig. 5. Average movement completion time by feedback type separated by the presence of errors for (A) amputee and (B) able-bodied participants. Error bars show standard error.

TABLE III

AVERAGE RECORDED SLIP COUNT PER MOVEMENT

Category	Average Slip Count
Amputee	
Tactile Feedback Alone	1.8±0.3
Vision+Tactile Feedback	3.4±1.7
Correct Vision Classification	3.7±2.3
Incorrect Vision Classification	2.6±1.7
Able-Body	
Tactile Feedback Alone	22.3±5.4
Vision+Tactile Feedback	24.1±5.9
Correct Vision Classification	18.7±10.7
Incorrect Vision Classification	27.7±7.2

both greater for incorrect than for correct classifications, again indicating the benefit of incorporating accurate vision feedback. However, overall performance may suffer if there is low visual classification accuracy. Additional trials with more accurate vision detection would be needed to examine these effects further.

Slip prevalence can also be used to compare trials that included tactile feedback alone to those that included both vision and tactile feedback. Slip count here reflects instances of slip detected by the neuromorphic tactile sensor and used to adjust the prosthesis grip force. Most notably, the trials completed by the amputee participant had much lower average recorded slip counts than the trials completed by the able-bodied participants, seen in Table III. This difference may reflect how well the participants are naturally able to use the prosthesis to grip an object without having it slip. When the object is classified correctly, the average slip count is lower than when only tactile feedback is used, indicating the benefit of having the fused feedback. However, the average slip count per trial with the combined feedback was greater than that with tactile feedback alone across all participants. After separating the combined feedback results by visual classification, we can see that incorrect classification may be responsible for bringing the slip count up. For able-bodied participants, the trials in which the vision classification was incorrect had an average slip count much greater than those with correct classification. This would make sense because an attempt to grab an object with the wrong orientation or grasp may increase the chances that it could slip.

IV. CONCLUSION

The neuromorphic vision sensor enables extremely fast, real-time processing of visual information that can be utilized along with spiking activity from neuromorphic tactile sensors to provide biologically relevant feedback to a prosthesis. The overall improvement in the participants' ability to use a prosthesis to pick up and manipulate objects with the addition of visual feedback to the prosthesis indicates that the fusion of visual and tactile feedback can provide valuable information in a neuromorphic prosthesis system. Future experimentation with an enhanced visual classification system, perhaps with higher classification accuracy or the extraction of additional visual features, could further illuminate the benefit of the fusion of these feedback modalities.

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REFERENCES

[1] P. J. Kyberd and W. Hill, "Survey of upper limb prosthesis users in sweden, the united kingdom and canada," *Prosthet Orthot Int*, vol. 35, no. 2, pp. 234–241, 2011.

[2] E. Biddiss, D. Beaton, and T. Chau, "Consumer design priorities for upper limb prosthetics," *Disabil Rehabil Assist Technol*, vol. 2, no. 6, pp. 346–357, 2007.

[3] E. A. Biddiss and T. T. Chau, "Upper limb prosthesis use and abandonment: a survey of the last 25 years," *Prosthet Orthot Int*, vol. 31, no. 3, pp. 236–257, 2007.

[4] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *J Rehabil Res Dev*, vol. 48, no. 6, pp. 643–659, 2011.

[5] D. Farina *et al.*, "Man/machine interface based on the discharge timings of spinal motor neurons after targeted muscle reinnervation," *Nat Biomed Eng*, vol. 1, p. 0025, 2017.

[6] J. Betthauser *et al.*, "Limb position tolerant pattern recognition for myoelectric prosthesis control with adaptive sparse representations from extreme learning," *IEEE Trans Biomed Eng*, vol. 65, no. 4, pp. 770–778, 2018.

[7] S. Wendelken *et al.*, "Restoration of motor control and proprioceptive and cutaneous sensation in humans with prior upper-limb amputation via multiple utah slanted electrode arrays (useas) implanted in residual peripheral arm nerves," *J Neuroeng Rehabil*, vol. 14, no. 1, p. 121, 2017.

[8] T. A. Kuiken *et al.*, "Targeted reinnervation for enhanced prosthetic arm function in a woman with a proximal amputation: a case study," *Lancet*, vol. 369, no. 9559, pp. 371–380, 2007.

[9] S. Raspopovic *et al.*, "Restoring natural sensory feedback in real-time bidirectional hand prostheses," *Sci Transl Med*, vol. 6, no. 222, p. 222ra19, 2014.

[10] D. W. Tan, M. A. Schiefer, M. W. Keith, J. R. Anderson, J. Tyler, and D. J. Tyler, "A neural interface provides long-term stable natural touch perception," *Sci Transl Med*, vol. 6, no. 257, p. 257ra138, 2014.

[11] C. M. Oddo *et al.*, "Intraneural stimulation elicits discrimination of textural features by artificial fingertip in intact and amputee humans," *eLife*, vol. 5, p. e09148, 2016.

[12] L. E. Osborn *et al.*, "Prosthesis with neuromorphic multilayered e-dermis perceives touch and pain," *Sci Rob*, vol. 3, no. 19, p. eaat3818, 2018.

[13] G. Ghazaei, A. Alameer, P. Degenaar, G. Morgan, and K. Nazarpour, "Deep learning-based artificial vision for grasp classification in myoelectric hands," *J Neural Eng*, vol. 14, no. 3, p. 036025, 2017.

[14] M. Markovic, S. Dosen, D. Popovic, B. Graimann, and D. Farina, "Sensor fusion and computer vision for context-aware control of a multi degree-of-freedom prosthesis," *J Neural Eng*, vol. 12, no. 6, p. 066022, 2015.

[15] G. K. Patel, J. M. Hahne, C. Castellini, D. Farina, and S. Dosen, "Context-dependent adaptation improves robustness of myoelectric control for upper-limb prostheses," *J Neural Eng*, vol. 14, no. 5, p. 056016, 2017.

[16] L. Everding and J. Conradt, "Low-latency line tracking using event-based dynamic vision sensors," *Front Neurorobot*, vol. 12, p. 4, 2018.

[17] L. Osborn, W. W. Lee, R. Kaliki, and N. V. Thakor, "Tactile feedback in upper limb prosthetic devices using flexible textile force sensors," in *Conf Proc Biomed Robot Biomechatron (BioRob)*, 2014, pp. 114–119.

[18] L. Osborn, R. Kaliki, A. Soares, and N. Thakor, "Neuromimetic event-based detection for closed-loop tactile feedback control of upper limb prostheses," *IEEE Trans Haptics*, vol. 9, no. 2, pp. 196–206, 2016.

[19] C. Hunt, R. Yerrabelli, C. Clancy, L. Osborn, R. Kaliki, and N. Thakor, "Pham: prosthetic hand assessment measure," in *Conf Proc Myoelec Controls Symp*, 2017, pp. 221–224.

[20] S. Tang, R. Ghosh, N. V. Thakor, and S. L. Kukreja, "Orientation estimation and grasp type detection of household objects for upper limb prostheses with dynamic vision sensor," in *Conf Proc IEEE Biomed Circuits Syst Conf (BioCAS)*, 2016, pp. 99–102.

[21] G. J. McLachlan, *Discriminant Analysis and Statistical Pattern Recognition*, ser. Wiley Series in Probability and Mathematical Statistics, Ney York, NY, USA, 1992.