# "Wink to grasp" – comparing Eye, Voice & EMG gesture control of grasp with soft-robotic gloves

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***Abstract*— The ability of robotic rehabilitation devices to support paralysed end-users is ultimately limited by the degree to which human-machine-interaction is designed to be effective and efficient in translating user intention into robotic action. Specifically, we evaluate the novel possibility of binocular eye-tracking technology to detect voluntary winks from involuntary blink commands, to establish winks as a novel low-latency control signal to trigger robotic action. By wearing binocular eye-tracking glasses we enable users to directly observe their environment or the actuator and trigger movement actions, without having to interact with a visual display unit or user interface. We compare our novel approach to two conventional approaches for controlling robotic devices based on electromyography (EMG) and speech-based human-computer interaction technology. We present an integrated software framework based on ROS that allows transparent integration of these multiple modalities with a robotic system. We use a soft-robotic SEM glove (Bioservo Technologies AB, Sweden) to evaluate how the 3 modalities support the performance and subjective experience of the end-user when movement assisted. All 3 modalities are evaluated in streaming, closed-loop control operation for grasping physical objects. We find that wink control shows the lowest error rate mean with lowest standard deviation of** ($0.23 \pm 0.07$, **mean** $\pm$ **SEM) followed by speech control** ($0.35 \pm 0.13$) **and EMG gesture control (using the Myo armband by Thalamic Labs), with the highest mean and standard deviation** ($0.46 \pm 0.16$). **We conclude that with our novel own developed eye-tracking based approach to control assistive technologies is a well suited alternative to conventional approaches, especially when combined with 3D eye-tracking based robotic end-point control.**

## I. Introduction

Exoskeletons of lower and upper limbs offer unique abilities for paralysed people to move again with their own body. While rapid progress is made in the domain of robotic actuation, the challenge remains how to provide intuitive, natural control of these devices for the end-user [1]. Here, we want to explore the best options for quick setup and easy control of a "flip trigger" or "mouse click" like mechanics, that enables a user to control an exoskeleton glove such that it opens and closes using the same user command. A number of modalities need to be considered: In robotic prosthetics one of the most utilised approach is electromyography (EMG) to measure residual muscle activation [2], [3]. For high level spinal injuries where this control signal is not available one can use invasive direct brain machine interfaces (BMI) where signals are recorded directly from the brain [4]. However,

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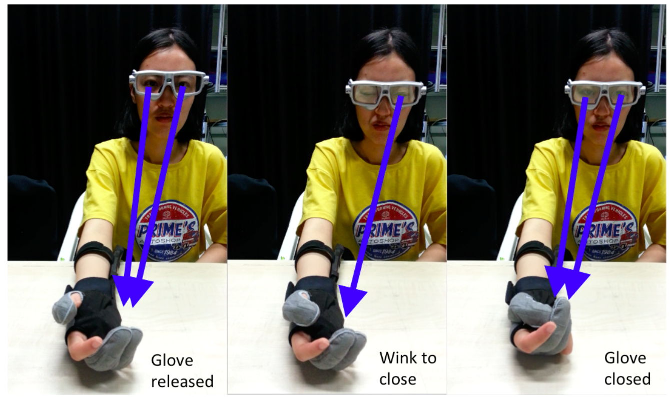


Fig. 1. Illustration of eye-based control using a wink on the right eye. The soft-robotic glove and eye-tracking glasses are worn by end-user. (Left) After positioning the hand around the object, (Middle) the user executes a wink, a unique voluntary signal, that triggers closing of the robotic glove, (Right) enabling the user to lift the object.

here we are looking for a simple system, that enables setup, operation and use within minutes, without need for surgery. Thus, we need to consider other non-invasive approaches using central brain signals based on electroencephalography (EEG), which use suffers from large time delays and poor response accuracy when operating in closed-loop [5], [6].

Another approach that has been shown to be successful in the control of human-robot interaction is the use of voice recognition [7]–[9]. However, these systems suffer from the disadvantage of commands being wrongly interpreted, having interference from other noise sources and, in a more practical sense, users might be unwilling to use the device due to attracting attention [10] or limiting their freedom to use voice for interpersonal communucation. The fact that both hands remain free with voice control is seen as a large convenience [11] against button operated tools, however, this does not present a clear advantage in the case of people that suffer from motor disorders.

We showed recently how 3D eye-movements can be easily measured using binocular eyetrackers to provide high resolution information of where we are directing our visual attention too. Eye movements are the only directly observable behavioural signals that are highly correlated with actions at the task level, and proactive of body movements and thus reflect action intentions [12]. Moreover, eye movements are preserved in many target groups, namely those suffering from movement disorders leading to paralysis from stroke (when brain areas that are unrelated to eye movements are not affected), spinal cord injury, Parkinson's disease, multiple sclerosis [12] and muscular dystrophy and other motor disorders [13]. Despite this benefit, eye-tracking is not widely used as control interface for robotic interfaces in movement impaired patients. This is because conventional eye-tracking based approaches require the use of display unit based user interfaces and uncomfortable user commands based around dwell times or gaze gestures, effectively requiring the user to stare at screen buttons for prolonged times or close their eyes in artificial blinks for long periods [14], [15]. These limitations were mainly due to conventional eye-tracking using monocular approaches, tracking one eye, instead of tracking both eyes. Binocular eye-tracking, however, not only enables tracking of eye-movements and their gaze-target in 3 dimensions [12], but also allows for distinguishing naturally occurring, involuntary blinks from voluntary winks that do not occur naturally. This effectively provides the end-user with 2 separate "mouse click"-like commands – by winking with their left or right eye. This enables the user to trigger actions without having to interact with a display unit and thus enables them to freely look at the location of intended action, making it ideal for direct control of robotic actuators and exoskeletons. Our aim is to combine a simple "mouse click" control, here of the opening and closing of a wearable robotic hand, with our 3D eye-tracking based end-point control of robotic actuators or exoskeletons [12], such as robotic arm support systems [16]. Here, a single wearable set of binocular eye-tracking glasses can provide both command execution trigger commands ("clicks") as well as high resolution end-point control in 3D. This also motivates why we do not want to consider multiple redundant eye movement measurement modalities, such as EOG (Electroculography), as these provide only low resolution gaze direction decoding compared to standard video based eye-tracking methods [17].

To evaluate the effectiveness and efficiency of our binocular eye-tracking based approach we developed a closed-loop control system that enables us to integrate a binocular eye-tracking system and other input modalities with soft-robotic glove designed to assist paralysed or "weak" users (e.g. stroke survivors) to execute or release a grasp. We compare the ability of naive users to control the glove using a. flip trigger-like control using winks, b. a simple voice command and c. a hand EMG gesture detected by multichannel EMG. We then ask the users to evaluate the 3 modes of operation with their satisfaction or confidence ratings.

## II. Methods

Three different system setups have been developed and their effectiveness assessed within the scope of this work. Those are eye winks, speech and muscle contractions to control a glove for assistive grasping.

*a) System integration:* To evaluate the multiple human-machine interaction modalities we made used of the ability of the Robot Operative System (ROS) [18] software framework to operate in a distributed manner transparently. This enabled us to use various computers in the lab dedicated to various functions (EMG gesture control, voice control, wink control) without having to transfer equipment or install software from different machines onto a single one.

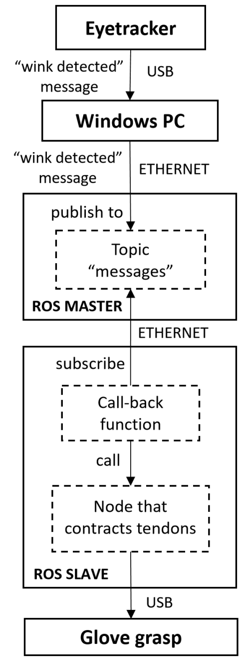


Fig. 2. Software architecture of the eye wink based control system for the glove. The full outline boxes represent all the hardware used, the boxes with dashed outline represent code or components of ROS architecture used, and the arrows represent the connections between each component. On the left of each arrow is the description of what the connection does, to the right of the arrow we list the hardware through which the connection is achieved.

The entire system used for the evaluation consists of four computers and two operating systems; two Microsoft Windows machine (8.1 and 10.1) and two Linux (both Ubuntu 14.4) machines. The Linux computers run ROS distribution indigo: one of both is the ROS Master and the other is a ROS Slave. Exchange of information between computer is done via a socket connection through an Ethernet network. The Soft Extra Muscle (SEM) Glove and a microphone for voice commands are both connected to the ROS Slave. The Windows computers are used as bridging devices to connect and read from the eye-tracker for gaze data and to read from the Myo armband.

*b) Actuation – SEM Glove:* The SEM Glove (Soft Extra Muscle Glove) is a commercial device developed for aiding the grasping capability of a weak hand or arm (Bioservo Technologies AB, Sweden). We had access to a modified computer interfacable version with proprietary ROS interface courtesy of Bioservo. The concept of the glove, as opposed to the majority of solutions for this problem, does not make use of rigid external structures but uses instead a system similar to the biomechanics of the hand. The glove has a. textile features that take into account the necessity to transfer forces and torques to the fingers and b. artificial tendons - incorporated in the ring and middle fingers and thumb - that are actuated by electrical motors controlled by mechanisms designed to transfer the required forces by means of a specific transmission system. The control system takes into account the information from tactile sensors located in the fingertips and force sensors in the palm, providing a servoing effect to the human grasp. The glove was designed with the goal of aiding the grasp only, so the actuators can only produce a pulling force that closes the hand. The glove itself contains the sensors and the artificial tendons, whilst the motor, actuators, batteries and the controller are in a separate unit connected by a cable. The SEM glove central processing unit, which also houses the tendon motors, was connected via a USB serial port to the ROS slave using a custom developed API.

*c) "Wink" – Eye-tracking based control:* The eye-tracking signal was streamed in real-time and used to control the glove in closed loop. Any binocular eye-tracking system can detect and in principle distinguish left and right eye winks from eye blinks. Here, we used binocular eye-tracking glasses SMI ETG 2W A (SensoMotoric Instruments, Germany) connected to a Windows 8.1 computer. Gaze data is constantly recorded and streamed to the ROS Master using the SMI API. Additionally on the Windows computer, the data is also analysed to detect winks, which are defined as any of the eyes being closed and the other kept open for at least 400 ms. Once a wink is detected the ROS master publishes a message under a defined topic (to which the ROS Slave subscribes). Every time a wink is detected a corresponding message is published under the designated topic within the ROS environment. The ROS slave then calls a function responsible for the contraction of the glove's artificial tendons and hence of the grasp of the hand. The glove can be in one of two states either 1. contracted or 2. relaxed. Our system detects in which the state the glove currently is in and changes it to the other state by calling the ROS node responsible for it. This node determined the tension on one of the fingers. That node is called three times (for each finger) with an interval of 200 ms so that the fingers are contracted as close in time as possible and providing a smooth grasping motion. For relaxation the tension of the tendons is set to zero, thus relaxing all tendons.

*d) "Voice" – Speech control:* The voice signal was processed in real-time and used to control the glove in closed loop. For speech control a slightly simplified system architecture has been chosen. A 4-microphone array (Sony PlayStation 3 Eye Camera, Sony, Japan) is connected to the Linux Slave to record audio and in particular user speech. The speech is recognised in streaming mode using the Sphinx-4 library [19] within a Java application. The improve speech recognition accuracy, the speech systems was given a computational grammar based with a one-word grammar consisting of the command word "action". No user specific calibration was required thereafter. Once a command has been recognised the glove is activated directly by calling the ROS node responsible for contracting the tendons on the Linux Slave. Background noise in the room (a large research lab) was controlled for by requesting quiet use of the space.

*e) "EMG" – myoelectric based control:* We used a commercial consumer grade electromygraphic sensor system, the Myo armband (Thalamic Labs, Kitchener, Ontario, Canada) to obtain EMG data that requires only a simple calibration procedure and is out-of-the-box able to distinguish 5 different hand/wrist motions. The Myo armband was placed according to the manufacturers instruction on the contralateral lower arm with respect to the glove. Note, that the contralateral arm was chosen, so as to emulate the setting where a hemiparetic stroke patient would need wear the glove on the ipsilateral side, but could reliably control it only on the contralateral side. The vendors setup and calibration procedure involving abducting the wrist was used to calibrate the Myo armband signal. The EMG control signal we used was the EMG pattern generated for the "double tap" EMG gesture. This vendor built-in EMG pattern involves opening and closing the middle, ring finger and thumb so the 3 finger tips touch each other. The executed muscle pattern was processed in real-time by the vendor's software system and its output used to o control the glove in closed loop. The decoded EMG gestures were streamed from the vendor's Myo armband API to our ROS control system. Once the EMG gesture is successfully detected the Myo system sends a signal to the Linux ROS Slave to operate the glove.

*f) User evaluation:* We measured the efficacy and efficiency of these three interaction systems. Users were verbally explained that: 1. wink-based control required them to perform wink for an unspecified amount of time, 2. voice based control required the user to speak the trigger word "action" and 3. Myo armband control required the user to perform the "double tap" EMG gesture (demonstrated by the experimenter). Users were asked to perform each interaction command once before the experiment to confirm their understanding and experience the consequence of their action. Consecutively, user were asked to open and glove the wearable robotic glove using the interaction command 10 times each. This required a user to at least trigger 20 open and close events. All attempts to trigger a grasp or a release have been recorded to obtain the error rate of the given interaction scheme (error rate was defined as the sum of accidental triggering and failed triggering over the requested 20 trigger events). To complement the objective evaluation subjects were asked to complete the Quebec User Evaluation of Satisfaction with assistive Technology (QUEST) questionnaire [20] and the System Usability Scale (SUS) questionnaire [21]. The QUEST questionnaire was adapted by removing questions with regard to service, durability and maintenance as these concepts would not apply in this study. this figure evaluates to which extend the interaction scheme conflicts with natural occurring behaviour or sensor or environment noise.

## III. RESULTS

Performance evaluation was conducted with healthy subjects (N=9) with normal or corrected to normal eye sight or eye sight, which was in all cases sufficient to perform a successful eye-tracker calibration. Eye tracker and Myo armband calibration was successful at first attempts with every subject. All users were able to control the glove with each of the three modalities 1. wink, 2. voice and 3. EMG gesture. However, the performance varied in the number of attempts needed to trigger the control (false negatives) and

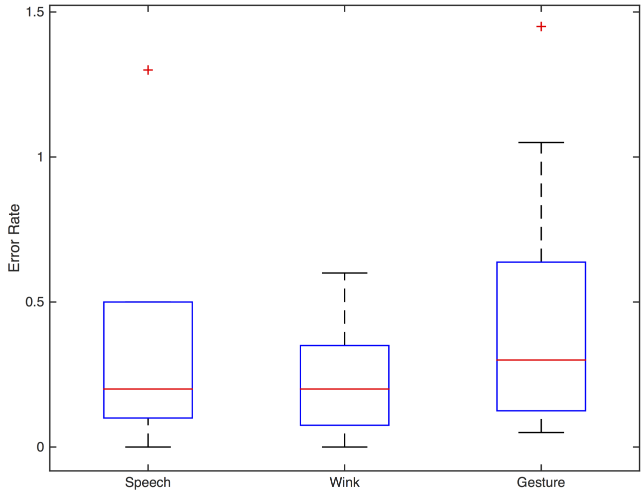


Fig. 3. The rate at which the interface system performed on average erroneously per intentionally triggered open/close events. Note, that EMG Gesture and Speech recognition are based on commercial/publicly released production systems, while the Wink system is a lab development proof-of-principle system

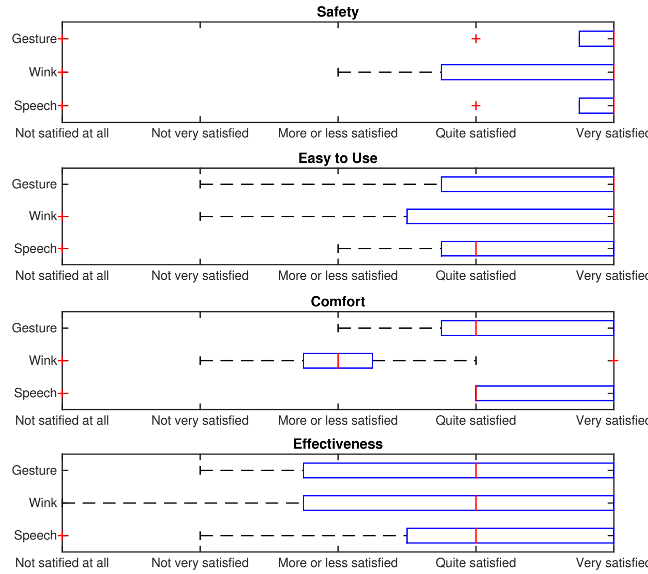


Fig. 4. Quebec User Evaluation of Satisfaction with assistive Technology (QUEST) evaluation results for the presented 3 different interface technologies for controlling the glove. Note, that EMG Gesture and Speech recognition are based on commercial/publicly released production systems, while the Wink system is a lab development proof-of-principle system

in of number of true negatives comprising false positives (i.e. unintended command triggering) and false negative (see Fig. III). On average wink control required $1.2 \pm 0.43$ (mean $\pm$ SD) attempts to invoke opening or closing the glove and had an error rate of $0.35 \pm 0.40$. With regards to wink control the error rate was lower with a rate of $0.23 \pm 0.21$. The average number of attempts to trigger the opening or closing of the glove was $1.21 \pm 0.23$. EMG gesture control was outperformed by both speech and wink control, as it required an average number of attempts of $1.4 \pm 0.5$ and had an error rate of $0.46 \pm 0.49$.

The objective part of the evaluation based on user performance was complemented by two subjective user questionnaires, the System Usability Scale (SUS, Fig. III) and the Quebec User Evaluation of Satisfaction with assistive Technology (QUEST, Fig. III) questionnaire . In the QUEST questionnaire we have split the questions into those that assess the interaction modality as a whole and those that assess physical characteristics of the device. This is because, the wink-based system is a lab developed proof-of-principle interaction system without a production-level hardware packaging, in contrast to commercial publicly released technology like the Myo armband and the speech recognition, as s a consequence it is expected that the commercial devices will score better in the subjective assessment. From the QUEST questionnaire we found that although there is general agreement with regards to safety for all three modalities, there is a discordance concerning easiness to use, effectiveness and comfort. Although EMG gesture control has shown to be less reliable than wink or speech control, the QUEST questionnaire reveals that the median of the subjects is "very satisfied" with the system being easy to use and "quite satisfied" with the effectiveness. The eye trackers has scored slightly lower with regards to comfort and and effectiveness which is a consequence of it being a lab developed interaction scheme compared to the other commercial solutions. The SUS questionnaire revealed that subjects would like to use the eye tracking system more frequently. Surprisingly, the median answered that eye tracking was less cumbersome than speech control.

## IV. Discussion

An ideal human-machine interface requires a signal that can communicate sufficient complexity at a low latency to dynamically guide and respond to environmental changes of everyday life. In addition, for patient acceptance, this interface must be very easy to learn, "feel" intuitive and provide them with confidence and a sense of mastery of the control. We evaluated here eye-tracking, voice and EMG gesture based flip trigger commands to control wearable robotic actuators. We conclude our developed eye-tracking based approach objectively outperformed both alternatives of speech and EMG gesture control for the purpose of controlling assistive technologies.

Whilst eye-tracking is very effective tracking what the user is interested in, initiating user interaction with eye-gaze is cumbersome relying on blinking or long dwell times. Fundamentally gaze-based human-machine interaction requires the differentiation of normal behavioural eye movements and intentional eye "commands", which is known as the Midas touch problem [22]. In the domain of human-computer interaction much of the focus has been on two dimensional interactions on a computer screen, where the locus of interaction is fully programmable and under full control of the user interface designer. Hence, gaze-based approaches have been also combined with other modalities to control

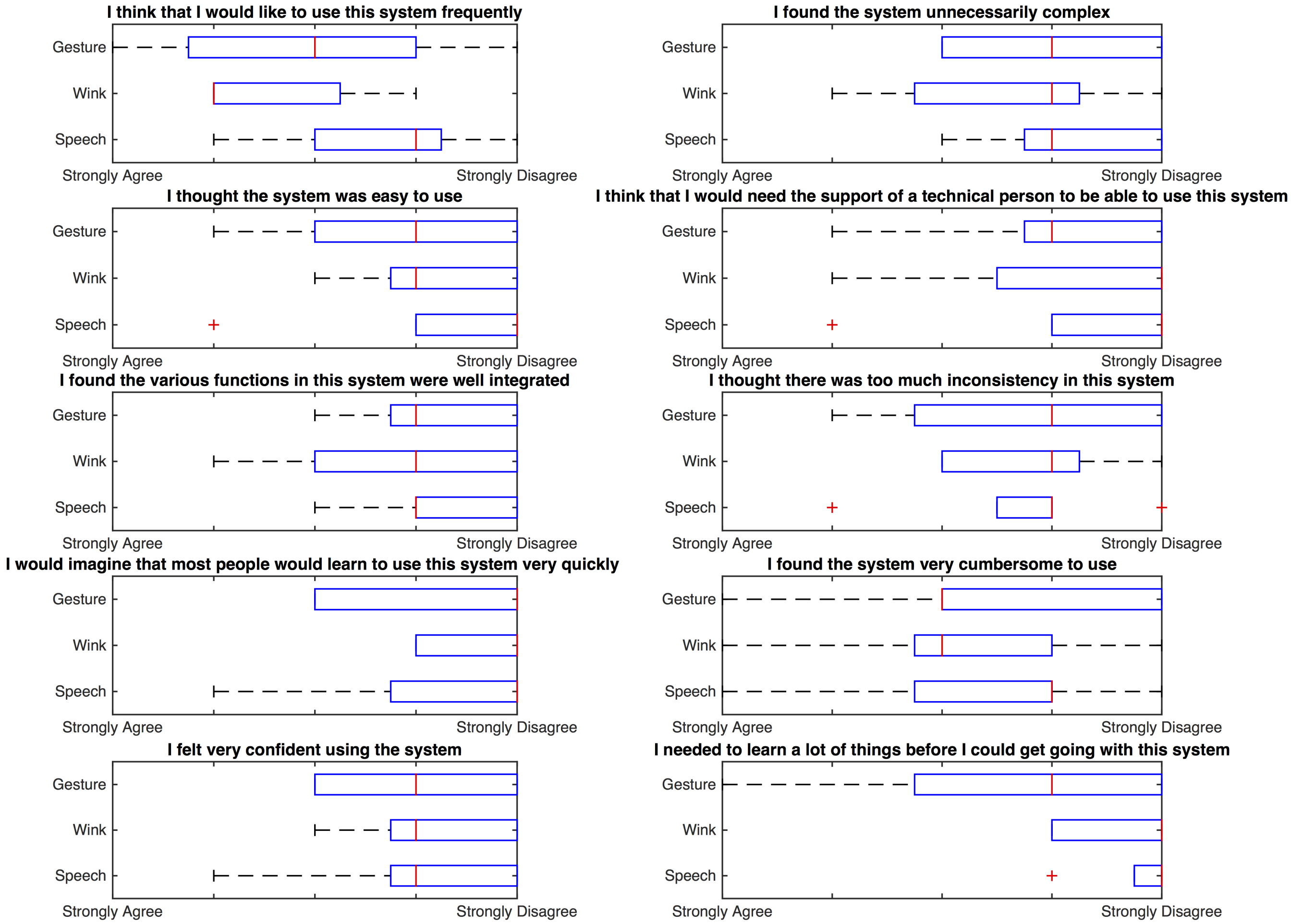


Fig. 5. System Usability Scale (SUS) evaluation results for wink-, speech- and EMG gesture- based glove control interface technologies. Note, that EMG Gesture and Speech recognition are based on commercial/publicly released production systems, while the Wink system is a lab development proof-of-principle system

actuators, for discrete end-point selection with e.g. EMG-based trigger commands [23], [24]. However, in the case of robotic interaction, the interaction occurs in three dimensions embedded in our physical reality. This poses a challenge in terms of having to observe both the physical environment where robotic actuation happens and potential visual user interfaces. Alternatives to visual user interfaces typically employ unnatural and uncomfortable "gaze gestures", such as long dwell times or artificially long blinks. Here, instead we solve the Midas Touch Problem using a binocular eye-tracker to detect wink-based commands, thereby eliminating dwell times or long blinking. We previously demonstrated that binocular eye-tracking control enables real-time closed-loop control that outperforms invasive (and non-invasive) brain-machine interfaces in terms of cost and read-out data rates [12] for continuous 3D end-point control of robot actuators [25] and/or for free-gaze navigation of wheel-chairs [26].

We evaluated our wink-based system against two other approaches: Myo armband EMG gesture triggers and voice based command which are alternative modalities to control an assistive glove. However we note that the suitability for EMG in day-long use has skin-contact based limitations [27], as well as electrical noise and humidity of the environment.

The subjective assessment of the technology in the user questionnaires showed the wink-based control was perceived as at least as or more Safe, Easy to Use and Effective to use as the other modalities, while the SUS revealed that learnability was rated equally high for all modalities. Other differences reported might have been affected by the hardware and setup procedure, which placed a commercial-grade systems (speech, EMG) against a lab proof-of-principle device (wink). Speech-based control had the fastest setup time with a couple of seconds for voice adjustment only, as the microphone was desk mounted. The voice-recognition system we used (Spinx-4) uses pre-trained models of generic human speech and does not require training on individual users, however it also means that the robotic glove can be remote triggered by other users. Eye-tracking based control required approximately 3 min for setup, this included the time to put on the eye-tracking glasses and fasten them with a headband and performing a calibration via a provisional software interface not optimised for usability. The Myo armband-based control required usually less than 2 min including calibration and testing if all five EMG gestures are can be successfully distinguished.

EMG-based control is difficult to realise for severely paralysed users such as spinal cord injured and may be complicated to be operated by the ipsilateral side in stroke survivors. We used the contralateral arm for obtaining control signs, which however restricts the usability of the contralateral arm for other purposes. In contrast the eyes link directly to the brain and are little affected by spinal cord injuries or stroke. Voice-based control of computer and portable devices is now common place, however for many paralysed users such as stroke survivors, speech-based commands are difficult to interpret due to speech impediments, and severely paralysed users with tracheal respirators are linked to the breathing cycle, being unable to execute movement commands fluently. Finally, end-users may prefer to use language for its original purpose of communication, while voice-based processing can lead to safety and security critical situations if voice recognition is not highly selective to who utters commands.

In conclusion, we have developed a novel system that makes use of binocular eye-tracking to control a glove for grasping aid. We have performed the first study that consistently compares the performance of EMG gesture control, voice recognition and eye-tracking as commands for controlling a robotic actuator. Furthermore, we showed that eye tracking had the lowest error rate among three all modalities. We were able to demonstrate that the SEM glove is easily controlled by using intended winks. There is no complex control algorithm to detect intention, it is merely used the ability to voluntarily close one of the eyes, while they can freely observe the environment.

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