

The Wouse: A Wearable Wince Detector to Stop Assistive Robots

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Abstract—Persons with severe motor impairments depend heavily upon caregivers for the performance of everyday tasks. Ongoing work is exploring the potential of giving motor-impaired users control of semi-autonomous assistive mobile manipulators to enable them to perform some self-care tasks such as scratching or shaving. Because these users are less able to escape a robot malfunction, or operate a traditional run-stop, physical human-robot interaction poses safety risks. We review approaches to safety in assistive robotics with a focus on accessible run-stops, and propose wincing as an accessible gesture for activating a run-stop device. We also present the wouse, a novel device for detecting wincing from skin movement near the eye, consisting of optical mouse components mounted near a user's temple via safety goggles. Using this device, we demonstrate a complete system to run-stop a Willow Garage PR2 robot, and perform two preliminary user studies. The first study examines discrimination of wincing from self-produced facial expressions. The results indicate the possibility for discrimination, though variability between users and inconsistent detection of skin movement remain significant challenges. The second experiment examines discrimination of wincing from external mechanical manipulations of the face during self-care tasks. The results indicate that the wouse, using a classifier trained with data from the first experiment, can be used during face-manipulation tasks. The device produced no false positives, but succeeded in correctly identifying wincing events in only two of four subjects.

I. INTRODUCTION

A. Motivation

According to the Christopher and Dana Reeve Foundation, approximately 900,000 people currently living in the U.S. report being "completely unable to move" (quadriplegia) [1]. These patients depend heavily on caregivers for basic self-care tasks. Robotic mobile manipulators present the possibility of serving as assistive devices for this population. Potential capabilities include allowing motor-impaired users to interact with their environment and perform self-care tasks. This could increase the independence of motor-impaired persons and reduce the burden on caregivers.

Many relevant tasks including scratching itches, shaving, wiping, feeding, and brushing teeth require the robot to make physical contact with the motor-impaired user, often on the head and face. As these users are less able to escape

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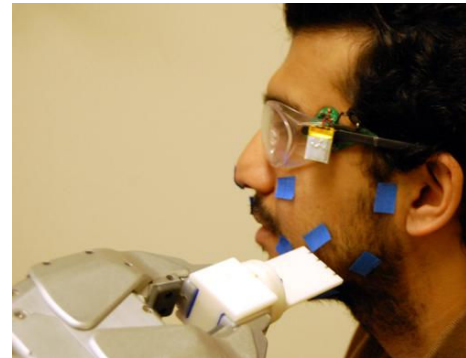


Fig. 1. A subject wearing the wouse, a wince-detecting accessible run-stop, while using a robot-held tool to perform a mock self-care hygiene task.

from a robot in case of emergency, failures during self-care tasks could be dangerous. For example, a system failure while feeding a motor-impaired user could lead to choking. Additionally, robot behaviors may obstruct the user's access to a control interface or occlude the subject from the robot's own sensors.

The use of a head-tracking mouse to interface with a computer provides a relevant example. If the robot's end effector is placed in front of the user's face, as required for shaving or feeding, a number of problems may arise:

- the user may not be able to view the interface
- the head-tracking mouse may be unable to track the user's head due to occlusions
- the task itself may prevent the user from moving his head as required

In addition, feeding tasks may limit the ability to speak, if possessed by the user at all. These dangers highlight the need for providing motor-impaired users with an accessible means of disengaging the robot.

B. Approach

Persons with severe motor impairments often have limited means of interacting with their environment. Furthermore, available means are often engaged when using assistive technology, further limiting the signals available for operating a run-stop. To overcome this challenge, we propose wincing (closing the eyes quickly and tightly) as a potential accessible gesture for run-stop devices.

Wincing involves three primary muscles, over which voluntary control is often retained in quadriplegia [2], [3]. Surrounding the eye, the orbicularis oculi closes the eyes tightly and raises the cheeks, pulling skin of the temple toward the eye. The corrugator supercillii draws the eyebrows together and forward over the eyes, and the procerus muscle on the

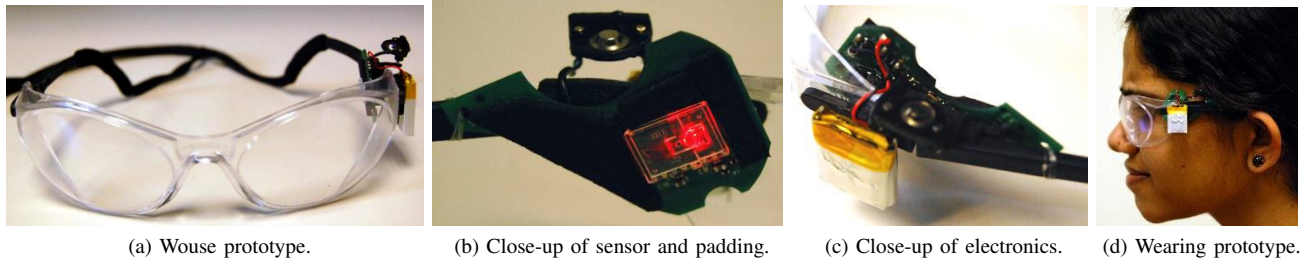


Fig. 2. Prototype Wouse Hardware: The internal components of a SwiftPoint SM300 wireless optical mouse, padded and secured to the frame of a pair of commercially available safety goggles to detect wincing from the movement of the skin near the eyes.

bridge of the nose brings the eyebrows further forward and down. Both serve to shield the eyes further and contribute to pulling the skin of the temples forward [4].

As wincing is a relatively distinctive motion, and occurs naturally at the onset of pain [5], [6], it serves as a natural gesture for communicating potential emergencies. Wincing might also serve as viable run-stop gesture in future industrial human-robot interaction scenarios, where humans may work in close quarters with robots, allowing ready access to a run-stop while leaving hands and feet free. However, to effectively serve as an accessible run-stop device in real-world use, a wince detector must not only recognize wincing reliably, but must also discriminate wincing both from other facial expressions and from the external mechanical manipulations of the face experienced during self-care tasks.

As a prototype device to perform wince detection as an assistive run-stop, we present the wouse (from "wince mouse"). The wouse consists of the position-tracking elements of an optical mouse mounted inside the temple of a pair of safety goggles (Fig. 2). This places the mouse sensor just behind the eye, where the sensor detects the motion of the skin during wincing.

Other wearable assistive input methods could be used to signal run-stop events, including wearable cameras, EMG, EEG, or Electrooculogram (EOG). While wearable cameras could be incorporated into a glasses-based design similar to the wouse, the remaining technologies typically require prepared electrical contacts on the user's skin, excessive wiring, and complex donning, which make them less desirable. In contrast, the wouse requires only a single mechanical fitting, and otherwise requires effort similar to a normal pair of reading glasses. Author Henry Evans is a mute quadriplegic as the result of a brain stem stroke, but retains the ability to wince voluntarily, and has provided significant input into the design of the wouse.

C. Related Work

1) *General Robot Safety*: Early robot manipulator designs often stressed stiff links and powerful actuation to provide strength and repeatability in industrial settings. Such robots can be dangerous and, despite safety regulations, have caused injuries and deaths [7]–[9]. Typical safety measures include physical barriers and exclusion zones preventing human access to active robots. These may take the form of mechanical interlocks or proximity sensors such as 'light screens' or pressure mats [10], [11]. In addition, the majority of systems

include run-stop buttons on either the robot, the enclosure, or a nearby control panel.

Emergency-stop (E-stop) and run-stop buttons are a common feature of many robots both in research and industry. Industry standards define the appearance and function of various categories of E-stops [12]. While run-stops (the focus of this paper) typically behave similarly, they do not necessarily fully adhere to E-stop standards. Such buttons are generally designed to be relatively large, obvious, and easy to press. When pressed, the robot is typically stopped in the most immediate and appropriate manner, which varies between hardware designs and applications. Cutting all system power, complete system braking, entering an unforced but actively gravity-compensated mode, or combinations thereof may be appropriate responses to a run-stop event. Despite their pervasiveness in the robotics community, and the highly varied effects they may produce, little explicit study of run-stop effects or use has been performed. One ergonomic study was found which evaluated the size and placement of the run-stop button on a teach-pendant [13].

While large and powerful robots require significant safety devices and warrant E-stops, this may not be necessary for future robots, thanks to improved hardware and software design with an emphasis on safe human-robot interaction [14], [15]. Already, some commercially available robots such as the iRobot Roomba/Scooba/Create, Looj, and Packbot do not possess run-stops [16]–[19]. Instead, sensors detect unusual conditions (such as being lifted off the floor), and halt operation. Given the rather limited potential for physical damage, and an abundance of safety warnings, the absence of a run-stop button seems reasonable in these cases. The Husqvarna Automower, a robotic lawnmower, does include a prominent "STOP" button which halts the device, in addition to bump, tilt, and lift sensors [20]. This button must be engaged to access the control panel, and prevents reactivation, constraining interaction toward safe operation.

2) *Assistive Robotic Safety*: While a run-stop can be an effective safety measure, the challenge of enabling motor-impaired individuals to access such a device remains. Motor-impaired users have reduced physical capabilities, and therefore decreased ability to activate a traditional run-stop, making safety a significant concern. Indeed, Tsui et al. cite safety as a notable gap in the application of current human-technology interaction models to assistive robotics [21].

A number of projects in assistive robotics for the motor-

impaired have addressed safety, including hardware and software design measures, in addition to providing run-stop or similar functionality. Busnel describes a number of safety features on the CEA MASTER assistive desktop robot, including velocity and acceleration limits, a minimal overlap of the robot's workspace with the user, and a run-stop button placed by an occupational therapist based on the specific user's residual capabilities (i.e. feet, chin, elbow, shoulder) [22]. When pressed, the run-stop button engages a series of chained, custom safety scripts.

The Desktop Vocational Assistant Robot (DeVAR) largely relies on voice commands, including a verbal "stop" to halt the robot. The robot also stops for loud noises or if it senses "an obstruction greater than about 2kg (5lb)" [23]. In addition, a "panic switch" is placed near the cheek of the motor-impaired user, and the overlap of the user and robot workspaces is limited. At the extent of its reach, the robot can bring tools such as a spoon, electric razor, or wipes, into contact with the user's face. This minimal overlap reduces the chance of dangerous interaction [24].

Seamone and Schmeisser describe another assistive robotic workstation that uses a powered prosthetic arm. This device can achieve limited force and velocity, has only limited overlap of the robot and user workspaces, and allows the user to stop any behavior with a single press of a chin-switch, which is also the primary input to the device [25].

Other assistive robots have been designed for assisting older adults. This target population may have mild physical impairments, but generally retains a high level of function. When originally developed primarily as a mobile navigation aid, the Care-O-Bot included a laser scanner for obstacle avoidance and bumpers which would immediately halt the robot on contact. To ensure the robot did not leave its designated region under a malfunction, magnetic sensors detecting a magnetic barrier strip surrounding the environment would halt the robot. Lastly, the robot has two run-stop buttons, which immediately halt the robot if activated [26].

Many other research efforts have only evaluated assistive robots in a clinical or research setting. The presence of trained observers in these situations typically eliminates the immediate need for user-accessible run-stop devices. KARES I & II attempt to ensure safety through compliant arms and allowing the user to stop current actions. A number of inputs are possible, including head tracking, eye tracking, and EMG [27]. The FRIEND I & II assistive robots allow for "user interrupts" of active behaviors through their graphical user interface, though no additional safety features are indicated [28]. In [29], Dario et al. make no mention of a run-stop accessible to motor-impaired users of the MOVAID robot.

3) *Challenges with previous methods:* In many cases above, the restricted overlap of user and robot workspaces is a primary safety feature. While effective, this is closely analogous to the exclusion zones enforced with industrial robots, and restricts the ability of the robotic system to perform care tasks on the user's body. Furthermore, such a constraint is difficult to enforce with a mobile robot, as the robot's workspace moves with it. Another advantage of

a wearable assistive run-stop over many previous methods is the separation of the safety mechanism from the task being performed. As assistive robots develop more general purpose capabilities, the experiences of real-world users will be highly varied, making it difficult to foresee all possible emergencies. For assistive mobile manipulators to be accepted as safe and effective, novel methods for ensuring safety, such as an accessible run-stop, will likely be required.

II. IMPLEMENTATION

A. Hardware

We have developed two versions of the wouse hardware: a simple prototype, used in the experiments described below, and an adjustable, more user-friendly design for use over normal glasses, which is described at the end of this paper.

The prototype device consists of a pair of wear-alone safety glasses, to which the sensing component, battery, and charging terminal of a SwiftPoint SM300 optical mouse have been attached (Fig. 2). The glasses are secured to the head using an adjustable glasses retainer. The circuit board with the mouse sensor is fixed inside the left temple of the glasses, and largely covered with thin foam padding to improve comfort and protect circuit board components. The battery is adhered to the outside of the temple so that it does not swing freely. The charging terminal, which mates magnetically with the USB-plug radio receiver, was cut from the plastic case of the mouse, sanded smooth, and re-connected to the circuit. It rests just above the temple of the glasses, and allows the device to be recharged.

B. Software

1) *Architecture:* All of the software associated with the wouse is open-source and freely available as a single Robot Operating System (ROS) package intended for use with a PR2 robot, though the design should allow porting to different hardware [30]. The software classifies time-stamped mouse movement events as "wincing" or "not wincing" via a two-class SVM with a radial basis function as implemented in the *scikit-learn* Python module [31]. The package includes a server ROS node that runs on the PR2's own computers and interacts with the PR2 power system nodes. A client node runs on the computer physically connected to the wouse USB-plug receiver and receives, filters, and classifies incoming data. If the client detects a wince event, it signals the server to halt the PR2's motors and place the robot into a low-power standby state, as if the physical run-stop had been pressed. In addition, the client provides a "heartbeat" signal to the server. If the server does not receive this signal for a specified length of time, the robot beeps and issues warnings, though this could alternatively run-stop the robot. The ROS package also contains utility scripts for collecting, processing, and evaluating training data to provide feedback on quality and content, and for classifier training.

2) *Data Processing:* During data collection, the client reads mouse movement events (relative motions along perpendicular x and y axes) and timestamps directly from the Linux device file. To avoid interference with normal cursor

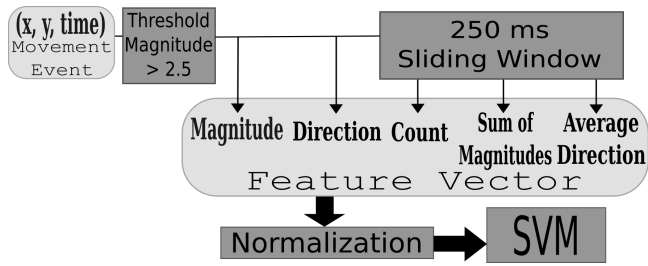


Fig. 3. A diagram of the wouse data processing. Light, rounded blocks represent data. Dark, square blocks are actions on that data. Incoming movement events $(x,y,time)$ are filtered, removing events with magnitude < 2.5 . The magnitude and direction of that event are the first two components of the feature vector. The event is then appended to a 250ms sliding window, and the count (number), sum magnitude, and average direction of events in that window are the final three components of the feature vector. All training feature vectors are then normalized to zero mean and unit standard deviation before being used to train a two-class SVM. Test data receive the same normalization before being evaluated by the SVM.

movement and allow non-root access, a udev rule creates a separate, global-access device file for the SwiftPoint mouse receiver which does not influence cursor movement.

The act of wincing tends to produce movement events larger in magnitude, greater in number, and along a more consistent direction than other actions. Algorithm 1 and Figure 3 both show the data processing used to collect features of the movement events reflecting these differences.

First, events of magnitude less than 2.5 are discarded as noise. These small movements arise from a variety of sources including subtle facial contortion and shifting of the glasses with head motion, and represent a significant portion of the recorded movement events (Fig. 4). The magnitude of 2.5 was chosen based on observation of preliminary data during developer testing. The magnitude and direction of remaining events are then calculated and appended to a sliding time window containing all above-threshold events in the previous 250 ms. Longer window durations provide marginally improved recognition, while shorter window durations provide a faster response. We selected 250 ms as a suitable trade-off between these two factors. The resulting five-dimensional feature vector associated with each movement event contains that event’s *instantaneous magnitude* and *instantaneous direction* along with the *number (count)*, *sum of magnitudes*, and *average angular direction* of all events in the associated window. The feature vectors are then normalized so that

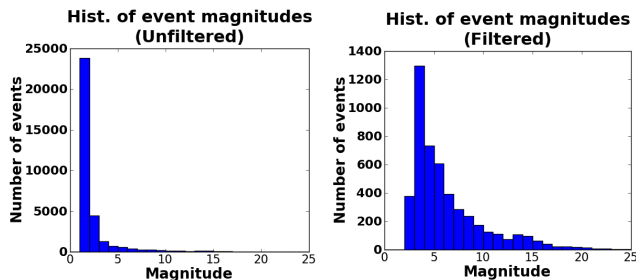


Fig. 4. Histograms of raw data magnitudes before and after filtering. The majority of all unfiltered data has magnitude less than 1.5. When data with magnitudes < 2.5 are removed, the remaining distribution becomes clear (note change in scale).

Algorithm 1 Wouse Data Processing

```

motion_event = (x, y, time)
window = [motion_events]
function PROCESS_MOTION(motion_event)
  if SQRT(x2 + y2) ≥ 2.5 then
    return
5:   mag ← SQRT(x2 + y2)
    dir ← ATAN2(y, x)
    window.APPEND(motion_event)
    cutoff_time ← motion_event.time - 0.25
  for all old_event in window do
10:    if cutoff_time > old_event.time then
      window.POP(old_event)
    win_x_sum ← SUM(window.[x])
    win_y_sum ← SUM(window.[y])
    win_count ← window.LENGTH
15:   win_mag ← SQRT(win_x_sum2 + win_y_sum2)
    win_dir ← ATAN2(win_y_sum, win_x_sum)
  return (mag, dir, win_count, win_mag, win_dir)

```

each component has zero mean and unit variance across the training data. The normalized feature vectors are used to train an SVM, and new data receive the same normalization before being evaluated by this classifier.

III. EVALUATION: WINCING VS. FACIAL EXPRESSIONS

Characterizing the real-world performance of the wouse requires evaluating the ability of the wouse both to recognize wincing when it occurs, and to discriminate wincing from other facial expressions.

A. Methods

In the first experiment we collected movement event data from able-bodied users performing a variety of facial expressions and actions for classifier training and cross-validation. Subjects were seated at a laptop computer and instructed to don the wouse glasses, making sure they were comfortable and secure. No further calibration or fitting was performed. The computer script in Algorithm 2 then instructed subjects to make a series of specific facial expressions and gestures (here *actions*). Each instruction was chosen randomly from: Wince, Shake Head, Nod Head, Look Angry, Look Disgusted, Look Joyful, Look Afraid, Look Surprised, or Look Sad. These actions were selected to cover the range of emotional expressions [32]. Instructions were given every 3.5 seconds with an alert tone and printed text. Mouse movement events were then recorded for two seconds and labeled with the instructed action. Recording then stopped, a different tone sounded, and the subjects used the remaining 1.5 seconds to resume a neutral expression. Each of the nine instructions was issued a total of thirty times, for a total of 270 action instances per subject. Figure 5 contains a selection of the expressions produced during this trial.

Before testing, subjects practiced until comfortable, allowing them to adjust to the timing and identify facial

Algorithm 2 Training Data Collection Procedure

```
actions=30*[Wince, Nod, Shake, Fear, Joy, Sadness,  
            Surprise, Disgust, Anger]  
actions.RANDOMIZE( )  
for all action in actions do  
    PLAY_SOUND(start_tone)  
    PRINT(action)  
    RECORD(2.0 seconds)  
    PLAY_SOUND(stop_tone)  
    WAIT(1.5 seconds)
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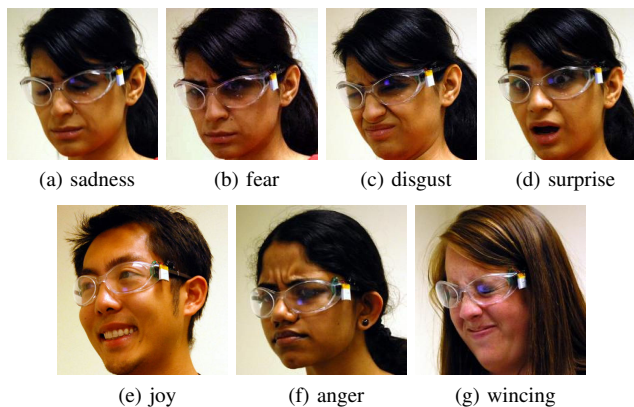


Fig. 5. Facial expressions of various subjects during data collection.

expressions they believed reflected the listed emotions. No attempt was made to elicit true emotional expressions given the difficulty and ethical concerns of producing repeated surprise, fear, involuntary wincing, etc.

We then evaluated the wouse performance using leave-one-out cross-validation. For each of thirty rounds, the movement features associated with one instance of each action were retained for testing, while the remaining twenty-nine were used for training, labeled only as ‘wincing’ or ‘non-wincing’. The trained SVM then classified all movement features from the retained action instances, separately for each action. If any of the features associated with an action instance was classified as wincing, that instance was considered classified as wincing. For true wince actions, this is a true positive, and for non-wince actions, a false positive. The number of false positives associated with each non-wincing facial expression was also noted.

If an instance contained no event features (no data over magnitude 2.5 collected during that instance) it is classified as non-wincing. Cross-validation was performed within data from each subject, as if each individual had trained the device individually. An additional round of cross-validation was performed with the combined data from all three subjects to evaluate the impact of variability between users.

B. Results

From self-reported demographics, the first experiment had ten subjects, five white and five Asian, six women and four men, age 28 ± 3.05 years (mean \pm std). 32,779 movement events were collected in total, though only three subjects produced the significant majority of these. Subject 9 produced

TABLE I

CROSS-VALIDATION RESULTS		
Subject	True Positives	False Positives
1	70.00% (21/30)	7.71% (18.5/240)
9	96.66% (29/30)	12.25% (29.4/240)
10	100.00% (30/30)	4.96% (11.9/240)
Combined	81.11% (73/90)	9.14% (65.8/720)

76.7% of the total events, Subject 10, 11.9%, and Subject 1, 7.7%, with five more combined producing the remaining 3.7%, and two subjects producing no movement events. As a result, only subjects 1, 9, and 10 produced enough events to successfully segment the action instances, as required for subsequent classifier training and analysis.

Figure 6 shows the distribution of feature components between wincing and non-wincing events for subjects 1, 9, and 10. Only three of five feature components are shown, as direction and magnitude show similar trends in instantaneous and time-windowed components. Given the identifying features of wincing stated above, the trends are as expected: wincing produced more events, of larger magnitude, along a more narrowly constrained direction than other facial expressions. However, the particular counts, directions, and magnitudes, as well as the variability, are significantly different between users.

The results of the cross-validation tests can be seen in Table I. All three subjects showed promising true positive detection rates and low false positive rates, though both show opportunity for improvement. Encouragingly, the true positive rate for subject 9, who produced the most data, was over 95%. Also, the results produced from the combined dataset (table I, row 4) are comparable to the results from single-individual data sets, though not as strong.

Figure 7 compares the false positives caused by each expression. Disgust and joy are the two largest contributors, which seems to support the importance of the orbicularis oculi in defining the detected wincing motion, as this muscle is responsible for the cheek raising seen in these emotions [33].

C. Discussion

The results of this preliminary evaluation indicate two important sources of error: failures of motion detection and failures of classification.

1) *Failed Motion Detection*: Failure to detect motion is functionally equivalent to a “non-wincing” classification. During a wince, this results in a false negative. The potential cost of a false negative is high when performing self-care tasks such as feeding for motor-impaired users. For this reason, the wouse must detect wincing motions reliably. The results for subjects 1, 9, and 10 show that it is possible for the wouse to detect motions of a user’s skin. However, this was not the case for the majority of subjects, making this a significant obstacle to reliable functioning. Using the recently improved wouse hardware and taking time to fit each user may provide more consistent movement detection. This could directly reduce the number of false negatives from failed movement detections, and indirectly improve

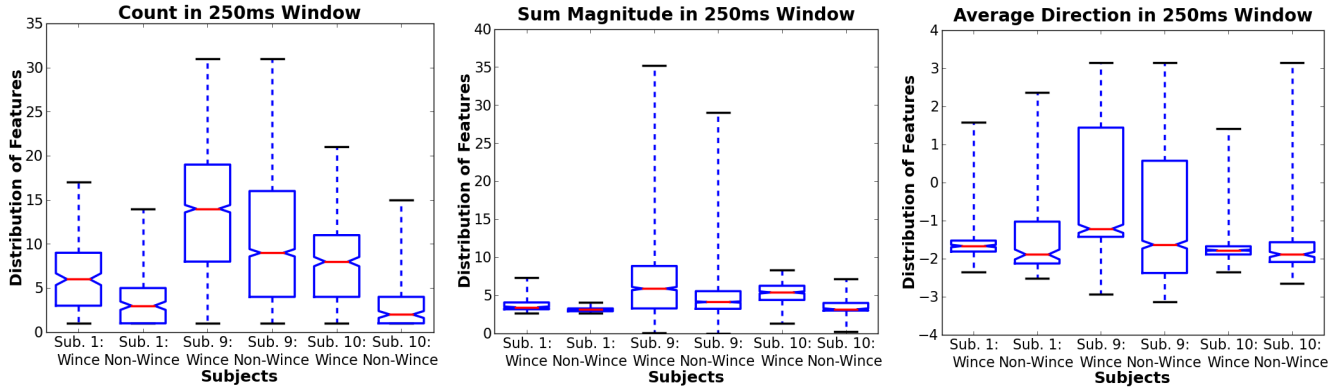


Fig. 6. Comparison of Distributions of Wincing and Non-Wincing features between three subjects. Boxes show the inter-quartile range (IQR), whiskers the range, and red line the median. Notches show median $\pm \frac{1.57 \cdot IQR}{\sqrt{n}}$.

the classifier performance through additional training. If the strong cross-validation performance seen with subjects 1, 9, and 10 can be readily reproduced or improved upon with improved hardware and fitting, it would suggest the wouse could be a viable assistive wince detector.

The reduced classifier performance in cross-validation on the combined data from multiple users suggests that overall performance may be improved by training the device for individual users. In addition, this could help account for variability in residual function between motor-impaired users. To further improve detection rates, it is possible to bias the classifier toward detection, though this necessarily comes at the cost of increasing false positives.

2) *False Positives*: False positive run-stop events present a non-negligible cost arising from frustration, lost time, and possible discomfort or minor injury such as might be caused by dropped objects. Excessive false positives could render the system unacceptable to users. One possible method of reducing this cost could be the inclusion of a “soft-stop” triggered by the wouse. Such a feature would engage a safety response from the robot without completely removing power and entering a full run-stopped state. A “soft-stop” could encourage the user to engage the wouse as potentially dangerous situations develop, rather than waiting until they occur. This in turn, may reduce both the total cost of false positives and the occurrence of dangerous situations,

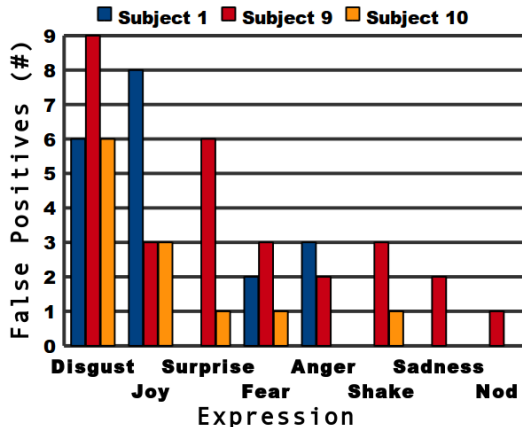


Fig. 7. The sources of false positives.

improving both acceptability and safety.

IV. EVALUATION: WINCING VS. TASK-RELATED FACIAL MANIPULATIONS

A. Methods

The second experiment evaluated the wouse performance during a mock face-cleaning task involving physical manipulation of the face. The task and the manner of its performance were intended to simulate self-care activities such as scratching, shaving, or cleaning as performed by motor-impaired individuals using an assistive robot. In this experiment, able-bodied subjects placed small squares of masking tape on nine specified locations on the left side of their faces (Fig. 8a). After donning the wouse, trained using data from the previous experiment, and adjusting to ensure data were being reported in response to facial contortions, a PR2 robot was positioned to hold a custom-made scratching tool (Fig. 1) near the subject’s face, such that the edge of the tool ran from the corner of the mouth to the jaw line (Fig. 8b). This position allowed all regions on that side of the face, the same side as the wouse sensor, to be brought to the tool by moving primarily the head and neck. Subjects were then asked to scrape off each piece of tape by moving their heads against the tool. An experimenter observed the subjects’ performance, and made note of any events which caused a wince to be detected. Once all of the tape was removed, the subject was asked to wince clearly, and note was made of the classification of this event as well. Subjects were given no feedback regarding wince detections during the experiment to avoid behavior adaptation.

B. Results

1) *Simulated Task Experiment*: The second experiment had five subjects. However, one withdrew early after technical difficulties were encountered, and no data were collected. The remaining four self-reported their demographics: two whites, one Asian, and one Hispanic, three men and one woman, age 23 ± 1.83 years (mean \pm std). To remove the tape, all four subjects produced significant contortions of the face both with facial muscles and by applying force to the tool, in addition to making contact with the wouse glasses. All four

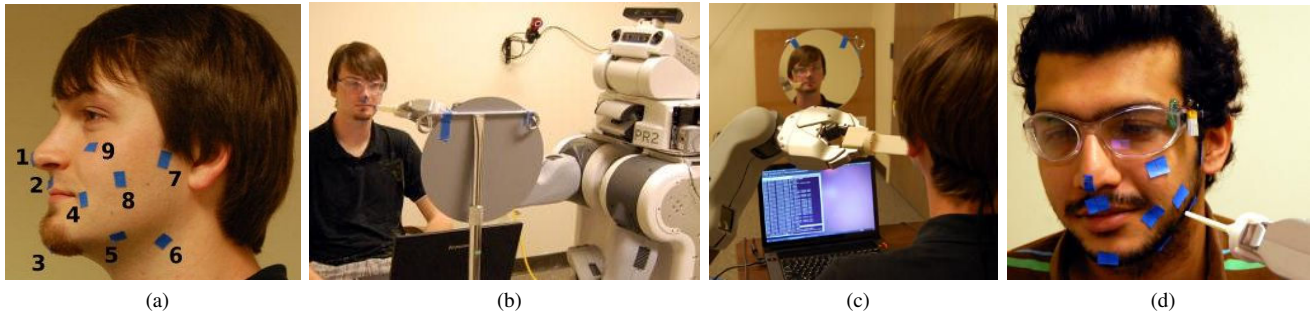


Fig. 8. The setup of the task-simulation experiment, including (a) the locations of tape on the subjects' faces, (b) a view from in front of subject, (c) a view from behind subject, and (d) a close-up of the subject and tool.

of the subjects produced very few events of magnitude > 2.5 and no false positives during the task. Two subjects' wincing were properly classified. Another subject's wince produced events above the magnitude threshold but was misclassified (a false negative), and the last produced no recorded movement over the magnitude threshold, despite care being taken to adjust the fit of the device so that it reported data upon facial movement before testing. In summary, only two of four total wincing were correctly detected.

C. Discussion

The results of the second experiment indicate that large movement events may not be produced often during real-world tasks. The manipulations and contortions required to remove the masking tape from the subjects' faces were large, and involved movement of skin around the eyes and contact with the glasses. As very few movement events over the magnitude threshold were produced by any of the subjects, this reduced the number of events which were passed to the classifier. In addition, none of the events of magnitude produced by manipulating the face or bumping the glasses were classified as wincing.

However, the magnitude threshold may have prevented the smaller motions associated with one subject's actual wince to go unclassified (a failed detection). Setting this threshold based upon data recorded from individual users may improve performance. Poor hardware adjustment, discussed previously, likely contributed to the other failed wince detection, despite additional fitting.

V. IMPROVED HARDWARE DESIGN

A. Wearability Results

Of the fourteen total subjects in both experiments, none reported problems with the glasses slipping. Four reported minor discomfort, typically citing that the glasses were tight or too small, though none of these subjects normally wear glasses. In contrast, none of the six subjects who do regularly wear glasses reported any discomfort. Thirteen subjects reported being completely unaware of the light from the mouse sensor, and the single subject who reported awareness stated that it was not bothersome.

B. Improved Hardware

Despite the encouraging wearability results, the need for improved hardware is clear. To this end, we have recently developed a more user-friendly, mechanically robust wouse design for use over normal corrective lenses (Fig. 9). The modified temple of the safety goggles houses the electronics from a SwiftPoint SM300 including wireless transmitter and rechargeable battery, along with a micro USB port for charging. The sensor hangs down from the temple of the glasses just below and behind the eye where the skin moves during wincing. The sensor needs to be placed near and parallel to the face, hovering 0.5–1.1 mm above the skin, but not touching. To achieve this, the wouse uses two spring-loaded push levers to adjust the plane of the mouse sensor. A rack of teeth receive notches on the levers to hold the levers in place once adjusted. The sensor is attached to the ends of the adjustable levers, and is held to the temple of the glasses at a third point. This is an improvement from previous designs, which were either free floating or adjusted with screws. The free floating design was not able to be easily adapted to work with safety glasses which go over vision glasses, and the screw adjustment was tedious, slow, and finicky to use. While prototyping the wouse with levers, we built and tested several iterations of the design to get a correct fit of the glasses and make the levers work with the user's face while staying out of the way of their normal corrective glasses. This more advanced hardware will hopefully prove easier to use and provide more consistent, higher quality data due to personalized fitting.



Fig. 9. A close-up of the more advanced wouse design, including springs and levers for adjusting the sensor position, battery (bottom left), and micro-USB charging receptacle (bottom left).

VI. CONCLUSIONS

Accessible run-stop devices have the potential to enable motor-impaired persons to more safely use assistive robots. By giving motor-impaired users a means to reliably stop assistive robots under a variety of circumstances, they may be better able to take advantage of general purpose assistive robots without supervision, increasing their independence. In this paper, we have identified accessible run-stops as a worthwhile research area and discussed potentially important factors for this type of device. We have also presented a novel concept for a class of accessible run-stop consisting of a wearable device to detect voluntary wince gestures. In addition, we presented an initial device prototype, the wouse, that uses optical mouse components to monitor skin motion at the temples to detect wincing.

Our evaluation of the wouse suggests that our concept for wearable wince detection may be worthwhile and that our current design may represent a feasible approach. For at least one of seven users, our device and algorithm distinguished wince gestures from other facial gestures with promising false-positive rates. Likewise, for two of four users, the wouse was able to distinguish wince gestures from mechanical perturbations of the face during a task. However, for many subjects in our experiments our prototype system performed poorly, highlighting the need for further research. Improved hardware, better hardware adjustment to individuals, improved threshold selection, and providing feedback to users during training all have the potential to improve system performance to an acceptable level.

It is also possible that monitoring skin motion at one or both temples using optical mouse components provides insufficient information for this type of device. If this becomes evident in further research, devices that provide additional information, such as cameras looking at the eyes and temples, may still make wearable wince detection for accessible run-stops a worthwhile proposition.

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