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Eye-Blink-Controlled Wheelchairs: A Critical Review of Blink Detection, Command Encoding, and Safety in EOG-Based Prototypes

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Abstract: ***A blink is one of the few voluntary actions left to wheelchair users who cannot operate a joystick, and electrooculography (EOG) records it cheaply with skin electrodes. Yet people blink all day without meaning to, so a blink-controlled chair must tell a chosen blink from a reflex.***
This review reads 25 papers. Twelve of them are eye-controlled wheelchair studies, published between 2007 and 2024 where a year is shown, which are analyzed in detail together with the blink-based systems they describe; the other thirteen give background and related methods.
For each study it notes the sensing arrangement, blink detection, the job given to the blink, safety provisions and test method. Six of the twelve use a blink or sustained eye closure as a command (toggle, stop, reverse or mode switch), one treats the blink purely as an artifact to be rejected, and the rest report no blink command.
Chosen and reflex blinks are separated by peak amplitude, pulse duration, timing windows or, in one study, a pruned decision tree. Reported command success lies between 87 and 100 percent, but the figures come from incompatible protocols and small groups, and none of the studies reports false activations from involuntary blinks per unit time, tests with motor-impaired users or measures eye fatigue. The paper closes with proposals for a shared blink-command benchmark, fail-safe command assignment and layered safety design.
Index Terms: eye blink, electrooculography, wheelchair control, human–machine interface, biosignal classification, literature review.

I. INTRODUCTION

Many smart wheelchairs still assume that the rider can steer with a joystick, which calls for fine control of the hand. For people with severe limb impairment, researchers have tried voice, head posture, facial muscles, brain signals and eye tracking [1], and every option trades one weakness for another: voice control suffers in noisy places, scalp EEG is awkward to set up, and camera-based gaze tracking is sensitive to lighting.

Many people with severe motor disorders keep voluntary control of their eyes. Electrooculography (EOG) measures the small potential change that eye rotation produces on the skin around the orbit. It needs only surface electrodes and a low-bandwidth front end, so it is often prototyped on cheap microcontrollers. Barea *et al.* [2] established the idea of assisting mobility through EOG-measured eye movements.

Within this family the eye blink deserves separate attention. It is probably the cheapest eye action to perform and the easiest to detect, so prototypes use it as a switch, a stop or a confirmation [3].

It is also the eye action most likely to happen by accident: blinks occur continuously, mostly without intent, and leave a large transient on the vertical EOG channel from which other commands must be told apart [4]. A blink command is therefore only as safe as the decoder that separates it from a reflex (Fig. 1).

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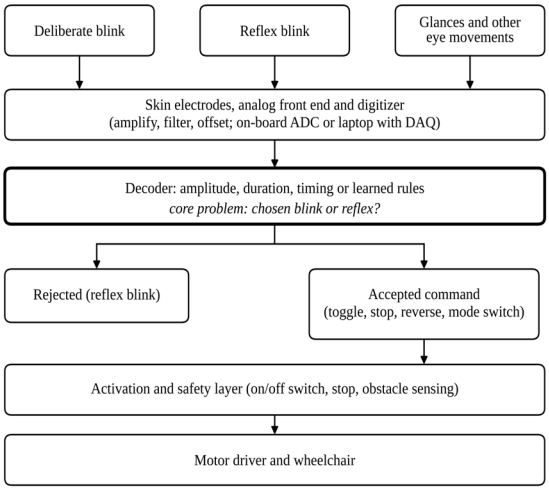


Fig. 1. Overview of a blink-controlled EOG wheelchair interface. The decoder must separate chosen blinks from reflex blinks and other eye movements before a command reaches the safety layer and the drive.

The literature is fragmented: each prototype brings its own electrode layout, filter chain, command set and test procedure, and reports a single success figure, so a reader cannot easily tell what has been shown. This review puts two questions to twelve primary eye-controlled wheelchair studies and to the blink-based systems they describe: how is a deliberate blink detected, given a meaning and kept apart from involuntary blinking and other eye movements, and what does the evidence say about readiness for the intended users? The contributions are a grouping of the studies by decoding strategy and blink role, a table that keeps each result next to its test protocol, a cross-study discussion, and gaps with matching research directions.

II. REVIEW SCOPE AND METHOD

This is a narrative review of 25 papers that the author collected and read in full. Twelve of them are the primary studies analyzed in detail in Table I; the other thirteen supply background, earlier interfaces and methods. Each primary paper describes a wheelchair, or a wheelchair prototype, driven by eye movements and gives enough technical detail to identify the sensing arrangement and the stage where eye movements become commands. Ten rely on EOG alone. One uses facial EMG for direction and EOG only for speed [5], and one is a camera-based design kept as a non-EOG comparator [6]. Every paper was read for the role it gives the blink, and a study that treats the blink as pure artifact stayed in because it shows what a decoder must reject. The set did not come from a registered database query and no risk-of-bias grading was applied, so the findings describe this corpus and not the whole field.

For each paper the following items were extracted: sensing arrangement, front end, processing platform, decoding method, command set, activation and safety provisions, role of the blink, participants, trial structure and reported results. Anything a paper does not state is marked NR (not reported). The copy of Shah and Kher [7] shows neither year nor venue, and that of Domínguez Sucres *et al.* [8] shows no venue; both are listed as they appear. Numbers are quoted as given; the totals of Rusydi *et al.* [3] and Rouillon-Sotomayor *et al.* [9] were rebuilt from their counts. Statements with a citation describe what that paper reports, and the rest is the reviewer's interpretation.

III. BACKGROUND: EOG FOR WHEELCHAIR CONTROL

A. Signal Origin and Electrodes

The eye behaves as a fixed electrical dipole with the cornea positive relative to the retina, so rotating the globe shifts the potential seen by skin electrodes around the orbit. Within about 30° of horizontal gaze the amplitude grows roughly linearly with angle, from about 50 µV to 3.5 mV [10]. The prototypes work in a narrower window: Yathunanthan *et al.* [4] cite 0 to 30 Hz and 100 to 1000 µV, while Al-Haddad *et al.* [11] place the eye-movement content between 0.1 and 20 Hz. Amplitude also varies with the person, electrode position and day [8].

Horizontal gaze is read from electrodes at the outer canthi and vertical gaze from a pair above and below one eye. Designs differ mainly in electrode count: three in Kuo *et al.*, four in Rusydi *et al.*, five in Yathunanthan *et al.*, and five plus two for single-eye blinks in Al-Haddad *et al.*

B. Processing Chain

The chain is similar across the prototypes: a differential instrumentation amplifier (most often an AD620), high-pass corners near 0.05 to 0.5 Hz against drift, low-pass corners between 27 and 50 Hz against noise, and in Yathunanthan *et al.* a 50 Hz notch. Because the conditioned signal is bipolar, microcontroller designs add a DC offset or scale the output to 0 to 5 V [12]. The digitized signal then reaches a laptop through a data-acquisition unit, as in Rusydi *et al.*, or the on-board converter of a microcontroller [13].

C. Earlier EOG Interfaces

Earlier interfaces set the pattern. Usakli and Gurkan [14] built an EOG virtual keyboard with a peak-based and time-based classifier. For wheelchair commands, Huang *et al.* [15] used a graphical interface with flashing buttons and blink confirmation, Bhuyain and Salim [16] classified gaze directions against preset thresholds, and Choudhari *et al.* [17] counted blinks within one second; Rusydi *et al.* [3] list movement accuracies of 91.7%, 90% and 93.89% for these three. Li *et al.* [18] proposed a start/stop switch that requires the user to blink in step with a flashing button, a method Rusydi *et al.* regard as slow.

D. The Eye Blink as Signal and as Command

A blink appears on the vertical channel as a large pulse pair, and it is the artifact discussed most often. Involuntary blinks happen all the time, whereas deliberate blinks are chosen by the user, and decoders separate them mainly by pulse size and length: a reflex blink gives a shorter and smaller pulse than a deliberate one [7]. Rusydi *et al.* add that conscious and unconscious blinks and upward glances share one polarity pattern. Al-Haddad *et al.* record single-eye blinks through two extra electrodes and state that such monocular blinks reach 10 to 20 times the amplitude of ordinary ones, which makes them easier to threshold.

Across the studies and the related systems they describe, the blink is given at least six different jobs. It toggles the system on and off in Rusydi *et al.*, stops the chair in Mulam *et al.* [19], drives it backward in Kuntal *et al.*, switches mode and starts autonomous navigation in Al-Haddad *et al.*, and confirms a selection on a flashing interface in Huang *et al.* In the system of Choudhari *et al.* blinks counted within one second form the command. A related family uses sustained eye closure instead: about three seconds stops the camera-based chair of Dwajan *et al.*, and 16 consecutive closed-lid frames stop the chair of Rajesh and Mantur [20]. The eyebrow-EMG click of Tsui *et al.* plays the same role through a non-ocular muscle. Table I gives the role of the blink in each reviewed study.

E. The Built-in Conflict of Eye Control

The eye channel stays available when limbs, speech and facial muscles do not, but the same eyes are needed to watch the surroundings. Steering by gaze stops the user from looking around freely, as Rusydi *et al.* observe; Rajesh *et al.* [21] note the constant need to look at the chair, eye fatigue has been linked to eye-movement characteristics [22], and Tsui *et al.* confine EOG to a secondary role for this reason.

IV. DECODING APPROACHES

Fig. 2 groups the twelve studies by how eye movements become commands. Ten rely on EOG alone, and the grouping cuts across hardware, because one front end can feed very different decoders.

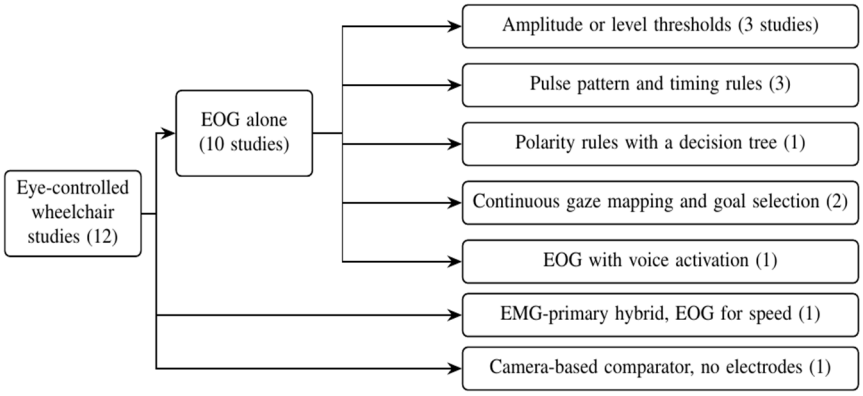


Fig. 2. Grouping of the reviewed studies by sensing modality and decoding strategy (number of studies in parentheses).

A. Amplitude and Level Decoders

The simplest decoders compare the conditioned signal with fixed levels. Kumar and Vinod [13] separate three gaze conditions by voltage; across five subjects the values fall in non-overlapping bands (about 273 to 295 mV for left, 320 to 351 mV for straight ahead and 396 to 414 mV for right), but the bands lie only a few tens of millivolts apart and no classification accuracy is given. Rouillon-Sotomayor *et al.* [9] write the decoder as conditions on analog-to-digital counts from two channels, for example a vertical count above 350 for an upward glance, and Kuntal *et al.* [12] compare amplitude with thresholds fixed during a start-up calibration in which the user follows visual cues. Such rules are easy to inspect but fragile, and Shah and Kher [7] note that pulse width and duration can ease the problems of pure amplitude comparison.

B. Pulse-Pattern and Timing Rules

A second group reads each eye movement as a pulse pair: an excursion away from the baseline followed by a return excursion of opposite sign, with timing limits on both. The decoder of Yathunanthan *et al.* [4] accepts a pulse only if it exceeds channel thresholds (1.5 V vertical and 1 V horizontal by default), lasts about 0.135 s and is followed by its opposite pulse within one second. That timing limit lets the processor discard unintended pulses and blink interference on the vertical channel. A trainer module measures noise peaks and durations per user, though the system also worked without it; consecutive commands must be at least 0.8 s apart. In Mulam *et al.* [19] the order of positive and negative peaks on the horizontal and vertical channels, together with a 750 ms limit, identifies right, left, up and down, and an extra 79 mV peak criterion separates a blink from an upward glance.

C. Polarity Rules with a Learned Stage

The only learned classifier among the EOG studies is the decision tree of Rusydi *et al.* [3]. Each movement gets an initial and a final polarity on two channels. Glances right, left and down have distinct patterns and are identified directly, whereas glances up, deliberate blinks and involuntary blinks share one pattern and are separated by a tree trained on peak amplitudes. On 4500 labeled rows split 70/30, an unpruned tree reaches 100% on training and 87% on test data, a pre-pruned tree 92% and 90%, and a post-pruned tree of depth 9 with 40 leaves 92% and 91%, which is the one selected. In the vehicle test with 15 respondents the system moved the chair correctly for 98.89% of 270 commands (three repetitions of six commands each), and the activation command had the lowest success rate at 95.56%.

In this review's reading the design is rule-first, learn-second: learning is confined to the three classes on which the polarity rules are silent. Two features limit what can be concluded about generalization: the text does not say whether the 70/30 split separated participants, and the 91% figure covers the three peak-feature classes only. No deep-learning EOG decoder appears among the twelve studies; a *k*-nearest-neighbor classifier [23] and a fuzzy classifier [24] are known only through related-work sections of the primary papers.

D. Continuous Gaze Mapping and Autonomous Guidance

Two studies treat gaze as a continuous quantity. In Kuo *et al.* [10] the horizontal gaze angle, limited to 30°, passes through a nonlinear steering coefficient that is deliberately insensitive near the center and, combined with a speed setting, gives wheel velocities through differential-drive kinematics; the user closes the loop visually. The platform cannot reverse. A trained volunteer drove smoother, collision-free paths than a novice, whose runs often triggered the proximity stop.

In Al-Haddad *et al.* [11] gaze angles define a goal point, with up to 45 goals from nine horizontal and five vertical angles. A deliberate single-eye blink then starts autonomous navigation with a Bug-family algorithm, during which the user may look around freely. The Bug family dates to Lumelsky and Stepanov [25]. Bug2 ran on a wheelchair, whereas TangentBug, which needs a range sensor, was only simulated. Bug algorithms cannot map the surroundings, so the chair may turn the wrong way on first contact with an obstacle; the user can switch back to manual guidance.

E. Hybrid Interfaces and a Camera Comparator

Tsui *et al.* [5] reverse the usual roles. Eyebrow EMG clicks counted inside a two-second window choose the motion state, while EOG only slows the chair as it moves forward. Five or more clicks suspend control, and a three-digit password restores it. In Domínguez Sucres *et al.* [8] an EOG channel supplies the lateral command and a trainable voice module handles activation, with reported recognition rates of 95% for voice and 97% for EOG with three persons; the paper describes the voice role inconsistently.

The camera-based design of Dwajan *et al.* [6] locates the pupil in webcam frames on a Raspberry Pi with Haar-cascade detection and a circle Hough transform. Pupil position selects the turn, and closing the eye for about three seconds stops the chair.

The authors report a delay of about four seconds, trouble tracking the pupil in dim light and no accuracy figure. In this review's reading the camera avoids skin electrodes but inherits illumination and latency limits, whereas EOG exchanges these for electrode contact and drift problems.

V. COMPARATIVE ANALYSIS OF EXISTING SYSTEMS

Table I lists the studies by year, with each result next to its protocol.

TABLE I
SIDE-BY-SIDE SUMMARY OF THE REVIEWED STUDIES

Ref., year	Sensing, front end and platform	Decoding method	Role of the blink	Safety aid	Evaluation and reported result
[5], 2007	Forehead band, EMG and EOG channels; PC with DSP controller	EMG click threshold; EOG threshold for speed	None; eyebrow EMG click fills the role	Password-locked non-control state; speed cut on EOG	10 runs on a 12–15 m course, users NR: mean 191 s per run
[4], 2008	5 Ag/AgCl; two AD620 stages; 0.16–30 Hz, 50 Hz notch; PIC	Pulse thresholds and timing state machine; trainer	Artifact, rejected by timing limits	Enable and emergency-stop buttons	>1000 movements, healthy people of various ages and people with vision problems: error <1%, miss <3%; 396 mW
[10], 2009	3 Ag/AgCl on eyeglass arms; AD620; laptop	Gaze angle to nonlinear steering gain; no reverse	No blink command reported	9 ultrasonic sensors, 15 cm stop	Novice and trained volunteers, 4.5 × 3.0 m area: trained user smoother, collision-free (qualitative)
[11], 2012	5 electrodes plus 2 for single-eye blink; EEG recorder; notebook with Arduino UNO	Gaze angles to goal point; Bug2 or Tangent-Bug	Deliberate single-eye blink starts navigation and switches mode	Bug obstacle following; manual override	Simulation (both), real chair (Bug2), users NR: no accuracy figure
[13], 2015	Ag/AgCl; MAX4209; PIC16F877A, toy car	Voltage level per gaze condition	No blink command reported	None	Five subjects: bands 273–295, 320–351, 396–414 mV
[8], 2019	Differential electrodes, reference behind ear; AD620; Arduino Uno with voice module	EOG level for side; trained voice for activation	No blink command reported	None	Three persons: voice 95%, EOG 97%
[6], 2020	Webcam, no electrodes; Raspberry Pi with Arduino	Haar cascade, Hough circle; closure stops	Eye closure of about 3 s stops chair	Ultrasonic stop	Prototype demonstration, users NR: no accuracy; delay about 4 s; fails in dim light
[12], 2020	3 Ag/AgCl; AD620; 30 Hz low-pass; Arduino Leonardo and Uno; 4-wheel chassis	Calibrated amplitude threshold; forward and backward only	Blink gives backward	None	Waveforms and motor response, users NR: no result figure
[19], 2023	Laboratory bioamplifier, 2 channels; MATLAB laptop, Bluetooth, Arduino Uno	Peak order and amplitude rules; 750 ms window	Blink stops chair; 79 mV peak criterion vs. upward glance	IR sensor cuts motor enable	4 volunteers × 20 random movements: 80 of 80 correct
[9], 2024	ECG electrodes; AD620; 0.2–40 Hz; Arduino Nano, small vehicle	ADC-range conditions on 2 channels	No blink command reported	None reported	60 laboratory trials, one test user: 92% overall, 87–100% per direction
[3], 2024	4 electrodes; NI USB-6008 DAQ; laptop with Arduino Nano	Polarity rules and post-pruned decision tree	Deliberate blink toggles on/off; reflex blink separated by tree	None (future work)	15 participants, 3 repetitions of 6 commands: 98.89% of 270 commands; 96% (72 of 75) track runs smooth
[7], NR	Disposable Ag/AgCl; INA128; 0.15–27 Hz; NI USB-6009 with LabVIEW, or MSP430	Amplitude and pulse-duration flow charts	Blink is a command (role NR); reflex blink shorter and smaller	None	Waveform checks, users NR: no accuracy figure

NR: not reported in the supplied copy. Years are those printed on the papers.

Three things stand out. First, the richer decoders (the learned tree of Rusydi *et al.*, the continuous mapping of Kuo *et al.*, the autonomous guidance of Al-Haddad *et al.* and the MATLAB classifier of Mulam *et al.*) depend on a laptop or acquisition unit, whereas the microcontroller-only designs use threshold or timing rules. Second, only four studies state how many people took part, between 3 and 15, and five report a command-level accuracy or error rate. Third, commands do not mean the same thing across designs: an upward glance means forward for Rusydi *et al.*, but a downward glance means stop for Al-Haddad *et al.*, and a blink means stop for Mulam *et al.*, backward for Kuntal *et al.* and an on/off toggle for Rusydi *et al.*

Direct comparison of the reported results is unsafe. Rusydi *et al.* count commands in an instructed sequence from 15 respondents; Mulam *et al.* count 80 randomly ordered movements from four volunteers; Rouillon-Sotomayor *et al.* count blocks of 15 repetitions of one direction, apparently from one test user; Yathunanthan *et al.* report error and miss probabilities over more than a thousand movements; and Domínguez Sucres *et al.* report recognition rates for three persons. Precision is uneven as well: eighty error-free trials bound the true error rate only below about 3.8% at 95% confidence (rule of three), and 55 successes in 60 trials correspond to a 95% Wilson interval of roughly 82% to 96% (this review's calculation).

The blink-role column shows that no two studies use the blink the same way. Six of the twelve give a blink or sustained closure a command role; Yathunanthan *et al.* treat it as an artifact rejected by timing limits, Tsui *et al.* replace it with an eyebrow click, and four studies report no blink command (Kuo *et al.*, Kumar and Vinod, Domínguez Sucres *et al.* and Rouillon-Sotomayor *et al.*). Only Rusydi *et al.* and Mulam *et al.* state quantitatively how a deliberate blink is separated from a reflex: a trained tree on peak amplitudes and an added 79 mV peak criterion, respectively.

VI. CRITICAL DISCUSSION

A. *User Variability and Calibration*

Every design with a fixed threshold admits that amplitude differs between users, and the five-subject table of Kumar and Vinod shows the spread directly. Rusydi *et al.* motivate their learned stage by individual differences in peak values. Yathunanthan *et al.* add a trainer module yet report that default settings worked for all their users, without a per-user breakdown, and Rouillon-Sotomayor *et al.* note that the most sensitive region around the eye differs between users.

The calibration burden is rarely quantified. The one concrete figure comes from Yathunanthan *et al.*: the user holds the eyes at the center for about 20 s before first use and about 10 s afterwards, followed by a guided sequence of five-second stages. The practice in Tsui *et al.* and Kuo *et al.* describes user learning, not system calibration. No study reports how long a calibration stays valid across days or electrode re-application, so whether the published accuracies survive such conditions is unknown.

B. *Blink Commands: Intent, Encoding and Failure Direction*

Eye control forces a choice between commanding and looking, and the studies handle it with a secondary switch: a blink in Rusydi *et al.*, buttons in Yathunanthan *et al.*, a click-count password in Tsui *et al.*, voice in Domínguez Sucres *et al.*, and autonomous navigation once a goal is chosen in Al-Haddad *et al.* Each prevents unintended motion while the user is not driving; none addresses it while driving. Rusydi *et al.* attribute 3 "quite smooth" ratings among 75 track runs to head movement, eye fatigue and user skill, but no study measures fatigue.

The blink encodings fall into four types: a single deliberate blink as toggle or stop, a blink count inside a time window, a blink synchronized with a flashing target, and a sustained closure. In this review's reading each trades false triggers against delay: the single blink is fastest but rests entirely on the decoder rejecting reflex blinks, counting and synchronizing cost time, and a roughly three-second closure resists reflex blinks but makes a weak emergency stop.

The meaning given to the blink also decides what a false trigger costs. In this reading, a blink that stops the chair fails in the safe direction, because a false trigger halts it, whereas a blink that switches the chair on or starts autonomous navigation fails in the unsafe direction, because a false trigger starts motion. The activation command had the lowest success rate, 95.56%, in the 270-command test of Rusydi *et al.* Only Yathunanthan *et al.* report false and missed commands separately, and no study reports involuntary-blink false activations per minute of rest, blink rates at the start and end of a session, or the effect of dry eyes or glasses.

C. *Artifacts, Latency and Hardware*

Blink interference on the vertical channel is the artifact discussed most often. Test conditions were controlled wherever described: Rouillon-Sotomayor *et al.* ran the circuit on batteries with laboratory equipment disconnected from the building network. Head movement and facial activity are named as error sources, yet no study reports trials outdoors, on uneven floors or over a long session.

Latency is reported in incompatible ways: under 1 s in Rouillon-Sotomayor *et al.*, 0.8 s command spacing in Yathunanthan *et al.*, a 750 ms window in Mulam *et al.*, a two-second window in Tsui *et al.* and about four seconds in the camera system; none measures onset-to-wheel delay consistently. A laptop leaves room for learned classifiers and navigation but makes the chair depend on a computer; Mulam *et al.* also depend on a Bluetooth link from a MATLAB session. Microcontroller-only systems are called low cost, yet no study gives a bill of materials, and Yathunanthan *et al.* give the only power figure, 396 mW. A depth-9, 40-leaf tree seems small enough for a microcontroller, but no study reports running one.

D. Safety and Navigation Assistance

Obstacle sensing is present in three implemented prototypes. Kuo *et al.* use nine ultrasonic sensors with a 15 cm stop distance, but the chair cannot reverse and has no rear sensing. Mulam *et al.* use an infrared sensor under one footplate that cuts the motor-enable lines whatever the eye command, a simple interlock with limited coverage, and Dwajan *et al.* stop on an ultrasonic reading. Tsui *et al.* propose shared control in which speed rises only when range sensors show free space, but did not use their sensors in the experiments. Al-Haddad *et al.* go furthest by planning a path to a goal, yet Bug algorithms have no map, while Rusydi *et al.* report no obstacle sensing. In this review's reading these provisions are stop-only, partly directional and tested apart from the decoder; no study examines what should happen after an obstacle stop while a gaze command is still active, or how motion restarts safely.

E. Validation Maturity and Real-World Usability

Five of the twelve studies demonstrate the decoder on scaled vehicles or models (Dwajan *et al.*, Kumar and Vinod, Kuntal *et al.*, Rouillon-Sotomayor *et al.* and Shah and Kher). Where participants are counted they number 3 to 15 and none is described as having a motor impairment; Yathunanthan *et al.* tested healthy people of different ages and people with vision problems. Measures of comfort, workload or independence are absent; the nearest is the smoothness rating of Rusydi *et al.* Claims that these systems give independence to quadriplegic users, as in Kumar and Vinod, are in this review's reading extrapolations from healthy-participant or scaled-model tests.

VII. RESEARCH GAPS AND FUTURE DIRECTIONS

Each gap below rests on evidence above and is paired with the direction that would close it.

1) No common evaluation protocol. Command sets, trials, error definitions and participant reporting differ, and only four studies state a participant count (largest: 15). A shared benchmark should fix the command set, randomize sequences, and report a per-command confusion matrix, false activations per minute of rest, onset-to-motion latency and participant characteristics. Raw recordings should be published so decoders can be compared on identical data.

2) No validation with the intended users. No study reports participants with a motor impairment, and five stop at scaled models. Validation should progress from scaled models to healthy participants on a full-size chair, then to motor-impaired users under clinical supervision, with comfort and workload measures.

3) Unquantified calibration burden and stability. Per-user tuning is the norm, yet only Yathunanthan *et al.* give calibration durations and none tests stability over days. Evaluation should include leave-one-subject-out testing and retesting after electrode re-application; baseline thresholds from a short rest period, as in Rusydi *et al.* and Yathunanthan *et al.*, are a cheap start.

4) Blink intent, fail-safe assignment and fatigue. False-command rates are separated from missed commands only by Yathunanthan *et al.*, involuntary-blink false activations go unreported, no study tests blink assignments against reflex blinking, and fatigue is invoked without being measured. A blink benchmark should record the involuntary-blink rate at rest and while driving and report hit rate and false activations per minute for each encoding. The blink should preferably carry commands that fail safe, such as stop, with a second confirmation (a counted blink) for anything that starts motion. Dwell-based activation could replace single-event triggers while driving, and blink rate and baseline drift could indicate fatigue.

5) Partial, untested safety integration. Proximity stops are single-purpose and partly directional. The interlock of Mulam *et al.* could be combined with lateral and rear sensing, distance-scheduled speed as in Kuo *et al.*, a defined restart rule and the shared control of Tsui *et al.*

6) Embedded learned decoding and wireless design. The one learned decoder runs on a laptop, the microcontroller designs are rule-based, and only one study each reports a wireless link or power. A wearable microcontroller could run the decoder, send only commands, report power and stop the chair when the link is lost, which Mulam *et al.* do not discuss.

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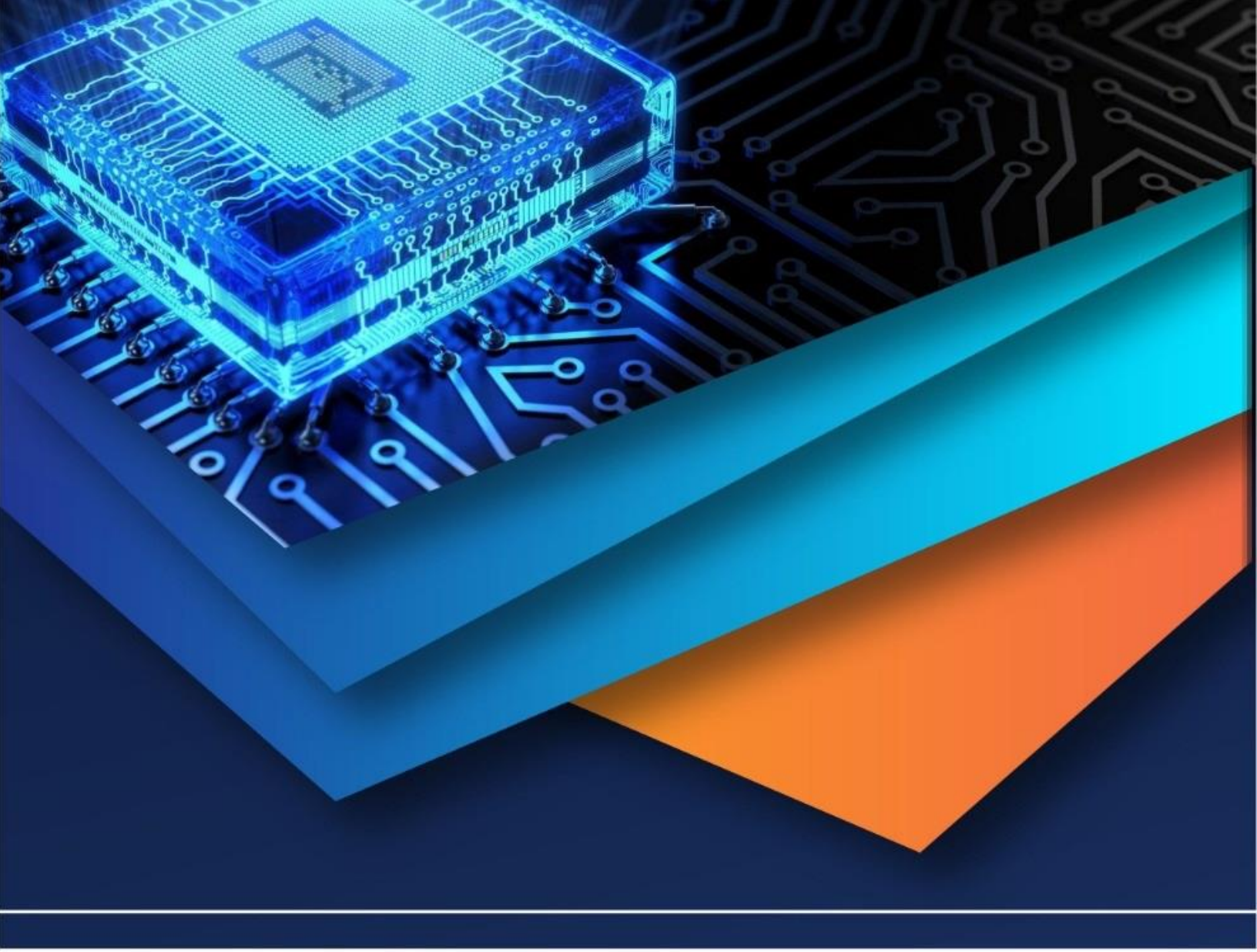
VIII. CONCLUSION

Across the twelve primary eye-controlled wheelchair studies, the blink works as a toggle, stop, reverse, mode switch or confirmation, or is rejected as an artifact, and deliberate blinks are told from reflex blinks by amplitude, duration, timing or a learned tree. Reported success rates are high but come from small, non-comparable protocols with healthy or unspecified participants, often on scaled vehicles. The recurring weaknesses are per-user calibration, unreported false activations from involuntary blinks, blink commands that fail in the unsafe direction, safety functions that sit beside rather than inside the decoder, and missing measures of fatigue, power and long-term use. A shared benchmark, adaptive decoders that fit wheelchair hardware, layered safety design and staged validation with the intended users are the steps the evidence supports. These conclusions rest on 25 papers, twelve of them analyzed in detail, and should be re-examined against a wider, systematically collected literature.

REFERENCES

[1] S. Mahmud, X. Lin, and J.-H. Kim, “Interface for human machine interaction for assistant devices: A review,” in Proc. 10th Annu. Comput. Commun. Workshop Conf. (CCWC), 2020, pp. 768–773.
[2] R. Barea, L. Boquete, M. Mazo, and E. López, “System for assisted mobility using eye movements based on electrooculography,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 10, no. 4, pp. 209–218, Dec. 2002.
[3] M. I. Rusydi, M. A. A. Boestari, R. Nofendra, Syafii, A. W. Setiawan, and M. Sasaki, “Wheelchair control based on EOG signals of eye blinks and eye glances based on the decision tree method,” in Proc. 12th Int. Conf. Inf. Commun. Technol. (ICoICT), 2024, pp. 152–159.
[4] S. Yathunanthan, L. U. R. Chandrasena, A. Umakanthan, V. Vasuki, and S. R. Munasinghe, “Controlling a wheelchair by use of EOG signal,” in Proc. 4th Int. Conf. Inf. Autom. Sustain. (ICIAFS), Colombo, Sri Lanka, Dec. 2008, pp. 283–288.
[5] C. S. L. Tsui, P. Jia, J. Q. Gan, H. Hu, and K. Yuan, “EMG-based hands-free wheelchair control with EOG attention shift detection,” in Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO), Sanya, China, Dec. 2007, pp. 1266–1271.
[6] B. A. Dwajan, M. S. Sowmya, N. P. Reddy, S. Bhavani, and M. R. Usha, “Eye gaze controlled wheelchair,” Int. J. Eng. Res. Technol., vol. 9, no. 5, pp. 667–673, May 2020.
[7] S. Shah and R. Kher, “Design of electrooculogram based wheelchair control,” G. H. Patel College of Engineering and Technology, Vallabh Vidyanagar, India, venue and year not shown on the copy reviewed.
[8] M. A. D. Sucres, S. S. F. Pérez, I. V. G. Zavala, D. L. I. Ramírez, and N. R. Hernández, “EOG-based interface and speech recognition for wheelchair control,” Universidad de Guadalajara, Guadalajara, Mexico, 2019, conference paper; venue and pages not shown on the copy reviewed.
[9] L. Rouillon-Sotomayor, J. Gutiérrez-Abanto, and C. Sotomayor-Beltran, “Implementation of a low-cost steering control system for a wheelchair based on electrooculography signals,” Int. J. Eng. Trends Technol., vol. 72, no. 3, pp. 260–267, Mar. 2024.
[10] C.-H. Kuo, Y.-C. Chan, H.-C. Chou, and J.-W. Siao, “Eyeglasses based electrooculography human-wheelchair interface,” in Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC), San Antonio, TX, USA, Oct. 2009, pp. 4746–4751.
[11] A. A. Al-Haddad, R. Sudirman, C. Omar, and S. Z. M. Tumari, “Wheelchair motion control guide using eye gaze and blinks based on Bug algorithms,” in Proc. IEEE EMBS Int. Conf. Biomed. Eng. Sci. (IECBES), Langkawi, Malaysia, Dec. 2012, pp. 398–403.
[12] K. Kuntal, I. Banerjee, and L. P. P., “Design of wheelchair based on electrooculography,” in Proc. Int. Conf. Commun. Signal Process. (ICCSP), India, Jul. 2020, pp. 632–636.
[13] S. U. Kumar and V. M. Vinod, “EOG based wheelchair control for quadriplegics,” in Proc. 2nd Int. Conf. Innov. Inf., Embedded Commun. Syst. (ICIIECS), 2015.
[14] A. B. Usakli and S. Gurkan, “Design of a novel efficient human-computer interface: An electrooculogram based virtual keyboard,” IEEE Trans. Instrum. Meas., vol. 59, no. 8, pp. 2099–2108, Aug. 2010.
[15] Q. Huang et al., “An EOG-based human–machine interface for wheelchair control,” IEEE Trans. Biomed. Eng., vol. 65, no. 9, pp. 2023–2032, 2018.
[16] F. Bhuyain and K. M. Salim, “Design and development of an EOG-based system to control electric wheelchair for people suffering from quadriplegia or quadriparesis,” in Proc. Int. Conf. Robot., Signal Process. Techn., 2019, pp. 460–465.
[17] A. M. Choudhari, P. Porwal, V. Jonnalagedda, and F. Mériaudeau, “An electrooculography based human machine interface for wheelchair control,” Biocybern. Biomed. Eng., vol. 39, no. 3, pp. 673–685, 2019.
[18] Y. Li, S. He, Q. Huang, Z. Gu, and Z. L. Yu, “A EOG-based switch and its application for ‘start/stop’ control of a wheelchair,” Neurocomputing, vol. 275, pp. 1350–1357, 2018.
[19] H. Mulam, M. Mudigonda, B. P. S. Kumar, and H. Kuchulakanti, “Electrooculogram based wheelchair control in real-time,” in Proc. ICETE 2023, Adv. Eng. Res., B. Raj et al., Eds., vol. 223, 2023, pp. 55–67.
[20] A. Rajesh and M. Mantur, “Eyeball gesture controlled automatic wheelchair using deep learning,” in Proc. IEEE Region 10 Humanitarian Technol. Conf. (R10-HTC), 2017.
[21] A. N. Rajesh, S. Chandralingam, T. Anjaneyulu, and K. Satyanarayana, “EOG controlled motorized wheelchair for disabled persons,” Int. Sch. Sci. Res. Innov., vol. 8, no. 5, pp. 302–305, 2014.
[22] R. Z. Marandi, P. Madeleine, Ø. Omland, N. Vuillerme, and A. Samani, “Eye movement characteristics reflected fatigue in both young and elderly individuals,” Sci. Rep., pp. 1–10, 2018.
[23] M. Vidal, A. Bulling, and H. Gellersen, “Analysing EOG signal features for the discrimination of eye movements with wearable devices,” in Proc. 1st Int. Workshop Pervasive Eye Tracking Mobile Eye-Based Interact., 2011, pp. 15–20.
[24] N. M. M. Noor and S. Ahmad, “Performance analysis of an electrooculography-based on intelligent wheelchair motion control,” in Proc. 10th Asian Control Conf. (ASCC), 2015.
[25] V. J. Lumelsky and A. A. Stepanov, “Dynamic path planning for a mobile automaton with limited information on the environment,” IEEE Trans. Autom. Control, vol. 31, no. 11, pp. 1058–1063, Nov. 1986.

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