

Multi-motion robots control based on bioelectric signals from single-channel dry electrode

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Abstract

This article presents a multi-motion control system to help severe disabled people operate an auxiliary appliance using neck-up bioelectric signals measured by a single-channel dry electrode on the forehead. The single-channel dry-electrode multi-motion control system exhibits several practical advantages over its conventional counterparts that use multi-channel wet-electrodes; among the challenges is an effective technique to extract bioelectric features for reliable implementation of multi degrees-of-freedom motion control. Using both time and frequency characteristics of the single-channel dry-electrode measurements, motion commands are derived from multiple feature signals associated with concentration demands and different eye-blink actions for use in a two-level control strategy that has been developed to control predefined multi degrees-of-freedom motion trajectories. Test paradigms were designed to pre-calibrate the users' feature signals to statistically account for individual variances. Experimental trials were then carried out on able-bodied and disabled volunteers to validate the universal applicability of the algorithms. The classification success rates for two different eye-blink feature signals were approximately 95% with an average time of 2.4 s for executing a concentration feature signal. The single-channel dry-electrode-based technique has been validated on a 6-degree-of-freedom robot arm demonstrating its significant potentials to help patients suffering severe motor dysfunctions operate a multi-motion auxiliary appliance in everyday living where the ease of use is a priority.

Keywords

Multi-motion control, bioelectric signals, single-channel dry electrode, electroencephalography, eye blink

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Introduction

In the past few decades, various auxiliary appliances (such as wheelchairs and artificial limbs) have been developed to help patients suffering severe motor dysfunctions improve their life qualities.¹ These appliances can be controlled by the patients' remaining muscle functions and unaffected neural paths utilizing human-machine interface (HMI) technologies. For patients who lost body motion functions below their neck, bioelectric signals such as electroencephalography (EEG), electromyography (EMG) and electrooculography (EOG) from neck-up are commonly recommended signals for controlling auxiliary appliances.^{2–4} Among the HMIs that base on neck-up bioelectric signals, brain-computer interface (BCI) or hybrid-BCI with bioelectric signals directly from cortical neurons are widely used.

Advancements in BCI and multi degrees-of-freedom (DOFs) motion control in robotics have provided a basis for developing mind-control machines to improve the life quality of patients suffering severe motor

dysfunctions, which requires multiple control commands derived from bioelectric signals. Thus, feature signals from one kind of bioelectric signals or a combination of them are employed, for example, P300 combined motor imagery from EEG, EMG combined EEG and eye gaze combined EEG.^{5–9} In a study by McFarland et al.⁶ simultaneous control of three-dimensional (3D) motion was realized by detecting

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multi-feature signals from specific frequency bands with a 64-channel wet-electrode system, where time-consuming trainings were required to receive a satisfactory result. In another study by Craig and Nguyen,¹⁰ three different feature signals generated by mental demands were recognized from EEG of a four-channel wet-electrode system with an overall success rate (SR) of 82.4%. Although good quality signals with a high information transfer rate (ITR) can be obtained from systems utilizing wet electrodes, their applications outside a laboratory environment have been limited due to high-cost, extensive troublesome preparations and inapplicability for long-term monitoring.^{11,12} Besides, various stimulations are required simultaneously to derive the multi-feature signals, which results in a more complex system keeping it from practical applications and causes users to feel tired easily.

Some research efforts have recently been driven toward developing more practical HMIs utilizing gel-free recording systems (such as dry electrodes and saline-based electrodes such as Emotiv) which are inexpensive, safe, portable and easy to use.^{13–19} In a study by Patki et al.¹⁹ selective commands were generated from P300 recorded by an eight-dry-electrode system with an average SR of 73.6%. A notable application utilizing a gel-free recording system is the single-DOF control of a wheelchair.^{15,16} In the work by Hashimoto et al.¹⁵ EOG and EMG signals related to eye and jaw movements, respectively, were extracted from bioelectric signals (recorded using threshold algorithms through three dry electrodes) for controlling a wheelchair. Li et al.¹⁶ derived motor imagery-related commands from EEG signals with 14 saline-based electrodes using Emotiv which requires long-time trainings before uses; the recognition rate of commands below 80% was reported when tested on able-bodied subjects. In another application, Gomez-Gil et al.¹⁸ derived feature signals from EMG that was generated by trained muscular events for single-direction control of a tractor. The current gel-free-based electrode systems focus exclusively on research involving single-DOF motion control.

Recently, a single-channel dry-electrode (SCDE) BCI device (NeuroSky, San Jose, CA, USA) has been developed commercially. Compared with conventional wet EEG systems, this low-cost device (less than US\$100) is gel-free, much easier and more comfortable to use and can capture a relatively large fraction of brain activities dynamically by means of volumetric conduction;²⁰ however, useful information recorded are underexplored. Recent researches employ a discrete reading on a scale from 0 to 100 with a NeuroSky built-in algorithm (distinguishing neutral and attentive mental states) for entertainments, or some simple rehabilitation and neurocognitive training.^{21–25}

Nevertheless, this device provides a function for original bioelectric signal recording, and its effectiveness has been validated by comparing with a research-grade EEG system (developed by Nuamps, Neuroscan

& Compumedics, Melbourne, Australia) with results suggesting positive correlations between the two methods and similar patterns of particular brain active conditions (relaxation, attention and cognitive load) in the corresponding band power.¹⁴ Researchers have further developed and applied their innovative methodologies based on the device, such as steady-state visual evoked potential-based BCI and P300-based BCI.^{26,27} The NeuroSky device also provides a possibility for developing a practical multi-motion appliance control system; however, a problem needed to be solved is to reliably extract multi-channel commands with limited information from SCDE recordings. There are published results on detecting eye-blink and concentration signals from neck-up bioelectric signals using a single-channel or multi-channel gel-free electrode systems.^{28–31} In an investigation by Yang et al.²⁸ where an SCDE NeuroSky device was studied for controlling a virtual keyboard for typing Chinese characters, conscious blinks were determined by comparing the measured amplitude of bioelectric signals against a predefined threshold. Since only amplitude parameters were involved, the method reportedly suffers three significant drawbacks: poor detection when signal amplitudes were weak, false detection and slow typing speeds (20–40 s per word). Concentration features (extracted from dry-electrode signals for studies in game control) were normally for cognitive state detection without transforming into binary-switch commands.³⁰ For examples, Lin et al.²⁹ utilized an SCDE NeuroSky device to detect attention signals for wheelchair control (however, no detail on the detection procedure was reported).

The above studies demonstrate feasible potentials of extracting eye-blink and concentration features from measured signals using dry electrodes. The challenges, however, are to develop an efficient method that ensures sufficiently high recognition rate without increasing hardware complexity and a good understanding of fundamental principles involved in converting demand-driven bioelectric signals into machine-executable commands. In this article, eye-blink and concentration signals are extracted in time and frequency domains, respectively, for the following considerations: (1) patients suffering motor dysfunctions generally have no difficulty to intentionally control eye blinks which have quick reflections and time-domain characteristics for recordings on the forehead followed by real-time identification and (2) concentration signals that have distinct characteristic in frequency domain are self-generated brain signals requiring no external devices dedicated for stimulations and reliable as they are direct brain-related bioelectric signals. For the above reasons, an SCDE-based system is proposed in this article that offers an efficient technique including the following methods:

- A feature signal classification algorithm has been developed, through which multiple feature signals

associated with a concentration demand (serving as a confirmation on-off switch before implementing an intended operation) and different eye-blink actions (using both amplitude and time-interval in the eye-blink feature signals) are extracted in real time from the SCDE recorded bioelectric signals in frequency and time domains, respectively, and multi-channel commands are output based on the parametrically determined status of the feature signals.

- Test paradigms have been designed to pre-calibrate the user-dependent feature signals accounting for individual variances based on statistics.
- A two-level control strategy based on the multi-channel commands has been developed to realize serial and predefined joint motion controls of multiple motors and (with the help of a PC-interface, human vision and sensors feedbacks) allow for patient self-assisted automated operations.
- The feasibility of the multi-motion control system has been evaluated on 10 (8 able-bodied and 2 disabled) individuals with a 6-DOF arm-reaching desktop robot. Unlike low-risk applications (e.g. word typing²⁸), the multi-DOF motion control of a robotic arm should eliminate any unintentional command due to a false detection to avoid potential accidents. As will be shown experimentally, the proposed method combining detections of concentration signals and enhanced eye blinks effectively avoids false detections and achieves a similar SR of approximately 95% reported by Cholula et al.³¹ with a multi-channel saline-based electrode system.

These improvements suggest that the SCDE-based system offers several incentives (safety, low-cost, efficiency, portable and ease-of-use) when developing various practical auxiliary appliance systems.

Methods

The design principles of the proposed multi-motion control system, including the SCDE recording system, feature signals extraction and status recognition algorithms, pre-calibration paradigms and control strategy, are introduced in this section.

SCDE-based recording system

A commercially sold SCDE BCI device (Mindwave, NeuroSky) is used as the recording hardware of the bioelectric signals. As shown in Figure 1, it consists of a dry active sensor, a dry reference sensor and an onboard chip (known as ThinkGear). The active sensor is placed on the anterior frontal scalp (located approximately equal to Fp1 in the international 10–20 system).³² The reference sensor is placed on the right earlobe. The chip processes and band-pass filters the measured data and detects/corrects for EMG/EOG artifacts from muscle activities and eye movements in time domain.

In this study, the raw recordings of bioelectric signal from the SCDE device are used to extract the feature signals employing the classification algorithm and control programs which will be introduced below.

Feature signal extraction and command generation

The multi-motion control relies on the recognizable multiple conscious feature signals extracted from raw measurements. There are evidences in support of that suppression of EEG Alpha rhythm (8–12 Hz) is associated with “attention” demands, which can be detected both in healthy people and patients suffering severe motor dysfunction over the occipital and frontal cortex.^{33–36} Besides, eye-blink signals can be detected over the frontal scalp. EEG Alpha rhythms associated with human concentration demand and EEG/EOG/EMG mixed signals associated with different eye-blink actions are extracted as feature signals for motion control.

The raw signal processing and command generation procedure are illustrated in Figure 2. The raw measured differential potentials between the pair of dry electrodes are band-pass (0.5–50 Hz) filtered to remove artifacts from eye movements and so on, which are then amplified with a gain of 2000 followed by an analog-to-digital conversion (ADC) sampled at 512 Hz for subsequent analyses. The conscious feature signals (due to voluntary eye blinks and/or concentration) are extracted to yield a device-driven command for a real-time operation. The former, which is classified into light eye-blink (LEB) and strong eye-blink (SEB) signals, is derived from the pre-processed signal V_i in time

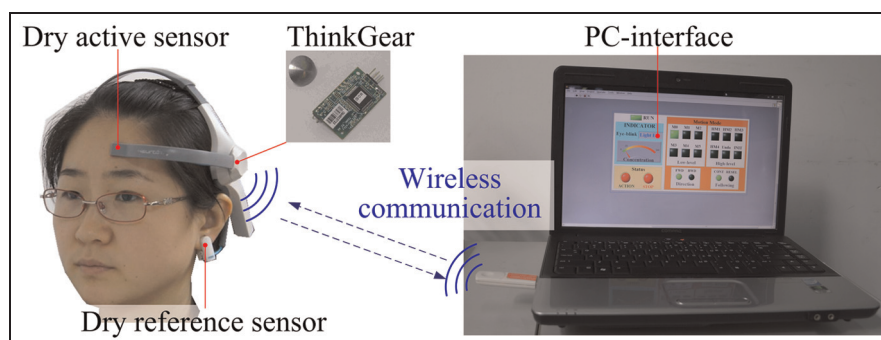


Figure 1. Single-channel dry-electrode recording system.

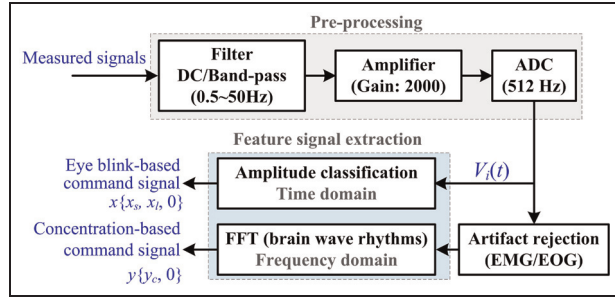


Figure 2. Block diagram illustrating the signal processing and command generation procedure.

domain and generates a command signal x , whereas the latter (concentration) is extracted from signals filtered by onboard artifact rejection methods of the dry-electrode system using frequency domain analysis to generate a command signal y . The mathematical definitions, identification and extraction of the voluntary eye-blink and concentration signals are explained below.

Voluntary eye-blink signal. Unlike feature extraction for word typing²⁸ where only the signal amplitude was used for detecting eye blinks, combined amplitude and time-interval characteristics are employed to extract two kinds of eye-blink signals here. LEB and SEB signals are derived using a 1-s time-window (512 samples) to generate an eye-blink-based command per second. Figure 3 shows two typical experimentally measured potential differences (EEG/EOG/EMG mixed bioelectric signals) from the dry electrode corresponding to voluntary light and strong eye blinks and illustrates their classification in time domain. LEB and SEB are quantitatively differentiated in terms of parameters ($V_{u\pm}$, $V_{l\pm}$, Δt_l and Δt_s) defined in Figure 3(b) and (c), where $V_{u\pm}$ and $V_{l\pm}$ are the upper and lower thresholds with subscripts $+$ and $-$ referring to the sign (positive and negative, respectively) of the i th sample V_i ; and Δt_l and Δt_s are the peak-to-valley time intervals for classifying LEB and SEB, respectively. Then, the LEB-based command x_l and SEB-based command x_s can be generated. The classification works as follows:

1. Examine whether V_i is bound by V_{l+} and V_{u+} :
 - If $V_{u+} > V_i > V_{l+}$, the valley value $V_-(\Delta t_l)$ of the samples within Δt_l is found;
 - Else if $V_i \geq V_{u+}$, $V_-(\Delta t_s)$ within Δt_s is found;
 - V_i is discarded if it does not satisfy the two conditions above.
2. Examine whether V_- is bound by V_{l-} and V_{u-} :
 - If $V_{l-} < V_-(\Delta t_l) < V_{u-}$, the LEB decision with x_l will be made;
 - Else if $V_-(\Delta t_s) < V_{l-}$, the SEB decision with x_s will be made;

- V_i is discarded if it does not satisfy the two conditions above.

Concentration signal. The concentration signal is identified using frequency domain analysis. Using hardware fast Fourier transform (FFT), the conscious signals can be detected from the power spectrums of the pre-processed signal V_i . The j th power spectrum P_j is obtained according to equation (1)

$$P_j = \frac{2\pi}{N} \int_{f_{j,\min}}^{f_{j,\max}} |X(f)|^2 df \quad (1)$$

where $j = 1, \dots, 5$ correspond to five frequency bands in Table 1; $X(f)$ is the FFT results of each epoch (1 s) of the pre-processed signal; N is the sample number (here equals 512) and $f_{j,\min}$ and $f_{j,\max}$ are the lower and upper frequency limits of the j th frequency band, respectively.

The relative power proportion of Alpha rhythm P_α in a 1-s time-window defined in equation (2) is used for deriving the concentration signal

$$P_\alpha = \frac{P_3}{P_{\text{sum}}} \times 100\% \quad \text{where } P_{\text{sum}} = \sum_{j=1}^5 P_j \quad (2)$$

In real-time operations, a user-dependent pre-calibrated baseline $\bar{P}_\alpha$ is defined to distinguish individual user's concentration state from normal/relaxation conditions and determines the concentration-based command signal y (concentration demand y_c and 0) according to equation (3)

$$y = \begin{cases} y_c & \text{if } P_\alpha < \bar{P}_\alpha \\ 0 & \text{else} \end{cases} \quad (3)$$

Pre-calibration paradigms

Since significantly high differences among individuals exist in bioelectric signals from eye blink and EEG reactivity, a pre-calibration of user-dependent thresholds for feature signals is needed individually.³⁷ The choice of the thresholds presents a tradeoff between the reaction time and error rate of the multi-motion control system and has a direct effect on its performance.

The thresholds are estimated statistically with the population mean μ based on samples (assumed to be randomly, independently and identically distributed) at a 98% confidence level. The following are test paradigms designed for pre-calibrations of eye-blink and concentration signals.

Eye-blink signal. In the pre-calibration paradigm of eye-blink signals, the subject sits in front of a computer on which his or her real-time eye-blink generated bioelectric potentials are displayed to help the subject notify his or her eye-blink strength level. Subject's eye actions

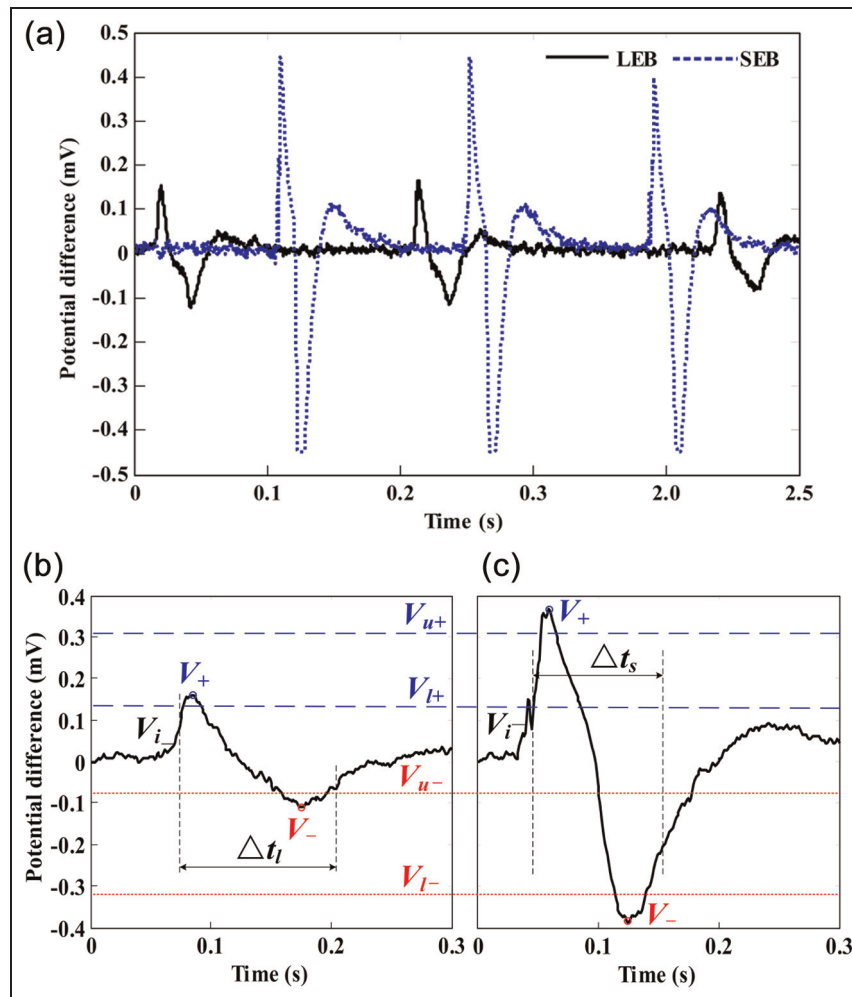


Figure 3. Illustration of typical (experimentally measured) eye-blink generated signals and threshold parameters: (a) pre-processed signals due to LEB and SEB, (b) threshold parameters of LEB signal and (c) threshold parameters of SEB signal.

Table 1. Frequency bands of five brain wave rhythms.

Types	j	$f_{j,min}$ (Hz)	$f_{j,max}$ (Hz)
Delta (δ)	1	1	3
Theta (θ)	2	4	7
Alpha (α)	3	8	12
Beta (β)	4	13	30
Gamma (γ)	5	31	50

are monitored by a camera to provide references for feature signal extraction. The test results are employed for comparison of different eye-blink strength levels between that of subject-reported and measured.

Concentration signal. Two paradigms are conducted in concentration signal pre-calibration for two active mental states: eye-open relaxation and concentration. In the relaxation paradigm, the subject sits in front of a computer screen watching a calm landscape video to reach a relaxation state. In the concentration paradigm, the subject is asked to focus on a dial (whose reading is

inversely proportional to immediate recorded relative power proportion of Alpha rhythm) on the screen and mentally enhance it so as to promote a concentration mental state.

Multi-motion control

The commands generated from feature signals are used for multi-motion control based on the two-level control system illustrated in Figure 4(a). Feedbacks from human and/or sensors provide bases for user to make decisions. Dedicated PC-interface, controlled by feature-driven commands, is developed with three functional sets of indications for visual communication, as shown in Figure 4(b):

- The *signal indicator* (top-left side) displays the quantitative level of the two conscious features for visually generating a feature-driven command.
- The *system status* (bottom-left side) indicates the two operation states of the motion, in action and stop standing still.

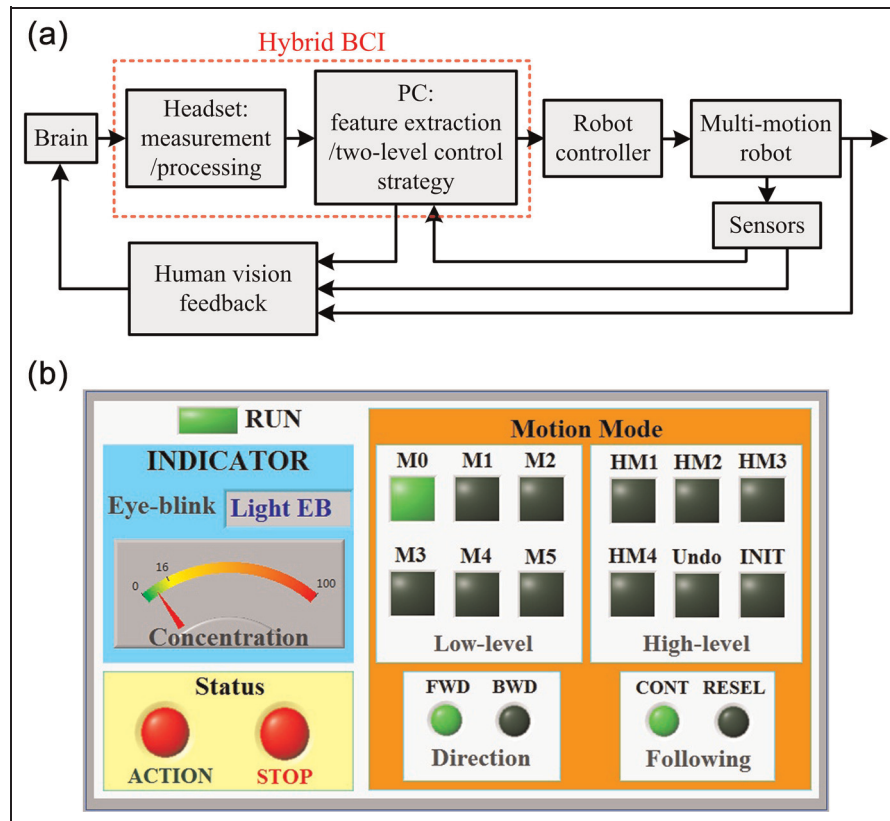


Figure 4. Illustration of the control system: (a) block diagram of the control system and (b) PC-interface for motion selection and status display.

- The *motion mode* selection panel (right side) provides a means to visually manipulate the target robot in different motion modes.

To enable a visual selection, each of the motion mode indicators of two levels is illuminated for a period of Δt in sequence. The user produces certain conscious feature signals to select a mode during the lightening period of the particular mode. If an opportunity is missed, the user may wait for the next time-slot or send a command to interrupt/reset the circulation.

In the motion mode part, two-level control strategy is provided to realize serial and predefined joint multiple motors' control:

- The *low-level* method executes a simple operation of a single motor (such as changing target motor or direction/speed) and serial motions of different motors. Figure 4(b), where three indicators (M0, FWD and CONT) simultaneously illuminate, shows an example of motion mode commanding motor M0 continuing its current rotation in the forward direction.
- With the *high-level* method, the robot automatically executes a multi-motion manipulation to complete a pre-designed task with a single motion mode selection, such as moving horizontally back and forth, and initializing system. With pre-designed

programs according to kinematics of target robot system, joint motions of multiple motors can be realized.

The control strategy will be clearly introduced by the application example below.

Experimental results and discussions

The experiments were conducted on volunteers to evaluate the conscious feature extraction methods and pre-calibration paradigms and to validate the feasibility of controlling a 6-DOF desktop robot arm using the proposed multi-motion control system. Each subject signed a consent form based on the approval given by the Ethics Committee of Zhejiang University.

Human subjects

Eight able-bodied volunteers (four males and four females, labeled A to H) and two disabled volunteers (one male and one female; one suffers from congenital deformity and lost motor motion under chest except for movable arms; one lost walking function; labeled I and J), ages ranging from 20 to 27 years old, participated in the experiments. In each experiment, dry electrodes and anterior frontal scalp site were cleaned with alcohol, and participants were instructed to minimize facial and

head movement to reduce artifacts. Considering that the bioelectric signals may be influenced by conditions of subjects, the pre-calibration and validation experiments were split into several sections and conducted in different time periods of a day and on different days for each subject.

Threshold pre-calibration

First, thresholds in feature signal extraction (eye-blink and concentration signals) of the 10 subjects were individually calibrated based on the proposed paradigms.

Eye-blink signals. The signal waveforms (Figure 3) induced by LEB, SEB and involuntary eye blink (IEB) were recorded for threshold definition; for each eye-blink type, $n = 40$ samples of full waveforms were analyzed in time domain. In Figure 5, the mean peak and valley potential values $\bar{V}_{\pm}$ of IEB, LEB and SEB were compared against the mean value of the maximum potential values V_m computed from measurements without eye blink; the mean V_m value for each subject was computed from 14 trials of 8000 samples.

As shown in Figure 5, the measured potential differences are closely correlated to the blink strengths providing a basis to classify LEB and SEB and distinguish them from IEB. The thresholds of LEB and SEB classification, which are defined in Figure 3(b) and (c), are summarized in Table 2 where $V_{u\pm}$ is determined by the lower band of the estimation interval; and $V_{l\pm}$, Δt_l and Δt_s are determined by the upper bands of the corresponding estimation intervals.

Concentration signals. The experiments of two active mental states were conducted to determine concentration signals, where $n = 280$ samples for each mental state were used to calculate the mean value and

estimation intervals of P_{α} . The results in Figure 6 show the computed minimum, mean and maximum P_{α} . To provide a more accurate extraction of concentration-derived command, the threshold $\bar{P}_{\alpha}$ for classifying the concentration state was determined by the lower band of the estimation interval as given in Table 2.

Validation of feature signal recognition

The experiments were conducted to evaluate the performance of the feature signal classification algorithm by investigating the SR and false detection rate (FR) of LEB/SEB recognition and the processing time (PT) required to derive a concentration signal:

SR (%) is the number of correct detection divided by the number of intended occurrences in a trial.

FR (%) is the number of false detection when no intended eye blink actually occurs divided by the total number of LEB and SEB in a trial.

PT (s) is the time required to enter a specified concentration state.

All the above parameters were evaluated in probability with a 95% confidence level. For a safe human-robot interface, false detections must be strictly avoided to prevent accidents due to unintended false commands.

Twenty trials were evaluated in the eye-blink detection experiments; for each trial, the participant voluntarily blinked 20 times his or her eyes (in alternating order; starting with five successive LEBs followed by another five but SEBs, and then repeated again five successive LEBs and five successive SEBs). For the concentration experiments where 20 trials were implemented, the participant was asked to focus on the "Concentration" indicator (Figure 4(b)) while imagining the decrease in the P_{α} signal level in each trial. Two different methods for eye-blink feature signal detection were evaluated: (1) eye-blink amplitude-only (presented in study of Yang et al.²⁸) and (2) eye-blink amplitude/time-interval (proposed in this article). The amplitude-only method provides a basis for comparison. The results and comparison of feature signal detection are summarized in Table 3 where some observations can be drawn from comparing the two methods:

The amplitude-only method²⁸ does not distinguish between LEB and SEB and has an 81.6% SR and a 3.6% FR averaged over 20 trial data obtained from 10 subjects. The errors were primarily contributed by other bioelectric signals from eye or facial movements. It is worth noting that all 10 subjects experienced some false detections.

The SR of eye-blink recognition using the amplitude/time-interval method ranges from 80% to 100% with an average of 94.5% and 94.0% for LEB and SEB, respectively, which are similar to 94.9% reported in study performed by Cholula et al.³¹ using multi-channel saline-based electrodes system, and there is no false

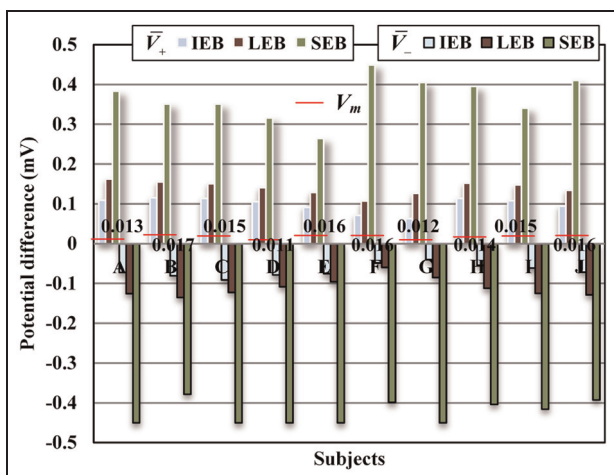
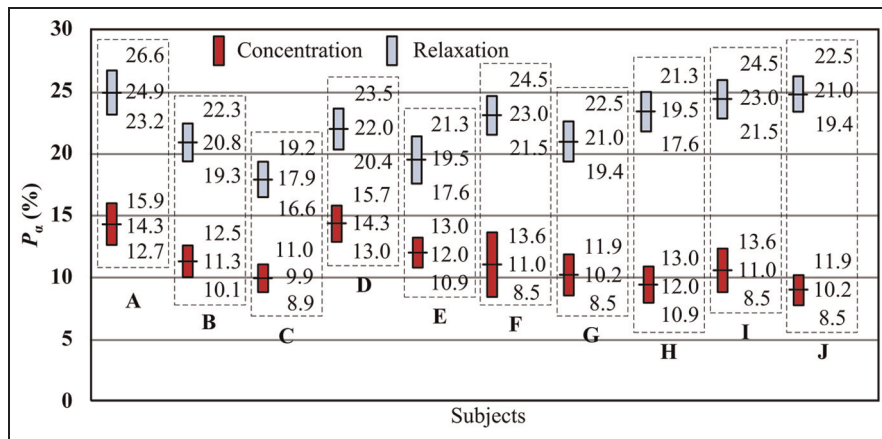


Figure 5. Mean peak and valley potentials for three different kinds of eye blink and mean maximum potential in normal condition without eye blink.

Table 2. Thresholds defined from pre-calibration data.

Subject	(V_{l+}, V_{u+}) (mV)	Δt_s (ms)	$(-V_{l-}, -V_{u-})$ (mV)	Δt_l (ms)	$\bar{P}_\alpha$ (%)
A	(0.156, 0.367)	173.0	(0.450, 0.115)	228.0	15.9
B	(0.144, 0.338)	187.0	(0.332, 0.123)	169.0	12.5
C	(0.142, 0.339)	223.0	(0.450, 0.116)	134.0	11.0
D	(0.131, 0.299)	138.0	(0.450, 0.101)	199.0	15.7
E	(0.121, 0.250)	153.0	(0.450, 0.085)	178.0	13.0
F	(0.100, 0.433)	179.0	(0.359, 0.050)	182.0	13.6
G	(0.136, 0.394)	183.0	(0.450, 0.076)	206.0	11.9
H	(0.151, 0.379)	147.0	(0.400, 0.103)	194.0	10.9
I	(0.138, 0.327)	157.0	(0.414, 0.118)	199.0	12.2
J	(0.126, 0.396)	175.0	(0.384, 0.123)	189.0	10.1

**Figure 6.** Relative power proportion of Alpha rhythm (minimum, mean, maximum).**Table 3.** Feasibility validation and comparison of results.

Subject	Eye blink (%)					Concentration (s)
	Amplitude-only		Amplitude/time-interval			
	LEB/SEB SR	FR	LEB SR	SEB SR	FR	
						PT ($t_{\min}$, $\bar{t}$, $t_{\max}$)
A	81 ± 1.3	4 ± 1.4	100 ± 0	80 ± 4.5	0	(1, 1.5 ± 0.4, 4)
B	80 ± 1.4	5 ± 1.2	95 ± 3.0	100 ± 0	0	(2, 3.1 ± 0.4, 6)
C	81 ± 1.0	3 ± 1.1	100 ± 0	95 ± 3.0	0	(2, 2.8 ± 0.3, 5)
D	82 ± 1.8	3 ± 1.1	100 ± 0	100 ± 0	0	(1, 1.4 ± 0.4, 5)
E	82 ± 1.8	3 ± 1.1	90 ± 2.5	95 ± 3.0	0	(2, 3.3 ± 0.3, 4)
F	82 ± 1.6	4 ± 1.2	85 ± 3.0	100 ± 0	0	(1, 2.1 ± 0.3, 5)
G	83 ± 1.9	3 ± 1.3	95 ± 3.0	95 ± 3.0	0	(2, 2.5 ± 0.3, 4)
H	83 ± 1.9	4 ± 1.0	85 ± 3.0	100 ± 0	0	(2, 2.3 ± 0.3, 5)
I	81 ± 1.3	3 ± 1.1	100 ± 0	85 ± 3.0	0	(2, 2.2 ± 0.2, 4)
J	82 ± 1.6	4 ± 1.1	95 ± 2.2	90 ± 2.8	0	(2, 2.6 ± 0.3, 5)
Average	81.6 ± 0.5	3.6 ± 0.4	94.5 ± 1.0	94.0 ± 1.2	0	(1.7, 2.4 ± 0.4, 4.7)

LEB: light eye-blink; SEB: strong eye-blink; SR: success rate; FR: false detection rate; PT: processing time.

detection. The detection time for eye-blink signal is less than 300 ms. The PT of the concentration signal ranges from 1.7 to 4.7 s with an average of 2.4 s. The total time spent on all the pre-calibration sections is less than an hour for each subject.

During a relatively long continuous operation (normally more than 30 min) driven by eye-blink derived

commands, the subjects were observed to make short bursts of rapid eye blinks (belong to IEBs) and reported some eye fatigue after experiments, which can also be observed from bioelectric potential recordings. However, the eye-blink detection method using both amplitude and time-interval successfully detects IEBs caused by eye fatigue and excludes them from the feature (LEB and SEB) signal classification; this

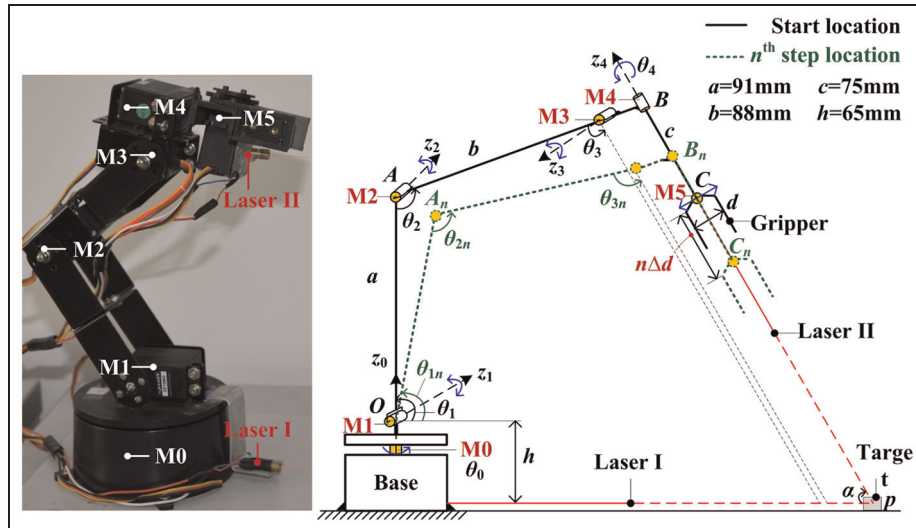


Figure 7. Structure of the laser-guided assistive arm-reaching robot.

effectively eliminates the potentials of triggering incorrect commands due to any false LEB/SEB detection (Table 3). In continuous operations driven by concentration-derived commands, the P_α level barely changed, but the time spent on getting into concentration state increases and almost reaches the upper band of average PT in Table 3. The experimental results performed in different time periods and days of the same subject agreed well with one another.

The experimental results suggest that the above threshold method for classifying the eye-blink and concentration signals works well with a relatively high accuracy. There are no significant differences between the thresholds of the feature signals for the able-bodied individuals and that for the disabled individuals, validating the feasibility of this proposed multi-motion control system for patients suffering severe motor dysfunction.

Validation of SCDE-based robot arm control

As a practical illustration, a prototype arm-reaching assistive system based on the multi-motion control system for picking up objects on the desk has been developed for experimentally validating and demonstrating the concept feasibility of using these feature signals to help patients perform visual control of an arm-reaching robot. A 6-DOF arm-reaching desktop robot and a laser system for visual guidance (Figure 7) are employed.

Experimental setup. In this prototype arm-reaching assistive system, the multi-channel feature signals serve three purposes: (1) an LEB-driven command x_l selects an operation; (2) an SEB-driven command x_s interrupts and resets a motion procedure and (3) the concentration-driven command y_c activates an execution of a motion procedure, providing the user an

opportunity to fine-tune operations and minimizing the chances of giving out false commands in practice.

The motion modes in Figure 4(b) include on/off/direction control of each individual motor at constant-speed, high-level robot control, undo the last operation, and system initialization. The high-level robot control mode executes five pre-designed task, including moving horizontally back/forth, moving vertically up/down, moving along the laser guidance on the gripper. The waiting period Δt for selecting a motion mode is 1.5 s.

The high-level method is best illustrated with an example of moving along the laser guidance on the gripper, that the robot automatically approaches the target with a single selection once the two lasers are locked onto the target. This task involves simultaneously controlling three motors (M1–3) as illustrated in Figure 7. The kinematics for calculating the i th joint angles θ_{in} at the n th time step in terms of initial joint angles and motion length ($n\Delta d$) are given in Appendix 1.

Experimental investigation. The performance of the arm-reaching assistive system was experimentally evaluated on a practical task, which involved picking up a cube sugar and placing it into a designated tiny bottle. The results in Figure 8 detail the operational steps, feature signals and experimentally registered time points at which specific commands derived from the conscious feature signals occur. To help visualization and gain physical insights to the time required to execute the sub-tasks, Figure 8(a) illustrates typical applications of low- and high-level (Step III) motion modes, as well as that of the selection/reselection commands derived from 35 LEB signals (red up-pointing triangles) and the activation commands derived from 10 concentration signals (blue down-pointing triangles), along with the gripper trajectory in Cartesian workspace and the corresponding time-referenced snapshots in Figure 8(b) and (c), respectively. The results in Figure 8 illustrate that the

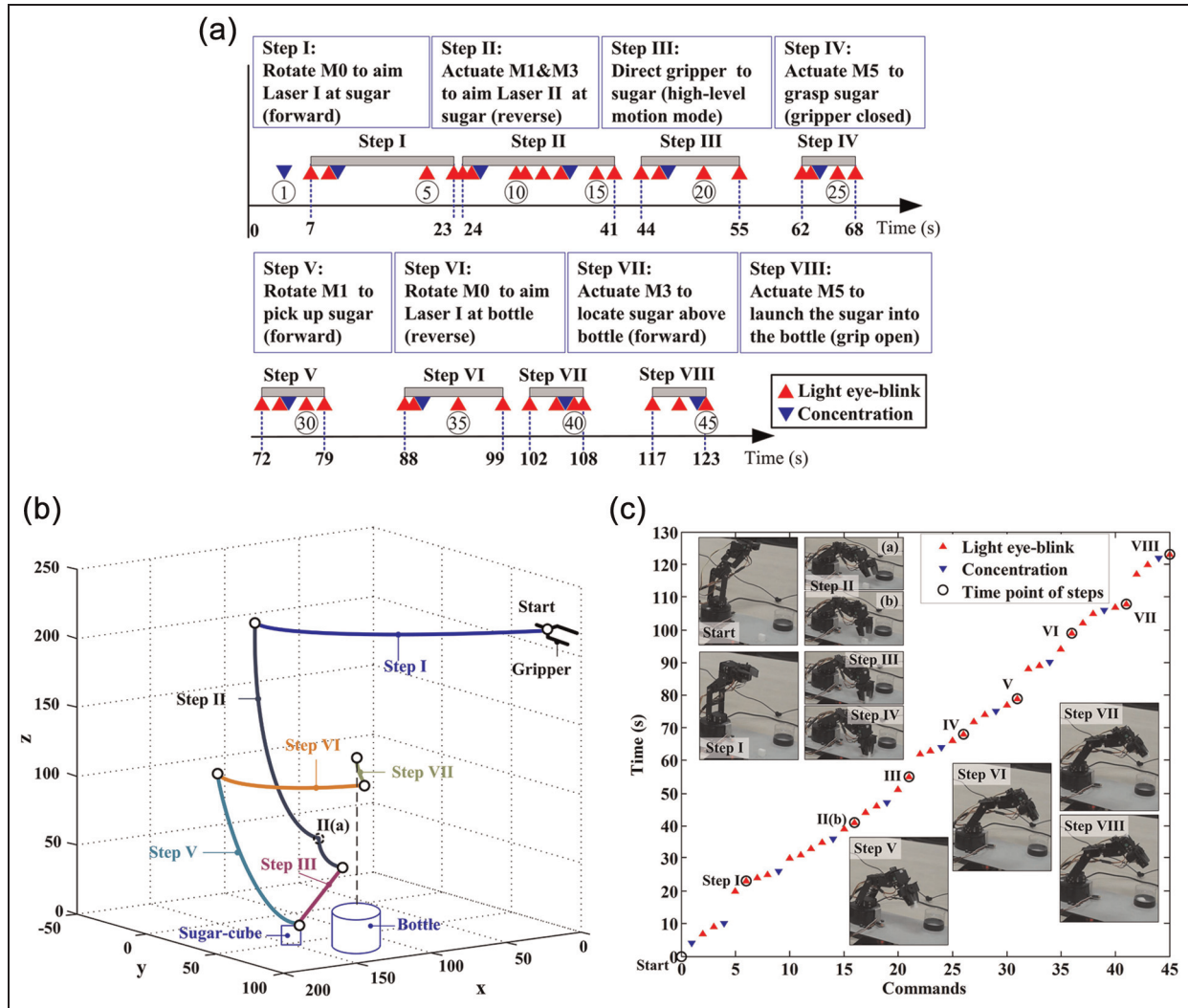


Figure 8. Experimental results of the arm-reaching assistive system in practical task: (a) operational steps, (b) trace illustration of the gripper through the operation procedure and (c) snapshots showing robot poses at the end of each operational step.

prototype multi-motion arm-reaching assistive system based on bioelectric signals faithfully executed the specified commands.

Discussion of results. Some observations and lessons learned are summarized as follows:

1. The total time is 123 s, of which 40 s were taken by the robot motion, 52 s were spent on the 1.5-s wait periods for motion mode selection and the remainder was spent to generate feature signals for selection or activation. As compared with a similar work by Hashimoto et al.¹⁵ where 104.8 commands were generated within 830 s for a single-DOF wheelchair control, the proposed system reported here requires only 45 commands within a relatively short duration of 31 s for this 6-DOF motion task.
2. No selection was missed (and thus no SEB command was registered) indicating that the 1.5-s wait period is sufficient for this specific participant.
3. Due to the practical high-level motion mode that helps users complete a pre-designed task with a

single selection, the performance is highly efficient in applications.

4. The ITR computed based on Wolpaw's definition² is 10.6 bits/min, which is about half of that in wet-electrode system³⁸ and acceptable for assistive control. It is expected that the ITR can be greatly increased with more training.

The results suggest that while limited in terms of scalp recording locations, the extracted feature signals can be effectually applied in assistive technologies where ease of use is a priority. Some factors (that could potentially improve the ease and efficiency of the method) deserve further investigation with disabled individuals, for example, the effects of variable intervals between motion mode selection and application of intelligent control strategies (such as artificial neural networks and fuzzy logic).

As a benchmark comparison, Table 4 summarizes key findings of several similar works based on gel-free neck-up bioelectric signal recording for practical HMI applications, where NR denotes information not

Table 4. Comparison of practical gel-free HMI systems in scientific articles.

References	Patki et al. ¹⁹	Gomez-Gil et al. ¹⁸	Lin et al. ¹⁷	Li et al. ¹⁶	Lin et al. ²⁹	This article
Applications (DOF)	NR	Tractor (1-DOF)	Wheelchair (1-DOF)			Robot arm (6-DOF)
Elect. contact	Ag/AgCl	Saline-based contact		Dry electrode	Single channel	
No. of channels	8	14	14	3	Eye blink and concentration	
Feature signals	P300 (EEG)	Eye and jaw (EMG)	motor imagery (EEG)	Eye (EOG) and jaw (EMG)	NR	
Recognition rate (%)	73.6	NR	< 80	95	NR	95
Failure rate (%)	NR	NR	NR	4	NR	0
Time (commands)	NR	NR	NR	830 (104.8)	NR	31 (45)

DOF: degree of freedom; NR: not reported; EEG: electroencephalography; EMG: electromyography; EOG: electrooculography.

reported in the reference cited. While prior studies (generally limited to single-DOF motion manipulation) focus primarily on demonstrating the concept feasibility, the new HMI technique proposed here advances the state-of-the arts by offering a means to control a full 6-DOF robot arm with an SCDE and by demonstrating a highly efficient method that generates a sequence of 45 commands within 31 s.

As summarized in Table 4 where published performance data are evaluated in terms of recognition rate, failure rate and efficiency (time required and number of commands to complete a specified task), the multiple feature-signal extraction algorithms along with the two-control strategy provide a potential means to realize failure-free multi-DOF motion applications with high efficiency and recognition rate. Clearly, the objective here is to demonstrate proof-of-concept feasibility; it is expected that the method introduced here can be extended to more sophisticated HMI applications when taking advantages of additional channels described in the published literatures.^{16–19}

Conclusion

This article offers a practical multi-motion control system using neck-up bioelectric signals from an SCDE device through a two-level control algorithm to help patients with severe motor dysfunction control auxiliary appliances, such as arm-reaching robot. Experimental investigations on able-bodied and disabled individuals with little training confirmed the following findings:

- An average SR as high as 94.5% and 94.0% was obtained from LEB and SEB signals, respectively, with no false detection. The average SR achieved with an SCDE-based system is comparable to a published 95% SR that used a multi-channel saline-based electrode system. The average time taken for reaching a predefined concentration signal threshold is about 2.4 s.
- The results in practical application of picking up a cube sugar and placing it to a tiny bottle demonstrate that the prototype multi-motion assistive system can faithfully execute 45 specified commands derived from eye-blink and concentration bioelectric signals with an ITR of 10.6 bits/min.
- The high-level motion mode (that helps users complete pre-designed tasks with a single selection) greatly simplifies the operation procedure and is highly desirable in application.

As an advanced communication technology, we expect that this practical and portable multi-motion control system based on bioelectric signals can be extended to several other applications and has a potential to improve the life quality of patients with disabilities.

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Declaration of conflicting interests

The authors have no conflicts of interest to declare.

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Appendix I

Robot kinematics for high-level motion mode

Consider the robot shown in Figure 7 executing the high-level motion mode, which moves the gripper in a stepwise manner (with step length Δd) along the straight-line path from the joint center B to the target point p . The kinematics for calculating the i th joint angles θ_{in} at the n th time step in terms of initial joint angles θ_i and motion length ($n\Delta d$) are given by equation (4)

$$\begin{cases} \theta_{1n} + \theta_{2n} + \theta_{3n} = 2\pi - \alpha \\ a \sin \theta_{1n} - b \sin(\theta_{1n} + \theta_{2n}) = a \sin \theta_1 - b \sin(\theta_1 + \theta_2) - n\Delta d \sin \alpha \\ a \cos \theta_{1n} - b \cos(\theta_{1n} + \theta_{2n}) = a \cos \theta_1 - b \cos(\theta_1 + \theta_2) + n\Delta d \cos \alpha \end{cases} \quad (4)$$

where a and b are the lengths of robot arms defined in Figure 7; θ_1 and θ_2 are the inclined angles of robot arms before combined motion; α is the inclined angle of Bp and horizontal line and Δd is the step length. The solutions to equation (4) are given as follows

$$\begin{cases} \theta_{1n} = \arccos\left(\frac{a^2 + m^2 + n^2 - b^2}{2a}\right) + \beta \\ \theta_{2n} = \arccos\left(\frac{a^2 - m^2 - n^2 - b^2}{2b}\right) - \theta_{1n} + \beta \\ \theta_{3n} = 2\pi - \theta_{1n} - \theta_{2n} \end{cases} \quad (5)$$

where

$$\begin{cases} \beta = \arccos\left(\frac{n}{\sqrt{m^2 + n^2}}\right), \quad \beta \in [0, \pi] \\ m = a \sin \theta_1 - b \sin(\theta_1 + \theta_2) - n\Delta d \sin \alpha \\ n = a \cos \theta_1 - b \cos(\theta_1 + \theta_2) + n\Delta d \cos \alpha \end{cases}$$