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Assessing the potential of electrodermal activity as an alternative access pathway

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Abstract

An embedded multiple-case study was conducted with six able-bodied participants to evaluate the potential of electrodermal activity (EDA) as an alternative access pathway to electronic aids to daily living. Electrodermal signals were recorded while participants alternated between rest and three different mental or breathing exercises. In a subsequent experimental session, the exercise exerting the greatest influence on EDA was used to volitionally generate an 'active' state. Two classification algorithms, namely, a probabilistic classifier and a handcrafted rule base were developed and tailored to each individual's physiological patterns to discriminate between participant states. Through cross-validation, participant state was correctly identified to an accuracy exceeding 80% using either classification algorithm. This result demonstrates that consciously controlled EDA could conceivably serve as a binary switch, and encourages further research towards EDA-based alternative access for people who are locked-in.

Keywords: Augmentative and alternative communication; Locked-in syndrome; Autonomic physiological signals; Electrodermal activity; Physiological signal classification

1. Introduction

Over half a million people worldwide are affected by locked-in syndrome, a condition in which individuals are cognitively aware and conscious, but paralyzed and unable to speak [1]. Common etiologies leading to this condition include amyotrophic lateral sclerosis (ALS) and brainstem stroke [2]. Currently, commercial augmentative and alternative communication devices rely on the user's voluntary generation of a reproducible, extant physical response, and therefore are not suitable for individuals who are locked-in. Recent research on brain computer interfaces (BCI) suggests the possibility of establishing new communication and control channels for individuals who are locked-in. Invasive BCIs involve implanting electrodes typically in the motor cortex, coupled with automatic decoding of neuronal firing patterns to control devices such as a computer mouse, or a prosthetic hand [3,4]. However, in a survey of 17 ALS patients, who were well informed of the enhanced communication ability of a surgically implanted electrode, most refused the procedure in favour of a slower and error-prone non-invasive device, the argument being that response time was not an issue when one is completely paralyzed [5]. Non-invasive BCIs extract signal features from scalp electroencephalography (EEG) such as visual evoked potentials, slow cortical potentials, the P300 potential and mu-rhythms [6,7]. Although the literature reports initial success with individuals who are locked-in, some outstanding challenges preclude its widespread clinical uptake at the present time. These issues include lengthy training regimens and high error rates [5], stigma and discomfort of wearing an electrode cap for extended durations, maintaining conductivity of the electrode–scalp interface and the demand for persistent attentiveness to a visual display [7]. A seldom-considered alternative to BCI is an interface that exploits autonomic signals such as skin conductance.

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Skin conductance, or electrodermal activity (EDA) measures the resistive properties of the skin [8] that change with the reaction of the autonomic nervous system to anticipation and recognition events [9], meditation [10], and stimuli such as music [11] and pain [12]. Unconscious changes in EDA also include electrodermal reactions (EDR) in response to affective stimuli and may provide insight into the functional intent of a locked-in patient. On this premise, Tsukahara and Aoki [13] developed a pilot device that discerned unconscious skin potential reactions to determine the letter being rehearsed in a participant's mind with 47% accuracy. Research on mental countermeasures in polygraphy and biofeedback has demonstrated that EDA can be brought under conscious control with appropriate training [14,15]. Using this evidence and a commercial police-grade polygraph system, Moore and Dua [16] trained a participant with ALS using biofeedback to self-regulate his EDA to reproduce a yes or no response with an accuracy of 61.78%. Through the exploration of different mental exercises and the identification of discriminatory EDA signal features, there remains an opportunity to further improve conscious control and automatic classification of EDA.

The current embedded, multiple-case study explores the possibility of using mental exercises in a controlled environment to produce voluntary, measurable changes in EDA while taking into account variation in each individual's physiological patterns and psychological preferences. Specifically, the study aims to:

(1) identify for each participant the most potent method of creating two discernable EDA states,
(2) create a classification algorithm that accounts for each participant's unique physiological patterns to distinguish between the two EDA states,
(3) investigate for one individual whether the inclusion of a complementary physiological signal (e.g. respiratory patterns) improves the accuracy of EDA state classification.

2. Methods

2.1. Design

The research was framed as an embedded, multiple-case study [17]. Data were collected in two separate sessions: the first session assessed the effect of three different mental and breathing exercises on EDA, and the second investigated the participant's ability to voluntarily generate two distinct EDA states using an individualized exercise chosen from session 1. Following data collection, two algorithms were developed for each individual to determine how accurately the two EDA states could be classified. The presence of circadian rhythms was investigated for all cases, and for one participant who exhibited rhythmic increases in EDA; the effect of physiological filtering using respiratory data on EDA classification accuracy was investigated.

2.2. Participants

A convenience sample of six able-bodied participants with a mean age of 26.3 ± 4.5 years (two females) was recruited. Participants were healthy and instructed not to eat or consume caffeine 1 h prior to data collection to mitigate metabolic influences on the autonomic nervous system. Ethical approval for this study was obtained from the University of Toronto and from Bloorview Kids Rehab (Canada).

2.3. Measures

Electrodermal activity (EDA) was recorded using a ProComp Infiniti multi-modality encoder from Thought Technology (Montreal, Canada) and a laptop computer. EDA was recorded from two 10 mm diameter Ag–AgCl electrodes, attached with adhesive collars on the medial phalanges of the index and middle fingers of the participant's non-dominant hand. A constant voltage (0.5 V) was applied between the two electrodes and EDA was sampled at a frequency of 256 Hz. The signal was displayed in real-time on the computer screen as visual feedback for the participant and investigator. For the case wherein physiological filtering was attempted, the participant donned a piezoelectric belt positioned around the thoracic area, which translated the stretch due to expansion and contraction of the lung cavity into changes in voltages. These changes were recorded simultaneously with EDA by the ProComp Infiniti system.

2.4. Data collection

2.4.1. Session 1

Prior to data collection, participants were familiarized with the following three sets of exercises, each composed of two activities: (1) alternating between a slower-than-normal and a faster-than-normal frequency of breathing; (2) alternating between mental relaxation and mental arithmetic (continuously subtracting 7 from an initial value of 1000); and (3) alternating between mental relaxation and mentally rehearsing a piece of pleasant music chosen by the participant. Participants alternated sequentially between each activity once every minute, repeating each activity three times for a total recording time of 6 min per exercise. Data were stored for future analysis to determine the physiological effects of each exercise.

2.4.2. Session 2

Participants were informed of the results of the previous session. In particular, the investigator advised each participant of his or her most successful method of generating a distinct and reliable change in EDA. Participants were then instructed to sequentially produce alternating resting

and active states by practicing the recommended mental or breathing exercise. To investigate the presence of circadian rhythms, data were collected on 2 different days, at different times (e.g. morning, afternoon or evening). The individual generated 10 resting and 10 active states on the first day, and 15 resting and 15 active states on the next day, for a total of 50 sets of signals. Prior to generating each state, each participant was given the opportunity to observe his or her EDA signal for a total of 10 s, and was instructed to produce the required state for the subsequent 10 s.

2.5. Feature extraction

The raw data collected in session 1 were used to determine the exercise that produced the most consistent and distinct changes in EDA. From the EDA signal corresponding to each 1-min activity, three features were derived for this purpose, namely, the mean EDA value, the range and the number of EDRs. Baseline EDA signals can naturally increase and decrease by 0.05 μS over a time interval of 30 s or more. Transient EDRs of similar magnitude, on the other hand, evolve over a much shorter timescale. Based on empirical observations, a 0.05 μS increase in EDA was considered a valid EDR only if the change occurred in five or fewer seconds. Each feature was calculated over the full minute of recording. The value of each of these three features was plotted against time for the 6-min exercise, with one data point for each minute. A saw–tooth plot, as shown in Fig. 1, indicated that the participant was able to voluntarily increase and decrease that feature of their EDA. For most participants, the 6-min recording sessions exhibited a dominant increase or decrease in the baseline EDA signal. This trend skewed the data and would have inflated the variance of the means, had they been pooled across similar activities. Consequently, the means of each activity were instead analyzed to determine whether EDA in one state differed significantly from EDA signals in the previous state by comparing successive resting and active states via a Student's *t*-test (e.g. resting trial 1 versus active trial 1, active trial 1 versus resting trial 2). If each of these EDA states was significantly different ($p = 0.05$) from the preceding EDA state, the mean was considered a distinguishing feature between states. For the EDR multiplicity and EDA range features, we simply confirmed that the slopes of the lines joining feature values of successive states alternated consistently between positive and negative values. The corresponding mental or breathing exercise was marked as having the potential to control EDA. For data collected in the second session, two different features were extracted, namely, the first difference of the EDA signal and the centroid of the EDA first difference histogram, for purposes of classification. These new features were selected because visual inspection of the EDA signals indicated that the slope of the signal might have more discriminatory potential than the three general features examined in session 1. The computation of these features will be explained below.

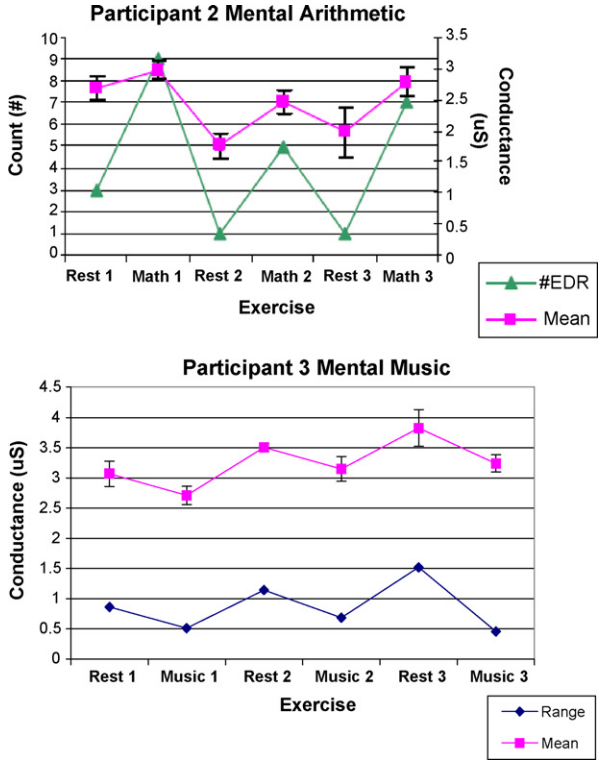

Fig. 1. Examples of saw–tooth patterns in EDA features due to mental exercises. Participant 2 was able to exert bi-directional control over EDR multiplicity and EDA mean through mental arithmetic while participant 3 was able to control EDA mean and range through mental music.

2.6. Classifier design

2.6.1. Handcrafted rule base

From the 50 signals collected in session 2, a random subset of 40 signals was used to derive a handcrafted rule base for each participant, using the first difference of his or her electrodermal signals. This rule base produced the cumulative evidence, E_{active} and E_{rest}, of the participant being in either a relaxed or an excited physiological state. The rule base exploited two observed behaviours: firstly, an individual's EDA tended to decay over time at rest (Fig. 2, top), causing the first difference of the signal to be smaller, predominantly negative numbers, and secondly, EDRs were typically present in active states (Fig. 2, bottom) causing the first difference of the signal to have large positive and negative numbers in comparison to the resting state. While these overall trends were consistent between participants, every individual's EDA signal characteristics (e.g. EDR amplitude, rise time or recovery time) were unique; consequently, a unique rule base was established for every individual. EDA values were collected with a 1 s time delay at times t_1 and t_2, where $t_2 = t_1 + 1$. The difference between the EDA values at these times was denoted as Δ. The size of the difference was assigned different weights of evidence, according to the rule base, which consisted of the following two families of if-then rules:

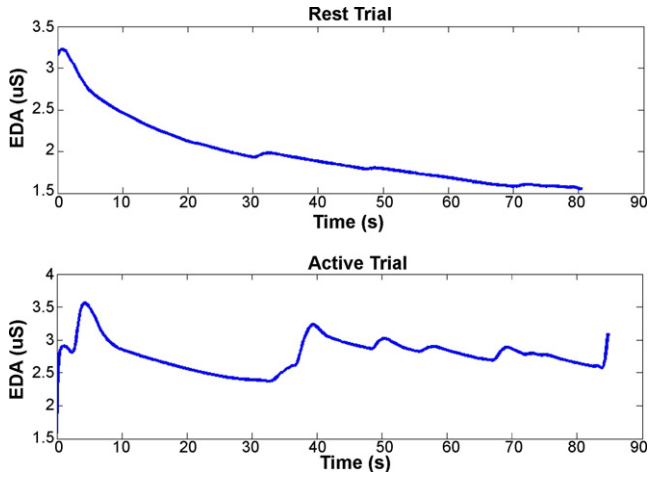

Fig. 2. Typical raw EDA signals from a resting trial (top) and an active trial (bottom).

If Δ is in the interval (A_{i-1}, A_i), then the evidence for active state, E_{active}, increases by W_i^{a}.
If Δ is in the interval (R_{i-1}, R_i), then the evidence for rest state, E_{rest}, increases by W_i^{r}.

where $i = 1, \ldots, n$ while A_i and R_i were real values that partitioned the range of possible difference values, Δ, into n bins. Hence, there were $2n$ rules in total. In the present experiment, n ranged from 3 to 7. The weights W_i^{a} and W_i^{r} were positive real numbers whose magnitude reflected the level of evidence for the active or rest states, respectively. Both the weights and partition values (A_i and R_i) were manually selected to minimize classification error on the training data. The flowchart outlined in Fig. 3 demonstrates the offline accumulation of evidence from the raw EDA signal. In accordance with the observations of overall EDA trends, positive Δ generally contributed to the evidence of an active state while negative Δ strengthened the evidence of a resting state. Evidence was accumulated every 0.1 s until the end of the 10-s recording. Fig. 3b illustrates the evaluation of evidence at $t = 20$ s to classify the observed EDA signal. The signal was classified as the state with the stronger evidence.

2.6.2. Probabilistic classifier

The second classifier used to analyze the individual's EDA state was based upon a histogram distribution of the EDA signal differences. Similar to the handcrafted classifier, EDA values were differenced between times t_1 and t_2, where $t_2 = t_1 + 1$ s, the values of which were incremented by 0.1 s for the duration of the 10-s signal. Subsequently, a 20-bin histogram of the trial's cumulative differenced signal was derived yielding a set of bin counts $\{n_1, n_2, \ldots, n_{20}\}$ and bin centres $\{x_1, x_2, \ldots, x_{20}\}$. From the bin counts and centres, the first difference histogram centroid was estimated, as depicted in Fig. 4a. For a given collection of training signals from the resting and active trials, this procedure yielded two sets of centroids. A maximum likelihood gamma fit to each set of data yielded F_{active} and F_{rest} as the estimated active and rest class distributions, respectively. As an example, the proba-

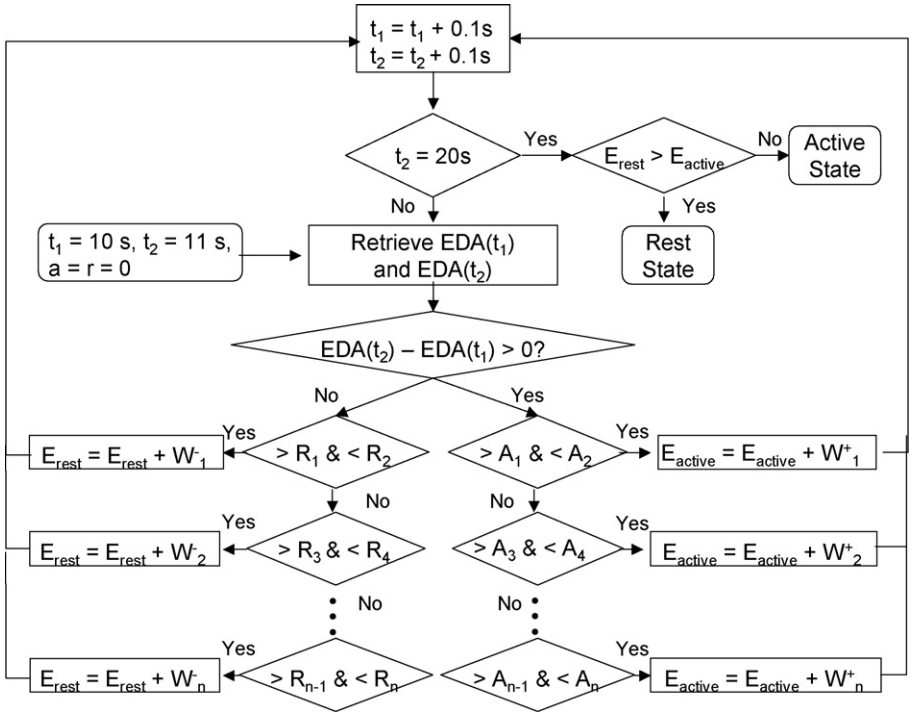

Fig. 3. A handcrafted algorithm for classifying 10 s of EDA data. Times t_1 and t_2 were initialized to 10 and 11 s, respectively. EDA values 0.1 s apart added a pre-defined weight to the evidence of either a resting or active state. The evidence is evaluated at $t = 20$ s. The observed EDA signal is classified as the state with the stronger evidence.

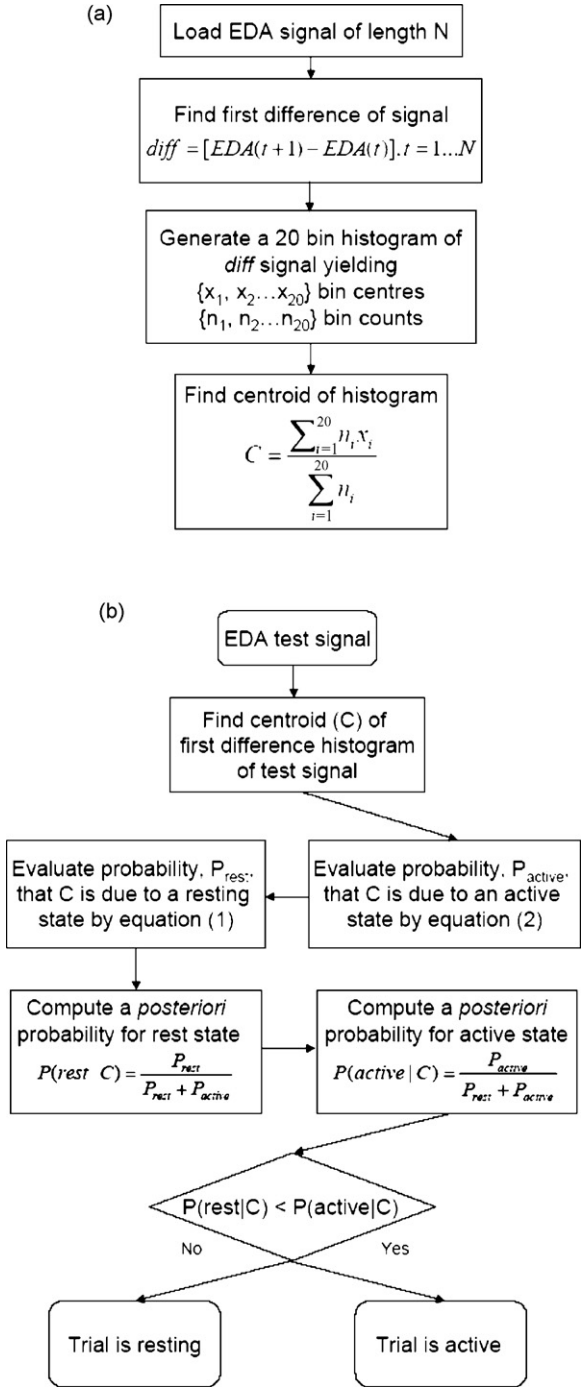

Fig. 4. (a) Generation of the centroid of the histogram of EDA first differences for an EDA signal of length N. (b) Probabilistic classification algorithm.

bility densities corresponding to these class distributions for participant 3 are depicted in Fig. 5.

For classification, a simple Bayes rule was implemented with equal class priors. For each EDA test signal, the centroid of the first difference histogram was computed and the probabilities of resting and active states were estimated from the corresponding class distributions. The probabilities of the centroid, C, arising from active and rest states are compactly

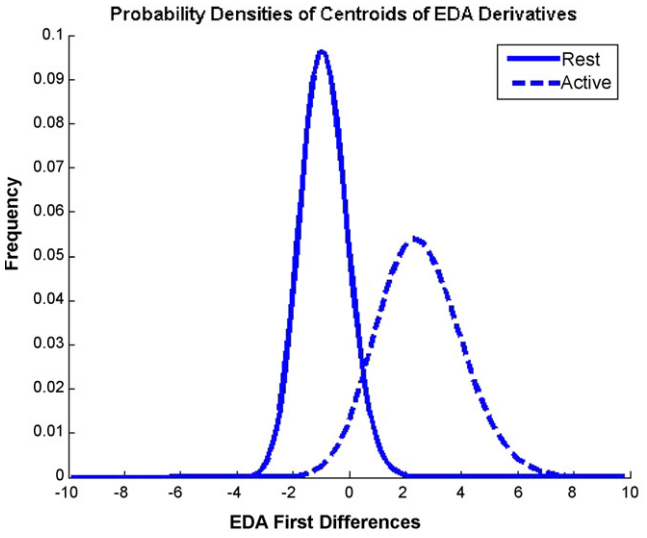

Fig. 5. The maximum likelihood gamma fit of the centroids of EDA first differences generated from 20 resting trials (solid line) and 20 active trials (dashed line) for participant 3.

written as

$$P(C|\text{rest}) = H(C - \mu_{\text{rest}}) - \text{sgn}(C - \mu_{\text{rest}})F_{\text{rest}}(C) \quad (1)$$

$$P(C|\text{active}) = H(C - \mu_{\text{active}}) - \text{sgn}(C - \mu_{\text{active}})F_{\text{active}}(C) \quad (2)$$

where $H(\cdot)$ and $\text{sgn}(\cdot)$ are the heaviside and sign functions, respectively, and μ_{rest} and μ_{active} are the means of the estimated gamma class distributions, F_{rest} and F_{active}. For example, in Eq. (1), if $C \geq \mu_{\text{rest}}$ then $P(C \mid \text{rest}) = 1 - F_{\text{rest}}(C)$ and likewise, if $C < \mu_{\text{rest}}$ then $P(C \mid \text{rest}) = F_{\text{rest}}(C)$. A maximum *a posteriori* probability decision determined whether the test signal would be classified as a rest or an active trial; this classification was compared against the true state of the participant for the particular trial. The classification procedure is summarized in Fig. 4b.

To evaluate each of the above classifiers, an 80–20 split cross-validation was performed on the data from each participant.

3. Results

3.1. Session 1

Each participant demonstrated at least one exercise that produced a distinct change in an EDA feature between resting and active states. Features that were thus affected by mental exercises are indicated for each participant in Table 1. The list of features corresponding to the exercise selected for session 2 is punctuated with an asterisk.

Table 1
EDA features affected by the three exercises

Participant	Exercise		
	Breathing	Math	Music
1	Mean*	Mean, #EDR	Mean, range, #EDR
2		Range	Mean, range*
3	Mean, range	Mean, range, #EDR*	Mean
4	#EDR*		
5	#EDR	Range	Range, #EDR*
6			Mean, range, #EDR*

The asterisk at the end of a feature list indicates that the corresponding exercise was recommended for the generation of an active state.

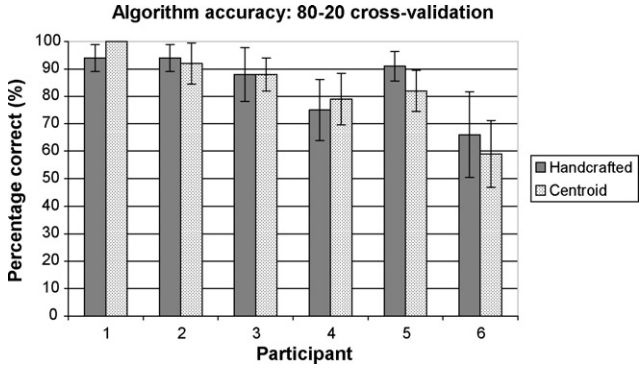

Fig. 6. Accuracy of the two classification algorithms for an 80–20 split cross-validation.

3.2. Session 2

Results from classifying the data with the handcrafted rule base and the probabilistic classifier are presented in Fig. 6. On average, participant mental state was classified to an accuracy of $84.7 \pm 11.6\%$ using the handcrafted rule base, and $83 \pm 14\%$ using the probabilistic classifier. Further analysis of the probabilistic classifier demonstrated a positive predictive value of participant's mental state of $91 \pm 6\%$.

4. Discussion

This study endeavored to evaluate whether or not individualized mental exercises could be used to produce discernible EDA. The results of the investigation demonstrate that this indeed is possible with able-bodied individuals, and encourage further study of EDA as an access point in individuals with severe motor disabilities. Current work with brain computer interfaces suggests that users may need several months of training to develop proficient control over their physiological signals [19]. Participants in this current study received no prior training on self-regulation of their electrodermal activity, and were able to generate the correct machine discernable state with over 80% accuracy.

4.1. Physiological basis

The components of the skin have constant electrical properties, with the exception of the sweat glands, which permeate the dermis and are innervated by the sympathetic nervous system [20]. When the autonomic nervous system is stimulated, ion channels in these sweat glands open and the glands fill with sweat, changing the overall electrical conductivity of the skin. Previous studies have demonstrated that mental arithmetic tasks and listening to music provide substantial stimulation to generate an autonomic response [11,21], which is confirmed by the changes in electrodermal activity observed in this study. The connection between a single deep breath and electrodermal reactions has also long been established, and research supports the theory of a cortical interaction between respiratory neurons and the central autonomic system [22]. This theory would account for the observed changes in electrodermal activity due to the breathing exercises in this study.

4.2. Individual tuning

To reduce the risk of technology abandonment and to maximize user satisfaction, a user-centred approach to assistive technology development is often recommended [23]. The present access system can be customized to the participant in several ways:

1. *Personalized mental exercises*. A unique set of mental exercises can be determined for each individual. This is critical to choosing a successful means of EDA control, as the effect of different cognitive tasks varies from individual-to-individual [24].
2. *Adaptive classification algorithms*. Both classification algorithms described above have free parameters (e.g. feature partitions in the handcrafted rule base and class distribution parameters in the probabilistic classifier) that are customizable to the individual's EDA patterns during the classifier training stage.
3. *Admission of unique physiological signals*. Physiological patterns unique to a given individual can be used to enhance classification. Consider for example, participant 6 for whom handcrafted and probabilistic algorithms yielded low classification accuracies (66% and 59%, respectively). Visual inspection of EDA data revealed a repetitive sinusoidal-like pattern of rise and falls, roughly corresponding to the participant's respiratory patterns. These non-specific EDRs overwhelmed the EDRs produced by voluntary control. During the second session, participant 6 donned a respiratory sensor thoracically to track respiratory patterns. Subtracting the respiratory signal from the EDA data roughly removed the EDRs that were not a result of mental stimulation, and significantly increased the classification accuracy of the handcrafted rule base from $66 \pm 15.6\%$ to $75 \pm 15.6\%$ (Student's t-test, $p = 0.05$). Other methods of removing the sinusoidal

breathing trend, such as wavelet detrending, may also be applied. While visual examination of the EDA patterns of the other participants did not reveal any rhythmic components similar to those of participant 6, these results indicate that for some individuals, exploitation of other physiological signals such as blood pulse volume and respiration rate may enhance the accuracy of classifying the participant state.

4.3. Effect of seasonal and biological rhythms

Studies have demonstrated that EDA levels increase linearly throughout the day [25], and are affected by season [26]. This raises the concern that a classifier trained on EDA signals from one isolated period of time will have difficulty with classification as the signals evolve over time. To capture the potential signal variability due to circadian rhythms, data for this study were collected on 3 different days and at different times (morning, afternoon, or evening) for each participant. The first session occurred on 1 day and the second session spanned 2 different days. Training and testing sets were drawn from the accumulation of data across the latter 2 days. The inherent assumption of this method of data collection was that the mental or breathing exercises exerted the same effect on EDA signals at different days and times, irrespective of baseline EDA levels. The approximately equivalent number of classification errors between the 2 days of testing suggests that transient EDA changes were similar on both days. Additionally, the overall accuracy of over 80% would imply that the exercises had similar effects over all 3 days of data collection. While these results support the assumption that the baseline circadian rhythms do not affect transient EDA behaviour, more extensive data collection is necessary to systematically gauge signal variability due to natural rhythms.

4.4. Detection times

In the present setup, participants were given 10 s to calibrate their EDA, and 10 s to generate the desired state for a total detection time of 20 s. Venables and Christie [20] recommend a latency window of 1–3 s to detect EDRs, and Fowles [29] suggests an even shorter window of 1-s post-stimulus, claiming that changes in EDA can be reliably detected in this timeframe. While a shorter EDA change detection time seems justified, it must be noted that these recommendations have stemmed from consideration of unconscious EDR in response to a stimulus. Detection times for voluntary changes in EDA will likely be user-dependent and several seconds longer taking into account the time required to mount the conscious response. However, EDA response detection time might be reduced by simultaneously monitoring other autonomic physiological signals to corroborate early signs of change. Furthermore, practice, as suggested by biofeedback research, may improve a user's ability to swiftly generate a desired autonomic state.

Using the handcrafted rule base, an average of 2.6% of the trials in the 80–20 cross-validation resulted in equal probabilities for the resting and active states. In an on-line bedside system, equal probabilities would lead to classifier indecision and consequently necessitate a repeat of the question posed to the user, thus reducing the overall rate of information transfer. In the present experiments, the probabilistic algorithm did not experience any indecisions.

4.5. EDA signal features

In the current study, EDA mean, range and derivative, and number of EDRs provided simple summary values of the participant's EDA signals. Other potentially more discriminating features, such as dominant spectral components or detrended signal spread, may be uncovered through further study of EDA signals representing relaxed and stimulated states.

4.6. Limitations of present study

This study was conducted with healthy individuals in a controlled environment. EDA results of able-bodied participants likely do not reflect performance with the target population. While EDA has been recorded from potential target populations such as people with multiple sclerosis and amyotrophic lateral sclerosis [27,28], it is likely that these etiologies may result in marked alterations in EDA signals. The proposed classification algorithms may accommodate such individual idiosyncrasies, but further research with the target population must be conducted before conclusions can be drawn about the practical viability of the EDA access channel.

Minimizing external noises and disturbances, which is likely not possible at a participant's bedside, idealistically suppressed contamination from non-specific EDRs in this experiment. Heightened occurrence of non-specific EDRs in unconstrained environments would decrease classification accuracy, necessitating the development of selective EDA filters.

Participants were cued to begin a given exercise to change their physiological state, enabling the investigator to hand-splice events in the offline analysis. To be viable as a bedside system, the user's voluntary EDA signal changes must be recognized by the classifier without an external cue, potentially via automatic segmentation of the signal.

5. Conclusions

This embedded, multiple-case study investigated the possibility of using mental or breathing exercises to generate two machine-discernible states in a participant's electrodermal activity. Each of the six able-bodied participants had at least one mental or breathing exercise that produced bi-directional control of an EDA signal feature. Handcrafted and probabilistic classifiers discriminated between excited and resting states

with an accuracy of $84.7 \pm 11.6\%$ and $83 \pm 14\%$ respectively. These results demonstrate the potential of voluntarily generating distinct EDA signals for the purposes of environmental control. However, future research with individuals who are locked-in will be necessary to ascertain the practical utility of EDA as an alternative access pathway.

Conflict of interest

None.

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