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Four-Way Classification of EEG Responses To Virtual Robot Navigation

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***Abstract*— Studies have shown the possibility of using brain signals that are automatically generated while observing a navigation task as feedback for semi-autonomous control of a robot. This allows the robot to learn quasi-optimal routes to intended targets. We have combined the subclassification of two different types of navigational errors, with the subclassification of two different types of correct navigational actions, to create a 4-way classification strategy, providing detailed information about the type of action the robot performed. We used a 2-stage stepwise linear discriminant analysis approach, and tested this using brain signals from 8 and 14 participants observing two robot navigation tasks. Classification results were significantly above the chance level, with mean overall accuracy of 44.3% and 36.0% for the two datasets. As a proof of concept, we have shown that it is possible to perform fine-grained, 4-way classification of robot navigational actions, based on the electroencephalogram responses of participants who only had to observe the task. This study provides the next step towards comprehensive implicit brain-machine communication, and towards an efficient semi-autonomous brain-computer interface.**

I. Introduction

When humans observe tasks being performed, the brain produces signals in response to what the human has seen, without the need for any conscious effort [1]. For example, when we perceive errors, error-related potentials (ErrP) are automatically produced [2]. ErrPs are typically characterised by two key features: the error-related negativity (ERN), and the error positivity (Pe). The ERN is a negative deflection, peaking fronto-centrally approximately 100ms after an error is committed [2], [3]. Following this, the Pe is a broader positive deflection, usually peaking centro-parietally around 200–500ms after the error occurs [3], [4].

ErrPs can be detected using electroencephalography (EEG) and classified against responses to correct actions on a single-trial basis [3]. It has been shown that the classification of ErrPs can be used as feedback for reinforcement learning (RL) and applied in brain-computer interfaces (BCI) to allow machines to find quasi-optimal routes to target locations [5], [6]. Theoretically, these RL-based systems work as long as classification accuracy is greater than chance level [3], [5].

However, if we can gather more detailed information than just whether an action is correct or erroneous, we could provide more efficient and comprehensive BCI control. For example, existing systems are able to navigate towards a target, but do not have sufficient information to know they should stop when they reach it. Acquiring this extra information would allow for a more autonomous system, driven by implicit communication between human and machine.

A small number of studies have shown that it is possible to use single trial EEG to differentiate ErrPs evoked by different error conditions, such as errors of different directions or severities [7]. Further to this, we recently compared two different types of errors committed in a robot navigation task: moves that started from a target location and stepped off it (rather than selecting the target), and moves that began in an off-target location but erroneously moved further away [8]. We were able to show that Pe amplitude was significantly greater in the case of moves that stepped off a target location [8]. Moreover, we showed that it is possible to distinguish these error types from each other using single-trial EEG [8].

Another signal that is produced as an automatic response to certain stimuli is the P300: a positive peak occurring approximately 300ms after the presentation of a given stimulus [9]. In particular, the P300 has been shown to be produced when subjects recognise a target stimulus amongst non-target stimuli [10]. P300 amplitude has been shown to vary based on target-to-target interval [11], and based on reward magnitude [12].

In a recent study, we compared two types of correct navigational actions: moves that got closer to the target but did not reach it, and moves that did reach the target [13]. We were able to show that both of these actions elicited a P300, and that the amplitude of the P300 was significantly greater in cases where the target was reached [13]. Furthermore, we showed that it is possible to differentiate between the two types of correct movement on a single-trial basis [13].

In the present study, we combine these recent advances into a single system. We implemented a multi-stage stepwise linear discriminant analysis strategy, first performing error detection, followed by subclassifying trials into specific types of error or correct action. As such, we aimed to show that detailed, 4-way classification of navigational actions is possible using single-trial EEG. To test our approach, we used data from two similar navigation tasks, and performed classification on EEG data collected from 8 and 14 participants, respectively.

II. Methods

A. Experimental Paradigms

Two slightly different virtual robot navigation tasks were used in this study. As shown in Fig. 1, participants of both tasks observed a virtual robot on a computer screen as it attempted to navigate towards a target, and identify when it had reached the target.

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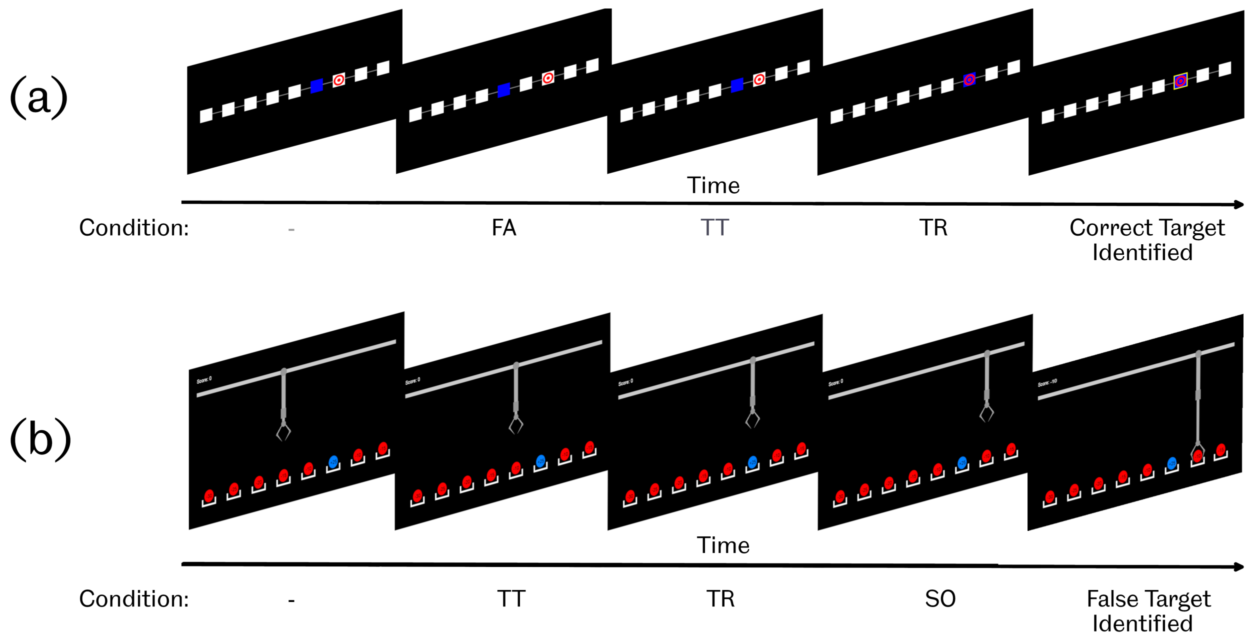

Fig. 1. Experimental paradigms. (a) shows the Cursor Task. In this example, we see a move further away from the target (FA condition), followed by a move towards the target (TT condition), and a move in which the target is reached (TR condition), before the correct target is identified. (b) shows the Claw Task. In this example, we see a move towards the target (TT condition), followed by a move in which the target is reached (TR condition), a move that steps off the target (SO condition), before the an incorrect target is falsely identified.

In the first task, hereafter referred to as the Cursor Task (Fig. 1a), the screen showed 9 squares, arranged horizontally. 1 square was coloured blue to denote the cursor, representing the virtual robot. 1 contained a red bullseye symbol to denote the target. All other squares were white.

In the second task, hereafter referred to as the Claw Task (Fig. 1b), the screen showed 8 circles, arranged horizontally. 1 circle was coloured blue to denote it as the target, and all others were coloured red. Above one of the circles was a depiction of a robotic claw, showing the robot's current location.

At the beginning of each run in both tasks, one location was selected at random as the target. The virtual robot was positioned either 2 or 3 steps away. Every 1.5s, the robot would either step to an adjacent position, or identify its current location as the target. In the Cursor Task, target identification was performed by drawing a yellow box around the cursor's current location. In the Claw Task, to identify that the robot was positioned above the target circle, the claw would extend straight down to grab the circle. After each run, the screen would be blank for 5s, and then a new run would begin.

Actions occurred with pre-programmed probabilities. If the robot was not positioned on the target, it would move towards the target 70% of the time, move away from the target 20% of the time, and falsely identify its current location as the target 10% of the time. If the robot was positioned on the target, it would correctly identify it 67% of the time, and step off it 33% of the time.

Movements by the robot were split into 4 categories: moves towards the target but not reaching it (hereafter referred to as the TT condition), moves in which the target was reached (TR condition), stepping off the target having been positioned on it (SO condition), and moving further away when already positioned off the target (FA condition). All conditions are illustrated in Fig. 1.

Participants observed the tasks in blocks of approximately 4 minutes, with breaks in between. Most participants observed 6 blocks of trials. However, two Cursor Task participants observed only 2 blocks, four Claw Task participants observed 3-5 blocks, and two Claw Task participants observed 7 and 8 blocks.

B. Participants

Ten participants (aged 18-43) observed the Cursor Task. Seventeen participants (aged 18-35) observed the Claw Task. All participants of both tasks reported no history of psychiatric illness, head injury or photosensitive epilepsy, had normal or corrected-to-normal vision, and had no history of color-blindness. Written informed consent was provided before testing began, and all procedures were approved by the University of Sheffield ethics committee and in accordance with the Declaration of Helsinki. Data have previously been published comparing FA and SO conditions in the Claw Task [8], and comparing TT and TR conditions in the Cursor Task [13].

C. Data Acquisition and Preprocessing

For the Cursor Task, EEG signals were recorded at 500Hz using an Enobio 8 headset. 8 channels were recorded, positioned at Fz, Cz, Pz, Oz, C3, C4, PO7, and PO8. For the Claw Task, an Enobio 20 headset was used, again recording at 500Hz. 20 channels were recorded: F7, F3, Fz, F4, F8, FC1, FC2, T7, C3, Cz, C4, T8, CP1, CP2, P3, Pz, P4, PO7, PO8, and Oz. In both tasks, a further reference electrode was placed on the earlobe. All data were band-pass filtered (frequencies are discussed in section II-D), and then resampled to 64Hz. Trials were baseline corrected using a period of 200ms immediately before virtual robot's movement. Any trials with a range of greater than 100μV between the highest and lowest amplitude in any channel was rejected due to artefact contamination.

D. Classification

A subject-specific 2-step classification strategy was implemented, first classifying each movement as either correct or an error, then subclassifying as either the TT or TR condition (if the initial classification was "correct"), or the FA or SO condition (if the initial classification was "error").

For error vs correct classification, time domain data from 3 electrode sites were used for the Cursor Task: Fz, Cz, and Pz. As more electrodes were available for the Claw Task, some further ones were included: FC1, FC2, CP1, and CP2. These were selected as fronto-central to centro-parietal electrodes around the midline are known to be associated with error-related potentials and are commonly used for such classifications [3]–[5]. The trials were filtered from 1 to 10Hz, as ErrP features are usually expressed at low frequencies [3]. A time window of 100 to 700ms was selected based on visual inspection of time domain data.

For subclassification of correct actions (TT vs TR condition), data from 6 channels (Fz, Cz, Pz, Oz, PO7, PO8) were used for each trial, with a time window of 200 to 700ms, and a filter band of 1 to 32Hz, as these parameters had previously proven successful for classifying these two correct conditions against each other [13].

For subclassification of error types (FA vs SO condition), due to the small number of trials available for these conditions, it had previously proven useful to pre-select 1 time domain feature from each channel, based on the correlation between the class labels and the signal amplitudes of each trial at the time point in question [8]. As such, we employed this strategy here, along with a filter band of 1 to 10Hz and a time window of 100 to 700ms.

Stepwise Linear Discriminant Analysis (SWLDA) was selected as the classification strategy for each stage of the class, as this has previously been shown to be effective in selecting features and classifying event related potentials [14], including in our previous work with observed robot navigation [8], [13]. Features were selected iteratively. Beginning with an empty feature set, regression analysis was performed on models created with and without each feature, providing a p-value for each one. If the p-value of any features not already in the model were below 0.025, the feature with the lowest p-value would be added to the model. If no p-values were below this threshold, then the feature in the model with the highest p-value, if above 0.075, would be removed from the model. Iterations continued until no features reached the thresholds to be added to, or removed from, the model. Linear classification models were then trained and tested, using the selected features.

The classification strategy was tested using leave-one-out cross validation. For example, to test each TT condition trial, an error vs correct SWLDA model would be trained using a training set consisting of all TT condition trials except the current trial and all TR condition trials combined to make one class, and all FA and SO condition trials combined to make the other class. The left-out trial would then be tested using the trained model. If the model predicted "correct", the trial would be subclassified using a model trained with all TT condition trials except the current trial as one training class, and all TR condition trials as the other class. If the initial prediction was "error", the trial would be subclassified using a model trained with all FA condition trials as one class and all SO condition trials as the other class. At each stage, the class with the fewest training trials was oversampled in order to balance the number of training trials per class.

For each participant, a chi^2 test was performed on the contingency table of actual conditions and predictions. The classification was called statistically significant if the p-value of the chi^2 statistic was less than 0.05.

A minimum of 12 trials are recommended to achieve a reasonable level of stability in the ERN and Pe [15], and literature suggests that a minimum of 20 trials are required for a stable P300 [16]. Therefore, in line with our previous studies [8], [13], participants were only included in the classification phase if they had produced at least 12 trials in each of the FA and SO error conditions, at least 40 trials from error conditions combined, and at least 20 trials in each of the TT and TR correct conditions. This meant that classification analysis was performed using data from 8 participants of the Cursor Task and 14 participants of the Claw Task.

III. Results and Discussion

For the Cursor Task, participants included in the classification phase produced an average of 157.6 ± 7.2 (mean $\pm$ standard deviation) TT condition trials, 85.0 ± 5.3 TR condition trials, 47.8 ± 11.5 FA condition trials, and 24.8 ± 4.1 SO condition trials. The mean overall accuracy was 44.3%. The mean classification rates for the TT, TR, FA and SO conditions were 49.9%, 43.3%, 32.2%, and 33.4%, respectively. Classification rates achieved for each individual Cursor Task participant are shown in Table I. Importantly, the overall accuracy was over 25% for every participant, and classification results were found to be significant for all Cursor Task participants.

For the Claw Task, participants included in the classification phase produced an average of 133.1 ± 33.4 TT condition trials, 72.1 ± 17.8 TR condition trials, 46.2 ± 16.4 FA condition trials, and 22.4 ± 5.4 SO condition trials. The mean overall accuracy was 36.0%. The mean classification rates for the TT, TR, FA and SO conditions were 39.8%, 30.5%, 32.6%, and 37.9%, respectively. Classification rates achieved for each individual Claw Task participant are shown in Table II. Again, the overall accuracy was over 25% for every participant. Classification results were found to be significant for all but one of the Claw Task participants.

TABLE I

CURSOR TASK 4-WAY CLASSIFICATION ACCURACY

Subject	TT	TR	FA	SO	Overall Accuracy
1	50.0%	36.0%	33.8%	40.0%	42.5%
2	42.7%	45.2%	20.5%	44.0%	40.8%
3	52.8%	43.8%	29.8%	50.0%	46.7%
4	55.5%	48.9%	32.4%	54.5%	50.8%
5	44.2%	23.5%	23.1%	17.4%	33.6%
6	50.0%	48.1%	40.4%	14.3%	45.6%
7	41.4%	35.5%	39.3%	12.5%	36.6%
8	62.7%	65.2%	38.3%	34.8%	57.9%
Mean	**49.9%**	**43.3%**	**32.2%**	**33.4%**	**44.3%**

Accuracy shown for each condition: TT (towards target), TR (target reached), FA (further away from target), SO (stepped off target). Overall accuracy is the percentage of trials, of any class, correctly classified.

TABLE II

CLAW TASK 4-WAY CLASSIFICATION ACCURACY

Subject	TT	TR	FA	SO	Overall Accuracy
1	42.2%	27.2%	33.3%	33.3%	35.8%
2	36.9%	24.7%	33.7%	33.3%	33.3%
3	28.8%	26.0%	27.5%	31.8%	28.1%
4	32.3%	16.7%	25.6%	43.5%	28.0%
5	46.3%	21.8%	45.7%	37.9%	38.2%
6	39.2%	40.0%	40.0%	42.9%	39.8%
7	40.5%	34.4%	37.5%	50.0%	39.1%
8	41.9%	26.8%	15.2%	37.9%	32.7%
9	44.2%	33.9%	38.8%	19.0%	38.4%
10	47.5%	41.8%	51.5%	42.1%	46.0%
11	30.8%	23.6%	32.4%	38.1%	29.6%
12	37.6%	45.8%	17.9%	46.2%	38.0%
13	44.0%	25.0%	29.5%	38.5%	36.4%
14	44.8%	39.4%	28.1%	36.4%	40.2%
Mean	**39.8%**	**30.5%**	**32.6%**	**37.9%**	**36.0%**

Accuracy shown for each condition: TT (towards target), TR (target reached), FA (further away from target), SO (stepped off target). Overall accuracy is the percentage of trials, of any class, correctly classified.

The accuracy levels achieved here are encouraging for 4-way classification, especially considering the similarity between the two error types and the two types of correct action. Crucially, the fact that classification levels were greater than chance level ($p < 0.05$ for the vast majority of participants, including all participants of the Cursor Task) means that the 4-way classification shown here could be utilised as detailed feedback in a reinforcement-learning-based BCI.

IV. CONCLUSIONS AND FURTHER WORK

For the first time, we have shown that it is possible to perform 4-way single-trial classification of different types of navigational actions, based on automatically generated EEG signals as participants only had to observe the virtual robot tasks.

In future it may be possible to improve the classification accuracy further, particularly with larger training data sets. Attempts could be made to utilise features other than the time domain features used here, such as common spatial pattern features or spectral power. Recent advances in transfer learning have proven promising in other areas of BCI [17], and could potentially be applied here. If the classification were applied online, adaptive algorithms may be useful in order to adjust to any changes in EEG responses over time.

This study represents an important step towards a semi-autonomous BCI. As users only need to observe the tasks, the mental workload is reduced. Nevertheless, we are able to gather detailed information about the robot's actions. Implicit communication such as this can lead us to a more efficient and user-friendly brain-machine interaction.

REFERENCES

[1] L. R. Krol, P. Haselager, and T. O. Zander, "Cognitive and affective probing: A tutorial and review of active learning for neuroadaptive technology," *J. Neural Eng. in press*, 2019.

[2] W. J. Gehring, B. Goss, M. G. H. Coles, D. E. Meyer, and E. Donchin, "A neural system for error detection and compensation," *Psychological Science*, vol. 4, pp. 385–390, Dec. 1993.

[3] R. Chavarriaga, A. Sobolewski, and J. del R Millán, "Errare machinale est: the use of error-related potentials in brain-machine interfaces," *Front. Neurosci.*, vol. 8, p. 208, Jul. 2014.

[4] S. Harty, P. R. Murphy, I. H. Robertson, and R. G. O'Connell, "Parsing the neural signatures of reduced error detection in older age," *Neuroimage*, vol. 161, pp. 43–55, 2017.

[5] I. Iturrate, R. Chavarriaga, L. Montesano, J. Minguez, and J. del R. Millán, "Teaching brain-machine interfaces as an alternative paradigm to neuroprosthetics control," *Scientific Reports*, vol. 5, p. 13893, Sep. 2015.

[6] T. O. Zander, L. R. Krol, N. P. Birbaumer, and K. Gramann, "Neuroadaptive technology enables implicit cursor control based on medial prefrontal cortex activity," *Proc Natl Acad Sci U S A*, vol. 113, pp. 14 898–14 903, 2016.

[7] I. Iturrate, L. Montesano, and J. Minguez, "Robot reinforcement learning using eeg-based reward signals," in *Proc. IEEE International Conference on Robotics and Automation (ICRA'10)*, Anchorage, AK, USA, May 2010, pp. 4822–4829.

[8] C. Wirth, P. M. Dockree, S. Harty, E. Lacey, and M. Arvaneh, "Towards error categorisation in bci: single-trial eeg classification between different errors," *J Neural Eng*, vol. 17, 2019.

[9] D. Smith, E. Donchin, L. Cohen, and A. Starr, "Auditory averaged evoked potentials in man during selective binaural listening," *Electroencephalogr. Clin. Neurophysiol.*, vol. 28, pp. 146–152, 1970.

[10] J. Polich, T. Brock, and M. W.Geisler, "P300 from auditory and somatosensory stimuli: probability and inter-stimulus interval," *Int J Psychophysiol*, vol. 11, pp. 219–222, 1991.

[11] C. J. Gonsalvez and J. Polich, "P300 amplitude is determined by target-to-target interval," *Psychophysiology*, vol. 39, pp. 388–396, 2002.

[12] N. Yeung and A. G. Sanfey, "Independent coding ofreward magnitude and valence in the human brain," *J Neurosci*, vol. 24, p. 6258–6264, 2004.

[13] C. Wirth, J. Toth, and M. Arvaneh, "You have reached your destination: A single trial eeg classification study," *Front. Neurosci. in press*, 2020.

[14] D. J. Krusienski, E. W. Sellers, F. Cabestaing, S. Bayoudh, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, "A comparison of classification techniques for the p300 speller," *J. Neural Eng.*, vol. 3, pp. 299–305, 2006.

[15] M. J. Larson, S. A. Baldwin, D. A. Good, and J. E. Fair, "Temporal stability of the error-related negativity (ern) and post-error positivity (pe): The role of number of trials," *Psychophysiology*, vol. 47, pp. 1167–1171, 2010.

[16] J. Cohen and J. Polich, "On the number of trials needed for p300," *Int. J. Psychol.*, vol. 25, pp. 249–255, 1997.

[17] A. Azab, H. Ahmadi, L. Mihaylova, and M. Arvaneh, "Dynamic time warping-based transfer learning for improving common spatial patterns in brain-computer interface," *J. Neural. Eng. in press*, 2019.