Asynchronous classification of error-related potentials in human-robot interaction *

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Abstract. The use of implicit evaluations of humans such as electroencephalogram (EEG)-based human feedback is relevant for robot applications, e.g., robot learning or corrections of robot's actions. In the presented study, we implemented a scenario, in which a simulated robot communicates with its human partner through speech and gestures. The robot announces its intention verbally and selects the appropriate action using pointing gestures. The human partner in turn implicitly evaluates whether the robot's verbal announcement matches the robot's action choice. Error-related potentials (ErrPs) are expressions of this implicit evaluation, which are triggered in case of discrepancies between the robot's verbal announcement and the corresponding actions (pointing gestures) chosen by the robot. In our scenario, the task takes a long time. Therefore, asynchronous EEG classifications that continuously segment EEGs are advantageous or even necessary. However, asynchronous EEG classifications are challenging due to the large number of false positives during the long task time of the robot. In this work, we propose an approach to improve asynchronous classification performance by selecting and extracting features that are only relevant for EEG classifications in the long time series that the robot needs to perform tasks. We achieved a high classification performance, i.e., a mean balanced accuracy of 91% across all subjects. However, we also found some differences between subjects in classification performance. In future work, it is useful to extend the proposed approach of forward and backward sliding windows and their combinations with individual feature selection adaptation to avoid the variability of classification performance between subjects.

Keywords: human-robot interaction, error-related potentials (ErrP), brain-computer interfaces (BCIs), human-machine interaction

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1 Introduction

In recent years, the use of intrinsic human feedback such as electroencephalogram (EEG)-based human feedback has increased relevance for robot applications, especially for human-robot interactions (HRIs). In recent studies, EEG-based human feedback have been applied in HRIs.

In particular, error-related potentials (ErrPs) evoked e.g., when observing erroneous or unusual actions of robots have been used as intrinsic feedback (i.e., implicit evaluations of the correctness of robot behavior) in order to adapt robot behavior strategies [6, 10]. In fact, the use of implicit evaluations of humans as intrinsic feedback is advantageous for learning complex behavioral strategies of robots, because the predefinition of the evaluation criterion (e.g., reward shaping) for robot behavior is not easy for complex robotic tasks.

Moreover, the error-related potential (ErrP) is a well investigated event-related potential (ERP) component and has been used in several research and application areas (see, review, [1]). In most applications, ErrPs have been applied in observation tasks [3–9, 12, 14].

In the presented study, we implemented a scenario, in which a simulated robot communicates with its human partner through speech and gestures. The robot announces its intention verbally (e.g., I will point to the hammer) and chooses the appropriate action using pointing gestures (Fig. 1). In turn, the subjects hear the verbal message of the robot and observe the action choice of the robot. The implicit evaluations of the subjects on the robot's action choices are recorded and extracted by using EEG.

Here, we used error-related potentials (ErrPs) as implicit human evaluations of robot actions. We expect ErrPs in the case of inconsistencies between the robot's verbal announcement and the corresponding actions (pointing gestures) chosen by the robot.

For extraction of implicit human evaluations (ErrPs), online EEG classification is required. Additionally, asynchronous EEG classifications are beneficial in detecting erroneous robot behavior, especially when the robot is performing complex tasks that take a long time. However, asynchronous EEG classifications are challenging due to the large number of false positives during the long task time of the robot(e.g., [12]).

In this work, we propose an approach to improve asynchronous classification performance by selecting and extracting features that are only relevant for EEG classifications in the long time series that the robot needs to perform tasks. The proposed approach uses a combination of forward and backward sliding windows. We continuously segment EEGs with a given window length (sliding windows) forward and backward with respect to relevant temporal reference points of the robot's action sequences. In this way, we extract only relevant features for ErrP classifications while observing the continuous actions of the robot.

2 Methods

2.1 Scenario

Figure 1 shows our scenario, in which the simulated robot announced verbally its intention (e.g., I will point to the hammer) and performs the corresponding actions (pointing gesture). In turn, the subjects hear the verbal message of the robot and observe the actions of the robot. The implicit evaluations of the subjects on the robot's action choice are recorded by using EEGs. For example, when the robot's verbal message and its action selection (pointing gesture) are congruent, we expect no ErrPs. Otherwise, we expect to detect ErrPs, which are used as implicit evaluation of the subjects.

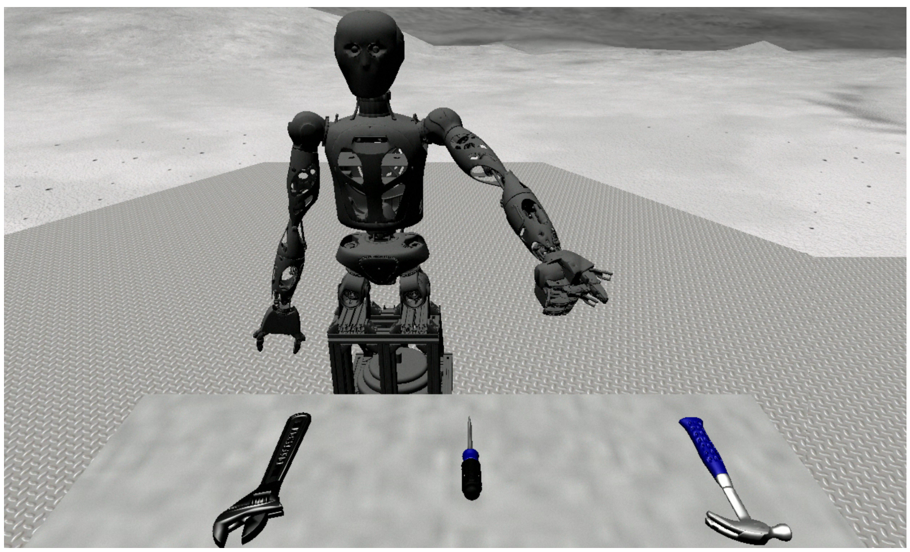

Fig. 1. Scenario. The robot announces its intention verbally (e.g., I will point to the hammer) and chooses the appropriate action using pointing gestures. In turn, the subjects implicitly evaluate the action choices of the robot. The implicit evaluation of the subjects are recorded and extracted by using EEGs to recognize incorrect action choices of the robot.

2.2 Approach

Figure 2A shows a single task of the robot), which takes 15s. In the experiments, we defined episodes, each lasting from the beginning of the robot's verbal announcement until the end of the robot's action. Each action of the robot consists of a movement of the arm in the direction of the workbench and a subsequent gesture lasting approximately 1s indicated by the change in finger configuration.

All episodes were divided into two different types: correct and incorrect episodes. Both labels (correct and incorrect episodes) were used to train an EEG classifier (i.e., ErrP decoder) and later to validate the test data (ground truth). We expected no ErrPs to occur in correct episodes, while ErrPs were expected in wrong episodes.

As shown in Figure 2B, we divided the robot's action into two phases in our application: directional movements and gesture movements (Fig. 2B), since the human observer can guess the robot's gesture at the beginning of the robot's action (directional movements) but cannot be absolutely sure that the robot's actions are correct until the robot performs a pointing gesture (gesture movements). We used the beginning of the robot's actions (directional movements to point at an object) and the beginning of the robot's gestures (change of finger configuration in the robot hand for a pointing gesture) as temporal reference points (see Fig. 2B) to extract features for EEG classifier. To this end, we used these two sent temporal reference points as markers, which sent to the EEG recording system.

Figure 2B shows our approach of feature selection/extraction using forward and backward sliding windows. In our scenario, we do not know the exact moment when the subject realizes that the robot's actions may or may not be correct. Therefore, we used asynchronous classifications. Two points in time are relevant for the detection of ErrPs: the beginning of the robot's actions (directional movements) and the beginning of pointing gestures (indicated by the change in finger configuration). First, the subject recognizes the robot's direction of movement and may tend to guess which tool the robot might select early after the start of an action (directional movements). However, the subject cannot be absolutely sure that the robot's action is correct until the robot performs a pointing gesture (second time point). Therefore, we defined two temporal reference points (see Fig. 2B): (a) directional movements towards one of the objects (3s-8s after verbal announcement) and (b) pointing gestures towards the selected object (8s-9s after verbal announcement) to frame the time period during which the subject makes a decision about the correctness of the robot's action. For training an ErrP decoder, we used these two temporal reference points for feature selection and extraction. As shown in Figure 2B, on the one hand, we continuously segmented the EEGs from the onset of the robot actions (i.e. forward windowing). On the other hand, we continuously segmented from the onset of the robot's gestures in the reverse direction (i.e., backward windowing). In this way, features are extracted using forward and backward sliding windows.

2.3 EEG recording

Nine subjects (two females, seven males, age: 25.5 ± 3.02 years, right-handed, normal or corrected-to normal vision) participated in this study. The experimental protocols were approved by the ethics committee of the University of Bremen. Written informed consent was obtained from all participants. EEGs were continuously recorded using a 64-channel eego mylab system (ANT Neuro

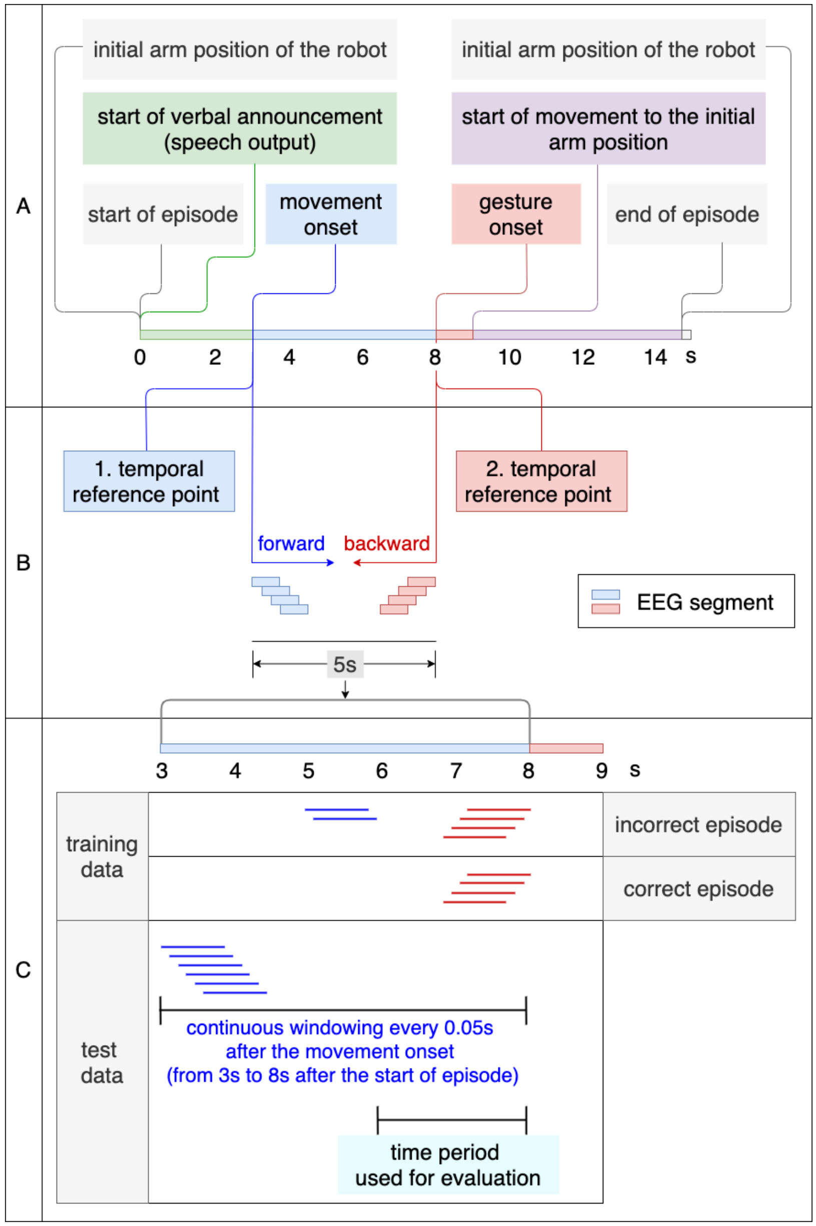

Fig. 2. Experiment design. (A) Episode: An episode begins with the start of the robot's verbal announcement and ends with the return to the initial position. (B) Concept of forward and backward sliding windows used for training a classifier: Features are extracted from the time period between the onset of movement and the onset of gesture using forward and backward sliding windows. Note that we divided the robot's action into different phases (directional movements and gesture movements), but the robot performs a continuous action to point to one of three objects. (C) Feature selection during training for correct and incorrect episodes and during continuous testing. Evaluation is based on the marked time period.

GmbH), in which 64 electrodes were arranged in accordance to an extended 10-20 system with reference at electrode CPz. Impedance was kept below $10\,\mathrm{k}\Omega$. EEG signals were sampled at 2 kHz amplified by one 64 channel amplifiers (ANT Neuro GmbH). For each subject we recorded nine data sets. For one of the subjects, only eight datasets were recorded. Each dataset contained 36 correct and 18 wrong episodes. In total, we recorded 324 correct episodes and 162 wrong episodes for each subject except for one subject. Since we only had eight complete data sets for all nine subjects, seven data sets were used to train an ErrP decoder and one dataset was used for testing to allow a fair comparison between subjects.

2.4 EEG processing

The EEG data were analyzed using a Python-based framework for signal processing and classification [11]. The continuous EEG signal was segmented into epochs from 0 s to 0.9 s after the start of the robot's action with the overlap of 0.05 s (sliding windows). All epochs were normalized to zero mean for each channel, decimated to 50 Hz, and band pass filtered (0.5 to 10 Hz). The xDAWN spatial filter [13] was used to enhance the signal to signal-plus-noise ratio and 7 pseudo channels were retained after spatial filtering.

For feature selection and extraction, we divided the robot's action into different phases (directional movements and gesture movements). However, we would like to point out that the robot performs a continuous action to point at one of the three objects. As mentioned earlier, the human observer can recognize the direction of movement and guess the robot's choice at the beginning of the robot's action (directional movements). However, the human observer cannot be absolutely sure that the robot's actions are correct until the robot performs a pointing gesture (gesture movements). Two temporal reference points were relevant for feature selection and extraction: The onset of the robot's action (i.e., the onset of directional movements) and the onset of gesture movements (see Fig. 2-B). Accordingly, we extracted features using forward and backward windowing based on the two temporal reference points (see Fig. 2-B).

Different strategies of feature selection and extraction were used depending on the episode type after a systematic investigation of different combinations of sliding windows across both types of episodes for each subject. We found different optimal time periods and different optimal combinations of forward and backward sliding windows for feature selection and extraction depending on the individual subject. However, to allow a fair comparison between subjects, we decided to choose the same time period for all subjects. Therefore, we used the same sliding windows and the same combinations of forward and backward sliding windows for all subjects to train a classifier.

The final selected time period for correct and incorrect episodes are as follows (see Fig. 2-C). For incorrect episodes, four windows of 0.9s in length were used, ending at 0s, −0.05s, −0.1s and −0.15s with respect to the beginning of the gesture movement (the second temporal reference point). That is, four windows were segmented from the beginning of the gesture movements in the reverse direction. In addition, two windows were used with a length of 0.9s from 2s and 2.5s with respect to the beginning of the directional movement (the first temporal reference point). For correct episodes, four windows of 0.9s length were likewise used, ending at 0s, -0.05s, -0.1s and -0.15s with respect to the onset of gesture movement (the second temporal reference point). However, we did not use the windows that can be segmented from the first temporal reference point (the beginning of the directional movement).

For testing, ErrPs are continuously detected every 0.05s with a window length of 0.9s from the start of the robot action (i.e., asynchronous classification). This means that ErrPs were continuously detected in the time period between the start of the robot's action and the end of the robot's pointing gesture. For evaluation, we used the time period between 6s and 8s after the start of the episode (i.e., from 3s to 5s after the movement onset) as the ground truth (see Fig. 2-C). This means that the sliding windows that end in this time period were used to evaluate the trained classifier. During this time period, we can ensure that the robot's arm position is unambiguous for the subjects' evaluation.

The features were normalized and used to train a classifier. The online passive aggressive algorithm variant 1 (PA1) [2] was used as classifier. The cost parameter of the PA1 was optimized using a grid search, in which an internal stratified 5 fold cross validation was performed on the training data (7 training datasets) and the best value of $[10^0, 10^{-1}, \dots, 10^{-6}]$ was selected. The performance metric used was balanced accuracy (bACC), which is an arithmetic mean of true positive rate (TPR) and true negative rate (TNR).

2.5 Evaluation

The evaluations were performed for each of the ten subjects individually. As mentioned in section 2.3. EEG recording, we recorded nine datasets for each subject. Seven data sets were used to train an ErrP decoder and one dataset was used for testing. For training an EEG classifier, seven data sets were concatenated. For performance metric, we used a balanced accuracy, i.e.,the arithmetic mean of true positive rate (TRP) and true negative rate (TNR). Note that the positive class stands for incorrect action choices of the robot and negative class stands for correct action choice of the robot.

3 Results and Discussion

Table 1 shows the classification performance for each subject. We achieved an average classification performance of 91% across all subjects. However, we found a high variability between subjects.

The inter-subject variability, i.e., the variability between subjects is not surprising, as we assume that subjects have different strategies to evaluate the robot's ongoing actions, i.e., each subject probably evaluates the correctness of the robot's action choices at different times. Indeed, the duration of the task was not short (5s from the beginning of the robot action to the beginning of the

Table 1. EEG classification performance. The balanced accuracy (bACC=(TPR+TNR)/2) and standard error of the mean (SEM) are given for each subject.

subjects	balanced accuracy (bACC)
subject 1	0.89
subject 2	0.94
subject 3	0.97
subject 4	0.83
subject 5	0.94
subject 6	0.92
subject 7	0.97
subject 8	0.90
subject 9	0.80
mean and standard deviation	0.91±0.06

robot pointing gestures). One can estimate the direction of the robot's movement immediately after the robot starts moving and focus less on the robot's pointing gestures. In this case, the pointing gestures can even be overlooked unintentionally. Another person may focus only on the robot's pointing gestures. Of course, some subjects also focus on the overall action of the robot. In particular, jerky movements of the robot can affect the accuracy of the correct estimation of the robot's direction of movement. In fact, some subjects reported that jerky movements affect the estimation of the robot's direction of movement. Furthermore, the evaluation by the subject can be changed during the execution of the action by the robot. For example, the robot's action may initially be evaluated as a correct action after the direction of the arm movement has been detected, but this evaluation may be changed with the execution of the pointing gesture.

For this reason, we proposed an approach using forward and backward sliding windows and their combinations. Nevertheless, we did not achieve high classification performance for some subjects. The reason for this could be that we used the same combination of forward and backward sliding windows for all subjects. As mentioned earlier, we investigated different combinations of sliding windows across both types of episodes for each subject.

In fact, we found different optimal time periods and the different optimal combinations of forward and backward sliding windows across both episode types (correct and incorrect episodes) for each subject. On the one hand, this means that the optimal time periods relevant for recognizing the correct actions differ from subject to subject. On the other hand, the optimal time periods that are relevant for detecting the wrong actions also vary from subject to subject. Furthermore, the combination of the optimal time periods for correct and incorrect actions also varies between subjects. We nevertheless chose to apply the same combination of forward and backward sliding windows to all subjects to allow a fair comparison between subjects.

Therefore, in the future, it makes sense to extend the proposed approach of forward and backward sliding windows and their combinations with an individual adjustment of feature selection so that high inter-subject variability in classification performance is avoided. With such an individual adjustment of feature selection, classification performance can be improved if we identify the best feature combinations for each subject. However, such investigations are time-consuming. Therefore, developing an automatic selection of best combinations to customize the feature selection is useful. In the future, it is useful to extend the proposed approach of feature selection using forward and backward sliding windows and their combinations for individual adaptions of feature selection, in which the best individual combinations are automatically computed depending on different context, e.g., different scenarios and different situations.

Furthermore, although we continuously detected ErrPs online (i.e., asynchronous classification), we did not use the results of online classification for intrinsic online corrections of the robot's erroneous actions or for robot learning (e.g., optimizing learning strategies based on ErrP-based human feedback) in this scenario, such as in our previous studies [6, 9, 10]. In this previous work, we have used ErrP-based human feedback online for intrinsic interactive reinforcement learning in real human-robot interaction to optimize the robot's learning strategy in real time, but ErrPs did not need to be classified asynchronously due to the short task duration of the robot. Therefore, in a next step, we plan to use ErrP-based human error evaluation for intrinsic interactive reinforcement learning, where continuous ErrP detections are necessary during continuous and long-lasting task execution of a robot (e.g. continuous complex robot behavior) and we therefore expect e.g., more than one type of error during the execution of a task.

References

1. Chavarriaga, R., Sobolewski, A., Millán, J.D.R.: Errare machinale est: The use of error-related potentials in brain-machine interfaces. Frontiers in Neuroscience **8**, 208 (2014). https://doi.org/10.3389/fnins.2014.00208
2. Crammer, K., Dekel, O., Keshet, J., Shalev-Shwartz, S., Singer, Y.: Online passive-aggressive algorithms. Journal of Machine Learning and Research **7**, 551–585 (2006)
3. Ehrlich, S., Cheng, G.: A neuro-based method for detecting context-dependent erroneous robot action. In: 2016 IEEE-RAS 16th International Conference on Humanoid Robots (Humanoids). pp. 477–482 (2016). https://doi.org/10.1109/HUMANOIDS.2016.7803318
4. Iturrate, I., Montesano, L., Minguez, J.: Robot reinforcement learning using eeg-based reward signals. In: 2010 IEEE international conference on robotics and automation. pp. 4822–4829. IEEE (2010). https://doi.org/10.1109/ROBOT.2010.5509734
5. Iturrate, I., Montesano, L., Minguez, J.: Single trial recognition of error-related potentials during observation of robot operation. In: 2010 Annual International

Conference of the IEEE Engineering in Medicine and Biology. pp. 4181–4184. IEEE (2010). https://doi.org/10.1109/IEMBS.2010.5627380
6. Kim, S.K., Andrea Kirchner, E., Kirchner, F.: Flexible online adaptation of learning strategy using EEG-based reinforcement signals in real-world robotic applications. In: 2020 IEEE International Conference on Robotics and Automation (ICRA). pp. 4885–4891 (2020). https://doi.org/10.1109/ICRA40945.2020.9197538
7. Kim, S.K., Kirchner, E.A.: Classifier Transferability in the Detection of Error Related Potentials from Observation to Interaction. In: 2013 IEEE International Conference on Systems, Man, and Cybernetics. pp. 3360–3365 (2013). https://doi.org/10.1109/SMC.2013.573
8. Kim, S.K., Kirchner, E.A.: Handling few training data: classifier transfer between different types of error-related potentials. IEEE Transactions on Neural Systems and Rehabilitation Engineering **24**(3), 320–332 (2016). https://doi.org/10.1109/TNSRE.2015.2507868
9. Kim, S.K., Kirchner, E.A., Schloßmüller, L., Kirchner, F.: Errors in Human-Robot Interactions and Their Effects on Robot Learning. Frontiers in Robotics and AI **7** (2020). https://doi.org/10.3389/frobt.2020.558531
10. Kim, S.K., Kirchner, E.A., Stefes, A., Kirchner, F.: Intrinsic interactive reinforcement learning – Using error-related potentials for real world human-robot interaction. Scientific Reports **7** (2017). https://doi.org/10.1038/s41598-017-17682-7
11. Krell, M., Straube, S., Seeland, A., Wöhrle, H., Teiwes, J., Metzen, J., Kirchner, E., Kirchner, F.: pySPACE—a signal processing and classification environment in Python. Frontiers in Neuroinformatics **7** (2013). https://doi.org/10.3389/fninf.2013.00040
12. Lopes-Dias, C., Sburlea, A.I., Breitegger, K., Wyss, D., Drescher, H., Wildburger, R., Müller-Putz, G.R.: Online asynchronous detection of error-related potentials in participants with a spinal cord injury using a generic classifier. Journal of Neural Engineering **18**(4), 046022 (2021). https://doi.org/10.1088/1741-2552/abd1eb
13. Rivet, B., Souloumiac, A., Attina, V., Gibert, G.: xDAWN Algorithm to Enhance Evoked Potentials: Application to Brain–Computer Interface. IEEE Transactions on Biomedical Engineering **56**(8), 2035–2043 (2009). https://doi.org/10.1109/TBME.2009.2012869
14. Salazar-Gomez, A.F., DelPreto, J., Gil, S., Guenther, F.H., Rus, D.: Correcting robot mistakes in real time using EEG signals. In: 2017 IEEE International Conference on Robotics and Automation (ICRA). pp. 6570–6577 (2017). https://doi.org/10.1109/ICRA.2017.7989777