EEG Recordings from Parent/Child Dyads in a Turn-Taking Game with Prediction Error

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Abstract

To investigate neural correlates of collaborative actions between parents and their children, EEG data was recorded during a social interaction. Four dyads of one parents and one of their children (mean age: 4.6 years) played a turn taking game with high and low reward outcomes. After learning the rule of the game, the reward contingency was reversed in 20% of trials, thereby eliciting a prediction error. Independent component analysis (ICA) was used to determine and exclude non-brain components. The children's data is inconclusive, possibly because of the small number of subjects. The parents' event related potential show P3a positivity dependent on reward outcome during their own actions. During observation of their child's action, the P3a component is effected by the reward expectation, not the actual outcome. Interestingly, this is in contrast with event related potentials of two unacquainted adults recorded during the same experiment.

1 Introduction

In our everyday life, actions are often motivated by the expectancy of a certain outcome. Continuously, we compare our predictions of the future with the actual outcome. A discrepancy between prediction and outcome is commonly called prediction error. Prediction errors play an important role in learning and decision making. They signalize the need to update our internal associations between action and outcome and thus lead to increased performance during similar situation in the future (Liao et al., 2011; 2015).

Of special interest is the effect of outcome expectancy and its violation during social interaction. In an EEG study with dyads of previously unacquainted adults, Deák et al. found neural correlates of expected and unexpected reward processing. Interestingly, these event related potentials (ERPs) could be found both while acting themselves and when observing their partner's actions. In this study, the same paradigm eliciting social interaction and prediction error was used in dyads of parents and their preschool children. It is intriguing to investigate if the special relationship that these humans share can be correlated to EEG data.

It has been established that the so-called P300 ERP component is influenced by attention during task processing (Polich and Kok, 1995). Hence, it can be assumed that the prediction of a certain outcome and the actual outcome itself have an effect on the amplitude of the P300 ERP. Generally, the P300 component can be divided into the earlier P3a and later P3b subcomponents. According to Polich (2007), while the definite source or processes underlying these positive potentials is not known with certainty, P3a seems to mainly related to attention and P3b to memory processing.

Over the past years, independent component analysis has been used and methods improved for applications on EEG data, especially the separation of non-brain signals (Jung et al., 2001). In this context ICA works under the assumptions that at the electrodes signals are mixed in a linear fashion, the signal propagation delays are negligible, component locations are spatially fixed and time course independent, and that the number of independent components is less or equal the number of scalp channels (Makeig et al., 1996).

In respect to brain components, ICA bypasses the so-called ‘inverse problem’ and simplifies the determination of signals source location within the brain. This is done by separating the recorded scalp data into distinct signals and modelling independent sources for each of these signals that are able to explain the recorded data most closely. Conversely, in respect to non-brain data, ICA is a useful tool to identify artifact data. It has been shown to efficiently separate data originating from muscle activity and eye movements such as blinks and saccades. However, non-stereotyped artifacts such as extreme movements of individual testing subjects cannot be separated. Comparing different ICA algorithms, Delorme et al. (2012) found Adaptive Mixture ICA (AMICA) to be best performing for decomposition of EEG data. The EEGLAB toolbox for MATLAB has been developed for user-friendly application of these principles (Delorme et al., 2004).

2 Methods

2.1 Participants

Four dyads of children and one of their parents volunteered to participate. The electroencephalogram (EEG) data of one child had to be excluded from the study owing to excessive artifacts. Two of the three remaining children were female, their mean age was 4.6 years (range between 3.8 and 5.0 years). Two of the four parents included in the study were female, their mean age was 35.75 years (range between 31.0 and 39.4 years). All participants were English speakers, right-handed, had normal or corrected to normal vision and no self-reported diagnosed neurological or psychological disorders. Two dyads did not finish the entire game. The experiment was approved by UCSD’s IRB. Participants received $20 and a toy for the child for their participation.

2.2 Experimental design and procedure

The parent-child dyads played a ‘bubble popping’ game while different physiological measures were recorded. They took turns to press one of two bubbles, as shown in figures 1 and 2. Depending on one’s action, pressing the bubble leads to “popping the bubble” (high reward) or “wobbling of the bubble” (low reward). The participants were instructed that their goal is to pop as many bubbles as possible, but aside from that, the sound during popping the bubble is more pleasant that the one played during the wobbling. The underlying rule is that if the partner’s action is matched, that is the same bubble is touched that was touch by the partner before, the outcome is the high reward. Conversely, if one touches the other bubble than the partner did before, that is, mismatching the action, the outcome is low reward. 150ms after touching the bubble, visual and auditory stimuli dependent on reward value appear for 400ms. The game consists of four blocks. During the first block (68 trials) participants should try to find the underlying rule leading to high rewards via trials and error. Block two and three each contain 200 trials, intermittent by a break. During these 200 trials the reward contingency is reversed in random 20% of the cases. During the break, both participants are offered drinks and snacks. The last block consists of 48 trials in which the matching rules applies in all cases. See figure 3 for an overview. In case one of the participants failed to take turns, the bubbles disappeared and reappeared again.

To summarize, when touching a bubble there are four conditions:

(1) Matching the partner’s actions → high reward
(2) Matching the partner’s actions → low reward
(3) Mis-matching the partner’s actions → low reward
(4) Mis-matching the partner’s actions → high reward

Condition (1) and (3) occur when the “normal” matching rule applies, conditions (2) and (4) occur when the reward contingency is reversed.

Consequently, the EEG signals can be compared between

- Reward outcome: high vs. low reward
- Satisfaction of prediction: expected vs. unexpected outcome
- Actor: self-acting vs. observing the other

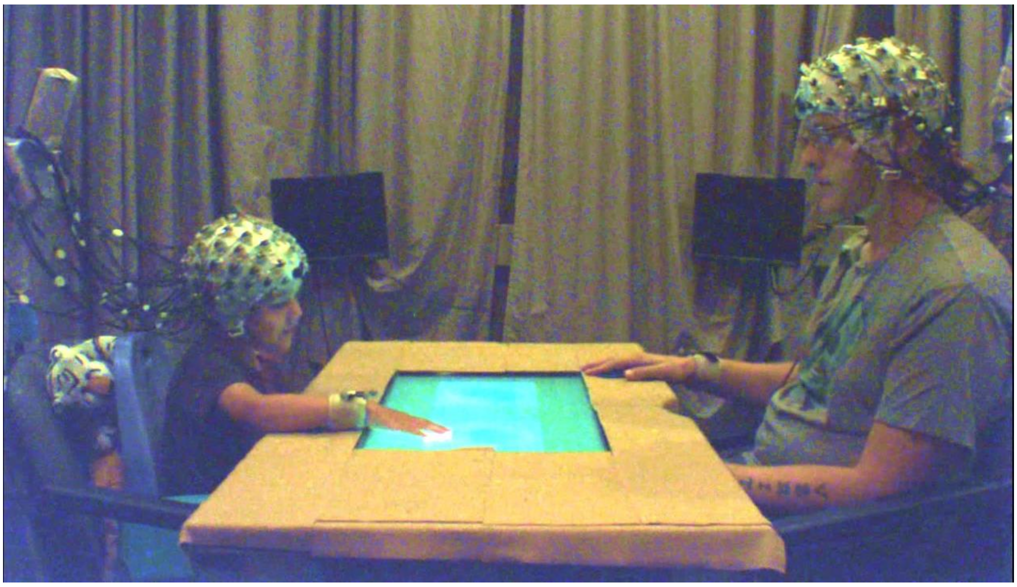

Figure 1: Child and parent playing the bubble game while EEG was recorded

2.3 Data acquisition

Each parent-child dyad was seated comfortably facing each other across a table-mounted capacitive touch screen monitor (diagonal:66-cm, Elo, California, USA) on which the game was presented (see figure 1). Average time of playing the game was 31.25min with an additional average break time of 5.9min. During the whole time, both child and parent wore elastic EEG caps with 64+1 active electrodes (actiChamp, BrainProducts, Germany). EEG was recorded continuously with a sampling rate of 500 Hz. One electrode was placed on the right mastoid and one on the left temple to record ocular movement. Electrocardiogram (ECG) was measured via three electrodes. Hand motion was recorded by means of a 6-camera NaturalPoint Optitrack system that registers the position of pre-calibrated rigid bodies with a sampling rate of 100 Hz. Reflective three-marker rigid frames (NaturalPoint, Oregon, USA) were placed on a soft band on both of the participants' right wrists. Video cameras captures HD videos (30 Hz) from four perspectives: a close-up view of each participant's head and upper body, a side view of the participants (see figure 1) and a view from above. In addition, both participants wore microphones. However, the ECG, and behavioral data was not analyzed in the scope of this project.

EEG and ECG recordings, motion capture markers, motion triggered events, touch screen events and locations, and programmed game events were synchronized using the MATLAB toolbox LabStreamingLayer (Delorme et al., 2011).

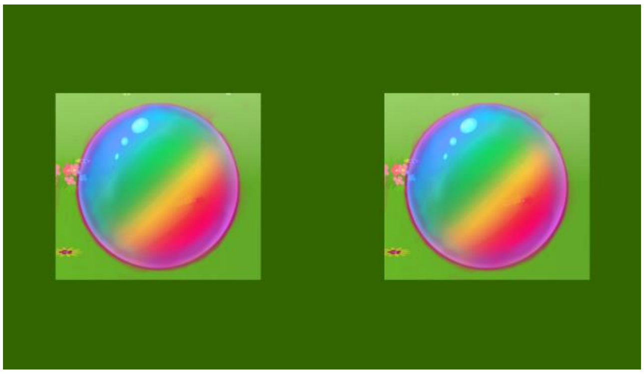

Figure 2: Screen during the bubble popping game. The squares with the bubbles are approximately 12x12 cm2, 35 cm apart. After touching one of the bubbles, visual and auditory stimuli according to high or low reward appear.

Figure 3: Overview of the four blocks during the experiment. The reward contingency during block one and four strictly follow the matching rule, during block two and three the reward contingency is reversed in 20% of the cases. Number of turns per person is half of the number of trials in each block.

2.3 EEG data analysis

EEG data was preprocessed using customized MATLAB scripts in the EEGLAB toolbox. EEG data was bandpass filtered with a low boundary of 1Hz and a high boundary of 59 Hz. Channels which recorded extremely high or low potentials (higher or lower than mean of all channels ± 5 SD) were rejected. On average, 60 channels (ranging from 55 to 62) could be used for analysis. These remaining channels were re-referenced to their average. Furthermore, the time between finishing the last trials of block two and the first trials of block three (the break time) was removed. The final EEG dataset had a mean length of 27.0min with a mean of 810k data points for ICA decomposition.

The remaining EEG data was analyzed using Adaptive Mixture Independent Component Analysis (AMICA). Thereby the data is separated into maximally independent activity sources (Palmer et al., 2008; Delorme et al., 2012). Non-brain components can be identified and separated from the actual signal from cortical sources. The dipfit algorithm of the EEGLAB toolbox finds dipoles within the brain that most closely explain the signal detected at the scalp. According to the location of these dipoles, the independent components are clustered together. Exemplarily, figure 4 illustrates signals that could be detected on the parents' scalps originating from different clusters of brain and non-brain independent components. In these scalp maps the source of the signal is (a) within the brain, (b) eye movement or (c) muscle artifacts.

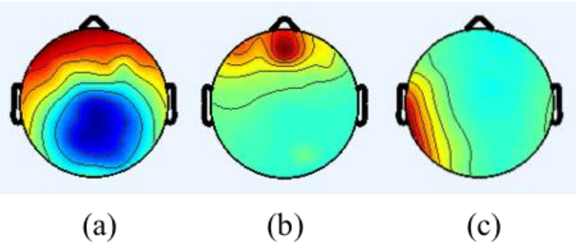

Figure 4: Scalp maps of signals originating from (a) source within the brain, (b) eye movement, (c) muscle artifact.

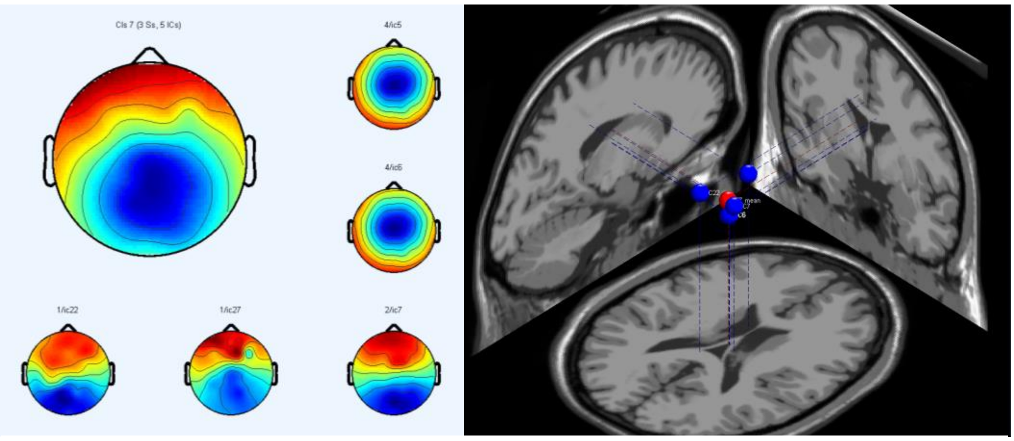

Figure 5: Independent components clustered together according to their location within the brain. Left: Average scalp map (in large) and single scalp maps of individual components. Right: Dipole localization within the brain. Red is the average localization of all independent components, blue are the independent components per se.

The brain component cluster in figure 4(a) consists of 5 independent components from three of the four parents (see figure 5). On the right panel, you can see the modelled cluster of independent components within the brain.

Subsequent of AMICA, epochs that still contained data with artifact were rejected with a probability based algorithm from EEGLAB. Channel level data was reconstructed after separation of non-brain artifacts via AMICA. In all event related potentials (ERPs) shown here, difference in potential between conditions was tested via ANOVA of the average values of each condition, and Bonferroni corrected for multiple comparisons. Furthermore, the peak amplitude overall and the mean potential between 680ms and 720ms was compared between reward outcome and satisfaction of prediction with repeated measures using single trial data for each condition. Significance level was set to 0.05.

3 Results

3.1 Parent and child performance

Table 1 displays the mean amount of trials in each condition for the parents and children (rounded to the next integer).

Table 1: Mean amount of trials by condition

	matching action		mismatching action	
	high reward	low reward	low reward	high reward
parent	59	26	38	21
child	68	23	37	19

Naturally, there are less trials of the conditions were the reward contingency is reversed. Interestingly, the amount of trials in each conditions is fairly similar between parents and children. The only exception might be when matching the partner's action and the matching rule applies. Children had this condition on average on 68 trials in comparison to 59 trials when the parent was playing.

3.2 Children's EEG data

Figure 6 shows the reconstructed Cz channel level data after rejection of non-brain components from the EEG data. The children's EEG data is inconclusive in respect to the effect reward expectancy or outcome on the ERP. After the children's own actions (lower panel), there are two relatively long time periods with significant differences between the conditions, the first between 200ms and 400ms, the second between 850ms and 1050ms. At both times the unexpected high reward after mismatching the parent's action elicits a (more) negative potential than the other three conditions. During observation of the parent touching a bubble (upper panel), there were two short time points at around 550ms and 700ms, and a longer period around 1000ms in which the ERP was significantly different between the four condition. However, these results have to be considered cautiously in the light of the fact that it comprises data from only three subjects.

3.3 Parents' EEG data

In comparison to the children's data, the parents' data does show distinct peaks in ERP (see figure 7). During their own action (lower panel), there is a significant difference at 350ms to 400ms. For all conditions the potential rises relatively fast. This well-established late positive component is called P300, or concretely the subcomponent P3a. We found that it is most positive for unexpected high reward condition, followed by the expected high reward, the expected low reward and the unexpected low reward conditions. That is, the amplitude of this positive potential is influenced by the actual outcome (high vs. low reward). On top of that, expectancy (violation) seems to have an influence. Furthermore, in the long time period between 550ms and 800ms, the potential is different between the four conditions. If the outcome is a high reward, independent if the partner's actions have been matched or not, the positive potential decreases faster and stays at around 2uV for 150ms (between 650ms and 800ms). In the low reward conditions however, the positive potential decreases more slowly and stays around 0uV afterwards.

When observing their own child play the game (touch a bubble), the periods when the potential is different for different conditions occurs at around the same time as when playing themselves. The amplitude of the P3a component shows a distinct correlation with predicted or unpredicted outcome, that is with appliance of the matching rule. If the child touches the same bubble as the parent before and the outcome is a high reward and if the child touches the other bubble as the parent before and the outcome is a low reward, the peak P3a amplitude is up to 6uV. That is around 2uV higher than during the other two conditions. However, the later difference in potential, between 650ms and 850ms, shows a similar pattern than during the parents own actions. If the outcome was low reward, the potential fluctuates around 0uV, whereas if the outcome was high reward the potential decreases to around -2uV for about 100ms.

Notably, the significance test used for the ERPs reduced the variance of the data by averaging over all single trials per condition. Application of repeated measures using single trial data of each condition does not reproduce the significant differences. The p-values of these test are displayed in table 2. All of them are above the significance level of 0.05. That is, from this data no significant effect of reward outcome or satisfaction of prediction can be concluded. However, in the light of the small number of testing subjects that participated in the study, it is interesting that at least for expected vs. unexpected outcomes a trend towards an effect on the peak amplitude can be found (p-values are 0.143 and 0.158 for self-acting and action observation, respectively).

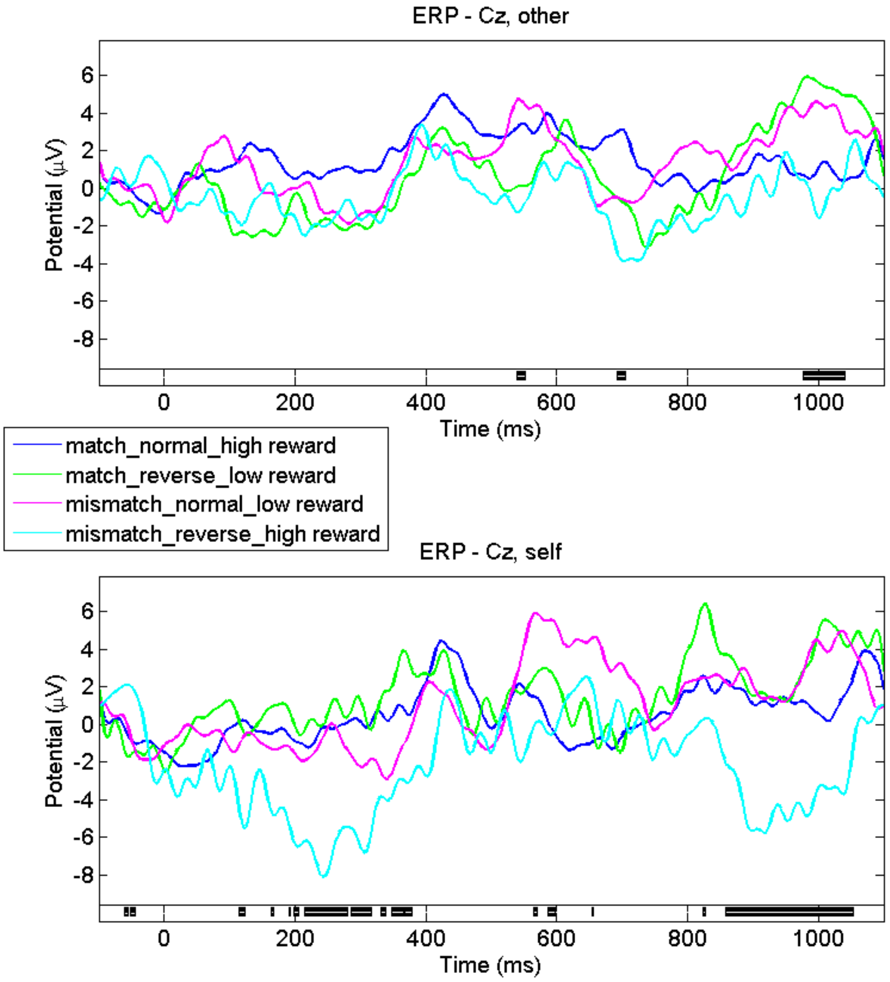

Figure 6: Event related potential (ERP) of children observing their parent play (upper panel) and playing themselves (lower panel). 0ms is touching the bubble, visual and auditory stimuli indicating the high or low reward start appearing at 150ms. The lower sect section of both panels displays the results of a Bonferroni corrected ANOVA. Black bars indicate a p-value of less than 0.05. N=4

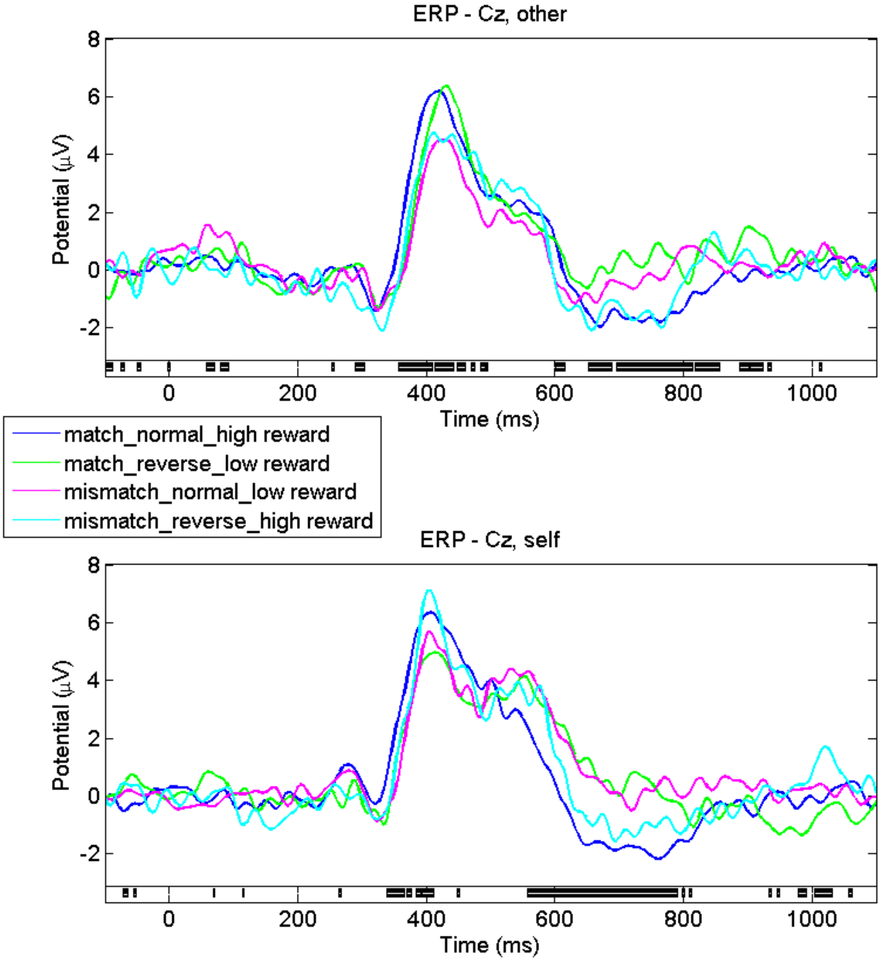

Figure 7: Event related potential (ERP) of parents observing their child play (upper panel) and playing themselves (lower panel). 0ms is touching the bubble, visual and auditory stimuli indicating the high or low reward start appearing at 150ms. The lower section of both panels displays the results of a Bonferroni corrected ANOVA. Black bars indicate a p-value of less than 0.05. N=4

Table 2: P-values of repeated measures from single trial data

	self (parent playing)		other (parent observ. child)	
	Peak amplitude overall	mean amplitude (680-720)ms	Peak amplitude overall	mean amplitude (680-720)ms
Reward outcome (high vs. low)	0.472	0.451	0.445	0.259
Satisfaction of expectation (expected vs. unexpected)	0.143	0.689	0.158	0.298

4 Discussion

4.1 Strength and limitations

Until today, most studies using EEG as imaging method still conduct experiments whereby testing subjects are set in a dark room and asked to look at a monitor, move as little as possible and if at all the only way in which they act is by pressing a button. Hence, one of the main strength of this study is how much more closely an everyday social interaction between two persons is mimicked. By letting a parent and their child play a game together while recording physiological measures, the behavior and neural correlates of such an omnipresent situation can be investigated.

On the other hand, precisely because we did not (excessively) restrict motion of our testing subjects, the data is more prone to include motion artifacts. This especially applies to the children's data. As mentioned above, since AMICA is unable to separate individual, spatially non-stereotyped artifacts, the recorded EEG data has to be cleaned before decomposition. This cleaning processes might not have been aggressive enough to result in sufficiently good data.

An obvious but fairly easily solvable shortcoming of this study is the very small number of testing subjects. With data included from only three children and four parents, our findings have to be considered cautiously until replicated. Furthermore, since different visual and auditory stimuli are used to indicate high or low reward, it has to be determined how much these stimuli alone influence the subsequent brain potential.

4.2 Comparison between parent/child dyads and dyads of unacquainted adults

Previous to this study, the same experimental design was used in a study with 21 dyads of unacquainted adults. Owing to the inconclusive data from the children, we are only comparing the parents' data with the findings of that study. In this comparison, several discrepancies and similarities are obvious. First, in the adult/adult study, the P3b ERP component is very distinct, which is not the case regarding the parents' ERP data. While a second positive peak is slightly apparent around 550ms after the parent's own actions, no such second ERP component can be detected after observation of the children's action. Second, during action observation (upper panel in figures 7 and 8) the late negative component at around 800ms is very similar between parents and unacquainted adults. In both cases, high reward (expected and unexpected) has a negative potential, while low reward has not. Therefore, this ERP component seems to be related to the actual outcome. Contrarily though, while the P3a component in adult/adult dyads also is mainly dependent on the actual reward outcome, the P3a component in parents is mainly dependent on reward expectancy. This might be an indication of the parents' increased attention for the consequences of the children's actions. This is a very fascinating result but, as stated above, it should be considered cautiously until the experiment is repeated with further subjects.

5 Conclusion and future directions

This unique study investigates the neural correlates of action related reward and prediction error during a social interaction between a parent and their child. Furthermore, the event related potentials not just during one's own actions but during observation of the partner's action have been recorded. The children's EEG data is inconclusive, most probably due to a high amount of motion artifacts that were not removed aggressively enough and due to data from only three testing subjects. The parents' data on the other hand revealed an interesting dependence of the peak P3a amplitude on reward outcome during their own actions, and, intriguingly, on reward prediction during observation of their children's actions. It is fascinating that this latter effect of reward prediction on P3a amplitude has not been found in an experiment using the same paradigm but with dyads of unacquainted adults. Hence, we conclude that this might be an indication of the parents' increased attention for the consequences of the children's actions.

Next steps are first to replicate these findings with at least ten more parent/child dyads. Thereafter, it would be interesting to see the neural correlates of these social interaction between other dyads with a special relationship to each other, such as siblings or couples. Furthermore, a similar effect of P3a dependence on reward prediction during observation of someone else's action might be able to be elicited by introducing asymmetry in reward outcome, such as having one of the partners getting higher and lower rewards as the other one.

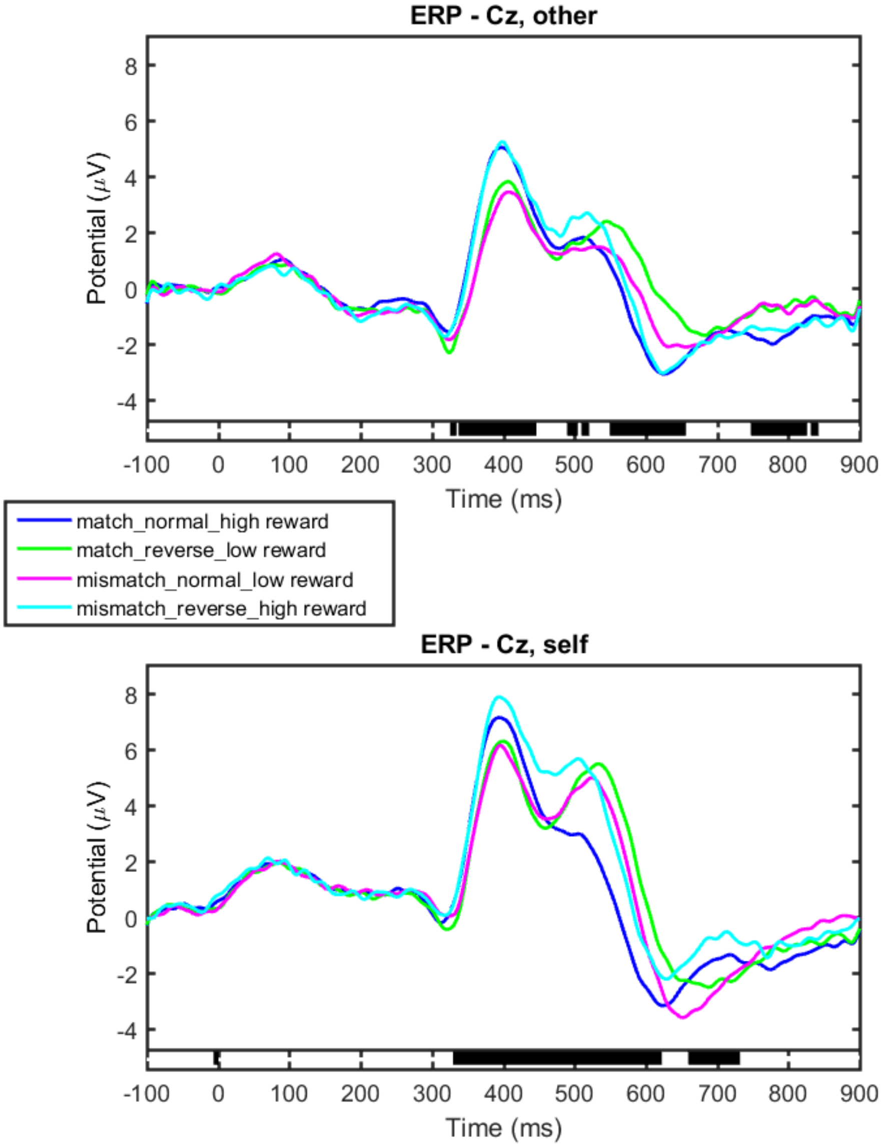

Figure 8: Event related potential (ERP) of adults observing an unacquainted adult play (upper panel) and playing themselves (lower panel). 0ms is touching the bubble, visual and auditory stimuli indicating the high or low reward start appearing at 150ms. The lower section of both panels displays the results of a Bonferroni corrected ANOVA. Black bars indicate a p-value of less than 0.05. N=42

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