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Using the Contralateral Delay Activity to Study Online Processing of Items Still Within View

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Abstract

In recent years, there has been growing research regarding the online nature of visual working memory (VWM). These online aspects are arguably the defining attributes of working memory, but they are challenging to study using traditional behavioral paradigms. One powerful tool to examine online processing in VWM is the contralateral delay activity (CDA), the ERP marker of VWM. We review studies that convincingly demonstrated that the CDA is a unique marker of VWM activity. This specificity joins the excellent temporal resolution of the CDA and the fact that it can be measured not only during memory retention but also when items are visible on the screen, to make the CDA an ideal tool for studying the online processing of items still within view. We present several lines of research that successfully utilized the CDA to uncover the role of VWM in online processing. Finally, we present basic guidelines for using the CDA to study online processes, along with examples from our recent research. We hope that this will enable more researchers to capitalize on the CDA's advantages, allowing new discoveries to be made regarding VWM as an online workspace.

Keywords Contralateral delay activity, Visual working memory, ERP, Online processing, Updating, Resetting

1 Introduction

Visual working memory (VWM) is our online workspace, responsible for the storage and manipulation of visual information [1]. VWM can hold a limited amount of information in an active state, ready to be manipulated by higher cognitive functions. Its storage capacity is extremely limited, typically estimated at only about 3–4 simple items' worth of information [2]. Two lines of work regarding this capacity limit corroborated the importance of VWM in guiding everyday behavior. First, capacity is specifically damaged in a range of conditions, including Alzheimer's disease, normal aging, attention deficit hyperactivity disorder (ADHD), and schizophrenia (e.g., [3–6]). Second, stable individual differences in capacity are tightly correlated with measures such as attentional control and fluid intelligence (e.g., [7–9]). The obvious importance of storage capacity motivated many researchers to investigate the nature of capacity limits, producing a wealth of interesting finding, sometimes even leading to fierce debates (e.g., as to whether capacity is limited by the number of items or by the overall information load; [10–12]).

Most research in the field focused on classic memory paradigms, such as change detection (e.g., [13–15]) or delayed continuous response (e.g., [16–18]) tasks, whose hallmark is the retention interval. However, VWM is involved not only when information is maintained over a retention period, but whenever we must hold visual representations in an accessible state. One example is indeed when we try to hold in mind visual information that is then removed from view, but a similar need arises in a range of situations in which the items remain visible. A prominent example of this is a recent study [19] which showed that performance on change detection tasks with and without a retention interval (i.e., a "pure" memory component) is highly correlated ($r \geq 0.8$) and they reach extremely similar capacity limits.

These results corroborate the argument that VWM's active maintenance is critical whenever we handle task-relevant perceptual input that is not stable from one moment to the next. For example, as we go about in the world, the incoming visual input changes constantly, and VWM is necessary for connecting the representations from one moment to the next, even though the relevant information still surrounds us. Moreover, every time we move our eyes, each part of the visual input changes its position across the retina, again necessitating VWM to bridge the gap [20]. One might even argue that the active nature of the representations is the defining characteristic of VWM, and in recent years, the "online" aspects of VWM were studied more closely, highlighting the "processing" aspects of VWM and not only its "storage" aspects.

Studying these online abilities creates a challenge that is hard to overcome with traditional paradigms. This is because they usually reflect only the end result of the process a representation went through. Additionally, they reflect only the outcome of a series of processing stages, most of which are actually external to working memory, e.g., perception or response selection [15]. To overcome this challenge, some researchers chose to use behavioral measures that were specifically developed to uncover the ongoing dynamics of VWM processing (e.g., [21, 22]). Here, we focus on another approach: utilizing an electrophysiological marker that allows uncovering the online nature of VWM processing, namely, the contralateral delay activity (CDA; [23–25]).

1.1 The CDA as a Marker of VWM

The CDA is an ERP marker, first introduced by Vogel and Machizawa in 2004 ([23]; although an earlier attempt to study VWM using ERPs was made by [26]). They employed a lateralized change detection task, in which the visual input was equated on both sides of the screen, but participants were asked to attend to only one side, as indicated by arrow cues presented before the memory array onset. ERPs were time-locked to the presentation of the memory array, and difference waves were computed by subtracting the activity in electrodes ipsilateral to the attended side from those contralateral to the attended side. About 300 ms after the onset of the memory array, a negative slow wave emerged in occipital-parietal electrodes (originally, at the OL/OR sites, corresponding to PO7/8 in the extended 10–20 system), persisting throughout the retention interval (hence, "contralateral delay activity").

Importantly, the CDA allows isolating VWM activity from processes that precede or follow it. Because the CDA is a difference wave, any activity that is common to the ipsilateral and contralateral sides (e.g., low-level visual processing of the similar items that are presented in both sides) is cancelled out by the subtraction, meaning that processes that precede attentional focusing, such as perception, will not be reflected in the CDA. Because the CDA is measured before a response can be prepared (e.g., during the retention interval), it cannot reflect response-related processes.

The key characteristic of the CDA is that its amplitude increases (i.e., becomes more negative) as more items are held in VWM [23]. Critically, this is exclusive to items that are actually held in VWM and does not simply reflect task difficulty: the set-size-dependent increase stops when average capacity is reached. Furthermore, the set-size effect (i.e., the difference in amplitude between set-sizes) is tightly related to individual capacity estimates, producing a correlation of ~0.6 in a meta-analysis [25]. Thus, the more information an individual can hold in VWM, the more the CDA will continue to rise. Similarly, the CDA has a reduced amplitude in incorrect trials compared to correct trials [24], in which participants presumably hold more information in VWM. All of these findings suggest that the CDA amplitude can be used as an ERP marker of VWM, creating a fruitful new way to study this cognitive process.

Over the years, several studies supported the notion that the CDA reflects VWM activity, by ruling out several confounding factors. First, the CDA does not reflect the number of active locations but rather the number of items held in VWM (although these two factors are usually confounded). When four items were presented across two consecutive memory arrays (two in each), the CDA amplitude was the same regardless of whether each item had a unique location or the items in the second memory array employed the same locations as those in the first array [27]. Thus, the CDA reflected the number of items (four in both cases) and not the number of locations (either two or four). Furthermore, when two distinct items are placed one on top of the other (e.g., an oriented bar on top of a colored square), the CDA is as high as when each of these items has a unique location [28–31]. Second, despite the spatial cue employed for extracting the difference waves, the CDA does not reflect the focus of spatial attention, because when participants had to encode items in one hemifield and then in the other, the CDA corresponded to the memory load across both hemifields [32]. Similarly, the CDA is unaffected by the distance between items [24], even though when items occupy a larger space, more spatial attention is needed. Third, even though the spatial cues might induce microsaccades in the relevant direction, these small eye movements are not the source of the CDA [33]. Fourth, the CDA is unaffected by the contrast of the items in the task [27, 34, 35]. Because brighter colors produce better change detection performance without affecting the CDA, this further shows that the amplitude does not reflect task difficulty. All of these results confirm that the CDA is specific to VWM processes, a unique feature which allowed it to serve as an excellent marker of VWM.

Aside from its general applicability in VWM research due to its specificity, the CDA has two critical attributes that make it ideal for studying online processing and manipulation. As mentioned above, the CDA is unaffected by whether or not the items are visible on the screen: similar amplitudes are found in a change detection that lacks a retention interval [19], and even in classic change detection memory tasks, the CDA does not abruptly change when the memory array disappears (although its amplitude might slightly and gradually decrease throughout the retention interval). The second feature is the precise temporal resolution of the ERP technique, meaning that the CDA tracks the development of representations over time instead of only giving a static view (e.g., [9, 28, 31]). Taken together, this enables the CDA to be used to uncover the moment-by-moment dynamics of the processing of information that continues to be visible.

1.2 Studies Utilizing the CDA in Online Processing Paradigms

Over the past few years, the CDA has been successfully used to study the processing of information still within view. Research on the storage and manipulation of visible information in a range of paradigms offered new insights on the role of VWM in these processes. Some of the studies revealed hidden involvement of VWM that was too delicate to study using behavioral tools alone, and others could identify several subprocesses that could not be identified with a single response measure.

1.2.1 Visual Search

While VWM had a central role in theories of visual search, behavioral evidence surprisingly suggested that search can be efficient even without relying on VWM to store the search items [36]. This puzzle was solved by research showing that the CDA is present when participants perform a lateralized visual search task, indicating the involvement of VWM in the search process [37]. This study further demonstrated that higher VWM capacity leads to more efficient search, which is portrayed not only behaviorally but also in faster-rising CDA amplitudes and, as shown later [38], also by lower CDA amplitudes. Accordingly, VWM involvement in visual search increases as the task becomes more difficult [38, 39], either "objectively" (when the task itself changes, e.g., from localization to identification) or "subjectively" (on slower reaction times trials of the same task). Subsequent research relied on the CDA to examine the processing of targets versus distractors in visual search, finding that although distractors draw attention, only targets elicit a CDA component, suggesting that only targets are stored in VWM during search [40]. The CDA was later used to study the influence of VWM training on visual search performance, again finding that improved search efficiency following VWM training decreases the reliance on VWM during search [41].

1.2.2 Multiple Object Tracking (MOT)

When participants track a subset of identical moving items, VWM is logically involved in their ongoing maintenance even though the items remain visible. Indeed, the CDA can be measured during MOT, with an increase in amplitude as more targets are tracked, until the individual capacity limit is reached [42]. The maintenance of items could be dissociated from the active updating of their locations, based on a surplus activity when the items are moving that was spatially distinct from the CDA [43].

The CDA reflects the current number of items being tracked, such that when targets are added or removed during the tracking period, the CDA amplitude increases or decreases accordingly [44]. The fact that the CDA can change online with the actual number of items being tracked allowed it to serve as an index for the potential sources of task difficulty in MOT, which behavioral performance could not distinguish between (because lower performance can be the result of any number of reasons). Specifically, when more distractors were added, the CDA indicated that the difficulty was due to swapping targets and distractors, while when movement speed increased, the CDA indicated the difficulty was due to a higher chance of targets being "dropped" [45]. While dropping was reflected in a lower CDA amplitude because less information was held in VWM, swapping did not affect the CDA, because participants were tracking the same number of items, simply the wrong ones.

1.2.3 Online Grouping

The CDA amplitude rises when more information is stored in VWM, but it seems to reflect the number of objects or "chunks," instead of the number of features. For example, the amplitude of a colored shape when participants maintain both color and shape is the same as the amplitude of a black shape in a shape-only task [30]. This makes the CDA an excellent tool for studying grouping in VWM, because its amplitude will be lower following the integration of information into one "chunk."

Indeed, several studies manipulated grouping by using Gestalt cues while monitoring the CDA. The results demonstrated that even when the grouping cues were task-irrelevant, VWM was sensitive to these cues and held an integrated representation of the grouped items. Specifically, joint movement ("common fate"), which is a strong Gestalt cue, caused separated items to be grouped in VWM: when two colored squares met and moved together, the color-color conjunction stimuli gradually became integrated in VWM after the joint movement [31]. This study also showed that this integration was not purely perceptual but was based on the movement history, because when the colors only met and did not move together, their representations remained separate, despite resulting in the same final visual input as in the joint movement condition.

A similar study manipulated Gestalt grouping cues of the different parts of a single object [46]. When two halves of a random polygon met and moved together, their integration was immediate. This deviates from what was observed for color-color conjunctions, whose integration took time [31]. Another difference between the two types of stimuli is the need for the joint movement for integration to take place. In a different study, color-color conjunctions that were presented together without movement were partially but not completely integrated [30]. Conversely, two shape-halves that were presented adjacently, to create one whole polygon, were perfectly integrated in a task that did not include movement [46]. These results suggest a dissociation between the integration of different features of a single object, which is fast and presumably mandatory, even for complex items, and the integration of distinct objects into one "chunk," which takes time to complete and requires strong grouping cues. Subsequent research demonstrated that online integration depends on strong grouping cues not only for color-color conjunctions but also for different-dimension stimuli such as orientation-color conjunctions (a tilted bar on top of a colored square; [28]) and that grouping is affected by the global context of the task, as determined by the other conditions included in the experiment [29].

1.2.4 VWM Resetting and Updating

One important aspect of online processing is the ability to change VWM's representations according to changes in the actual items in the environment. Recently, we used the CDA to distinguish between two processes that can modify VWM's representations, namely, updating and resetting. When a represented item changes, the change can either be incorporated into the existing representation in an updating process, or the original representation can be discarded and a new post-change representation established, in a process we termed "resetting" [47]. We argued that for VWM to be able to access the appropriate representation and update it, the representation must be mapped to a unique object and, if this mapping is invalidated, VWM must discard the representation and start over, by resetting. Accordingly, when a single shape moved coherently but then separated into two independently moving parts, we observed a sharp decrease in CDA amplitude, followed by a gradual recovery [47]. Presumably, the shape was originally represented as one object in VWM along with a single mapping to support that representation (as indicated by a CDA amplitude as low as a single shape-half), but following the separation, there were now two independent objects, none of which corresponds to the original object. This caused VWM to remove the integrated object, as indicated by the drop in CDA amplitude, and to encode the shapes as two separate representations (as indicated by a CDA amplitude as high as two separate shape-halves). These results are shown in Fig. 1, where it can also be observed that the CDA is extremely stable regardless of whether the items are visible on the screen (until 1300 ms from trial onset) or are only held in VWM.

In a set of control experiments, we further demonstrated that separation is neither necessary nor sufficient to produce a CDA-drop, meaning to trigger a resetting process [47]. For example, as can be seen in Fig. 2, resetting took place also after object switching, where one relevant object had to be discarded and another one abruptly replaced it. Additionally, when the two shape-halves first moved separately, allowing them to be individuated, and only then met, moved together, and re-separated, the CDA indicated there was no resetting, presumably because two independent mappings could be created to begin with (during the initial separate movement phase). Finally, we confirmed that the CDA-drop is specific to situations involving a loss of object-to-representation mapping, while extremely similar situations result in updating, as long as they allow the mapping to hold [48]. These results are shown in Fig. 3, corroborating the interpretation of the CDA-drop as a unique marker of the resetting process and the mapping invalidation that triggers it.

2 Methods

Because most of the studies that used the CDA relied on classic VWM retention tasks (e.g., change detection), it is important to highlight some guidelines for using it in the less conventional (although gradually growing) way of examining the processing of items within view (*see* **Note 1**). Below, we discuss several issues to consider when designing an online processing CDA experiment. We use our recent CDA studies of updating and resetting as an example.

2.1 General Task Structure

Broadly speaking, there are two different logics for using the CDA to study online processing, dictating two different types of tasks. The first is to use the CDA as a marker for the involvement of VWM

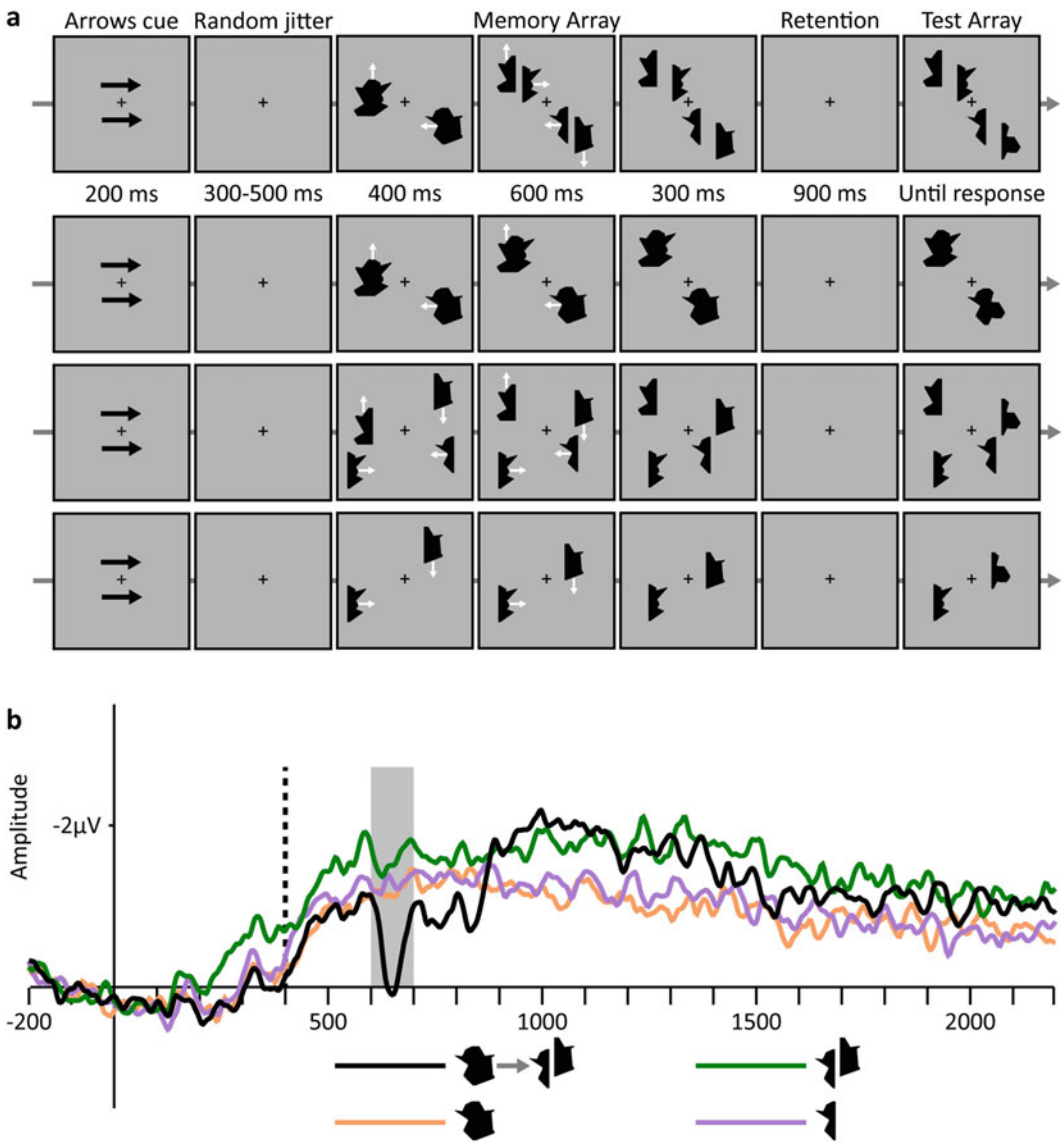

Fig. 1 The paradigm and results of Experiment 2 from Balaban and Luria [47]. (**a**) Examples of trials in the different conditions (white arrows indicate movement directions and were not presented). From top to bottom: separating polygon, integrated polygon, two polygon-halves, and one polygon-half. Note that the task was a shape change detection and the movement was completely irrelevant. (**b**) Grand-averaged CDA waves (averaged across the P7/8, PO3/4, and PO7/8 electrodes), time-locked to memory array presentation. Negative voltage is plotted upward. The vertical dashed line depicts the time of separation. The "drop" time window is depicted by a gray rectangle, and during it, the amplitude of the separating polygon condition significantly dropped

in processes other than classic memory maintenance. For example, one can investigate the involvement of VWM in a visual search process. For this goal, the preferred task is a bilateral version (see below) of a classic task involving the studied process (e.g., visual search).

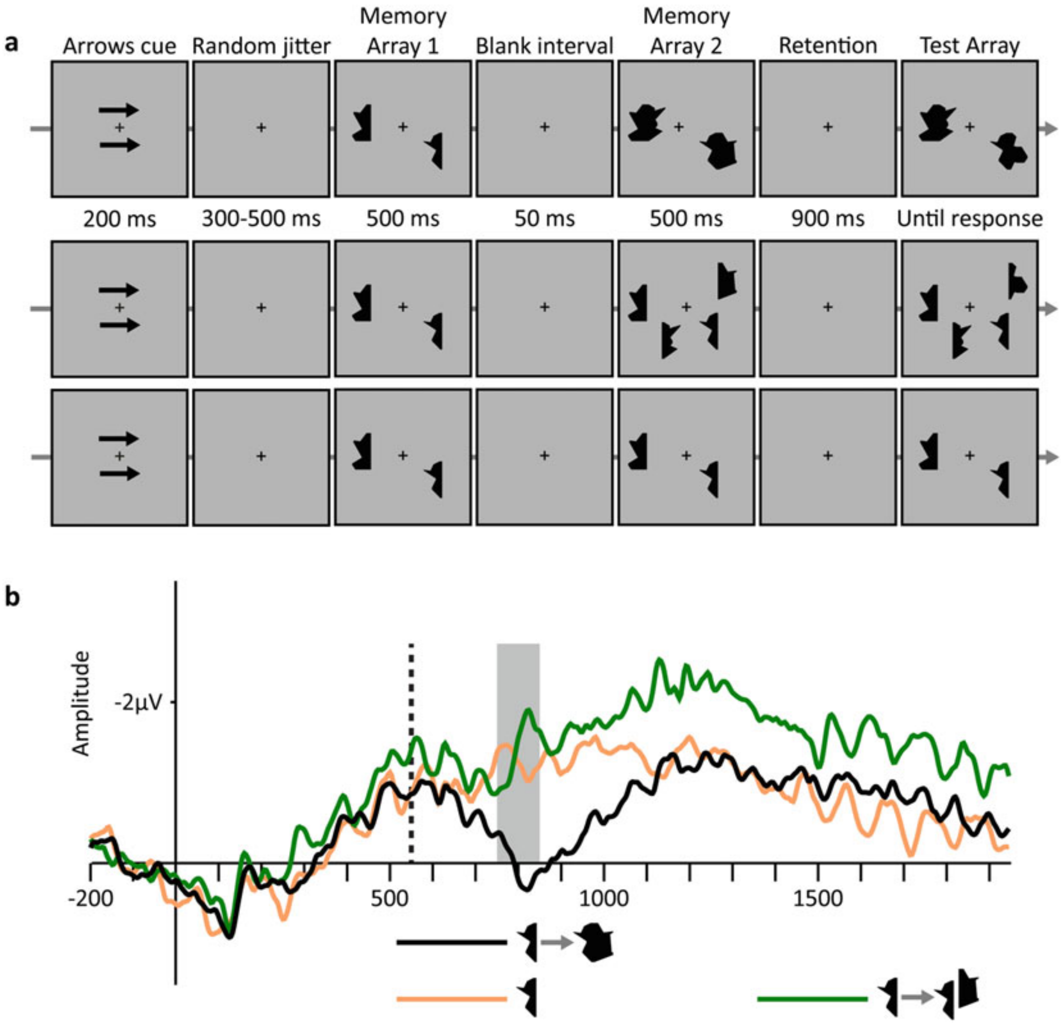

Fig. 2 The paradigm and results of Experiment 3 from Balaban and Luria [47]. (**a**) Examples of trials in the different conditions. From top to bottom: switch, add, and half-polygon repeat. Note that participants were instructed to remember only the shape(s) in the second memory array (making the first one irrelevant) and that the switch and add conditions include the same information, but in different locations. (**b**) Grand-averaged CDA waves (averaged across the P7/8, PO3/4, and PO7/8 electrodes), time-locked to memory array presentation. Negative voltage is plotted upward. The vertical dashed line depicts the time of the presentation of the second memory array. The "drop" time window is depicted by a gray rectangle, and during it, the amplitude of the switch condition, but not the add condition, significantly dropped

The alternative logic is to use the CDA to examine subprocesses of VWM, such as updating, resetting, and other online manipulation processes. If this is the goal, the task is usually a classic VWM task—typically change detection or delayed continuous response—that includes some additional manipulation during the memory array presentation. The VWM task guaranties the involvement of VWM, and the additional manipulation is used to trigger the

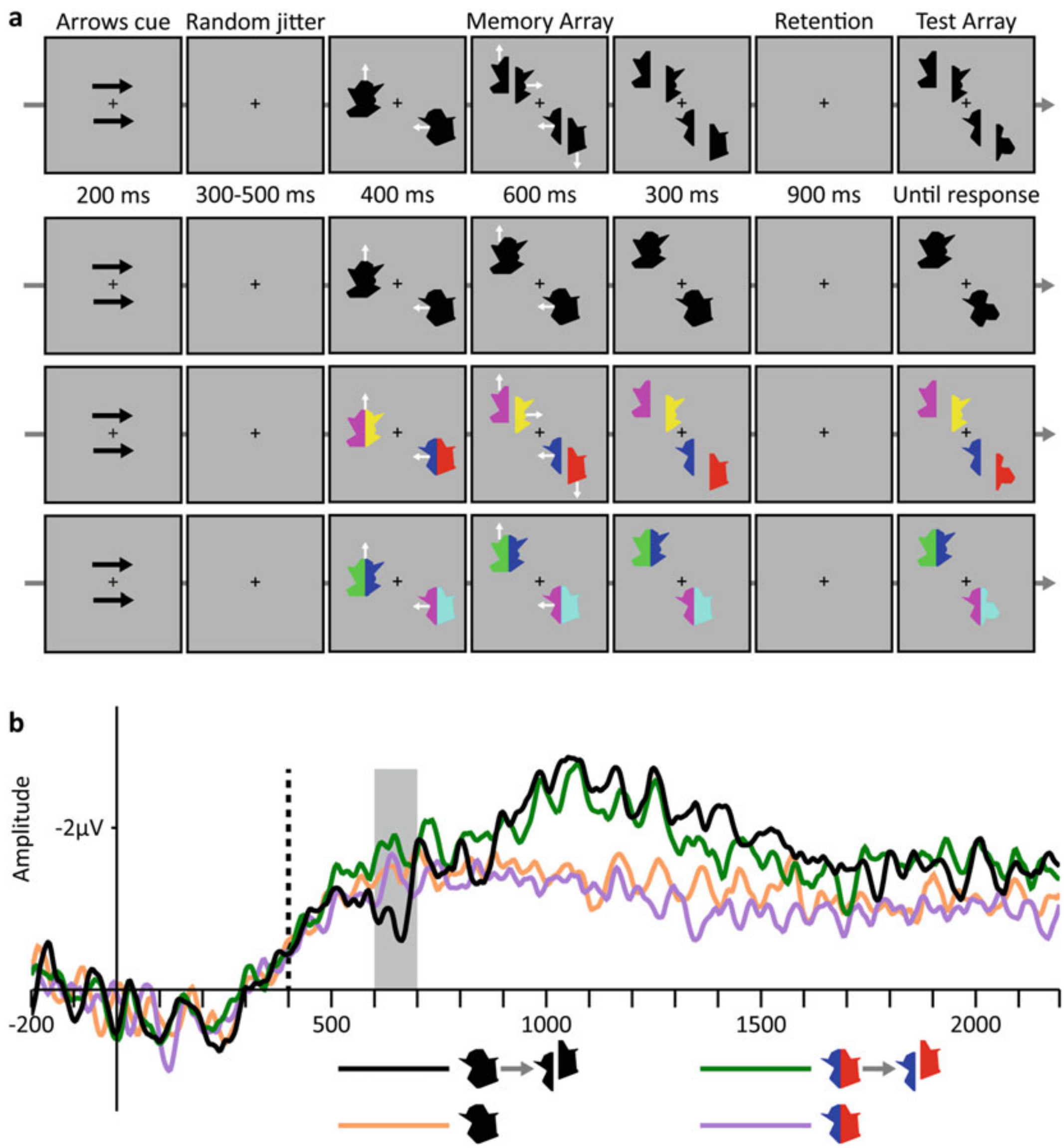

Fig. 3 The paradigm and results of Experiment 1 from Balaban et al. [48]. (**a**) Examples of trials in the different conditions. From top to bottom: black separating polygon, black integrated polygon, bicolored separating polygon, and bicolored integrated polygon. Note that the task was a shape change detection and the colors and movement were completely irrelevant. (**b**) Grand-averaged CDA waves (averaged across the P7/8, PO3/4, and PO7/8 electrodes), time-locked to memory array presentation. Negative voltage is plotted upward. The vertical dashed line depicts the time of separation. The "drop" time window is depicted by a gray rectangle, and during it, the amplitude of the black separating polygon, but not the bicolored separating polygon, significantly dropped

process of interest. An example is using a change detection task with movement that serves as a grouping cue, to study online integration in VWM (e.g., [31]). Note that in this case, the grouping manipulation was task-irrelevant (participants only monitored for a potential color change), to examine whether the items will be integrated despite their joint movement being irrelevant. Indeed, the additional manipulation in this kind of CDA studies can be orthogonal to the memory task, but it can also be a task-relevant manipulation.

Once the task is chosen, it is critical to adapt it to a lateralized display. As mentioned above, the CDA is a difference wave, allowing to control for low-level visual processing. To enable a correct subtraction, each trial should include similar stimuli in the left and right sides of the central fixation point. It is important to equate the left and right sides in terms of factors that are expected to affect the CDA: the number of items, their type (e.g., complex stimuli have higher CDA amplitudes; [34]), and the experimental condition they belong to (e.g., whether they include only relevant items or also distractors; [9]). Conversely, although the two sides should be generally quite similar, it is not necessary to perfectly balance them in terms of low-level features, such as the items' exact brightness, color, size, location, or centrality (*see* **Note 2**). Duplicating the display of one side in the other side is not recommended, because it might lead participants to adopt unwanted strategies (e.g., attending to the wrong side).

There are two main ways to make the task lateralized. The dominant one is to present spatial cues (e.g., arrows above and below the fixation) before the onset of the items in each trial. These cues should be 100% valid, and participants must be aware of that (*see* **Note 3**). If pre-cues are used, it's necessary to include a blank screen (with only a fixation point) between the cues and the task, and as explained below, the duration of this blank screen should be variable. Typically the duration is randomly jittered between 300 and 500 ms, making sure there is enough time to serve as the baseline for the ERP analysis, which is usually the 200 ms immediately before the task. The duration cannot be constant, otherwise the cues will precede the task by a constant lag, and any time-locking to the task locks to the cues as well, making interpretation of the ERPs problematic.

Another possibility is to define the target side by a task-irrelevant feature (usually color), which remains constant throughout the experiment. For example, in a shape task, the cue could be color, such that on each trial, all of the shapes in one side (left or right, randomly determined) have color A and all the shapes in the other side have color B, with half of the participants instructed to attend to color A and half to color B.

When considering the number of trials included in the task, it is important to remember that trials containing artifacts (mostly eye movements and blinks) and/or incorrect responses are excluded from the analysis. We usually include 200–250 trials per condition, leaving a minimum of roughly 100 trials per condition per subject for the most difficult conditions and the noisiest subjects (*see* **Note 4**). Importantly, including a large number of trials allows examining the individual datasets, identifying the effect of interest not only in the grand average, and testing for possible individual differences, as has been successfully done with the CDA in the past (see [25], for a review).

To show the influence of the number of trials on the CDA in online processing tasks, we reanalyzed the data from Experiment 2 in [47], which included 15 blocks of 60 trials (with about 225 trials per condition per subject, before removing artifacts and incorrect responses). We compare the CDA of two conditions in the task (a resetting condition and a baseline condition) for the entire set of blocks with the CDA obtained from dividing the experiment in two halves (blocks 1–7 versus 8–15; about 112 trials per condition per subject, before removing artifacts and incorrect responses) or in four quarters (blocks 1–3, 4–7, 8–11, and 12–15; about 56 trials per condition per subject, before removing artifacts and incorrect responses). As can be seen, using ~100 trials per condition is enough for clean CDA waveforms at the grand average level, as well as for a clear CDA-drop following resetting. Conversely, using ~50 trials produces waveforms that are too noisy, although the CDA-drop can still be observed. Aside from the grand average of all 12 subjects, we also show the individual datasets of two participants: the one with lowest rejection rate (1.4%) and the one with the highest rejection rate (18.7%), to demonstrate the effect of the number of trials at the individual level. The results are shown in Fig. 4, and they suggest that the CDA-drop is still present at the individual level with ~100 trials per condition, but the difference between the different conditions in the CDA becomes quite blurry.

2.2 Avoiding Eye Movements and Blinks

An important issue in visual paradigms generally, and online processing tasks specifically, is the need to control for eye movements and blinks. These artifacts are detrimental not only because of the large direct effect they have on the EEG waveforms but also because of indirect changes they likely cause. This is because an eye movement or a blink, by definition, causes the participant to see different visual information than intended: an eye movement causes the middle of the display to be shifted from the central fixation to another point on the screen, which is critical for the CDA as a difference wave, and a blink means seeing nothing for ~300 ms. This issue is especially important for online processing paradigms, because they typically involve a much longer presentation time than memory paradigms, producing more opportunities for artifacts to occur. Note that mathematically removing these artifacts (e.g., by using ICA) does not solve the problem of these trials being different in terms of their cognitive processing.

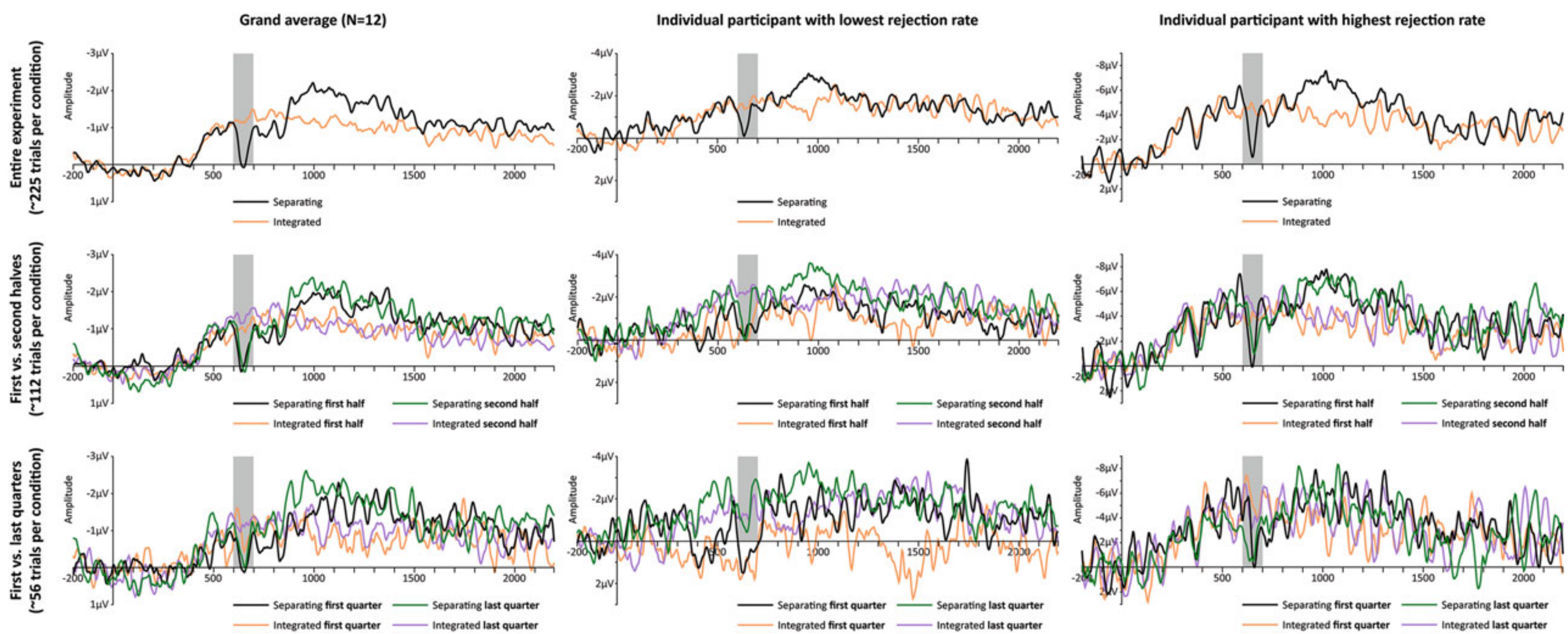

Fig. 4 The results of the separating polygon and integrated polygon conditions of Experiment 2 from Balaban and Luria [47], by the number of trials included. The vertical dashed line depicts the time of separation. The “drop” time window is depicted by a gray rectangle. The left column shows the grand average of all 12 participants, the middle column shows the individual waveforms for the participant with the lowest rejection rate, and the right column shows the individual waveforms for the participant with the highest rejection rate. The top row shows the results for the entire experiment, the middle row shows the results for the first and second halves of the experiment, and the bottom row shows the results for the first and fourth quarters of the experiment. Note that each column has a different scale

Before listing several technical ways to minimize eye movements and blinks, we would like to note that the best way to reduce them is by instructions (*see* **Note 5**). Before the experiment begins, participants must be told that eye movements and blinks are to be avoided, preferably with a short explanation as for the reasons and a demonstration of the effect they have on the raw EEG data. Additionally, the practice phase of the experiment should be used to help participants getting used to not moving their eyes and blinking only between trials (see below), with ongoing feedback from the experimenter. Feedback should also be used throughout the experiments (in real time or at least between blocks), drawing the participant's attention to events of breaking fixation or blinking in the wrong time. With these artifacts, like with any other source of noise, it is always better to not record them in the first place than to struggle removing them during offline processing [49].

Alongside the appropriate task instructions, there are practical tools that can help participants maintain these instructions more easily, mainly by providing them with enough opportunities to rest their eyes throughout the experiment. First, it is critical to include a designated blinking time after each response, by presenting a blank screen for about 1–2 s before the onset of the next trial. Second, breaks should follow every few (no more than 5) minutes of trials. Third, the length of the task itself, including breaks, should be no longer than about an hour and a half. If more trials are needed than can be included in this time frame, the experiment can be divided into two sessions. Fourth, in tasks including movement, which induces more eye movements, if possible, it is better to restrict the movement direction so that items do not move away from the fixation point but only toward it or vertically. Finally, it is always recommended to examine the EOG, to ensure that it is not the source of the effect of interest.

Having highlighted the importance of controlling for eye movements, it is also important to note that the CDA does not reflect these artifacts [33]. Once the proper instructions and task structure are used, the remaining artifacts are minimal and can be removed using standard procedures, such as a moving window peak-to-peak analysis (see [49]). Furthermore, our data suggests that eye movements are not the source for the CDA-drop, even in online paradigms that include movement. Figure 5 shows the horizontal EOG for two experiments, i.e., difference waves of the left EOG electrode minus the right EOG electrode (so that any leftward eye movement creates a negative deflection and any rightward eye movement creates a positive deflection). The results allow comparing situations with and without a CDA-drop (i.e., the switch condition vs. the add condition of Experiment 3 from [47] and the black separating polygon condition vs. the bicolored separating polygon condition of Experiment 1 from [48]) in terms of eye movements. As can be seen in the figure, eye movements are quite minimal across

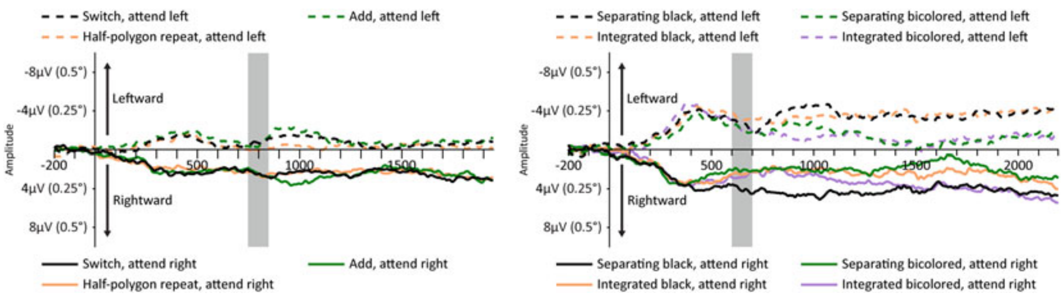

Fig. 5 HEOG waveforms (left minus right) for Experiment 3 from Balaban and Luria [47] (left) and Experiment 1 from Balaban et al. [48] (right), by condition and attended side. The "drop" time window is depicted by a gray rectangle. As a reference point, we used 4 and 8 μV, which correspond to about 0.25° and 0.5° of drifting eye movement, respectively [53]

all conditions, and furthermore, during the relevant time window of the CDA-drop, eye movements are very similar between the different conditions and therefore cannot distinguish between the two CDA patterns.

2.3 Data Analysis

CDA waveforms are typically comprised of only trials that include a correct response (due to the assumption that errors might involve other processes that would complicate the interpretation of the results) and do not include any artifacts: eye movements, blinks, and general noise, all of which are to be removed at the offline processing stage. Activity is time-locked to the onset of the task (e.g., the presentation of the memory array) and baselined to a portion of the blank interval preceding the task. The trials are divided into attend-left and attend-right and averaged by condition. Then, for each electrode pair, the contralateral activity is defined as the average of the right-hemisphere activity in attend-left trials and left-hemisphere activity in attend-right trials, and the ipsilateral activity is defined as the average of the left-hemisphere activity in attend-left trials and right-hemisphere activity in attend-right trials. The CDA is computed as the contralateral minus ipsilateral activity, and mean amplitude of this difference wave is the dependent variable of main interest (*see* **Note 6**). We next discuss the electrodes and timing in which the relevant effects are expected to appear.

The CDA is a parietal-occipital component, mostly observed over the P7/8, PO3/4, and PO7/8 (sometimes referred to as OL/OR) electrode pairs [24]. Usually the strongest activity is in the PO7/8 electrodes, and therefore they are used for statistical analyses. Another common practice is to use the average of all three electrode pairs. While this might attenuate the effects in some cases, it also guarantees that extreme patterns in a single electrode pair will not dominate the interpretation. Figures 6 and 7 present the spatial distribution of the CDA in two of our experiments (using

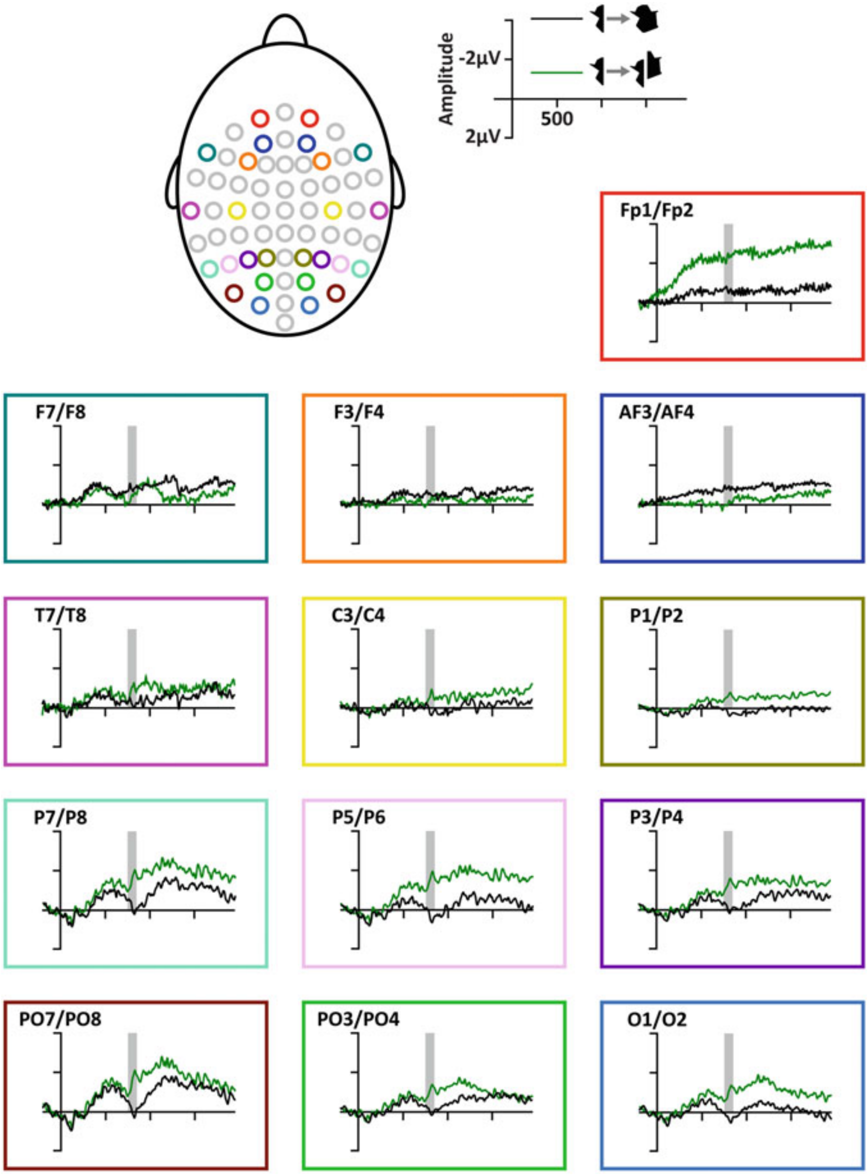

Fig. 6 CDA waveforms for two conditions from Experiment 3 from Balaban and Luria [47], by condition and electrode pair (midline electrodes are not presented). The "drop" time window is depicted by a gray rectangle. The colors of the frames correspond to the colors of the electrodes in the schematic drawing of the head, to show the position of the pair

32 scalp electrodes in a subset of the extended 10–20 system), showing that the spatial distribution is very similar for items' maintenance, updating, and resetting.

The time window used for classic CDA tasks is typically from 300 ms after memory array onset, allowing the CDA time to stabilize, and until the end of the retention interval. However,

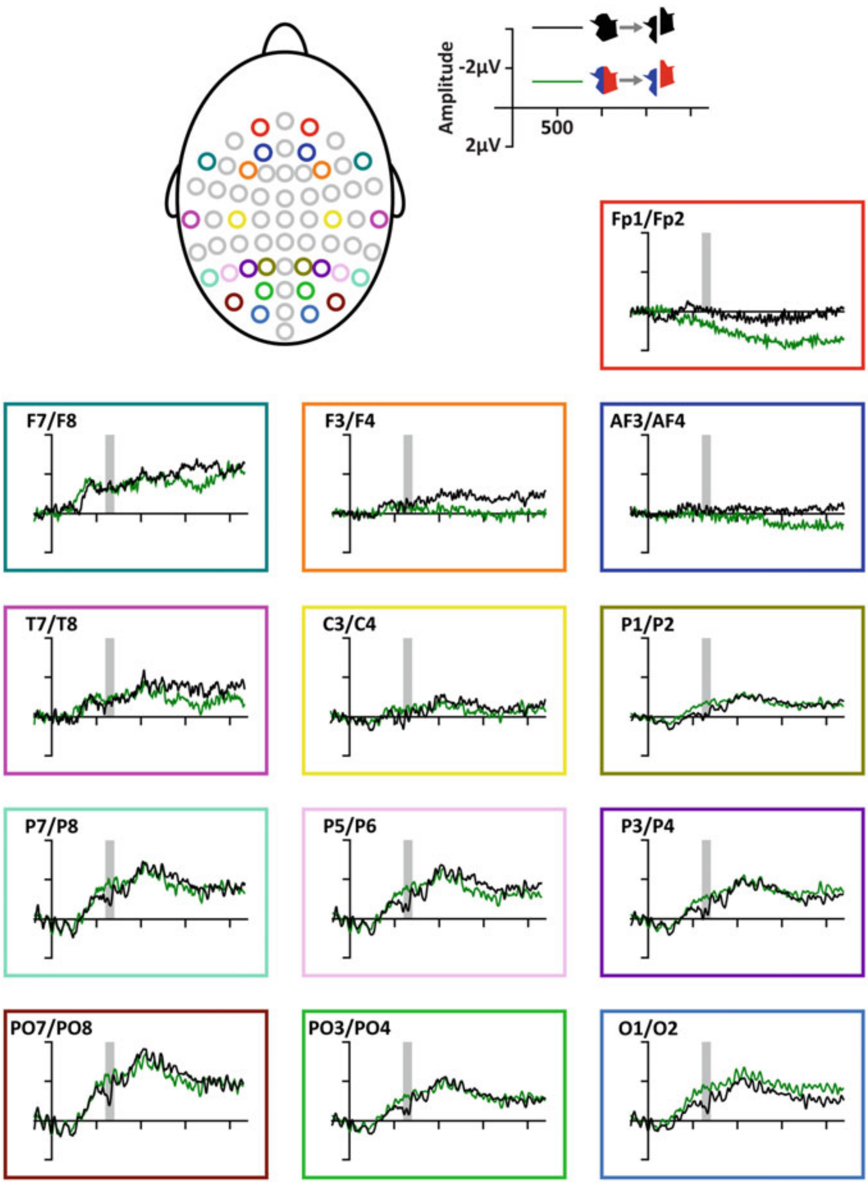

Fig. 7 CDA waveforms for two conditions from Experiment 1 from Balaban et al. [48], by condition and electrode pair (midline electrodes are not presented). The "drop" time window is depicted by a gray rectangle. The colors of the frames correspond to the colors of the electrodes in the schematic drawing of the head, to show the position of the pair

when online processing tasks are used, this is not always suitable. Each task and research question will have slightly different time windows, but several general guidelines can be provided. First, the CDA takes about 200 ms to respond, for example, to initially rise [9], or to drop in VWM resetting [47, 48]. Therefore, time windows should start about 200 ms after the relevant event. Second, if

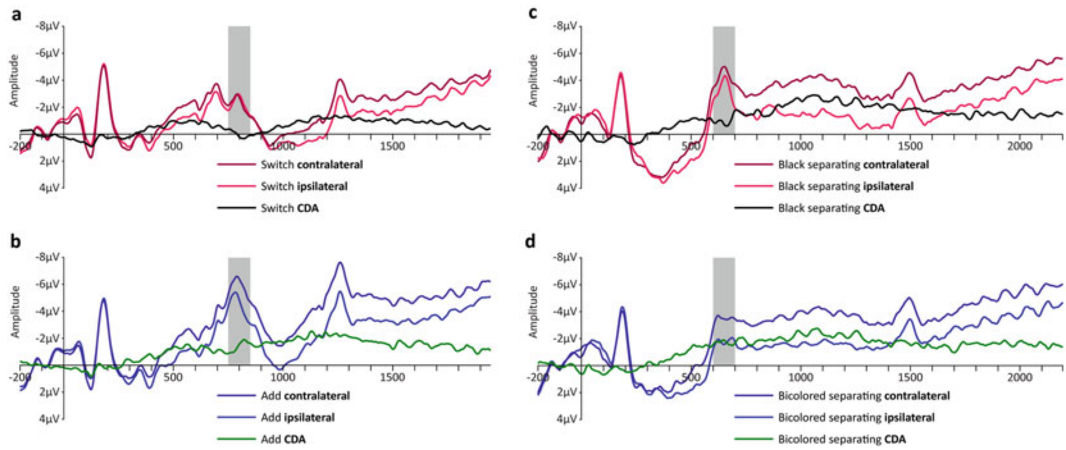

Fig. 8 Contralateral and ipsilateral waveforms for two conditions from Experiment 3 from Balaban and Luria [47] (left) and Experiment 1 from Balaban et al. [48] (right) and the resulting CDA difference wave. The "drop" time window is depicted by a gray rectangle. (**a**) The switch condition of Experiment 3 from Balaban and Luria [47], which resulted in a CDA-drop. (**b**) The add condition of Experiment 3 from Balaban and Luria [47], which did not result in a CDA-drop. (**c**) The black separating polygon condition of Experiment 1 from Balaban et al. [48], which resulted in a CDA-drop. (**d**) The bicolored separating polygon condition of Experiment 1 from Balaban et al. [48], which did not result in a CDA-drop

online dynamics are to be examined, it is usually best to divide the trial into several time windows of interest. For example, in Drew et al.'s [44] MOT paradigm, after an initial tracking period, the targets could change (e.g., adding additional targets). Comparing the CDA before and after this change allowed the researchers to demonstrate the differential ongoing tracking load (e.g., the CDA was higher after more targets were added). Third, each time window should be long enough to minimize the influence of transient fluctuations. Finally, if the resetting process is of interest, the CDA-drop is expected between 200 and 300 ms after the relevant event (e.g., object separation).

2.4 Contralateral and Ipsilateral Waves

As mentioned above, VWM studies usually focus on the CDA as a difference wave. This is mainly because this allows controlling for low-level visual processing, making sure any observed effects are specific to VWM. However, it is always recommended to examine the contralateral and ipsilateral waveforms as well. Figure 8 presents these waves for two of our experiments. Comparing updating and resetting reveals that the CDA-drop originates from an interesting pattern. Namely, while the contralateral wave rises (i.e., becomes more negative) after the critical even (e.g., object separation) in both resetting and updating situations, in updating, it maintains its distance from the ipsilateral wave that rises to the same degree, and thus the CDA is unaffected, while in resetting, the ipsilateral wave rises more than the contralateral wave, and the decreased distance between them is reflected in the CDA-drop. The sharp rise of the contralateral and ipsilateral waves is similar to what happens after the items are first presented, and both effects occur ~200 ms after the relevant event, i.e., in the time window of N1 or N2 components [50], but notably, in most attentional effects, the negative deflection is larger in the contralateral side, while during resetting, we see the increased activity on the ipsilateral side. It might be that the negative deflection reflects the reinstatement of the object-to-representation mappings, similar to their initial creation when the items are first encoded. Alternatively, it could be that there are two superimposed processes that are manifested in the same electrodes, an attentional effect which is the same for the contralateral and ipsilateral sides, as is suggested by updating situations, and another effect of VWM that removes the previous contralateral surplus negativity, thus bringing the contralateral and ipsilateral waves to the same point. This is an interesting path for future research.

3 Notes

1. The CDA emerges when VWM is active, meaning the task has to involve VWM. Specifically, the task has to encourage active *visual* maintenance of the items. If verbal rehearsal of the memoranda could be performed, it should be prevented, e.g., by including verbal suppression. This is especially problematic when using long presentation times with familiar namable stimuli (e.g., colors).
2. If possible, do not present the items at the same locations throughout the task. Instead, randomize locations across trials, or choose the locations on each trial from a large set of locations. Our experience is that using predetermined locations might attenuate the CDA.
3. When explaining the task to participants, some of them (especially those who perform many psychology experiments) become suspicious as for the bilateral nature of the task. They might not say so, but they sometimes do not believe that the uncued side is indeed irrelevant. Because the CDA depends on an effective manipulation of attention, it is critical that participants try the best they can to completely ignore the irrelevant side and not encode it in VWM. Usually the best way to convince them that there is no “trick” and the cues are to be trusted (apart from specifically telling them that) is by explaining the logic of difference waves: a surplus activity of VWM would be present in the contralateral side only if they manage to attend to the relevant side.

4. This large number of trials per condition means the experiment will be quite long and participants tend to get tired. Make sure to encourage them between blocks to reestablish their engagement in the task. Offer them to take breaks that are not too long and not too short, so they can remain focused. Getting them as "on board" as possible is highly recommended and is also the best way to minimize alpha waves that reflect fatigue.
5. Because only one side of the screen is relevant on each trial, a very natural way to perform the task is by moving one's eyes to fixate on the relevant side, which will completely eliminate the CDA and therefore cannot be a legitimate strategy. This points to the fact that the way in which participants should perform the task is often unintuitive for them, and this should be made explicit when explaining the task. The practice phase of the experiment should be long enough to allow participants time to get used to not only the task itself but also its technical constraints, especially not moving their eyes and not blinking. A small percentage of all participants do not succeed in holding fixation without blinking and therefore cannot begin the experiment at all. People that wear contact lenses daily are more prone to this (even when using glasses, as should be done in these experiments), because they are used to blink a lot.
6. Custom scripts for analyzing the CDA using EEGLAB [51] and ERPLAB [52] can be found in our lab website: https://people.socsci.tau.ac.il/mu/royluria/cda-package/.

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