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Analyzing the pupil response due to increased cognitive demand: An independent component analysis study

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ABSTRACT

Pupillometry is used to indicate the relative extent of processing demands within or between tasks; however, this analysis is complicated by the fact that the pupil also responds to low-level aspects of visual input. First, we attempted to identify "principal" components that contribute to the pupil response by computing a principal component analysis (PCA) and second, to reveal "hidden" sources within the pupil response by calculating an independent component analysis (ICA). Pupil response data were collected while subjects read, added or multiplied numbers. A set of 3 factors/components were identified as resembling the individual pupil responses, but only one ICA component changed in concordance to the cognitive demand. This component alone accounted for about 50% of the variance of the pupil response during the most demanding task, i.e. the multiplication task. The highest impact of this factor was observed for 2000 to 300 ms after task onset. Even though we did not attempt to answer the question of the functional background of the components 1 and 3, we speculated that component 2 might reflect the effort a subject engages to perform a task with greater difficulty.

1. Introduction

Pupillometry, the observation of the dilation of the eye's pupil, has well-described potential to uncover the processing activity that accompanies mental effort (Beatty and Brennis, 2000; Heitz et al., 2008; Hupe et al., 2009; Steinhauer et al., 2000; Vo et al., 2008). It has long been known that the extent of pupil dilation indicates the relative extent of processing demands within a task from moment-to-moment and, moreover, between tasks (Beatty and Kahneman, 1966; Heitz et al., 2008; Hess, 1972; Hess and Polt, 1964; Hess and Howell, 1988; Kahneman et al., 1969; Porter et al., 2007).

The main difficulty in detecting "cognitive-induced" pupillary responses is that the pupil also responds to low-level aspects of visual input (Goldwater, 1972; Porter et al., 2007), for example, changes in luminance or spatial frequency or accommodation responses. Because of the magnitude of the light reflex and induced pupil responses due to accommodation, precautions must be taken to avoid a "masking" of the small changes that are evoked by mental operations by responses produced by optic reflexes. Moreover, for most specific task-conditions, the degree to which the pupil response is reflex-based or cognitively driven remains unknown. One solution for coping with these difficulties might be to identify each "hidden" source within the overall pupil response and outline the one that selectively responds to the cognitive demand. The current study aimed to describe hidden sources in the overall pupil response—with a specific interest in revealing one component that might react to variations in cognitive demand.

As described later in detail, we altered the cognitive demand by changing an arithmetic task. Arithmetic tasks have been previously used to vary overall pupil responses (see, for example, Matthews et al. (1991)) or the pupil–light reflex (see for example, Steinhauer et al. (2000)); however, to the authors' knowledge, a component analysis (i.e., "hidden" source identifications) of pupil response data has not been previously published. We found examples for other tasks. For example, in a recent paper, Kuchinke et al. (2007) used a principle component analysis (PCA) to identify components in the pupillary responses in a lexical decision task and replicated the common structure of three temporal components (Granholm and Steinhauer, 2004; Nuthmann and van der Meer, 2005). However, one assumption of PCA is that component sources are spatially orthogonal to each other and there is *a priori* no reason to think that this is the case for pupillary components.

Regarding the latter aspect of PCA, we questioned whether it might have an impact on pupil response analysis. Therefore, we first applied a PCA to our pupil response data in order to compare our data to previously established implicit structures. In addition, we further analyzed our data by applying an independent component analysis (ICA). This approach takes advantage of the fact that underlying input processes have some inherent response-to-response variability, and this variability can be used to identify process (i.e., component) contributions to the total response—in our case, the pupil response. Generally, the aim of an ICA is to minimize the statistical dependence

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between the underlying components, which might not be orthogonal to each other. In terms of the pupil response, this might be a direct advantage: the regulation of the pupil size is a result of the complex interrelationship of the parasympathetic and the sympathetic pathways (Loewenfeld, 1958, 1999; Lowenstein and Loewenstein, 1969) and, as mentioned above, the pupil responds to low-level aspects of the visual input as well as to higher-level activities such as mental effort (see, for example, Goldwater (1972) or Heitz et al. (2008)). All of these processes interact and there is no physiological reason to expect that these processes work on orthogonal dimensions, as is assumed for PCA. Thus, for physiological or biological systems, the ICA has assumptions that are more reasonable. In this context, ICA has been utilized in numerous applications in biomedical studies including, for example, the decomposition of the vergence step response (Semmlow and Yuan, 2002), and, more prominent, the analysis of the electroencephalogram (Vigario et al., 2000). In the EEG literature (in which the same questions of source separation arise), ICA is generally preferred because of its strength in segregating the EEG sources as non-orthogonal (oblique) factors (Jung et al., 1998; Jung et al., 2000). Besides noise-reduction and artifact control (see, for example, Jung et al. (1998)), the ICA is used to identify (see, for example, Hoffmann and Falkenstein (in press)) or localize (see, for example, Lei et al. (in press) or Eichele et al. (2009)) different functional processes reflected in EEG signals. Further, the ICA has been utilized in evaluations of the electrocardiogram (ECG, see, for example, Chawala et al. (2008)) or the analysis of photoplethysmography (see, for example, Abe et al. (2008)). It should be noted that signals that have been decomposed with an ICA typically include multiple detectors (for example, multiple electrodes for the EEG or ECG), while the pupil has only a single output channel. In contrast to the use of the ICA in multi-channel applications, the ICA had been used successfully by Semmlow and Yuan (2002) to perform a "dry dissection" of the vergence step response: the authors used the single vergence signal from the eye movement recordings and extracted two ICA components which resembled the sustained and transient component of the vergence step response, respectively (see also: Semmlow et al. (2007)). This example encouraged the present use of the ICA for a single data channel, i.e. the pupil response measure.

In sum, we accepted that the pupil response is driven by different reflexes and cognitive aspects. In order to account for all hidden sources within the pupil response, additional experimentations that vary known low-level aspects of the visual input as well as cognitive demand are needed. For our purpose, we analyzed pupil responses that were measured during a simple arithmetic task, while performance measures ensured cognitive demand variations. Furthermore, the visual presentation was the same for all conditions. Nevertheless, a relatively early component within the overall pupil response is generally expected to reflect reflex aspects of the pupil response, which are driven by changes in the visual presentation when, for example, trials change from one to another (Kuchinke et al., 2007). A cognitive-induced component of the pupil response was expected to influence the overall pupil response during the course of the task, while a later component might reflect response or post-processing monitoring (Kuchinke et al., 2007; Nuthmann and van der Meer, 2005). Nevertheless, by analyzing the present pupil responses, we were able to describe general experiences of ICA results for a simple arithmetic task and found qualitative hints of a "hidden" source for cognitive-induced component of the overall pupil response.

2. Methods

2.1. Participants

We tested 10 male subjects (average age ± SD: 23 ± 3) with a minimal visual acuity without correction of 1 (in decimal units) in the measured right eye. Myopic, hypermetropic, and astigmatic refractive errors did not exceed the amount of 0.5 D. Each subject provided informed consent prior to the experiments; the research followed the tenets of the Declaration of Helsinki.

2.2. Task

Subjects were asked to read, add or multiply a two-digit and a one-digit number; number combinations were selected in order to avoid trivial combinations such as "20 1". All numbers changed from trial to trial, so that the change in visual input was approximately equivalent for each trial. The arrangement of the numbers is shown in Fig. 1. When reading the numbers, subjects had to react as fast as possible to an "L" or "R" with the left or right mouse button, respectively. During adding and multiplying periods, the presented result could be correct or incorrect by ± 1 or ± 10 and subjects were asked to indicate the result as correct or false, again as fast as possible. Each number combination (i.e., one trial) was presented for 5 s and number presentations changed without a time gap from one frame to the next. A complete block of 32 trials lasted 160 s and the tasks (reading, adding or multiplying) were presented in separate blocks. The sequence of these blocks (reading, adding or multiplying) was counterbalanced across subjects.

We measured pupil diameter, reaction time and errors during task processing.

2.3. Apparatus and stimuli

The targets were presented monocularly on a LCD screen (thin-film transistor (TFT)-LCD, Fujitsu Siemens) as black on white numbers with a mean background luminance of 30 cd/m². Each number subtended 0.29 deg × 0.37 deg (width × height) at a viewing distance of 5 D (20 cm). The surrounding room lighting was adjusted individually in order to set the initial pupil size at an individual intermediate size to avoid ceiling effects. The resulting room lighting varied between 2 and 15 lx across subjects. Pupil size was measured dynamically (25 Hz) using a remote, automatic eccentric infrared photorefractor, the PowerRef II (PlusoptiX) (Allen et al., 2003; Wolffsohn et al., 2002), which is specified by the manufacturer to measure pupil size with a resolution of 0.1 mm. The camera was placed in line with the right eye and a chin and forehead rest was used. During data screening, blink artifacts were removed from the records. A blink was identified when the pupil signal was below 60% of the median size for at least 50 ms. Blinks separated by less than 100 ms were aggregated to a single blink. In addition, all trials were visually inspected for undetected artifacts (approximately 5% of the complete data set). If there were three or more blinks within a trial, this trial was excluded from further analysis (approximately 15% of the complete data set). Blink periods were then linearly interpolated.

2.4. Pupil data preparation

In order to consider pure pupil diameter changes, we subtracted the average pupil size from each trial; thus, pupil size changes were independent of the initial pupil size and comparable between subjects. Additionally, we selected a response (n) by considering the reaction time in the single task before ($n-1$). When the reaction time

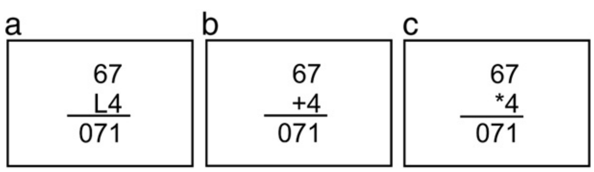

Fig. 1. The task layout for reading (a), adding (b) and multiplying periods (c), for comparison.

of the task $n-1$ deviated from the average by half the SD or when the subject failed to provide an answer, the response (n) was excluded from analysis (approximately 18% of the trials for the multiplication task). This procedure was implemented to avoid the enduring processing of task $n-1$ while task n was presented.

For our PCA and general ICA analysis, we averaged the single trials (5 s) across repetitions within one subject for each task. The analyses run on these individual averages (across subjects and tasks) were considered to describe a common structure within the average pupil responses. Then, we calculated single ICAs (one for each subject) on a trial-by-trial basis to reflect individual structures before comparing the influence of specific components on the overall average pupil response.

2.5. Principal component analysis (PCA)

A principal component analysis transforms correlated variables into uncorrelated variables, the so-called principal components. The first principal component accounts for the greatest amount of the variability in the data, and each succeeding component accounts for as much of the remaining variability as possible. PCA is theoretically the optimum transformation for data in least square terms. For our analysis, two criteria were employed to extract the factors: an eigenvalue greater than 1 (Kaiser criterion) and a significant contribution to the accounted variance. We used the *prcomp* of the statistical package R-Development-Core-Team (2008) for analysis of our data.

2.6. Independent component analysis (ICA)

An independent component analysis is another analytical method that isolates individual components from a mixture of signals while the mixing system is unknown. It attempts to explain how the non-Gaussian and mutually independent latent components are mixed to generate the observed signals by maximizing the statistical independence of the estimated components. The basic principles behind ICA are described, for example, by Hyvärinen et al. (2001). The number of components to be extracted is predefined by the number of PCA components. We used the *fastICA* algorithm of the statistical package R-Development-Core-Team (2008).

The ICA is based on a generative model; it attempts to explain how the "hidden sources" (i.e., the components) are mixed to create the observed signals assuming a linear mixing model (Comon, 1994). A comparable simple linear equation represents this model:

$$x = \boldsymbol{A}\mathbf{s} + \text{noise}$$

where **s** is the number of vectors containing signals from the "hidden sources" and x are the vectors containing the observable signals, that is, the components after they have been linearly mixed. These are the actual pupil responses that we measured. $\boldsymbol{A}$ is a matrix that describes how the signals have been mixed together. The noise vector represents disturbances in the form of additive noise independent of the "hidden sources". The basic assumption of the ICA is that the measured signal (the pupil response: x) is a simple linear combination of the "hidden source" signals (**s**) plus noise. In matrix terms, the mixing reflected by $\boldsymbol{A}$ can be interpreted as a rotation and a scaling of the "hidden source" signals (**s**). There should be one rotation and scaling that when applied to the observable signal (x), recovers the "hidden source" signals (s). This recovery operation is reflected by the *unmixing* matrix ($\boldsymbol{U}$)—that is, the inverse of $\boldsymbol{A}$. In accordance with the fact that mixtures of independent signals have distributions that are closer to Gaussians than unmixed signals, ICA algorithms rotate and scale the data set using an optimization procedure to search for a result that is the least Gaussian (Hyvärinen et al., 2001). Using the *fastICA* algorithm of the statistical package R-Development-Core-Team (2008), we extracted the components simultaneously and approximation to neg-entropy was used, which is more robust than kurtosis-based measures (Comon, 1994; Hyvärinen et al., 2001).

3. Results

3.1. Reaction time, errors and average pupil size

Before running the PCA and ICA analyses, we determined whether our experimental manipulation (i.e., the change of the task from reading and adding to multiplying the numbers) had an effect on average reaction time, errors and pupil size. These average changes are typically expected if a change in cognitive demand is imposed by the different task (for pupil size changes, see, for example, Bradshaw (1967), Goldwater (1972), Hess and Polt (1964), Matthews et al. (1991)). Average (±SD) reaction time increased from 1772 ms (±790) for reading up to 2145 ms (±722) for adding and to 3234 ms (±680) for multiplying the numbers ($F_{(2,27)}=8.54$, $p<0.01$; effect size: $f=0.90$). The average error was low (<1%) for reading and increased from 2% (±4) for adding to 30% (±16) for multiplying the numbers ($F_{(2,27)}=28.65$, $p<0.01$; effect size: $f=1.46$). Additionally, average pupil size was 4.7 mm (±0.8) for reading and it increased from 4.8 mm (±0.9) for adding to 5.9 mm (±0.5) for multiplying ($F_{(2,27)}=7.26$, $p<0.01$; effect size: $f=0.73$). For reaction times, the difference between reading and adding the numbers was significant ($t_9=-2.82$; $p=0.02$; effect size: $d=0.49$), while for the average error and average pupil size, no change was observed ($t_9=-1.0$; $p=0.34$ and $t_9=-1.84$; $p=0.09$, respectively). For all three parameters, the difference between reading/adding and multiplying the numbers was statistically significant, as indicated by the ANOVA above (i.e., reaction time ($t_9=-2.82$; $p=0.02$; effect size: $d=0.49$), errors ($t_9=-2.82$; $p=0.02$; effect size: $d=1.83$) and pupil size ($t_9=-2.82$; $p=0.02$; effect size: $d=1.77$) differed for reading and multiplying the numbers; in addition, reaction time ($t_9=-2.82$; $p=0.02$; effect size: $d=1.55$), errors ($t_9=-2.82$; $p=0.02$; effect size: $d=1.84$) and pupil size ($t_9=-2.82$; $p=0.02$; effect size: $d=1.24$) significantly differed for adding and multiplying the numbers). The average pupil responses for the three tasks are shown in Fig. 2.

We calculated separate t-tests for each sampling point in order to compare the average pupil dilation for each task. As expected from the average data above, the pupil response for the reading and adding task only statistically differed for a short period of time, starting approximately 2440 ms after target onset ($t_9=-1.76$; $p=0.04$; effect size: $d=0.52$). Reading and multiplying the presented numbers

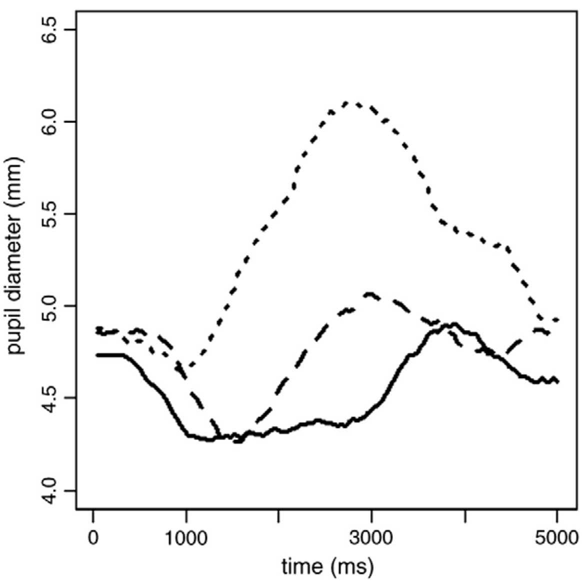

Fig. 2. Average pupil responses during the reading task (solid line), the adding task (broken line) and the multiplication task (dotted line).

began to significantly differ after 1160 ms ($t_9 = -2.45$; $p = 0.02$; effect size: $d = 1.15$), while adding and multiplying began to differ 1360 ms after task onset ($t_9 = -2.65$; $p = 0.02$; effect size: $d = 1.17$; see Fig. 2 for comparison).

3.2. PCA results

Computing the PCA, four factors (or components) with eigenvalues over one were identified. Comparable to Kuchinke et al. (2007), visual inspection of the screeplot revealed that only 3 factors differed from the others; these 3 factors accounted for 81.3% of the overall variance. In a second PCA, with a limiting factor number of 3, the accounted variances were 44% for the first factor, 31.7% for the second factor and 5.6% for the third factor. We plotted the factor loadings after a varimax rotation, where the number of a factor represents its order along the timeline (see Fig. 3). (Note here that we plotted the complete curves of factor loadings with horizontal lines indicating the boarders of factor loadings, which are considered to be “meaningful”. If the interested reader attempts to compare our results with, for example, those of Kuchinke et al. (2007), bear in mind that they only plotted the range from 0.4 to 1. “Cutting” our plot at the border of 0.4 would provide a comparable figure.).

Calculating factor scores (according to the factor loadings for each subject and task) and running both an ANOVA and a Friedman Two-Way-ANOVA (X (df); non-parametric test statistics because of a small N) showed no difference between tasks and components (all $F < F_{(crit)}$; $X < X_{(crit)}$). Thus, the contribution of each component did not differ between the tasks. Nevertheless, the previously reported three-factor structure was evident within our data; therefore, we calculated an ICA on the average response data, assuming three components.

3.3. ICA results

Fig. 4 shows a plot of the corresponding 3 components identified by the *fastICA* algorithm. The *fastICA* provided 3 components for the average pupil response (matrix ***S***) and a mixing matrix (***A***); multiplying $A \times S$ would restore the original data set.

The three components were again named by the order of their peak, e.g., component 1 showed a peak at around 1.5 s after task onset,

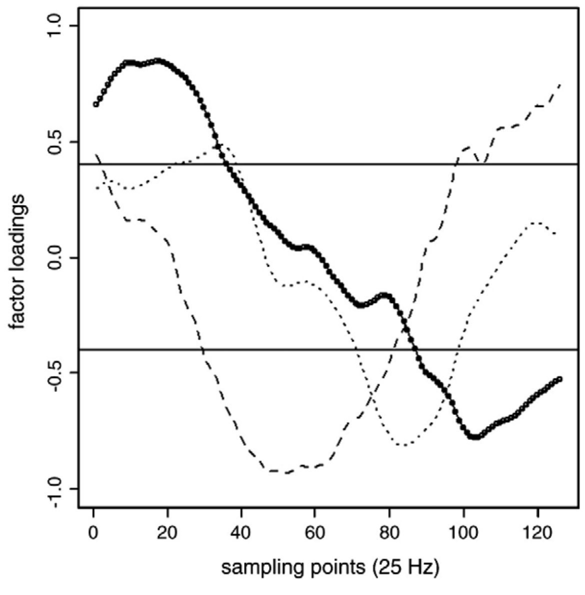

Fig. 3. PCA analysis identified 3 factors, which are named by the order of their peak, e.g., factor 1 (solid line including dots), factor 2 (broken line) and factor 3 (dotted line). Note that for illustration purposes, we fitted a smooth spline to the “raw” factor loadings of the PCA algorithm. Horizontal lines at −0.4 and 0.4 indicate the border of factor loadings, which are considered to be “meaningful”.

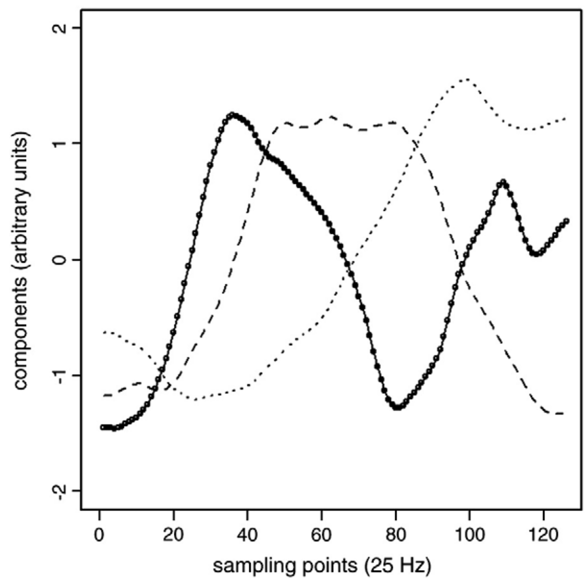

Fig. 4. FastICA analysis identified 3 components, which are named by the order of their peak, e.g., component 1 (solid line including dots), component 2 (broken line) and component 3 (dotted line). Note that for illustration purposes, we fitted a smooth spline to the “raw” component outcome of the fastICA algorithm.

component 2 showed a plateau-like peak from 2 s to 3 s after task onset and component 3 showed a late peak around 4 s (i.e., 1 s before the end of the task).

To disentangle the input of each component into the overall pupil response, we selected each single component (column in matrix ***S***) and multiplied it with the mixing matrix ***A***. As a result, the average input of each component into the pupil response for each task (over time) was plotted (see Fig. 5).

Due to to the largely different slopes of the three components, we did not compare single peak amplitudes across tasks or components.

In order to evaluate the significance of each extracted ICA component, we calculated the percentage of clarified variance (i.e., the variance that is due to each component within the average pupil response) (see Acknowledgements). First, we calculated the sum of squares for the average pupil data for each task (SS_{raw}). Then, as mentioned above, we reprojected each component (as extracted by the ICA) separately into the pupil response for each task (see Fig. 5). Further, we calculated the difference between the reprojected component and the average pupil response for each task. Next, we extracted the sum of square for this difference (SS_{diff}). By calculating $100\ (1 - SS_{diff}/SS_{raw})$, we described the reduction of variance in the pupil response when the component was subtracted from the average response. In other words, the larger the resulting percentage of the component, the more the component contributes to the variance within the average pupil response. Table 1 shows the corresponding percentages of variance. As expected from Fig. 5, component 2 accounted for the largest amount of the variance in the pupil response during the multiplication task.

3.4. Replicating the average ICA component structure for each subject

The ICA provided a component structure based on the average pupil response, excluding the individual trial-by-trial variation for each subject. Taking this into account, we ran a *fastICA* for each subject and restored the individual influence of each component for the three tasks before averaging. Thus, running 10 *fastICAs* (one for each subject) provided three components, which were categorized (by inspection of peak appearance and overall slope) to resemble the corresponding components 1 to 3. Considering the influence of each component during the different tasks, we multiplied each single (individual) component (column in S) with the (individual) mixing

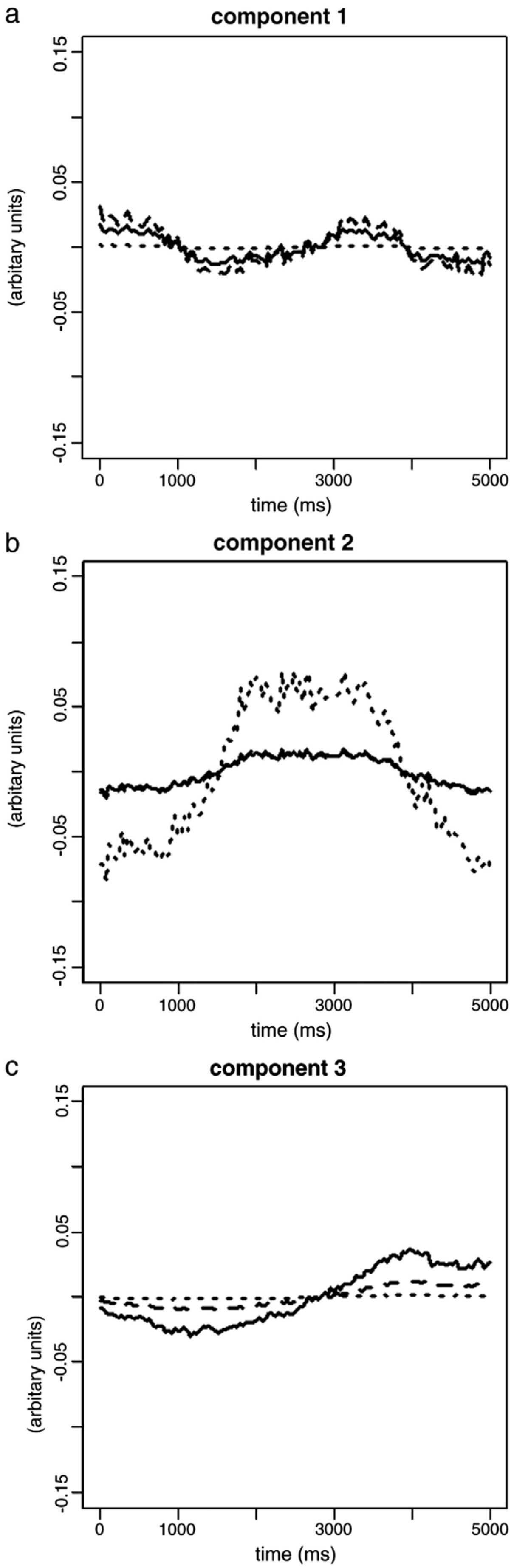

Fig. 5. After multiplying the single components with the mixing matrix A, the influence of each component for each task was plotted. Each component (1 to 3 and a to c, respectively) is plotted over time (in sampling points); the solid line reflects the reading task, the broken line the adding task and the dotted line the multiplying task.

Table 1
Reduction of variance (%) in the average pupil response when the influence of a single component (1, 2 or 3) was subtracted. Note that the sum for each task might be less than 100%; the ICA components are not orthogonal to each other.

		Component		
		C1	C2	C3
Task	Reading	7.1	9.3	65.7
	Adding	39.4	11.3	24.2
	Multiplying	0.7	51.7	0.9

matrix ***A***. This calculation resulted in a data matrix for each subject with columns that reflected the considered component (1 to 3) reprojected into the raw data and varying over time; different tasks were grouped into different column sections of this matrix. Averaging these column sections for a specific task provided the average individual influence of the considered component for the specific subject (comparable to those shown in Fig. 5, but for a single subject).

3.5. Comparing the "energy" of each component

In order to compare these single, individual results across subjects, tasks and components, we calculated an energy (Johannsen, 1976) for each individual component observation as follows:

$$E_i = 1/T * {}_1\sum^T (c_i)^2$$

with

E_i the resulting energy (i reflected the components 1 to 3)
T the sampling points (125 for 5 s with a sampling rate of 25 Hz)
c_i the component value (arbitrary units).

(Note: The resulting energy value was quite small because of the small millimeter-range of pupil changes; thus, we multiplied it by 1000 to ease the graphical and numerical illustration.).

Next, the resulting energy scores were analyzed by running an ANOVA and a Friedman Two-Way-ANOVA (X (df); non-parametric test statistics because of a small N). As expected from Fig. 5, the second component showed the largest increase in energy by changing the task from adding to multiplying relative to the other two components ($F_{(2,27)} = 3.55$, $p < 0.05$; effect size: $f = 0.51$; $X_{(2)} = 7.2$, $p < 0.05$). The same comparison for the other two components remained non-significant (for both: $F < 1$; $X < X_{(crit)}$).

3.6. Comparing the "energy" of component 2 and the error rate

In order to further explore our data, we selected the error rate as a basis for exploration: change in the error rate was strongest due to the task and between subjects, respectively. We speculated that if the components of the pupil response reflect processes induced by the task, one of the components might co-vary with this strong change in error rate. We explored the between-subjects aspect of the increase in error rate for the multiplying task, which was the most demanding task in our experiment and reflected the largest effects. Thus, we used a cluster analysis (statistical package R: hclust including Ward's method for hierarchical clustering) to divide our sample of 10 people into 3 groups of different error rates: low ($N = 3$), intermediate ($N = 2$) and high ($N = 5$) (see Fig. 6a).

Grouping the entire data set accordingly revealed a systematic pattern: the average increase in pupil diameter was largest for high error rates; subjects with intermediate and low error rates did not

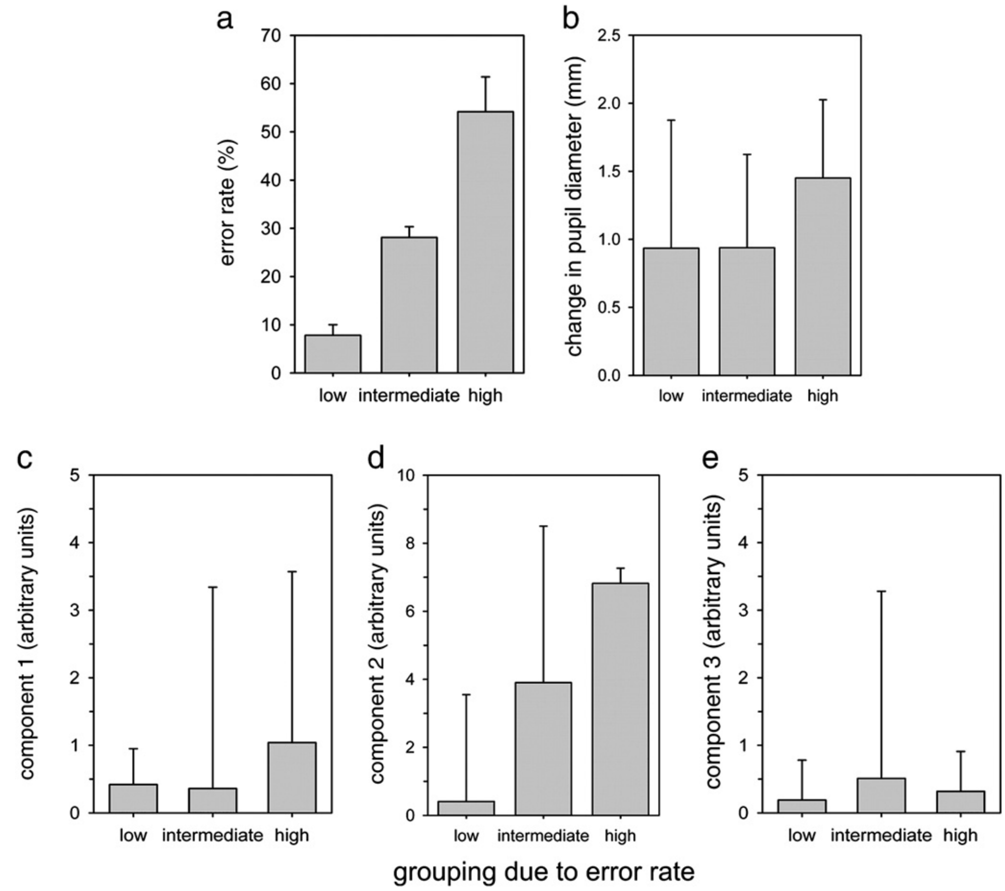

Fig. 6. The sample of 10 subjects was divided according to the average error rate (low, intermediate, and high). Further, we calculated the change in (a) error rate (%) and (b) pupil diameter (mm) when changing the task from reading to multiplying the numbers. Additionally, the changes in energy of the components are shown in (c) for component 1 (arbitrary units), (d) for component 2 (arbitrary units) and (e) for component 3 (arbitrary units).

differ. Additionally, the larger the increase in error, the larger is the increase in the energy in component 2 (see Fig. 6d). While components 1 and 3 showed inconsistent patterns, the gradual increase of errors is well reflected by component 2. The average pupil diameter failed to indicate differences between low and intermediate error rates.

4. Discussion

Even though pupillometry is used to indicate the relative extent of processing demands within a task and between tasks (Beatty and Kahneman, 1966; Heitz et al., 2008; Hess, 1972; Hess and Polt, 1964; Hess and Howell, 1988; Kahneman et al., 1969; Porter et al., 2007; Vo et al., 2008), the difficulty in detecting "cognitive-induced" pupillary responses remains that the pupil also responds to low-level aspects of visual input. We attempted to identify a "hidden" source of cognitive impact within the overall pupil response by calculating an ICA for multiple pupil response data collected while subjects read, added or multiplied numbers. In detail, we aimed to determine whether one component might be selective or sensitive to the variation of the cognitive demand.

First, a set of 3 components were extracted by a PCA run prior to the ICA. Running a PCA first was important in order to define the basic number of components for our ICA analysis and to explore whether our data resembled commonly described factor structures for the overall pupil response. The results of the PCA were comparable to those reported previously (see for example, Kuchinke et al. (2007)). We identified 3 factors (or components), one primarily loaded at the beginning of the task and, therefore, may be correlated to presentation changes at task onset; another factor loaded at the end of the task, eventually monitoring the motorical response or post-processing stages (see, for example, Nuthmann & van der Meer (2005)). Finally, one factor loaded intermediate to the task, eventually reflecting response preparation (Kuchinke et al., 2007) or cognitive demand. For the latter speculation, we would have expected that this factor would have changed with tasks (i.e., to co-vary with reaction times or error rates accordingly); however, in contrast to previous reports for other tasks, these changes did not occur in our data. This might be due to the small sample size. Nevertheless, all factors showed slopes comparable to previous reports, even though the percentage of accounted variance and the factor loadings were a bit smaller for our sample. Regardless of the missing effect due to cognitive demand for the PCA factors, the PCA confirmed a three-component structure within our data. Thus, we calculated an ICA and, first, described the three extracted components across tasks: in parallel to the PCA factors, the first component showed a peak relatively early in respect to the task, whereas the third component showed a peak near the end of the task. Additionally, the intermediate component, the second component, showed a plateau-like peak between 2 and 3 s (on average), which resembled the average range of the reaction times for the three tasks. Similar to the PCA components, we speculated that this component was at least related to response preparation. By visual inspection, the figure of this component (reprojected into the raw data) showed the largest change in amplitude due to the task. Furthermore, we showed that this second component accounted for approximately 50% of the variance within the pupil response for the multiplying task, which was the most demanding task (significantly more errors, longer reaction times and larger pupil sizes) within our experimental design.

Before conducting our study, we speculated about the theoretical differences between PCA and ICA results in terms of pupil responses. As stated in the introduction, the ICA is based on more reasonable assumptions for physiological or biological systems and has been previously utilized in numerous applications in biomedical studies (Abe et al., 2008; Chawala et al., 2008; Hoffmann and Falkenstein, in press; Lei et al., in press; Semmlow and Yuan, 2002; Vigario et al., 2000). As for the vergence step response (Semmlow et al., 2007; Semmlow and Yuan, 2002), we used an ICA to describe “hidden” components within a single data channel, i.e. the pupil response. In this context, our study is a first description of ICA components for pupil responses due to cognitive demands.

In order to further compare the extracted ICA components across tasks and subjects, we calculated ICAs for each subject and replications of the structure were obtained for each individual subject. Then, we calculated an energy value for each trial. This energy value took into account that the three components differed in slope and that a single peak amplitude might underestimate the component, which might have been especially true for component 1 (which had a more periodic curve). As expected from the visual inspection of the component influences co-varying with the task, the second component changed significantly when the task changed from reading/adding to multiplying the presented numbers.

Moreover, in order to understand the reflected process contributing to this change, the closest relationship was described to correspond to the error rate: while changing the task from adding to multiplying, the component's increase in contribution to the overall pupil response was largest in the subgroup of subjects with largest error rates and lowest in the subgroup with the best performance. Pupil data and behavioral data are often described as two sides of the information processing: reaction times and error rates reflect speed and accuracy while pupil responses reflect a measure of the cognitive resources required by the task (Kuchinke et al., 2007; Nuthmann and van der Meer, 2005). In this context, even though we do not attempt to answer the question of the functional background of the 2 other components (components 1 and 3), we speculated that component 2 might reflect the effort (or resource) a subject is engaging to perform a task with greater difficulty. These supposed efforts reached a maximum between 2000 and 3500 ms after target onset. However, it is important to note that these first speculations are purely descriptive in nature and were based on small sample sizes.

In general, the sample size of 10 subjects might limit the statistical power of the analyses and the generalizability of the presented results. The lack of statistical power may account for the lack of significant effects regarding the PCA analysis, while for the ICA analysis, the coherence of the component structure (i.e., the replications of the ICA structure for each individual subject) is evident, as mentioned above.

In sum, while varying the cognitive demand of simple arithmetic tasks without changing low-level aspects, only one component identified by an Independent component analysis (ICA) changed in parallel to the changes in cognitive demand. Our analysis provided a general description of this ICA component and we speculated about a connection to response preparation or engaging additional effort. Further research might show the details of the underlying processes.

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