Proceedings of the
7th Graz Brain-Computer Interface Conference 2017 DOI: 10.3217/978-3-85125-533-1-65

YES OR NO? – BINARY BRAIN-BASED COMMUNICATION UTILIZING MOTOR IMAGERY AND FNIRS

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ABSTRACT: Past research into motor-independent communication for the severely disabled has mainly focused on developing brain-computer interfaces (BCIs) implementing neuroelectric signals. More recently, also hemodynamic brain signals have been explored for BCI purposes. Here, we introduce a novel, straightforward, and easy-to-implement yes/no communication paradigm relying on mental imagery (mental drawing) and portable functional near-infrared spectroscopy. To hemodynamically encode answers to binary questions, participants either performed mental drawing (for encoding "yes") or did not change their mental state (for encoding "no"). Participants' answers were decoded offline using univariate and multivariate statistics. In approximately half of the participants, accuracies reached 70% or higher, which is considered a sufficient performance for binary communication BCIs. As the proposed communication technique requires relatively little cognitive capabilities, it might not only serve as a useful communication means but also as a diagnostic tool for detecting preserved conscious awareness in non-responsive patients.

INTRODUCTION

Communication is an essential element of human interaction. In the so-called 'locked-in' syndrome (LIS) [1], fully aware and conscious patients have lost the ability to naturally communicate due to severe motor paralysis. To help affected patients in this fateful condition, motor-independent communication through brain-computer interfaces (BCIs) has been suggested [2]. BCIs rely on brain signals that an individual can intentionally generate to encode an intention (e.g., to communicate a "yes" or a "no" answer). These brain signals are then measured with a functional neuroimaging method and finally decoded back into their originally intended meaning using signal-classification methods. In the field of BCI an accuracy of at least 70% is considered sufficient for a two-class communication BCI [3]. For almost 30 years now, BCI research has focused on developing communication BCIs using neuroelectric signals mainly based on noninvasive electroencephalography (EEG) [e.g., 4-6]. Though these 'classic' communication BCIs have been applied successfully in affected patients [e.g., 7,8], not all individuals achieve proficiency in EEG-based BCI control (a phenomenon referred to as 'BCI illiteracy' [9]). Thus, there is an urgent need to explore further possibilities for brain-based communication. Recently, hemodynamic brain signals as measured with functional magnetic resonance imaging (fMRI) [10-13] and functional near-infrared spectroscopy (fNIRS) [14-16] have been suggested and tested in this context. For example, our group has developed a letter speller based on differently timed mental-task performance and real-time fMRI that allows convenient back-and-forth communication of any word [17]. The robust letter speller requires almost zero pre-training or preparation time and can be of great benefit for short-term communication. However, the fMRI-based BCI approach is costly and tied to clinical or research institutions making it unsuitable for everyday-life usage. A primary need of LIS patients and their families, however, is immediate access to and frequent use of BCI communication. FNIRS is a functional neuroimaging method that relies on the same (hemodynamic, i.e., vascular) brain response as fMRI [18]. While being spatially less specific than fMRI, fNIRS is relatively easy to apply, inexpensive, safe and, most importantly, portable [19]. These factors open the possibility to transfer the developed fMRI communication paradigms to the more compact and portable fNIRS technology, making fNIRS an ideal candidate for future daily-life application. Due to its straightforward implementation it could be readily handled maybe even by the patient's care givers.

 DOI: 10.3217/978-3-85125-533-1-65

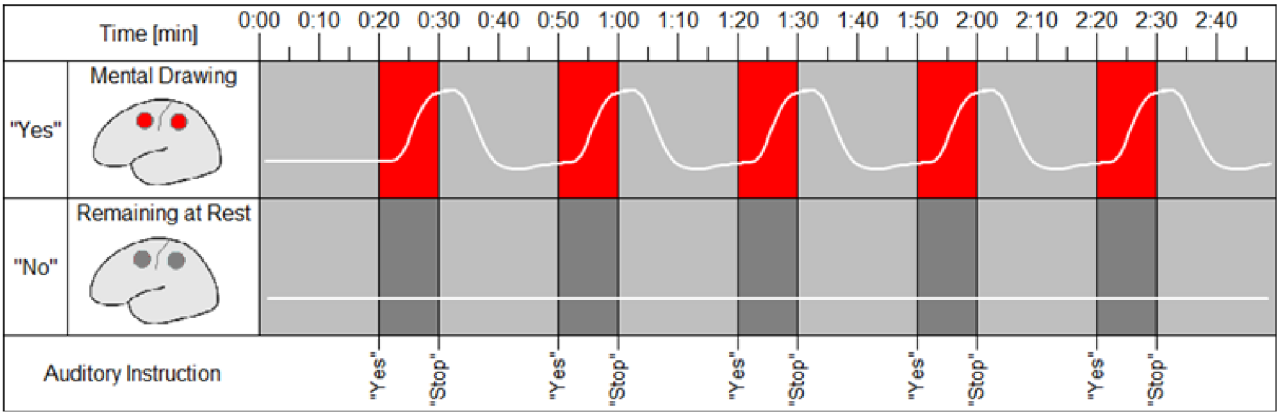

Figure 1: Encoding scheme for an answer-encoding run including expected oxyhemoglobin changes (white curve/line) in motor imagery-related brain regions. When a participant wants to encode "yes", he/she performs motor imagery causing oxygenated hemoglobin to rise. When a participant wants to encode "no", he/she stays at rest causing no relative change in oxygenated hemoglobin. Note that participants encoded the same answer five times in one run.

Here, we suggest a novel, straightforward yes/no communication procedure employing mental imagery and fNIRS. In our suggested procedure, participants performed two localizer runs, one at the beginning of the experiment and one at the end. Each of these runs consisted of twenty 10 s periods of mental-task performance that alternated with twenty-one 20 s baseline blocks, adding up to 10 min 20 s per run. Between localizer runs, six answer-encoding runs were performed, during which participants were asked to answer biographical questions (e.g., "Do you live in Maastricht?") by intentionally modulating their brain activation. For encoding "yes", participants were asked to start mental drawing as soon as "yes" was aurally presented and to halt mental-task performance as soon as "stop" was presented. For encoding "no", participants were asked to stay at rest for the whole length of the run. Each answer-encoding run consisted of five 10 s answer-encoding trials, alternated with six 20 s baseline periods, adding up to 2 min 50 s (Fig. 1). Participants' brain responses were decoded offline.

MATERIALS AND METHODS

Participants: Twenty healthy subjects (nine female, three left-handed, age = 26.0± 8.0 years [mean ± SD], all with normal or corrected-to-normal vision and reportedly normal hearing) participated in the study. Tab. 1 documents individual participants' characteristics. All participants gave written informed consent according to procedures approved by the local ethics committee and received financial compensation.

Mental-drawing paradigm: To intentionally evoke fNIRS signals, participants were instructed to: "Imagine drawing simple geometric figures (such as circles, triangles, cubes, etc.) or small contour drawings (e.g., a butterfly, star, car, tree, boat, or house) with the right hand at a comfortable but consistent speed. Imagine using a pen. This might support your imagination."

Participant preparation: Prior to the experiment, participants were familiarized with the general procedure of the study. They shortly practiced mental drawing and answer encoding until they felt comfortable (ca. 15 min). Moreover, a list of 45 binary biographical questions, simple yet unobtrusive enquiries about their lives, was provided. Six of those questions were selected by an independent experimenter: three to be answered with "yes" and "no", to assure equal distribution of answer options. After placement of the cap with the fNIRS optodes, participants were seated comfortably in a noise-dimmed cabin, which was equipped with a loudspeaker and microphone to enable verbal communication between participant and experimenter during the experiment.

Data acquisition: Self-induced hemodynamic brain signals were obtained using a NIRScout-816 system (NIRx Medizintechnik GmbH, Berlin, Germany) equipped with six detector and three source optodes (LEDs emitting wavelengths of both 760 nm and 850 nm). Sources were positioned according to the international 10-20 EEG system on FC3 (1), C3 (2) and CP3 (3) and detectors were positioned on FC5 (1), C5 (2), CP5 (3), FC1 (4), C1 (5) and CP1 (6) (Fig. 2).

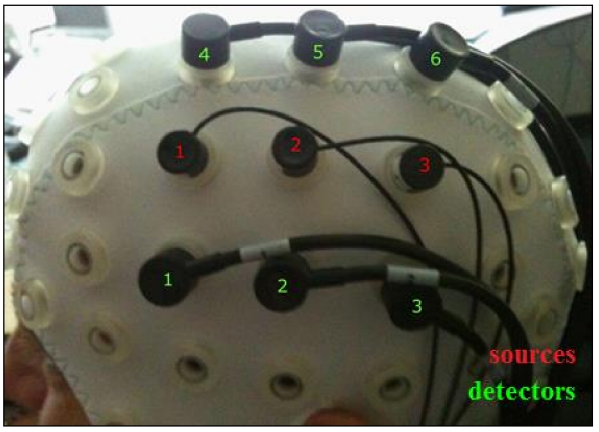

Figure 2: fNIRS optode set-up with the source optodes in red (optodes 1, 2 and 3 in the middle horizontal line) and detector optodes 1-6 in green.

This limited number of optodes was chosen to ensure clinical applicability (i.e., reasonable optode-placement time allowing for rapid bedside measurements of patients). Recorded optical signals were sampled at a rate of 12.5 Hz. Due to the limited number of sources and detectors, the optodes' montage covered a confined

 DOI: 10.3217/978-3-85125-533-1-65

area above the left-hemispheric fronto-parietal (sensorimotor) cortex (Fig. 2). Auditory stimuli were presented using in-house stimulation software [20].

Subjective ratings: After each run, participants rated the experienced fNIRS comfortability according to a Likert-scale ranging from 0 (extremely uncomfortable) to 10 (extremely comfortable). We predicted that comfortability ratings would decrease over time. After completion of the experiment, the participants rated the general easiness and pleasantness of the employed mental-imagery paradigm (mental drawing) again using a Likert-scale ranging from 0 (extremely difficult/unpleasant) to 10 (extremely easy/pleasant).

Data analysis: FNIRS time series were analyzed using Satori (v0.92, Brain Innovation B.V., Maastricht, The Netherlands). During preprocessing, raw data time course values were converted to oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) values. Linear trend removal, temporal low-pass filtering (Gaussian full width at half maximum [FWHM]: 40 data points) and high-pass filtering (cut-off: 10 cycles [localizer runs] or 2 cycles [answer-encoding runs] per time course) were applied. These filtering parameters correspond approximately to a band-pass filter of 0.1-0.016 Hz for the localizer runs and 0.1-0.012 Hz for the encoding runs. The subsequent data analysis was focused on the 14 'direct-neighbor' channels (i.e., channels emerging from sources-detector combinations of close proximity; see Fig. 3). Two types of analyses were conducted: univariate general linear model (GLM) analysis and multi-channel pattern (MCP) analysis.

(1) GLM analysis. First, a single channel of interest was determined individually for each participant using the data of the first localizer run (called 'best channel' in the following). For this purpose, channel-wise (whole-run) GLM analysis was performed separately for oxy- and deoxy-Hb time series using a predictor corresponding to the motor-imagery condition and applying the statistical contrast "motor imagery vs. resting". For selecting the best channel we calculated a criterion value by averaging the obtained oxy-Hb and deoxy-Hb t-values per channel. The channel with the highest criterion value was considered the best channel and selected for further analysis. As a next step, the data of the first "yes" and "no" answer-encoding run per participant was analyzed as follows: For each of the ten trials (five "yes" and five "no" trials) the individual criterion value was calculated. Then, a mean across these ten individual criterion values was computed. This average value was used as 'cut-off' value for decoding the answers of the remaining four answer-encoding runs. Values above or below the cut-off value resulted in decoding the answer-encoding data as "yes" or "no", respectively. Encoded answers were compared post hoc to the actually intended answers given by the participant. Next to individual and group-mean single-trial (ST) accuracies, we computed multi-trial (MT) accuracies for each individual and for the group. Multi-trial accuracies were derived by integrating the five separate yes/no decisions per run using majority voting (e.g., three answers encoded as "yes" and two answers encoded as "no" were considered as a "yes" answer). Resulting single-trial accuracies were evaluated in a confusion matrix per participant using a Chi square test to assess if decoding accuracies were significantly above chance level ($p < 0.05$).

(2) MCP analysis. MCP analysis was conducted using a support vector-machine as classifier [21]. For this analysis, all channels (n = 14) were used to define the spatial features for the MCP analysis. In order to 'train' (and 'test') the classifier, means of raw values for oxy- and deoxy-Hb were estimated in a time window from 6 s to 17 s after trial onset of the mental drawing trials. This window was defined for the mental drawing trials as it corresponds to the time points where the mean hemodynamic response was expected to be the highest. For the rest conditions an 11 s time window was chosen from 11 s to 22 s after trial onset of the rest conditions, during which the mean hemodynamic response is expected to be at baseline. The single-trial data of the two localizer runs served as training data. Analysis of the six answer-decoding runs resulted in five single-trial predictions (corresponding to the five separate answer-encoding trials) per run. As in the GLM approach, each prediction was compared to the actual answer given by the participant. Again, mean single- and multi-trial accuracies were calculated individually and for the group as described above for the GLM approach. Resulting single-trial accuracies were tested for significance ($p < 0.05$) using permutation tests (10.000 permutations). For both the GLM and MCP analysis, the average sensitivity – P(yes decoded | yes encoded) – and specificity – P(no decoded | no encoded) – was calculated. Correlations were run between the single-trial and multi-trial accuracies of both approaches.

Means and SEs will be calculated with the subjective ratings.

RESULTS

GLM analysis: For each subject, a best channel could be selected based on the procedure described above (see Tab. 1 for selected channels and individual criterion values). Fig. 3 illustrates how often each channel was selected across participants. Using the GLM approach, participants' answers could be decoded correctly with an average accuracy of 64.25% on a single-trial basis (theoretical chance level being 50%). Individual single-trial accuracies varied from 35.00-95.00% (Tab. 1). In eight participants, single-trial accuracies were significantly above chance level as assessed with a Chi-Square test (Tab. 1). The classifier showed no bias, as "yes" and "no" answers were decoded respectively on 50.25% and 49.75% of the 400 trials. The average sensitivity was 65.00% and the average specificity was 65.50%. On a group level, the multi-trial accuracy was 65.00%. Individual multi-trial accuracies varied from 25.00-100.00% (Tab. 1). For the group of nine subjects with individual single-trial accuracies of 70% or higher, the average single-trial

 DOI: 10.3217/978-3-85125-533-1-65

accuracy was 79.44% (SE = 2.82), whereas their average multi-trial accuracy was 84.09% (SE = 4.20). For the eleven other subjects, the average single-trial accuracy was 51.82% (SE = 2.88), whereas their average multi-trial accuracy was 47.73% (SE = 5.28).

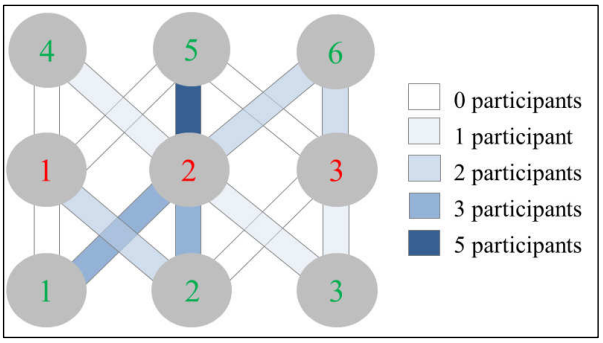

Figure 3: Frequency of best-channel selections within the GLM approach. The red and green numbers indicate source and detector optodes, respectively. Note that the most frequently selected channels correspond to brain areas [22] commonly associated with motor imagery.

MCP Analysis: Using the multi-variate approach, participants' answers could be decoded correctly from single trials with an average accuracy of 62.33%. Individual single-trial accuracies ranged from 33.33-76.67% (Tab. 1). In eleven subjects, single-trial decoding accuracies were significantly above chance level as revealed by permutation tests (Tab. 1). "Yes" and "no" answers were decoded respectively on 62.00% and 38.00% of the 600 trials. The sensitivity was 75.67% and the specificity was 51.67%. The multi-trial accuracy was 63.33% on the group level and individual multi-trial accuracies ranged from 33.33-100.00% (Tab. 1). When focusing the analysis on the ten subjects with single-trial accuracies of 70% or above, the single-trial accuracy was 72.33% (SE = 0.87), whereas the multi-trial accuracy was 85.71% (SE = 2.38). For the group of ten subjects with individual single-trial accuracies below 70%, the average single-trial accuracy was 52.33% (SE = 3.06), whereas their average multi-trial accuracy was 59.09% (SE = 7.22).

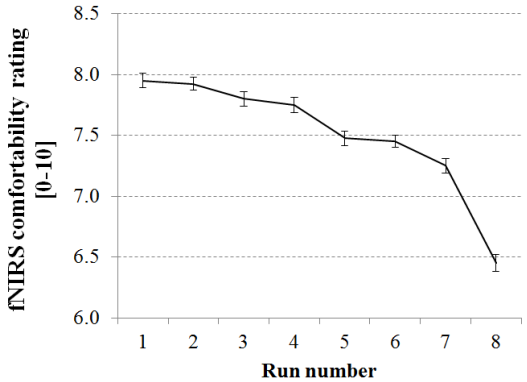

Figure 4: FNIRS comfortability ratings (group means and SEs) across runs. Values range from 0 (extremely uncomfortable) to 10 (extremely comfortable). Note that the first and eighth run were localizer runs.

Subjective ratings: FNIRS comfortability ratings were medium to high (see group means in Fig. 4). Comfortability decreased across time and dropped considerably for the last run (second localizer). Participants generally experienced the mental-drawing task as pleasant (M = 7.2, SE = .07) and easy to perform (M = 8.0, SE = .07).

Accuracy correlations: Correlations between the accuracies of the different approaches were all insignificant ($p > .05$): GLM MT and MCP MT ($r = .21$); GLM ST and MCP ST ($r = .36$).

DISCUSSION

A novel yes/no communication paradigm using mental drawing and fNIRS was tested in healthy participants. In LIS patients an fNIRS-based binary BCI has been tested recently [15,16]. However, in those studies a classifier was trained for several sessions over several days. The current approach has the potential of enabling immediate communication in the order of ca. 30 min (±15 min training; ±10 min localizer, ±6 min encoding). Of course, this should be tested using real-time decoding and in affected patients. We deem this will be successful as Naito et al. [14] found an accuracy rate above 75% in 23 out of 40 LIS patients with their fNIRS-based binary BCI using mental calculation/singing. Our results indicate that it is possible to obtain sufficiently high (≥ 70%, [3]) and reliable answer-decoding accuracies in healthy subjects by using the current paradigm and various data-analyses methods. On average, multi-trial accuracies were only marginally higher than single-trial accuracies. However, when focusing on participants reaching an accuracy of 70% or higher, there is a trend for multi-trial accuracies to be higher than single-trial accuracies in both GLM and MCP analysis. Closer inspection of these participants' data indicated relatively prominent hemodynamic responses, suggesting that the multi-trial approach is most advantageous when single-trial measurements have a sufficiently high signal-to-noise ratio.

The GLM approach might be particularly suited in the context of a communication BCI due to its simplicity. We expect that at least some LIS patients are also able to use the binary BCI presented here, as accuracies of 70% or higher were reached by approximately half the participants after a mere 15 min of training. Since our communication BCI relies on only a single fNIRS channel, preparation time can in principle (when having determined the best channel in a previous fNIRS session) be rather short. The similar sensitivity (65.00%) and specificity (65.50%) emphasizes that there is no bias to either "yes" or "no". The MCP approach might be especially useful in the context of detection of remaining consciousness in non-responsive patients because in contrast to the GLM approach, it does not require the calculation of a yes/no cut-off value. Nevertheless a localizer containing differential activity (mental imagery vs. rest) is still required to train the classifier, which might not be easily obtained in this

 DOI: 10.3217/978-3-85125-533-1-65

patient group. Encouraging is the high specificity (75.67%) of this approach. In three of the four cases in which participants intentionally changed their brain states, this change was detected.

The two data-analysis approaches differ in the number of subjects reaching a level of significance (9 in the GLM vs. 11 for the MCP approach; see Tab. 1). In addition, GLM analysis accuracies do not correlate significantly with any of the MCP analysis accuracies. However, comparison of the two methods is hampered by several fundamental differences: (1) In the GLM analysis, the data from only one channel was considered, whereas all channels are considered in the MCP analysis. (2) In the MCP analysis, more single-trials could be considered, resulting in a higher chance of getting significant results. (3) Due to the fundamentally different nature of both approaches, different significance tests were employed (Chi-square vs. permutation testing).

A general shortcoming of our study, affecting both the GLM and MCP analysis accuracies, is the absence of localizer data for the "no" condition. As there was no separate localizer to identify signal characteristics while participants do not change their brain state, the training data for encoding "no" answers was selected as the time window in the end of the resting period after each task performance. Obtaining proper localizer data for the "no" condition should be done it future experiments, albeit this would be at the cost of additional measurement time.

We noted large differences between individual participants' classification accuracies: some participants performed exceptionally well whereas for others classification accuracy was at chance level. Blood pressure, respiration and heart rate are known to influence the fNIRS signal [23]. Future studies taking into account these physiological measures may filter out such influences in order to improve the contrast-to-noise ratio of the fNIRS measurements. Moreover, given the very short training period, participants with chance-level performance may be retested after providing them with additional training.

We monitored comfortability over time and measured perceived easiness and pleasantness, as it is known that subjective motivation can influence BCI performance [24, 25]. Comfortability ratings across the experimental session decreased slightly with a drop in the last run. This could be due to the fact that performing a localizer run after the answer-encoding runs was experienced as comparatively boring. Overall, application of our BCI in affected patients is encouraged by the fact that our participants gave overall positive easiness and pleasantness ratings.

Table 1: Participant characteristics, subjective rating, channel selection and classification results.

			MD SR				*GLM accuracies*		*MCP analysis accuracies*	
P	*H*	*S*	*E*	*P*	*BS*	*Crit.*	ST (%)	MT (%)	ST (%)	MT (%)
1	R	M	8	7	2-4	16.69	75.00°	75.00	53.33*	66.67
2	R	F	9	8	2-5	5.28	55.00	50.00	33.33	33.33
3	R	F	10	10	3-3	101.44	70.00	75.00	70.00*	66.67
4	R	M	9	8	2-5	313.42	95.00°	100.00	76.67*	83.33
5	R	F	8	7	1-2	291.52	75.00°	75.00	70.00*	66.67
6	L	M	4	6	2-1	44.25	60.00	75.00	56.67	50.00
7	R	F	9	9	2-2	90.16	60.00	50.00	73.33*	100.00
8	R	M	7	6	3-6	71.26	45.00	50.00	53.33	50.00
9	R	M	7	7	2-1	177.18	70.00	75.00	76.67*	83.33
10	R	F	8	9	2-5	90.60	40.00	25.00	70.00*	66.67
11	R	F	6.5	6	2-3	73.27	60.00	50.00	66.67	66.67
12	R	F	7.5	5	1-2	26.03	45.00	25.00	63.33	83.33
13	R	M	6	4	2-6	2.59	85.00°	100.00	43.33	33.33
14	R	F	9	8	2-5	85.33	55.00°	75.00	70.00*	66.67
15	R	M	10	8	2-2	44.18	75.00°	100.00	73.33*	83.33
16	R	M	8	6	2-2	49.52	85.00°	100.00	73.33*	83.33
17	R	M	9	8	3-6	35.18	65.00	50.00	56.67	83.33
18	L	M	8	8	2-6	24.08	35.00	25.00	46.67	16.67
19	L	M	8	7	2-5	114.92	50.00	50.00	50.00	33.33
20	R	F	8	7	2-1	58.75	85.00°	75.00	70.00*	50.00
Mean			7.92	7.20			64.25	65.00	62.33	63.33
SE			.07	.07			3.72	5.56	2.77	4.93

Notes. P = participant, H = handedness, R = right, L = left, S = sex, M = male, F = female, MD SR = mental drawing subjective rating, E = average easiness rating across runs, P = average pleasantness rating across runs, BS = best channel, Crit. = Criterion, ST = single trial, MT = multi-trial, ° $p < .05$ based on Chi-Square, * $p < .05$ based on permutation testing.

 DOI: 10.3217/978-3-85125-533-1-65

CONCLUSION

The presented yes/no communication procedure using fNIRS and mental imagery might constitute a useful communication means for LIS patients. Moreover, as the suggested encoding paradigm requires relatively little effort from individuals, it has potential as a diagnostic means to detect preserved conscious awareness in non-responsive patients.

ACKNOWLEDGEMENT

This work was supported by the European Commission (7th Framework Programme 2007-2013, DECODER project) and the Netherlands Organisation for Scientific Research (Research talent grant 406-15-217 to L.N.-C.).

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