# EXTRACTION OF COGNITIVE ACTIVITY RELATED WAVEFORMS FROM FUNCTIONAL NEAR INFRARED SIGNALS

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## ABSTRACT

*We address the problem of prototypical waveform extraction from functional near infrared spectroscopy (fNIRS) signals in cognitive experiments. Extracted waveforms represent the brain hemodynamic response (BHR) to visual stimuli provided in an oddball type experimental protocol. We use and evaluate two statistical signal processing tools, namely independent component analysis (ICA) and waveform clustering, in a comparative manner. Based on the conformance to a parametric BHR model, we determine that the ICA waveform extraction method is superior. We measure and comment on the intra-subject and inter-subject waveform and parameter variability.*

## 1. INTRODUCTION

Most neuroimaging studies involve single-event trial cognitive or motor stimulation studies. They are invariably based on the blood oxygen level dependent (BOLD) signal, and the main instrument to analyze these signals has been functional magnetic resonance imaging (fMRI). In the fMRI approach the signals have been decomposed into their relevant components [1, 2] and their parameters estimated with a view to quantify physiological responses and neurovascular coupling within brain [1-3].

An alternative to BOLD-fMRI signal is the hemoglobin (Hb) and the oxyhemoglobin ($HbO_2$) signals captured via functional near infrared spectroscopy (fNIRS). fNIRS measurements determine the concentrations of hemoglobin agents based on a modified version of the Beer-Lambert law [4]. A recent study has demonstrated that strong correlations exist between BOLD-fMRI data and diffuse optical $HbO_2$ data [5]. In other words, functional neuroimaging studies performed by both fMRI and fNIRS methods confirm that the increase of regional cerebral blood flow towards activated areas exceeds the regional oxygen consumption, and hence the signal pattern observed in the BOLD response resembles the $HbO_2$ signal of fNIRS [4,5].

In this paper, we propose a framework to process the event-related fNIRS signals evoked during a target categorization task via hypothesis-driven data analysis methods. The data consist of time-series of the $HbO_2$ signal samples that are obtained from optical absorption measurements. Our goal is to decompose these signals into their source components, conjectured to be consisting of: (i) cognitive activity related component, that is, the brain hemodynamic response; (ii) baseline physiological component; (iii) all other nuisance factors such as noise, movement artifacts and higher frequency components. To these ends, we test two statistical signal-processing tools, namely independent component analysis (ICA) and waveform clustering as presented. Then we use a model-guided identification method for extracting the brain hemodynamic response, in that the identified sources are sorted with respect to their conformance to the so-called Gamma model waveform. Such a model-based approach has been proposed in fMRI studies, where time-averaged BOLD responses have typically yielded a bell-shaped curve skewed towards its falling side. These curves could conveniently be modeled by a Gaussian, Gamma, or Poisson function [1, 2]. These issues are addressed in Section 2. In Section 3, we present the results of both ICA and waveform clustering approaches. In Section 4, we discuss our findings and draws conclusions for further research on fNIRS signal analysis.

## 2. WAVEFORM EXTRACTION

Most of the techniques to estimate and extract cognitive activity-related waveforms from evoked responses are based on coherent averaging. In this work, we intend to extract brain hemodynamic waveforms using two newly proposed non-parametric waveform estimation techniques, namely, independent component analysis and waveform clustering. We assume that the cognitive hemodynamic waveforms are embedded within a background activity, including respiration and heartbeat artifacts as well. Furthermore, we assume that time span of the evoked BHR is approximately known so that we can operate on the computed $HbO_2$ data from the inter-stimulus intervals. The measurements are multi-site in that they are taken from the prefrontal cortex using an array of sensors, and they are multi-session in that, repetitive stimuli and time-uncorrelated measurements are taken. The extracted waveforms from the two non-parametric methods (ICA and clustering) are validated based on the conformance to a known parametric waveform model, namely the Gamma model. In this sense, we follow an "informed" non-parametric approach.

### 2.1 Independent component analysis approach

We assume that the short-time fNIRS signal can be projected onto a basis in which each direction stands for different neurophysiological changes, such as background activity, cognitive responses, respiration and heartbeat artifacts, etc. Furthermore, we hypothesize that the components along the basis vectors, i.e., the contributions of each activity to the fNIRS signal, are statistically independent. The recorded data form a multivariate time-series since we record fNIRS signals from several channels (detectors on the frontal lobe) for the duration of the experiment that contains multiple trials.

ICA uses higher-order statistical information to find a suitable basis in such a way that the statistical independence between the projections of the signal onto these basis vectors is maximized [6]. In contrast, principal component analysis (PCA) uses only second-order statistics to separate a signal into uncorrelated components. We have observed that PCA falls short of extracting the brain hemodynamic response and hence we do not consider it in this work. Let $\mathbf{x}$ be an $m$-dimensional observation vector, $\mathbf{x}=[x(i)], i=1,...,m$, where each component represents one of the measured $m$-time samples starting right after the presentation of a cognitive stimulus or a target. A cognitive stimulus may be a special visual pattern appearing on a screen, or a particular sound presented randomly or periodically. The observation vectors $\mathbf{x}$ can be obtained in time succession from a single detector, as the targets are presented, and/or from different detectors. These different sample vectors will be indexed by the subscript $k$ and denoted as $\mathbf{x}_k$. In ICA, we find a linear transformation **A,** according to the generative model $\mathbf{x}=\mathbf{A}\mathbf{s}$, where the $n$ columns of the matrix $\mathbf{A}$ constitute a basis spanning the observation vector space and where $\mathbf{s}=[s_j], j=1,...,n$, are the vectors of coefficients. A coefficient $s_j$ quantifies the contribution of the $j^{\text{th}}$ basis vector ($j^{\text{th}}$ column of $\mathbf{A}$) to the observation vector $\mathbf{x}$. Any two such coefficients $s_k$ and $s_l$ are assumed to be statistically "as independent as possible", for $k \neq l$. The matrix $\mathbf{A}$ is the $m \times n$ basis matrix. This decomposition operation must be effected based solely on the information given by the multivariate dataset $X=\{\mathbf{x}_k\}_{k=1}^{K}$ that consists of $K$ realizations of the random vector $\mathbf{x}$. These multiple realizations are obtained from different target presentation epochs on the same detector and/or from different detectors. The columns of the matrix $\mathbf{A}$ are said to form an ICA basis suitable for representing the multivariate observations. Rewriting the generative model as

$$\mathbf{x}=\begin{bmatrix} x(1) \\ \vdots \\ x(m) \end{bmatrix}=\begin{bmatrix} & & \\ \mathbf{a}_1 & \cdots & \mathbf{a}_n \\ & & \end{bmatrix}\begin{bmatrix} s_1 \\ \vdots \\ s_n \end{bmatrix}=\mathbf{a}_1 s_1+\cdots+\mathbf{a}_n s_n \ , \qquad (1)$$

the data vector $\mathbf{x}$ is expressed as a linear combination of the columns of $\mathbf{A}$, where the weights $s_j$ are the independent components and the set $\{\mathbf{a}_j\}_{j=1}^{n}$ forms the basis vector set. Obviously, there will be $K$ of the vectors $\mathbf{s}_k=[s_{jk}]$, $j=1,...,n$ one for each measurement vector $\mathbf{x}_k$. The set of ICA basis vectors $\{\mathbf{a}_j\}_{j=1}^{n}$ correspond to, in our case, hopefully to cognitive activity related waveform, background activity and other artifacts.

### 2.2 Clustering Approach

We explored an alternative waveform extraction method, namely smoothing the fNIRS-$HbO_2$ waveforms with B-splines and then clustering the B-spline coefficients. The cluster centroids represent the most commonly occurring waveforms, among which we expect to find the cognitive response.

*Spline smoothing*: The B-spline approximation is useful in putting into evidence the functional nature of the data and in eliminating irrelevant high-frequency noise [8]. It is also known to have superb summarizing property for the waveforms by just using a few coefficients. Thus we first computed, for all $m$-component vectors $\mathbf{x}_k$ in a given dataset $X$, the corresponding B-spline approximation coefficients $\mathbf{y}_k$ of dimensionality $m' \leq m$.

*Clustering*: The B-spline feature set $Y=\{\mathbf{y}_k\}_{k=1}^{K}$ is input to a clustering algorithm. We form $n$-clusters $Q=\{Q_c, \mathbf{q}_c\}_{c=1}^{n}$, where $\mathbf{q}_c$ is the centroid of the cluster $Q_c$ in order to explore the presence of cognitive response. We adopt an agglomerative clustering approach [7], where we start with singleton clusters, $\mathbf{y}_k$ (hence as many clusters as the $K$ data points), and then group them to form the $n$ clusters $Q_c$. To avoid any confusion, we point out that both $K$'s (in ICA and waveform clustering) refer to the number of observation vectors (or realizations). In the waveform clustering approach, we project an observation vector $\mathbf{x}$ (of dimension $m$) to a basis spanned by $m'$ B-splines to obtain its representation in terms of B-spline coefficients $\mathbf{y}$ (of dimension $m'$). For the distance metric, we use the *one-minus-the-normalized correlation coefficient*, which is defined by

$$d(\mathbf{y}_k, \mathbf{y}_l)=1-\langle \mathbf{y}_k, \mathbf{y}_l \rangle / \|\mathbf{y}_k\| . \|\mathbf{y}_l\|, \qquad (2)$$

and where the vectors $\mathbf{y}_k$, $\mathbf{y}_l$ are centered (zero-mean) and $\|\cdot\|$ represents the Euclidean norm of a vector. As for similarity criterion, we adopt the *average linkage* criterion, such that the pair of clusters with minimum average distance between their elements is merged at each step till we reach the goal number of clusters. The dendrogram organization of the vectors $\mathbf{y}_k$ is finally pruned in order to get the $n$-cluster set $Q$. It may turn out that none of the centroids resembles the model Gamma waveform. This can be due to the absence of any cognitive activity-related waveform or due to the weak evidence submerged in heavy baseline activity.

### 2.3 Model guided selection of waveforms

Both the ICA algorithm and the waveform clustering approach outputs $n$ waveforms, and there exists some ambiguity as to which ones, if any, of these waveforms correspond to the cognitive activity. This ambiguity can be resolved by considering the conformance of the waveforms to a brain hemodynamic response model. This has been the common practice in fMRI studies [1,2]. Note that ICA does not provide a natural ordering of the independent components [6], as for example PCA. Second, independent components can be estimated up to a sign [6], and to remedy it we allow for polarity reversals in estimated components. In waveform clustering approach, the centroid of the most populated cluster does not automatically correspond to the brain hemodynamic response, but instead it may be modeling some baseline activity. In other words, a conformance-based selection is also necessary in the clustering approach. The response model is the Gamma function (see Figure 1) defined as

$$h(t) = \begin{cases} B(t-T)^2 e^{-(t-T)/\tau} & \text{for } t \geq T \\ 0 & \text{for } t < T \end{cases}, \qquad (3)$$

where $\tau$ is the time-constant that characterizes the reaction duration, $B$ is the strength parameter and $T$ is the delay in responding to the target stimulus. Let $\mathbf{h}$ be the vector with $i^{\text{th}}$ component $h(iT_s)$, $i = 1,...,m$, the periodic samples of the model waveform in (3). Any one of the identified components (say, the $l^{\text{th}}$ ICA basis vector or the $l^{\text{th}}$ cluster centroid) $\mathbf{a}_l = [a_l(i)], i = 1,...,m$ (for $l = 1,...,n$ in ICA or in waveform clustering), is qualified according to its matching degree to the waveform in (2), after that the parameters $B$, $T$ and $\tau$ have been estimated. Given the $l^{\text{th}}$ estimated vector $\mathbf{a}_l$ (by ICA or waveform-clustering), the $B_l, T_l, \tau_l$ parameters are estimated by a mean squared error procedure, i.e.,

$$\{B_l, T_l, \tau_l\} = \underset{B,T,\tau}{arg\,min} \sum_{i=1}^{m} [a_l(i) - h(i; B, T, \tau)]^2 \qquad (4)$$

so that we obtain $h_l(i) = h(i; B_l, T_l, \tau_l)$, $i$=1,…,$m$. Notice also that $B$ is allowed to take negative values as well for ICA, in order to be able to account for the ambiguous sign of the ICA basis vectors, while for waveform clustering, there is no such need. We set an upper limit to the reaction delay $T$, that is ~2-3 secs, and similarly the time constant $\tau$ is constrained to be in the range of (1, 4). This signifies that the elapsed time between the 10 percent rise and decay instances of the BOLD signal have durations between extremes 6.5 to 25.9 seconds. Each of the estimated vectors $\mathbf{a}_l$, ($l = 1,...,n$) is qualified as representative of the brain hemodynamic response based on its correlation with the model $\mathbf{h}_l$ whose parameters are estimated as in (4). The waveform with index $l$ possessing the highest normalized correlation coefficient, provided this correlation is above a threshold, is declared as the cognitive activity related waveform.

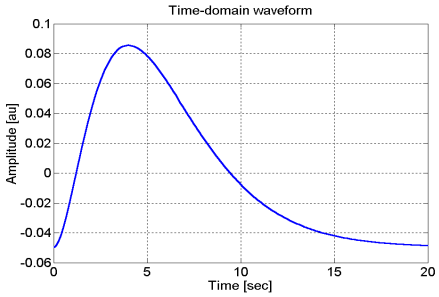


Figure 1 - Gamma model waveform, $B$=1/($\tau^3$), $T$=0, $\tau$=2, signal is mean-removed

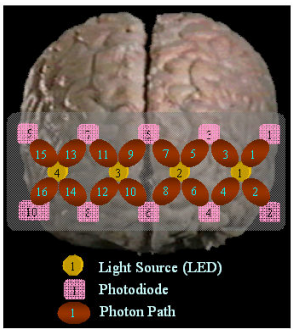


Figure 2 Source-detector configuration on the brain probe and nomenclature of photodetectors

## 3. EXPERIMENTAL RESULTS

### 3.1 fNIRS data

Data were collected at two different sites: MCP Hahnemann University - Eastern Pennsylvania Psychiatric Institute (EPPI); Drexel University and Biophotonics Laboratory, Bogazici University, Istanbul, Turkey. Both systems house a probe that contains four LED light sources each emitting at three near infrared wavelengths and twelve photodetectors. This setup, with the time and wavelength-multiplexing, ends up with four non-overlapping quadrants of photodetectors as depicted in Figure 2. In other words, the detectors (optodes) are grouped into quadrants according to their anatomic location over the forehead. Each quadrant consists of 4 receiving optodes separated 2.5 cm from the source positioned in the middle of each quadrant. Hence in one scan of the forehead a total of sixteen measurements at each wavelength can be acquired totaling to 48 three-band optic signals.

The source and detectors are equidistantly placed on the probe as seen in Figure 2. At the center of every quadrant, a photon source emits light at three different wavelengths, namely 730 nm, 805 nm and 850 nm. It is possible to compute the Hb and $HbO_2$ concentration changes based on modified Beer-Lambert Law explained elsewhere [4, 5].

*Task Procedure*: The procedure consists of simple discrimination task, or "oddball" paradigm, in which subjects are presented with two stimuli (target and non-target) in a Bernoulli sequence in the center of the screen. The participants are asked to press the left button of a mouse for non-targets and right button for the targets. Overall 1024 stimuli are presented 1500 ms apart (total time, 25 minutes); targets are

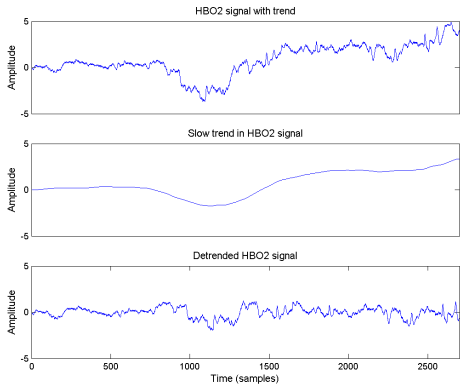


Figure 3 A typical fNIRS-$HbO_2$ signals (top), estimated trend (middle), and the signal after trend removal

presented on 64 trials, that is, on the average once every sixteen trials. The target instances are jittered randomly, but such that a minimum of 12 context stimuli is guaranteed between any target presentations. Duration of stimuli is 500 ms, hence there are blank intervals of one second. Recording is done at a sampling rate of 1.7 Hz.

*Preprocessing*: The target categorization experiments have been carried out on twelve subjects. Since every subject is monitored via 16 measurements, one should end up with a total of 3×16 = 48 signal sequences (optical density signals) per subject. However, due to sensor defects (clipping, saturation, defects due to head movements), we did not take into account data from some of the detectors. There were no particular patterns of defective photodetectors. Each $HbO_2$ time-series consisted of approximately 2700 samples, corresponding to 25-minutes duration of the cognitive task experiment. These signals were detrended by simple moving average filtering, which effectively removed very low frequency components below 0.003 Hz. The detrending filter (one minus a low-pass) is in fact a high-pass filter, which removes only the very low frequencies (Figure 3). Each target is expected, in principle, to trigger some $HbO_2$ signal corresponding to cognitive activity, as depicted in Figure 1. Since our purpose in this study is the extraction of waveforms associated with cognitive activity, we focus on the fNIRS segments that consist of the $m$ samples taken just after target stimuli onsets. In other words, we window out the $m$ sample intervals after the presentation of a target stimulus, and there are 64 such windowed segments per detector.

### 3.2 ICA results

As is typical of the ICA decomposition via FastICA algorithm [6], we first reduce the dimensionality of the data via PCA. The reduced dimension $n$ is selected based on the proportion of variance (PoV), set to 90 per cent for the fNIRS-$HbO_2$ vectors, leading to $n$=4. This operation smoothes the data, removes the high frequency fluctuations, and fixes the maximum number of ICA basis vectors that can be estimated by FastICA algorithm. Four basis vectors seem plausible since one can expect one or two cognitive activity-

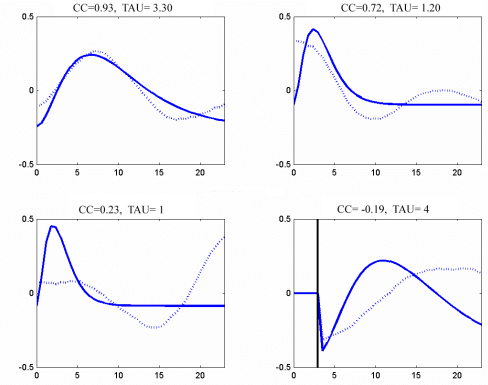


Figure 4 The ICA basis vectors estimated from a quadrant of a given subject (CC: correlation coefficient, TAU: time-constant).

related basis vector(s) and the remaining two or three to represent the baseline activity. To illustrate the case in point, let's consider a single dataset, which consists of 256 vectors from mid-left photodetectors of a subject (4 detectors × 64 target presentations = 256 fNIRS segments of 40 samples each). The FastICA algorithm is applied to these vectors to yield four basis vectors as shown in Figure 4, where solid curves correspond to the best fitted Gamma functions, and the thick bars mark the estimated delay $T$. Top left plot in Figure 4 corresponds to the basis vector that best fits the model function (with a correlation value of 0.90). Other basis vectors, in decreasing correlation order, are displayed in the remainder of Figure 4. Obviously the waveforms with low conformance to the Gamma function model do not appeal to our expectation of cognitive activity response, and hence they must somehow originate from the baseline activity. In the context of waveform extraction from fNIRS signals, the performance of the ICA approach in the large can be quantified by the average correlation coefficient between the extracted waveform and the corresponding Gamma model. The average is taken subject-wise (i.e., over 12 people) on a per quadrant basis as shown in Table 1. The high correlation figures convince us for the capability of ICA in extracting cognitive activity related waveforms from fNIRS-$HbO_2$ signals. On the other hand, our visual investigation of the best fitting ICA basis vectors also proves to be compatible with the Gamma waveform model. Figure 5 displays all the subjects' responses on an error-bar plot, each of which reflects the results for a given quadrant. It can be observed, as expected, that there can be significant variations among subjects. To summarize, ICA proves to be a viable scheme in extracting cognitive activity related waveforms, observed per detector group. It is also capable of providing signals in which a deeper understanding of the physiological processes can be investigated.

### 3.3 Clustering results

We approximate the $m$-sample fNIRS-$HbO_2$ signals by $m'$ B-spline coefficients. To this end, we implemented Unser's algorithm [9] for cubic B-splines on regular grids. We have observed that setting $m' = 5$ was satisfactory based on assessment of the compromise between waveform smoothness

Table 1 Average correlation coefficients (CC) between best-fitting ICA basis vectors and the corresponding Gamma model

| Quadrant | Left | Mid-Left | Mid-Right | Right |
|---|---|---|---|---|
| Avg. CC | 0.90 ± 0.07 | 0.90 ± 0.05 | 0.88 ± 0.06 | 0.87 ± 0.05 |

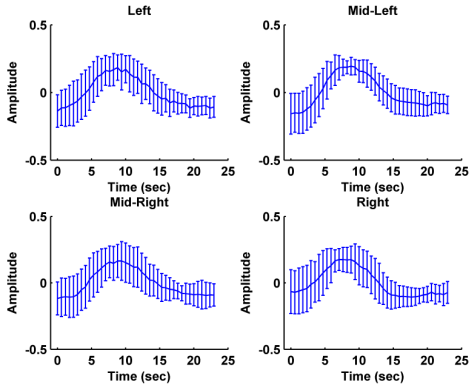


Figure 5 Error bar plot for best-fitting ICA basis vectors shown quadrant-by-quadrant

Table 2 Average correlation coefficients (CC) between best-fitting waveforms by clustering and the corresponding Gamma model

| Quadrant | Left | Mid-Left | Mid-Right | Right |
|---|---|---|---|---|
| Avg. CC | 0.83 ± 0.09 | 0.83 ± 0.08 | 0.79 ± 0.08 | 0.84 ± 0.09 |

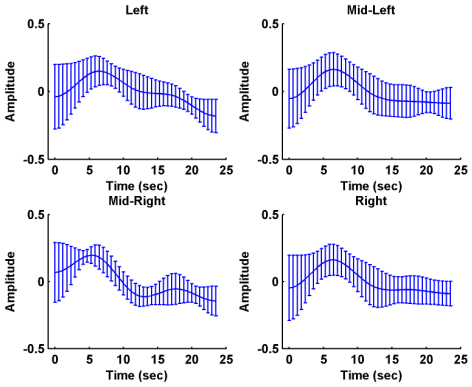


Figure 6 Error bar plot for best-fitting waveforms by clustering shown quadrant-by-quadrant

and preservation of the essential shape. To choose the number of $n$ clusters we consider a criterion that minimizes the ratio of within-cluster scatter and maximizes between-cluster scatter with a penalty term to bound the number of clusters. We have found that the choice of five clusters ($n$ = 5) is suitable for our purposes. The correlation scores obtained from the clustering approach are lower as compared to those in the ICA approach (Table 2). In terms of conformance to Gamma model, the waveforms found by clustering, shown in Figure 6, are somewhat less plausible.

## 4. DISCUSSION AND CONCLUSION

With the goal of identifying the brain hemodynamic response waveform to a single cognitive stimulus obtained by fNIRS, we explored two non-parametric methods, namely, independent component analysis and waveform clustering. Since both methods are exploratory, their outcomes were benchmarked against a model waveform, the so-called Gamma waveform with time-constant parameter $\tau$.

Our first conclusion is that, waveforms estimated by ICA were found to be plausibly related to cognitive activity, based on their conformance to the Gamma function model. The other components of ICA could possibly be used to model the baseline interference. Our second conclusion was that there exists considerable variability of waveforms both within a subject and among subjects. This intra- and inter-subject variability of waveforms has also been observed by related studies in the literature.

Our work on fNIRS signal analysis continues with data collected from a larger set of subjects and on new protocols that include lie experiments, emotional data, Stroop tests and arithmetic tests.

## 5. ACKNOWLEDGEMENTS

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## REFERENCES

[1] K.J. Friston, P. Jezzard, R. Turner, "The Analysis of Functional MRI Time-Series", *Human Brain Mapping*, vol. 1, pp. 153-171, 1995.

[2] P. Ciuciu , J-B. Poline, G. Marrelec, J. Idier, C. Pallier, H. Benali, "Unsupervised Robust Non-Parametric Estimation of the Hemodynamic Response Function for any fMRI Experiment", *IEEE Trans. On Med. Imag.*, vol. 22, pp. 1235-1251, 2003.

[3] J.R. Duann, T.P. Jung, W.J. Kuo, T.C. Yeh, S. Makeig, J.C. Hsieh, T.J. Sejnowski, "Single-trial variability in event-related bold signals", *NeuroImage*, vol. 15, pp. 823-835, 2002.

[4] G. Strangman, D. Boas, J. Sutton, "Non-invasive Neuroimaging using Near-Infrared Light", *Soc. of Biological Psychiatry*, vol. 17, pp. 679-693, 2002.

[5] G. Strangman, J.P. Culver, J.H. Thompson, D.A. Boas, "A Quantitative Comparison of Simultaneous BOLD fMRI and NIRS Recordings during Functional Brain Activation" *NeuroImage*, vol. 17, pp. 719-731, 2002.

[6] A. Hyvärinen, J. Karhunen, E. Oja, *Independent Component Analysis*, John Wiley & Sons, 2001.

[7] R.O. Duda, P. E. Hart, D. G. Stork, *Pattern Classification*, John Wiley & Sons, 2001.

[8] F. Ferraty, P. Vieu, "Curves Discrimination: a Nonparametric Functional Approach", *Computational Statistics and Data Analysis*, vol. 44, pp. 161-173, 2003.

[9] M. Unser, A. Aldroubi, M. Eden, "B-Spline Signal Processing: Part II-Efficient Design and Applications", *IEEE Trans. on Signal Processing*, vol. 41, pp. 834-848, 1993.