Neural mechanisms of action-selective and stimulus-selective stopping

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1. Introduction

1.1. Background

Simple stopping

Cognitive control encompasses a broad set of processes that support flexible adjustments to behavior in response to changes in our environment. A radical form of control is simple stopping. It involves inhibitory control that is all-or-none and is often studied with the standard stop-signal task (Verbruggen & Logan 2008). In this task, subjects respond quickly to go stimuli but try to cancel their response when a stop-signal follows a go stimulus after some delay (stop-signal delay, t_d). There are two main trial types: no-signal trials and stop-signal trials. Stop-signal trials can be further divided based on whether stopping succeeds (stop-inhibit trials) or fails (stop-respond trials). Stopping performance is characterized by three main findings: probability of responding given a stop-signal (P_r) increases with t_d; stop-respond response time ($RT_{stop-respond}$) is shorter than no-signal response time ($RT_{no-signal}$); $RT_{stop-respond}$ increases with t_d.

The independent race model provides a theoretical framework from which these findings can be understood (Logan & Cowan 1984; Logan et al. 2014). According to this model, stopping performance is determined by the outcome of a race between a process that executes the response (GO process) and a process that cancels the response (STOP process). If the GO process finishes before the STOP process, the response is executed; if the STOP process finishes before the GO process, the response is canceled. Under these assumptions, the model predicts exactly the pattern of findings observed in the standard stop-signal task. Besides a theory of simple stopping, the independent race model provides methods to estimate the latency of the covert STOP process, known as the stop-

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signal reaction time ($SSRT$). $SSRT$ can be estimated from the proportion of stop-respond trials and the distribution of no-signal RTs.

Neuroscience studies have demonstrated that simple stopping manifests in the motor system and also involves areas in the frontal lobe and basal ganglia. Neurophysiology studies in animals have shown that eye movement-related activity of neurons in frontal eye field (Hanes et al. 1998) and superior colliculus (Paré & Hanes 2003) as well as limb movement-related activity of neurons in dorsal premotor cortex (Mirabella et al. 2011) and basal ganglia nuclei (Schmidt et al. 2013) decays in response to the stop-signal within the time required to cancel the movement (Schall & Boucher 2007; Stuphorn 2015). Transcranial magnetic stimulation studies in humans show similar dynamics for primary motor cortex excitability (Coxon et al. 2006; van den Wildenberg et al. 2010). Human imaging, stimulation, and lession studies suggest that simple stopping relies on the inferior frontal cortex (Aron et al. 2003; Aron & Poldrack 2006; Chambers et al. 2006; Swick et al. 2008; Verbruggen et al. 2010), pre-supplementary motor area (Chen et al. 2009; Floden & Stuss 2006; Li et al. 2006), and basal ganglia structures such as striatum (Zandbelt & Vink 2010; Zandbelt et al. 2013) and subthalamic nucleus (Aron & Poldrack 2006; Jahfari et al. 2011; van den Wildenberg et al. 2006).

Selective stopping

A more flexible form of control is selective stopping. It comprises control that is targeted at specific actions or triggered by specific stimuli and has been studied with selective stopping tasks. Selective stopping research is gaining popularity and it has been suggested to have greater ecological validity and clinical relevance than simple stopping (Aron 2011). However, several factors currently complicate the interpretation of data from selective stopping research.

1.2. Problems

It is uncertain whether the independent race model extends from simple stopping to selective stopping

Although selective stopping research has relied on the independent race model, it is uncertain whether the model extends from simple stopping to selective stopping. One reason is that studies to date have reported tests of predictions of the independent race model incompletely or not at all. Another reason is that the available data provides mixed evidence. For example, although at least one selective stopping study showed that all three predictions of the race model held (Smittenaar et al. 2013), many others reported violations of at least one of the predictions (De Jong et al. 1995; Dimoska et al. 2006; van de Laar et al. 2010; Bissett & Logan 2014; Verbruggen & Logan 2015) in as many as 61% of participants (Bissett & Logan 2014). A final reason is that tests of race model predictions are often performed for the group as a whole rather than

for each individual separately, which may mask violations occurring in a subset of individuals. To illustrate, a stimulus-selective stopping study reported that one of the predictions (stop-respond RT should be shorter than no-signal RT) held for the group as a whole, but also reported that the very same prediction was violated in 32% of the participants (Sebastian et al. 2015). Together, this state of affairs is unsatisfactory, because if it turns out that the independent race model does not extend generally from simple stopping to selective stopping, then $SSRT$ estimates reported by previous selective stopping studies may be invalid and conclusions derived from them may be flawed (De Jong et al. 1990; Band et al. 2003). To address this problem, a systematic investigation of predictions of the independent race model across different forms of selective stopping and performed at the individual level is necessary. This will help clarify how often violations of predictions of the independent race model occur.

It is unclear whether selective stopping is a homogeneous or a heterogeneous construct

As pointed out by Bissett & Logan (Bissett & Logan 2014), selective stopping research has used a heterogeneous set of tasks, yet all of them are called selective stopping, as if selective stopping is a homogeneous construct. In some tasks (e.g. Aron & Verbruggen 2008; Coxon et al. 2009; Coxon et al. 2016; Majid et al. 2013; Smittenaar et al. 2013), participants are instructed to stop certain actions (e.g. a left-hand response), while continuing others (e.g. a right-hand response). We will call this action-selective stopping[1]. In other tasks (e.g. Dimoska et al. 2006; van de Laar et al. 2010; Bissett & Logan 2014; Verbruggen & Logan 2015; de Ruiter et al. 2012; Sebastian et al. 2015; Sharp et al. 2010), participants are instructed to stop to certain signals, while ignoring others. We will call this stimulus-selective stopping. It remains unclear whether action-selective and stimulus-selective stopping tap into the same form of control, as these tasks have never been compared directly. On the one hand, several findings seem to suggest that they do involve the same form of control, including $SSRT$s that are in the same range, response strategies that show striking resemblances (Bissett & Logan 2014; MacDonald et al. 2012), and activation in seemingly similar brain regions, such as ventrolateral frontal cortex, dorsal frontal cortex, and basal ganglia (Coxon et al. 2009; Coxon et al. 2016; de Ruiter et al. 2012; Majid et al. 2013; Sebastian et al. 2015; Sharp et al. 2010; Smittenaar et al. 2013). On the other hand, violations of the independent race model have mainly been reported for stimulus-selective stopping (Dimoska et al. 2006; van de Laar et al. 2010; Bissett & Logan 2014; Verbruggen & Logan 2015) and rarely for action-selective stopping (De Jong et al. 1995). Moreover, action-selective stopping may involve at least two choices (discriminating the signal, selecting the action to be cancelled) and stimulus-selective stopping only one (discriminating the signal). Consequently, action-selective stopping may rely more heavily on motor-related brain regions, such as pre-supplementary motor

[1]Note that Bissett and Logan (2014) have called this unconditional motor-selective stopping

area (pre-SMA), supplementary motor area (SMA), and the dorsal premotor area (PMd), and possibly the basal ganglia. To address this problem, a direct comparison of action-selective and stimulus-selective stopping tasks in terms of behavioral and neural measures of stopping is necessary.

1.3 Research questions, hypotheses, and predictions

We will tackle these problems by addressing two research questions:

Does the independent race model extend to selective stopping?

We formulate two hypotheses:

H_0: If the independent race model does not extend to selective stopping, then we will find that stopping performance violates *any* of the model's qualitative predictions.

H_1: If the independent race model extends to selective stopping, then we will find that stopping performance is in line with *all* the model's qualitative predictions.

To test these hypotheses, we will analyze response probabilities (P_r) and response times ($RT_{stop-respond}$) on stop trials. However, we will analyze only a subset of stop-respond trials, namely those involving a bimanual response. As explained in §2.2, our selective stopping task instructs participants to report the identity of the go-stimulus with a bimanual response and try to cancel one response (action-selective stopping) or both responses (stimulus-selective stopping) when the go-stimulus is followed by a stop-signal. Consequently, stop trials never require a bimanual response and stop-respond trials involving a bimanual response likely reflect failures of stopping. In contrast, stop-respond trials involving a unimanual response do not necessarily reflect failures of stopping: they may occur when participants successfully stop both prepared responses, but then erroneously discriminate the signal (e.g. confusing stop-left for stop-right) and execute the wrong response. Thus, we will analyze the probability of responding bimanually given a stop-signal ($P_{r,bi}$) and stop-respond trials involving a bimanual response ($RT_{stop-respond,bi}$).

We will conclude that H_0 is supported when *any* of the following predictions are confirmed:

1. $P_{r,bi}$ does not increase with t_d.
2. $RT_{stop-respond,bi}$ is not shorter than $RT_{no-signal}$.
3. $RT_{stop-respond,bi}$ does not increase with t_d.

We will conclude that H_1 is supported when *all* of the following predictions are confirmed:

1. $P_{r,bi}$ increases with t_d.

2. $RT_{stop-respond,bi}$ is shorter than $RT_{no-signal}$.
3. $RT_{stop-respond,bi}$ increases with t_d.

We will test the above predictions at the individual level and for action-selective stopping and stimulus-selective stopping tasks separately in Analyses 1-3. We will report frequencies of race model violations for both tasks. For completeness and comparison with previous reports, we will also test these predictions at the group level in Analyses 4-6. We will adopt a Bayesian hypothesis testing approach based on the Bayes Factor, which will allow us to quantify evidence for each of the hypotheses (for details, see §2.6.1).

Is selective stopping a homogeneous or heterogeneous construct?

We formulate two hypotheses:

H_0: If selective stopping is a homogeneous construct, then we will find that action-selective stopping and stimulus-selective stopping do not differ in terms of stopping performance and brain activation measures of selective stopping.

H_1: If selective stopping is a heterogenous construct, then we will find that action-selective stopping and stimulus-selective stopping do differ in terms of stopping performance and brain activation measures of selective stopping.

Stopping performance

To test the hypotheses at the level of performance, we will analyze three measures of stopping:

1. Stop-signal reaction time ($SSRT$)
   $SSRT$ reflects the time it takes to stop and is estimated using methods of the independent race model. It is the most frequently used measure of stopping performance. However, because of violations of the independent race model, we may be able to compare $SSRT$ between action-selective and stimulus-selective stopping only in a subset of participants. Therefore, we will compare $SSRT$ between action-selective and stimulus-selective stopping only in participants who meet all three assumptions of the independent race model, both for action-selective and stimulus-selective stopping, and only if this is the case for at least 10 (33%) participants.
2. Probability of responding bimanually given a stop-signal ($P_{r,bi}$)
   $P_{r,bi}$ reflects the outcome of the race between the GO process and the STOP process. It is not often used to compare stopping performance between conditions (or tasks, or groups), because it depends on multiple factors: t_d, no-signal RT, and $SSRT$ (Logan & Cowan 1984). However, $P_{r,bi}$ is a useful alternative to $SSRT$ when race model assumptions are violated, provided that t_d and no-signal reaction times are comparable between conditions. Here, we guarantee that these requirements are met by presenting no-signal trials, action-selective stop trials, and stimulus-selective stop trials within the same block, by requiring preparation of

a bimanual response on all trial types, and by using the same t_d values across trial types.

3. Stop-respond response time ($RT_{stop-respond,bi}$)
   $RT_{stop-respond,bi}$ reflects the speed of responses that escape the stop-signal. Responses that escape the stop-signal are sometimes slower than predicted by the independent race model (Colonius et al. 2001; Boucher et al. 2007; Gulberti et al. 2014), especially in selective stopping (De Jong et al. 1995; Dimoska et al. 2006; van de Laar et al. 2010; Bissett & Logan 2014; Verbruggen & Logan 2015). This slowing is thought to reflect the influence of the STOP process onto the GO process. Like $P_{r,bi}$, it is not often used to compare stopping performance between conditions, because it depends on t_d, no-signal RT, and $SSRT$. However, provided that t_d and no-signal RT are comparable between conditions, $RT_{stop-respond,bi}$ can be used to quantify differences in the STOP process. As explained above, our task design guarantees that these requirements are met.

We will conclude that H_0 is supported when all of the following behavioral predictions are confirmed[2]:

1. $SSRT$ does not differ between action-selective and stimulus-selective stopping.
2. $P_{r,bi}$ does not differ between action-selective and stimulus-selective stopping.
3. $RT_{stop-respond,bi}$ does not differ between action-selective and stimulus-selective stopping.

We will conclude that H_1 is supported when any of the following behavioral predictions are confirmed[2]:

1. $SSRT$ differs between action-selective and stimulus-selective stopping.
2. $P_{r,bi}$ differs between action-selective and stimulus-selective stopping.
3. $RT_{stop-respond,bi}$ differs between action-selective and stimulus-selective stopping.

If $SSRT$ can be estimated in fewer than a 9 (30%) participants (see above), then we will conclude that H_1 is supported when either prediction 2, or prediction 3, or both are confirmed.

We will test the above predictions in Analyses 7-9, again adopting a Bayesian hypothesis testing approach.

Stopping-related activation

To test the hypotheses at the level of brain activation, we will analyze activation on stop-inhibit trials (for details, see §2.6.2.). We will test for differences between action-selective and stimulus-selective stopping and look at activation

[2]If SSRT, due to violations of the independent race model, can be estimated in fewer than 10 participants, then we will not test prediction 1

in each of these forms of selective stopping in isolation. We will perform two region-of-interest (ROI) analyses and one whole-brain analysis:

1. ROI analysis, using focal, functional ROIs and Bayesian hypothesis testing
   We will analyze brain activation within focal, functional ROIs using a Bayesian hypothesis testing approach based on the Bayes Factor. The ROIs are defined on the basis of local maxima reported by previous fMRI studies of action-selective and stimulus-selective stopping. The Bayesian hypothesis testing approach will allow us to compare activation in the same way as we compared task performance and find evidence in favor of and against the null hypothesis.

   We will conclude that H_0 is supported when the following prediction is confirmed for *all* focal, functional ROIs:

   1. A ROI is activated on both action-selective and stimulus-selective stop-inhibit trials, but activation does not differ between these trials.

   We will conclude that H_1 is supported when *any* of the following predictions are confirmed in *any* of the focal, functional ROIs:

   1. A ROI is activated on action-selective stop-inhibit trials and activation is greater on action-selective than stimulus-selective stop-inhibit trials.
   2. A ROI is activated on stimulus-selective stop-inhibit trials and activation is greater on stimulus-selective than action-selective stop-inhibit trials.

   We will test these predictions in Analyses 10-12, using an Bayesian hypothesis testing approach.

2. ROI analysis, using broad, anatomical ROIs and classical hypothesis testing
   We will perform another ROI analysis, now using ROIs defined more broadly based on probabilistic anatomical atlases and a classical hypothesis testing approach. The more broadly defined ROIs enable us to assess activation within key areas of inhibitory control that fall outside the focal ROIs on which the first analyis focused. The classical hypothesis testing approach will allow us to take advantage of the statistical parametric mapping approach that is widely used in functional neuroimaging research, but will allow us to reject H_0 only.

   We will reject H_0 when *any* of the following predictions are confirmed in *any* of the broad, anatomical ROIs:

   1. A ROI is activated on action-selective stop-inhibit trials and activation is greater on action-selective than stimulus-selective stop-inhibit trials.
   2. A ROI is activated on stimulus-selective stop-inhibit trials and activation is greater on stimulus-selective than action-selective stop-inhibit

trials.

We will test these predictions in Analyses 13-15, using classical hypothesis testing.

3. Whole-brain analysis - classical hypothesis testing
We will perform a whole-brain analysis to detect any stopping-related activation outside key areas of inhibitory control. Like the previous analysis, this whole-brain analysis will allow us to reject H_0 only.

   We will reject H_0 when *any* of the following predictions are confirmed in *any* region of the brain

   1. A cluster is activated on action-selective stop-inhibit trials and activation is greater on action-selective than stimulus-selective stop-inhibit trials.
   2. A cluster is activated on stimulus-selective stop-inhibit trials and activation is greater on stimulus-selective than action-selective stop-inhibit trials.

   We will test these predictions in Analyses 16-18, using classical hypothesis testing.

2. Methods

2.1. Participants

Sampling plan

To determine the sample size for this experiment, we have performed a sample size calculation. We focused this sample size calculation on the fMRI part of the investigation and determined the sample size necessary to detect stopping-related activation in a whole-brain voxel-wise analysis with 80% power and a family-wise error (FWE)-corrected alpha of 0.05. We performed these analyses using using the PowerMap software (Joyce & Hayasaka 2012), running in MATLAB (Mathworks, Natick, MA, USA). This software can generate sample size images for fMRI studies based on statistical parametric maps of a previous experiment. Here, we based our sample size estimation on maps from published fMRI studies of simple stopping (Zandbelt & Vink 2010) and simulus-selective stopping (Sebastian et al. 2015). The resulting sample size images, together with the key regions of interest are shown in Figures 1-2. Based on these analyses, we decided to collect data in a total of 30 subjects.

Inclusion and exclusion criteria

To be eligible for participation in this study, participants must meet all of the following criteria:

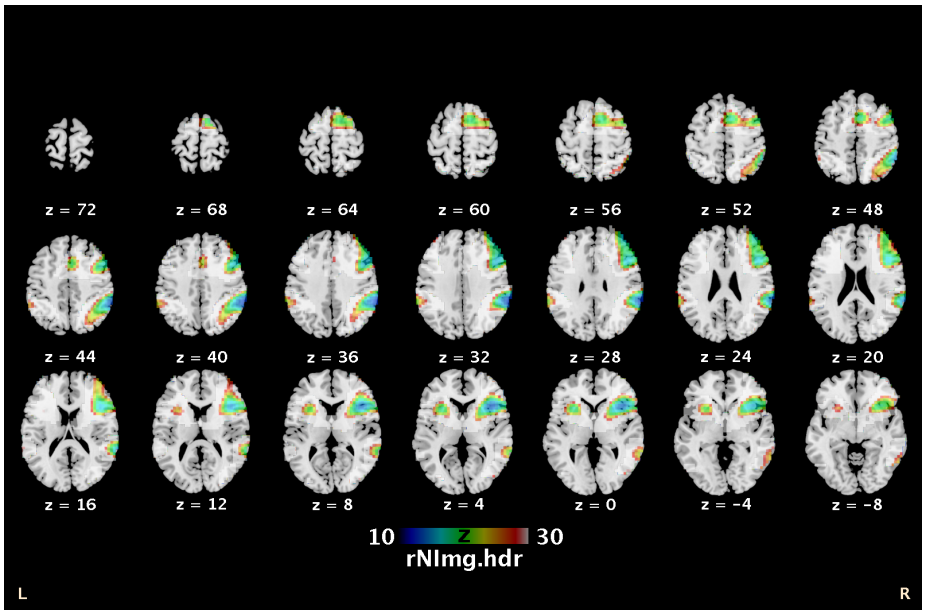

Figure 1: Sample size map, based on the StopSuccess > Go contrast from Zandbelt and Vink (2010). Overlay indicates areas where stopping-related activation can be detected with 80% power and a FWE-corrected alpha of 0.05.

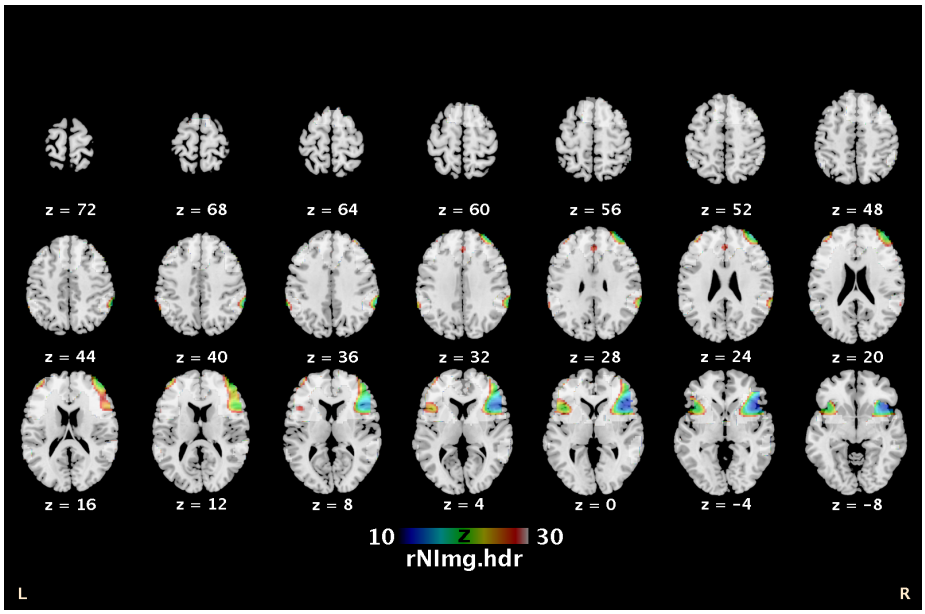

Figure 2: Sample size map, based on the stop > attentional capture contrast from Sebastian et al. (2015). Overlay indicates areas where stopping-related activation can be detected with 80% power and a FWE-corrected alpha of 0.05.

- healthy, competent adult volunteers
- normal or corrected to normal vision
- normal uncorrected hearing
- willingness and ability to understand the nature and content of the study
- ability to participate and comply with study requirements

Participants will not be able to participate if they meet any of the following criteria:
- history of or current neurological or psychiatric treatment
- history of or current brain surgery or epilepsy
- pregnancy
- MRI incompatibility (metal parts in upper body, implants, medical devices or medicinal plasters)
- claustrophobia

Exclusion criteria after acceptance in the study are described in §2.7.

Recruitment strategy

Participants will be recruited through an online database for subjects interested in participating in research at the Donders Institute and Behavioral Science Institute (Sona Systems Ltd., Tallinn, Estonia).

Ethical considerations

The study procedures are in accordance with the Declaration of Helsinki and have been approved by the local Institutional Review Board (Committee on Research Involving Human Subjects Arnhem-Nijmegen, registered under CMO2014/088). Written informed consent will be obtained from all participants before enrollment in the study.

2.2. Task

All stimuli are presented in the center of the screen on a grey background. The fixation stimulus is a white cross, subtending 3 degrees along its vertical axis. The primary stimulus (go stimulus) is a white Hiragana character, subtending 6 degrees along its vertical axis. It is chosen from a set of two. The secondary stimulus (signal) is a playing card suit symbol at 80% opacity, subtending 3 degrees along the vertical axis and presented on top of the primary stimulus. It is chosen from a set of four: an orange diamond, a cyan heart, a yellow club, or a purple spade.

Each trial starts with the presentation of a fixation stimulus for 200 ms. The fixation cross is immediately followed by the go stimulus and remains on the screen for 1200 ms, regardless of response time. Following go stimulus offset, feedback is presented for 500 ms. The next trial starts after a further 200 ms, during which a blank screen is shown.

The primary task is to report the identity of the Hiragana character with a bimanual response. One character is mapped onto the two upper keys of a response pad, the other character is mapped onto the two lower keys. The character-to-key mapping is counterbalanced across participants. Participants control the two upper keys with their left and right middle fingers and the lower keys with their left and right index fingers. Participants are instructed to respond as accurate, fast, and simulatenous as possible.

On 40% of trials, one of four secondary stimuli is presented. These may or may not require adjustment of the response to the go stimulus. One stimulus acts as the stop-left (SL) signal; it instructs participants to stop their left-hand response, but not their right-hand response. A second stimulus acts as the stop-right (SR) signal; it instructs participants to stop their right-hand response, but not their left-hand response. A third stimulus acts as the stop-both (SB) signal; it instructs participants to stop both their left-hand response and their right-hand response. A fourth stimulus acts as the ignore (IG) signal; it should be ignored and the response should continue as planned. The stimulus-to-signal mapping is counterbalanced across participants. The primary (go) and secondary stimulus are separated by a stimulus onset asynchrony (t_d). The stimulus onset asynchronies will be 66, 166, 266, 366, and 466 ms, each occurring with equal probability.

2.3. Procedure

The experiment consists of a practice session and an experimental session, taking place on different days.

2.3.1. Practice session

The experiment begins with both written and verbal instructions, followed experimenter-supervised practice in three stages.

Stage 1

Participants will perform one block of 50 no-signal trials. The goal of this phase is to acquaint participants with the primary task. At the end of this block, a feedback screen is displayed, showing mean no-signal trial RT, mean RT difference between the left- and right hand on no-signal trials, and no-signal choice performance. Task performance should be in line with the following criteria:

- Mean no-signal response time: < 650 ms
- Mean difference between the left- and right hand response time on no-signal trials: < 50 ms
- No-signal choice performance: $> 85\%$ correct

If task performance is not in line with one or more criteria, participants will receive additional feedback. If mean no-signal RT is longer than 650 ms, participants will see the following: "remember to respond as fast as possible". If mean RT difference between left and right fingers on no-signal trials is greater than 50 ms, participants will also see the following feedback: "remember to respond simultaneously with your left and right fingers" If no-signal choice performance falls below 85% %, participants will receive the following feedback: "remember to be as accurate as possible". Stage 1 will be repeated until all criteria have been met. If feedback does not bring performance in line with requirements over five subsequent blocks then the experiment will be terminated and the participant will be excluded.

Stage 2

Participants will perform one action-selective stopping block and one stimulus-selective stopping block, the order being counterbalanced across participants. The goal of this phase is to acquaint participants with the action-selective and stimulus-selective stop tasks, while maintaining go task performance. The action-selective stopping block consists of 60 no-signal trials, 20 stop-left trials, and 20 stop-right trials. The stimulus-selective stopping block consists of 60 no-signal trials, 20 stop trials, and 20 ignore trials. At the end of this block, a feedback screen presents participants with the same descriptive statistics as above as well as the probability of responding for each of the signals. Task performance should be in line with the criteria specified above as well as the following:

- Action-selective stopping:
  - Stop-left trials: P(respond | stop-left signal) $< 80\%$
  - Stop-right trials: P(respond | stop-right signal) $< 80\%$
- Stimulus-selective stopping:
  - Stop-both trials: P(respond | stop-signal) $< 80\%$
  - Ignore trials: P(respond | stop-signal) $> 80\%$

If task performance is not in line with one or more criteria, participants will receive additional feedback. If overall probability of responding given a stop-signal is greater than 80%, subjects will see the following: "remember to try to [stop your left finger/right finger/left and right finger] when you see a [color and name of stop stimulus]". If overall probability of responding given an ignore-signal is smaller than 80%, subjects will see the following: "remember to try to respond when you see a [color and name of ignore stimulus]". Stage 2 will be repeated until all criteria have been met. If feedback does not bring performance in line with requirements over five subsequent blocks then the experiment will be terminated and the participant will be excluded.

Stage 3

Participants will perform one block in which action-selective stop trials and stimulus-selective stop trials are intermixed. The goal of this phase is to let subjects become acquainted with the task as performed in the scanner. This block consists of 60 no-signal trials, 10 stop-left trials, 10 stop-right trials, 10 stop-both trials, and 10 ignore trials. At the end of the block, task performance should be in line with all criteria specified above. Stage 3 will be repeated until all criteria have been met. If feedback does not bring performance in line with requirements over five subsequent blocks then the experiment will be terminated and the participant will be excluded.

2.3.2. Functional MRI session

Before the experiment begins, participants are reminded of task instructions and will perform one or more blocks of practice (Stage 3). Next, they will perform two runs of 6 experimental blocks while being scanned with fMRI. Each block includes 60 no-signal trials, 10 stop-left trials, 10 stop-right trials, 10 stop trials, and 10 ignore trials, and ends with a 12.6-s feedback screen (identical to the practice session). Each block lasts 3 minutes and 43 seconds, each run lasts 22 minutes and 16 seconds. Trials will be presented in a pre-determined pseudo-random sequence. In order to determine the most optimal trial order, we have generated 100,000 pseudo-random trial sequences and have selected the two sequences (one for each fMRI run) with the highest detection efficiency of the the contrast between action-selective and stimulus-selective stopping and the lowest variance inflation factor, as determined with MATLAB-software for optimization of fMRI designs (Wager & Nichols 2003).

2.4. Data acquisition

2.4.1. Task performance data

The experiment will be run in PsychoPy (Peirce 2007; Peirce 2008, release 1.83.04) running under Windows 7 on a Dell Precision T3500 computer with two Intel Xeon Quad Core 2.80 GHz processors and 12 GB of RAM. Visual stimuli will be projected on a screen positioned 75 cm from the subject and are viewed through a mirror mounted on the head coil. Responses will be collected using two MR-compatible fiber-optic response pads (Current Designs, Inc; Philadelphia, PA, USA), one for each hand.

2.4.2. Neuroimaging data

The experiment will be performed on a 3.0 T Siemens Magnetom Skyra MRI scanner (Siemens Medical Systems, Erlangen, Germany) at the Donders Institute. Images will be acquired using a 32-channel head coil. During task performance, a total of 1214 images with blood-oxygen level-dependent (BOLD)

contrast will be acquired using a whole-brain T2*-weighted gradient echo multi-echo echo planar imaging (EPI) sequence (34 slices per volume; transversal acquisition; repetition time, 2100 ms; echo times, 8.5, 19.3, 30, and 41 ms; field of view: 224 x 244 mm; flip angle 90 $^\circ$; 64 x 64 matrix; 3.5 mm in-plane resolution; 3 mm slice thickness, 0.5 mm slice gap) in 2 run(s). The first 6 scans will be discarded to allow T1 saturation to reach equilibrium. Before the first run, 30 images with the same pulse sequence used for the task will be acquired during resting-state, for determining optimal weighting of echo times for each voxel. In between the two runs, a whole-brain structural image will be made for within-subject registration purposes, using a T1-weighted magnetization prepared, rapid-acquisition gradient echo sequence (192 sagittal slices; repetition time, 2300 ms; echo time, 3.03 ms; field of view: 256 x 256 mm; flip angle, 8 $^\circ$; 256 x 256 matrix; 1.0 mm in-plane resolution; 1.0 mm slice thickness).

2.5. Behavioral variables

2.5.1. Manipulated variables

We will manipulate the following variables:

Go stimulus identity ($s1$)

$s1$ (nominal variable) has two levels:
- go stimulus mapped onto the index fingers of the left and right hand (I)
- go stimulus mapped onto the middle fingers of the left and right hand (M)

Trial type ($trial$)

$trial$ (nominal variable) has five levels:
- no-signal (NS) trial
- stop-left signal (SL) trial
- stop-right signal (SR) trial
- stop-both signal (SB) trial
- ignore signal (IG) trial

Signal delay (t_d)

t_d (ordinal variable) is defined as the onset asynchrony between the go stimulus and the signal and has five levels:
- 66 ms
- 166 ms
- 266 ms
- 366 ms
- 466 ms

In analyses of $RT_{stop-respond,bi}$, the first three levels will be pooled in order to

have a sufficient amount of data per level, resulting in three levels:
- short: 66, 166, and 266 ms
- intermediate: 366 ms
- long: 466 ms

2.5.2. Measured variables

We will measure the following variables on a trial-by-trial basis, separately for each of the four fingers used in the task:

Finger-level response count (RC_{finger})

RC_{finger} (ratio variable) is defined as the number of responses recorded for a given finger between go-stimulus onset and go-stimulus offset. There are four RC_{finger} variables:
- Left index finger response count (RC_{LI})
- Right index finger response count (RC_{RI})
- Left middle finger response count (RC_{LM})
- Right middle finger response count (RC_{RM})

This variable will be used to define the variable response category (r).

Finger-level response time (RT_{finger})

RT_{finger} (ratio variable) is defined as the onset of a finger's first response minus the onset of the go-stimulus. There are four RT_{finger} variables:
- Left index finger response time (RT_{LI})
- Right index finger response time (RT_{RI})
- Left middle finger response time (RT_{LM})
- Right middle finger response time (RT_{RM})

This variable will be used to define the variable trial-level response time (RT_{trial}).

2.5.3. Indices

Based on the manipulated and measured variables, we will construct the following trial-level and subject-level indices:

2.5.3.1. Trial-level indices

Response category (r)

r (nominal variable) is defined as the type of response recorded on a given trial. It is determined on the basis of combinations of $s1$ and RC_{finger} variables

(Table 1). All other combinations of $s1$ and RC_{finger} will be classified as "not otherwise categorized (NOC)".

Table 1: Definition of response category (r) on the basis of go stimulus ($s1$) and finger-level response count (RC_{finger})

r	Description	$s1$	RC_{LM}	RC_{RM}	RC_{LI}	RC_{RI}
RB	Bimanual response, fingers compatible with the go-stimulus	M	1	1	0	0
RL	Left-hand response, finger compatible with the go-stimulus	M	1	0	0	0
RR	Right-hand response, finger compatible with the go-stimulus	M	0	1	0	0
RBO	Bimanual response, fingers compatible with the other go-stimulus	M	0	0	1	1
RLO	Left-hand response, finger compatible with the other go-stimulus	M	0	0	1	0
RRO	Right-hand response, finger compatible with the other go-stimulus	M	0	0	0	1
NR	No response	M	0	0	0	0
RB	Bimanual response, fingers compatible with the go-stimulus	I	0	0	1	1
RL	Left-hand response, finger compatible with the go-stimulus	I	0	0	1	0
RR	Right-hand response, finger compatible with the go-stimulus	I	0	0	0	1
RBO	Bimanual response, fingers compatible with the other go-stimulus	I	1	1	0	0
RLO	Left-hand response, finger compatible with the other go-stimulus	I	1	0	0	0
RRO	Right-hand response, finger compatible with the other go-stimulus	I	0	1	0	0
NR	No response	I	0	0	0	0

This variable will be used to define the variables bimanual response recorded

(r_{bi}), trial label - performance ($trial_{performance}$), trial label - fMRI ($trial_{fMRI}$), probability of responding given a signal ($P_{r,bi}$), and response time (RT).

Bimanual response recorded (r_{bi})

r_{bi} (nominal variable) is defined as whether or not a bimanual response (i.e. consisting of one left-hand and one right-hand response) is recorded on a given trial. It is determined on the basis of r. This variable will be used in Analysis 1.

Trial-level response time (RT_{trial})

RT_{trial} (ratio variable) is defined as the mean response time across fingers on a given trial. It is computed on the basis of the RT_{finger} variables. This variable will be used to define response time category ($RT_{category}$) and will be used as dependent variable in Analyses 2-3.

Trial label - performance ($trial_{performance}$)

$trial_{performance}$ (nominal variable) is used to categorize trials for analyses of task performance. It is determined on the basis of $trial$ and r (Table 2).

Table 2: Definition of trial label - performance ($trial_{performance}$) on the basis of trial type ($trial$) and response category (r)

$trial_{performance}$	$trial$	r
$NS_{correct}$	NS	RB
$NS_{commission-error-bi}$	NS	RBO
$NS_{commission-error-uni}$	NS	RL,RR,RLO,RRO
$NS_{commission-error-other}$	NS	NOC
$NS_{omission-error}$	NS	NR
$SL_{stop-respond-bi}$	SL	RB or RBO
$SL_{stop-respond-uni}$	SL	RL,RLO,RRO
$SL_{stop-respond-other}$	SL	NR,NOC
$SL_{signal-inhibit}$	SL	RR
$SR_{stop-respond-bi}$	SR	RB or RBO
$SR_{stop-respond-uni}$	SR	RR,RLO,RRO
$SR_{stop-respond-other}$	SR	NR,NOC
$SR_{signal-inhibit}$	SR	RL
$SB_{stop-respond-bi}$	SB	RB or RBO
$SB_{stop-respond-uni}$	SB	RL,RR,RLO,RRO
$SB_{stop-respond-other}$	SB	NOC
$SB_{signal-inhibit}$	SB	NR
$IG_{correct}$	IG	RB
$IG_{commission-error-bi}$	IG	RBO
$IG_{commission-error-uni}$	IG	RL,RR,RLO,RRO

$trial_{performance}$	$trial$	r
$IG_{commission-error-other}$	IG	NOC
$IG_{omission-error}$	IG	NR

This variable will be used to define response time category ($RT_{category}$)

Response time category ($RT_{category}$)

$RT_{category}$ (nominal variable) is defined for the purpose of the fMRI analysis. It is determined on the basis of RT_{trial} and $trial_{performance}$. It indicates for correct no-signal trials and correct ignore trials whether these are associated with a fast or a slow RT. This procedure, called latency-matching (Hanes et al. 1998; Schmidt et al. 2013; Thakkar et al. 2014; Mallet et al. 2016), is based on the idea that signal and no-signal trials differ in terms of the speed of the GO process and that analyses of brain activity should control for this by using different sets of no-signal trials.
Correct no-signal trials will be split into fast RT and slow RT trials at the percentile corresponding to the overall stop-respond rate. Slow no-signal trials will be used in the comparison with stop-inhibit trials; these are slow enough to have been successfully cancelled had a stop-signal been presented. Fast no-signal trials will be used in the comparison with stop-respond trials; these are fast enough to have resulted in a response had a stop-signal been presented.
Correct ignore trials will also be split into fast RT and slow RT trials. It has been argued that slow RTs on ignore trials are due to the temporary activation of a STOP process (Bissett & Logan 2014). By splitting correct ignore trials into fast RT and slow RT trials, we can distinguish ignore trials in which a STOP process has likely interfered with the GO process (i.e. slow ignore trials) and trials in which a STOP process has unlikely interfered with the GO process (i.e. fast ignore trials). The fast ignore trials can then be used to control for activation related to the presenation of a signal. We will split the trials at the percentile corresponding to the stop-both-respond rate, separately for each t_d.

This variable will be used to define trial label - fMRI ($trial_{fMRI}$).

Trial label - fMRI ($trial_{fMRI}$)

fMRI trial label (nominal variable) is used to categorize trials for the first-level fMRI analysis (§ 2.6.2.2). It is determined on the basis of $trial$, r, and $RT_{category}$ (Table 3).

Table 3: Definition of trial label - fMRI ($trial_{fMRI}$) on the basis of trial type ($trial$) and response category (r)

$trial_{fMRI}$	$trial$	r	$RT_{category}$
$NS_{correct-fast}$	NS	RB	fast

$trial_{fMRI}$	$trial$	r	$RT_{category}$
$NS_{correct-slow}$	NS	RB	slow
NS_{other}	NS	RBO,RL,RR,RLO,RRO,NR,NOC	-
$SL_{stop-respond-bi}$	SL	RB or RBO	-
$SL_{stop-respond-other}$	SL	RL,RLO,RBO,NR,NOC	-
$SL_{signal-inhibit}$	SL	RR	-
$SR_{stop-respond-bi}$	SR	RB or RBO	-
$SR_{stop-respond-other}$	SR	RR,RLO,RBO,NR,NOC	-
$SR_{signal-inhibit}$	SR	RL	-
$SB_{stop-respond-bi}$	SB	RB or RBO	-
$SB_{stop-respond-other}$	SB	RL,RR,RLO,RBO,NOC	-
$SB_{signal-inhibit}$	SB	NR	-
$IG_{correct-fast}$	IG	RB	fast
$IG_{correct-slow}$	IG	RB	slow
IG_{other}	IG	RBO,RL,RR,RLO,RRO,NR,NOC	-

This variable will be used in the first-level fMRI analysis (see §2.6.2.2.).

2.5.3.2. Individual-level indices

These variable will be used in statistical analyses.

Stop-signal reaction time ($SSRT$)

$SSRT$ (ratio variable) is defined as the average time it takes to stop the response to the go stimulus. It is computed according to the integration method of the independent race model (Logan & Cowan 1984), collapsed across t_d levels. It will be computed separately for action-selective and stimulus-selective stopping. These variables will be used in Analysis 7.

Probability of responding given a stop-signal ($P_{r,bi}$)

$P_{r,bi}$ (ratio variable) is defined as follows:

$$P_{r,bi} = P((r = RB \cup r = RBO)|s, t_d) = \frac{P((r = RB \cup r = RBO) \cap trial \cap t_d)}{P(trial \cap t_d)}$$

, where r is response category, $trial$ is the trial type, and t_d is delay. We will compute $P_{r,bi}$ for each combination of selective stopping type and t_d. These variables will be used in Analyses 4 and 8.

Response time (RT)

RT (ratio variable) is defined as the mean response time to the go stimulus across trials. We will compute RT for all levels of $trial_{performance}$ that involve a response, both separately and collapsed across levels of t_d. These variables will be used in Analyses 5, 6, and 9.

2.6. Data analysis

2.6.1. Behavior

Bayesian hypothesis testing

For analysis of behavioral data, we will adopt a Bayesian hypothesis testing approach based on the Bayes Factor (Jeffreys 1961; Kass & Raftery 1995; Rouder et al. 2009; Rouder et al. 2012). Bayesian hypothesis testing is comparative in nature and the Bayes Factor quantifies the support that the data provide for one hypothesis (e.g. the null hypothesis, H_0) over another (e.g. the alternative hypothesis, H_1). This approach has several advantages over classical hypothesis testing based on the p-value. Most importantly, it allows for obtaining evidence both in favor of and against H_0 rather than against H_0 only. In addition, it provides a continuous measure of support for one hypothesis over another instead of forcing an all-or-none decision. Bayesian hypothesis testing is relevant in our study, because we are investigating whether or not selective stopping performance is in agreement with predictions of the independent race model and whether or not action-selective and stimulus-selective stopping differ in terms of stopping performance.

The Bayes Factor describes the relative probability of the data under competing hypotheses. In Bayesian hypothesis testing, one evaluates the relative odds of the hypotheses themselves:

$$\underbrace{\frac{P(H_0|Data)}{P(H_1|Data)}}_{posterior\ odds} = \underbrace{\frac{P(Data|H_0)}{P(Data|H_1)}}_{Bayes\ Factor\ (B_{01})} \times \underbrace{\frac{P(H_0)}{P(H_1)}}_{prior\ odds}$$

Here, the prior and posterior odds describe the beliefs about the hypotheses before and after observing the data, respectively. The primary measure of interest, however, is the Bayes Factor that quantifies the change in odds from prior to posterior. In other words, the Bayes Factor describes how the evidence from the data should change our beliefs (Good 1985). The Bayes Factor prefers the hypothesis under which the observed data are most likely. To illustrate, if $B_{01} = 5$, the data are five times as likely to have occurred under H_0 than under H_1; if $B_{01} = 1$, the data provide equal support for H_0 and H_1. While the Bayes Factor is easy to understand, it can be useful to summarize its value in words. For this purpose, we will use a set of labels listed in Table 4, proposed

by Wetzels & Wagenmakers (Wetzels & Wagenmakers 2012), based on Jeffreys (Jeffreys 1961) and Raftery (Raftery 1995).

Table 4: Bayes Factor (B_{01}) categories

B_{01}	Interpretation
> 100	Extreme evidence for H_0
30 - 100	Very strong evidence for H_0
10 - 30	Strong evidence for H_0
3 - 10	Moderate evidence for H_0
1 - 3	Anecdotal evidence for H_0
1	No evidence
1/3 - 1	Anecdotal evidence for H_1
1/10 - 1/3	Moderate evidence for H_1
1/30 - 1/10	Strong evidence for H_1
1/100 - 1/30	Very strong evidence for H_1
$<$1/100	Extreme evidence for H_1

Bayesian hypothesis testing requires specification of priors, which descibe the distribution of effect size. Prior distributions should be specified for both the null hypothesis and the alternative hypothesis. Here, we adopt an approach that attempts to specify prior distributions that convey little information while maintaining desirable properties (Rouder et al. 2009; Morey et al. 2016). In this approach, priors are placed on standardized effect sizes (δ) for H_0 and H_1, as well as on the variance (σ^2). The standardized effect size is assumed to be 0 under H_0 and distributed according to a Cauchy distribution with scale parameter τ under H_1:

$$H_0 : \delta = 0$$
$$H_1 : \delta \sim Cauchy(\tau)$$

The Cauchy distribution is a t-distribution with one degree of freedom and is now a common default prior on the alternative hypothesis (Rouder et al. 2009; Rouder et al. 2012). The parameter τ scales the distribution, such that $|\delta| > \tau$ has a prior probability of 0.5. It is recommended that τ is set to the standardized effect size reported in the literature or, if this information is unavailable, to 0.5 (Rouder et al. n.d.). In our analyses, we will assume $\tau = 0.5$. The prior for σ^2 is less important, because it is the same for both hypotheses and cancels out in the Bayes Factor. Following Rouder and colleagues (Rouder et al. 2012), we assume that σ^2 follows an inverse chi-square distribution with one degree of freedom.

To test our hypotheses, we will use Bayesian t-tests (Rouder et al. 2009), Bayesian ANOVAs (Rouder et al. 2012), and Bayesian logistic regression analysis (Kruschke 2015; Wagenmakers et al. 2010). The Bayesian t-tests and

ANOVAs are implemented in the Bayes Factor package in R and JASP (JASP Team 2016). The Bayesian t-test involves model comparison between H_0 and H_1.

The Bayesian ANOVA involves comparison between all possible models based on the factors in the analysis (Rouder et al. 2012). For instance, a design with two fixed factors A and B involves model comparison between five models:
1. the null model
2. the model with a main effect of A
3. the model with a main effect of B
4. the model with a main effect of A and a main effect of B
5. the model with a main effect of A, a main effect of B, and an interaction between A and B

Each model is assumed to have equal prior probability (p(M)). The Bayesian ANOVA determines the Bayes Factor associated with each of the models against the hypothesis that all effects are 0. The model with the largest Bayes Factor is considered the winning model.

Bayesian logistic regression analysis are not yet included these programs at the time of registration, although it is planned to be included (personal communication with R.D. Morey on February 3, 2016). If this analysis is included in this package before analyses have finished, then we will perform Bayesian logistic regression with this package. Otherwise, we will follow either Kruschke (Kruschke 2015) or Wagenmakers and colleagues (Wagenmakers et al. 2010).

Analysis 1 - Effect of stop-signal delay on probability of responding given a stop-signal (individual level)

- *Statistical model*:
  - Type: Bayesian logistic regression
  - Dependent variables: r_{bi}
  - Independent variables: t_d (66, 166, 266, 366, 466 ms)
- *Transformations*: None.
- *Inference criteria*:
  - If the winning model does not include t_d as a factor, then H_0 is supported
  - If the winning model includes t_d as a factor, then H_1 is supported
- *Data exclusion*: No trials will be excluded.

Analysis 2 - Difference between no-signal and stop-respond RT (individual level)

- *Statistical model*:
  - Type: Bayesian independent t-test
  - Dependent variable: RT_{trial}
  - Independent variables: $trial_{performance}$ (no-signal, stop-respond-bi)
- *Transformations*: RT_{trial} will be inverse transformed.

- *Inference criteria*:
  - If $B_{01} > 1$, then H_0 is supported
  - If $B_{01} < 1$, then H_1 is supported
- *Data exclusion*: Trials with $RT_{trial} < 150$ ms are assumed to reflect anticipations and will be excluded.

Analysis 3 - Effect of stop-signal delay on stop-respond RT (individual level)

- *Statistical model*:
  - Type: Bayesian repeated-measures ANOVA
  - Dependent variable: $RT_{trial,stop-respond,bi}$
  - Independent variables: t_d (short, intermediate, long)
- *Transformations*: $RT_{trial,stop-respond,bi}$ will be inverse transformed
- *Inference criteria*:
  - If the winning model does not include t_d as a factor, then H_0 is supported
  - If the winning model includes t_d as a factor, then H_1 is supported
- *Data exclusion*: Trials with $RT_{trial} < 150$ ms will be excluded.

Analysis 4 - Effect of stop-signal delay on probability of responding given a stop-signal (group level)

- *Statistical model*:
  - Type: Bayesian logistic regression
  - Dependent variable: $P_{r,bi}$
  - Independent variable: t_d (66, 166, 266, 366, 466 ms)
- *Transformations*: None.
- *Inference criteria*:
  - If the winning model does not include t_d as a factor, then H_0 is supported
  - If the winning model includes t_d as a factor, then H_1 is supported
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

Analysis 5 - Difference between no-signal and stop-respond RT (group level)

- *Statistical model*:
  - Type: Bayesian paired t-test
  - Dependent variable: RT
  - Independent variable: $trial_{performance}$ (no-signal, stop-respond)
- *Transformations*: None.
- *Inference criteria*:
  - If $B_{01} > 1$, then H_0 is supported
  - If $B_{01} < 1$, then H_1 is supported
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

Analysis 6 - Effect of stop-signal delay on stop-respond RT (group level)

- *Statistical model*:
  - Type: Bayesian repeated-measures ANOVA
  - Dependent variable: $RT_{stop-respond,bi}$
  - Independent variable: t_d (early, intermediate, late)
- *Transformations*: None.
- *Inference criteria*:
  - If the winning model does not include t_d as a factor, then H_0 is supported
  - If the winning model includes t_d as a factor, then H_1 is supported
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

Analysis 7 - Effect of selective stopping type on stop-signal reaction time

- *Statistical model*:
  - Type: Bayesian paired t-test
  - Dependent variable: $SSRT$
  - Independent variable: selective stopping type (action-selective, stimulus-selective)
- *Transformations*: None.
- *Inference criteria*:
  - If $B_{01} > 1$, then H_0 is supported
  - If $B_{01} < 1$, then H_1 is supported
- *Data exclusion*: Data from participants whose performance does not follow all predictions of the independent race model for both action-selective stopping and stimulus-selective stopping will be excluded. In addition, the general exclusion criteria (§ 2.7.) apply.

Analysis 8 - Effect of selective stopping type on probability of responding given a stop-signal

- *Statistical model*:
  - Type: Bayesian logistic regression
  - Dependent variable: $P_{r,bi}$
  - Independent variable: selective-stopping type (action-selective, stimulus-selective), t_d (66, 166, 266, 366, 466 ms)
- *Transformations*: None.
- *Inference criteria*:
  - If the winning model does not include selective-stopping type as a factor, then H_0 is supported
  - If the winning model includes selective-stopping type as a factor, then H_1 is supported

- *Data exclusion*: General exclusion criteria (§ 2.7.) apply. ##### Analysis 9 - Effect of selective stopping type on stop-respond response time
- *Statistical model*:
  - Type: Bayesian repeated-measures ANOVA
  - Dependent variable: $RT_{stop-respond,bi}
  - Independent variable: selective-stopping type (action-selective, stimulus-selective), t_d (early, intermediate, late)
- *Transformations*: None.
- *Inference criteria*:
  - If the winning model does not include selective-stopping type as a factor, then H_0 is supported
  - If the winning model includes selective-stopping type as a factor, then H_1 is supported
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

2.6.2. Functional MRI analysis

2.6.2.1. Preprocessing

Image data will be preprocessed using Statistical Parametric Mapping 12 (SPM12) running in MATLAB, unless stated otherwise. Preprocessing will include the following steps:

1. The T1-weighted anatomical scan will be skull-stripped using the FSL Brain Extraction Tool (Smith 2002).
2. Multiecho images will be combined based on the parallel acquired inhomogeneity desensitized algorithm (Poser et al. 2006), using in-house build MATLAB software. Using the resting-state scans that will be collected before the start of the task, the software computes the optimal weighting of echo times for each voxel (after applying a smoothing kernel of 3mm full-width at half-maximum) by calculating the contrast-to-noise ratio for each echo per scan. Next, for head motion correction, the software estimates the iterative rigid body realignment that minimizes the residual sum of squares between the first echo of the first scan and all other scans. These estimated parameters will then be applied to all other echos, realigning all echos to the first echo of the first scan. Finally, the four echo images of each scan will be combined into single images using the computed optimal echo time weightings.
3. The anatomical image will be co-registered to the mean functional image using the normalized mutual information criteria method (Studholme et al. 1999).
4. The anatomical image will then be normalized to the International Consortium for Brain Mapping space template for European brains using linear and non-linear deformations (Ashburner et al. 1999; Ashburner & Friston

2005). The normalization parameters will then be applied to both the functional and anatomical images.

5. The normalized functional images will be spatially smoothed using a 6-mm full-width at half-maximum Gaussian kernel.

2.6.2.2. First-level statistical analysis

First-level statistical analysis involves a mass-univariate approach based on general linear models in SPM12. It comprises three steps:

Model specification

Each subject's whole-brain BOLD data will be modeled with a general linear model, including the following 15 event-related predictors (see also Table 3):

1. $NS_{correct-fast}$
2. $NS_{correct-slow}$
3. NS_{other}
4. $SL_{stop-respond-bi}$
5. $SL_{stop-respond-other}$
6. $SL_{stop-inhibit}$
7. $SR_{stop-respond-bi}$
8. $SR_{stop-respond-other}$
9. $SR_{stop-inhibit}$
10. $SB_{stop-respond-bi}$
11. $SB_{stop-respond-other}$
12. $SB_{stop-inhibit}$
13. $IG_{correct-fast}$
14. $IG_{correct-slow}$
15. IG_{other}

For regressors 4-15, we will alsi include a parametric modulator coding for t_d. Parametric modulators will be orthogonalized with respect to their mean. Event-related predictors and their parametric modulators will be created by convolving delta functions coding for go stimulus onset with a canonical hemodynamic response function. In addition, to account for residual head motion effects, we will include the motion parameters from the realignment procedure in the statistical model, as well as their squared and first-order derivatives (Lund et al. 2005). Taken together, we will include a total of 51 regressors (15 predictors + 12 parametric modulators + 24 motion parameters) per run. Low frequency drifts will be controlled using a discrete cosine transform with cutoff of 128 s. Serial correlations in the fMRI signal will be estimated using restricted maximum likelihood estimates of variance components using a first-order autoregressive model. The resulting non-sphericity will be used to form maximum-likelihood estimates of the activations.

Model estimation

Time series statistical analysis will be performed using restricted maximum likelihood.

Contrast specification

A challenge in neuroscience studies of stopping is to disentangle brain activity related to stopping from activity related to other processes. To determine the optimal contrast for isolating activation associated with action-selective stopping, stimulus-selective stopping, and their difference, we made an overview of hypothetical cognitive processes involved in the most important trial types of our experiment (Table 5, cf. (Boehler et al. 2010)).

Table 5: Hypothetical cognitive processes involved in key trial types of the selective stop-signal task

$trial-type_{fMRI}$	GO: stimulus perception	GO: decision-making & response preparation	GO: response execution	STOP: signal perception	STOP: decision-making & response preparation	STOP: response inhibition	outcome evaluation
$NS_{correct-fast}$	1 stimulus	fast	1 bimanual response	-	-	-	success

$trial-type_{fMRI}$	GO: stimulus perception	GO: decision-making & response preparation	GO: response execution	STOP: signal perception	STOP: decision-making & response preparation	STOP: response inhibition	outcome evaluation
$NS_{correct-slow}$	1 stimulus	slow	1 bimanual response	-	-	-	success
$SL/SR_{stop-respond}$	1_{bi} stimulus	fast	1 bimanual response	1 signal	slow?	possibly	failure
$SL/SR_{stop-inhibit}$	1 stimulus	slow	1 unimanual response	1 signal	fast?	yes	success
$SB_{stop-respond-bi}$	1 stimulus	fast	1 bimanual response	1 signal	slow?	possibly	failure
$SB_{stop-inhibit}$	1 stimulus	slow	-	1 signal	fast?	yes	success
$IG_{correct-fast}$	1 stimulus	fast	1 bimanual response	1 signal	slow?	-	success

$trial-type_{fMRI}$	GO: stimulus perception	GO: decision-making & response preparation	GO: response execution	STOP: signal perception	STOP: decision-making & response preparation	STOP: response inhibition	outcome evaluation
$IG_{correct-slow}$	1 stimulus	slow	1 bimanual response	1 signal	fast?	possibly	success

We will specify first-level contrasts to isolate activation associated with action-selective stopping, stimulus-selective stopping, and the difference between them.

First, to isolate activation associated with action-selective stopping, we will specify contrasts separately for SL and SR trials that control for the attentional capture of the stop-signal as well as the speed of the GO process:

$$S_{AS,left} = (SL_{stop-inhibit} - NS_{correct-slow}) - (IG_{correct-fast} - NS_{correct-fast})$$

$$S_{AS,right} = (SR_{stop-inhibit} - NS_{correct-slow}) - (IG_{correct-fast} - NS_{correct-fast})$$

The subtractions within parentheses control for differences in the speed of the GO process between signal and no-signal trials. That is, the GO process on signal-inhibit trials is assumed to be slow (hence the response can be inhibited). The subtractions between parentheses control for the attentional capture of the stop-signal: a signal occurred both on stop and ignore trials, but a STOP process was activated on stop trials only. Note that we will use only the fastest subset of ignore trials, because on the slowest subset a STOP process may have been activated temporarily (Bissett & Logan, 2014). Further note that these contrasts will isolate not only activation related to action-selective stopping, but also activation associated with the execution of the remaining response (i.e. a left-hand response on $SR_{stop-inhibit}$ trials and a right-hand response on $SL_{stop-inhibit}$ trials). To control for this, we will test for activations occurring both in $S_{AS,left}$ and $S_{AS,right}$ using conjunction analyses (see §2.6.2.3.).

Second, following the same line of reasoning, we will isolate activation associated with stimulus-selective stopping using the following contrast:

$$S_{SS} = (SB_{stop-inhibit} - NS_{correct-slow}) - (IG_{correct-fast} - NS_{correct-fast})$$

Third, to isolate differences between action-selective and stimulus-selective stopping, we compute the following two contrasts:

$$S_{AS,left} - S_{SS} = SL_{stop-inhibit} - SB_{stop-inhibit}$$

$$S_{AS,right} - S_{SS} = SR_{stop-inhibit} - SB_{stop-inhibit}$$

Note that these contrasts, like the action-selective stopping contrasts will also isolate activation related to the execution of an unimanual response. To control for this, we will test for activations occurring both in $S_{AS,left} - S_{SS}$ and $S_{AS,right} - S_{SS}$ using conjunction analyses (see §2.6.2.3.).

2.6.2.3. Second-level statistical analysis

Second-level statistical analyses consist of two region-of-interest (ROI) analyses and one whole-brain analysis on the first-level contrasts.

1. ROI analyses using Bayesian hypothesis testing

First, we will analyze brain activation within predefined ROIs using a Bayesian hypothesis testing approach based on the Bayes Factor. This will allow us to compare activation in the same way as we compared task performance and find evidence in favor of and against the null hypothesis. ROIs are defined as 6-mm spheres around local maxima in key regions of inhibitory control reported by previous fMRI studies of action-selective and stimulus-selective stopping (Table 6, Figure 3): inferior frontal gyrus (IFG), inferior frontal junction (IFJ), striatum (Str), pre-supplementary motor area (pre-SMA), supplementary motor area (SMA), dorsal premotor area (PMd), and primary motor cortex (M1). For each key region, we will also define a a 6-mm sphere ROI in the other hemisphere, flipping the sign of local maximum's x coordinate.

Table 6: ROIs defined on the basis of local maxima reported by previous fMRI studies of selective stopping

ROI	MNI [x,y,z] coordinates (mm)	Reference	Contrast in reference
IFG	52, 10, 6	Majid et al. (2013)	MaybeStopRight+Left (Stop > Go)
IFJ	45, 8, 25	Sebastian et al. (2015)	AttentionalCapture > Go
Str	9, 6, 0	de Ruiter et al. (2012)	SuccessfulInhibition > Control
pre-SMA	20, 6, 62	Sharp et al. (2010)	stop > continue

ROI	MNI [x,y,z] coordinates (mm)	Reference	Contrast in reference
SMA	15, -2, 72	Coxon et al. (2016)	StopLeftGoRight > StopAll ∩ StopLeftGoRight > Go ∩ StopRightGoLeft > StopAll ∩ StopRightGoLeft > Go
PMd	28, -2, 65	Coxon et al. (2016)	StopLeftGoRight > StopAll ∩ StopLeftGoRight > Go ∩ StopRightGoLeft > StopAll ∩ StopRightGoLeft > Go
M1	-36, -24, 63	de Ruiter et al. (2012)	SuccessfulInhibition > Control

From these ROIs, we will extract the mean activation level (i.e. parameter estimate) of the first-level contrasts we specified. These data are then analyzed in the following analyses.

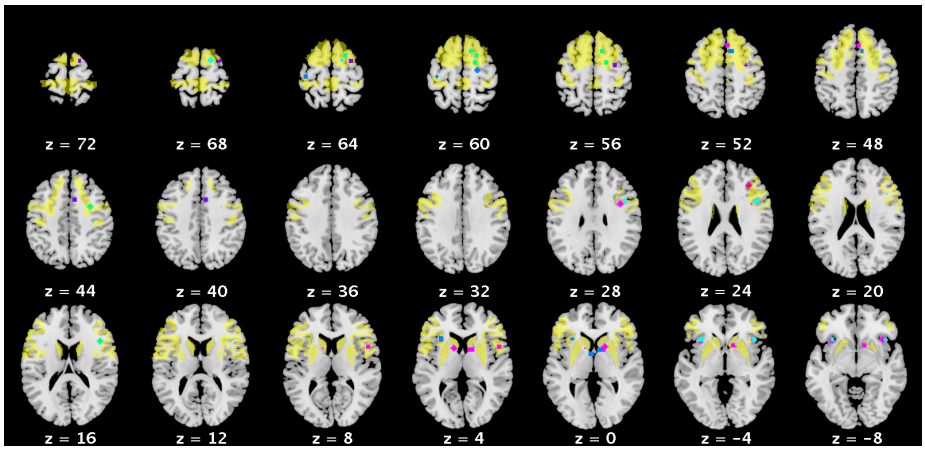

Figure 3: Regions of interest. Spheres represent local maxima from previous fMRI studies of action-selective and stimulus-selective stopping: purple, Coxon et al. (2016); magenta, Majid et al. (2013); red, Smittenaar et al. (2013); blue, de Ruiter et al. (2012); cyan, Sebastian et al. (2015); aqua, Sharp et al. (2010). Transparent yellow regions represent probabilistic neuroanatomical maps of ventrolateral frontal cortex, dorsal frontal cortex, striatum, and primary motor cortex.

Analysis 10 - Identification of activation associated with action-selective stopping

- *Statistical model*:
  - Type: 2 Bayesian one-sample t-tests (test-value = 0)
  - Dependent variable: ROI mean contrast estimate in $S_{AS,left}$, ROI mean contrast estimate in $S_{AS,right}$
- *Transformations*: None.
- *Inference criteria*:
  - If $B_{01} > 1$ in both tests, then we will conclude that the ROI is not activated in association with action-selective stopping
  - If $B_{01} < 1$ in both tests, then we will conclude that the ROI is activated in association with action-selective stopping
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

Analysis 11 - Identification of activation associated with stimulus-selective stopping

- *Statistical model*:
  - Type: Bayesian one-sample t-test (test-value = 0)
  - Dependent variable: ROI mean contrast estimate in S_{SS}
- *Transformations*: None.
- *Inference criteria*:
  - If $B_{01} > 1$ then we will conclude that the ROI is not activated in association with stimulus-selective stopping.
  - If $B_{01} < 1$ then we will conclude that the ROI is activated in association with stimulus-selective stopping.
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

Analysis 12 - Effect of selective stopping type on stopping-related activation in predefined functional regions-of-interest

- *Statistical model*:
  - Type: 2 Bayesian one-sample t-tests (test-value = 0)
  - Dependent variable: ROI mean contrast estimate in $S_{AS,left} - S_{SS}$, ROI mean contrast estimate in $S_{AS,right} - S_{SS}$
- *Transformations*: None.
- *Inference criteria*:
  - If $B_{01} > 1$ in both tests, then we will conclude that activation in the ROI does not differ between action-selective and stimulus-selective stopping.
  - If $B_{01} < 1$ in both tests, the grand mean contrast estimate is positive, and Analysis 10 supported involvement in action-selective stopping, then we will conclude that the ROI is activated on action-selective stop-inhibit trials and activation is greater on action-selective than stimulus-selective stop-inhibit trials.
  - If $B_{01} < 1$ in both tests, the grand mean contrast estimate is negative, and Analysis 11 supported H_1, then we will conclude that the ROI

is activated on stimulus-selective stop-inhibit trials and activation is greater on stimulus-selective than action-selective stop-inhibit trials.

- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

2. ROI analyses using classical hypothesis testing

Second, we will perform another ROI analysis, now using a classical hypothesis testing approach and ROIs defined more broadly based on probabilistic anatomical atlases. The classical hypothesis testing approach will allow us to analyze the fMRI data in a more common framework. The more broadly defined ROIs enable us to assess activation within key areas of inhibitory control that fall outside the spheres the first ROI analyis focused on. We will assess activation in four ROIs defined using human probabilistic neuroanatomical atlases (Table 7): ventrolateral frontal cortex (vlFC, including IFG and IFG), dorsal frontal cortex (dFC, including pre-SMA, SMA, and PMd), striatum, and primary motor cortex. Each ROIs is composed of a number of subregions, also listed in Table 7. The probabilistic map of each of the subregions is thresholded at 25% and the resulting maps are combined in one binary mask. This mask will be used for small volume correction for multiple comparisons.

Table 7: Regions of interest based on probabilistic neuroanatomical atlases

ROI	Subregions included	Reference
vlFC	ventral premotor, inferior frontal junction, 44v, 44d, 45, inferior frontal sulcus	(Neubert et al. 2014)
dFC	supplementary motor area, pre-supplementary motor area, and dorsal premotor area	(Sallet et al. 2013)
Str	executive, rostral motor, caudal motor	(Tziortzi et al. 2014)
M1	area 4a, area 4p	(Geyer et al. 1996)

Analysis 13 - Identification of activation associated with action-selective stopping within broad, anatomical regions of interest

- *Statistical model*:
  - Type: Conjunction analysis (Nichols et al. 2005) across action-selective stopping contrasts in SPM12
  - Dependent variables: $S_{AS,left}$, $S_{AS,right}$
- *Transformations*: None.
- *Inference criteria*: We will report activations that are significant at $P < 0.001$ uncorrected for multiple comparisons and that survive small volume

correction at P $<$ 0.05 family wise error-corrected for multiple comparisons.
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

Analysis 14 - Identification of activation associated with stimulus-selective stopping within broad, anatomical regions of interest

- *Statistical model*:
  - Type: One-sample t-test in SPM12
  - Dependent variable: S_{SS}
- *Transformations*: None.
- *Inference criteria*: We will report activations that are significant at P $<$ 0.001 uncorrected for multiple comparisons and that survive small volume correction at P $<$ 0.05 family wise error-corrected for multiple comparisons.
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

Analysis 15 - Effect of selective stopping type on stopping-related activation within broad, anatomical regions of interest

- *Statistical model*:
  - Type: Conjunction analysis (Nichols, Brett, Andersson, Wager, & Poline, 2005) across contrasts testing for differences between action-selective and stimulus-selective stopping in SPM12
  - Dependent variables: $S_{AS,left} - S_{SS}$, $S_{AS,right} - S_{SS}$
- *Transformations*: None.
- *Inference criteria*: We will report activations that are significant at P $<$ 0.001 uncorrected for multiple comparisons and that survive small volume correction at P $<$ 0.05 family wise error-corrected for multiple comparisons.
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

3. Whole-brain analyses using classical hypothesis testing

Third, to explore activation associated with action-selective and stimulus-selective stopping outside key areas of inhibitory control, we will perform whole-brain voxel-wise random effects analyses.

Analysis 16 - Identification of activation associated with action-selective stopping at the whole-brain level

- *Statistical model*:
  - Type: Conjunction analysis (Nichols et al. 2005) across action-selective stopping contrasts in SPM12
  - Dependent variables: $S_{AS,left}$, $S_{AS,right}$
- *Transformations*: None.

- *Inference criteria*: We will report activations that are significant at P < 0.001 uncorrected for multiple comparisons and that survive cluster-level correction at P <0.05 family wise error-corrected for multiple comparisons.
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

Analysis 17 - Identification of activation associated with stimulus-selective stopping at the whole-brain level

- *Statistical model*:
  - Type: One-sample t-test in SPM12
  - Dependent variable: S_{SS}
- *Transformations*: None.
- *Inference criteria*: We will report activations that are significant at P < 0.001 uncorrected for multiple comparisons and that survive cluster-level correction at P <0.05 family wise error-corrected for multiple comparisons.
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

Analysis 18 - Effect of selective stopping type on stopping-related activation at the whole-brain level

- *Statistical model*:
  - Type: Conjunction analysis (Nichols, Brett, Andersson, Wager, & Poline, 2005) across contrasts testing for differences between action-selective and stimulus-selective stopping in SPM12
  - Dependent variables: $S_{AS,left} - S_{SS}$, $S_{AS,right} - S_{SS}$
- *Transformations*: None.
- *Inference criteria*: We will report activations that are significant at P < 0.001 uncorrected for multiple comparisons and that survive cluster-level correction at P <0.05 family wise error-corrected for multiple comparisons.
- *Data exclusion*: General exclusion criteria (§ 2.7.) apply.

2.7. Exclusion criteria after acceptance in the study

At any stage of the study participants and/or their data may be excluded if any of the following criteria are met. If participants are excluded, they will be replaced so that the total number of participants will be 30.

2.7.1. Exclusion based on task performance

Data from participants will be excluded and replaced if their data meets any of the following criteria

- No-signal choice accuracy < 85% overall, or in five consecutive blocks
- Stop-left trial accuracy < 20% overall, or in five consecutive blocks
- Stop-right trial accuracy < 20% overall, or in five consecutive blocks

- Stop-both trial accuracy < 20% overall, or in five consecutive blocks
- Ignore trial accuracy < 80% overall, or in five consecutive blocks
- Mean no-signal RT > 650 ms overall, or in five consecutive blocks

2.7.2. Additional criteria for exclusion:

- Unanticipated technical failures during data acquisition, including failures of any of the hardware used for stimulus presentation (computer, projector) and data acquisition (e.g. response pad, MRI scanner components, image reconstruction hardware)
- MR artefacts in any of the imaging data
- Excessive head motion
- Participant withdraws from the study for any reason

For Analyses 4-18, data from participants will be excluded on an anlysis-by-analysis basis if data points are more than 2.5 standard deviations from the group mean.

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