

Motion Coherence and Decision Making

Amanda L. Collier

Faculty Advisors:

Mark Wheeler, PhD and Elisabeth Ploran, M.A.

University of Pittsburgh
Pittsburgh, PA

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Abstract

In this behavioral study, motion detection thresholds and perceptual decision making are tested using random dot displays. Participants viewed directional motion within the displays with varying levels of coherence (i.e.- the percentage of dots moving together divided by the total number of dots within the display). Coherence levels that are at, above, and below the sensory thresholds are used in order to obtain measures of accuracy for a wide range of motion coherence levels. The results of this study will be used to in designing a functional magnetic resonance imaging (fMRI) experiment which will employ the same random dot displays as stimuli for a perceptual decision making task. The fMRI will seek to discover the neural correlates of decision making.

Introduction

Decision making is essential to everyday life, and although progress has been made towards discovering its neural correlates, they are not yet fully understood. This project aims to improve the understanding of the behavioral and neural mechanisms involved in the decision making process.

Sensory tasks can be used as an effective test of human decision making since many behavior-guiding decisions are based on sensory inputs to the brain (Kim & Shadlen, 1999). For example, when considering an appropriate time to cross a busy street, one must gather sensory information from the environment before making a decision. Is there a sign indicating a good time to cross? Is the traffic light about to change? Are there

sirens approaching? All of this surrounding sensory data must be gathered and interpreted before a “decision maker region” of the brain can decide whether or not to cross the street.

One theory of decision making, accumulation theory, conceptualizes decision making as a process where evidence is gathered in favor of one choice or the other. It also proposes that separate areas of the brain are carrying out different tasks leading up to the goal of making a decision. Sensory areas of the brain gather signals from the environment, while other areas store this information, analyzing it in the context of the intended goal. These “evidence accumulator” regions would weigh evidence in favor of either choice. For instance, if there is the sound of a siren, an ambulance must be approaching. However, it is far off and you can safely cross the street before it arrives. Then the choice is made to cross the street and a behavior is enacted. This result is because information in favor of crossing the street has accumulated more, and thus reaches its threshold faster than the choice of not crossing the street yet.

However, had there had been no ambulance and no other traffic approaching, this decision could have been made much faster because there would be less evidence against your choice to cross the street. Slower decisions are made when sensory signals are more difficult to detect, like trying to cross the street on a foggy morning. It would be much more difficult to see approaching cars, thus more time would have to be spent on gathering evidence and making that decision.

Many findings from previous studies strongly support accumulation theory. One study used blurred pictures of faces and houses as stimuli in a decision making task while recording brain activity with fMRI. When the pictures were more blurred and therefore more difficult to decide whether it was a face or a house, the rate of increase of neuronal activity was slower in certain regions. These regions include superior frontal sulcus, posterior dorsolateral prefrontal cortex (DLPFC), cingulate cortex, and the superior frontal gyrus (SFG). The pictures that were more blurry had less evidence in support of one option or the other, requiring more time to be spent deciding the identity of the picture. Therefore, because these regions took more time on hard decisions and less time on easy ones, they are believed to be an important part of the decision making process (Heekeren, Marrett, Bandettini, & Ungerleider, 2004). This pattern of slow increase was opposite to the one observed in sensory and attentional areas. In many studies, activity in sensory and attentional brain regions often increases when the difficulty of the task increases because more information must be gathered before a decision can be made.

The idea of decision making happening in one or more discrete areas of the brain has been extensively tested in monkeys. It is difficult, however, to acquire the same results in humans, since monkey studies often involve the study of single neurons and can be very precise in terms of timing, strength of activity, and location (Shadlen & Newsome, 2001; Kim & Shadlen, 1999; Platt & Glimcher, 1999). Due to obvious technical and ethical constraints, single-unit studies are not run on humans for purely research purposes. Area LIP (the lateral intraparietal area) in parietal cortex has emerged as a strong candidate for a “decision making region” or “moment-of-recognition area”. Shadlen and Newsome

(2001) discovered certain neurons in the posterior parietal cortex of rhesus monkeys whose altered activity was predictive of the monkey's response when deciding the direction of motion within a random dot display. Similarly, this study concludes that the timing and magnitude of the response was related to the strength of the motion signal. However, studies done on monkeys use implanted electrodes, which are incredibly precise recording instruments. Human studies are done with fMRI techniques which have somewhat limited temporal and spatial resolution, yet fMRI results still parallel the findings from monkey studies (Heekeren, et al., 2001, Thielscher & Pessoa, 2007). In the Thielscher and Pessoa study, participants were asked to decide if a face looked more disgusted or more fearful. The hypothesis was that brain activation, recorded by fMRI, would predict the perceptual choice. This idea has been tested before, but most often in single-unit studies on monkeys (Shadlen & Newsome, 2001; Kim & Shadlen, 1999). Their idea was to look at time courses from individual voxels (small sections of the brain from which fMRI scans record activity) and see if time courses from each voxel could predict perceptual choice, just as single cells in monkeys predict choices. They found that activity within a single voxel could predict whether the participant would choose "fearful" or "disgusted" to describe the stimuli. This result was found when voxels were averaged across the group and also for single participants.

Studies that test perceptual decision making in humans most often use highly complex stimuli, such as pictures or words, and involve a fairly complicated task. The motion detection tasks that are used with monkeys during single-unit studies are quite simple in

comparison. The motivation behind using a simple motion detection task in this study is to determine if the results from the monkey studies can be paralleled in humans.

This study is designed to test the paradigm and determine its effectiveness for discovering motion detection thresholds. Like many tests of psychophysical thresholds, it is predicted that accuracy of motion detection will increase as a sigmoidal function of the coherence level. The coherence level is the independent variable which will be the measure of difficulty of the task, and accuracy should change as a function of these different levels.

Random dot displays are ideal for testing perceptual decision making because of their precision of measurement. Unlike many other studies, which use different types of sensory “noise” to occlude the stimuli, the amount of noise present in a random dot display is precisely quantified by using a percentage. Motion coherence is defined as the number of coherent dots (i.e.- dots moving in one unified direction) divided by the total number of dots within the display. Therefore, the degree of stimulus difficulty can be easily measured with the motion coherence percentage. It is also simple to alter this degree of difficulty and have a set of stimuli which can be presented below, above, and at a participant’s threshold. In a study that tested the effects of velocity, density, type of movement of coherent dots, and type of movement of random dots, there were no large differences of motion detection threshold depending on these variables. Some interactions were observed, and there was a main effect of noise type, but between subjects, thresholds varied by no more than 3% (Scase, Braddick, & Raymond, 1995).

Once satisfactory results are obtained from this experiment, more factors can be manipulated and analyzed. This project is the first step towards achieving the ultimate goal of discovering the neural mechanisms of decision making. This paradigm presents motion at discrete coherence levels, meaning that one trial presents motion at high coherence level, the next trial presents motion at a low coherence level, etc. The extension of the study will test gradual increases of motion coherence so that in some trials, the level of coherence will start out well below threshold and then increase in gradual segments. It is hypothesized that when motion is presented in this manner, motion at lower coherence levels will be able to be detected more quickly and more accurately than when it is presented discretely because the nervous system is gathering the below-threshold motion signals before they enter consciousness. When the scanning phase of this experiment begins, the gradual increase task will reveal activity in the sensory regions that collect the motion signals from the environment, from the evidence accumulators that are storing and analyzing more and more of this sensory data as it is processed, and also from regions which will only show activity when motion is detected and a decision is made.

The results from the current experiment will show behavioral patterns in terms of accuracy for motion detection at a wide range of coherence levels. Most importantly, it will determine a general motion detection threshold for humans and determine if the pattern of results fits the expected psychometric curve. Currently, accuracy is the only variable being analyzed, but reaction time will be considered later, when testing begins

using the gradual increase coherence paradigm. The behavioral patterns being acquired with this experiment will help to make sense of the neural patterns of activity that will be observed with the fMRI experiment.

Stimuli

Visual stimulus was consistent for all three experiments. The random dot display consisted of 170 white dots on a black background. The dots moved within a circular aperture of approximately 5-10 degrees visual angle and were randomly replotted to create the random noise. During periods of coherent motion, the same dots moved coherently across the screen, instead of different dots being moved coherently from frame to frame. The random dot display remained on the screen during the entire procedure, and did not switch off and on during trials. A fixation cross remained centered on the screen to discourage eye movement. For all experiments, coherent motion moved only right or left.

Participants each viewed a total of 576 trials divided into six equal blocks with two-minute break periods in between. Each trial began with a 2000 ms fixation period which consisted of a white fixation cross in the center of the random dot display while the dots moved with 0% coherence. After the fixation period, the cross would switch to green and remain green for 2000 ms to denote a trial period during which coherent motion would appear. In Experiments 1 and 3, some trials contained no motion and were meant to control for false alarms. Participants were not informed how many zero motion trials each run contained. Motion onset would occur at different intervals within this window (at either 500 ms, 750 ms, 1000 ms, or 1250 ms into the trial), but never within the first or

last 500 ms of the trial period. Coherent motion was presented for 250 ms. Each direction of motion and time of motion onset appeared equally often for each coherence level.

Experiment 1

Four subjects (two female) were tested in the initial piloting phase, which was used to determine a general motion detection threshold. Motion coherence levels ranged from 0% to 100% in increments of 5%. A larger number of trials concentrated in the 20% to 50% range, in which it was hypothesized that the threshold would occur. Subjects were instructed to view the random dot display and respond with a button press as soon as they could detect coherent motion within the display. Subjects were instructed to withhold button presses when they did not detect motion.

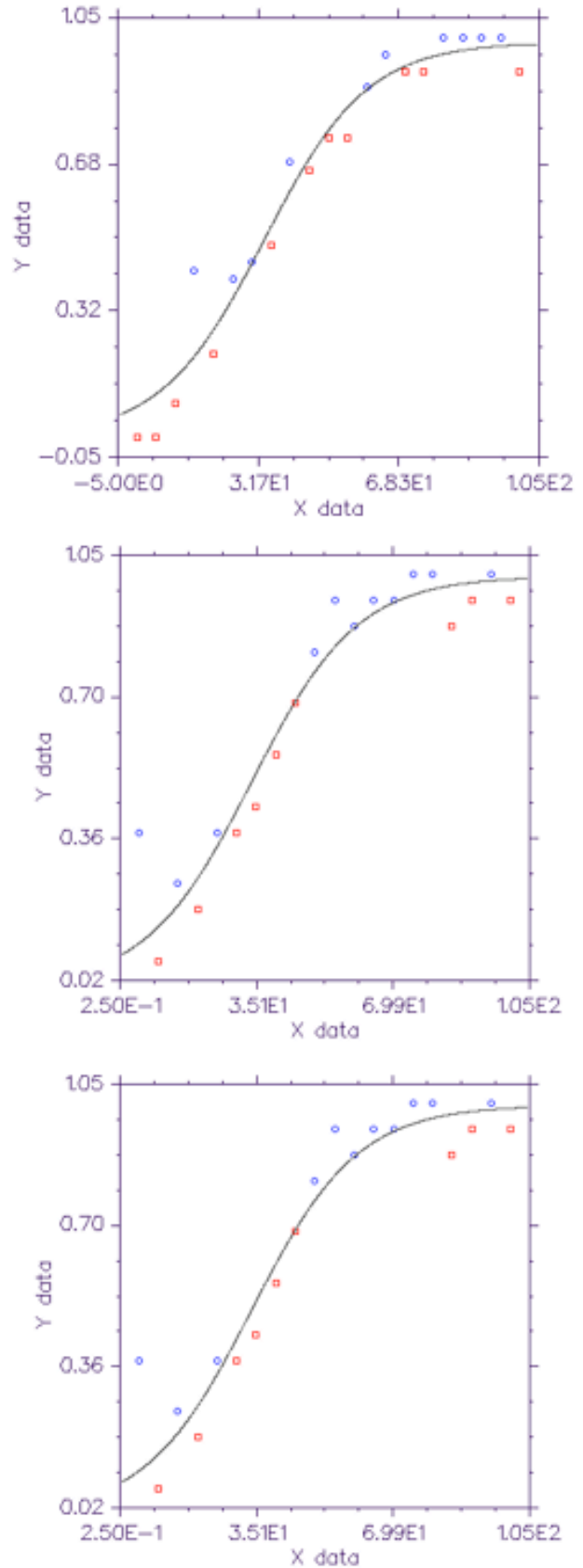


Figure 1. Each graph represents a single subjects' data. Data is plotted as a function of $y = a / (1.0 + b(\text{LOG}^{(c)}(x)))$. Accuracy is plotted along the y-axis and coherence level is the x-axis.

Results—Experiment 1

After initial analyses, one subject's data was excluded because of an excessive false alarm rate (subject responded to 60% of zero motion trials). The behavioral results of Experiment 1 show that accuracy increases as a logistic function of motion coherence. When plotted using the formula:

$$y = a / (1.0 + b * (LOG^{-cx}))$$

each data set displayed the expected sigmoidal curve (see Figure 1). Online computational programs were used to determine coefficients and plot graphs (www.zunzun.com). To calculate the coherence level at which subjects responded with 50% accuracy, the inverse of the original formula was obtained:

$$x = -\{[LN(-y + a) / (y * b)] / c\}$$

By solving this with each subjects' individually determined coefficients and using 0.50 as the y -value, x would then represent the coherence level that yielded 50% accuracy. The coefficients used are based on each accuracy score for every coherence level. Thus, the x -value derived from this equation gives a threshold level that takes into account a subject's full range of accuracy scores, not just the point where the plotted line crosses 50% accuracy. The 50% level represents the sensory threshold for detecting motion.

The range of 50% threshold levels for the three subjects was 33.97—37.84. At 50% accuracy, the mean level of coherence was 35.29, with a standard deviation of 2.21.

Experiment 2

After data was obtained for the motion detection threshold, the range of coherent motion was narrowed to 20% through 65% in increments of 5%, with 10% and 70% coherence levels added to obtain data from the ends of the distribution. Every participant was presented with each coherence level 48 times during the experiment. Data were gathered from nine participants (five female). Stimulus and experiment setup remained unchanged from Experiment 1 with the following response differences. During this phase of testing, participants were required to respond by pressing an arrow key indicating the direction of motion. Two versions of this task were created, forced choice and non-forced choice. Participants were tested with one task or the other, not both. Three participants had the non-forced choice task, and four had the forced choice task. Non-forced choice runs exactly like Experiment 1, except that participants choose a direction when they see motion. Participants continue to withhold a response when no motion is perceived. This task generates data regarding participants' false alarm rate and correct rejections as well as accuracy and reaction time. The forced choice required participants to respond to every trial, regardless of whether they detected the motion or not. The experiment remained unchanged, except that participants were instructed to respond during a 2000 ms fixation period following a cued trial period to avoid early guesses prior to actual motion. Results for this version are expected to show the same sigmoidal curve, but accuracy for the lowest coherence levels are not expected to dip below 50% simply due to chance guessing. This version of the task was designed to produce data that would reveal left-right biases, and will be of particular interest in the scanning phase of the study.

Experiment 3

After not obtaining the desired sigmoidal curves from the short range of coherence levels that were tested in Experiment 2, the range of coherence levels was expanded to include 0%-5% and 75%-80%. Nine participants (6 female) were tested using this range of levels, with three of them taking the forced choice task. Each coherence level was presented 36 times per test, and appeared equally often traveling right or left. Times of motion onset were concentrated around the middle two time slots, with each motion coherence level beginning onset one time each in the outer two time slots and two times each in the middle two time slots for each of the six blocks.

Experiment 2 and Experiment 3 Results

Again, thresholds were calculated and graphs plotted for each subjects' data. One participant was excluded due to a high d-prime value (0.65) indicating too much of a response bias for motion traveling left, and another was excluded for misunderstanding of instructions. For the non-forced choice data, threshold levels were calculated when participants responded with 50% accuracy. For the forced choice data, the thresholds were computed for 75% accuracy, since the forced choice condition should yield accuracy no lower than 50% due to chance guessing. An ANOVA was done to determine if the thresholds were significantly different, and therefore not able to be collapsed across experiments or tasks. The first ANOVA was a 2 x 2 comparing task (forced choice and non-forced choice) and the different ranges between Experiments 2 and 3 (10% - 70%

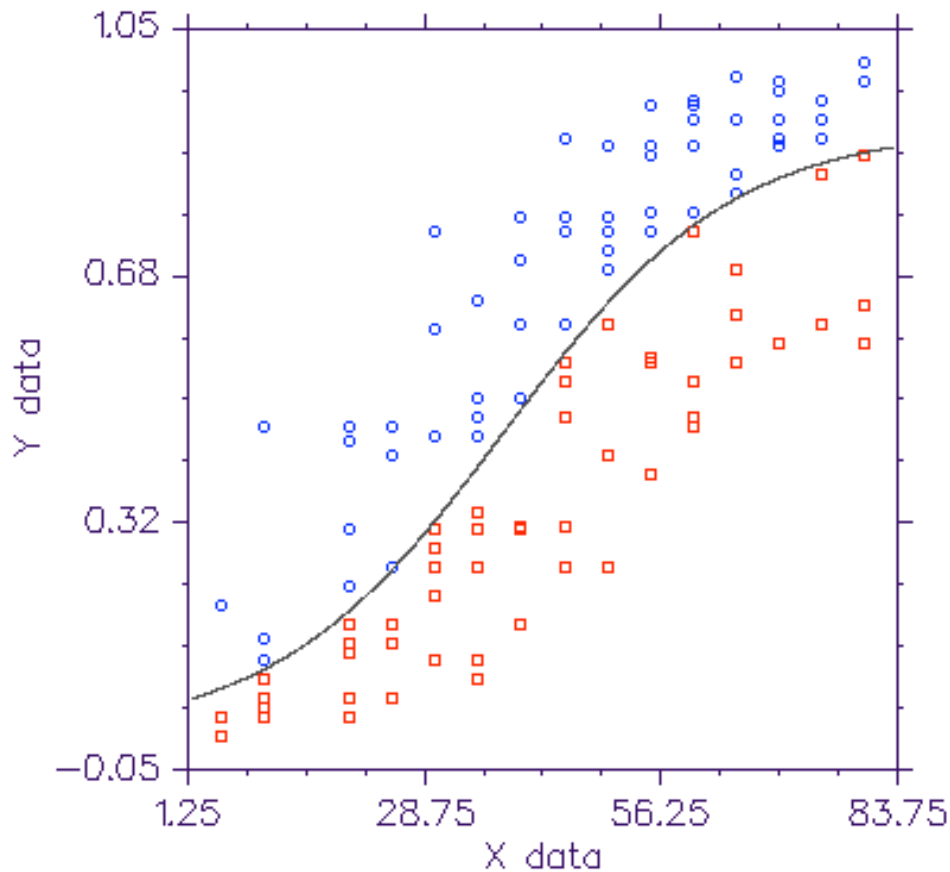


Figure 2 shows the curve plotted from non-forced choice data from Exp 2 and 3. Each point represents an individual score of accuracy at the given coherence level. The plotted curve is a best fit of all the points when graphed with the formula $y = a / (1.0 + b * (LOG^{-cx}))$. Points from all coherence levels are included in the graph, except zero points. Blue points denote values that fall above the averaged curve from all participants, and the red points are values that fall below the average. False alarm rate averaged over all nine non-forced choice participants was 6.48%.

and 0%-80%). The results of the ANOVA did not reach 0.05 alpha-level significance, $F(1, 14) = 0.757, p = 0.539$. This result allowed for the groups with different ranges between Experiment 2 and Experiment 3 to be collapsed across task. A second ANOVA compared these combined thresholds according to task. Again, the results were not significant, $F(1, 14) = 1.072, p = 0.318$. The results from the two tasks were kept

separate for further analysis, however, while results from between experiments were combined.

For the non-forced choice groups, the range of threshold was 19.61%—63.08% , with a mean threshold of 41.80% coherence level for 50% accuracy, and $SD = 14.16$. The forced choice group had a range of 35.14%--63.67%, and a mean threshold of 48.04% coherence level for 75% accuracy threshold, and $SD = 11.39$. Like the pilot data, all of the individual non-forced choice data fit a sigmoid function when plotted with the logistic equation (see Figure 2.). The curves illustrated by the individual data plotted in Figure 1 and the group data in Figure 2 show that the paradigm used in this experiment is able to measure a participants motion detection threshold accurately and consistently, and it produces the desirable results. The data from the forced choice experiments does not fit the sigmoid logistical curves as well due to its element of chance guessing, which does not allow the accuracy to increase in the normal pattern exhibited in the non-forced condition. The forced choice task will be of much more use in the scanner than it is for the behavioral results.

Discussion

Overall, the results from these initial experiments confirm the hypothesis that a motion detection paradigm would produce data that show accuracy increasing as a function of coherence level. It was discovered, however, that these curves are not obtained when a condensed range of coherence levels are used, (i.e.- the 10%-70% range) and that the range must be extended well beyond threshold in either direction for the desired pattern to take shape. A possible explanation for this was that equation used to plot the curves

works best when y-values (accuracy) begins at 0%. Most participants were more accurate than 0% at 10% coherence, and this is why the range was extended to include 0% and 5% coherence.

These satisfactory results bring the project a step closer to its intended goal of running this experiment in an fMRI scanner and mapping out the neural correlates of decision making in the brain. Since the results signify that the paradigm accurately measures motion detection thresholds, it can now be used in the scanner as an accurate test of sensory thresholds and related perceptual decision making processes. It can also be modified into a gradual increase motion detection paradigm that will be used in the scanning phase as well.

Although the total outcome of these experiments was successful, there are still a few issues that remain unsolved. The first of these issues is the large amount of variation seen in the thresholds of all the participants. During the behavioral testing, no clear reason why some participants' thresholds were much higher or lower than others' emerged. Other literature which tests human motion detection with random dot displays often tests participants prior to scanning to find each individual's threshold (Shulman et al. 1999; Shulman et al., 2003). This procedure signifies that perhaps threshold variation is common, and it also shows that it is easily controlled for after initial testing is done. In the future behavioral studies, age and handedness will be controlled so that they will be eliminated as possible confounds.

Another obstacle encountered was the failure of the forced choice data to fit the sigmoid logistic functions as well as the non-forced choice data. The graphs made with the non-forced choice data illustrate the effectiveness of the paradigm to test sensory thresholds. Using the same paradigm with the forced choice task, however, those same curves were not obtained. It was hypothesized that the curves for each task would look identical, but the forced choice graphs would simply be on a smaller scale, with the y-axis extending from 50% to 100% instead of from 0% to 100%. The element of chance guessing that the forced choice task included threw off the sigmoid patterns of motion detection increase, which existed within the non-forced choice data. Nonetheless, the forced choice task will continue to be used, particularly for the scanning experiments. Although the forced choice task does not provide behavioral results identical to the non-forced choice data, it will help reveal interesting neural patterns of activity. When a subject is presented with a zero motion trial in the non-forced choice task, that subject makes the decision to withhold a response based on lacking sensory input in favor of one direction or another. In the forced choice task, there is no option to withhold a response. While a participant may be aware that there is no coherent motion, he or she must decide anyway. The fMRI scans will reveal what type of activity is occurring while this participant makes that “chance” decision, and what, if not sensory inputs, is causing the participant to choose a particular direction.

This behavioral experiment was an essential step towards the goal of using random dot displays to test and understand human decision making. It established a human motion

detection threshold, verified that the paradigm could produce results that fit the intended sigmoid curves, and created two tasks that will be used in later parts of this experiment.

References

- Heekeren, H. R., Marrett, S., Bandettini, P. A., & Ungerleider, L. G. (2004). A general mechanism for decision-making in the human brain. *Nature*, *431*, 859-862.
- Kim, J.-N., & Shadlen, M. N. (1999). Neural correlates of a decision in the dorsolateral prefrontal cortex of the macaque. *Nature Neuroscience*, *2*, 176-181.
- Platt, M. L., & Glimcher, P. W. (1999). Neural correlates of decision variables in parietal cortex. *Nature*, *400*, 223-238.
- Scase, M. O., Braddick, O. J., & Raymond, J. E. (1996). Research note: What is noise for the motion system? *Visual Research*, *36*, 2579-2586.
- Shadlen, M. N., & Newsome, W. T. (2001). Neural basis of a perceptual decision in the parietal cortex (area LIP) of the rhesus monkey. *Journal of Neurophysiology*, *86*, 1916-1936.
- Shulman, G. L., McAvoy, M. P., Cowan, M. C., Astafiev, S. V., Tansy, A. P., d'Avossa, G. et al. (2003). Quantitative analysis of attention and detection signals during visual search. *Journal of Neurophysiology*, *90*, 3384-3397.
- Shulman, G. L., Ollinger, J. M., Akbudak, E., Conturo, T. E., Snyder, A. Z., Petersen, S. E., et al. (1999). Areas involved in encoding and applying directional expectations to moving objects. *The Journal of Neuroscience*, *19*, 9480-9496.
- Thielscher, A., & Pessoa, L. (2007). Neural correlates of perceptual choice and decision making during fear-disgust discrimination, *The Journal of Neuroscience*, *27*, 2908-2917.