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Contribution of eye-tracking to the study on perception of the complexity

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Abstract. In studying the way human beings evaluate randomness and produce random objects, cognitive psychology showed that the mind finds it difficult to recognize true randomness as well as to produce it because it is influenced by numerous biases. Studying them can help to understand better the way it is structured. In parallel, mathematics showed that more random objects have a higher algorithmic complexity. Computing lately provided practical means to calculate the algorithmic complexity of objects of finite size and also produced new encounters between mathematics and cognitive psychology by allowing the latter to envision new models for the brain, inspired by algorithmic logic. In this context, our research applied eye-tracking techniques to the study of the perception of complexity. Forty subjects had to order images belonging to ten groups of four according to decreasing (perceived) complexity. The hypothesis was that images with the higher algorithmic complexity would be perceived as more complex as well and would cause longer fixation times. However, experimental results did not confirm these hypotheses as the correlation between algorithmic and perceived complexities was low, and the relation between complexity and fixation time was not linear but closer to an inverted "U" shaped curve. This may be due to contextual effects and to choose images with complexities too close to each other, as subjects found it difficult to order them as requested. Further experiments must then be carried out with conditions better controlled and modified parameters.

Keywords. Cognitive psychology, theory of complexity, randomness, visual perception, perceived complexity, eye-tracking

Introduction

This research in the framework of cognitive psychology is concerned explicitly with the studies on randomness. Cognitive psychology has long been studying the ability of humans to recognize random objects and their ability to produce them. These capabilities have certain limits in both cases: humans fail to recognize objects constructed from simple algorithms, and they have difficulties in generating truly random objects.

Thus there is an important difference between "human random" and "mathematically random", and this is this difference sparked my interest, although I am not a mathematician.

Intuitively, random objects are more complex than those built from an algorithm. The question of the precise characteristics of randomness is thus closely linked to the one of knowing how to measure complexity. Mathematics indeed developed ways to measure it, and recently using the computer, and it has become possible to devise pragmatic methods of calculation for the complexity of objects of finite size.

Based on a review of the relevant literature, the first two parts of this study are devoted to providing the theoretical background in which our research developed. Chapter 1 presents this background from a more mathematical point of view, addressing the question of the characteristics of randomness and showing the link between randomness and complexity. It then comes to the issue of the computability of computational complexity and introduces the pragmatic method used to calculate it. It also presents a number of biases specific to the way human beings assess and produce random objects.

Chapter 2, also based on a literature review, this time looks at the context of the research from the perspective of cognitive psychology. Based on several earlier research, the human limitations and biases mentioned in the previous chapter try to examine the different parameters that can influence the perception of randomness and complexity.

Our literature review for both chapters also shows that human limitations and biases mentioned above can be used by researchers to make assumptions about brain structure, and since the inception of computers, these assumptions are much based on the way these “electronic brains are structured. Computing thus led to new ways of building models for the human brain. This can be seen in Chapter 2, where it is clear that the mathematical concepts appearing in Chapter 1 can help to suggest interpretations for the observed limitations of human brain.

Chapter 3 provides details of the experiment, its unfolding, the equipment used and the results obtained. In the context defined in the first two chapters, we sought to investigate the relationship between complexity as perceived by human beings and computational complexity calculated from the new methods mentioned in Section 2. Our first hypothesis, based on earlier publications we scanned, was that the images offering the highest computational complexity would actually be preceived as the most complex. The second hypothesis from our literature review was that the subjects would stare longer at the more complex images.

As previous research made little use of eye-tracking measurements, we took this orientation and proposed an experiment where participants would be requested to rank forty images in order of decreasing complexity, while their eye movements were recorded.

The experimental setup was as follows: each participant was installed in front of a computer screen to which an eye tracker had been installed. The screen showed (in the same order for each participant) ten successive patterns of four images of a known algorithmic complexity. Each pattern was displayed for a limited time, during which the subject had to select images with the mouse, according to what he considered as the order of decreasing complexity. The eye tracker, after data processing, provided the duration of participant’s fixation of each image on the screen.

Not having confirmed the hypotheses, the results obtained are discussed at the end of this work, opening the field to new research and perspectives by proposing studies that explore the oculometric data with more finesse and on larger samples.The results did not confirm the previous assumptions. Their discussion at the end of this work will open the field to new research and perspectives by proposing studies that explore the eye tracking data with more precision and using more extensive samples.

1 –Randomness and complexity

1.1. Why studying random objects ?

The study is concerned with examining the relationship between objective (algorithmic) and cognitive (perceived) complexity. Chapter 1 introduces its mathematical context, in link with cognitive psychology.

Cognitive psychology has an interest for the way humans perceive randomness, because studying this allows gaining knowledge about intuition and forms of reasoning, which in turns makes pôssible to develop hypotheses on the structure and functioning of human brain. Random situations provide proper experimental situations to address these two issues, whether we study how subjects *perceive* randomness, or how they *produce* random objects or events (or at least the most random possible).

1.2. Human biases

Human beings evaluate the degree of randomness of objects presented to them according to their spontaneous or acquired conceptions, *i.e.* from their own biases, and conversely, they produce “random” objects that bear the mark of these biases. The study of these biases, in perception as in production, and more generally, the study of the relationship between randomness and human beings, may provide important information on the mode of operation of the human brain. Among the observed bias, we can quote: include *agreement bias* (positive answers to a question are more numerous than they should be), *positivity bias* (“favorable” responses are more common), and *precedence bias* (the *first* choice offered is selected more often).

One of the most important human biases concerning randomness is *alternation bias*: the probability of alternation within a string produced by a human subject is higher than the one that can be calculated for a truly random sequence. This can be explained by the limitation of human working memory. As it possesses only 5-10 “boxes”, the brain divide the string into chunks on which the law of large numbers is then applied “locally”, whereas it is true only at the limit. This suggests that the human intellect has a *memory* component (which manages storage proper) and an *algorithmic* component (which can devise the workaround to the memory limitation by defining new data structures).

1.3. Relationship between “human” and “mathematical” randomness

Researchers have tried to compare in a concrete manner “human randomness” (perceived or produced) to “objective randomness”, which required to have available an objective measure of the degree of randomness of an object. This is where the needs in mathematics and psychology meet.

What criteria can be used to distinguish in an objective manner a sequence which is random from another which is not? Intuitively, random objects are mathematically more complex than objects that can be built following specific rules. The first question is thus whether it ispossible to calculate the complexity of an object (another remark is that human beings also have an imperfect intuition of complexity: they perceive the frequent, familiar, prototypical (or easy to learn, “learnable”) visual information as less complex).

1.4. Turing machines and binary sequences

Considering the *binary sequence* ({001110101110101 ...}) as the archetypal object – an object to which any other may ultimately be reduced – and in order to address the issue of determining the complexity of a sequence, the Turing Machine (hereafter *TM*) may be used. It is a simple model of computer, receiving instructions on a input tape, and producing a result on its output tape.

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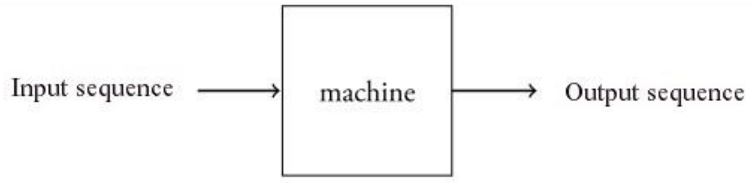


Principle of a Turing Machine

Such a system can also be described as a *finite state automaton*, representable by a graph or by the formalism of the λ-calculus devised by Church (it is through the use of these various representations that it has been proved, in response to the Hilbert "decidability question", that it existed *non-computable* or *undecidable* problems, *i.e.* mathematical statements for which there exists no algorithm for deciding whether they are true or not).

1.5. Calculating algorithmic complexity

Intuitively, the more random a chain is, the more it should be complex, i.e. complicated to generate. The algorithm allowing to build it must be of greater length. An undecidable problem should then have an infinite complexity (the algorithm for generating it would be of infinite length). If an infinite sequence is generated by a finite length program on an universal *TM*, it can thus be generated on any *TM* (any finite sequence is necessarily generable by a finite length program, e.g. an instruction to copy the input sequence to the output tape ("photocopier" *TM*).

According to this reasoning, the complexity of a series is *the minimum size of a program able to produce it*. Thus, in the case of a program p producing the series $\boldsymbol{s}$ on a universal *TM* called T, the complexity K_T of $\boldsymbol{s}$ est:

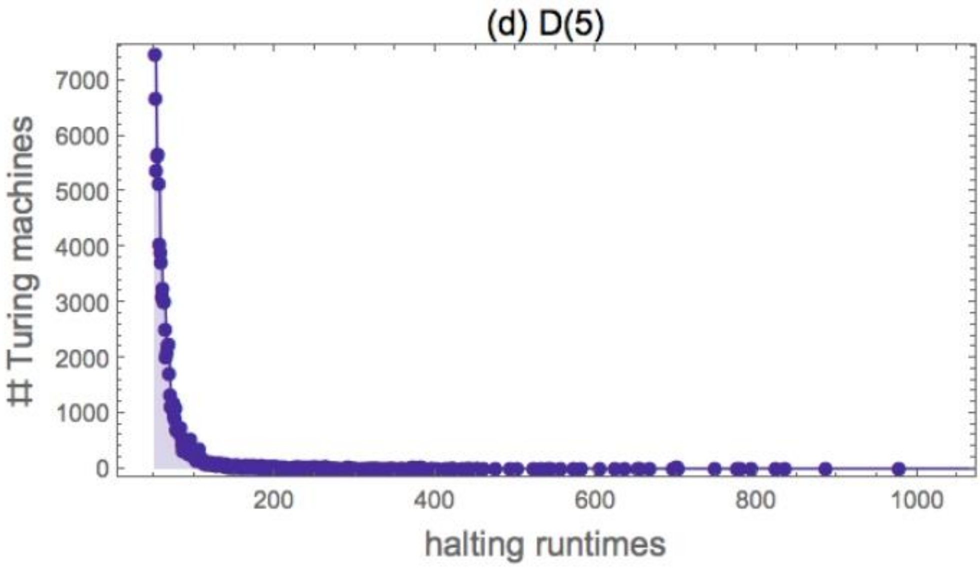
$$K_T(\boldsymbol{s}) = \min \{|p|, T(p) = \boldsymbol{s}\}$$

This measure also allows to decide the degree of randomness of $\boldsymbol{s}$. A series is considered the more "random" as its complexity is high for its length. If the shortest program producing it is longer than it, then $\boldsymbol{s}$ is considered random. In the case of an infinite sequence, if $\boldsymbol{s}_n$ is the series truncated to its first n terms, then $\boldsymbol{s}$ is random if and only if there exists an integer c as the complexity $K(\boldsymbol{s}_n) > n - c$ for whatever value of n.

The Kolmogorov Complexity theoretically applies only to infinite series. But practically, for psychology experiments where subjects are asked to evaluate or produce chains rarely exceeding 50 characters, it is extremely important to approach the Kolmogorov-Chaitin complexity of *short* chains.

As there is no algorithm to tell whether a *TM* will stop (*halting problem*), it is theoretically impossible to calculate the function K, a fact which implies the *non-computability of Kolmogorov complexity*. However the latter has been usually estimated by pragmatic ways, for example through the use of compression algorithms as lossless LZW (Lempel-Ziv-Welch): the more compressible a string is, the lower its complexity.

The Levin-Solomonoff algorithmic probability of a sequence is connected to the Kolmogorov complexity as the probability of obtaining this result from an *TM* receiving a random sequence of instructions – provided that the *TM* accepts only programs containing an "End" instruction. Soler-Toscano and his colleagues were able to calculate this probability pragmatically in 2014 through a calculation limited to 5-state *TM*s, and by limiting the duration of operation to 500 steps (the curve below shows that most *TM*s stop before 100 steps). They also used "busy beaver" functions that predict after how many calculation steps a *MT* will not stop anymore.



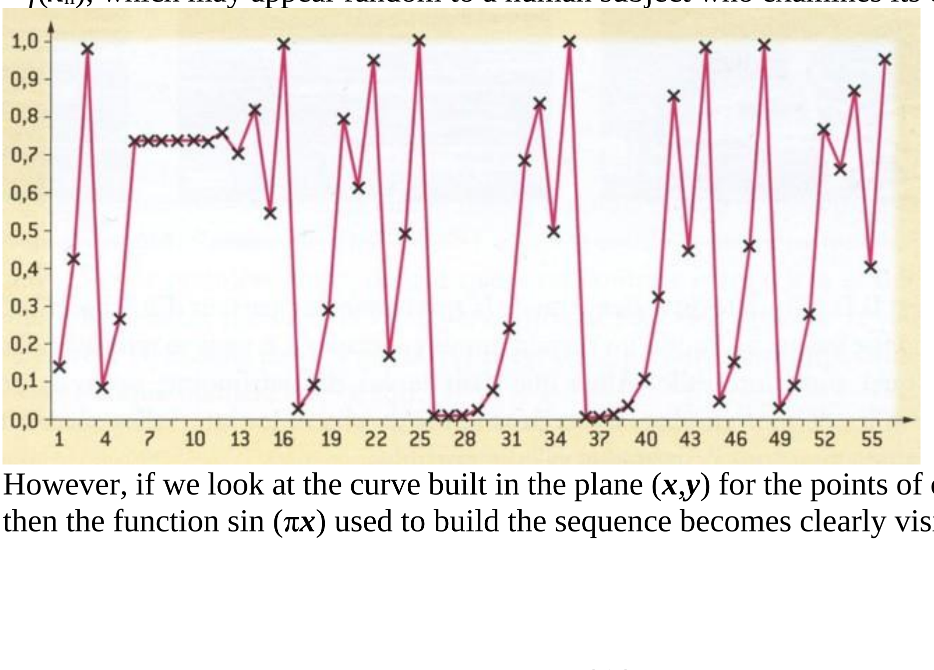
x-axis: number of calculation steps before stop.
y-axis : number of 5-state Turing Machines.

This allowed to obtain a formal definition of algorithmic complexity that would be appliquable for experimental situations of cognitive psychology, as it may apply to finite-size objects – a size adapted to studying human perceptions.

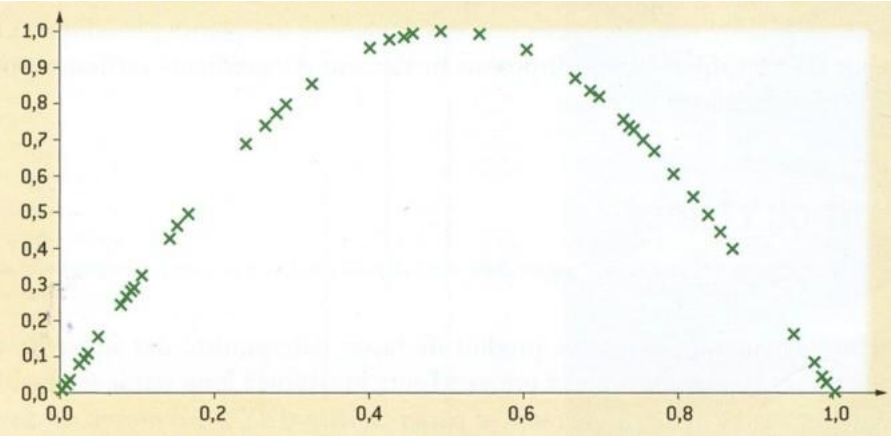
2 - Visual perception and processing of complexity

2.1. The "intuition of probable" and its limitations

Human mind seems to have a certain *intuition of probable*: if an experimenter repeatedly pulls balls from a bag in front of children, when the bag content is shown to them, they stare longer at statistically surprising contents. This could indicate the existence of a human innate – or at least very early – intuition of randomness. Experiments also show that computational complexity is a good predictor of the *subjective* (perceived) level of randomness. But this human intuition is itself limited: a sub-suite from the sequence of π decimals is not spontaneously recognised and is evaluated as random. Another example is this sequence $\boldsymbol{x}_n + 1 = f(\boldsymbol{x}_n)$, which may appear random to a human subject who examines its curve (below).



However, if we look at the curve built in the plane $(\boldsymbol{x},\boldsymbol{y})$ for the points of coordinates $(\boldsymbol{x}_n, \boldsymbol{x}_{n+1})$, then the function $\sin(\pi \boldsymbol{x})$ used to build the sequence becomes clearly visible :



Although algorithmically very simple, those two sequences appear very complex in terms of *subjective randomness*.

Human brain finds difficult to memorise chains with a too high subjective complexity. For the capacity of memorisation as well, computational complexity appears to be a good predictor. Presented with too complex chains, subjects generate instead chains of lower complexity. Experiments of memorisation of patterns with children – who have a lower processing capacity than adults – show a faster emergence of patterns that are more structured, hence easier to learn / memorise. This is in line with the hypothesis mentioned in chapter 1 that the brain, because of its limited processing capacity, tends to "create structures" in complex objects, i.e. manipulate their complexity in the sense of a simplification. One of these methods for creating structures is *chunking*, i.e. splitting objects into sub-elements, sometimes already known through prior learning, a prior knowledge that should be taken in account.

The probability of having previously seen an object influences its familiarity, hence its learnability. An objective factor of familiarity is its frequency of appearance, which means its objective probability. The algorithmic probability of a given binary string can be defined as the probability of obtaining this sequence through the execution of a random program. If each instruction is chosen randomly, shorter programs (thus less complex sequences) are logically more likely. An experiment where subjects were asked to rate the degree of randomness of 4x4 tables extracted from photos of natural scenes (Wikimedia commons pictures) – i.e. to attribute them a subjective randomness – showed that *subjective* and *natural* randomness are indeed correlated ($r = .75$, $p < .0001$), as well as computational complexity and subjective rabndomness ($r = .52$, $p < .0001$).

This result suggests that our perception of the complexity depends in part on our perception of natural scenes. It is possible that the brain learns *visually* to distinguish randomness, through looking at the world. Among the prior knowledge used in remembering contexts, there would be then what one might call a "statistical knowledge of the world".

Psychologists also use another parameter: *learnability* is not only based on the structure of the object itself (its complexity), or its relationship to the context (its shape proximity to other objects, as in the case of natural scenes) but on what could be characterised as how a community perceives it. The most learnable elements are better remembered and thus move more easily across the community. The learnability of an item thus appears as a measure of its adaptation to the human community where it spreads. Experiments with short stories show that more complex ones are generally less learnable, although there are exceptions, based on interest, oddity or even degree of humor.

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Another parameter, the *prototypicality* of an object, is the degree of correspondence between this object and *what people have learned to expect*: the object is “typical” or “prototypical” of a class of objects known by previous experience. Some studies on web sites show a preference for sites “matching expectations”. In the “prototypicality bias”, the oak, for instance, is quoted more often when subjects are asked for a tree. It appears as the representative for the whole class and concept of “tree”. This could be due to the serial storage of the class elements in the brain, the oak being the first element and hence accessed first.

Complexity and preference

Several experiments show the influence of various parameters onto the attention given to the objects by the subjects – attention being after all the first necessary element to establish a possible preference.

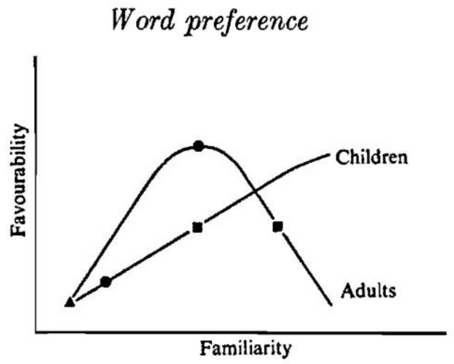
A study on the influence of the complexity of the packaging on consumers attention has shown that increasing the quantity of information units on the packaging also increases visual attention (number and duration of eye fixations). This can be explained by the need for a longer processing time, due to the limitations of processing capabilities. But another study found that consumer *motivation* – a parameter independent of object complexity – as well as the time given to the subject to reach a decision also influence the choice of the information visually processed. Besides, ads with a degree of originality attract more attention – and ads both original and familiar are even more attractive (see the relationship learnability-prototypicality).

However, conclusions differ as to whether simplicity or complexity should be favoured. Some authors even define new complexity parameters (*feature* complexity vs. *design* complexity). Indeed, if limitations on processing capacity should lead to avoid a too high perceived complexity, conversely, too low complexity (although it would theoretically allow easier storage) would appear as annoying, hence unattractive... This led to the Berlyne theory, which predicts average complexities to be the best, with an “inverted U”-shaped complexity-attractivity relationship. However, empirical evidence proved quite inconclusive.

A study using websites screenshots showed that websites with low visual complexity and high prototypicality were perceived as very attractive, and demonstrated a linear (rather than “inverted U”) relationship between aesthetics and visual complexity. This can however be explained by the fact that websites are highly complex objects, and might be located on the right side of the inverted-U curve. The study also suggests a positive relationship between prototypicality and aesthetics.

Subjects’ gender seems to be a parameter as well: several experiments showed that boys preferred high complexity websites, while girls favoured those with medium or low complexity.

Familiarity and preference



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Relation familiarity – appreciation according to Colman

Finally, a rather old experiment showed an inverted-U curve connecting attractiveness (appreciation) to familiarity for groups of letters, some of them only forming words. In this experiment, familiarity was dependant on three same (and increasing) age groups.

3 - Experimentation

The context of the question

The invention of computers has provided a new paradigm and hence new hypotheses to study humain brain organisation. Hypotheses on its structure are now much influenced by computer, with algorithmitic as well as storage characteristics. Our research follows on this context, with such characteristics as chunking, serial access, or structure creation that we introduced in preceding sections. Hence we tried to compare the algorithmic way of working of the computer and human brain through the study of cognitive complexity.

Researchers still debate to decide if the human tendency to perceive and process complexity (randomness) is or not innate, but in any case, experiments point to an ability acquired extremely early. Whatever the case, experiments have shown that, compared to the machine, human brain knows some weaknesses, resulting in biases, and might precisely use thoses biases to facilitate its processing. Thus it would favour and select *frequent*, *familiar*, *protoypical* and *learnable* visual information as it perceives it as less complex. Another finding is that more complex information is examined longer, maybe because finding structures in such data is more difficult and takes more time.

Although original, those previous experiments have limits. So we decided to study the pêrception of complexity using eye tracking, a method that have not been yet used on this topic. Or aim was more specifically to evaluate the fixation time for scenes of different complexities, and we made the following hypotheses:

The images perceived as more complex are indeed more complex ;

As a consequence, we expect the more complex images to be stared at longer.

The experiment

40 participants comfortably installed at 50 cm from a computer screen on which simple geometric images were shown were requested to order these images according to decreasing complexity. Their aye movements were recorded during their work. The following table shows participants' demographic characteristics.

	Number	Mean age	Standard deviation
Men	14	30	4.39
Women	26	15	3.60

The computer was a laptop AMILO Pro V3545, Fujitsu / Siemens, modèle M-52202 under UBUNTU, the screen set to a 800x600 resolution. Eye movements were recorded at 30 Hz through a USB 1,3 megapixels *Microsoft - LifeCam VX-2000* 1381 camera (photo). The eye tracking programme was REBOL, also used to prepare the interface. Part of the software was written in C++.

The 40 images shown to the participants were those already used in a previous 2015 experiment by Kempe, Gauvrit et Forsyth. Ten successive screens were displayed, from A to J, each consisting in a 4-image (2x2) grid, numbered 1 to 4.

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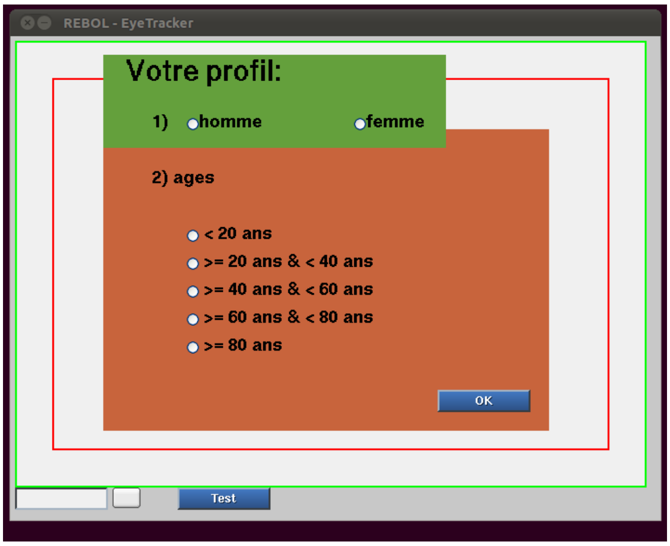

Figure2: Initial screen (participant profile fill up)

Figure on the left shows as example the group screen A (images A1 to A4). The images were shown in the same order to each participant.
The participant was asked not to move his/her head during the experiment. S/he was first requested to fill age and gender on a form (next page).

Then, after a calibration phase, the participant receives on-screen the precise instructions on the task : ordering the images in each group of 4 according to decreasing complexity. The set time to do so was 10 seconds. When a beep was heard, the subject had only 4 more seconds to complete the ordering.

The task proper started after a training phasis, in order to ascertain the participant had well understood what s/he had to do.

Next figure shows again images A1 to A4, with the interface the subject must use to order the images by clicking on each button in good order.

Analysis of the data

An index of the perceived complexity is given by the mean rank given to each image by the subjects. Real complexity is measured with the ***R*** acss package. The table below gives the correlations between those two complexities.

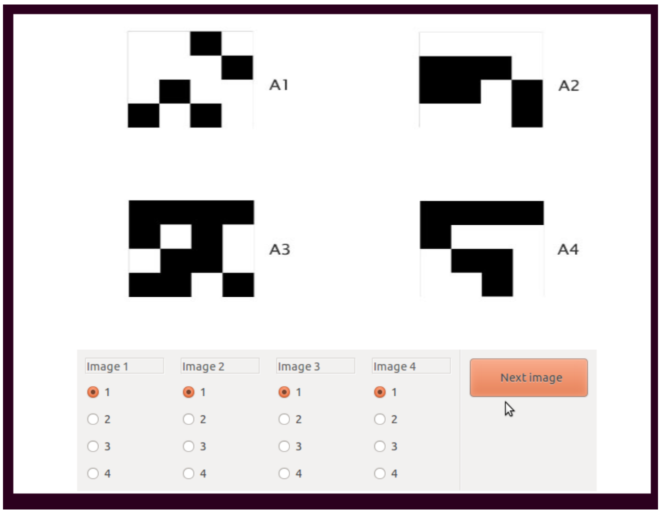

Figure3: The interface with the buttons where the participant clicks to order the images.

Pattern	***R***
1.	0.5426
2.	-0.05384
3.	-0.9212
4.	-0.3228
5.	-0.4743
6.	-0.8969
7.	-0.3202
8.	-0.5057
9.	-0.8582
10.	0.7383

Table 3 : Correlation coefficient R real and subjective complexity.

The values do not confirm our 1st hypothesis of a correlation between perceived and real complexities. Unlike in previous studies, out of 10 stimuli, 2 give a positive correlation.

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Our 2nd hypothesis was that more complex pictures would be stared at longer. An hierarchical ANOVA with repeated measures was used to see the effect of the pattern and the rank attributed to an image onto the fixation time :

$$y_{ij} = \beta_0 + \beta_1 X1_{ij} + \beta_2 X1_{ij} * X2_{ij} + \varepsilon_{ij}$$

y : fixation time, $X\mathbf{1}$: pattern, $X\mathbf{2}$: rank

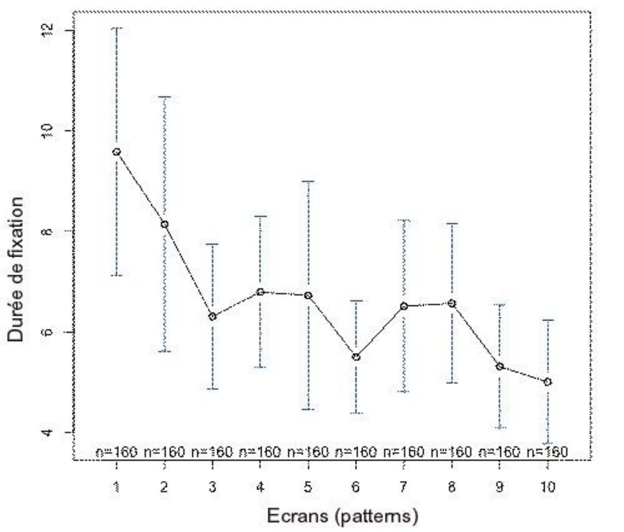

Figure 5: Fixation time per pattern

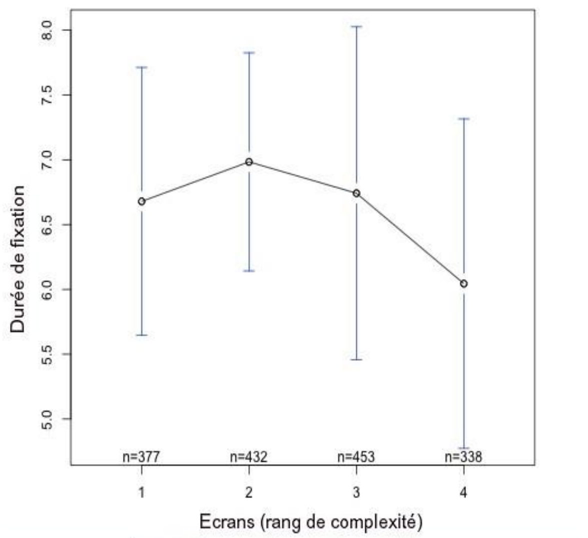

Figure 6 : Relation perceived complexity / fixation time

	Df	*Sum Sq*	*Mean Sq*	*F value*	*Pr (>F)*
Screen (pattern)	1	1849	1849	14.29	0.00016 ***
Rank (Complexity)	1	192	192	1.48	0.22365
Residuals	1596	206433	129		

Table 4 : Values F, *influence of pattern and rank given to each image on fixation time*

This table shows a significant pattern effect, which is explained by the fatigue of the participants, as the fixation time tends to decrease along the experiment (figure left). On the other hand, there is no significant effect of the rank onto fixation time. In opposition to our 2nd hypothesis, we found no relation between perceived complexity and fixation time. However, the sample shows a inverted-U curve suggesting the relation is not linear (figure right)

The next table, that gives the list of correlations entre between fixation time and real complexity for each of the 10 patterns, confirms the same tendency : there is no global confirmation of any relation between these parameters, although some values of *R* are significant.

Pattern	R	Pattern	R
1.	-0.02761	6.	-0.23
2.	0.16	7.	0.08
3.	0.01	8.	-0.02
4.	-0.03	9.	0.04
5.	-0.03	10.	-0.18

Tableau 5. Correlation coefficients R *fixation time / real complexity*

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Conclusion

The aim of this research was to examine how cognitive complexity is perceived visually. To choose our hypotheses, we were inspired by the work of earlier researchers, which produced the result that the more complex scenes are actually those perceived and judged as such. Using eye-tracking methods, these previously conducted experiments also showed longer fixation times on visually more complex scenes.

However, contrary to these previous results – and to our expectations – these hypotheses were not validated. Results show the lack of any significant relationship between subjective complexity and real complexity. It is the same for the relation between fixation time and real complexity. A link (although not significant) between perceived complexity and fixation time seems nevertheless to exist. This relationship is nonlinear. Finally a link, probably due to fatigue, is found between pattern and fixation time.

Several explanations can be put forward to explain these results:

- We may have missed power for this experiment, as its design did not allow to measure with precision the perceived complexity, whereas the expected relation was rather weak and therefore difficult to reveal (the correlation reported in other studies is around r = .5 between actual and perceived complexity).
- Contextual effects may have been skewing the perception of complexity. Such effects have been demonstrated in previous experiments. Indeed, the existence of a visual fatigue effect in our results confirm the importance of taking into consideration all the parameters in the environment likely to influence the visual performance of the subject. This question of ergonomy is extensively taken in account in studies on visual perception using eye tracking devices.
- It is finally possible that the selected images were too close in terms of complexity, as suggested by the significant number images rated equally by the subjects (25%).
- Finally, there is the ranking question: when a person rates two images as equivalent, the rank "4" disappears, which could also influence the results. Thus, according to the physiological laws on the differential threshold (the Weber-Fechner law), the discrimination between two images fairly close in complexity is made difficult.

These results should therefore be considered with caution, and further research with a larger number of participants and an experimental protocol allowing more precision is strongly recommended. It would also be interesting to analyse further the eye tracking data. Indeed for a first exploration, measuring the fixation time is interesting, but it is not enough to make assumptions about the cognitive processing of complexity. Examining the totality of the eye movements (saccades and micro-saccades included) with an eye tracking data analysis software as Bigaze and focusing on the areas of interest "AOI" for the fixations might provide more information about the way complexity is evaluated.

Finally, making comparisons according to the age of the participants and their level of experience (how much time they have been working on screen, screen size, type of scenes observed...) might allow us to get more convincing results.

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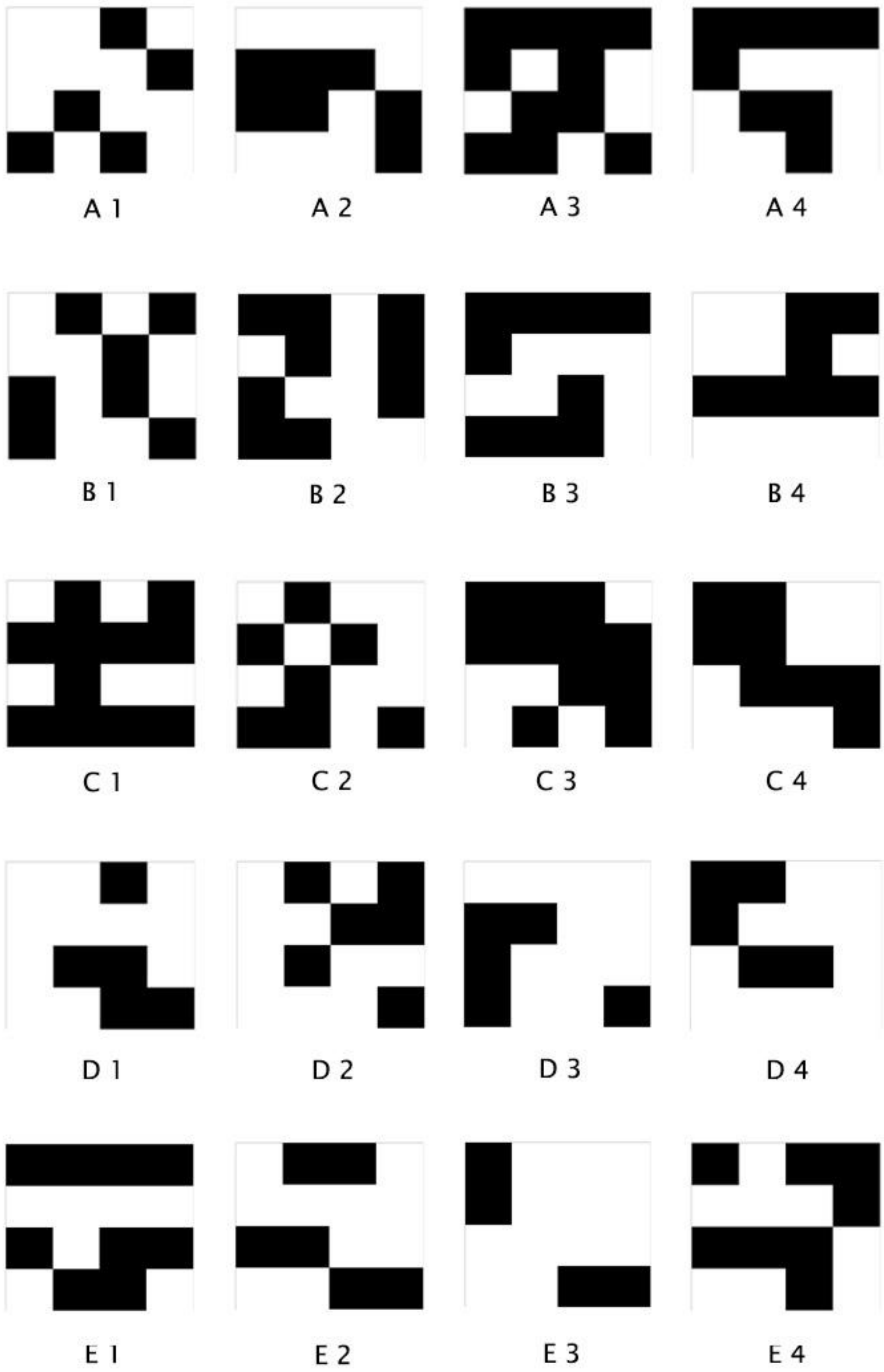
Appendix

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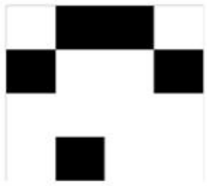
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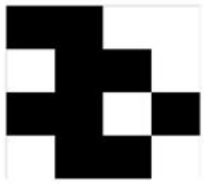
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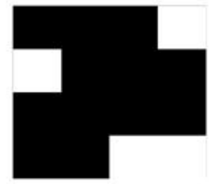
G 4

H1

H 2

H 3

H 4

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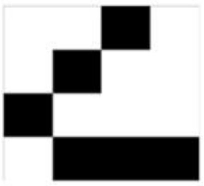
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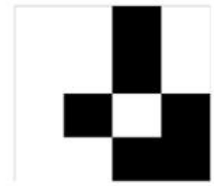
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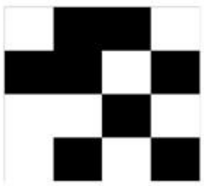
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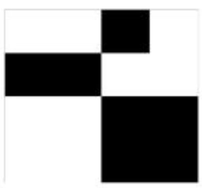
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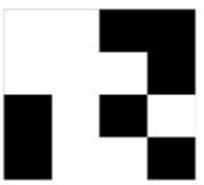
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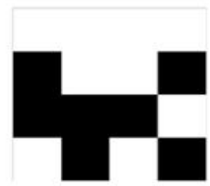
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