# Examining visual complexity and its influence on perceived duration

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**We investigated whether visual complexity of novel abstract patterns affects perceived duration. Previous research has reported that complex visual stimuli led to an underestimation of durations. However, to clarify the nature of the time estimation process, it is necessary to establish which component of image complexity, spatial or semantic, plays the critical role. Here we tested the impact of specific spatial properties. We used unfamiliar and abstract patterns made using black-and-white checkerboards in which the difference between stimuli was exclusively in configuration. Visual complexity was quantified by the GIF index based on a compression algorithm, which scanned the pattern in both horizontal and vertical directions. This metric correlated positively with subjective complexity (Experiment 1A). In the second study, we increased variability in the stimuli by changing the number of items across patterns while keeping overall size constant. A high positive correlation was found between objective and subjective complexity ($r = 0.95$) (Experiment 2A). In Experiments 1B and 2B, observers estimated pattern durations in seconds using a continuous scale. A multilevel linear analysis found that perceived duration was not predicted by visual complexity for either of the two sets of stimuli. These results provide new constraints to theories of time perception, hypothesizing that complexity leads to an underestimation of duration when it reduces attention to time.**

## Introduction

A visual scene can be perceived as more or less complex depending on multiple factors, including the type and amount of elements it contains and their spatial layout. Some studies have reported that visual complexity influences the perception of stimuli duration (Cantor & Thomas, 1977; Cardaci, Di Gesù, Petrou, & Tabacchi, 2006, 2009; Folta-Schoofs, Wolf, Treue, & Schoofs, 2014; Hogan, 1975). Importantly, no study has distinguished between visual and semantic components to establish their effect on perceived duration. This is important because an effect of perceptual complexity would help to clarify how time is evaluated. The current study aimed to (a) define and quantify visual complexity for a specific class of abstract unfamiliar stimuli and (b) examine the influence of visual complexity on perceived duration.

## Time perception and biases: The role of image complexity

For any perceived image, observers analyze spatial properties, but they can also simultaneously process presentation duration. The way these two aspects interact is still relatively unknown. Research on time perception has not yet clarified precisely how people judge duration (see Merchant, Harrington, & Meck 2013, for a recent discussion). Cognitive psychology

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has applied an information-processing framework, which proposes an internal clock as a central mechanism to estimate stimulus duration (Gibbon, Church, & Meck, 1984; Meck, 2003; Wearden, 2003). According to Scalar Expectancy Theory (Gibbon et al., 1984) duration is processed by a pacemaker-accumulator clock in which pulses are transferred from the pacemaker to the accumulator via a switch between the two. When attention is paid to time, the switch is closed and accumulation occurs; when no attention is paid to time, the switch is open and accumulation ceases. Duration judgments are based on the number of accumulated pulses.

Two main factors are known to influence subjective duration: arousal and attention. Changes in arousal following drug administration (Meck, 1983), temperature change (Wearden & Penton-Voak, 1995), emotional stimulation (Droit-Volet, Brunot, & Niedenthal, 2004), and repetitive prestimulation (Penton-Voak, Edwards, Percival, & Wearden, 1996) have been found to alter subjective duration by changing pacemaker speed. Increases in arousal increase the rate at which pulses are emitted from the pacemaker; thus, more pulses are accumulated within the same physical time unit, and subjective time lengthens. Although many studies have attributed increases in subjective duration to increases in arousal, arousal is not precisely defined within the timing literature (Angrilli, Cherubini, Pavese, & Manfredini, 1997; Droit-Volet, 2003; Droit-Volet & Gil, 2009; Fox, Bradbury, Hampton, & Legg, 1967; Rose & Summers, 1995; Tse, Intriligator, Rivest, & Cavanagh, 2004).

It is also known that when attention is diverted away from timing, duration is underestimated (Zakay & Block, 1997). Processing other stimulus attributes (i.e., nontemporal elements of the to-be-timed stimulus) or additional stimuli (i.e., secondary tasks) diverts attention away from the internal clock. This causes the connector between the pacemaker and the accumulator to open; consequently, there is a loss of time units, and perceived duration is underestimated (Buhusi & Meck, 2006). Evidence for this comes from dual-task paradigms in which participants simultaneously complete timing and nontiming tasks (Brown, 2006, 2008; Ogden, Salominaite, Jones, Fisk, & Montgomery, 2011; Zakay, 1998) and from comparisons of the perceived duration of relatively more or less attention-grabbing stimuli (Gil, Rousset, & Droit-Volet, 2009).

The complexity of the stimulus being timed can also divert attention away from timing and thereby alter subjective duration (Cantor & Thomas, 1977; Folta-Schoofs et al., 2014; Hogan, 1975). Hogan (1975) used color slides of line drawings and abstract paintings. The number of each drawing's interior angles defined five levels of complexity. He applied a time interval estimation procedure in which he first presented a standard slide (moderate complexity; 15 s), followed by a test slide (more or less complex than the standard one; 15 s). Participants indicated whether the time interval of the test slide was shorter, equal to, or longer than the interval of the standard slide. The result was that stimuli that are both the least and most complex were experienced as lasting for more time than stimuli of moderate complexity.

Thomas and Cantor (1975) found that perceived duration increased with the size of circles. Cantor and Thomas (1977) examined both the area and the perimeter of checkerboard patterns (see Figure 1). They found that perceived duration increased with an increase in area but decreased with an increase in perimeter. Cardaci et al. (2006) developed a fuzzy model of complexity based on local and global spatial features extraction defined by an entropic distance function. The authors used perceived time as an indirect measure of complexity. In line with the attentional model, they found that paintings (an illustration of the stimuli used by Cardaci et al., 2006, is provided in Figure 1) with a high entropic complexity level generated shorter estimations of perceived time. Some years later, the same authors confirmed a relationship between the visual complexity of high-semantic heterogeneous paintings (selected from the stimuli range of the previous study) and their perceived duration (Cardaci et al., 2009). Visual complexity for this class of stimuli was computed by objective local features algorithms, which extract information about edges and symmetries. However, the authors did not focus on subjective evaluation of complexity. In line with their previous work, they found that paintings with high complexity levels were perceived as being exposed for a shorter period of time. Similarly, Folta-Schoofs et al. (2014) observed that high-complexity distractors, presented during the reproduction of a previously learned duration, lengthened reproductions to a greater extent than low-complexity distractors. Here complexity was defined by subjective ratings of the amount of detail or intricacy of lines in the picture. Folta-Schoofs et al. suggest that high-complexity distractors detracted attention away from timing, affecting switch operation and reducing the accumulation of pulses from the pacemaker.

In summary, arousal and attention are associated with opposite effects on perceived duration. Arousal elongates subjective duration, and visual complexity takes attention away from timing and shortens subjective duration. So far, this has been found mainly with stimuli containing a certain amount of semantic content and therefore possible memory associations or in dual tasks (i.e., judging the intensity and the duration of a stimulus). One exception is the recent

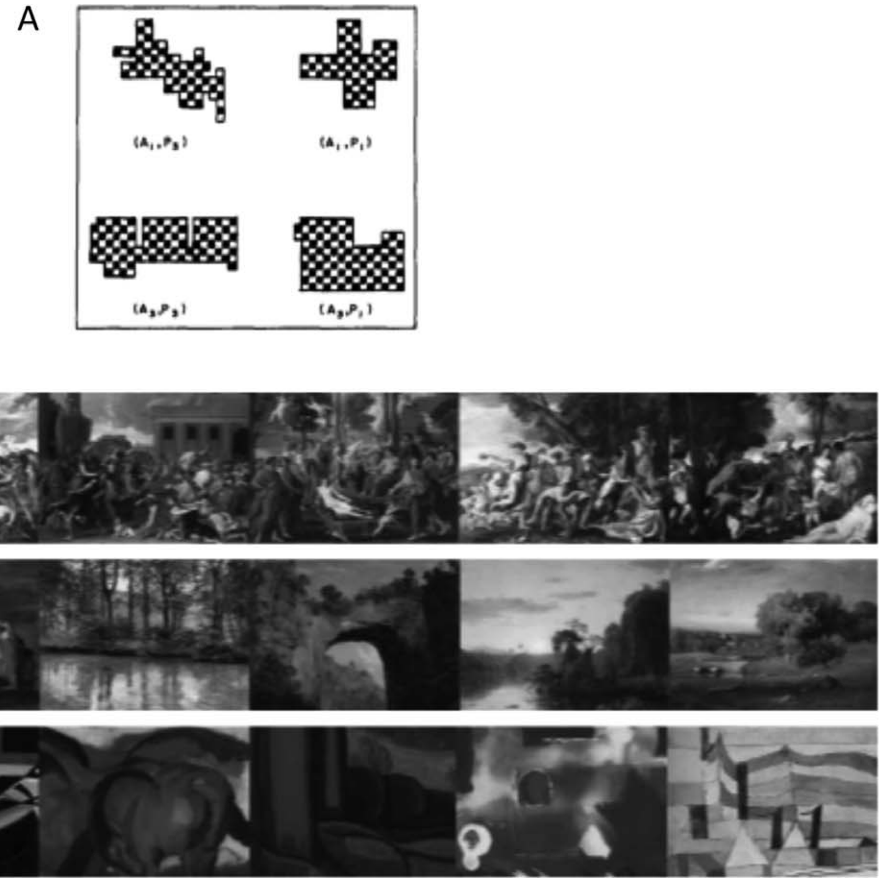



Figure 1. (A) Stimuli adopted by Cantor and Thomas (1977) to examine the role of pattern area and perimeter on temporal judgments. (B) Examples of test images from Cardaci et al. (2006). These images were classified by intuitive complexity: high complexity (top), medium complexity (middle), low complexity (bottom). Figure 1 is an adapted picture with permission from the copyright holders.

work by Aaen-Stockdale, Hotchkiss, Heron, and Whitaker (2011). The authors tested the role of spatial frequency on estimated durations using an oddball paradigm. Typically, the duration of unexpected oddball stimuli is overestimated relative to the expected or standard stimuli (Tse et al., 2004). Aaen-Stockdale et al. showed a standard stimulus for 320 ms followed by a blank screen of variable interstimulus interval and then the oddball stimulus ranging between 260 and 380 ms at incremental steps of 20 ms. They found midrange spatial frequencies (2 c/°) of the oddball stimulus to be judged as longer in duration than high (8 c/°) or low (0.5 c/°) frequencies, and this was irrespective of oddball-related temporal expansion. This study suggests that the relationship between spatial frequency and perceived duration may not be linear and that low-level visual properties can affect perceived duration.

The question of which aspect of visual complexity modulates perceived duration is still open. In relation to the internal clock theory, an important question is whether the number of time units being accumulated depends upon the visual properties of the stimuli. This is because, even in a single-task condition, we cannot exclude the possibility that nontemporal information-processing load, resulting from the visual complexity of the stimuli, may interfere with attention to time. In principle, different amounts of visual complexity could modulate the short-term description of the information or "attentional template" (Duncan & Humphreys, 1989) and, to a certain degree, visual working memory (Baddeley, 1986). The question as to whether such an influence on attention would be enough to generate a bias in perceived duration has not been tested. Similarly, it is unclear whether nonsemantic image properties alone are sufficient to detract attention from timing. This is relevant because it would distinguish perceptual processes that have an effect on attention, at least at the point of bias temporal processing, and those that do not have it. Moreover, any study of complexity faces the problem of selecting a definition and a measure of visual complexity. The current work tried to unravel this research issue by analyzing both subjective complexity and subjective duration.

## What is visual complexity, and how can we measure it?

The concept of complexity applied to visual images has been the subject of investigation in different disciplines, including cognitive science, psychology, and computer science. Several definitions of visual complexity as well as methodologies to measure it have been proposed. Visual complexity is broadly defined as the level of detail or intricacy contained within an image (Snodgrass & Vanderwart, 1980). It has been suggested that perceived complexity correlates positively with the amount of variety in a picture (Heylighen, 1997) and that it corresponds to the degree of difficulty people show when describing a visual stimulus (Heaps & Handel, 1999). In psychology, there has been a focus on subjective measures of complexity, relying on participants' reaction times or evaluations through rating scales. Recently, a study based on the method of hierarchical grouping of real indoor scenes, in which participants divided scenes into successive groups of decreasing complexity, identified different factors that contribute to perceived complexity: number of objects, clutter, organization, symmetry, and changes in colors (Oliva, Mack, Shrestha, & Peeper, 2004).

It is clear that stimulus complexity is multidimensional and that the representation of image complexity can be influenced by memory. This is confirmed by evidence that familiarity correlates negatively with perceived complexity (Forsythe, Mulhern, & Sawey, 2008). McDougall, de Bruijn, and Curry (2000) showed that visual complexity modulates response latency for icon/symbol concreteness (i.e., the extent to which icons depict objects or people from the real world) and semantic distance (the closeness of the relationship between an icon and its function).

In summary, the role of complexity depends on the kind of stimuli employed and on the way in which visual complexity is defined, manipulated, and measured. The use of visual scenes, for instance, makes it difficult to establish which dimension of visual complexity (i.e., low-level spatial properties or high-level semantic properties) affects perceived duration. Therefore, it is necessary to find an index of visual complexity that quantifies perceived complexity reliably.

Theories of image processing describe local feature extraction. Basic perceptual components of an image are taken into consideration, such as edges, which combine to form shapes and detail (Beck, Graham, & Sutter, 1991). For instance, a perimeter detection measure locates edges by examining sudden changes in intensity (Zhang & Lu, 2004). These contour-based techniques are not sensitive to familiarity effects. Other approaches include the Structural Information Theory (Leeuwenberg, 1968; Leeuwenberg & van der Helm, 2013), which provides a unique measure of complexity and which is beyond the scope of this work.

## Complexity and image compression

A different approach is based on algorithmic information theory (in computer science) and compression (Donderi, 2006a, 2006b). The compression of a picture generates a string of numbers that corresponds to the organization of that picture, thus revealing its information content. A more complex picture will have more elements, less redundancy, and a longer file string. The ratio between the compressed file format and its original version provides an index of image complexity. Forsythe, Sheehy, and Sawey, (2003), inspired by McDougall and colleagues (2000), adopted a computer compression algorithm expressing six icon properties: icon foreground, number of discrete objects, number of holes, icon edges, and homogeneity in icon structure. The strongest correlates of perceived complexity (McDougall et al., 2000) were structural variability ($r_s = .65$) and edge information ($r_s = .64$).

Although computer-based measures of visual complexity, such as the GIF ratio, correlate with subjective judgments (Donderi, 2006b; Forsythe et al., 2008; Forsythe et al., 2003), these tests employed electronic charts and radar screens (Donderi, 2006b), icon designs (Forsythe et al., 2003), or line drawings (Forsythe et al., 2008). In the current studies, we extended this approach to abstract images that were unfamiliar to our observers. We used checkerboards with black and white squares, and in every trial, the configuration was different while total size, luminance, and numerosity were controlled for.

It has been reported that objective complexity metrics tend to correlate highly with one another (see Simon, 1972; see also van der Helm, 2000, chapter 2 in van der Helm, 2014). In our study, we decided to measure complexity by means of image compression and, in particular, the GIF algorithm. We adopted the GIF index because there are previous studies that used it for assessing visual complexity and also because it is lossless unlike other compression algorithms such as JPEG (Forsythe et al., 2008).

## Summary of studies

We report two studies, using two different sets of images. Each study is divided in two parts; Experiments 1A and 2A evaluated the link between indexes of complexity and subjective complexity for that specific set of images. Experiments 1B and 2B tested the link between complexity and perceived duration.

To measure complexity, we used the GIF index defined as the ratio of the size of the original image and the compressed version of the image. A GIF index of one means that there was no reduction in size; an index close to zero means that a minimal code was sufficient to encode the image. We preferred the GIF index to the inverse, known as GIF ratio (Forsythe et al., 2008) because the GIF index can be thought of as measuring complexity (higher values, less redundancy).

Experiments 1A and 2A confirmed that the GIF index is a useful tool for capturing visual complexity for this type of images. It was therefore included as a predictor for perceived duration in Experiments 1B and 2B.

# Study 1

In Experiment 1A, we validate the use of the GIF compression algorithmic index as a measure of objective complexity of meaningless, abstract patterns. Previous research found a correlation between computational measures of complexity, especially based on JPEG compression, and human judgments of complexity with highly detailed and colored stimuli (Donderi, 2006a). However, for different classes of images, different measures of complexity may be required. The GIF compression is based on the Lempel-Ziv-Welch "lossless" data compression algorithm. By contrast, the JPEG technique is a "lossy" compression and works better with limited colorization and line drawings (Forsythe et al., 2008). The stimuli used in Experiment 1A were novel black-and-white block patterns for which the correlation between objective and subjective measures of complexity was unknown. The aim was to evaluate structural and compression methods that provide a quantification of perceived complexity for this class of stimuli.

In Experiment 1B, subjective duration for the same type of patterns was measured with a prospective paradigm: Participants were required to estimate the duration of the visual pattern selecting one temporal value (in seconds) among different options on a continuous scale. Based on the findings of Cardaci et al. (2006, 2009) one might expect that visual complexity could lead to an underestimation of duration. However, when complexity is manipulated in the context of scenes, it involves a certain degree of cognitive and associative processes. In this case, a distinction between visual complexity and a more general cognitive complexity is difficult (Harper, Michailidou, & Stevens, 2009). Therefore, the effect found on perceived duration may be due to the interaction between higher cognitive processing and the analysis of image duration.

## Experiment 1A

### Method

*Participants*: Ten participants took part in Experiment 1A (age range: 19–45; one left-handed; five females). All participants had normal or corrected-to-normal vision. They provided written consent for taking part and received £10 as reimbursement. The experiment was approved by the Ethics Committee of the University of Liverpool and was conducted in accordance with the Declaration of Helsinki (2008).

*Stimuli and apparatus*: Stimuli consisted of a matrix with $10 \times 10$ squares ($320 \times 320$ pixels, each square $32 \times 32$ pixels). The spatial distribution of the items changed from pattern to pattern whereas the black/white ratio (40 black dots/60 white dots) was the same as to keep contrast, luminance, and surface area constant (Figure 1A). In total, 1,500 patterns were created in Psychopy software (Peirce, 2007).

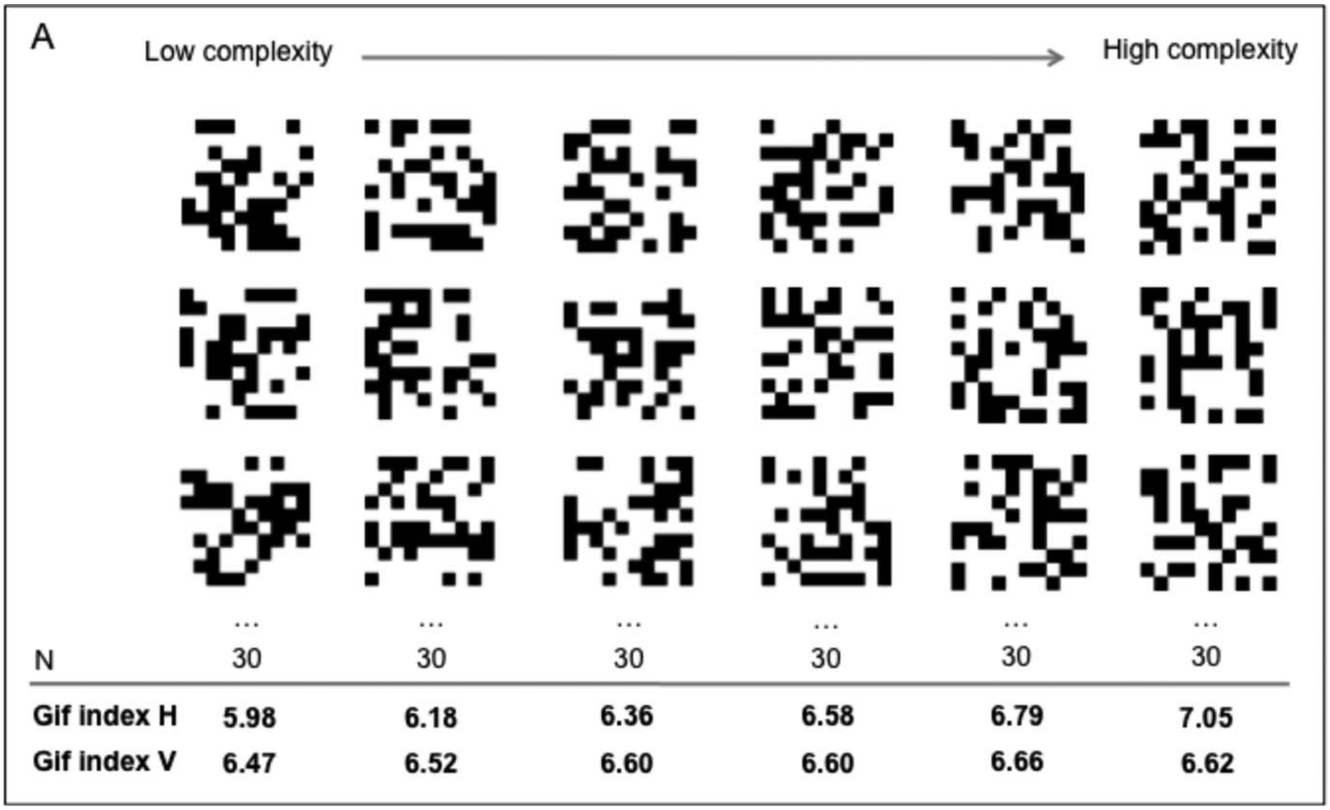
Each image was exported in GIF and BMP formats. Subsequently, these two files were processed in MATLab R2010b to obtain the GIF compression index for each image. A GIF index is defined as the percentage of the image after compression (i.e., 50 means the image size if half after compression). The patterns were scanned from left to right (for simplicity, we call it the horizontal GIF index). This index ranged between 5.89 and 7.14 (i.e., 7.14 = high complexity; 5.89 = low complexity).

Next, 180 stimuli were selected on the basis of their GIF index. This selection avoided a normal distribution of images in which the majority would fall into a middle level of complexity. The selected 180 patterns ranged from the lowest to the highest complexity rates obtained for these images, thus ensuring greater variability and sampling of the whole range. This generated six subsets of 30 images each. Within each subset, images shared the same GIF index value (see Figure 2A) within a narrow tolerance margin.

In addition to a horizontal GIF index, a vertical GIF index was also generated for each image. The horizontal and vertical compressions are sensitive to different structure in the image, and including both of them gives a much better overall measure of internal structure for these patterns.

Participants sat at approximately 60 cm of the distance from the screen. Stimuli were presented on a $1280 \times 1024$ DELL M993s 19-in. CRT monitor at 60 Hz.

*Experimental design and procedure*: The experiment started with the instructions, followed by the presentation of the stimuli in a random sequence. In a first



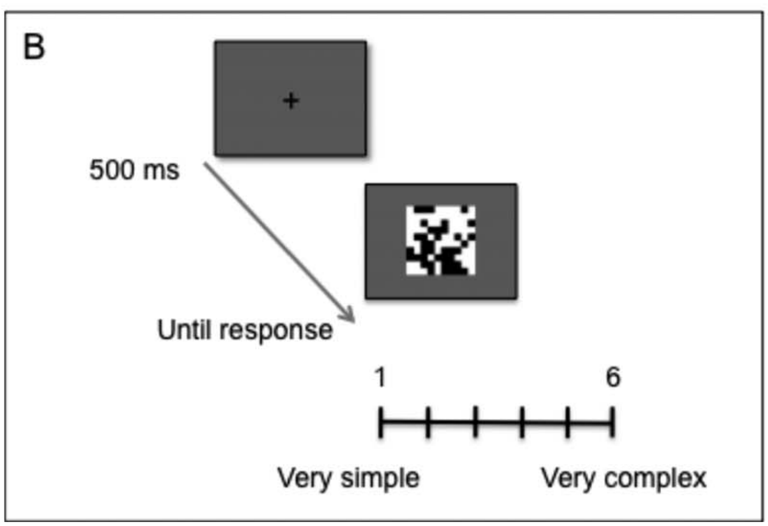




Figure 2. Experiment 1A. (A) Illustration of the stimuli. GIF horizontal (H) and vertical (V) refer to the mean values for all 30 images belonging to each complexity level. Only three examples are shown here for reason of space. (B) Illustration of the procedure.

familiarization stage, each pattern was presented on a gray background for 500 ms, and observers did not have to express any judgments. This slideshow provided participants with information about the type and range of the experimental stimuli.

Next, the procedure changed so that each trial started with a fixation cross at the center of a gray background for 500 ms, then the image appeared and remained on screen until response. The task was to rate complexity on a six-point scale, ranging from very simple (1) to very complex (6) by pressing the corresponding number on the keyboard (Figure 2B).

Participants first completed a practice block of 12 trials. They then completed 12 blocks of 15 experimental trials. The experimental trials were identical to the practice with the exception that novel images were

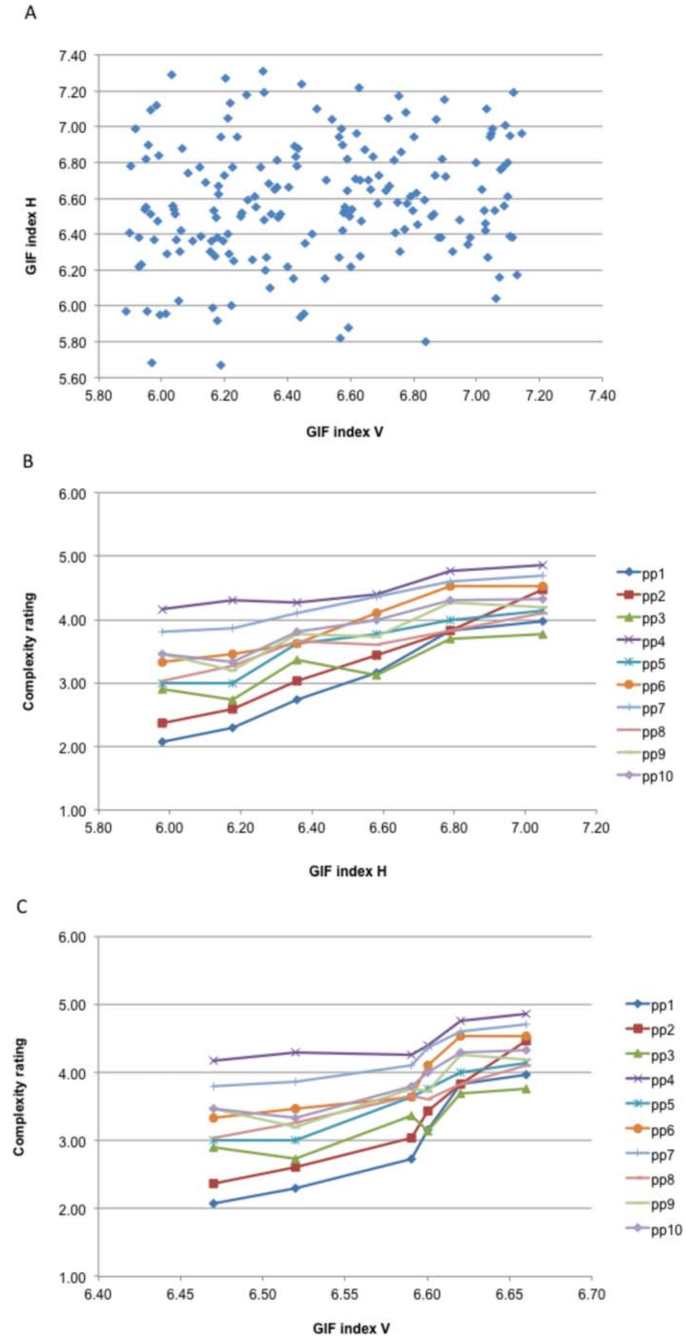



Figure 3. Results of Experiment 1A. (A) GIF horizontal plotted against GIF vertical. (B) Participants' perceived complexity (y-axis) as a function of GIF horizontal index (x-axis). (C) Participants' perceived complexity (y-axis) as a function of GIF vertical index (x-axis).

presented. Participants were encouraged to take a break at the end of each block. The experiment lasted approximately 20 min.

### *Analysis*

Ratings for each image were correlated to the corresponding GIF horizontal and vertical indexes. A correlation analysis was also conducted to assess the agreement between participants' judgments.

### *Results*

The results are illustrated in Figure 3. Descriptive statistics showed that mean responses on the six-point scale ranged between 3.16 (low complexity) and 4.43 (high complexity).

Interestingly, there was a weak correlation between GIF horizontal and vertical ($r = .160$, $p < 0.032$). However, both GIF indexes correlated positively with subjective measure of complexity (GIF horizontal: $r = .643$, $p < 0.001$; GIF vertical: $r = .592$, $p < 0.001$) although the correlation was stronger with the horizontal index. Moreover, subjective measures of complexity did correlate across participants (mean $r = .637$, $SD = .09$; $p$s $< 0.05$).

### *Discussion*

This study showed that compression-based complexity measures can differentiate visual complexity for unfamiliar, abstract, black-and-white block patterns. The comparison between GIF horizontal and GIF vertical revealed that the scanning direction of the pattern produced different complexity indexes although there was a positive correlation between the two. Importantly, the agreement between individual judgments was also moderately high ($r = .64$), which suggests that humans can provide consistent evaluations of visual complexity.

In Experiment 1A, we found that participants were still able to judge visual complexity in a systematic way even if the range of differences in complexity across patterns was limited and all images looked quite similar. Participant complexity judgments were related to the measure of visual complexity based on the GIF index. Next, the stimuli employed and processed in Experiment 1A were used in Experiment 1B to assess the influence of visual complexity on perceived pattern durations.

## Experiment 1B

We employed the abstract patterns that were generated in Experiment 1A because they had no semantic content. Visual complexity for these images was defined on the basis of the GIF indexes (horizontal and vertical), and we measured whether this would predict perceived duration. As Experiment 1A revealed a difference between horizontal and vertical GIF indexes, in Experiment 1B, we assessed whether the two indexes predicted duration in a different fashion. The evaluation of pattern duration was achieved by

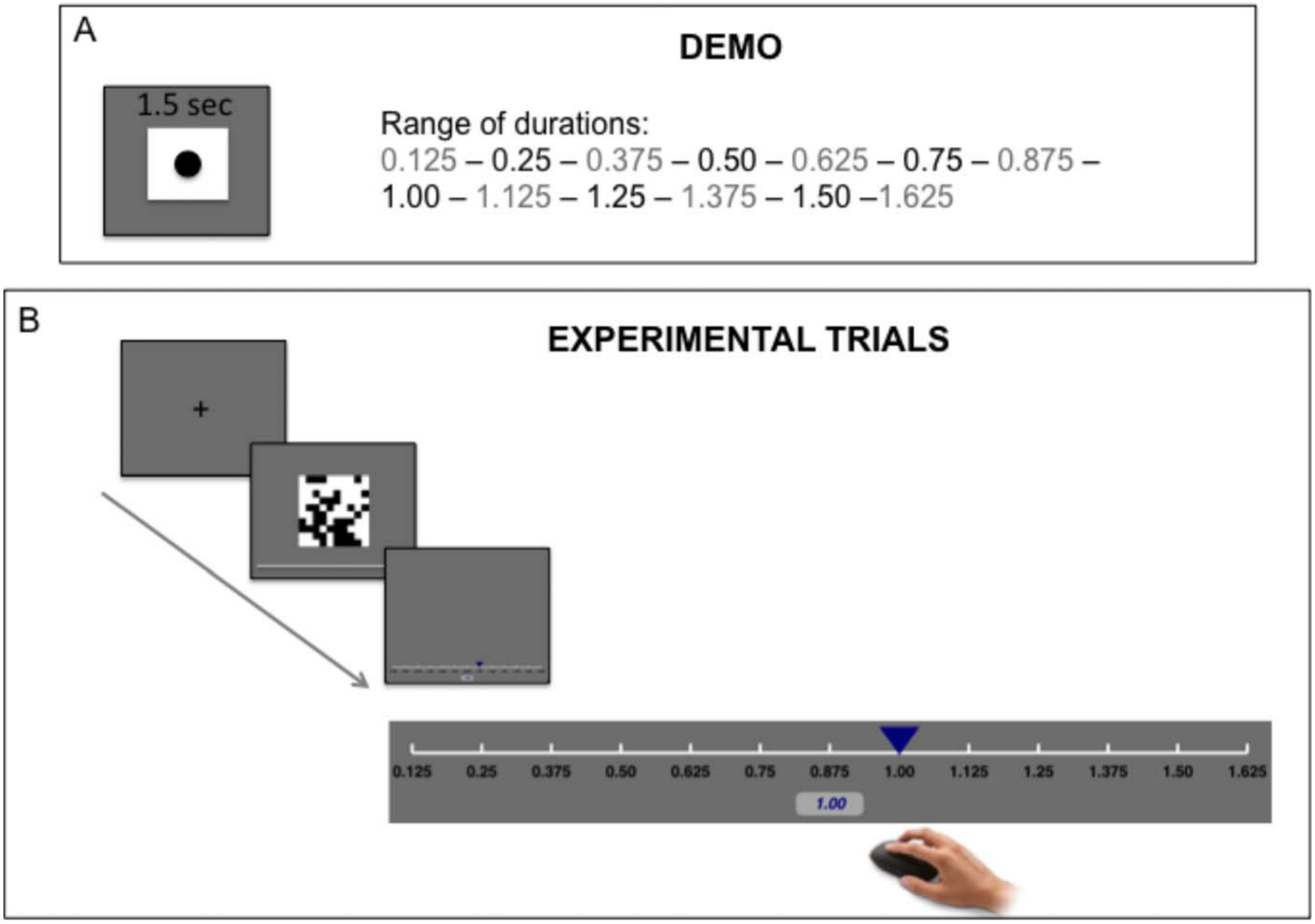



Figure 4. Experiment 1B. (A) List of durations in seconds. The numbers in gray were included in the visual scale used to respond but were not used in the actual stimulus presentation. (B) Example of the structure of one trial.

employing a prospective timing paradigm in which participants were required to estimate the duration of the visual pattern, selecting one temporal value (in seconds) from different options on a continuous scale.

### *Method*

Sixteen participants with normal or corrected-to-normal vision were employed in the current experiment (age range: 17–76; three left-handed; six females). Stimuli were the same visual patterns employed in Experiment 1A, in which complexity was defined by the GIF compression method. The stimuli were presented through the same apparatus used in Experiment 1A.

We employed a repeated-measure design with factors of GIF index (continuous variable ranging from 5.89 to 7.14) and duration expressed in seconds (six levels: 0.25, 0.50, 0.75, 1.00, 1.25, 1.50). In addition, seven duration levels (0.125, 0.375, 0.625, 0.875, 1.125, 1.375, 1.625) were inserted throughout the experiment to add more variability in the temporal scale and contrast habituation effects. The dependent variable was the estimated duration of pattern presentation.

The experiment started with the instructions followed by a demo showing the entire range of pattern durations that participants needed to estimate in the experiment. In the demo, the stimulus consisted of a white quadrant (500 $\times$ 500 pixels), which, at the center, contained a full black circle (100 $\times$ 100 pixels). The duration was indicated on the top of the quadrant (Figure 4A). Following the demo, 12 practice trials were presented to train participants with the task. Each trial started with a black fixation cross on a gray background displayed at the center of the screen for 500 ms followed by the pattern. As soon as the stimulus disappeared, the response scale showing the entire range of durations was displayed on the bottom of the screen. Participants provided their response by clicking the temporal value on the scale with a mouse. The intertrial interval varied between 1.50 and 2.50 at equal steps of 0.25 s. The order of trials was randomized across participants. Once the practice was completed, participants received 12 blocks of 15 experimental trials (see Figure 4B for a trial illustration). The experiment lasted 30 min.

| | Mean estimated duration | | |
|---|---|---|---|
| | $\beta$ | *SE* | *Z* |
| Intercept | 0.583 | 0.044 | 13.250 |
| Duration | 0.544 | 0.008 | 68.000 |
| GIF horizontal | 0.003 | 0.014 | 0.214 |
| GIF vertical | 0.008 | 0.014 | 0.571 |
| Subjective complexity | −0.005 | 0.009 | −0.556 |
| GIF horizontal × GIF Vertical | −0.025 | 0.043 | −0.581 |

Table 1. Regression outcome in which mean of estimated duration was the DV. *Notes*: Z scores $\geq$ 1.96 mean that $\beta$ is significant at the 5% level.

### *Analysis*

We first tested whether actual duration predicted subjective duration, which would merely show that participants were doing the task. More interestingly, we tested whether pattern complexity, as measured by GIF indices and subjective complexity, would predict subjective duration. Rather than using a standard regression analysis with several predictors (actual duration, GIF horizontal, GIF vertical, and subjective complexity), we used the more powerful multilevel linear analysis, which takes data points from every trial as well as summary statistics from each participant.

Random and fixed parts form a random intercept multilevel model. In the random part, parameters are calculated to reflect variability at the various levels of hierarchy in the model. We inserted participants and trials, the latter nested within the former, as random factors. In the fixed part, statistically unbiased intercepts are calculated through taking the random parameters of variability into account. Fixed factors in our design were horizontal and vertical GIF indexes, subjective ratings of complexity and actual pattern duration. The analyses involved only the trials with the six main experimental durations (0.25, 0.50, 0.75, 1.00, 1.25, 1.50 s), thus excluding the filler trials. In a second model, only the fixed part was entered. A likelihood ratio test was conducted by comparing the likelihood values of the two models with a chi-squared analysis. This comparison determines if participants represent a significant factor of variability. The analysis was carried out in MLwiN (Rasbash, Charlton, Browne, Healy, & Cameron, 2009). In the model, predictors were grand-mean centered. Estimated durations were continuous dependent variables with parameter estimates being established through iterative generalized least squares (Rasbash, Steele, Browne, & Goldstein, 2012).

### *Results*

Results of the first model are reported in Table 1 and illustrated in Figure 5. Overall pattern durations were

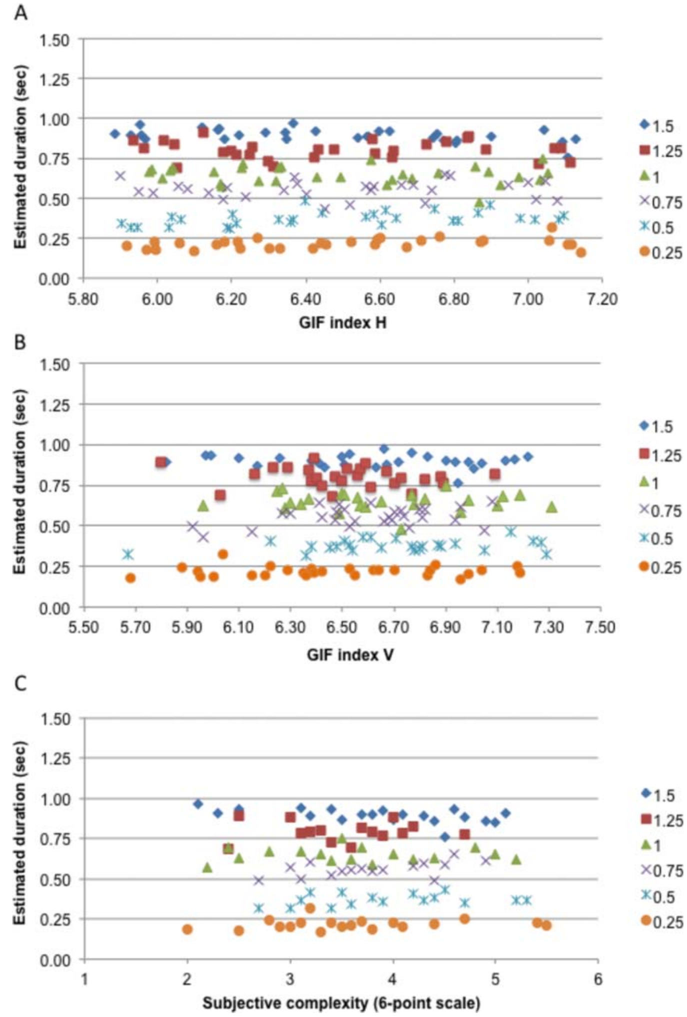



Figure 5. Results of Experiment 1B. (A) Estimated duration (y-axis) as a function of GIF horizontal index (x-axis) and duration (separate lines). (B) Estimated duration (y-axis) as a function of GIF vertical index (x-axis) and duration (separate lines). (C) Estimated duration (y-axis) as a function of subjective complexity (x-axis) and duration (separate lines).

underestimated. The multilevel linear analysis showed that experimental durations predicted estimated durations. However, the analysis also revealed that GIF indexes, horizontal and vertical, and subjective evaluations of complexity were not significant predictors of estimated durations. The likelihood ratio test revealed that participants carried significant variability in the data ($p < 0.001$).

### *Discussion*

The main result of Experiment 1B was that visual complexity as measured by GIF index did not affect subjective durations of abstract patterns. Therefore, perceived duration is not influenced by visual complexity per se, and other factors, such as the type of content, may be critical. This outcome suggests that it is only when images have semantic content, which leads to an increase in attention, that complexity exerts an influence on perceived duration.

At this stage, a conclusive explanation for the lack of effect is premature: The images had a limited range in complexity. Although we selected exemplars ranging from the lowest to the highest GIF index, the patterns were all relatively complex (participants selected the middle points on the scale) and this, in line with the attention model within the internal clock framework, could explain why participants' tendency was to underestimate durations. Therefore, the range of complexities may have been too limited for an effect on perceived duration to manifest.

Study 1 established that the visual system is sensible to subtle variations of visual complexity although these variations did not influence perceived durations. In Study 2 (see Experiment 2A), we generated a new set of stimuli with more distinctive levels of complexity.

# Study 2

## Experiment 2A

In Experiment 2A, we defined visual complexity in terms of the number of items contained in each pattern (numerosity). We adopted this parameter to increase differences in complexity across the stimuli, thus obtaining a new set of black-and-white block patterns. Moreover, we also examined both GIF horizontal and GIF vertical and their relationship to perceived complexity. The aim was the same as that of Experiment 1A but with an increased range of stimuli. We expected to find a higher correlation between GIF and numerosity.

### Method

Ten participants took part in the experiment (age range: 17–76; all right-handed; six females), and all had normal or corrected-to-normal vision. In this experiment, the matrix contained a number of squares ranging from 25 ($5 \times 5$) to 900 ($30 \times 30$). As in Experiment 1A, the black/white ratio (40/60) was kept the same. This means that the size of the items differed as a function of numerosity (i.e., the least the number of items and the largest the size of each item), and as such, the stimuli contained low and high spatial frequencies. There were six types of matrices; the difference in numerosity served as one measure of complexity (Figure 6A).

The GIF indexes were computed for each image and resulted in 4.47 (GIF horizontal) and 4.45 (GIF vertical) for low complexity ($5 \times 5$ items in the pattern) and in 10.43 (GIF horizontal) and 10.42 (GIF vertical) for high complexity ($30 \times 30$ items in the pattern). As the stimulus was approximately 10° of visual angle wide, the main spatial frequencies were 0.5 c/° and 3 c/°. We adopted the same design and procedure as for Experiment 1A. The only difference was in the way stimuli were constructed. The relationship between numerosity and subjective complexity was tested with a correlation analysis. Participants' ratings were correlated with both numerosity and GIF horizontal and vertical indexes. A correlation analysis was also carried out to verify the level of agreement across participants.

### Results

Results are shown in Figure 7. Responses ranged between 1.43 (low complexity) and 5.81 (high complexity). In Experiment 2A, we found a strong correlation between GIF horizontal and vertical ($r = .972$, $p < 0.000$). Both numerosity and GIF indexes highly correlated with subjective judgments (numerosity: $r = .963$, $p < 0.001$; GIF horizontal index: $r = .971$, $p < 0.001$; GIF vertical index: $r = .977$, $p < 0.001$). A high correlation was found between numerosity and both GIF indexes (numerosity with GIF horizontal: $r = .982$, $p < 0.001$; with GIF vertical: $r = .981$, $p < 0.001$). Finally, subjective measures of complexity strongly correlated across participants (mean $r = .937$, $SD = .02$; all $p$s $< 0.001$).

In addition, a survey was conducted with 12 participants (age range: 19–34, six males) in order to assess whether they would use "numerosity" as a concept to describe the range of the new stimuli set. On a sheet of paper, we illustrated six examples of patterns, one for each level of complexity (see second row in Figure 6). A list of concepts that would describe the stimuli was provided: contrast, numerosity, density, size, and complexity. Participants indicated how much each of the concepts described the range of the stimuli. The response was given by placing a tick along a visual scale (from "not much" to "a lot"), one for each of the dimensions. The position of each tick was measured with a ruler. The two dimensions that were deemed most appropriate to describe the stimuli were numerosity ($M = 10.03$ cm; $SD = 3.88$ cm) and density ($M = 10.98$ cm; $SD = 3.09$ cm).

### Discussion

Experiment 2A showed that the numerosity of items in a pattern can be used as a measure of complexity that matches subjective ratings of complexity. The GIF indexes of the stimuli were also

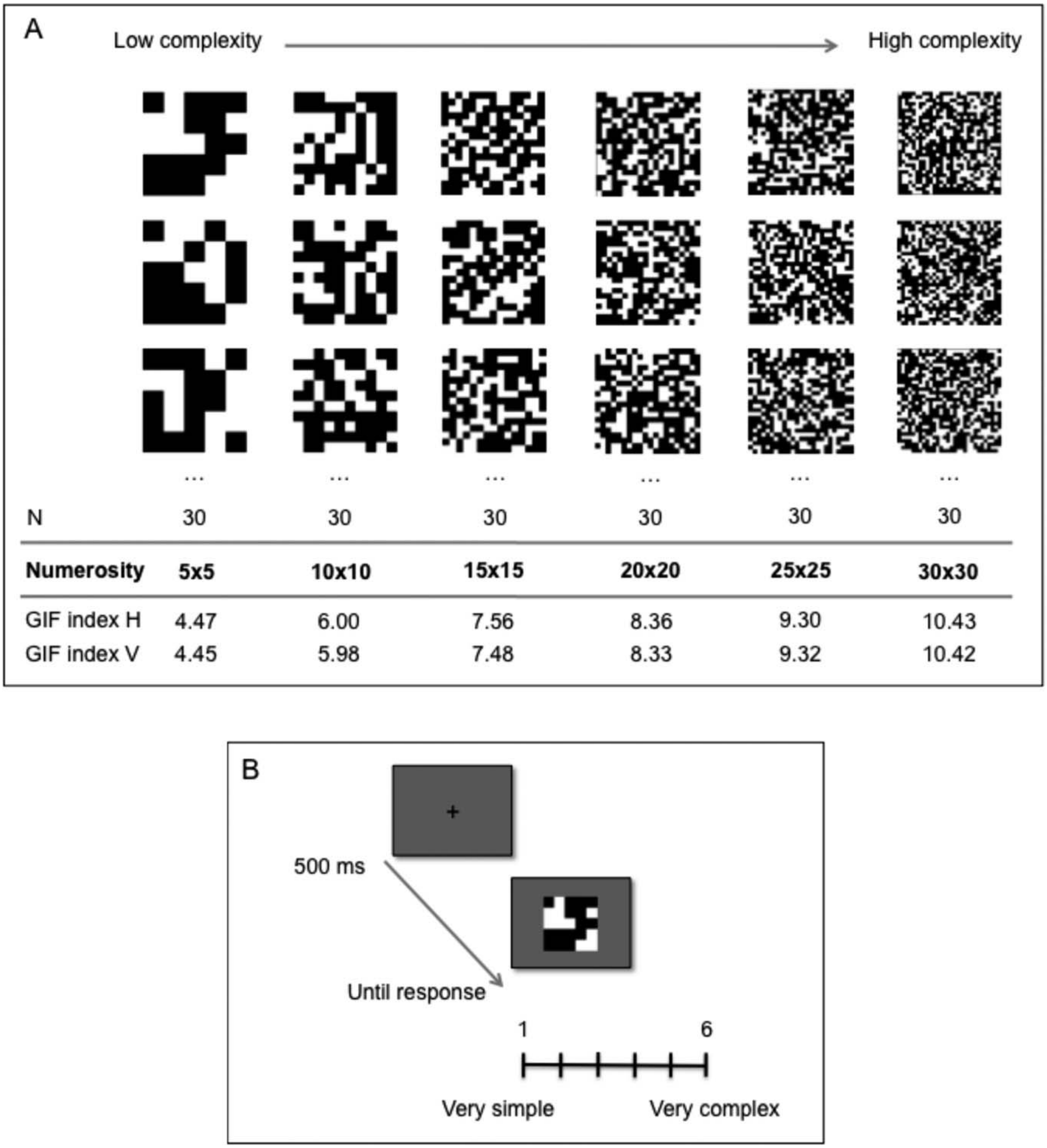



Figure 6. (A) Illustration of the six types of matrices. GIF horizontal (H) and vertical (V) refer to the mean values for all 30 images belonging to each numerosity level. Only three examples are shown here for reason of space. (B) Illustration of the procedure.

different for different levels of numerosity, and it provided a good measure of perceived complexity as in Experiment 1A. From Experiment 2A, it emerged that participants could easily detect the differences in complexity, and they used a wider range of points on the scale as compared to Experiment 1A. Moreover, the correlation between objective and subjective measures of complexity are higher in Experiment 2A than in Experiment 1A. Therefore numerosity rendered the complexity of images more distinguishable. In the next experiment, the new set of stimuli was employed to examine the influence of visual complexity, as defined by item numerosity and GIF indexes, on perceived duration.

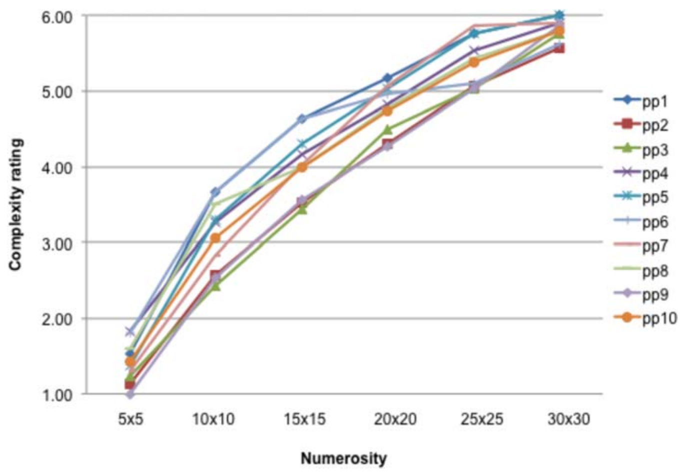



Figure 7. Results of Experiment 2A. (A) Estimated complexity (y-axis) is plotted as a function of numerosity (x-axis).

## Experiment 2B

In Experiment 1B, visual complexity did not predict estimated durations. One possible explanation for this was the limited range of stimulus complexity. Despite the fact that observers could discriminate levels of complexity, perhaps greater differences are necessary to affect perceived duration. In Experiment 2B, we employed stimuli with a wider range of complexity. We employed the same prospective paradigm used in Experiment 1B in which participants estimated the duration (in seconds) of the visual pattern, selecting the appropriate temporal value on the continuous scale.

Both symbolic and nonsymbolic representations of number influence perceived duration (Dormal, Seron, & Pesenti, 2006; Dormal & Pesenti, 2013; Oliveri et al., 2008; Vicario et al., 2008; Xuan, Zhang, He, & Chen, 2007). The duration of presentation of small Arabic digits are underestimated relative to the duration of large Arabic digits (Oliveri et al., 2008). When timing the duration of nonsymbolic numerical displays (i.e., dots on a screen), congruent numerical information facilitates temporal processing and incongruent numerical information impairs temporal processing accuracy (Dormal et al., 2006; Xuan et al., 2007). Thus, in the current experiment, we may expect longer duration estimates for more complex displays when complexity is defined by number of items in a pattern.

### *Method*

Twenty-five participants with normal or corrected-to-normal vision took part in the experiment (age range: 18–71; four left-handed; 15 females). We used the stimuli that were selected in Experiment 2A, and the complexity levels were defined by the numerosity parameter ($5 \times 5$ to $30 \times 30$). The stimuli were presented with the same apparatus used in Experiment 2A. The experimental design involved two within-subjects factors: numerosity (six levels: $5 \times 5$, $10 \times 10$, $15 \times 15$, $20 \times 20$, $25 \times 25$, $30 \times 30$ items) and duration in seconds (six levels: 0.25, 0.50, 0.75, 1.00, 1.25, 1.50).

As with Experiment 1B, the variability of the scale was increased, adding other seven duration levels (0.125, 0.375, 0.625, 0.875, 1.125, 1.375, 1.625). The procedure was identical to the one in Experiment 1B. Participants received instructions and observed the demo with the range of durations that they needed to rate in the experiment (Figure 8A).

### *Analysis*

One aspect of the current experiment was that to increase variability in complexity a high number of small-sized items (high complexity = 30 small items per side) was contrasted to a low number of large-sized items (low complexity = five large items per side). Although this manipulation made pattern complexity pop out, here complexity entailed two spatial properties (number and size of items) that could have opposite effects on perceived durations. It has been reported that large-sized items generate overestimations of duration (Ewart & Cantor, 1975; Xuan et al., 2007) whereas a low numerosity of items results in shorter perceptions of duration (Oliveri et al., 2008; Xuan et al., 2007). Therefore, having both these two properties in the stimuli could, in principle, lead to a null effect of complexity on perceived durations. A multilevel linear analysis allowed verifying the contribution of each of these factors to the variability of perceived duration. In the random intercept model, we inserted numerosity and the horizontal and vertical GIF indexes as the fixed factors, and we controlled for their interaction effect. A third fixed factor was the actual durations of the stimuli (0.25, 0.50, 0.75, 1.00, 1.25, 1.50 s). The random part of the model consisted of participants and trials, the latter nested in the former. A second model was generated only with the fixed part. A likelihood ratio test was conducted to determine if intraparticipant variability was statistically significant.

### *Results*

Results are illustrated in Table 2 and in Figure 9. The multilevel linear analysis confirmed that estimated durations were predicted by the actual durations and that neither numerosity nor GIF indexes were significant predictors of estimated duration. The likelihood ratio tests revealed that participants' differences were statistically significant ($p < 0.000$).

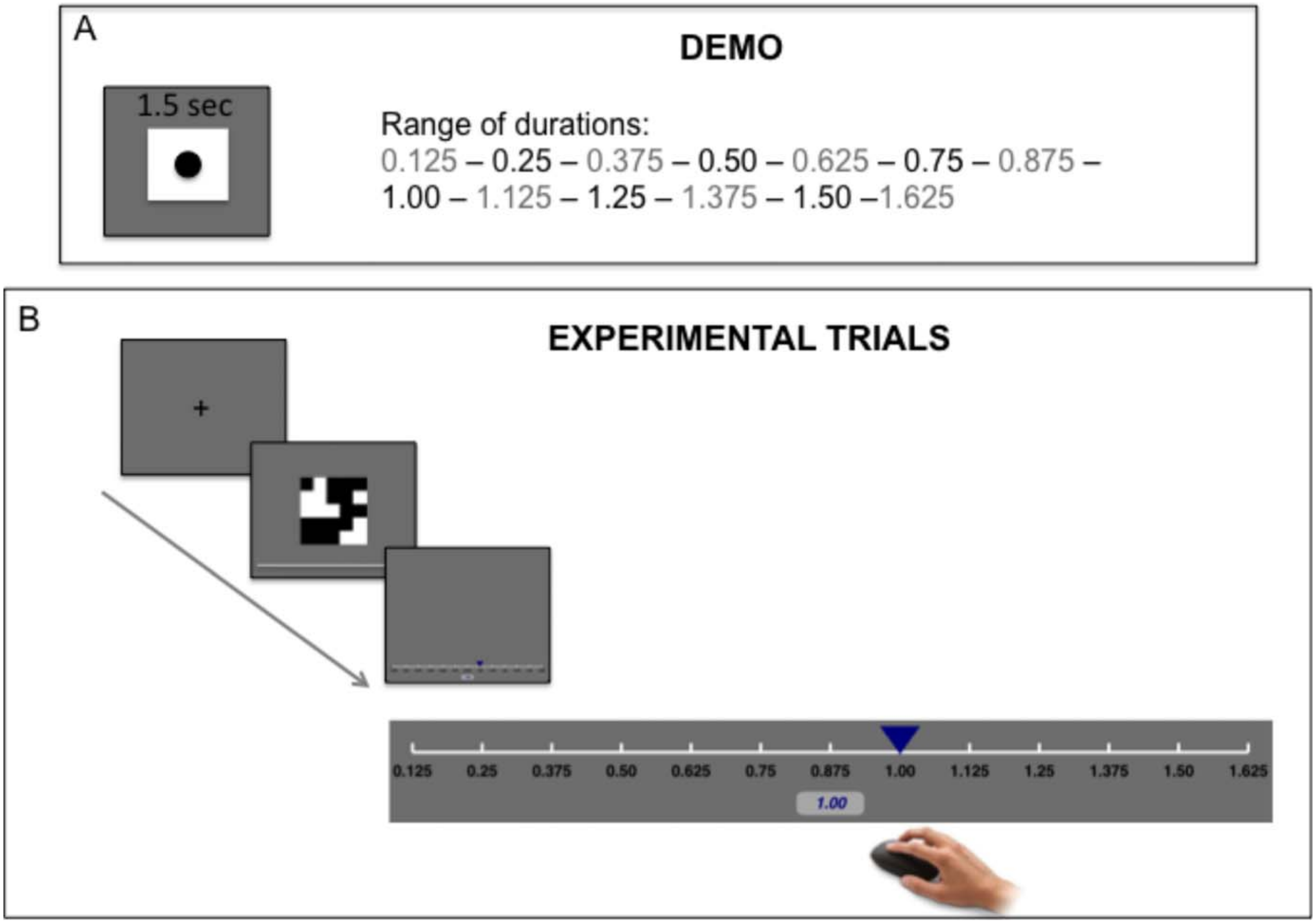



Figure 8. Experiment 2B. (A) List of durations in seconds. The numbers in gray were included in the visual scale used to respond but were not used in the actual stimulus presentation. (B) Example of the structure of one trial.

### *Discussion*

The results of Experiment 1B were confirmed by Experiment 2B. Subjective duration was not affected by visual complexity, either when it was expressed in terms of compression indexes or when it was defined by item numerosity or different spatial frequencies. This was despite the increased range of complexities used. Our results are in contrast to those reported in the literature, in which complexity did affect image duration (Cantor & Thomas, 1977; Folta-Schoofs et al., 2014; Hogan 1975). However, in the past literature, different dimensions of visual complexity were manipulated, i.e., by changing the area or the perimeter of the patterns (Cantor & Thomas, 1977). Importantly, in other studies (Cardaci et al., 2006, 2009), visual complexity was applied to the context of scenes or textured/colored objects. These classes of stimuli entail associative, semantic operations and engage participants in higher cognitive processing. Therefore, an increase in complexity in these stimuli led to an increased use of attentional resources, which, in turn, affected the perception of time as reflected in an underestimation of image durations.

Conversely, in our studies, we generated visual patterns that lacked meaning and semantic content so that the manipulation of complexity strictly altered only the spatial properties of the stimuli. This manipulation failed to modulate attention and therefore perceived duration.

Similarly, our findings also contrast previous studies showing an effect of numerosity on perceived duration (Dormal et al., 2006; Dormal & Pesenti, 2013; Xuan et

| | Mean estimated duration | | |
|---|---|---|---|
| | $\beta$ | *SE* | *Z* |
| Intercept | 0.736 | 0.027 | |
| Duration | 0.682 | 0.008 | 85.250 |
| Numerosity | −0.005 | 0.003 | −1.667 |
| GIF horizontal | 0.013 | 0.009 | 1.444 |
| GIF vertical | 0.012 | 0.009 | 1.333 |
| GIF horizontal × GIF Vertical | −0.007 | 0.008 | −0.875 |

Table 2. Regression outcome in which mean estimated duration was the DV. *Notes*: Z scores $\geq 1.96$ mean that $\beta$ is significant at the 5% level.

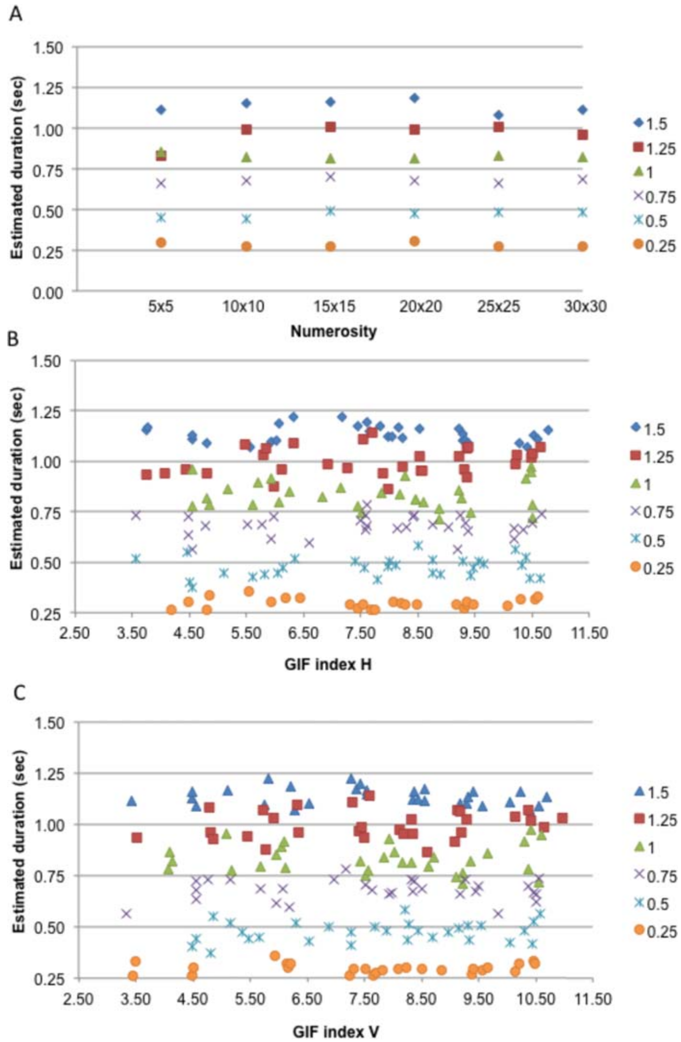



Figure 9. Results of Experiment 2B. (A) Estimated duration (y-axis) as predicted by numerosity (x-axis) and duration (separate lines). (B) Estimated duration (y-axis) as predicted by GIF horizontal index (x-axis) and duration (separate lines). (C) Estimated duration (y-axis) as predicted by GIF vertical index (x-axis) and duration (separate lines).

al., 2007). Generally, these studies have demonstrated that longer duration estimates are given for greater numerosity. It is important to note, however, that previous work has generally used symbolic number representations (Xuan et al., 2007) or nonsymbolic representations in which surface area was not controlled for (Dormal et al., 2006). The absence of control for surface area means that previously used representations of "many" not only contained more items than representations of "few," but they also covered a greater surface area. In our studies, surface area remained constant as numerosity varied; thus, the absence of an effect of numerosity on perceived duration suggests that increased surface area may have contributed to the previously observed effects. Finally, our results were inconsistent with Aaen-Stockdale et al. (2011): Spatial frequency had no effect on subjective duration. However, a direct comparison between the two outcomes is difficult due to different stimuli and paradigms involved.

## General discussion

Previous studies have suggested that complexity biases the perception of duration. For example, Cardaci et al. (2006, 2009) reported that perceived durations tend to be underestimated when stimuli contain a high level of complexity. However, this might depend on the type of stimuli used and on how complexity is manipulated and whether the semantic content is altered. Previous work is unclear about the effect of purely visual changes in complexity on subjective duration.

First, we tested whether two GIF algorithms (scanning the pattern in horizontal and vertical directions) correlated with subjective visual complexity. The results confirmed a positive correlation between the two GIF indexes although they did not fully overlap. This suggests that the direction in which the pattern is scanned affects the structure that is computed.

Second, we tested the effect of visual complexity on subjective duration. There were no effects of complexity on perceived duration in Experiment 1B. In Experiment 2B, the range of complexity was increased by use of patterns with a varying number of elements. This resulted in a high correlation between the GIF indexes and subjective judgments; however, complexity still had no effect on subjective duration.

Therefore, in Experiment 2B, the lack of effect on perceived duration was similar to Experiment 1B although the difference in complexity across patterns was more evident. Our study shows that when visual complexity (free of any semantic info) varies in a subtle (Study 1) or in a less subtle way (Study 2), observers can discriminate the difference without this affecting time perception.

### When does the complexity of stimuli affect perceived duration?

The current study showed that there are different ways to define and quantify the complexity of visual stimuli, and this is related to the kind of stimuli used. Moreover, our experiments clarified that not all kinds of complexity have an effect on perceived duration. When complexity entails specific spatial/structural properties (mere visual complexity) of abstract stimuli, complexity has no effect on subjective duration.

Although a recent study has reported an effect of spatial frequency (Aaen-Stockdale et al., 2011), there were too many differences in the task and in the stimuli to compare our results directly.

What about the element size–complexity confound in Experiment 2B? Ewart and Cantor (1975) and Oliveri et al. (2008) reported that low numbers and small objects reduce subjective duration whereas high numbers and large objects increase subjective duration. Could this have nullified the effect of complexity on duration? We examined this possibility in our analysis, which took into account complexity differences within each level of numerosity, and found no evidence for an effect of complexity.

There might be another reason why we did not find an effect of visual complexity on perceived duration. In principle, visual complexity can also have an effect on arousal. Increased levels of arousal could make the internal clock accumulate more time units, which is reflected in temporal overestimations (Gil & Droit-Volet, 2012; Gupta & Cummings, 1986; Penton-Voak et al., 1996). This could have cancelled the opposite effect, in which complexity increases attention to the stimuli, distracts from the timing task, and ultimately results in temporal underestimation. However, there are no obvious reasons why our stimuli should have modulated arousal. Factors that typically affect arousal involve dynamic stimuli (i.e., high-frequency auditory or flickering images at certain frequencies; Droit-Volet, 2003), physiological variations (i.e., heart rate, skin temperature; Gupta & Cummings, 1986; Wearden & Penton-Voak, 1995), or emotional aspects (i.e., predictability of stimuli, emotional content; Angrilli et al., 1997; Rose & Summers, 1995). In our experiments, visual complexity entailed only structural variations of the patterns that did not involve any of the factors above. Moreover, the way we manipulated the stimuli kept luminance and contrast the same across stimuli. Hence, it is unlikely that our stimuli had an impact on arousal.

We started with the following research question: Do differences in perceived complexity always affect perceived duration? On the one hand, visual complexity implies an increase of visual processing and also attentional resources. This increased attentional load at the perceptual level could reduce the amount of attention paid to time, resulting in a reduction in subjective duration. On the other hand, temporal monitoring could recruit higher-level networks that are independent from visual analysis. If so, an increased attentional load at the perceptual level would not result in a reduction of subjective duration.

Our empirical results support the second hypothesis. This is important because it suggests that complexity alters subjective duration only when visual complexity has semantic content and engages participants in associative and cognitive processes. Therefore, our studies extend past results in that they reduce the range of possible dimensions of visual complexity that have an effect on the perception of pattern duration.

## Conclusion

It is possible to define and measure visual complexity by adopting different methods. We explored the use of a computer-based technique to measure complexity for black-and-white block abstract patterns. This part of our study extended the current knowledge on the use of objective and computer-based indices to quantify complexity for a new class of stimuli. Observers' ratings of complexity were significantly related to the GIF index. The second part of our study tested how complexity relates to perceived duration. We found that when visual complexity entails only spatial/structural aspects of the stimulus, it does not lead to underestimation of stimulus duration. Previous positive results (Cardaci et al., 2006; Harper et al., 2009) may be due to variations in complexity at a higher semantic or associative level. Our results clarified that these two complexity dimensions, visual and associative, play a different role on the perception of stimuli duration.

*Keywords: visual complexity, image compression, attention, estimated durations*

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