Electrophysiological Evaluation of Perceived Complexity in Streetscapes

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Abstract

This study represents an experimental research based on the electrophysiological evaluation of perceived complexity in streetscapes. Two physical measurements of perceived complexity, based on RMS contrast statistics and fractal information, were compared to human judgmental responses issued from brainwaves using Epoc Emotiv neuroheadset. The results indicated that frequency bands showed significant results in alpha and beta power bands in occipital and frontal electrodes, respectively. The higher the degree of familiarity with the streetscape image, the higher the degree of relaxation reflected by the increase of alpha power. Alpha power increased in dark streetscape images. RMS contrast statistics as well as fractal dimension values showed a positive correlation with beta band power associated with arousal and attention.

Keywords: perceived complexity; cognitive appraisal; RMS contrast statistics; fractal dimension; electrophysiological responses

1. Introduction

Electrophysiological analysis became recently popular as a tool of Kansei/affective studies. It has been used together with other techniques in different research fields such as architecture, urban environment studies and environmental psychology.

Different studies investigated the effects of the degree of complexity of a stimulus on the electrophysiological responses of participants. Berlyne and McDonnell (1965) argued that complex and incongruous visual stimuli produce a long desynchronization of alpha activity. They emphasized that arousal positively correlates with the degree of surprise and novelty in visual stimuli. In the studies conducted by Christie and colleague (1972), slideshows containing different numbers of items (2, 4, 8, 16 and 32) were presented to participants. Their findings highlighted a negative correlation of alpha activity with the number of items and a positive correlation with the level of relaxation. The study of Matsumoto *et al.* (2002) focused on the prediction of emotional changes induced by urban spaces using data obtained from psychological rating (SD method) and brainwave measurement. In a development of the previous study, Matsumoto *et al.* (2004) developed a sensitivity analysis system based on VTR and CG images to grasp the emotional changes induced by urban spaces in terms of four dimensions of meaning extracted from the relationship between psychological quantities and brainwave values.

In this paper, the physiological responses of participants related to perceived complexity were examined using electrophysiological analysis EEG in order to explore any significant relationship between the intrinsic responses of participants and the visual structure of the streetscape images.

2. Aims of the Study

The aim of this study was to:
- Examine the brain oscillations of participants while watching different streetscape images with different complexity levels.
- Explore the physiological responses of participants related to perceived complexity using electrophysiological analysis.
- Investigate the relationship between perceived complexity and arousal.

Because of time limits, six channels were selected for data acquisition and processing (F3, F4, P7, P8, O1 and O2). The analysis was carried out with Alpha and Beta frequencies. Power bands were calculated with fast-Fourier transform.

3. Physiological and Behavioral Methods

In this study, the aim of physiological signal measurement is to reflect brain activity and to

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identify cognitive and emotional states of human subjects towards urban streetscapes with different degrees of complexity. In physiological measurement, participants are monitored by physiological sensors that require contact with the human body through electrolyte sensors (e.g. electroencephalography EEG, electrocardiography ECG), while others are standoff sensors (e.g. eye tracking devices).

3.1 The Brain

The brain is the main part of the central nervous system. Anatomically, it can be divided into three parts, which are: hindbrain, midbrain and forebrain (Nykopp 2001). Functionally, the brain is divided into three parts:

- The first part is called large brain (forebrain or cerebrum). It controls higher mental activities such as analytical thinking and language.
- The second part is called brainstem. It is responsible for the visual and auditory functions.
- The third part is the cerebellum. It handles the motor control and the movement of the limbs and the body.

The human brain is categorized into four different lobes, that is to say: frontal, temporal, parietal and occipital (Fig.1.).
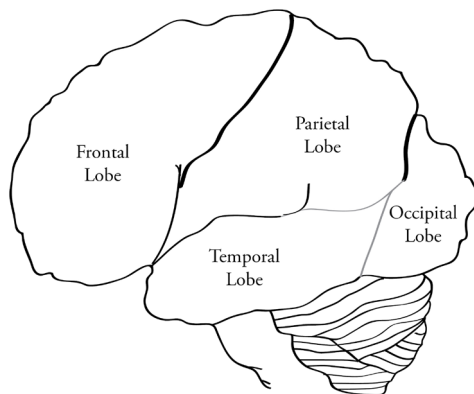

Fig.1. Brain Lobes

The frontal lobe controls complex cognitive actions, language programs, executive functions, emotions and behavioral control.

The temporal lobe is used for storing visual memory, processing language and other audio related functions.

The parietal lobe processes and receives sensory information by connecting all senses.

The occipital lobe processes all visual information tasks sent from the eye. It plays also a role in object recognition.

3.2 Types of Signals

There exist five major brainwave forms distinguished by their different frequency ranges. These frequency bands (from low to high frequencies) are called alpha, theta, beta, delta and gamma.

Delta wave is a large amplitude brainwave with low frequency, which lies within the range of 0.5~4 Hz. This wave is associated with deep sleep in normal individuals.

Theta wave lies within the range of 4~7.5 Hz. It is associated with creative thinking and deep meditation.

Alpha wave is a rhythmic oscillation that occurs between 8~13 Hz. This wave has higher amplitude compared to other wave types. It is best seen in a relaxed position with closed eyes.

Beta wave consists of an irregular wave that occurs at the frequency of 13 to 50 Hz. It can be found in frontal and central regions of the brain when a person is involved in mental or physical activities.

Gamma wave has very low amplitude with a rhythmic activity that occurs to sensory stimuli. It lies within the range of 30 Hz and higher frequencies.

3.3 Electrophysiological Analysis Process

The process of EEG analysis consists of the following steps:

- Removal of baseline.
- Filtering the signal by applying a band-pass filter (high and low).
- Rejecting artifacts such as eye blinks, eye movements, horizontal eye movements, and muscle activity.
- Analysis of the filtered EEG data.
- Classification of the obtained data.

4. Method
4.1 Data Collection

Because of research feasibility, this study could not cover a large number of cities in both Algeria and Japan. To avoid generalization of the concepts that will issue from this research, the authors based the collection of streetscape images on the idea of selecting two cities from each country in which the collection will be carried out. All images were taken during the summer in two phases. The first phase was carried out in Algeria between the 17th and 19th of June 2010. The second phase was carried out in Japan between the 4th and 5th of August 2010. A total number of 80 pictures were shot in daytime and nighttime. However, 6 pictures were cancelled because of their inadequacy. Therefore, the dataset was composed of 74 streetscape images. 37 images were shot in Al-Kantara and Batna cities. The other 37 images were taken in the cities of Kyoto and Tokyo (Fig.2.). Within the dataset, 40 images were taken during daylight hours and 34 images at nighttime using a digital camera Nikon D300S with Nikkor lens system AF-S DX 35mm f/1.8G. All images were shot from the right side of each street to avoid heterogeneity in the vision fields.

The camera was fixed on a tripod in order to avoid artifacts caused by camera shaking (Fig.3.). ISO sensitivity was set to 200. Shutter speed and aperture were set manually for each image, depending on light conditions, and exposure was set to 0EV. The aim was to measure perception within the real conditions that pedestrians encounter in their daily life.

Image files were recorded in uncompressed color NEF format (Nikon's raw file designation). The size

of the RAW images was 4288 × 2848 pixels and image quality was 14 bits/pixel. For the ranking and electrophysiological experiments as well as the estimation of perceived complexity α, described in the next sections, images were presented to participants in a 30" display (model Dell UltraSharp 3008WFP, color temperature: 6500k, luminance: 120 cd/m2). The display's highest resolution was 2560×1600 pixels, which prevented the exhibition of images in RAW size. Therefore, images were pre-processed by decimation. This process consisted in low-pass filtering followed by down sampling of the images by a factor of 2. In this way, the size of the pre-processed images became 2144×1424 pixels, which can be exhibited on the display. Finally, decimated images were converted to 8 bit integer arrays so that their pixel's luminance varies within the range [0, 255].
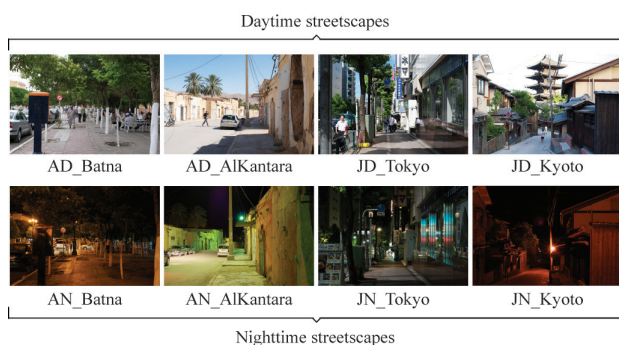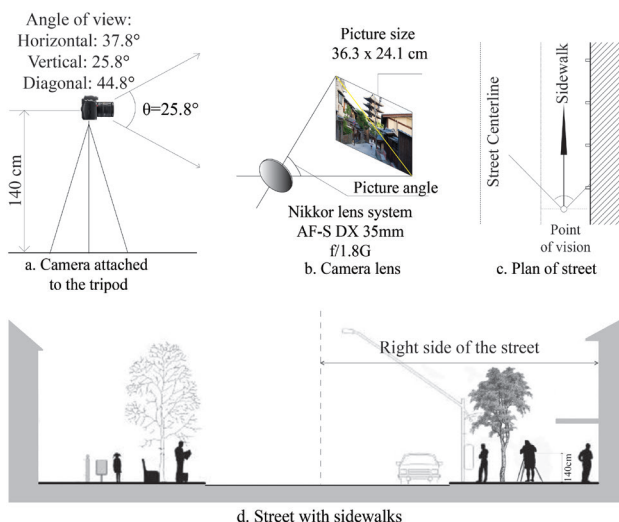

Fig.2. Example of Streetscape Images

Fig.3. Data Collection Method

Ranking method helped in arranging the dataset images according to their degrees of complexity and in dividing them into 3 categories: simple, ordinary and complex. Streetscape images were analyzed by 40 participants. Among the participants, 27 were Japanese, 13 were Algerian, 25 were males and 15 were females. Subjects were asked first to cluster the images seen on the display into three groups: simple, ordinary and complex on the basis of their own perception of complexity. Then, they were asked to sort images inside each group in an increasing order of complexity. After gathering the ranked data, it was necessary to represent the divisions among simple, ordinary and complex categories. These divisions could be identified by including two more imaginary items, with additional ranking positions that represent two axes of separation within the dataset. For example, if the simple group contained 10 streetscapes, the division between simple and ordinary categories occupied the 11th position in the ranking. The ranking positions "i" (where $i=1,2,....,76$) were scaled down to c-scores "$c(i)$".

$$c(i)=2.\frac{i-38.5}{22}+5$$

The final rank "r" of each picture was calculated on the basis of its average positioning:

$$r = \frac{1}{3}\sum_{i}^{76}[v_i.c(i)]$$

Where v_i is the number of times a specific image was located by the subjects at a position i.

Because of time limits, the number of selected streetscape images to be used in the analysis was limited to 16. These images were selected as follows:

Simple: Two images, one daytime and one nighttime (because all images in this group were taken from the town of Al-Kantara and they mainly look similar).

Ordinary: Eight images (four Japanese and four Algerian, four daytime and four nighttime).

Complex: Six images (four Japanese and two Algerian, three daytime and three nighttime).

4.2 Perceived Complexity

4.2.1 Fractal Characteristics of Texture Edge in Streetscape Images

Fractal geometry describes fractured shapes, which show repeating patterns that demonstrate "scale invariance" or "self-similarity" at different fine magnifications. This description is based on a parameter called fractal dimension (Taylor *et al.*, 1999a; 1999b; 2002; Gouyet, 1996).

Used first to study natural forms (Mandelbrot, 1977), fractal analyses covered also urban studies by linking urban hierarchy to fractal geometry. Other studies explored the relationship between the fractal character of townscape and environmental perception, such as: preference, aesthetics, complexity, interest, etc.

Fractal dimension in urban and architectural studies has been investigated by a number of authors according to different objectives in order to analyze: (A) the structure of spatial growth of cities (Batty and Longley, 1994; Frankhauser 1994; Ohuchi 2011), (B) natural and urban skyline (Oku, 1990; Cooper, 2003; 2005; Heath *et al.*, 2000) and (C) historic street plans (Kakei and Mizuno, 1990; Rodin and Rodina, 2000).

4.2.1.1 Image Preprocessing

To analyze fractal information in streetscapes, images in the dataset were transformed into binary bitmap files (*.bmp) using Sobel algorithm in order to detect their edges. The process was based on detecting white edges on a black background.

4.2.1.2 Estimation of Fractal Dimension D$_b$

A key feature of any fractal object is its fractal dimension, denoted as "D". It measures the degree of irregularity and fragmentation. It can be measured according to various methods that depend on the research problem. However, all these methods are based on a power law that generates scale-invariant properties (Taylor *et al.* 2008). The box-counting method is one of the most commonly used mathematical approaches to determine the approximate fractal dimension of an image because it can measure images that are not entirely self-similar.

In this study, a large grid was placed over each streetscape image. Each square in the grid was checked to determine the existence of white pixels (Fig.4.). Then, boxes that contain white pixels were recorded. In the following step, a grid of smaller scale was placed over the same streetscape image and the same process was applied in order to search for possible white pixels (details) in the boxes of the grid. Finally, a comparison was made between the number of boxes with details in the first grid and the number of boxes with details in the second grid. This comparison was made by plotting a log-log diagram for each grid size. Repeating this process over multiple grids of different scales produced a log-log linear correlation between the number of counted boxes and the associated sizes of the grid. This study used Benoit 1.3© software, which is based on the box counting method.

In Benoit software, fractal dimension is defined as the exponent "D" in the relationship (Kacha *et al.* 2013a):

$$N(d) = \frac{1}{d^{D_s}}$$

Where N(d) is the number of boxes of linear size d, necessary to cover a data set of points distributed in a two-dimensional plane.
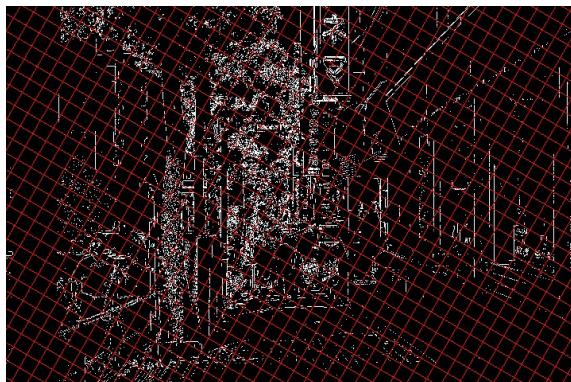

Fig.4. Box-Counting Method

4.2.2 Contrast Statistics of Streetscape Images

Human capacity to discern information includes the ability to perceive differences in luminance within a field of vision. This creates different patterns of contrast that provide visual information to the viewer.

The definition of image contrast depends on its application. Various methods of contrast measurement emerged from each application, that is to say: simple contrast, Weber contrast, Michelson contrast and RMS (root-mean-square) contrast.

RMS contrast is defined as the standard deviation of pixel intensities, commonly applied for non-periodic targets (noise, textures and images) (Frazor and Geisler, 2006; Bex *et al.* 2009). It does not depend on spatial frequency content neither on spatial distribution of contrast within an image. It is considered by Levien (2003) in his study on contrast in natural images, as the most reliable indicator of visible images. It represents the most commonly used measure to quantify image details in image processing systems as well as a good predictor of the subjective/apparent contrasts of compound grating images and random noise patterns (Moulden *et al.* 1990).

4.2.2.1 Image Preprocessing

Images were transformed from color scales to grayscale and resampled to 1072×712 pixels because of the complexity of color images and the hardness of their processing whereas contrast can be efficiently estimated using grayscale images. A "gray" color is the one in which red, green and blue components all have equal intensity in RGB space. Grayscale images are entirely sufficient for many tasks because less information needs to be provided for each pixel. It is only necessary to specify a single intensity value for each pixel, as opposed to three intensities needed to specify each pixel in a full color image.

4.2.2.2 Image Contrast and Measure of Complexity α

In this study, let us consider around every pixel **I***(i,j)* of the input image, a neighborhood of 2L x 2L pixels denoted by a vector **n**. σ_n represents the RMS contrast of luminance, which is the standard deviation of luminance values in a neighborhood n' (Fig.5.). For all possible locations *(i,j)*, the respective n is processed by a workflow. Then, a contrast map **C** is built, so that each value **C***(i,j)* is the RMS contrast of n.

$$\sigma_n = \sqrt{\frac{1}{4L^2} \sum_{i=1}^{4L^2} (n_i - \bar{n})^2}$$

σ_n represents the RMS contrast of luminance
n_i represents one pixel inside the neighborhood n
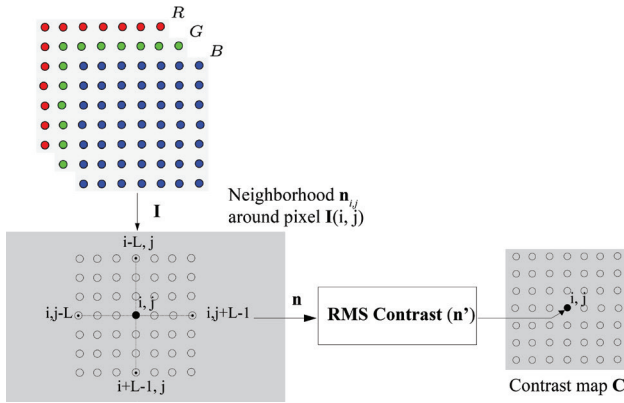*n represents the mean value of $\bar{n}$*

Fig.5. Block Diagram of RMS Contrast Measure

By considering a specific pixel $I(i,j)$ and its respective n, the contrast map **C** is calculated as:

$$C(i,j) = \sigma_n$$

The proposed measure of perceived complexity was based on the statistical analysis of contrast distribution within each streetscape image. For an objective appraisal of perceived complexity α, this study defines α as the mathematical product of the mean value of a neighborhood **n** and the standard deviation of pixel intensities (Kacha *et al.* 2013b):

$$\alpha = \mu_c.\sigma_n$$

α is the perceived complexity
μ_c is the mean of RMS contrast values C(i,j)
σ_c is the standard deviation of RMS contrast values C(i,j)

4.3 Electrophysiological Analysis EEG
4.3.1 Participants

Six right-handed participants from the department of architecture of Nagoya Institute of Technology voluntarily took part in this experiment. Participants were three males and three females, all being approximately the same age (Mean = 23.16 years, Stand. Dev. = 0.75 years). They all had normal or corrected-to-normal vision.

4.3.2 Procedure

The experiment was conducted in Japan between the 23rd of May and 3rd of June 2013. The time of the experiment was from 10:00 am to 12:00 pm and from 15:00 pm to 19:00 pm. The order of the picture flow was the same for all participants. Images were presented in the same display used in the previous experiment (model Dell UltraSharp™ 3008WFP 760). The distance between each participant and the display was about 100 cm (Fig.6.). To avoid artifacts and noises in the recording data, participants were asked to follow the following guidelines during the experiment:
- Try to not blink, nor move your eyes or any other part of your body.
- Try to stay relaxed and do not tense up.
- Keep your eyes open.

- You can blink, move and relax in the lapsus between two streetscape images (black image).

The duration for each streetscape image was limited to ten seconds, because researchers reported that a minimum of 10-15 seconds of activity must be collected from each stimulus (Niemic 2002).

The slideshow of the 16-streetscape images was presented as explained in Fig.7.

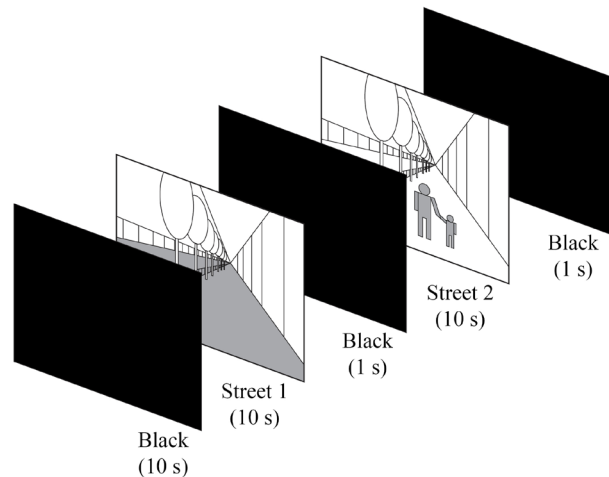Fig.6. A Participant during the Experiment

Fig.7. Flow of Images During the Experiment

4.3.3 Hardware

This study used the Research Edition of Emotiv Epoc neuroheadset, which is a non-invasive high resolution, neuro-signal acquisition and processing wireless neuroheadset. It contains 14 channels (plus CMS/DRL references, P3/P4 locations). Channel names, based on the International 10-20 locations are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 (Fig.10.). The headset connects to the computer via Bluetooth using a USB dongle (Fig.8.).

Fig.8. Epoc Emotiv Neuroheadset

4.3.4 Software

The software used with the Emotiv Epoc neuroheadset was TestBench v1.5.1.2. It records, processes the data received from the headset, provides a real-time display of the data and allows the user to see the EEG data coming in from each sensor. The program can also display a Fast Fourier Transform (FFT) of any incoming channel and can display the Delta, Theta, Alpha, and Beta bands (Fig.9.).

Fast Fourier Transform (FFT) is usually used in the treatment of signals in order to convert time into frequencies.

Fig.9. FFT Measurements in TestBench Software

4.3.5 Data Acquisition and Processing

EEG signals were recorded for ten seconds per streetscape image, using only six electrodes from frontal, parietal and occipital brain lobes, that is to say: F3, F4, P7, P8, O1 and O3 (the selected channels are surrounded by a circle in Fig.10.). These signals were sampled at 250 Hz. After recording the data from all participants, the data was divided into 16 portions; each portion represented the obtained signal from each participant looking into a streetscape image. Then, power bands were calculated using fast-Fourier transform (256 points) using Hanning window from the TestBench software. The analysis was carried out with alpha (7-13 Hz) and beta (13-30 Hz) frequencies.

The analysis was carried out based on the average of the whole time portions (ten seconds) for each streetscape image.
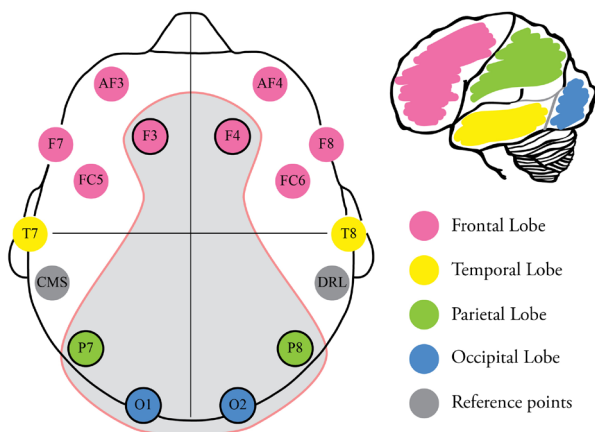

Fig.10. Selected Channels Used in the Study

5. Results

5.1 Analysis of Significant Differences among All Channels for Time Variable

Analysis of variance (ANOVA) in the variable time (1: daytime, 2: Nighttime) showed a significant difference at the $p<0.05$ level for alpha band power in the right occipital area (O2 channel) $F(1,14) = 6.32$, $P = 0.02$. The alpha band power was larger in the nighttime compared to the daytime (Fig.11.), which means that participants showed a more relaxed state for nighttime streetscape images than for daytime streetscape images.
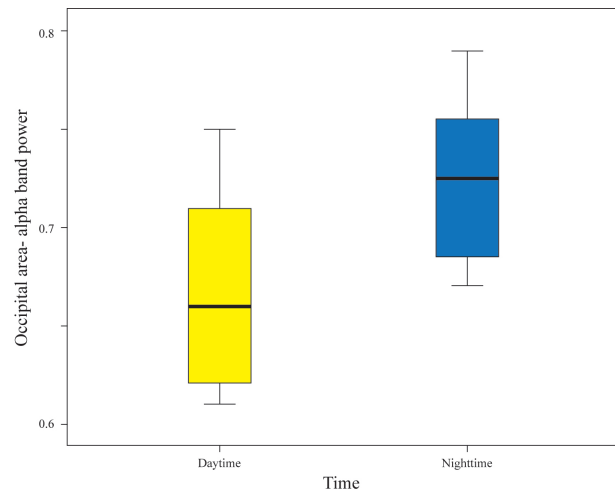

Fig.11. Boxplot Showing Time Differences in Alpha Band Power in the Right Occipital Area (O2)

5.2 Analysis of Significant Differences among All Channels for Country Variable

Analysis of variance (ANOVA) in the variable country (1: Algeria, 2: Japan) showed a significant difference at the $p<0.05$ level for alpha band power in the left occipital area (O1 channel) $F(1,14) = 6.5$, $P = 0.02$. The alpha band power was larger in Japanese streetscapes compared to Algerian streetscapes (Fig.12.). This means that participants showed a
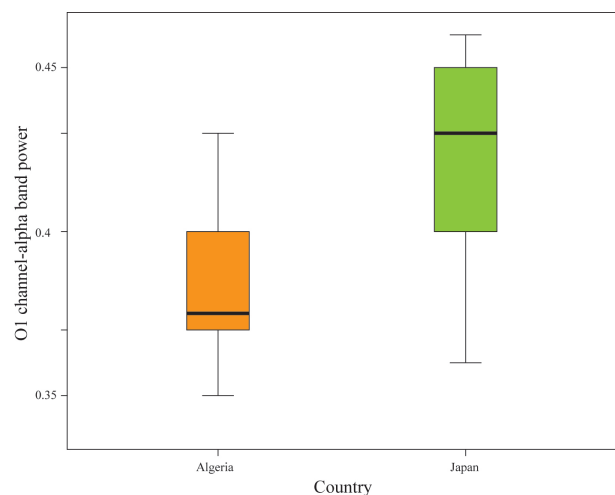

Fig.12. Boxplot Showing Country Differences in Alpha Band Power in the Left Occipital Area (O1)

relaxed state towards Japanese streetscape images compared to Algerian streetscape images. This is due to the familiarity of Japanese participants with Japanese streetscapes. Algerian streetscapes represented a new environment for them, which attracted their attention.

5.3 Linear Regression Analysis for Perceived Complexity "α"

A linear model was performed using the forward stepwise method. The model explained 49.6% of accuracy. The predictor importance showed significant results only with the beta band power of the right frontal area (F4=0.59), the right occipital area (O2 = 0.37) and the left occipital area (O1 = 0.04).

5.4 Linear Regression Analysis for Fractal Dimension "D_b"

Linear model was performed using the forward stepwise method. The model explained 44% of accuracy. The predictor importance showed significant results only with the beta band power for the left frontal area (F3 = 0.57), the right occipital area (O2 = 0.27) and with the alpha band power for the left occipital area (O1 = 0.17).

5.5 Arousal Beta/Alpha Ratio

Beta waves are linked to an alert state, whereas alpha waves are linked to a relax state. The beta/alpha is a ratio that indicates the arousal state of a participant (Oude Bos 2006). By examining the arousal state, only one significant difference for country variable was found at the $p<0.05$ level in the left occipital area (O1 channel) $F(1,14) = 13.82$, $P = 0.002$. The ratio band power was larger for Japanese streetscapes compared to Algerian streetscapes (Fig.13.). This means that participants showed a relaxed state for Japanese streetscape images compared to Algerian streetscape images. Fig.14. shows the relationship between arousal and perceived complexity issued from both RMS contrast statistics and fractal dimension.

A principal axis factor analysis (PAF) with Varimax (orthogonal) rotation of the ratio of band power of six channels of the 16-streetscape images was conducted
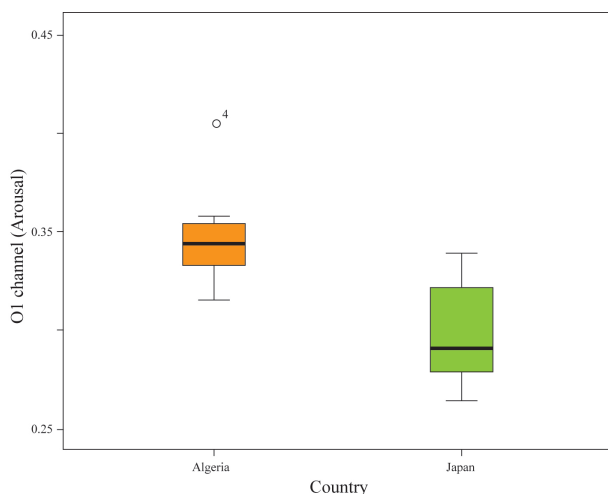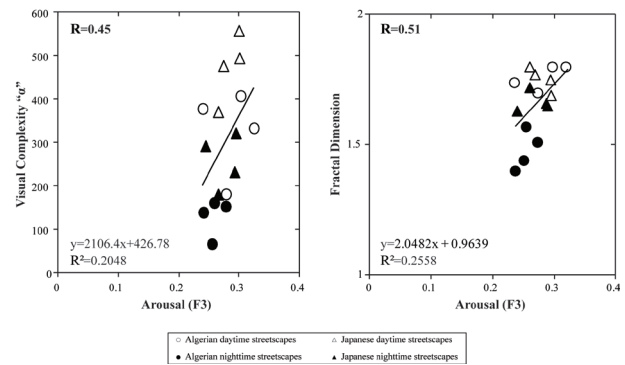

Fig.14. Scatter Plots of Arousal and (A) Perceived Complexity, (B) Fractal Dimension

on the gathered data from the six participants. An examination of the Kaiser-Meyer Olkin measure of sampling adequacy indicated that the sample was factorable (KMO = 0.65, above of 0.6).

The results of Varimax rotation of the solution are shown in Table 1. The analysis yielded a two-factor solution. Four channels from the frontal and the occipital areas (F3, F4, O1 and O2) were merged into the same factor and explained 45.54% from the total of variance, contrary to the parietal area channels (P7 and P8), which explained 19.80% of the variability. The resulting factor scoring and factor matrix were classified using cluster analysis (ward method) (Fig.15.).
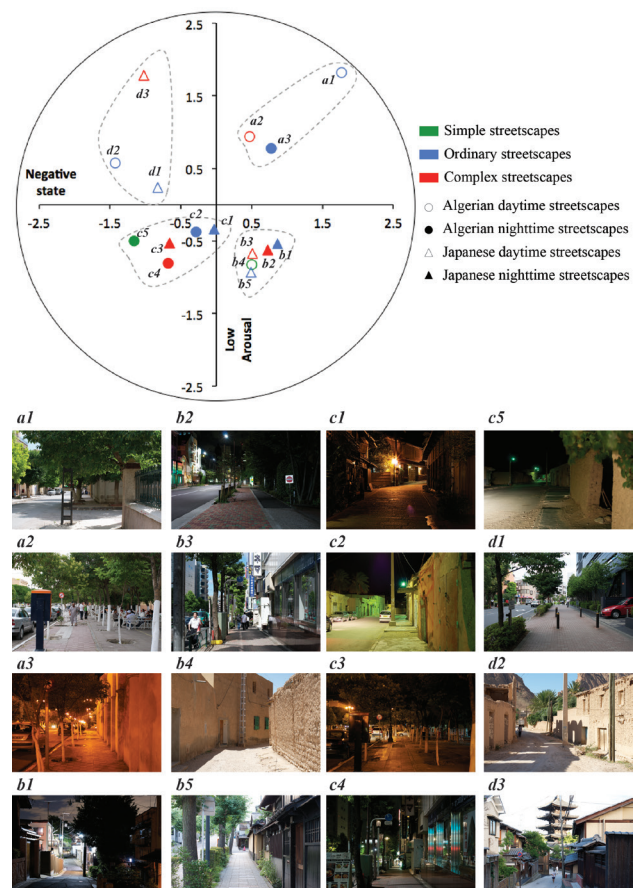

Fig.15. Clustering of Streetscapes Based on their Arousal Level

Fig.13. Boxplot Showing Country Differences in Ratio Power for the Left Occipital Area (O1)

Table 1. Results of Factor Analysis

	Factor 1	Factor 2	Communalities
F4	**0.82**	-0.08	0.67
O2	**0.65**	0.51	0.68
F3	**0.63**	0.47	0.62
O1	**0.33**	0.17	0.14
P8	0.06	**0.89**	0.80
P7	0.17	**0.48**	0.26
Eignvalue	2.73	1.19	
Contribution ratio (%)	45.54	19.80	Extraction Method: Principal Axis Factoring
Cumulative contribution ratio (%)	45.54	65.34	

6. Conclusion

The aim of this study was to explore the physiological responses of participants related to perceived complexity using electrophysiological analysis.

The experiment was conducted with six participants. The number of streetscape images in the slideshow was 16, carefully selected from each group of complexity (simple, ordinary, complex). The recording of electrophysiological data was done using EPOC Emotiv neuroheadset (research edition). The recording and processing software of EEG data collected from the headset was TestBench v1.5.1.2.

Because of time limits, six channels were selected for data acquisition and processing. These channels were:

- F3 and F4 from the frontal brain lobe, which controls complex cognitive actions, emotions and behavioral control.
- P7 and P8 from the parietal brain lobe, which controls sensory information.
- O1 and O2 from the occipital brain lobe, which controls visual information.

The analysis was carried out with Alpha and Beta frequencies. Power bands were calculated with fast-Fourier transform.

The electrophysiological analysis helped in obtaining the following results:

- Alpha and Beta band powers showed significant results in the occipital and frontal electrodes, respectively.
- Alpha power increased with the degree of familiarity of the participant with the streetscape stimuli. The higher the degree of familiarity, the higher the degree of relaxation reflected by the increase of Alpha power.
- Alpha power increased in dark streetscape images (e.g. Nighttime streetscape images).
- Because of the association of Beta waves with arousal and attention, perceived complexity and fractal dimension values showed a positive correlation with Beta band power in the frontal lobe.

The positive correlation between familiarity and relaxation as well as among contrast, fractal dimension and Beta band power associated with arousal and attention reflect the main outlines for future studies on this subject. In terms of research limitations, the authors believe that future experiments should include more participants who are unfamiliar with Algerian and Japanese streetscapes. Increasing the number of sessions within the experiments is also recommended.

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