Entropy, Emergence and Cognitive Patterns of Complexity in the Visual Composition of Streetscapes in Algeria and Japan

日本とアルジェリアの街路景観構成における
エントロピーおよびエマージェンスと複雑性の形態認識との関係

Dissertation

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By

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Abstract

The study of complexity in the urban contexts is a touchy subject. The reviewed literature influenced the orientation of this research by concepts from researches done in Japan about disorder in the street view (Matsumoto 2002), and concepts from architectural design theories (Gero 2007).

The aim of this research is to explore complexity, as seen by subjects, in the visual composition of streetscapes in Algeria and Japan. Then, to try to find out the origin of this complexity according to 2 levels of perception:

1. Low level vision that deals with textures and small scales. Entropy is an expression of disorder and complexity in this level of analysis of pixel intensities.

2. High level vision, which is a more perceptual level. The probabilities of the classes that compose a streetscape were analyzed in order to study the articulation among these classes and the possibility of any perceptual complexity.

80 streetscape pictures have been selected then presented to different groups of subjects (Japanese and foreigners). The analysis was done as follows:

1. Typological clustering: Cluster analysis helped in finding out the typological clusters within the selected streetscapes.

2. Cognitive patterns clustering: factor analysis (using a 7-point scale) helped in finding out some cognitive features related to complexity in the collected streetscapes. The experiment was done twice. First, the data was presented in CMYK format (Printed CMYK quality), then in RGB format (30” HD screen).

The results of the physical analysis of the streetscapes were as follows:

1. Low level (Chapter 5): Entropy analysis in this chapter was done according to the nearest neighbor method of entropy estimation. The results showed that entropy is directly proportional to the degree of complexity in all the streetscapes.

2. High perceptual level (Chapter 6): 5 different classes (building, sky, vegetation, ground and actors) were segmented and categorized within each streetscape. The analysis of the articulation among these classes in terms of size using Shannon's model showed that complexity is inversely proportional to the difference of size between classes. When the classes get similar in size, the degree of complexity within a streetscape increases.

Future researches will aim to explore the real nature and characteristics of these articulated classes composing the complexity of a streetscape.

Introduction

Introduction

Exploring complexity within urban contexts is a very interesting and very delicate research subject. Therefore, the literature mainly related to complexity, within different fields of research in Architecture opened my mind to new possible horizons of research in streetscape visual composition, specifically with regard to two concepts: emergence and entropy.

My short experience in studying the complexity of Architectural design creativity in 2001, opened my mind to these interesting concepts through the writings of Prof John Gero about unexpectation, emergence and recently his works on entropy in Architectural design. The researches done by my supervisor Prof. Dr. Naoji Matsumoto about disorder and the application of Fourier transform in the study of fluctuation in streetscape as well as in street space; opened my mind to try to explore both these research dimensions at once, that is to say, the study of emergence and entropy in the visual composition of streetscapes.

This research encountered a lot of difficulties. It began from my master's research about fractal dimension and the attractiveness of the street view, using brainwave analysis (2004). Dealing with a 3 dimensional complex space is not an easy matter. Professor Matsumoto and I decided to explore the complexity of a streetscape from the visual array level, according to the concepts developed in Gestalt psychology, Gibson (1977) and Kaplan (1988) with his concept of affordance.

This research work tried to explore and analyze complexity of a streetscape visual composition as a 2 dimensional array according to two kinds of data, human as well as physical. Different behavior analyses methods have been used throughout this study, that is to say: Cluster analysis, Hayashi

quantification method type III and finally factor analysis to deal with human data.

The analysis of physical data was done by the analysis of the visual composition of streetscapes from the pixel intensity scale using nearest neighbor distance method to estimate entropy to the composing classes scale using Shannon's model from information theory.

The thesis is structured in 3 main parts, each part including 2 chapters. Part one represents the theoretical background of the study. It includes chapter one related to the conceptual background of the study, and chapter two related to the methodological background of the study.

Part two is mainly related to DATA clustering, with chapter three oriented towards the typological clustering of the streetscapes and chapter four oriented towards the cognitive patterns clustering of the subjects' evaluation of the streetscapes complexity.

Finally part three is the one of entropy estimation, dealing only with streetscape arrays as physical data. It includes chapter five that is focused on the estimation of entropy based on the probabilities of pixel intensities using the nearest neighbor method. Chapter six is related to the analysis of the classes composing the selected streetscapes by the analysis of the probability of the perceived classes using Shannon's model of entropy estimation.

The author hopes to pursue deeper researches on entropy in the urban as well as the Architectural context. The researches and thoughts done throughout these years would be an important background in the future.

Chapter. 1

Conceptual background of the study

1.1 Introduction

Studies related to complexity are often confronted by a multitude of concepts and definitions that reflect different meanings, depending on the field of the study or the background of the researcher. Therefore, it seems important to define at the early stages of this research; the meaning of each concept to be used or analyzed.

Complexity has many different meanings from mathematics, physics, computer science and biology. It is a holistic concept that includes many corollary concepts such as disorder, irregularity, ambiguity, etc. . This research tries to study complexity as a phenomenon in urban contexts, using concepts from environmental psychology, complexity theory and mathematics. The aim of this chapter is to design a conceptual framework of the key-concepts to be used throughout this research and to present an overview of the different researches related to complexity in the Architectural as well as in the urban context.

1.2 Research background

This research is the result of a series of researches and literature reviews about complexity in architecture and urban contexts. Its idea was influenced by many different research orientations related to complexity and its corollary concepts in the urban context; that is to say:

1. Concepts developed throughout the researches done by Ding and Gero (2001, p.714)[1], (Gero and Ding 1997)[2] about emergence of style in Architecture and also generative models of designing based on the concept of emergence (Gero 1996)[3].

2. The researches done in Japan about order and complexity in streetscapes

(Yamagishi, Uchida and Kuga 1988, p.27)[4] as well as disorder in streetscape views (Matsumoto, Teranishi and Senda 1991, p.73)[5], (Seta et al. 2002, p.181)[6] greatly influenced the strategies used in this study.

3. Finally, the concepts developed by Kaplan (1988)[7] represent the conceptual frame that structured the theoretical dimension of this study.

1.3 Early stages and orientation of the Research

The main lines of the research developed from a series of researches done by the author about Emergence in Architectural design[8], the exploration of architectural creativity[9], the study of attractiveness and fractal geometry in the composition of streetscapes in Japan using brainwave analysis[10] and the study of the role of fractal dimension in the image attractiveness of European townsquares[11]. The difficulties encountered throughout this series of studies helped in orienting this one towards a more feasible approach entropy and complexity in the visual composition of streetscapes.

1.4 Basic concepts of the research

Before addressing this study to the visual composition of streetscapes, it will be necessary to obtain a basic understanding concerning the main key-concepts that will be used throughout this study.

1.4.1 Street

Streets are the channels along which the observer moves. This research is more focused on the physical as well as the perceptual aspects of the street, as seen within a human eye perspective (Cullen, 1961). Celik, Favro and Ingersoll (1994)

define street as an enclosed 3 dimensional space between two lines of adjacent buildings[12]. According to Krier (1979) a street is morphologically seen as the product of the spread of a settlement providing a framework for the distribution of land and gives access to individual plots[13]. Rapoport's definition (1987) seems to cover more aspects of a street. It considers streets as physical entities seen as the more or less narrow, linear spaces lined by buildings found in settlements and used for circulation and, sometimes, other activities[14] (fig.1).

Fig.1 Example of a street in Tokyo (August, 2010)

1.4.2 Perception

Perception refers to the process of perceiving, whose content is the percept, the conscious experience of the distal objector scene. For the purpose of studying perception, it is assumed that Euclidean geometry provides a good approximation of the structure of the physical world. As suggested by Uttal (1988) perception is also the relatively immediate mental response evoked as a partial result of impinging multidimensional stimuli[15]. Low-level perception is relat-

ed to edges, motion and texture while high-level perception is related to objects, faces and scene recognition.

Studies related to perception attempt to explore 2 entities simultaneously[16]:

- The subjective experience of perception.
- The intrinsic neurophysiologic mechanisms within the brain.

Therefore, the fact that knowledge related to neurophysiologic principles is still incomplete represents a major problem in studies of perception and cognition.

1.4.2.1 Visual array

An array is defined as the systematic arrangement of objects, usually in rows or columns. Kaplan (1988) argues that human being seems to relate to the information they pick up in two different ways[17]. They react to the two dimensional visual array as though the environment in front of them was a flat picture, as well as to the three dimensional pattern of space that unfolds before them. The pattern of light and dark on the photograph and the organization of its picture plane constitute the basis of this level of analysis.

1.4.2.2 Affordance

According to Gibson (1977), affordance refers to what a perceived object or scene has to offer as far as the individual perceiver is concerned[18]. It is a quality of an object or an environment that allows an individual to perform an action.

1.4.2.3 Coherence

Kaplan (1988) defines coherence as the making sense component. It includes factors that make the picture plane easier to structure. Coherence is strengthened by the inclusion of repeated elements and smooth textures that identify a region or an area of the picture plane, making it easier to organize the visual rray into a manageable number of major objects and areas.

According to Kaplan, anything in a scene that helps divide it into approximately 5 major units will aid the comprehension process[19]. The greater the complexity of a scene, the more structure is required to organize it.

1.4.3 Complexity

Complexity is used to characterize any system with many parts in intricate arrangement. Complexity theory states that interacting components self-organize to form potentially evolving structures exhibiting a hierarchy of emergent system properties.

In the urban context, Kaplan (1988) defines complexity as the involvement component at the surface level (visual array or picture) of analysis. It reflects how much is going on in a particular scene, how much there is to look at[20]. In the street scale, sidewalks permit local interactions and create a complex order dealing with the sensory overload and making the human nervous system stretched by the built environment.

Complexity is a multi-faceted concept. Hierarchical or structural complexity refers to the existence of a hierarchy on several scales or levels within a system or a domain (fig.2). The different hierarchical levels may be apparently autonomous or related and can vary in their intrinsic complexity. A visual array is an example of hierarchically ordered system, in which hierarchical order increases potential aesthetic impact by increasing the range of elements included[21].

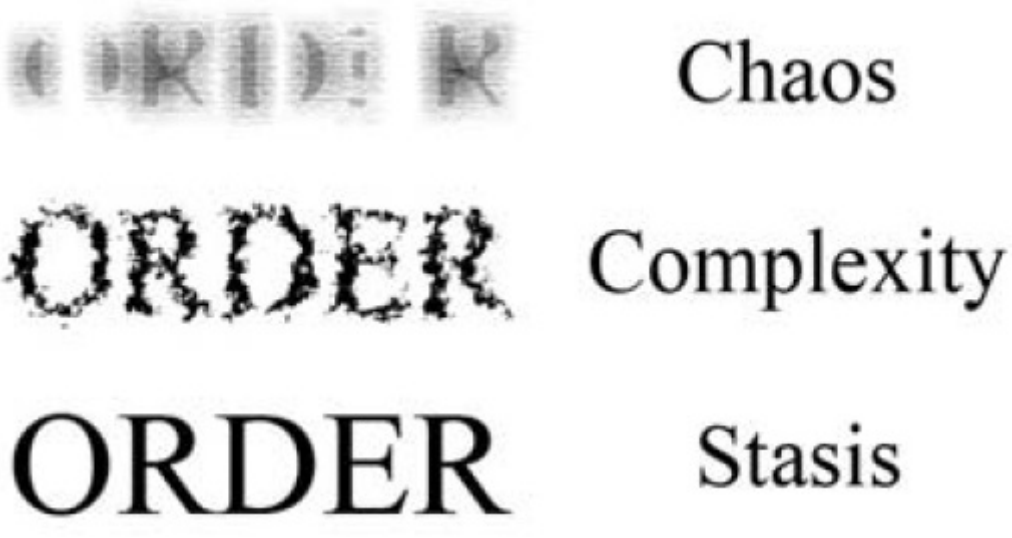

Fig.2 Chaos, complexity and order

1.4.3.1 Complex adaptive systems

A complex adaptive system is a system composed of articulated parts that as a whole exhibit one or more properties not obvious from the individual parts. Emergent behavior is among the features of Complex adaptive systems (table 1).

Table 1 Some features of complex adaptive systems

Aggregation (a)	The ability to group agents within a system into common categories.
Aggregation (b)	The ability of agents to act together to produce large effects or trends within a complex system.
Nonlinearity	There is not a direct and easily predictable linear relationship between an agent's actions and the consequence of that action.
Flows	While agents may be autonomous, they can interact. Flows are the interactions.
Diversity	Agents within a system will take on different forms to match the environment. Since the environment is changing, the array of agent forms will also change, but match the environment in some way.

1.4.3.2 Articulation

The word articulation generally refers to how the pieces of a system are joined together; for example, how syllables are connected to make a word. Articulation depends on what is happening at the beginning and end of each segment, as well as in between the segments[22].

1.4.3.3 Emerging properties and reification

Emergence is a concept that tries to explain the way complex systems and patterns arise from a multiplicity of relatively simple interactions. Any system that exhibits emergence involves articulated agents or parts that interact together.

In Gestalt theory, emergence is a common property of certain kinds of physical systems, which cannot be lawfully predicted from their present state. Emergence in perception indicates that the neurophysiologic processes involved in perception produce a final perceptual state that is the result of many tiny processes, which cannot be reduced to simple laws[23] (fig.3).

In design, Gero defines emergence as the process of making properties explicit that were previously implicit, This definition is more related to another concept of Gestalt theory, which is perceptual reification, Reification is a general principle of perceptual processing that refers to the filling-in of a more explicit perceptual entity based on a less complete visual input[24] (fig.4).

1.4.3.4 Entropy

As defined by Shannon (1948), entropy is the amount of information needed to specify the potential disorder within a system.

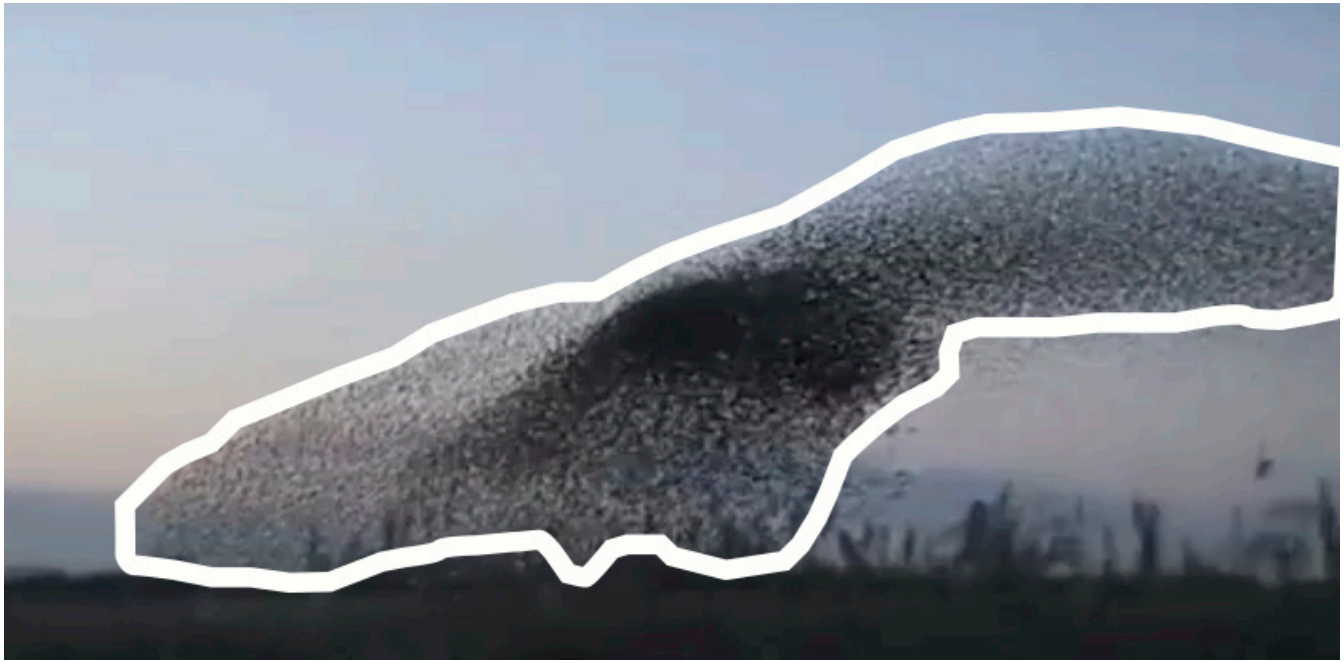

Fig.3 Example of emerging shape from a bird storm

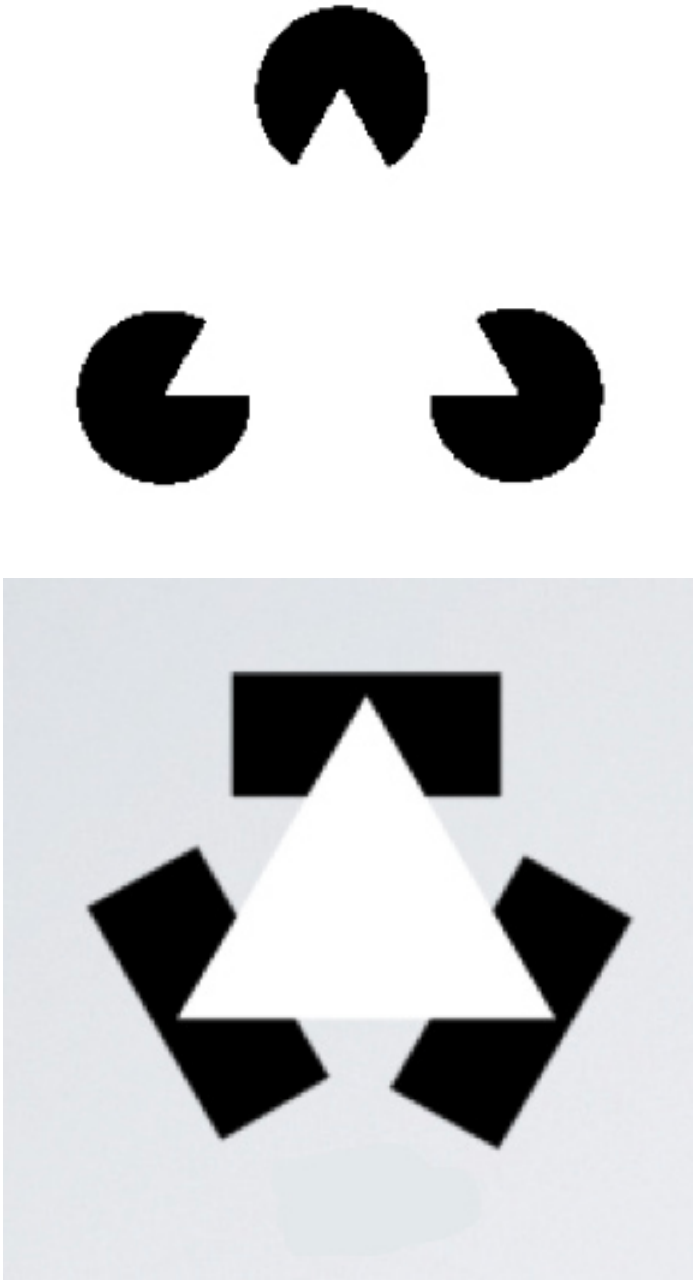

Fig.4 Examples of perceptual reification

1.5 Summary

The aim of this chapter was to outline the background to this research as well as to define the main concepts to be explored in this study.

The research tried to focus two different research orientations, one on design and another one on streetscape composition, into a study that uses concepts from the first and analysis techniques from the second. The definitions of the key-concepts of this research will be reflected in the theoretical explanations and interpretations throughout this dissertation.

As a multi-faceted concept, complexity in visual array (picture) is hierarchical. This hierarchy can be seen from the low level of textures to the higher level of articulated classes or patterns within the visual array. Kaplan (1988) suggested 5 major units that help the comprehension process of a scene. The greater the complexity of a scene, the more structure is required to organize it.

Within a defined system, self-organized evolving structures exhibit a hierarchy of emergent system properties. Emergence is a concept that describes the arising properties and patterns from the articulation of the system components. In a lower level, entropy reflects the amount of information necessary to describe the potential disorder within a system.

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Chapter. 2

Methodological background of the study

2.1 Introduction

This chapter is about the methodology that structured this research works. In order to explore the concept of complexity in the visual composition of streetscape, this research encountered a lot of methodological as well as technical obstacles that helped in improving, through a trial-error process, the quality as well as the credibility of the obtained results. This study will try to include the fruitful approaches as well as the unfruitful ones, in a way that may help further researches in this subject.

The study of complexity and entropy, which is so far a delicate subject, is a study of uncertainties. This study tried to explore complexity in the visual composition of streetscapes by dealing with 2 kinds of data: human as well as physical. The human category of data included participants with different cultural backgrounds. The physical category included different versions of the same visual arrays, taken by different digital cameras, in order to be subject to different types of entropy analysis.

2.2 The research problem and strategy

Given the increasing complexity within our built environments that stretches the human nervous system to its extreme, questioning the nature and the mechanisms behind the concept of complexity seems to draw attention to many research possibilities. However, the literature review for this study showed that the major part of research dealing with complexity in the urban environment is mostly one-sided. In other words, these researches deal only with one aspect of complexity. Whether it is the effects of complexity on human behavior or the physical expressions of complexity in urban environments.

This study tried to explore complexity according to two different kinds of data: human (cognitive patterns of complexity) and physical (fig.5). The second aim of the research is the multi-scale analysis of entropy, within the physical data (pictures), according to low level analysis using the nearest neighbors distance method to estimate entropy, and to a higher level of analysis concerned with the perceptual components of the visual arrays (classes) using Shannon's method of entropy estimation. The research tried to find out any possible emergent behavior as well as any possible relationship between the entropy of the pictures and the degree of complexity evaluated by subjects.

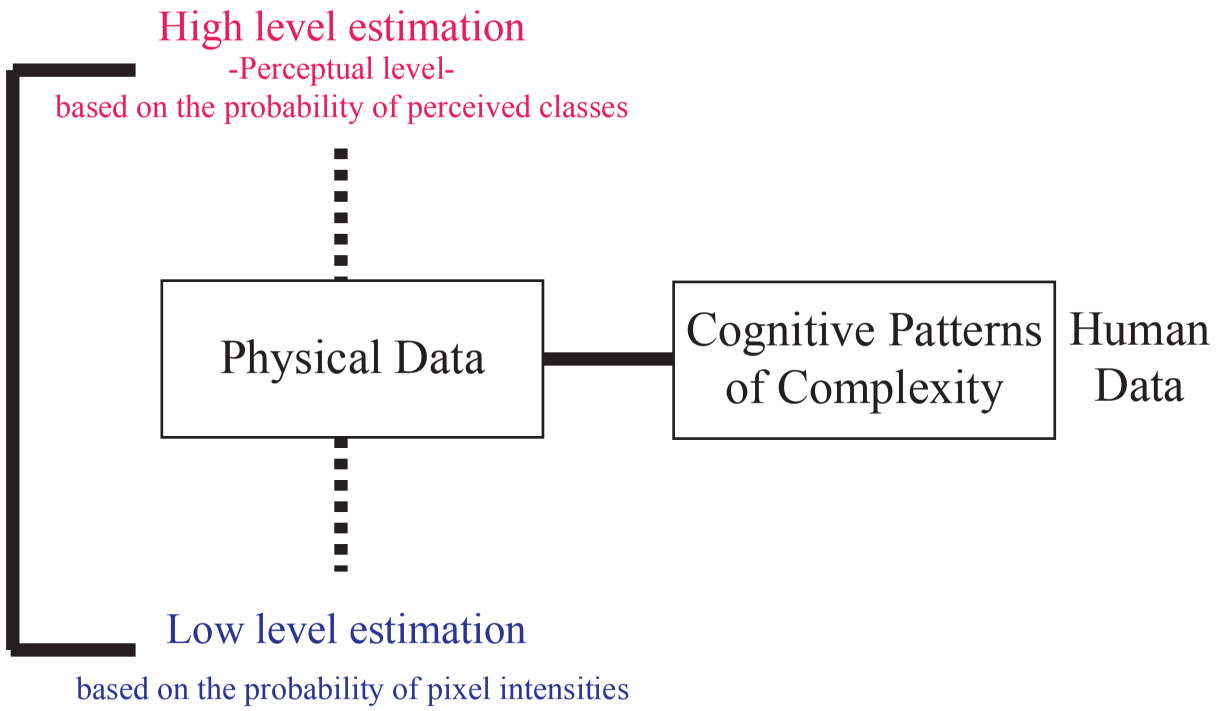


Fig.5 The research strategy

2.3 Structure of the thesis

The thesis is structured according to 3 main stages (fig.6). Stage One includes Chapter 1 related to the conceptual background of the study and Chapter 2 related to the methodological background of the study.

Stage Two is based on data clustering, both human and physical. This stage includes Chapter 3 focused on the typological clustering of the streetscapes, and Chapter 4 mainly related to the clustering of the cognitive patterns issuing from the complexity ranking and categorization of streetscapes.

Finally, Stage Three is based on the analysis and estimation of entropy within the collected streetscapes. It is composed of Chapter 5, covering the estimation of entropy based on the probability of pixel intensities; and Chapter 6, on the estimation of entropy based on the probability of perceived classes within a streetscape.

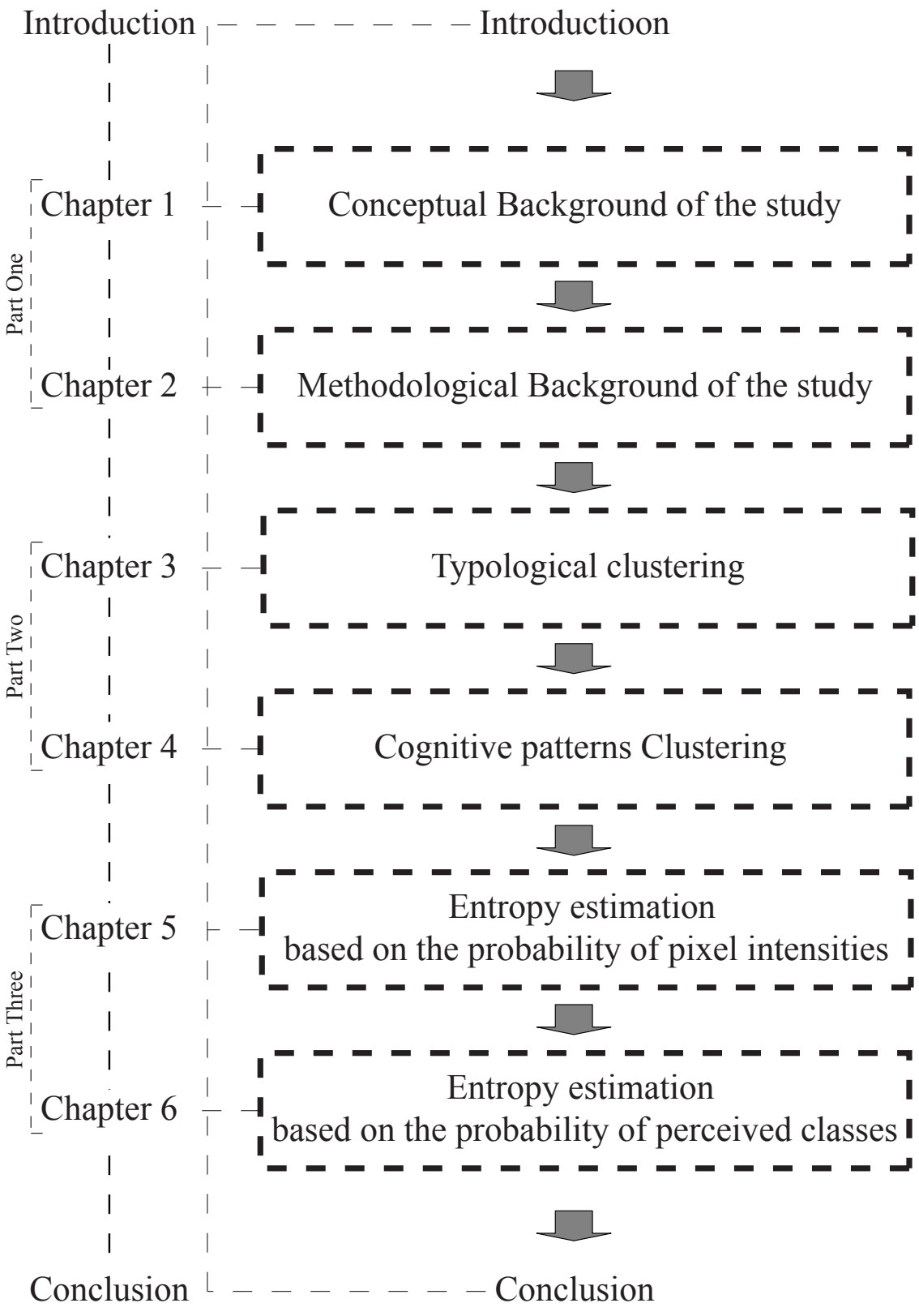


Fig.6 Structure of the thesis

2.4 Summary

This chapter summarized the aims, the strategy and the methodology of this study. The dissertation is structured around 3 main stages that constitute the parts through which the research went from dealing with human data to physical. Analyses, sub-methodologies and techniques used in each part of the research will be the subject of the following chapters.

Chapter. 3

Typological clustering

3.1 Introduction

This chapter is a comparative study of the visual composition of streetscapes in Algeria and Japan. 80 visual arrays of streetscapes in Algeria and Japan have been collected and then presented to 20 subjects from different cultural backgrounds in order to be categorized according to their typology. The analysis has been based on cluster analysis generated by complexity matrices issued from the categorizations of the subjects.

3.2 Data collection

Because of research feasibility in terms of means and time limits, this research could not cover a large number of cities in both Algeria and Japan. In order to avoid over-simplification and generalization of the concepts that will issue from this research, the authors based the collection of the samples (visual arrays) on the idea of selecting 2 cities from each country in which the collection will be done (Fig.9). Tokyo and Batna were chosen because they offer many urban landscapes with aspects of modernity. Kyoto and Al-Kantara were chosen as cities rich in traditional built environments. The data collection was done according to 2 phases. The first phase was done in October and December 2008 and the streetscape pictures were shot in JPEG format using a Panasonic Lumix DMC-FZ5-K digital camera. The second phase was done in June and August 2010 and the streetscape pictures were taken in RAW format using a Nikon D300S digital camera.

3.2.1 First visual arrays collection (Panasonic Lumix DMC-FZ5-K, JPEG format)

The process of sample collection was based on the idea of taking two visual arrays of the same streetscape, from the same shooting location, one in daytime

Table 2 First visual arrays collection

Country	City	Period	Collected Data	Selected Data
Japan	Kyoto	10-2008	24	20
	Tokyo	10-2008	62	20
Algeria	Al-Kantara	12-2008	58	20
	Batna	12-2008	32	20
	Total		176	80

and another in nighttime (Fig.7). The collection of the different visual arrays was done in 2008 during 2 phases. The 1st phase was done on the 14th of September in Kyoto and on the 16th of October in Tokyo. The 2nd phase was done on the 26th of November in Al-Kantara and on the 3rd of December in Batna. All the phases were done between 14:00-17:00 in daytime and between 19:00-21:00 at nighttime using a Panasonic Lumix DMC-FZ5-K digital camera (fig.8) & (table 3). The selection of shooting times and locations respected the common features between the visual arrays in matters of activity (vehicles, people), street size, lighting, etc., in order to avoid any fallacious judgment by the subjects. A total number of 176 visual arrays were collected from different sites within these 4 cities. After a random selection, the authors selected 80 visual arrays with an equal number of 40 Pictures (20 daytime and 20 nighttime samples) from each country (Table 2, 4 & 5). These samples represent the object of the experimental phase in this study.

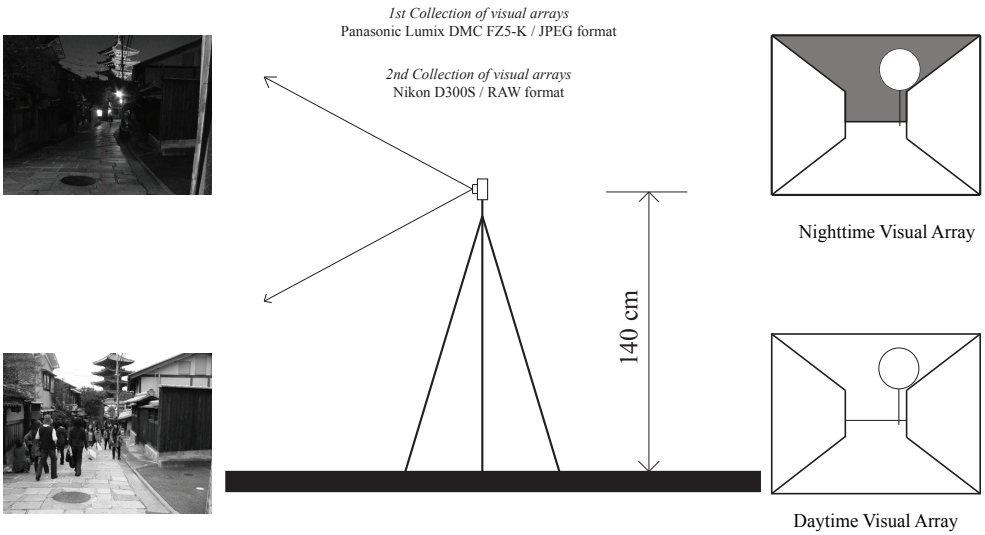


Fig.7 Data collection method

Table 3 Panasonic Lumix DMC-FZ5-K specifications

Panasonic Lumix DMC-FZ5-K	
Lens type	Supports lens converters or interchangeable lenses or zoom with widest focal range possible
Phot file format	JPEG, RAW
Exposure controls	Automatic, aperture and shutter priority, manual, choice of metering modes, bracketing
Focus controls	Automatic with selectable focus points, manual
Features	Compatibility with existing 35mm camera lenses and accessories

Fig.8 Panasonic Lumix DMC-FZ5-K

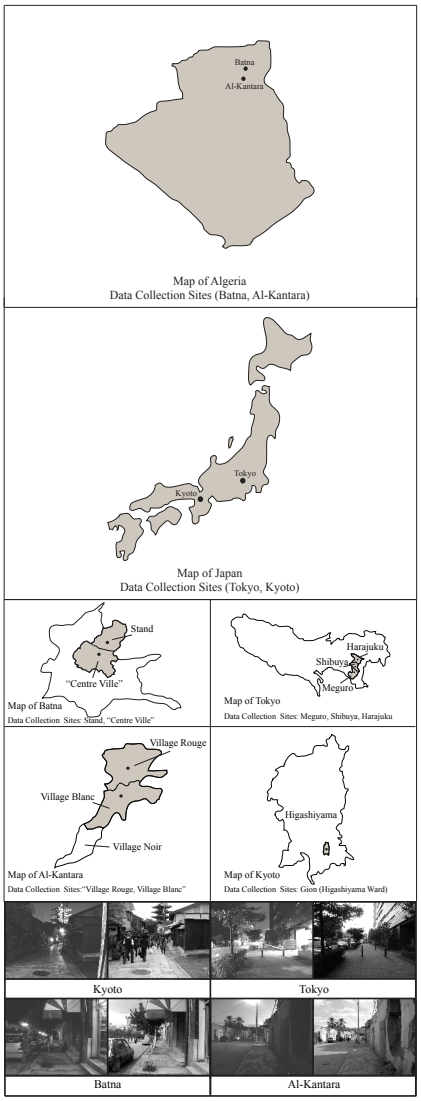


Fig.9 Sites of the samples collection

Table 4 Japanese streetscapes (daytime and nighttime)

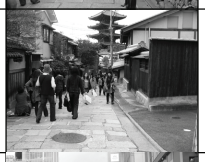
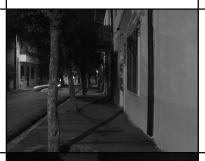
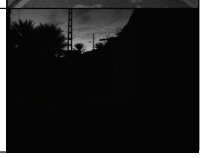
Name	Daytime visual array	Name	Daytime visual array	Name	Nighttime visual array	Name	Nighttime visual array
JD1		JD11		JN1		JN11	
JD2		JD12		JN2		JN12	
JD3		JD13		JN3		JN13	
JD4		JD14		JN4		JN14	
JD5		JD15		JN5		JN15	
JD6		JD16		JN6		JN16	
JD7		JD17		JN7		JN17	
JD8		JD18		JN8		JN18	
JD9		JD19		JN9		JN19	
JD10		JD20		JN10		JN20	

Table 5 Algerian streetscapes (daytime and nighttime)

Name	Daytime visual array	Name	Daytime visual array	Name	Nighttime visual array	Name	Nighttime visual array
AD1		AD11		AN1		AN11	
AD2		AD12		AN2		AN12	
AD3		AD13		AN3		AN13	
AD4		AD14		AN4		AN14	
AD5		AD15		AN5		AN15	
AD6		AD16		AN6		AN16	
AD7		AD17		AN7		AN17	
AD8		AD18		AN8		AN18	
AD9		AD19		AN9		AN19	
AD10		AD20		AN10		AN20	

3.2.1.1 The experiment

Twenty students from Nagoya Institute of Technology and Nagoya University agreed to participate in this experiment (Table 6). The strategy was to have 2 groups of subjects; the first group composed of 10 Japanese students and the second composed of 10 foreign students with different cultural backgrounds (Kenya, Brazil, Germany, Pakistan, Indonesia and Morocco).

Table 6 Number of subjects

Subjects	Japan	Germany	Morocco	Pakistan	Kenya	Indonesia	Brazil	Total
Japanese	10							10
Foreigners		1	1	2	2	1	3	10

3.2.1.2 Typological clustering

The first analysis phase was the typological classification of the samples using cluster analysis (Ward method) in order to determine the typology of the samples that will be analyzed. The 80 visual arrays were printed out in A4 paper format (CMYK color format), then presented to 10 subjects (5 Japanese and 5 foreigners). They were requested, one by one, to categorize the 80 samples into different groups according to their physical and functional features (for example residential streets, traditional streets, etc.). The data collected from their different classifications helped in designing a similarity matrix that connects all the samples together (Fig.11, 12 & 13). This similarity matrix served as a basis for the application of cluster analysis (Ward method) to figure out the different types of streetscapes included within these 80 samples (table 7 & 8). The resulting typology could be summarized as follows (Fig.10), (Fig.14) & (Fig.15):

Algerian Daytime Streetscapes: “GrD.1(Alg)”: Traditional streetscapes. “GrD.2(Alg)”: Avenues with green infrastructure. “GrD.3(Alg)”: Quiet, residential streetscapes.

Japanese Daytime Streetscapes: “GrD.A(Jp)”: Avenues, Commercial streetscapes. “GrD.B(jp)”: Quiet streetscapes with green infrastructure. “GrD.C(Jp)”: Traditional streetscapes.

Algerian Night Streetscapes: “GrN.1(Alg)”: Quiet, wide, traditional night streetscapes. “GrN.2(Alg)”: Dark, narrow, quiet, traditional night streetscapes. “GrN.3(Alg)”: Residential, quiet, wide, modern night streetscapes. “GrN.4(Alg)”: Well-lit avenues.

Japanese Night Streetscapes: “GrN.A(Jp)”: Traditional, a bit dark, night streetscapes. “GrN.B(Jp)”: Wide, a bit dark, modern night streetscapes. “GrN.C(Jp)”: Well-lit Avenues.

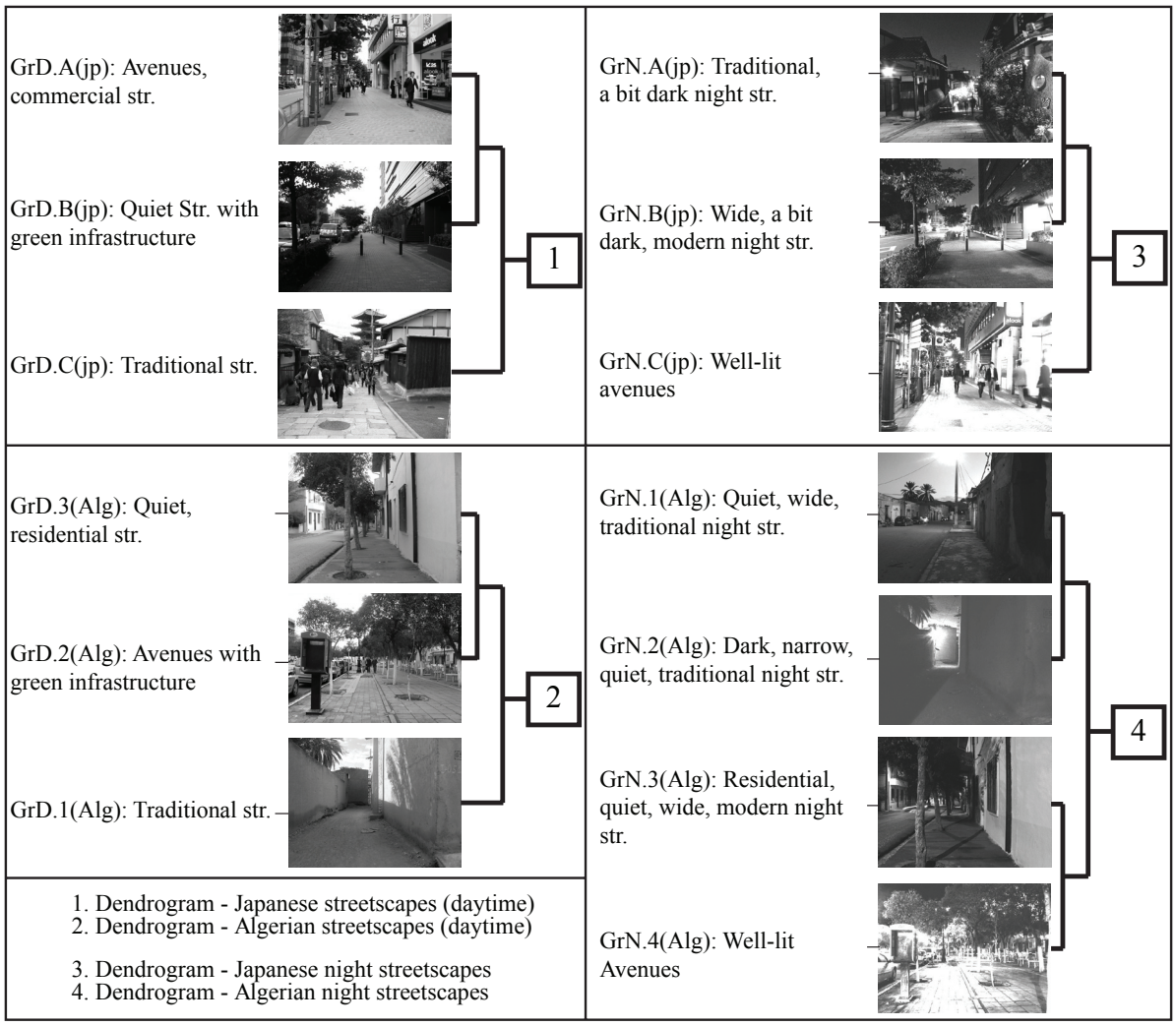


Fig.10 Detailed Typological clustering

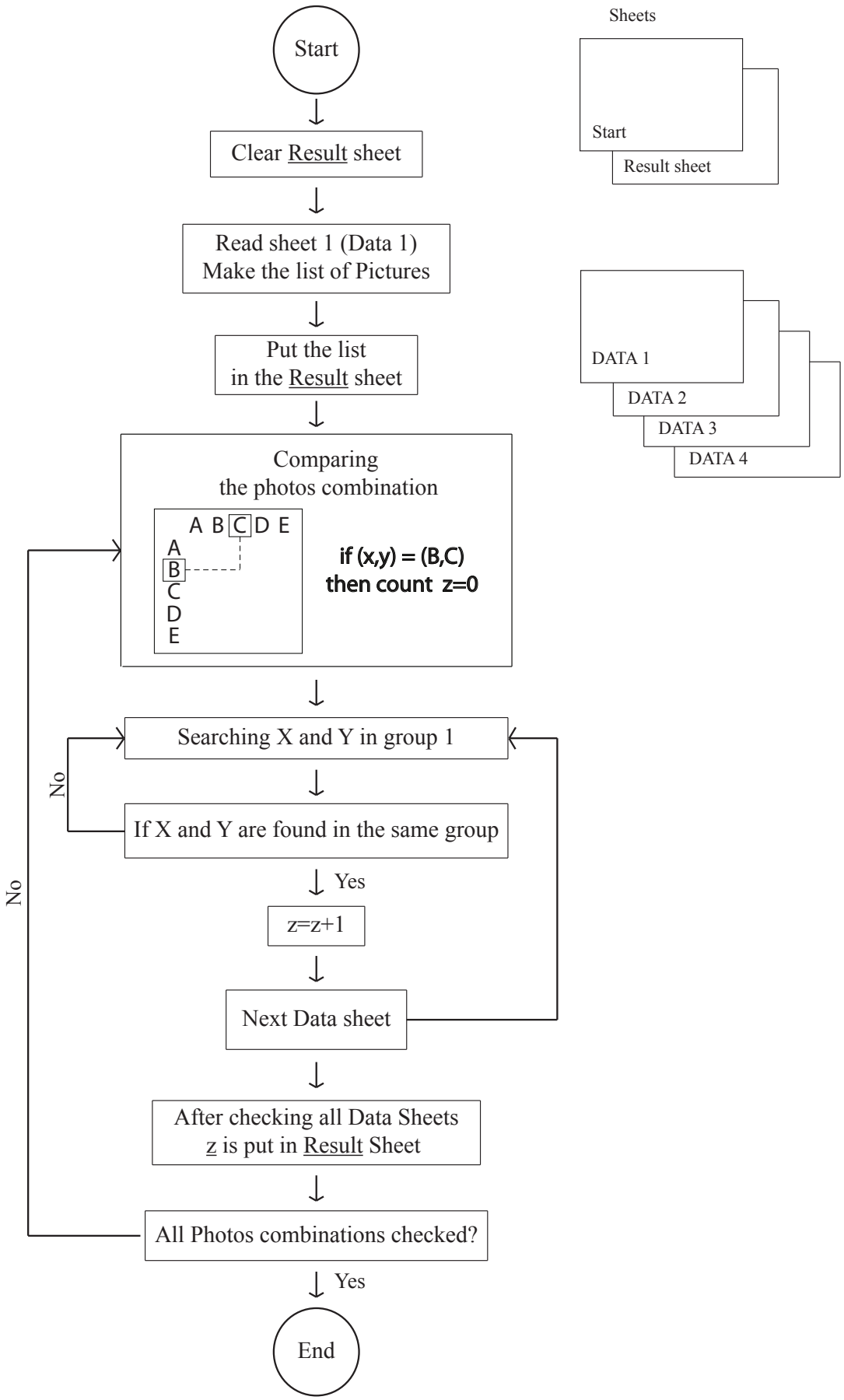


Fig.11 Algorithm of the similarity matrix

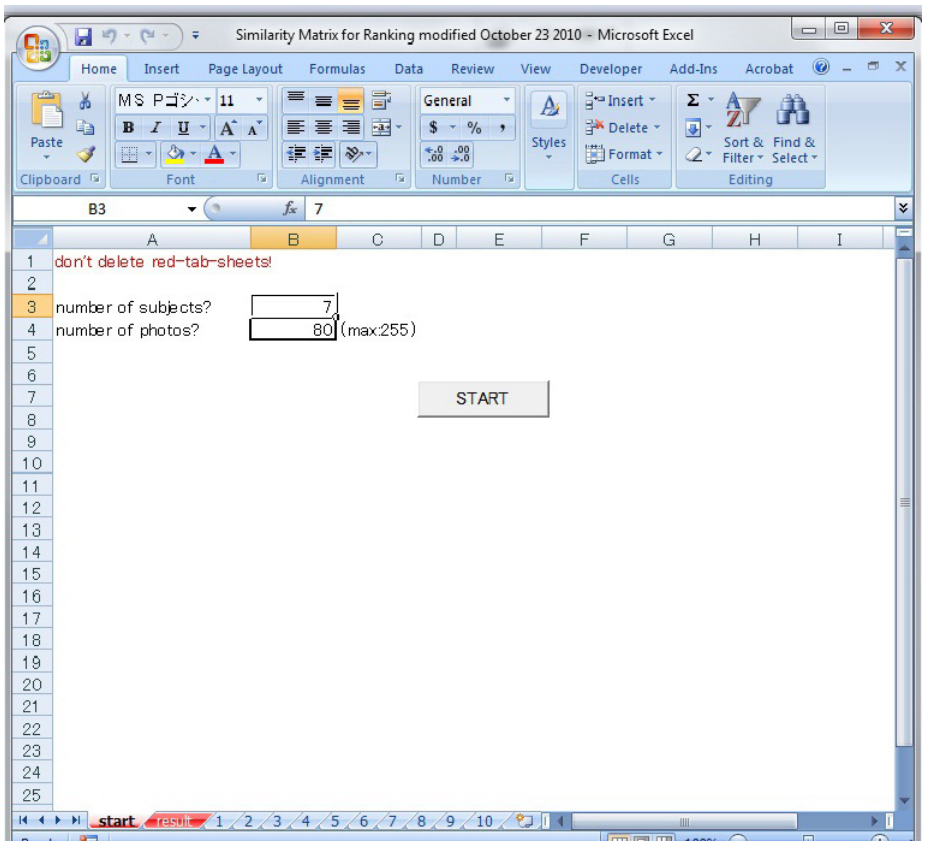
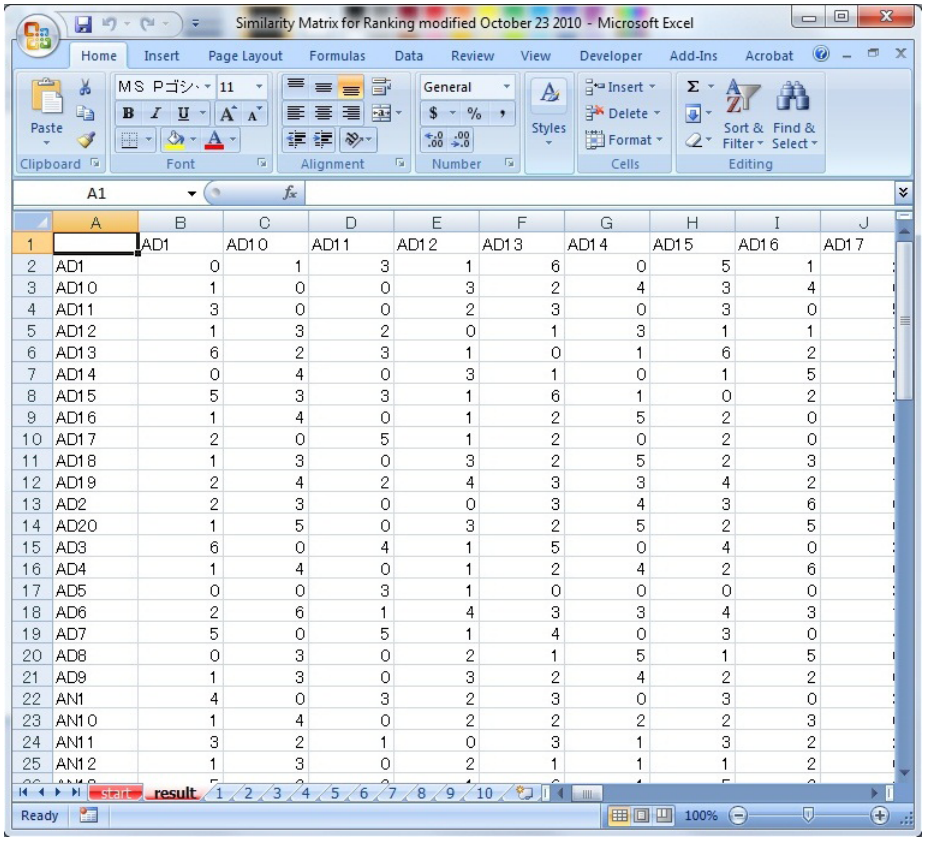


Fig.12 Similarity matrix sheet



	AD1	AD10	AD11	AD12	AD13	AD14	AD15	AD16	AD17
AD1	0	1	3	1	6	0	5	1	
AD10	1	0	0	3	2	4	3	4	
AD11	3	0	0	2	3	0	3	0	
AD12	1	3	2	0	1	3	1	1	
AD13	6	2	3	1	0	1	6	2	
AD14	0	4	0	3	1	0	1	5	
AD15	5	3	3	1	6	1	0	2	
AD16	1	4	0	1	2	5	2	0	
AD17	2	0	5	1	2	0	2	0	
AD18	1	3	0	3	2	5	2	3	
AD19	2	4	2	4	3	3	4	2	
AD2	2	3	0	0	3	4	3	6	
AD20	1	5	0	3	2	5	2	5	
AD3	6	0	4	1	5	0	4	0	
AD4	1	4	0	1	2	4	2	6	
AD5	0	0	3	1	0	0	0	0	
AD6	2	6	1	4	3	3	4	3	
AD7	5	0	5	1	4	0	3	0	
AD8	0	3	0	2	1	5	1	5	
AD9	1	3	0	3	2	4	2	2	
AN1	4	0	3	2	3	0	3	0	
AN10	1	4	0	2	2	2	2	3	
AN11	3	2	1	0	3	1	3	2	
AN12	1	3	0	2	1	1	1	2	

Fig.13 Similarity matrix results

Table 7 Example of similarity matrix used for typological clustering of all daytime streetscapes

	AD1	AD10	AD11	AD12	AD13	AD14	AD15	AD16	AD17	AD18	AD19	AD2	AD20	AD3	AD4	AD5	AD6	AD7	AD8	AD9	JD1	JD10	JD11	JD12	JD13	JD14	JD15	JD16	JD17	JD18	JD19	JD2	JD20	JD3	JD4	JD5	JD6	JD7	JD8	JD9
AD1	0	1	3	1	6	0	5	1	2	1	2	2	1	6	1	0	2	5	0	1	0	1	0	2	0	0	0	1	1	1	1	2	0	1	0	0	0	1	1	0
AD10	1	0	0	3	2	4	3	4	0	3	4	3	5	0	4	0	6	0	3	3	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0
AD11	3	0	0	2	3	0	3	0	5	0	2	0	0	4	0	3	1	5	0	0	0	4	0	4	0	2	0	0	0	0	2	1	0	0	0	1	1	1	0	0
AD12	1	3	2	0	1	3	1	1	1	3	4	0	3	1	1	1	4	1	2	3	0	1	0	1	1	0	1	1	0	1	0	0	1	0	0	1	0	1	0	0
AD13	6	2	3	1	0	1	6	2	2	2	3	3	2	5	2	0	3	4	1	2	0	1	0	2	0	0	0	1	1	2	0	1	0	1	0	0	0	0	1	0
AD14	0	4	0	3	1	0	1	5	0	5	3	4	5	0	4	0	3	0	5	4	0	0	0	0	1	0	1	1	0	2	0	0	1	0	0	1	0	1	0	0
AD15	5	3	3	1	6	1	0	2	2	2	4	3	2	4	2	0	4	3	1	2	0	1	0	1	0	0	0	1	0	2	0	2	0	0	0	0	0	0	1	0
AD16	1	4	0	1	2	5	2	0	0	3	2	6	5	0	6	0	3	0	5	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
AD17	2	0	5	1	2	0	2	0	0	0	1	0	0	3	0	3	1	4	0	0	2	4	0	4	0	3	1	0	1	1	3	2	1	1	1	2	2	2	2	0
AD18	1	3	0	3	2	5	2	3	0	0	2	4	5	1	3	0	2	0	4	4	0	0	0	0	1	0	1	2	0	3	0	1	1	0	0	1	0	1	1	0
AD19	2	4	2	4	3	3	4	2	1	2	0	1	2	2	2	0	5	2	3	3	0	0	0	0	1	0	1	1	0	2	0	1	1	0	0	1	0	1	0	0
AD2	2	3	0	0	3	4	3	6	0	4	1	0	4	1	5	0	2	0	4	3	0	0	0	0	0	0	0	1	0	2	0	1	0	0	0	0	0	0	1	0
AD20	1	5	0	3	2	5	2	5	0	5	2	4	0	0	5	0	4	0	4	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
AD3	6	0	4	1	5	0	4	0	3	1	2	1	0	0	0	1	1	6	0	1	0	2	0	3	0	1	0	1	1	1	2	3	0	1	0	0	1	1	1	0
AD4	1	4	0	1	2	4	2	6	0	3	2	5	5	0	0	0	3	0	6	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
AD5	0	0	3	1	0	0	0	0	3	0	0	0	0	1	0	0	0	2	0	0	1	5	0	5	0	2	1	0	1	1	4	2	1	1	0	1	2	2	2	0
AD6	2	6	1	4	3	3	4	3	1	2	5	2	4	1	3	0	0	1	2	3	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0
AD7	5	0	5	1	4	0	3	0	4	0	2	0	0	6	0	2	1	0	0	0	0	3	0	4	0	1	0	0	1	0	3	2	0	1	0	0	1	2	0	0
AD8	0	3	0	2	1	5	1	5	0	4	3	4	4	0	6	0	2	0	0	2	0	0	0	0	1	0	1	1	0	2	0	0	1	0	0	1	0	1	0	0
AD9	1	3	0	3	2	4	2	2	0	4	3	3	2	1	1	0	3	0	2	0	0	0	0	0	1	0	1	2	0	4	1	2	1	0	1	1	0	2	1	0
JD1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	1	4	1	2	2	4	2	3	1	1	1	3	3	3	3	2	1	3	4
JD10	1	0	4	1	1	0	1	0	4	0	0	0	0	2	0	5	0	3	0	0	1	0	0	6	0	2	1	0	1	1	4	2	1	1	1	1	3	2	3	0
JD11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	4	2	5	5	3	0	0	0	4	3	3	3	2	0	1	7
JD12	2	0	4	1	2	0	1	0	4	0	0	0	0	3	0	5	0	4	0	0	1	6	0	0	0	2	1	0	2	1	3	2	1	2	0	1	2	2	2	0
JD13	0	0	0	1	0	1	0	0	0	1	1	0	0	0	0	0	0	0	1	1	2	0	4	0	0	2	4	4	2	3	0	1	3	2	2	4	2	3	0	4
JD14	0	0	2	0	0	0	0	0	3	0	0	0	0	1	0	2	0	1	0	0	2	2	2	2	2	0	1	1	5	0	1	1	0	5	4	2	6	0	3	2
JD15	0	0	0	1	0	1	0	0	1	1	1	0	0	0	0	1	0	0	1	1	4	1	5	1	4	1	0	5	1	2	1	1	6	1	1	5	1	2	1	5
JD16	1	0	0	1	1	1	1	0	0	2	1	1	0	1	0	0	0	0	1	2	2	0	5	0	4	1	5	0	1	2	0	1	5	1	1	3	1	1	1	5
JD17	1	0	0	0	1	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	3	1	3	2	2	5	1	1	0	0	0	0	0	7	5	1	5	0	4	3
JD18	1	1	0	1	2	2	2	1	1	3	2	2	1	1	1	1	1	0	2	4	1	1	0	1	3	0	2	2	0	0	2	4	2	0	1	2	0	5	2	0
JD19	1	0	2	0	0	0	0	0	3	0	0	0	0	2	0	4	0	3	0	1	1	4	0	3	0	1	1	0	0	2	0	4	1	0	2	1	2	4	2	0
JD2	2	1	1	0	1	0	2	0	2	1	1	1	0	3	0	2	1	2	0	2	1	2	0	2	1	1	1	1	0	4	4	0	1	0	1	1	1	4	2	0
JD20	0	0	0	1	0	1	0	0	1	1	1	0	0	0	0	1	0	0	1	1	3	1	4	1	3	0	6	5	0	2	1	1	0	0	0	4	0	2	1	4
JD3	1	0	0	0	1	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	3	1	3	2	2	5	1	1	7	0	0	0	0	0	5	1	5	0	4	3
JD4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	3	1	3	0	2	4	1	1	5	1	2	1	0	5	0	1	5	1	4	3
JD5	0	0	1	1	0	1	0	0	2	1	1	0	0	0	0	1	0	0	1	1	3	1	3	1	4	2	5	3	1	2	1	1	4	1	1	0	1	2	1	3
JD6	0	0	1	0	0	0	0	0	2	0	0	0	0	1	0	2	0	1	0	0	2	3	2	2	2	6	1	1	5	0	2	1	0	5	5	1	0	0	4	2
JD7	1	0	1	1	0	1	0	0	2	1	1	0	0	1	0	2	0	2	1	2	1	2	0	2	3	0	2	1	0	5	4	4	2	0	1	2	0	0	1	0
JD8	1	0	0	0	1	0	1	0	2	1	0	1	0	1	0	2	0	0	0	1	3	3	1	2	0	3	1	1	4	2	2	2	1	4	4	1	4	1	0	1
JD9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	7	0	4	2	5	5	3	0	0	0	4	3	3	3	2	0	1	0

Table 8 Example of similarity matrix used for typological clustering of all nighttime streetscapes

	AN1	AN10	AN11	AN12	AN13	AN14	AN15	AN16	AN17	AN18	AN19	AN2	AN20	AN3	AN4	AN5	AN6	AN7	AN8	AN9	JN1	JN10	JN11	JN12	JN13	JN14	JN15	JN16	JN17	JN18	JN19	JN2	JN20	JN3	JN4	JN5	JN6	JN7	JN8	JN9
AN1	0	0	2	0	3	0	1	1	4	1	2	0	0	4	0	1	1	3	0	1	0	2	0	1	0	1	0	0	0	2	2	1	0	0	2	1	1	1	0	1
AN10	0	0	1	6	3	3	5	2	0	5	3	4	3	1	5	1	3	1	4	5	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1
AN11	2	1	0	1	3	1	2	2	3	1	1	1	1	4	1	3	1	4	1	1	1	1	0	1	1	2	0	0	1	0	1	0	0	1	2	1	1	1	2	1
AN12	0	6	1	0	2	4	6	3	0	4	2	5	4	1	4	1	2	0	5	4	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
AN13	3	3	3	2	0	1	3	1	1	3	1	2	1	5	3	2	1	4	2	2	0	2	0	0	1	1	0	0	1	0	1	1	0	0	1	1	0	0	0	2
AN14	0	3	1	4	1	0	4	4	0	4	1	6	7	1	5	1	1	0	6	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AN15	1	5	2	6	3	4	0	3	1	4	1	5	4	2	4	1	1	1	5	3	0	2	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1
AN16	1	2	2	3	1	4	3	0	2	3	3	4	4	1	3	1	2	1	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AN17	4	0	3	0	1	0	1	2	0	0	2	0	0	2	0	2	1	3	0	1	0	3	0	3	0	0	0	0	0	2	3	1	0	0	1	0	1	1	0	0
AN18	1	5	1	4	3	4	4	3	0	0	3	5	4	1	6	1	3	1	5	4	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1
AN19	2	3	1	2	1	1	1	3	2	3	0	1	1	0	2	0	6	2	1	4	0	0	0	0	0	0	1	1	1	0	0	1	1	0	0	1	0	0	0	1
AN2	0	4	1	5	2	6	5	4	0	5	1	0	6	1	6	1	1	0	7	3	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
AN20	0	3	1	4	1	7	4	4	0	4	1	6	0	1	5	1	1	0	6	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AN3	4	1	4	1	5	1	2	1	2	1	0	1	1	0	1	3	0	4	1	1	0	1	0	0	1	1	0	0	1	1	1	1	0	0	1	1	0	0	1	1
AN4	0	5	1	4	3	5	4	3	0	6	2	6	5	1	0	1	2	1	6	4	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1
AN5	1	1	3	1	2	1	1	1	2	1	0	1	1	3	1	0	0	1	1	1	0	2	0	4	0	0	0	0	1	0	2	0	0	0	0	0	0	0	1	0
AN6	1	3	1	2	1	1	1	2	1	3	6	1	1	0	2	0	0	2	1	3	0	0	0	0	0	0	1	1	1	0	0	1	1	0	0	1	0	0	0	1
AN7	3	1	4	0	4	0	1	1	3	1	2	0	0	4	1	1	2	0	0	1	0	2	0	1	1	1	0	0	2	1	2	0	0	0	2	1	1	1	1	1
AN8	0	4	1	5	2	6	5	4	0	5	1	7	6	1	6	1	1	0	0	3	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
AN9	1	5	1	4	2	3	3	4	1	4	4	3	3	1	4	1	3	1	3	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
JN1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	4	3	2	1	2	2	0	1	3	4	2	2	2	4	3	0
JN10	2	1	1	1	2	0	2	0	3	1	0	1	0	1	1	2	0	2	1	0	0	0	0	3	1	1	1	1	0	1	6	2	0	2	2	0	2	1	2	1
JN11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	2	1	3	2	4	2	1	2	4	2	0	1	1	1	2	4
JN12	1	0	1	0	0	0	0	0	3	0	0	0	0	0	0	4	0	1	0	0	2	3	0	0	1	1	0	0	0	2	3	0	1	1	2	2	1	3	0	0
JN13	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	4	1	2	1	0	5	2	1	2	1	1	2	1	6	4	1	4	3	5	0
JN14	1	0	2	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	3	1	1	1	5	0	1	1	1	0	1	1	0	5	6	3	4	2	4	1
JN15	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	2	1	3	0	2	1	0	6	1	2	1	3	5	2	1	2	2	1	2	3
JN16	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	1	2	0	1	1	6	0	0	1	1	2	4	1	1	2	1	0	1	3
JN17	0	1	1	0	1	0	0	0	0	1	1	0	0	1	1	1	1	2	0	1	2	0	4	0	2	1	1	0	0	3	0	3	1	2	0	0	1	2	3	2
JN18	2	0	0	0	0	0	0	0	2	0	0	0	0	1	0	0	0	1	0	0	2	1	2	2	1	0	2	1	3	0	1	4	2	1	1	1	2	4	1	1
JN19	2	0	1	0	1	0	1	0	3	0	0	0	0	1	0	2	0	2	0	0	0	6	1	3	1	1	1	1	0	1	0	1	1	2	2	0	2	1	2	0
JN2	1	1	0	1	1	0	1	0	1	1	1	1	0	1	1	0	1	0	1	0	1	2	2	0	2	1	3	2	3	4	1	0	2	2	1	1	2	2	2	3
JN20	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	3	0	4	1	1	0	5	4	1	2	1	2	0	1	0	3	1	2	1	3
JN3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	2	2	1	6	5	2	1	2	1	2	2	1	0	4	1	4	3	6	0
JN4	2	0	2	0	1	0	0	0	1	0	0	0	0	1	0	0	0	2	0	0	2	2	0	2	4	6	1	1	0	1	2	1	0	4	0	3	5	3	3	1
JN5	1	0	1	0	1	0	0	0	0	0	1	0	0	1	0	0	1	1	0	0	2	0	1	2	1	3	2	2	0	1	0	1	3	1	3	0	1	2	0	3
JN6	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	2	2	1	1	4	4	2	1	1	2	2	2	1	4	5	1	0	3	4	0
JN7	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	4	1	1	3	3	2	1	0	2	4	1	2	2	3	3	2	3	0	2	0
JN8	0	0	2	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	3	2	2	0	5	4	2	1	3	1	2	2	1	6	3	0	4	2	0	0
JN9	1	1	1	1	2	0	1	0	0	1	1	1	0	1	1	0	1	1	1	0	0	1	4	0	0	1	3	3	2	1	0	3	3	0	1	3	0	0	0	0

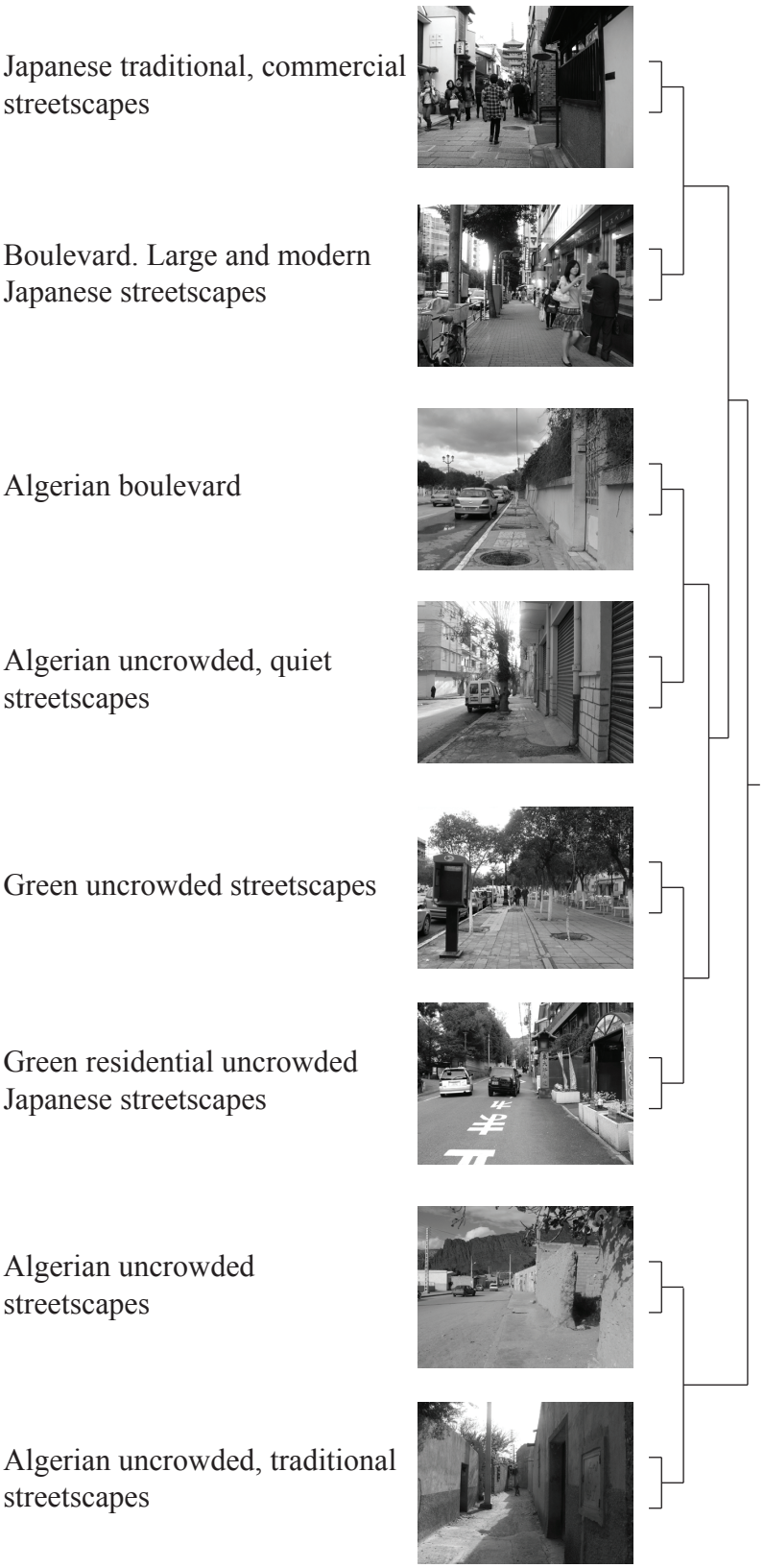


Fig.14 Typological clustering of daytime streetscapes (Algerian and Japanese)

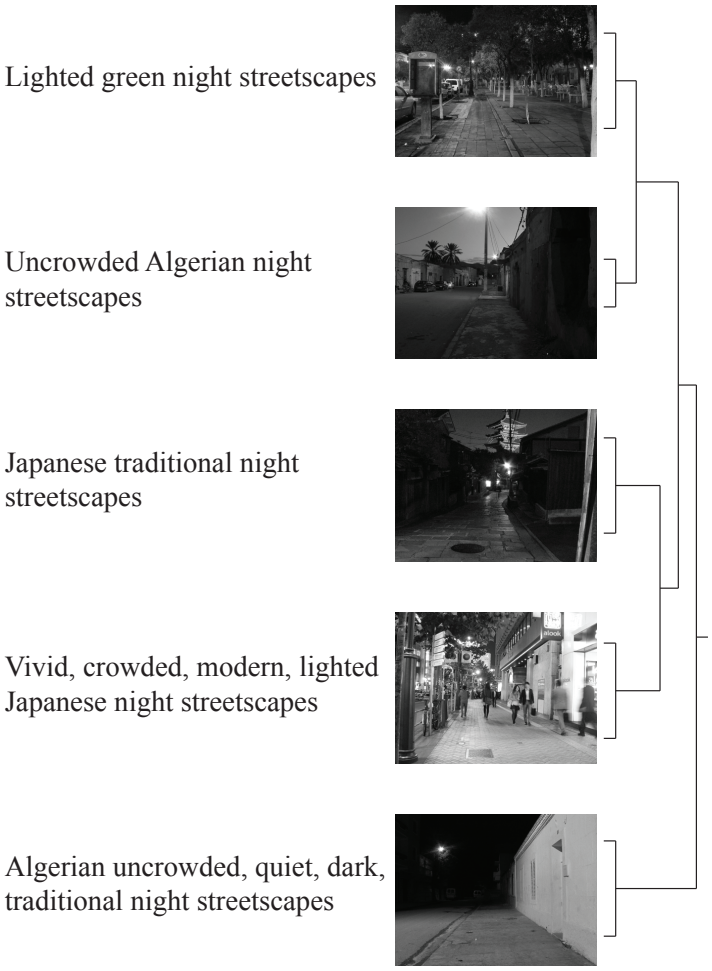


Fig.15 Typological clustering of nighttime streetscapes (Algerian and Japanese)

3.2.2 Second visual arrays collection (Nikon D300S, RAW format)

A second Data collection was done in June 2010 in Algeria and in August of the same year in Japan because of the necessity of RAW format for the estimation of pixel intensities (table 9). The pictures were taken in the same locations and following the same rules and conditions. During this second data collection, the author used a Nikon D300S digital camera (fig.16) & (table 10), with Nikkor AF-S DX 35mm f/1.8G lens (fig.17) & (table 11).

A total number of 80 pictures were shot in daytime and in nighttime. However, 6 pictures were canceled because of some technical problems.

Table 9 Second visual arrays collection

Country	City	Period	Collected Data	Selected Data
Algeria	Al-Kantara	6-2010	20	17
	Batna	6-2010	20	20
Japan	Kyoto	8-2010	20	20
	Tokyo	8-2010	20	17
	Total		80	74

Fig.16 Body of the Nikon D300S

Table 10 Nikon D300S specifications

Sensor	• 12.3 million effective pixel CMOS
	• DX format
A/D converter	14-bit
Image processor	Nikon EXPEED
Image sizes	• 4288 x 2848
	• 3216 x 2136
	• 2144 x 1424
RAW files	NEF / Compressed NEF 14-bit
TIFF files	Yes
Dust reduction	Self-cleaning sensor unit
Auto focus	• 51-point Multi-CAM 3500DX
	• 15 cross-type sensors
	• Contrast detect in Live View mode
Focus tracking by color	Yes
AF area mode	• Single point AF
	• Dynamic Area AF [9 points, 21 points, 51 points, 51 points (3D-tracking)]
	• Automatic-area AF
Sensitivity	• Default: ISO 200 - 3200
	• Boost: ISO 100 - 6400
	• 1/3, 1/2 or 1.0 EV steps
Continuous shooting	• With built-in battery: up to 6 fps
	• With AC adapter or MB-D10 pack and batteries other than EN-EL3e: up to 8
Image Parameters	• Picture Control (4 presets)
	• Sharpening
	• Contrast
	• Brightness
	• Saturation
	• Hue
Active D-Lighting	Yes (also adjusts exposure)
Viewfinder	100% frame coverage
LCD monitor	• 3.0 " TFT LCD
	• 922,000 pixels
LCD Live View	• Handheld mode (phase detect AF)
	• Tripod mode (contrast detect AF)
Compact Flash	Type I / II (UDMA support)
Vertical grip	MB-D10
Video output	HDMI (HD)
Menu languages	14
Dimensions	147 x 114 x 74 mm (5.8 x 4.5 x 2.9 in)
Weight (no batt)	825 g (1.82 lb)

Table 11 Nikkor AF-S DX 35mm f/1.8G specifications

Nikkor AF-S DX 35mm f/1.8G	
Focal length	35mm
Maximum Aperture	f/1.8
Minimum Aperture	f/22
Format	DX
Maximum Angle of view (DX-format	44°
Minimum Angle of view (DX-format	44°
Lens elements	8
Lens groups	6
Minimum focus distance	0.98ft (0.3m)
Maximum reproduction ratio	0.16x

Fig.17 Nikkor AF-S DX 35mm f/1.8G

3.3 Summary

This chapter was focused on the typological clustering of the different collected streetscapes in Algeria and Japan. The aim was to categorize the data to serve as a basis for different psychometric as well as physical analyses in the following chapters. The data were collected twice in 2 different formats and using 2 different digital cameras. The pictures shot by the Panasonic Lumix DMC-FZ5-K digital camera were the main object of the psychometric methods applied in chapter 5. They were printed in CMYK quality and presented to 2 different groups of subjects. The pictures shot in RAW format using Nikon D300S digital camera with Nikkor AF-S DX 35mm f/1.8G lens, were presented to subjects in RGB quality, ranked according to their degrees of complexity and then analyzed in order to estimate their degrees of entropy.

The following chapter will focus on the study of the cognitive patterns of complexity related to the collected streetscape visual arrays.

Chapter. 4

Cognitive patterns clustering

4.1 Introduction

This chapter is a comparative study of the cognitive patterns of complexity in the visual composition of streetscapes in Algeria and Japan. 80 visual arrays of streetscapes in Algeria and Japan have been collected and then presented to 20 subjects from different cultural backgrounds in order to be categorized according to their degrees of complexity. The analysis has been structured according to 2 phases:

1. The lexicon-based clustering phase, using Hayashi quantification method type III as well as cluster analysis, which represents analyses oriented mainly towards the visual arrays as physical data.

2) The cognitive patterns clustering phase using factor analysis and cluster analysis, which is oriented towards subjects as human data.

4.2 Conceptual Background

Complexity is a concept that covers many aspects of the urban environment. Nowadays, city dwellers deal with an increasing complexity ascending from the smallest details to the whole urban scenery. The common question that emerges from this phenomenon is related to the origin of this complexity. This has been the subject of many researches dealing with a variety of aspects of the built environment, from its morphological aspects to its visual dimension. This chapter focuses on the determination of the cognitive patterns related to the degrees of complexity within series of different streetscapes from different physical environments in Algeria and Japan.

According to Rapoport (1987), a street is a more or less narrow and linear urban space lined by buildings, found in settlements and used for circulation and other

activities. At the street scale, sidewalks permit local interactions and create a complex order dealing with the sensory overload and making the human nervous system stretched by the built environment. This chapter is a preliminary study about the concept of complex order within streetscape composition as a visual array. In environmental psychology, complexity is related to the involvement component, which means: “How much there is to see in a visual array?”, and to the concept of affordance , which refers to what a perceived scene has to offer as far as the perceiver is concerned (Kaplan, 1988). As complexity emerges from the collective behavior of many interactive units, this research considers a streetscape composition as a visual array within which many classes, all composed of smaller subsystems, exist in a continuous interaction. “Sky, Ground, Buildings, Vegetation and Actors” could be identified as the 5 main classes within a streetscape visual array (Fig.18).

4.3 The strategy

The aim of this study is to explore the degree of complexity that a streetscape composition can express and the evaluation of this complexity according to different subjects (individuals) with different cultural backgrounds.

The strategy behind this study was structured throughout 3 general steps. First, collecting the visual arrays (samples). Second, conducting the experiments (3 experiments were done in this study). Third and finally, analyzing the results. The experimental and the analysis steps were done in parallel, following the logic and the objectives of each experiment. The analysis step has been structured into 3 phases. The first is a typological clustering phase, using cluster analysis. The second is a lexicon-based clustering phase oriented towards the visual arrays as

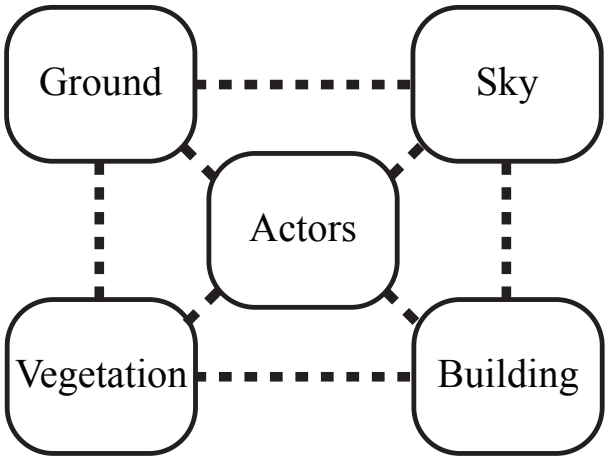


Fig.18 The different classes within a streetscape system

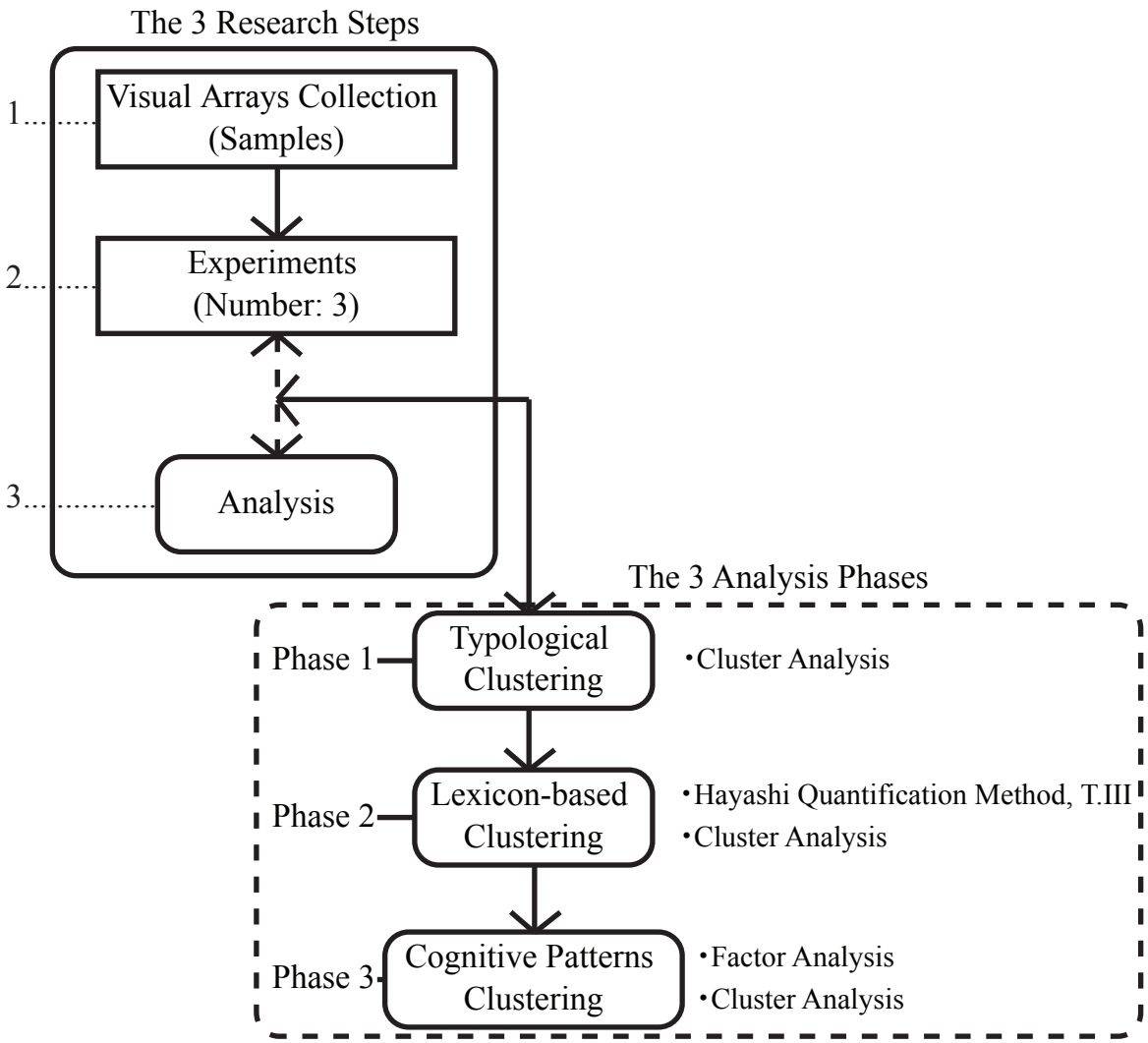


Fig.19 The Cognitive research steps and analysis phases

physical data (samples) and using Hayashi quantification method (type III) as well as cluster analysis. Finally, the third phase is related to the cognitive patterns clustering phase using factor analysis and cluster analysis, which is oriented towards subjects (human data), (Fig.19).

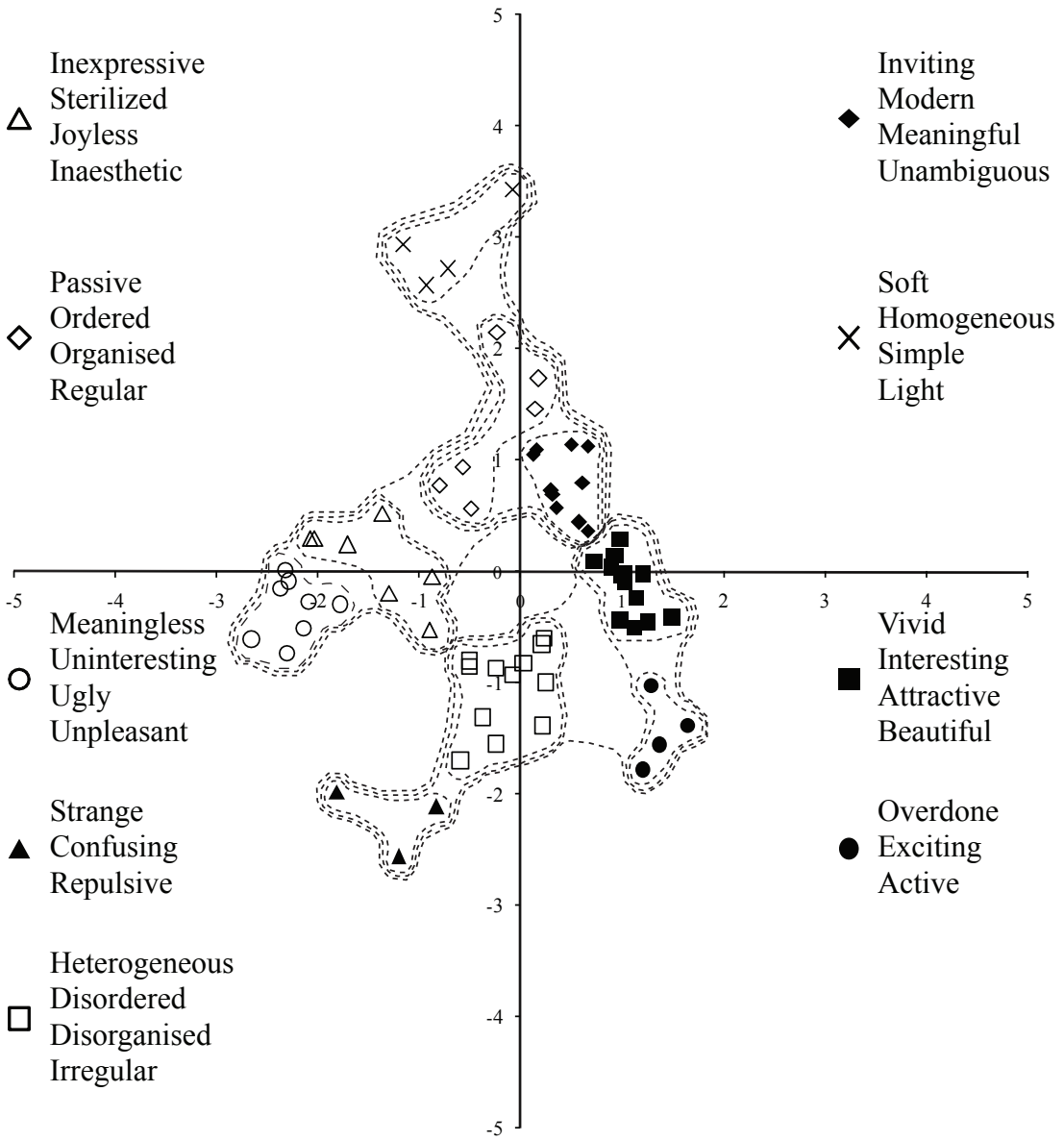
4.3.1 Lexicon based clustering

This phase is concerned with the study of samples as physical items. Hayashi quantification method (Type III) was applied in order to cluster these samples into different groups according to a lexicon based on the concept of complexity and to determine the characteristics of each typological group of samples (see typological clustering). This lexicon included many concepts corollary to complexity, such as: irregularity, heterogeneity, disorder, ambiguity, etc. The experiment was done individually by the main author according to a 2- point scale scoring (1,0). All the 80 samples were evaluated, one by one, following the list of adjectives of this lexicon. The results of the scoring served as a basis for the application of Hayashi Quantification Method (Type III) and Cluster Analysis (Ward method) in order to classify all the samples into groups according to their corresponding Complexity-based vocabulary (Fig.20, 21, 22 & 23).

The authors determined that order characterized traditional streetscapes in the Algerian daytime category. The residential streetscapes and avenues seemed to be attractive; therefore richness was more related to avenues. In the Japanese daytime category, disorder was the aspect of traditional streetscapes whereas avenues were characterized by balance and attractiveness. Complexity, heterogeneity, irregularity, unbalance and disorganization were more related to the Japanese streetscapes with green infrastructure. In the Algerian nighttime category, traditional night

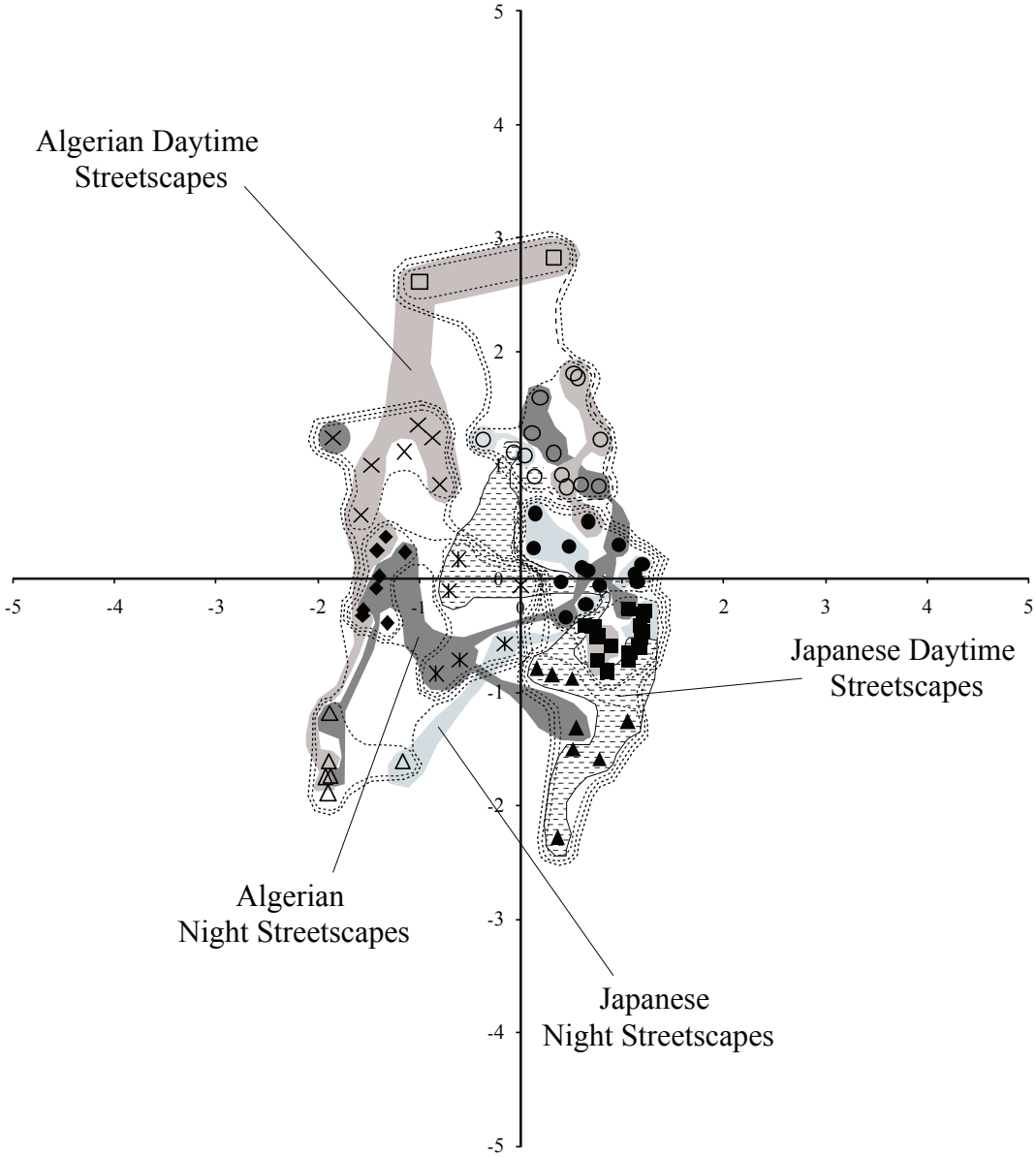
streetscapes as well as avenues were irregular and disorganized. Therefore, wide traditional night streetscapes had some aspects of order and the narrow traditional night streetscapes were joyless and uninteresting. balance was an aspect of avenues nightscapes and wide residential night streetscapes had some aspects of or ganization, regularity and variation. In the Japanese nighttime category, balance, disorder and irregularity characterized traditional nightscapes. Well-lit avenues were varied but unambiguous and wide modern night streetscapes had some aspects of disorder, balance and attractiveness.

On a more general scale, Algerian daytime streetscapes were balanced, ordered, regular and organized with some aspects of simplicity and homogeneity. Japanese daytime streetscapes were vivid, attractive and beautiful with some aspects of unbalance and regularity. Algerian night streetscapes seemed to be ambiguous, unbalanced and ordered with some aspects of confusion and repulsion. Attractiveness, order, organization and regularity characterized Japanese night streetscapes with some aspects of confusion, repulsion and inelegance.



Japanese & Algerian Streetscapes (Daytime & Nighttime)
- Category -

Fig.20 Lexicon-based clustering (Category Score)



Japanese & Algerian Streetscapes (Daytime & Nighttime)
- Sample Score -

Fig.21 Lexicon-based clustering -Sample Score-

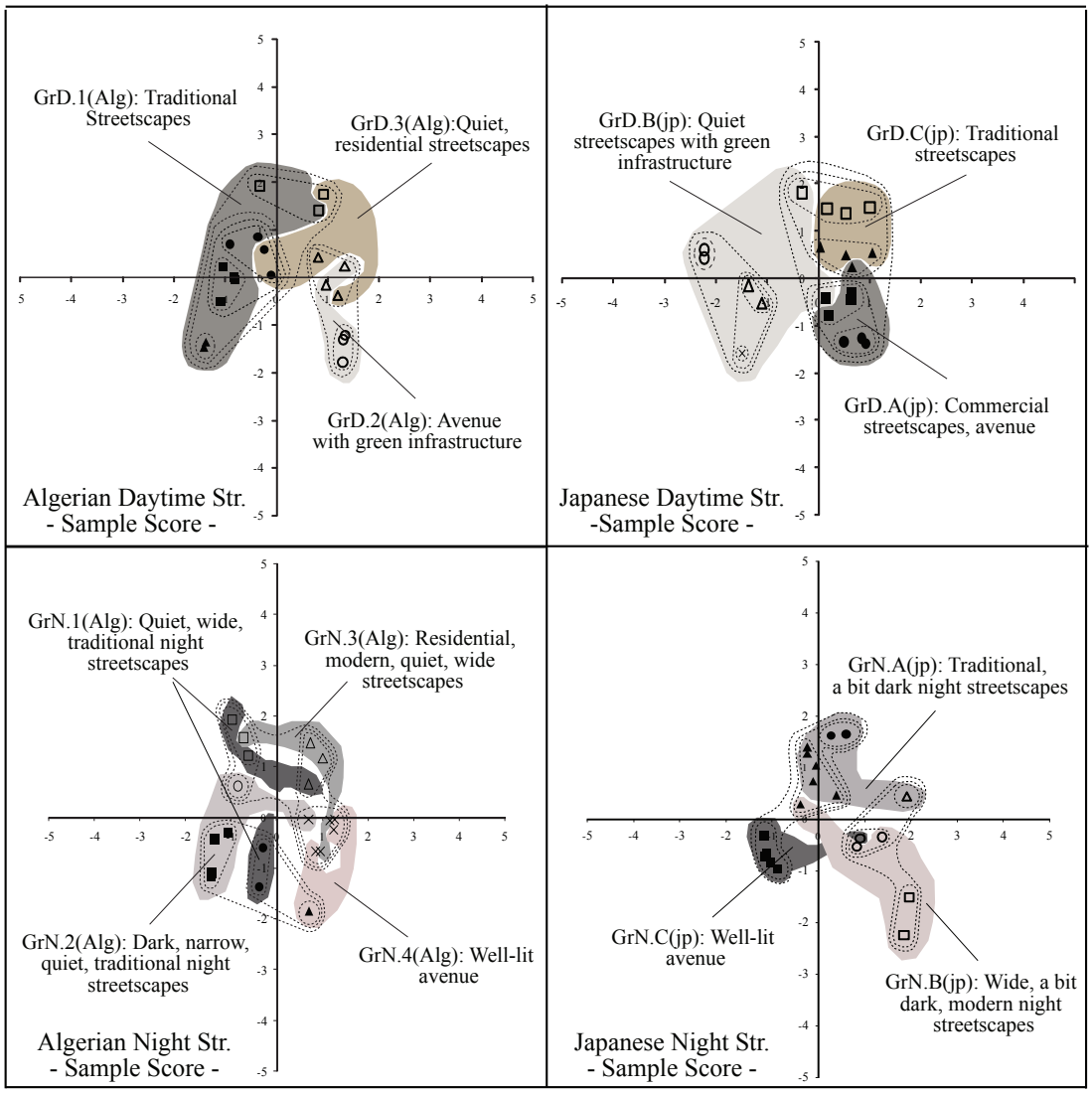


Fig.22 Lexicon-based clustering -Detailed Sample Score-

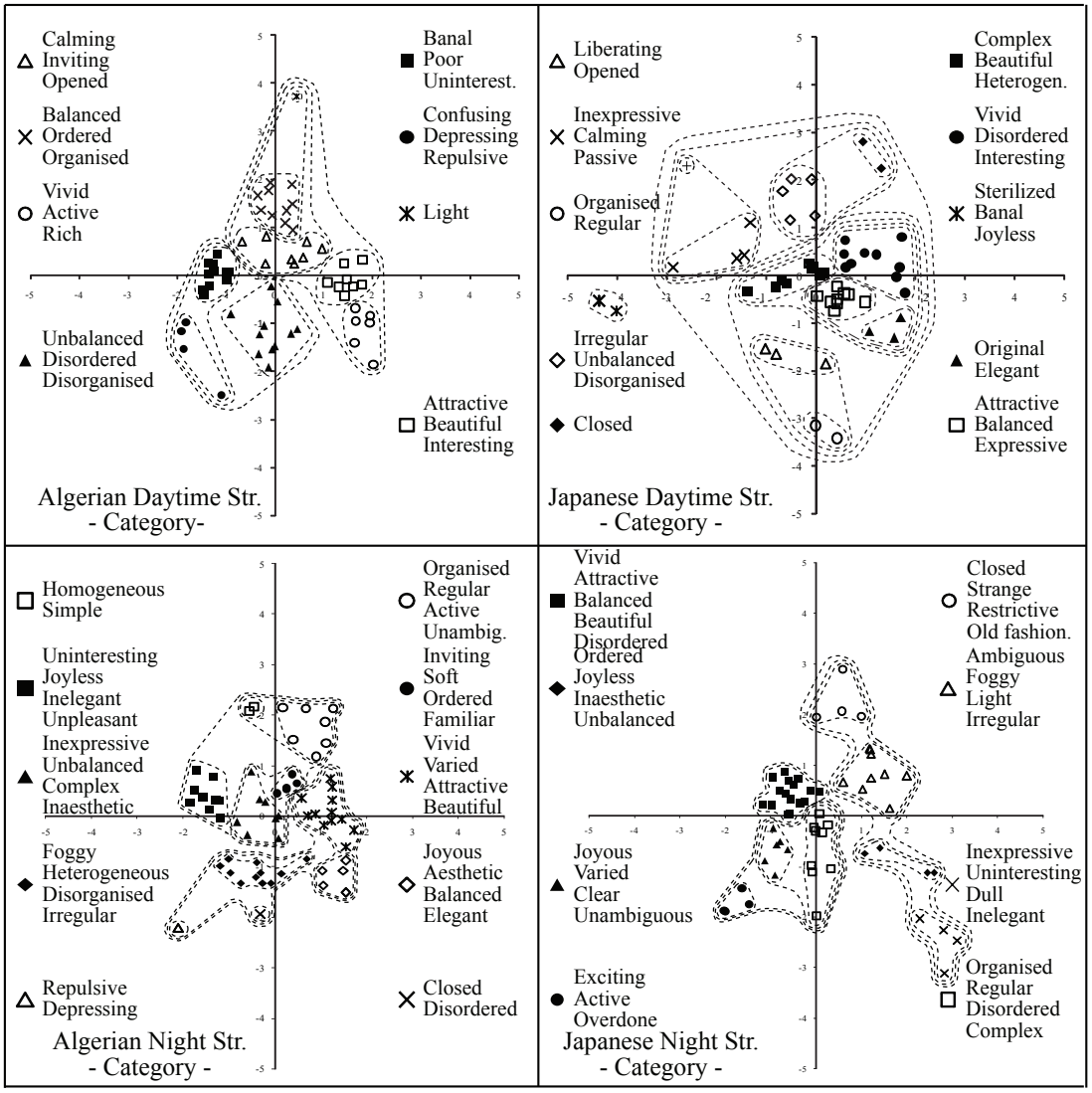


Fig.23 Lexicon-based clustering -Detailed Category Score-

4.3.2 Cognitive patterns clustering using CMYK data

The main aim of this phase was the study of the subjects (participants) in order to figure out the way they see complexity within the range of the collected samples. 20 subjects were asked to classify and categorize 80 samples in CMYK format (fig.24), according to a 7-point scale of complexity (fig.25).

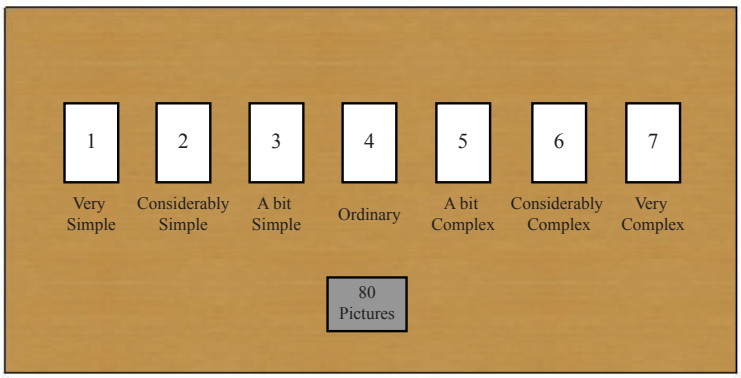
4.3.2.1 CMYK color model

CMYK (Cyan, Magenta, yellow, Black) is a subtractive color model used in offset printing for all color documents. It is a color model in which all colors are described as a mixture of these 4 process colors. CMYK is limited by outside factors including the qualities of the paper, the integrity of the ink and the halftone dot size.

4.3.2.2 The experiment and analysis

The idea was to open the boundaries of the research from a two (1,0) scales scoring method (lexicon-based clustering) focused on physical data (samples) to a wider range of scoring (1 to 7) analysis focused on human data (subjects). The Japanese subjects classified the pictures according to a 7-point scale written in Japanese, whereas foreign subjects classified the pictures according to a seven 7-point scale written in English. Before the experimentation, the authors explained the aim of the experiment to the subjects and asked them to consider first each visual array as a whole set of interacting classes and elements. Then, to classify these visual arrays according to the given scale of complexity, with regard to their feelings towards each set of interacting classes (actors, vegetation, building, sky, ground).

The results of this experiment were collected into a large matrix that includes the scoring of the samples from each subject (fig.26, 27 & 28).



Subject evaluating streetscape pictures in printed CMYK format

C Cyan	M Magenta
Y Yellow	K Black

CMYK Color Model

Example of printed Streetscape in CMYK, A4 format

Fig.24 Subject evaluating streetscape data in CMYK color format

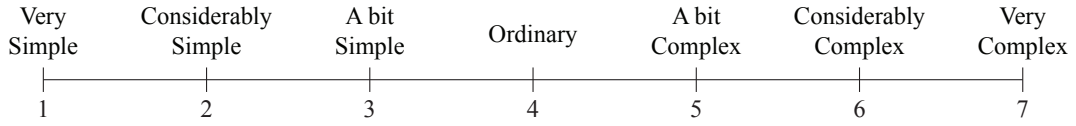


Fig.25 7-point ranking scale of complexity

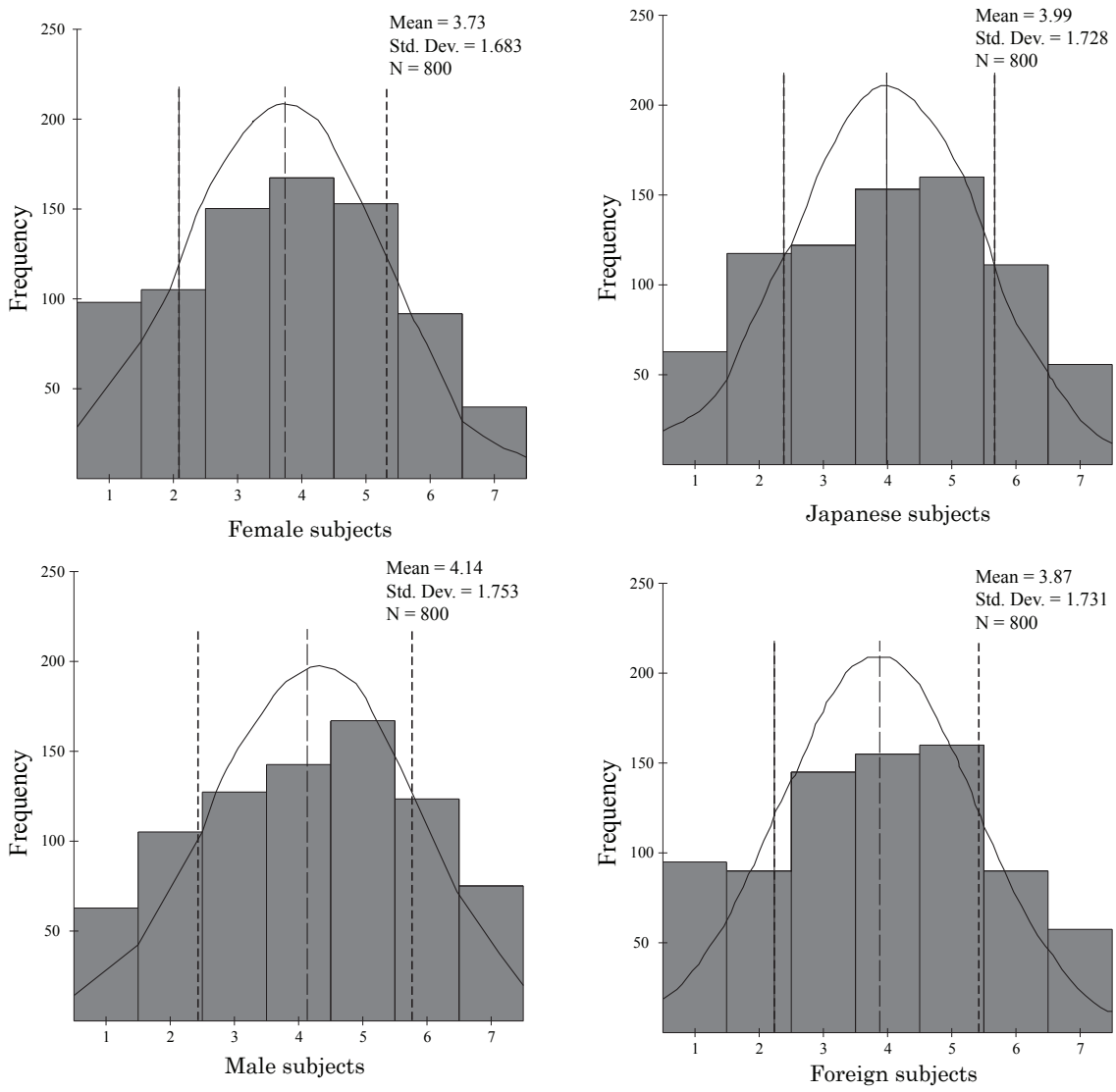
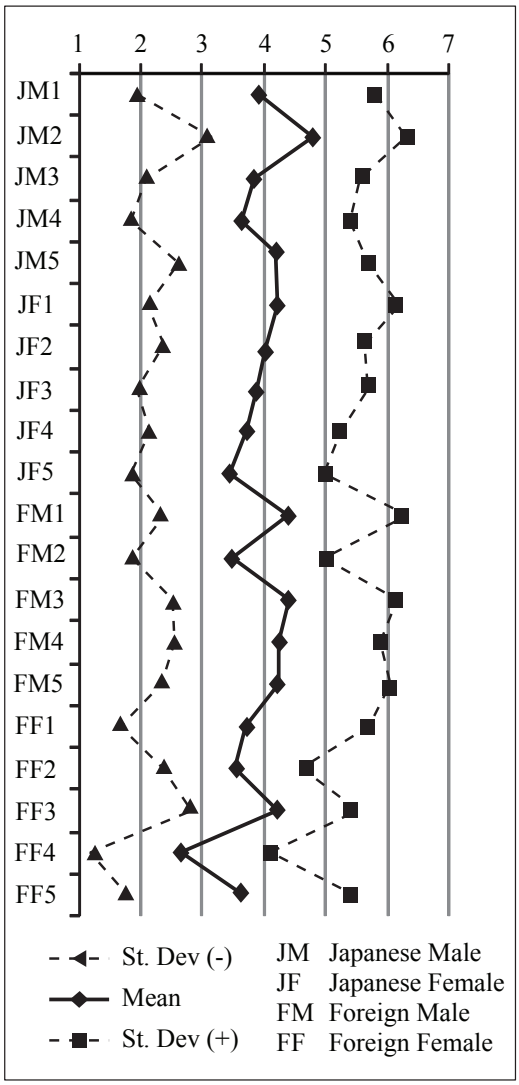
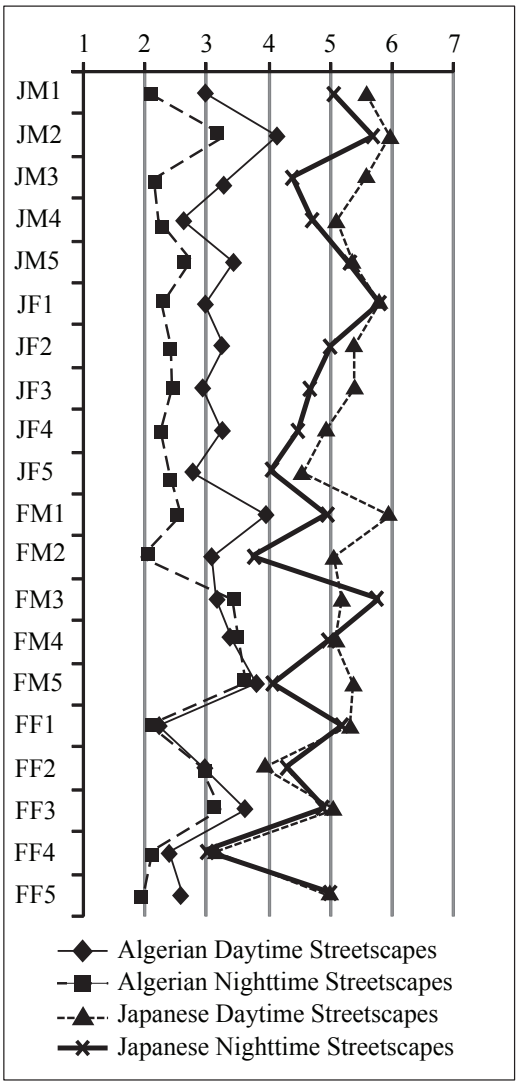


Fig.26 Subject Histograms



Samples general chart

Fig.27 Samples Chart



Samples' categories chart
(Daytime & Nighttime)

Fig.28 Samples categories chart

Table 12 Results of factor analysis according to 7-point scale, after Varimax rotation

Variables	Factors			Communalities
	1	2	3	
JM3	**0.843**	0.365	0.280	0.918
FM1	**0.805**	0.349	0.168	0.817
JF4	**0.782**	0.438	0.304	0.901
JM1	**0.733**	0.494	0.284	0.879
JM2	**0.730**	0.515	0.277	0.896
JF5	**0.704**	0.188	0.422	0.739
JM4	**0.666**	0.539	0.362	0.861
FM5	**0.665**	0.356	-0.276	0.649
FM2	**0.665**	0.408	0.324	0.790
FM3	**0.655**	0.502	0.218	0.798
JF2	**0.646**	0.489	0.493	0.901
JF3	**0.641**	0.469	0.367	0.829
JM5	**0.629**	0.594	0.281	0.846
FF2	**0.589**	0.425	0.036	0.656
FF1	0.444	**0.795**	0.102	0.782
FF5	0.430	**0.681**	0.261	0.739
FF3	0.240	**0.633**	0.120	0.475
JF1	0.553	**0.616**	0.336	0.860
FF4	0.071	0.061	**0.689**	0.444
FM4	0.250	0.327	**0.487**	0.591
Eigen Value	13.438	1.385	0.928	*Extr. Method: Principal Axing Factoring* *Rot. Method: Varimax with Kaiser Normalisation*
% of Variance	67.190	6.923	4.641	
Cumulative Contribution Rate	67.190	74.113	78.755	
Factors Description	Actors-Activity	Style-Actors-Vegetation	Materials-Activity-Style	

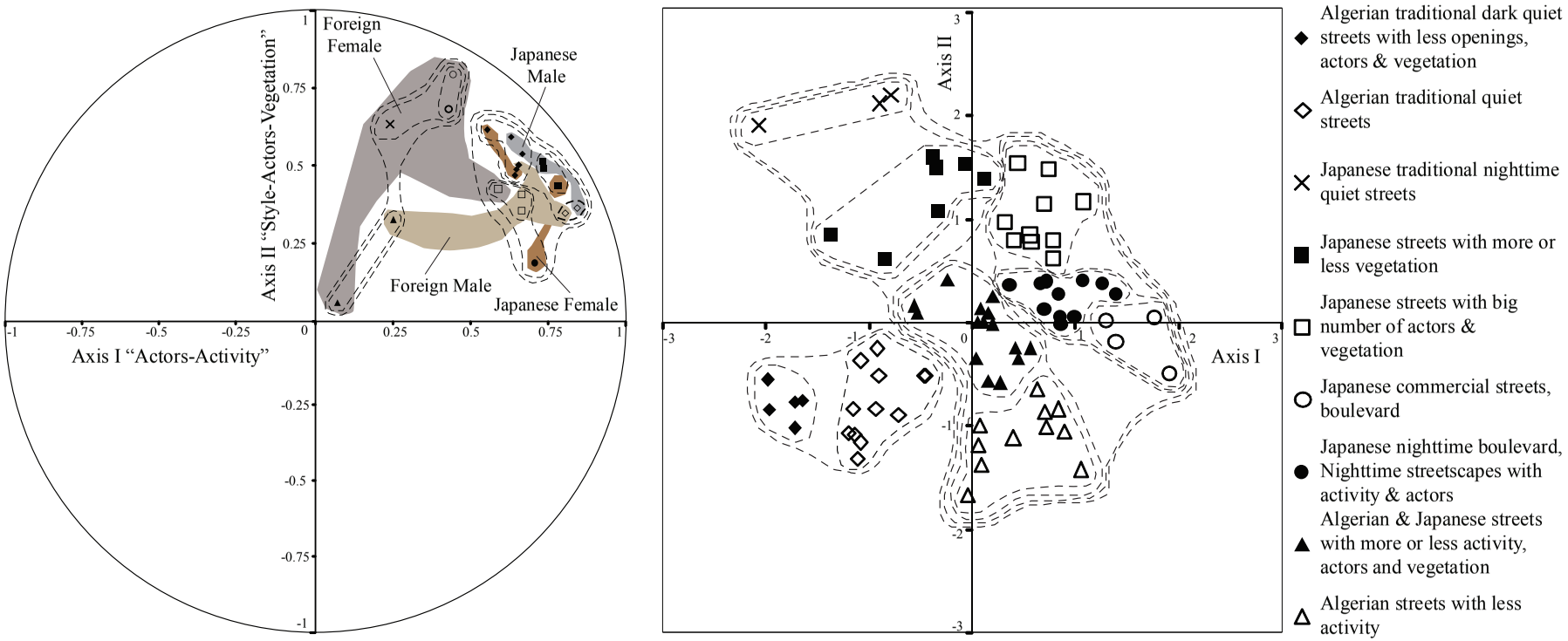


Fig.29 Factors I & II according to 7-point scale (subjects & visual arrays)

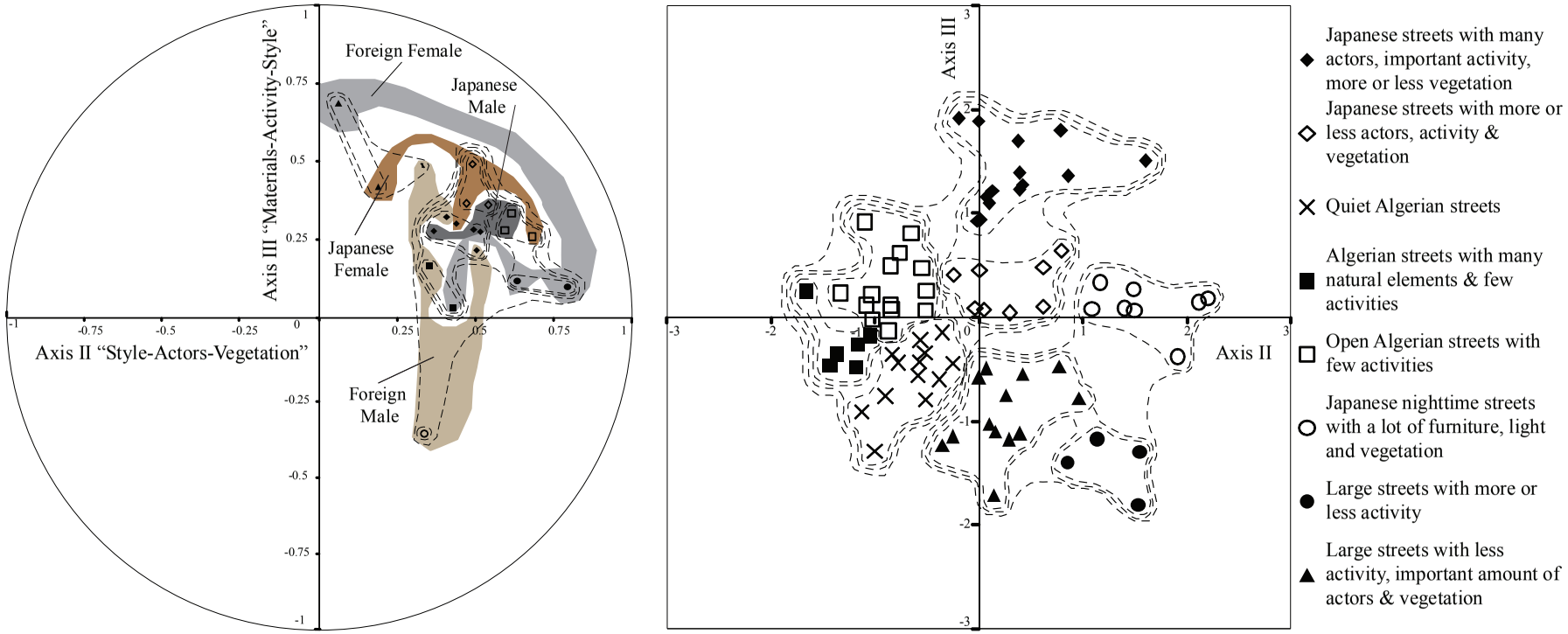


Fig.30 Factors II & III according to 7-point scale (subjects & visual arrays)

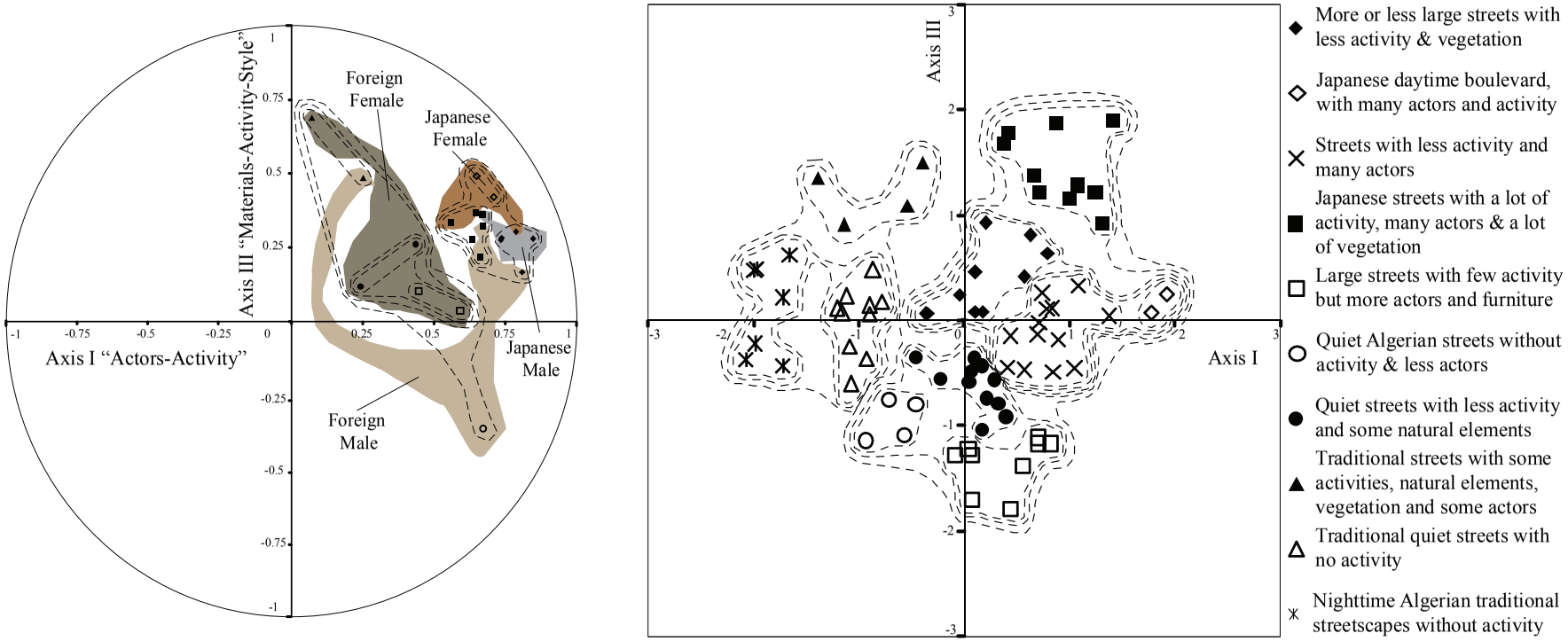


Fig.31 Factors I & III according to 7-point scale (subjects & visual arrays)

Factor Analysis (focused on the human scoring (subjects)) was used in order to find out the factors that may reflect possible cognitive patterns related to the estimation of complexity within the visual composition of the collected streetscapes (table 12).

The results of factor analysis served also as a basis for cluster analysis (Ward method) in order to categorize the samples as well as the human cognitive patterns (fig.29, 30 & 31). Three factors could be identified as a result of factor analysis. The first factor was the one of "Actors-Activity" . "Actors" means the set of components that includes any kind of man-made elements, urban furniture, vehicles, human, creatures, etc. This study found a relationship between the number of "actors", as a class, and the degree of complexity of a visual array. The higher the number of "actors", the higher the degree of complexity. Complexity increases also with the number of openings and activity, as a result of the dynamic components (human, vehicles) within the "Actors" class. The second factor was characterized by "Style-Actors and Vegetation" that determine the degree of complexity. Within this factor, almost all Japanese streetscapes were classified as complex, whereas the Algerian streetscapes were classified as simple or ordinary. Finally, the third factor represented a combination of 3 features: "Materials-Activity-Style" . Materials, details and Style make Japanese streetscapes look more complex than the Algerian ones.

4.3.3 Cognitive patterns clustering using RGB data

From the previous experiment focused on the cognitive clustering of the samples, the author established that subjects were confused when asked to categorize the visual arrays into 7 different groups. This confusion was evident when we tried to make a primary estimation of entropy.

Faced with this potentially misleading stituation, the author opted for the idea of simplifying the complexity grouping and ranking scale into three main classes (simple, ordinary and complex) in order to ensure more credible results (fig.33). The data was also presented in different way. Subjects had to categorize and rank data presented on a 30” HD monitor. HD monitors ensure a color quality range in RGB format more close to the human visual range (fig.32).

4.3.3.1 RGB color model

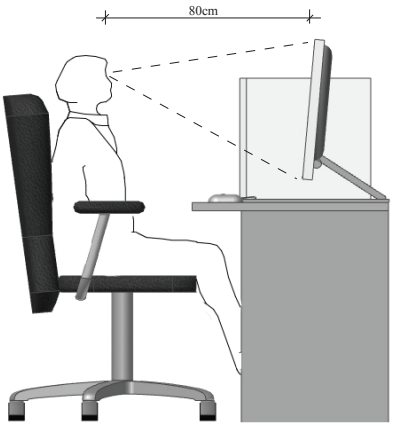
RGB (Red, Green and Blue) is an additive color model used in scanners, digital cameras and computer monitors. Therefore, it produces a different range of colors than the CMYK color model. RGB is a convenient color model for computer graphics because the human visual system works in a way similar to that of RGB color space. The most commonly used RGB color spaces are Adobe RGB and sRGB. sRGB is by far the most commonly used RGB color space.

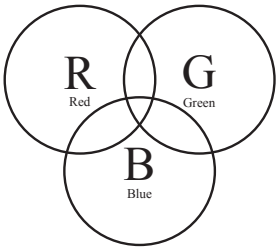
Color matching represents one of the most difficult aspects in publishing. It is related to the proper conversion of RGB colors into CMYK ones so that the quality of printed documents or pictures looks the same as what appears on the monitor.

Dell UltraSharp™ 3008WFP 30" widescreen LCD Monitor

Features

* 30" (76cm) Wide screen Monitor, Black
* High definition 30" (76cm) S-IPS Panel using WCCFL backlight, able to show 117% of NTSC color gamut
* sRGB & Adobe RGB presets for color calibration
* 2560x1600 Native resolution
* 3000:1 Dynamic contrast ratio
* True HD 1080





RGB Color Model

Subject evaluating Streetscape Data in RGB format

Fig.32 Subject visualizing the streetscape data in RGB color format

4.3.3.2 Factor analysis and Ranking method

10 Japanese students at Nagoya Institute of Technology were asked to rank and categorize 74 visual arrays in RAW format into 3 main groups, according to 3 degrees of complexity (fig.33).

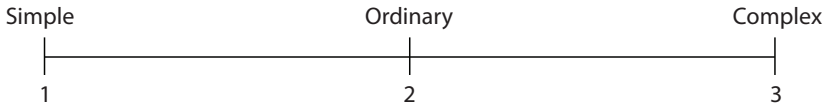


Fig.33 3-point scale of complexity

Factor analysis helped in defining 2 main factors of complexity within these visual arrays (table 13). That is to say:

Factor I: Vegetation-Actors, which means vegetation and all man made forms as well as human beings.

Factor II: Vegetation-quiteness seem to describe the features of this factor.

Cognitive patterns clustering helped in defining 10 cognition clusters that will represent references for the following chapters (fig.34 & 35).

The results of ranking method could show that the cognition cluster CC1 (Green crowded Boulevard) reflects a higher degree of complexity whereas the cognition cluster CC6 is classified as the most simple cognition cluster (table.14, 15, 16, 17 & 18).

The cognition cluster CC6 with Algerian Data is considered as simple. The most complex category of streetscapes was dominated by Japanese streetscapes. These results will be used in the following chapters in order to find out any relationship between patterns of complexity and articulation of the classes composing the selected streetscapes.

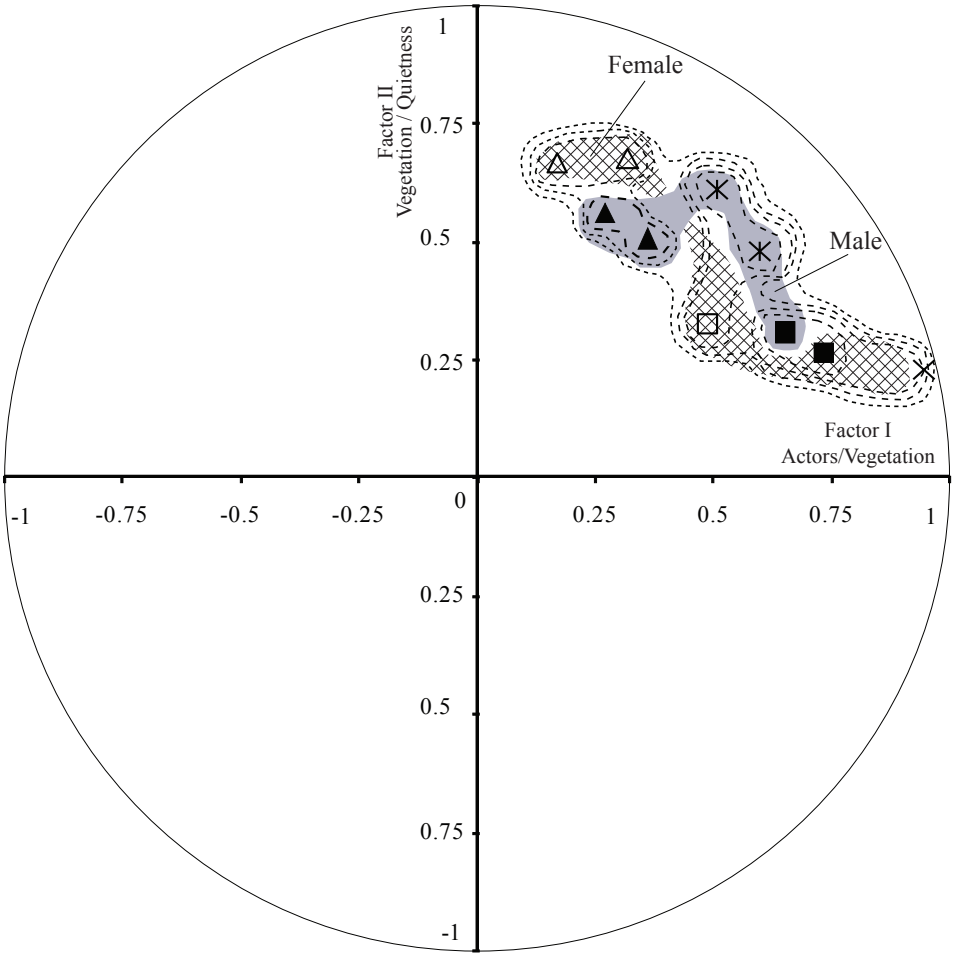


Fig.34 Subjects factoring according to 3-point scale (Factors I and II)

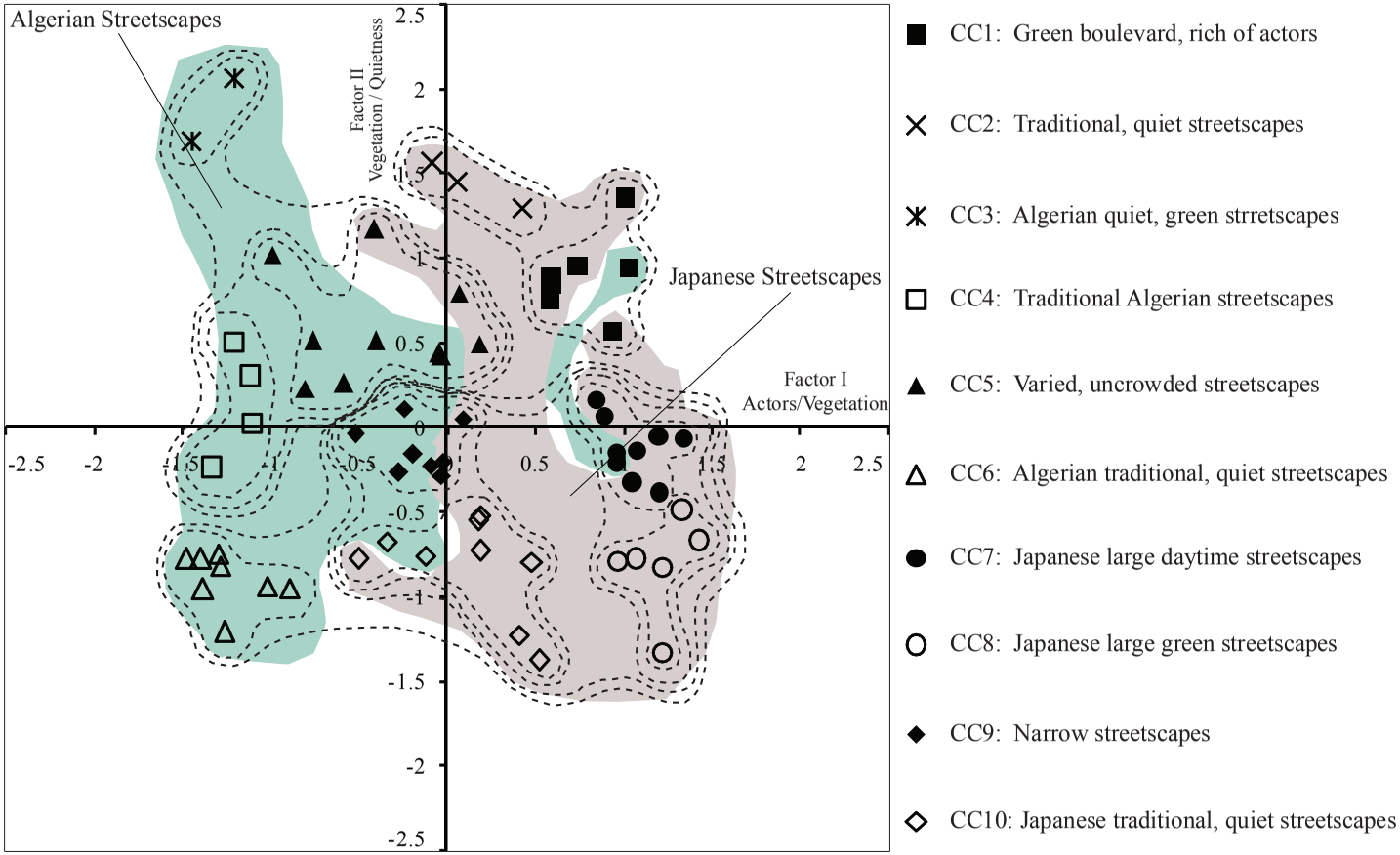


Fig.35 Visual arrays factoring according to 3-point scale (Factors I and II)

Table 13 Results of Factor analysis according to 3-point scale, after Varimax rotation

Variables	Factors		Communalities
	Factor I	Factor II	
Female 1	**0.87**	0.24	0.690
Female 2	**0.73**	0.28	0.607
Male 1	**0.65**	0.32	0.575
Male 2	**0.60**	0.50	0.564
Female 3	**0.49**	0.34	0.377
Female 4	0.32	**0.71**	0.579
Female 5	0.17	**0.70**	0.456
Male 3	0.51	**0.64**	0.650
Male 4	0.27	**0.59**	0.415
Male 5	0.36	**0.53**	0.389
Eigen Value	5.279	1.075	0.87
% of Variance	52.792	10.748	*Extraction Method: . Principal Axing Factoring* *Rotation Method: . Varimax with Kaiser Normalisation*
Cumulative Contribution Rate	52.792	63.54	
Factors Description	Actors/vegetation (Man made / Natural)	Vegetation / Quietness	

Table 14 Complexity ranking of the streetscapes (1 to 16)

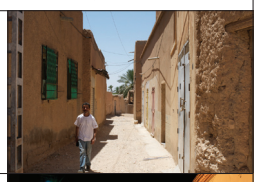
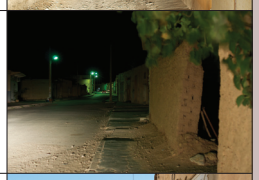
Complexity rank	Visual array		Complexity rank	Visual array	
1	AD4		9	AD16	
2	AN2		10	AN15	
3	AD2		11	AD20	
4	AN4		12	AD12	
5	AN10		13	AD14	
6	AN16		14	AD15	
7	AN12		15	JN7	
8	AD10		16	AD6	

Table 15 Complexity ranking of the streetscapes (17 to 32)

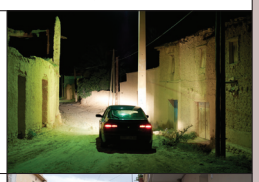
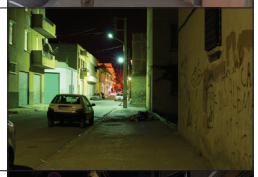
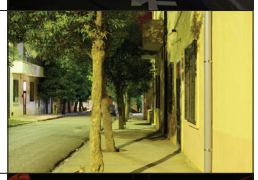
Complexity rank	Visual array		Complexity rank	Visual array	
17	AN18		25	JN11	
18	AD9		26	JN20	
19	AD18		27	JD7	
20	AD7		28	AD1	
21	AD8		29	AN19	
22	AD13		30	JN2	
23	AN6		31	AN1	
24	AN9		32	JN16	

Table 16 Complexity ranking of the streetscapes (33 to 48)

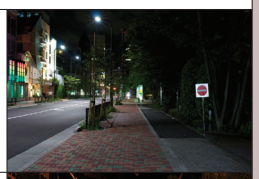
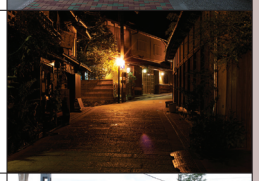
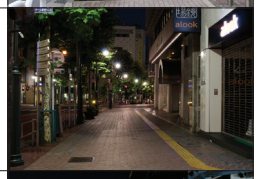
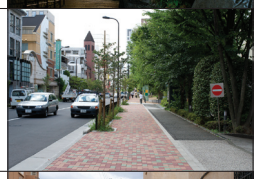
Complexity rank	Visual array		Complexity rank	Visual array	
33	JN12		41	JN8	
34	JN13		42	JD15	
35	AD11		43	JD19	
36	JD10		44	JN6	
37	AD17		45	JN15	
38	AN17		46	JD12	
39	JD13		47	AD19	
40	AD3		48	JN10	

Table 17 Complexity ranking of the streetscapes (49 to 64)

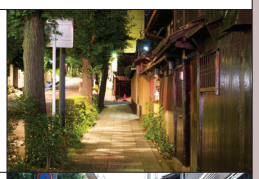
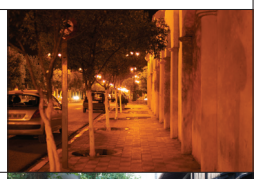
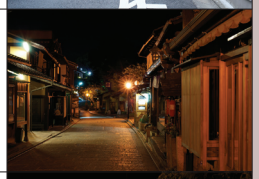
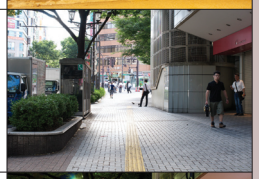
Complexity rank	Visual array		Complexity rank	Visual array	
49	JN5		57	AN3	
50	JD2		58	JD5	
51	JN9		59	AN13	
52	AN7		60	JD11	
53	JN19		61	JD9	
54	AN11		62	JD18	
55	JD4		63	JD8	
56	JN4		64	JD6	

Table 18 Complexity ranking of the streetscapes (65 to 74)

Complexity rank	Visual array	
65	AN5	
66	JD17	
67	JN18	
68	JD20	
69	AD5	
70	JD16	
71	JD1	
72	JN14	

Complexity rank	Visual array	
73	JD3	
74	JD14	

4.4 Summary

Complexity is a multidimensional concept. Throughout this study, many results revealed that some concepts related to complexity, such as disorder, irregularity and disorganization are often conflicting and contradictory. In many cases, order was related to disorganization and complexity was related to regularity and organization. Therefore, this study disclosed that concepts, such as variety, richness and irregularity, with some aspects of order and organization, seem to be the major aspects of Algerian night streetscapes. Japanese night streetscapes tend to be attractive, balanced, regular, ordered and organized, with some aspects of confusion and ambiguity. Concepts like balance, order, regularity and homogeneity seem to characterize Algerian daytime streetscapes, whereas unbalance, regularity, vividness and attractiveness seem to be the major characteristics of Japanese daytime streetscapes. As a factor, "Actors" seems to be a generator of complexity in streetscape composition. It has other corollary factors such as Activity, reflected by human and urban components. Vegetation and other natural elements, as well as building style and materials also represent components that contribute in generating this complexity. Research about complexity is made difficult by its close dependence on many different corollary concepts. This chapter tried to explore complexity in streetscape composition through three methods of data clustering related to typology, lexicon and cognitive patterns. The author believes that the use of other methods, such as the semantic differential method, would open the boundaries of this research and other perspectives. Therefore, exploring the geometric logic and the origins of this complexity should be the aim of the following chapters about the intrinsic concepts behind complexity and disorder in streetscape composition.

Chapter. 5

Entropy estimation based on the probability of pixel intensities

5.1 Introduction

This chapter is concerned with the low level of vision and the probability of pixel intensities (fig.36). Entropy is estimated according to the nearest neighbor method. This method is based on the concept of nearest neighbor search (NNS), also known as proximity search, similarity search or closest point search. It is an optimization approach in order to find closest points in metric spaces.

5.2 Theoretical overview

The nearest neighbor search consists on the closest point to a query q within a metric space M that includes a set S of points in a metric. M is often considered as d-dimensional Euclidean space and distance is measured by Euclidean distance or Manhattan distance. There exist many different types of entropy estimations. Entropy can be estimated from the distribution of the nearest-neighbour-distances of a dataset (fig.37).

5.2.1 Mathematical interpretation of the nearest neighbor method

Let us assume $[X_1, X_2, ..., X_n]$ for a continuous random variable X, $H\left(\hat{f}_{\Im_i}\right) = E\left[-\log\left(\frac{1}{n}\frac{m}{A_k \varepsilon_i^k}\right)\right] = E\left[\log\left(\varepsilon_i^k\right) + \log\left(\frac{A_k n}{m}\right)\right]$ $[X_i] \in \Re^k$ is a set of realizations drawn according to the unknown $f_x(x)$.

For a specific realization X_i(target), let us define a partition $\Im_i \in X$, which contains all realizations (neighbors) such that

$$\sqrt{\left(X_i - X_j\right)^2} \le \varepsilon_i, j \ne i, j = 1, ..., n-1 \quad (1)$$

For a certain ε_i,the partition $\Im_i$can be viewed as a k-dimensional hyper sphere or radius ε_i . The volume of this hypersphere of dimension k is given by:

$$V_i = \frac{\pi^{k/2}}{\Gamma\left(k/2 + 1\right)} \varepsilon_i^k \quad (2)$$

Where $\Gamma(z)=(z-1)!$ is the gamma function.

For instance, if $k=1$(a line segment), $V_i=2\varepsilon_i$; for $k=2$(a disk), $V_i=\pi\varepsilon_i^2$

Now, since the aim is to look for the nearest neighbor of X_i(small distance ε_i , small hypersphere), let us suppose that inside the hypersphere, the probability density is uniform. This way, we can define the probability mass of the partition $\Im_i$ as

$$\hat{f}_{\Im_i}=\frac{1}{n}\frac{m}{V_i} \qquad (3)$$

Where m is the number of elements inside the hypersphere. Let us now write the entropy $H\left(\hat{f}_{\Im_i}\right)$ in terms of a sample mean estimator (represented by $E[\ ]$)over targets X_i:

$$H\left(\hat{f}_{\Im_i}\right)=E\left[-\log\hat{f}_{\Im_i}\right]=E\left[-\log\left(\frac{1}{n}\frac{m}{V_i}\right)\right] \quad (4)$$

Where A_k is the volume of a unit k-dimensional hypersphere (unit radius). Thus we have

$$H\left(\hat{f}_{\Im_i}\right)=E\left[-\log\left(\frac{1}{n}\frac{m}{A_k\varepsilon_i^k}\right)\right]=E\left[\log\left(\varepsilon_i^k\right)+\log\left(\frac{A_k n}{m}\right)\right] \quad (6)$$

Finally, we can define the entropy estimator based on neighbor distance ε_i as

$$H\left(\hat{f}_{\Im_i}\right)=kE\left[\log\varepsilon_i\right]+\log\left(\frac{A_k n}{m}\right) \quad (7)$$

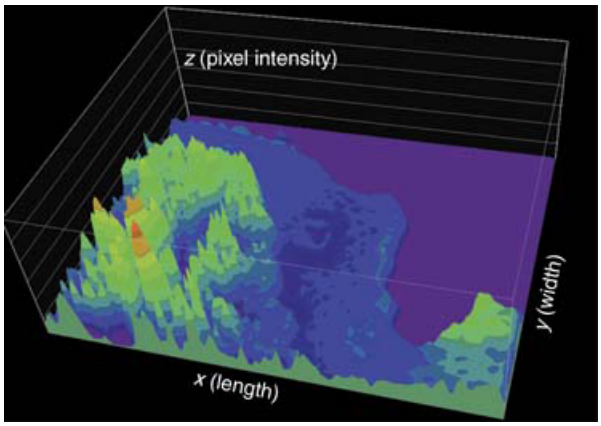


Fig.36 Example of pixel intensities

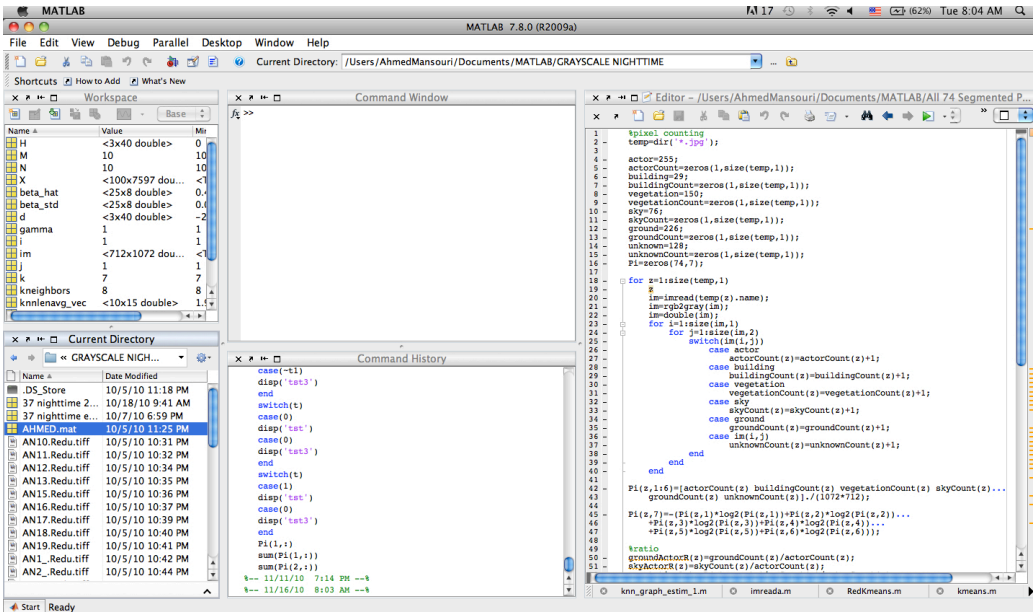


Fig.37 Example of entropy estimation using nearest neighbor algorithm in Matlab environment

5.3 Entropy estimation according to the nearest neighbor method

Throughout this study, the author applied a series of psychometric methods in order to clarify and distinguish the cognitive patterns of complexity related to the selected streetscapes. However, as entropy is a very sensitive concept to estimate, the author realized that subjects got very confused when they were asked to deal with and rank the data according to a 7-point scale. It was very difficult for them to put the picture in order of complexity when the scores were too close.

This persuaded the author to simplify the experiment by asking 10 Japanese subjects, all students in Architecture to categorize and rank the data according to a 3-point scale. That is to say: simple, ordinary and complex.

After estimating entropy (entropy is given in bits/pixel), the author tried to compare the results with the complexity ranking and the cognitive patterns clustering (table 19, 20, 21, 22, 23, 24, 25 & 26).

Table 19 Average entropy of Algerian streetscapes (bits/pixel)

Complexity Group	Entropy Average
Simple	0.560
Ordinary	0.617
Complex	

Table 20 Average entropy of Algerian daytime streetscapes (bits/pixel)

Complexity Group	Entropy Average
Simple	0.622
Ordinary	0.648
Complex	

Table 21 Average entropy of Algerian nighttime streetscapes (bits/pixel)

Complexity Group	Entropy Average
Simple	0.477
Ordinary	0.584
Complex	

Table 22 Entropy estimation (bits/pixel) according to the nearest neighbor method -Part 1-
(All streetscapes)

Cognition cluster	Complexity Group	Array	Complexity Rank	Entropy	Entropy Average
CC6	Simple	AD4	1	0.562	0.560
CC6		AN2	2	0.429	
CC6		AD2	3	0.490	
CC6		AN4	4	0.631	
CC6		AN10	5	0.351	
CC6		AN16	6	0.609	
CC6		AN12	7	0.406	
CC6		AD10	8	0.527	
CC6		AD16	9	0.722	
CC6		AN15	10	0.438	
CC6		AD20	11	1.081	
CC6		AD12	12	0.572	
CC4		AD14	13	0.594	
CC10		AD15	14	0.431	
Axis A					
CC10	Ordinary	JN7	15	0.106	0.620
CC10		AD6	16	0.351	
CC4		AN18	17	0.617	
CC9		AD9	18	0.633	
CC5		AD18	19	0.791	
CC9		AD7	20	0.513	
CC5		AD8	21	0.582	
CC4		AD13	22	0.841	
CC4		AN6	23	0.417	
CC9		AN9	24	0.590	
CC10		JN11	25	0.350	
CC10		JN20	26	0.291	
CC10		JD7	27	0.648	
CC9		AD1	28	0.369	
CC5		AN19	29	0.655	
CC10		JN2	30	0.515	
CC5		AN1	31	0.792	
CC9		JN16	32	0.320	
CC10		JN12	33	0.739	
CC9		JN13	34	0.500	
CC5		AD11	35	0.656	
CC8		JD10	36	0.715	

Table 23 Entropy estimation (bits/pixel) according to the nearest neighbor method -Part 2- (All streetscapes)

Cognition cluster	Complexity Group	Array	Complexity Rank	Entropy	Entropy Average
CC3	Ordinary	AD17	37	0.765	0.620
CC5		AN17	38	0.649	
CC9		JD13	39	0.717	
CC7		AD3	40	1.021	
CC8		JN8	41	0.724	
CC10		JD15	42	0.603	
CC8		JD19	43	0.495	
CC8		JN6	44	0.637	
CC9		JN15	45	0.778	
CC8		JD12	46	0.730	
CC2		AD19	47	0.608	
CC8		JN10	48	0.776	
CC5		JN5	49	0.714	
CC7		JD2	50	0.741	
CC7		JN9	51	0.646	
CC1		AN7	52	0.359	
CC5		JN19	53	0.424	
CC1		AN11	54	0.436	
CC7		JD4	55	0.933	
CC7		JN4	56	0.814	
CC1		AN3	57	0.582	
CC7		JD5	58	1.018	
CC3		AN13	59	0.744	
Axis B					
CC5	Complex	JD11	60	0.790	0.670
CC5		JD9	61	0.488	
CC7		JD18	62	0.584	
CC1		JD8	63	0.716	
CC7		JD6	64	0.851	
CC1		AN5	65	0.369	
CC7		JD17	66	0.656	
CC2		JN18	67	0.515	
CC1		JD20	68	0.811	
CC1		AD5	69	0.760	
CC2		JD16	70	0.859	
CC1		JD1	71	0.697	
CC1		JN14	72	0.588	
CC1		JD3	73	0.702	
CC1		JD14	74	0.657	

Table 24 Average entropy of Japanese streetscapes (bits/pixel)

Complexity Group	Entropy Average
Simple	
Ordinary	0.622
Complex	0.686

Table 25 Average entropy of Japanese daytime streetscapes (bits/pixel)

Complexity Group	Entropy Average
Simple	
Ordinary	0.733
Complex	0.710

Table 26 Average entropy of Japanese nighttime streetscapes (bits/pixel)

Complexity Group	Entropy Average
Simple	
Ordinary	0.555
Complex	0.551

5.3.1 Discussion

The results of the entropy estimation as well as the ranking of the streetscapes according to their degrees of complexity show a direct proportion between the degree of complexity of the selected streetscapes and their estimated degrees of entropy (Table). Algerian streetscapes were ranked simple or ordinary. The cognition cluster (CC6) related to the "Algerian traditional, uncrowded streetscapes" is ranked as simple cluster with an average entropy of 0.560 (bits/pixel). Entropy in Algerian daytime streetscapes is higher than in nighttime.

The highest average entropy was the one of Japanese daytime streetscapes. In nighttime, average entropy in ordinary Japanese nighttime streetscapes was close to the one of complex category. The cognition cluster CC1 that represents crowded Green Boulevard, full of actors was categorized as a complex cluster with average entropy of 0.670 (bits/pixel).

5.4 Summary

This chapter is about entropy and complexity at the lower scale of pixel intensities. The entropy estimation by the nearest neighbor method showed a direct proportion between entropy and the degree of complexity of the selected streetscapes, as ranked by the subjects.

Entropy in Algerian streetscapes is lower than in Japanese streetscapes. Japanese streetscapes show higher entropy, especially in daytime.

Green, crowded boulevards (CC1) were ranked as complex according to the ranking method and the cognitive patterns clustering. The cognition cluster CC6 was the simplest cluster with low entropy. It is composed essentially by Algerian uncrowded traditional streetscapes.

The next chapter will aim to estimate the entropy of each visual array according to higher scale related to the perceived classes within each streetscape.

Chapter. 6

Entropy estimation based on the probability of perceived classes

6.1 Introduction

This chapter is about perception, complexity and entropy of streetscape as a system. Entropy is considered as an expression of the articulated classes or components within a streetscape. As suggested by Kaplan (1988), the author selected 5 classes within each streetscape; that is to say: building, ground, vegetation, sky, and actors (human, vehicles, openings, etc.), (fig.18). The author suggested a class called "actors" in order to include any element that may attract the attention of the subjects, like: light, openings, human, vehicles, furniture, shadow, etc.

This chapter tries to explore some possible ways of articulation of the classes composing a streetscape. According to information theory, there exist many interpretations of articulation. This study considers articulation as the way the parts of a system are joined, depending on what is happening at the beginning and end of each part, as well as between the parts.

There exist different ways to explore the articulation of streetscape classes. The author applied two approaches. The first approach is to compare the difference of size (counted in pixel) between classes and the second one consists in estimating the probability of each class that composes a streetscape (counted in bits/pixel). The author figured out that comparing the size of classes by simple mathematical operations is potentially misleading.

In this chapter, the articulation of classes is analyzed according to Shannon's model by estimating the class probabilities in each visual array. All the analyzed visual arrays were shot in RAW format using a Nikon D300S digital camera.

6.2 The approach

6.2.1 The segmentation of classes within each visual array

In order to identify the 5 suggested classes within each streetscape, as human beings see them, the author tried to apply a Hybrid approach. This approach used K-means clustering in order to identify the possible classes within a streetscape (fig.40). The results showed that k-means clustering is quite uninformative with regard to the aim of this study. Perfect algorithms for image segmentation are very complicated. They are machine based methods that do not reflect the real human way to determine classes within a visual array.

6.2.1.1 K-means clustering

6.2.1.1.1 K-means clustering algorithm

K-means clustering is a method of cluster analysis that aims to identify clusters or groups of data points within a multidimensional space. The k-means algorithm clusters *n* points into *k* clusters, where *k* is provided as an input parameter. Each point is assigned to clusters based upon its proximity to the mean (fig.38).

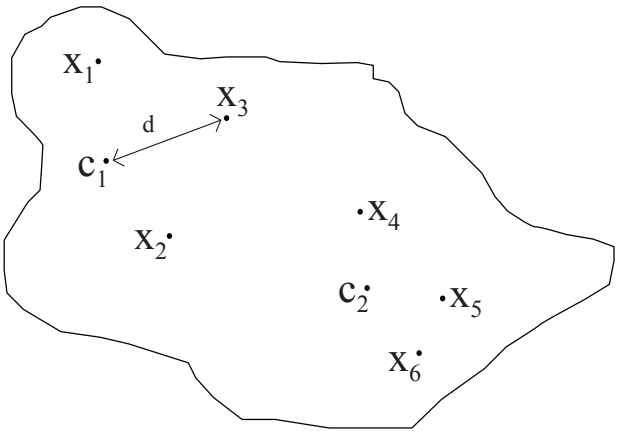


Fig.38 Graphical representation of the data set

Let us assume that we have a data set

$$\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\},$$

1. The first step of the algorithm consists of selecting k points as the initial means c_i of the clusters. $\mathbf{x}_i$ represents a data point in the multidimensional space and may represent one pixel value or an entire image of *(m x m)* pixels.
2. The second step consists of calculating the position of the cluster centroids (means) $\{\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_K\}$ within the data set $\mathbf{X}$.
3. Each point in the dataset is assigned to the closest cluster, based upon the Euclidean distance between each point x_i and each cluster center c_i.

$$d(\mathbf{x}_i, \mathbf{c}_j) = \|\mathbf{x}_i - \mathbf{c}_j\|_2$$

Data points with distance d are classified as belonging to the same cluster

$$d(\mathbf{x}_i, \mathbf{c}_j) \leq D, \text{ (D is minimum distance determined a priori)}$$

After clustering the data points, each centroid (mean) is recalculated. If the points $\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3\}$ have been previously assigned to cluster with a centroid $\mathbf{c}_1$, the new value of the centroid is determined by:

$$\mathbf{c}_j = E\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3\}$$

E represents the mean operator for the Nth dimensional space. This process repeats until all the centroids converge to the same values (fig.39).

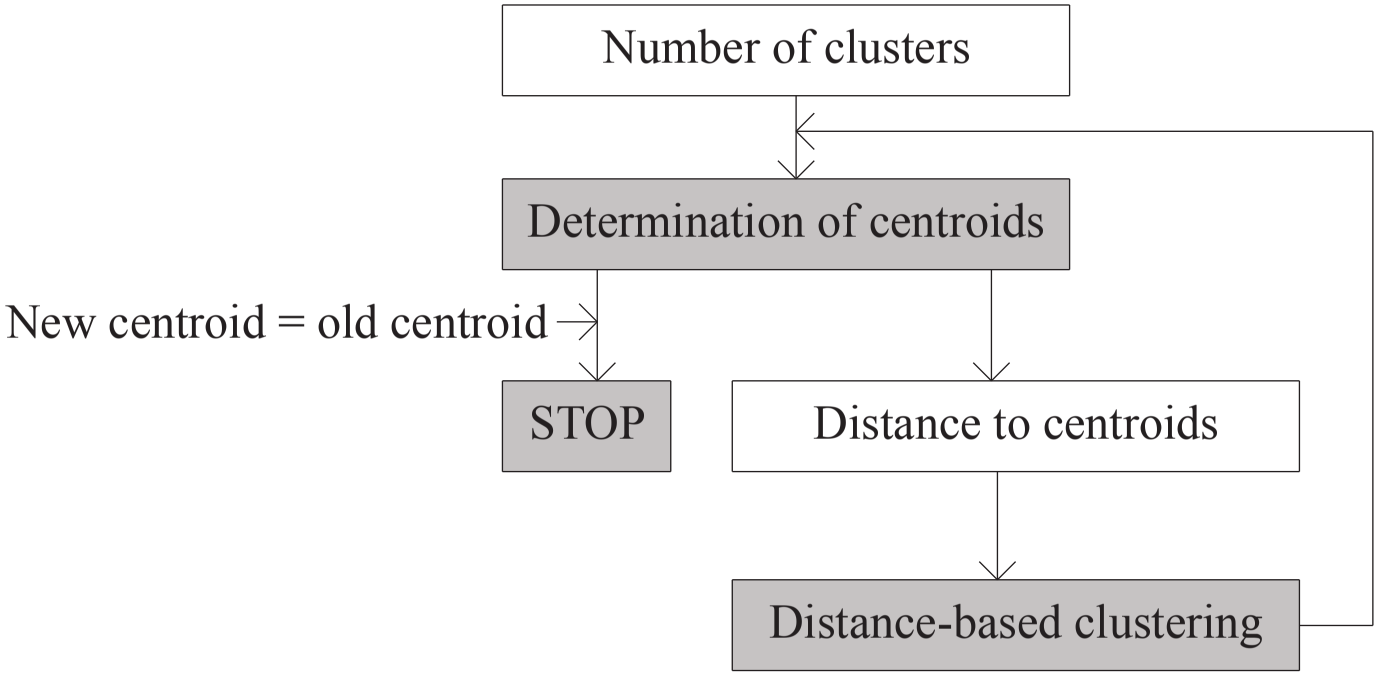


Fig.39 K-means clustering algorithm

Fig.40 Example of k-means clustering of a Japanese streetscape

6.2.1.2 Image segmentation

6.2.1.2.1 The experiment

The second step of the image segmentation and classes clustering was a heuristic approach. The author asked 10 Japanese students in Architecture, who have good skills in Adobe Photoshop, to segment each picture of the 74 streetscape visual arrays into 5 classes (6 pictures in RAW format having been canceled because of some technical constraints). The author explained the meaning and features of each class, and then let them cluster the classes by themselves as they saw fit (fig.41 & 42).

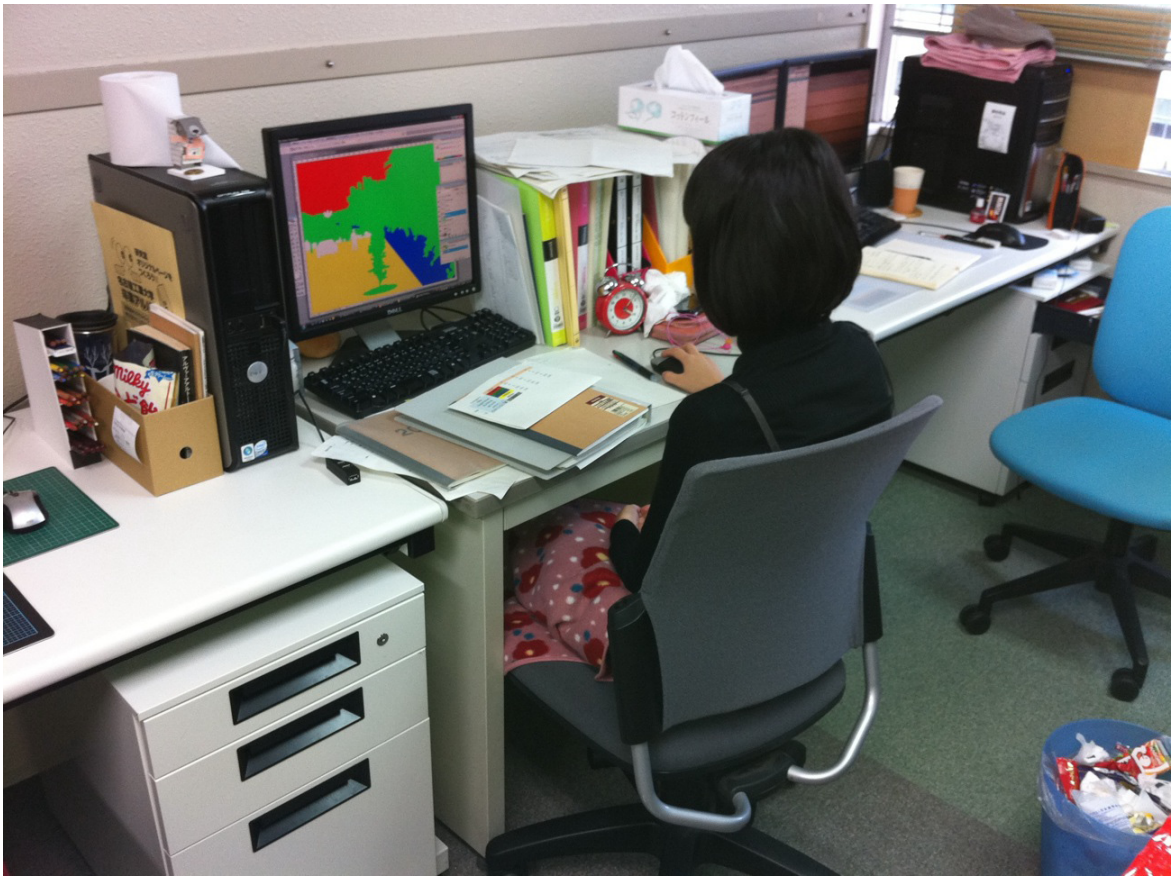


Fig.41 Subject segmenting a streetscape visual array using Adobe Photoshop

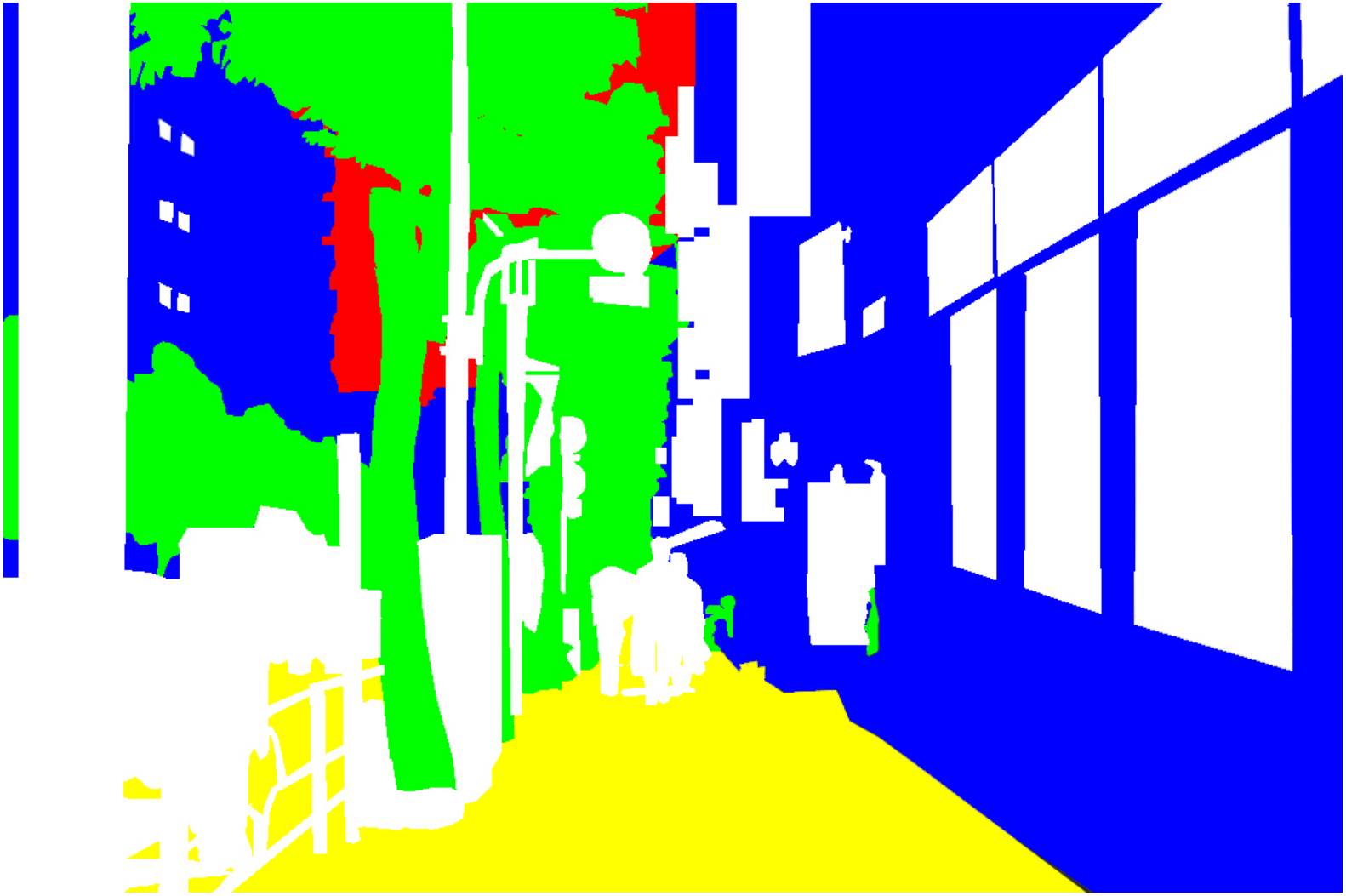


Fig.42 Example of a Japanese streetscape segmented into 5 classes

6.2.1.3 Complexity Ranking of the segmented visual arrays

The Author asked the subjects who participated in the Data segmentation, to rank the different streetscapes from the simplest to the most complex one according to a 3-point scale (table 27, 28, 29, 30, 31, 32, 33, 34, 35 & 36). Ranking method allowed the author to rank and to categorize the streetscapes into 3 categories: simple, ordinary and complex.

6.3 Entropy estimation based on the probability of perceived classes

6.3.1 Shannon's model of entropy estimation

The aim of this stage of the study is to study the way of articulation of the different classes within each streetscape in terms of size. The concept behind the strategy of this research stage is based on the probability of perceived classes within each streetscape. The entropy of each streetscape visual array is based on the size of its perceived classes and estimated according to Shannon's model.

The probability of occurrence of a class P_i is:

$$P_i = \frac{C_i}{\alpha}$$

P_i: Probability of the ith class

α : Size of the picture

C_i : Size of the ith class

Entropy is estimated according to the following equation, and counted in bits/pixel:

$$H(I) = -\sum_i P_i \log_2(P_i)$$

$$i = 1,2,3,...,n$$

Table 27 Complexity ranking of the segmented visual arrays (1 to 8)

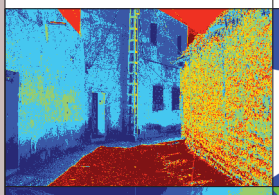
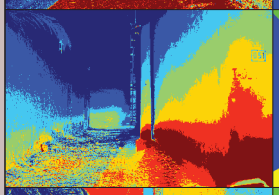
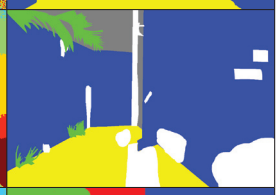
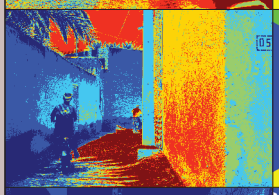
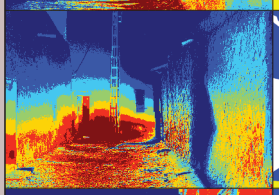
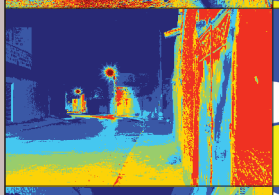
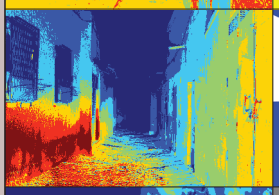
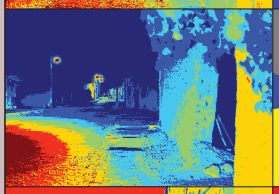
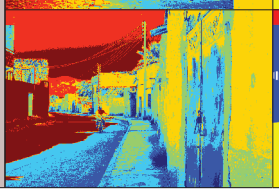
Complexity rank	Visual array		K-means	Segmentation
1	AD4			
2	AN2			
3	AD2			
4	AN4			
5	AN10			
6	AN16			
7	AN12			
8	AD10			

Table 28 Complexity ranking of the segmented visual arrays (9 to 16)

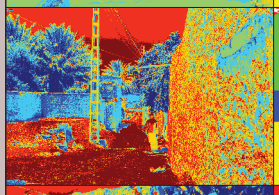
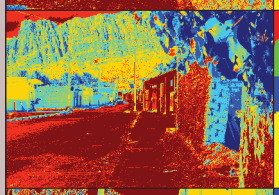
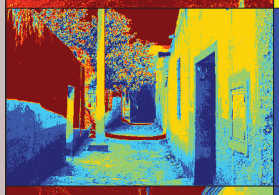
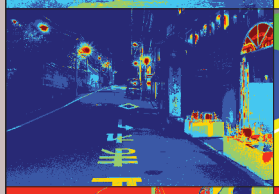
Complexity rank	Visual array		K-means	Segmentation
9	AD16			
10	AN15			
11	AD20			
12	AD12			
13	AD14			
14	AD15			
15	JN7			
16	AD6			

Table 29 Complexity ranking of the segmented visual arrays (17 to 24)

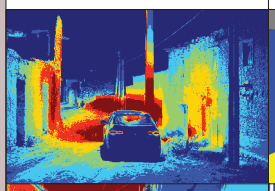
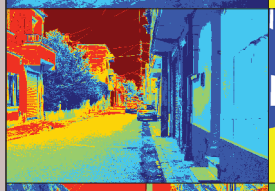
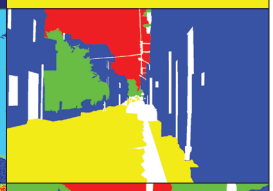
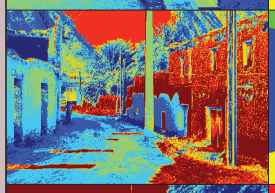
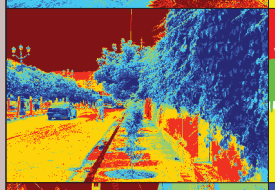
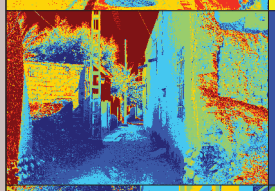
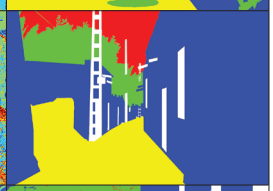
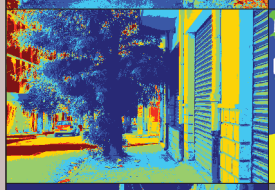
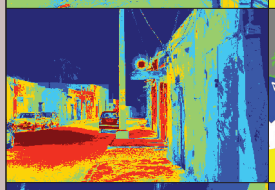
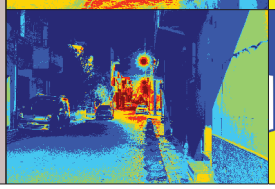
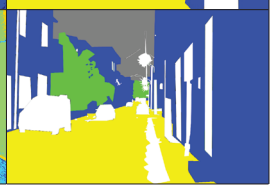
Complexity rank	Visual array		K-means	Segmentation
17	AN18			
18	AD9			
19	AD18			
20	AD7			
21	AD8			
22	AD13			
23	AN6			
24	AN9			

Table 30 Complexity ranking of the segmented visual arrays (25 to 32)

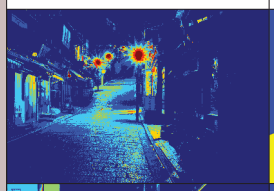
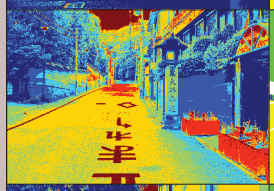
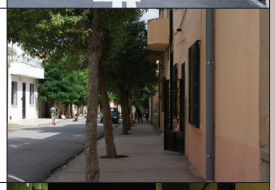
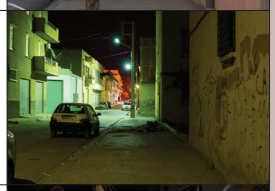
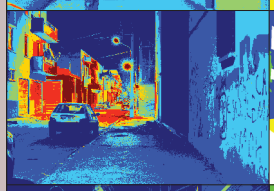
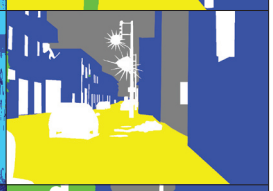
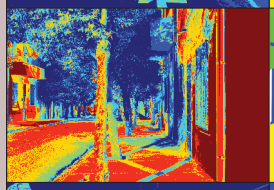
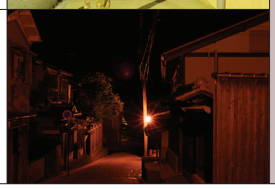
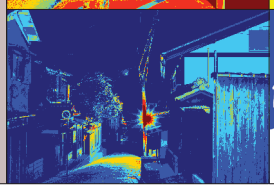
Complexity rank	Visual array		K-means	Segmentation
25	JN11			
26	JN20			
27	JD7			
28	AD1			
29	AN19			
30	JN2			
31	AN1			
32	JN16			

Table 31 Complexity ranking of the segmented visual arrays (33 to 40)

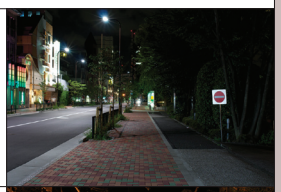
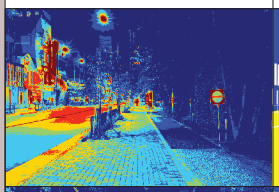
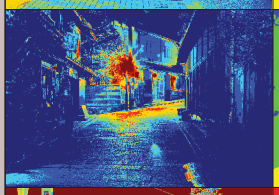
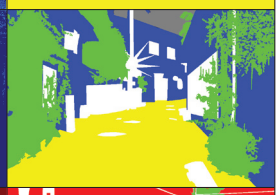
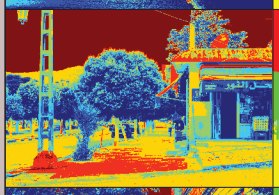
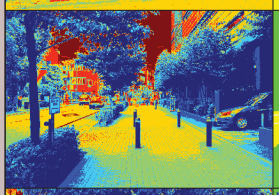
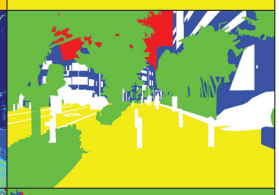
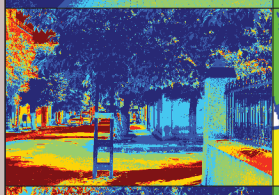
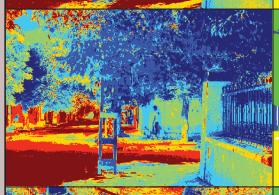
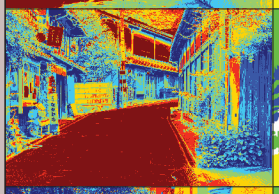
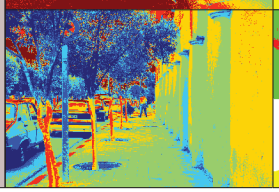
Complexity rank	Visual array		K-means	Segmentation
33	JN12			
34	JN13			
35	AD11			
36	JD10			
37	AD17			
38	AN17			
39	JD13			
40	AD3			

Table 32 Complexity ranking of the segmented visual arrays (41 to 48)

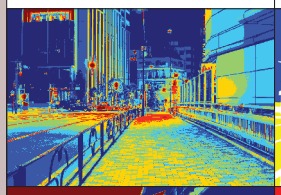
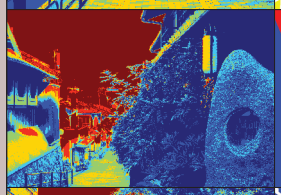
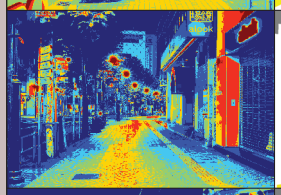
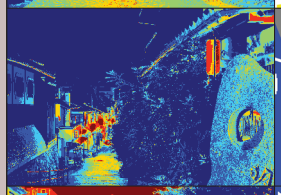
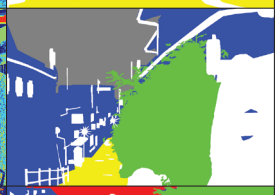
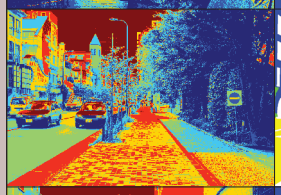
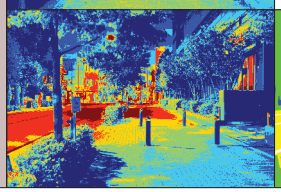
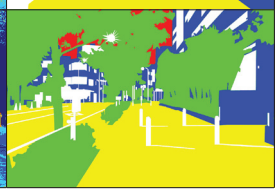
Complexity rank	Visual array		K-means	Segmentation
41	JN8			
42	JD15			
43	JD19			
44	JN6			
45	JN15			
46	JD12			
47	AD19			
48	JN10			

Table 33 Complexity ranking of the segmented visual arrays (49 to 56)

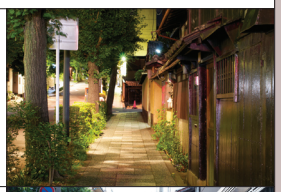
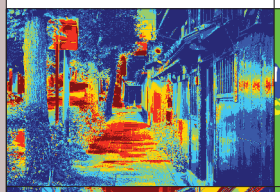
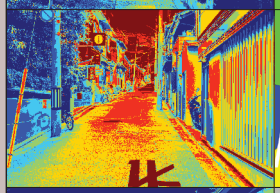
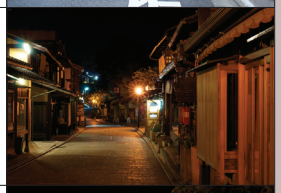
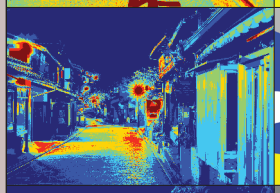
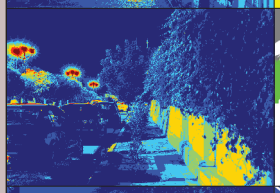
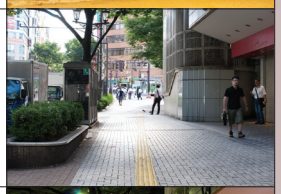
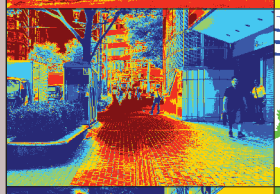
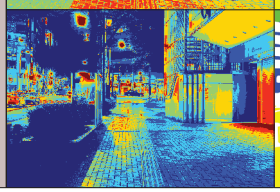
Complexity rank	Visual array		K-means	Segmentation
49	JN5			
50	JD2			
51	JN9			
52	AN7			
53	JN19			
54	AN11			
55	JD4			
56	JN4			

Table 34 Complexity ranking of the segmented visual arrays (57 to 64)

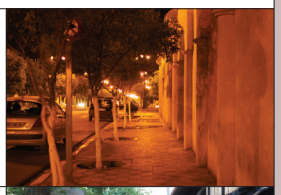
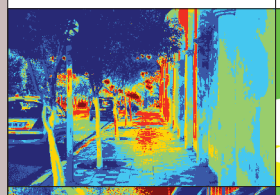
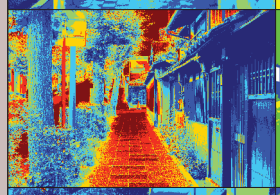
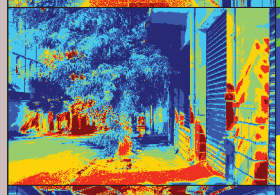
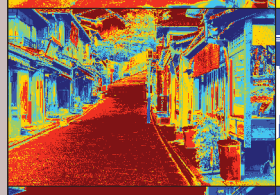
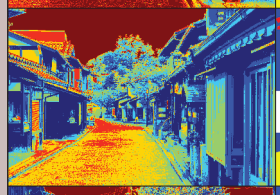
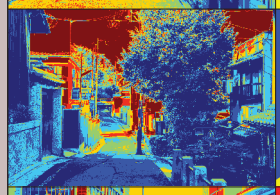
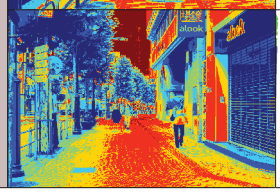
Complexity rank	Visual array		K-means	Segmentation
57	AN3			
58	JD5			
59	AN13			
60	JD11			
61	JD9			
62	JD18			
63	JD8			
64	JD6			

Table 35 Complexity ranking of the segmented visual arrays (65 to 72)

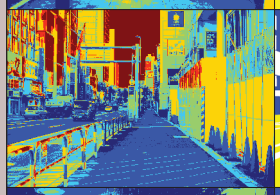
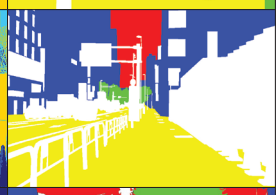
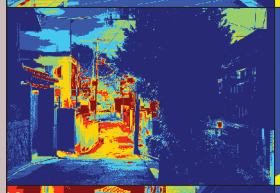
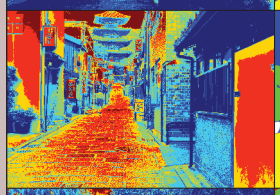
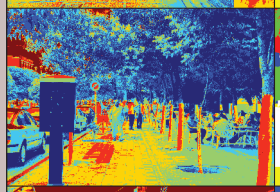
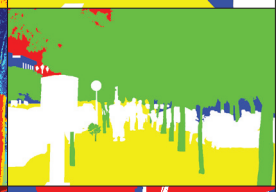
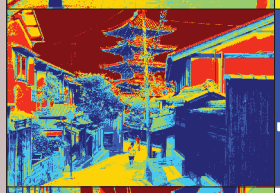
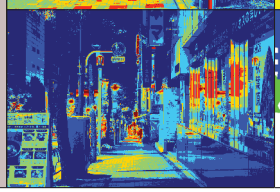
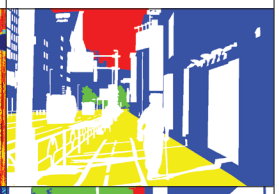
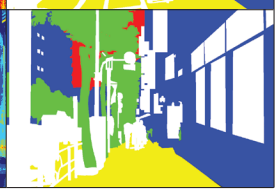
Complexity rank	Visual array		K-means	Segmentation
65	AN5			
66	JD17			
67	JN18			
68	JD20			
69	AD5			
70	JD16			
71	JD1			
72	JN14			

Table 36 Complexity ranking of the segmented visual arrays (73 to 74)

Complexity rank	Visual array		K-means	Segmentation
73	JD3			
74	JD14			

6.3.2 Discussion

The study of the articulation among classes in terms of size represents a preliminary approach for the study of the concept of emergence in streetscape composition. There exist 2 kinds of emergence as a concept in this field of study. The first one is related to perception as proposed by Gestalt theory. The second one is related to the way the parts of the streetscape articulate with each other.

The results of the entropy estimation according to shannon's model shows that the average entropy is increasing from the simple category to the complex one. In this chapter, entropy is an expression of the sizes of the articulated classes within each streetscape. The results show that entropy increases when the classes get close or similar in terms of size (table 37, 38, 39, 40, 41, 42, 43 & 44). This means that complexity within a streetscape, expressed by its degree of entropy as a system, increases when the difference between classes in terms of size decreases.

Table 37 Entropy and class probabilities in all streetscapes (Japanese and Algerian) -Part 1-

Cogn. cluster	Compl. Gr	Rank	Pic.	Actor	Build.	Veget.	Sky	Ground	Unkn.	H(I)	Aver. H(I)
CC6	Simple	1	AD4	0.075	0.731	0.000	0.019	0.159	0.016	1.237	1.799
CC6		2	AN2	0.127	0.627	0.039		0.135	0.072		
CC6		3	AD2	0.034	0.713	0.047	0.049	0.139	0.018	1.434	
CC6		4	AN4	0.144	0.661	0.001	0.000	0.140	0.054	1.428	
CC6		5	AN10	0.144	0.342	0.004	0.000	0.246	0.265	1.968	
CC6		6	AN16	0.355	0.404	0.000	0.000	0.132	0.110	1.794	
CC6		7	AN12	0.017	0.255	0.137		0.325	0.265		
CC6		8	AD10	0.164	0.392	0.036	0.162	0.222	0.024	2.166	
CC6		9	AD16	0.169	0.606	0.011	0.076	0.118	0.019	1.701	
CC6		10	AN15	0.148	0.377	0.109		0.240	0.125		
CC6		11	AD20	0.036	0.459	0.165	0.108	0.198	0.035	2.095	
CC6		12	AD12	0.031	0.222	0.361	0.025	0.340	0.021	1.946	
CC4		13	AD14	0.113	0.597	0.097	0.040	0.126	0.027	1.829	
CC10		14	AD15	0.103	0.378	0.110	0.092	0.290	0.027	2.193	
Axis A											
CC10	Ordinary	15	JN7	0.196	0.223	0.001		0.337	0.243		2.051
CC10		16	AD6	0.220	0.233	0.070	0.204	0.225	0.048	2.401	
CC4		17	AN18	0.155	0.354	0.030	0.048	0.220	0.192	2.249	
CC9		18	AD9	0.075	0.508	0.068	0.092	0.230	0.028	1.988	
CC5		19	AD18	0.106	0.370	0.177	0.055	0.265	0.027	2.195	
CC9		20	AD7	0.025	0.084	0.488	0.162	0.218	0.023	1.967	
CC5		21	AD8	0.041	0.589	0.080	0.072	0.188	0.030	1.809	
CC4		22	AD13	0.199	0.264	0.333	0.001	0.173	0.030	2.099	
CC4		23	AN6	0.199	0.321	0.036	0.000	0.196	0.247	2.123	
CC9		24	AN9	0.145	0.445	0.058	0.000	0.218	0.134	2.031	
CC10		25	JN11	0.011	0.167	0.007	0.000	0.270	0.545	1.541	
CC10		26	JN20	0.127	0.494	0.038		0.241	0.100		
CC10		27	JD7	0.192	0.179	0.223	0.015	0.351	0.040	2.190	
CC9		28	AD1	0.110	0.358	0.303	0.002	0.206	0.022	2.011	
CC5		29	AN19	0.130	0.440	0.002	0.000	0.248	0.181	1.864	
CC10		30	JN2	0.217	0.320	0.116	0.000	0.280	0.067	2.141	
CC5		31	AN1	0.139	0.322	0.313	0.000	0.195	0.032	2.065	
CC9		32	JN16	0.091	0.551	0.067	0.000	0.082	0.208	1.818	
CC10		33	JN12	0.038	0.125	0.369	0.000	0.000	0.468	1.601	
CC9		34	JN13	0.107	0.235	0.315	0.000	0.263	0.080	2.160	
CC5		35	AD11	0.190	0.061	0.256	0.196	0.268	0.029	2.323	
CC8		36	JD10	0.108	0.097	0.401	0.031	0.305	0.057	2.117	
CC3		37	AD17	0.100	0.167	0.480	0.005	0.221	0.027	1.933	

Table 38 Entropy and class probabilities in all streetscapes (Japanese and Algerian) -Part 2-

Cogn. cluster	Comp. Gr	Rank	Array	Actor	Build.	Veget.	Sky	Ground	Unkn.	H(I)	Aver. H(I)
CC5	Ordinary	38	AN17	0.030	0.232	0.483	0.013	0.224	0.018	1.819	2.051
CC9		39	JD13	0.138	0.271	0.281	0.000	0.255	0.054	2.151	
CC7		40	AD3	0.112	0.371	0.298	0.012	0.187	0.019	2.045	
CC8		41	JN8	0.272	0.328	0.016		0.287	0.096		
CC10		42	JD15	0.207	0.328	0.223	0.186	0.030	0.027	2.222	
CC8		43	JD19	0.095	0.123	0.424	0.054	0.238	0.066	2.199	
CC8		44	JN6	0.276	0.235	0.081	0.000	0.241	0.168	2.223	
CC9		45	JN15	0.237	0.276	0.232	0.000	0.034	0.220	2.142	
CC8		46	JD12	0.114	0.118	0.365	0.067	0.301	0.035	2.205	
CC2		47	AD19	0.200	0.461	0.014	0.093	0.197	0.035	2.016	
CC8		48	JN10	0.069	0.116	0.434	0.014	0.299	0.068	2.021	
CC5		49	JN5	0.191	0.376	0.325	0.000	0.079	0.029	1.952	
CC7		50	JD2	0.248	0.272	0.116	0.021	0.302	0.040	2.197	
CC7		51	JN9	0.149	0.013	0.022	0.000	0.174	0.643	1.458	
CC1		52	AN7	0.215	0.086	0.451		0.064	0.184		
CC5		53	JN19	0.181	0.100	0.450	0.055	0.176	0.039	2.149	
CC1		54	AN11	0.188	0.070	0.244		0.260	0.238		
CC7		55	JD4	0.276	0.245	0.131	0.019	0.297	0.033	2.182	
CC7		56	JN4	0.255	0.290	0.122	0.017	0.271	0.045	2.203	
CC1		57	AN3	0.107	0.365	0.315		0.181	0.032		
CC7		58	JD5	0.161	0.299	0.355	0.010	0.143	0.030	2.100	
CC3		59	AN13	0.199	0.262	0.334	0.001	0.175	0.029	2.095	
Axis B											
CC5	Complex	60	JD11	0.188	0.384	0.077	0.003	0.311	0.037	1.993	2.012
CC5		61	JD9	0.246	0.341	0.010	0.120	0.190	0.092	2.234	
CC7		62	JD18	0.068	0.342	0.327	0.090	0.128	0.044	2.213	
CC1		63	JD8	0.421	0.273	0.009	0.061	0.200	0.036	1.980	
CC7		64	JD6	0.319	0.220	0.160	0.011	0.243	0.047	2.204	
CC1		65	AN5	0.142	0.009	0.519	0.000	0.001	0.329	1.487	
CC7		66	JD17	0.389	0.253	0.009	0.052	0.261	0.037	1.995	
CC2		67	JN18	0.078	0.342	0.320	0.092	0.113	0.054	2.244	
CC1		68	JD20	0.237	0.402	0.040	0.013	0.253	0.056	2.022	
CC1		69	AD5	0.187	0.017	0.521	0.017	0.227	0.032	1.785	
CC2		70	JD16	0.083	0.571	0.087	0.150	0.071	0.037	1.925	
CC1		71	JD1	0.379	0.316	0.035	0.032	0.202	0.036	2.023	
CC1		72	JN14	0.365	0.353	0.175		0.050	0.058		
CC1		73	JD3	0.351	0.382	0.008	0.058	0.143	0.057	1.990	
CC1		74	JD14	0.378	0.314	0.159	0.015	0.098	0.036	2.070	

Table 39 Average entropy in all Japanese streetscapes (daytime and nighttime)

Complexity Group	Average Entropy
Simple	
Ordinary	2.046
Complex	2.074

Table 40 Average entropy in Japanese daytime streetscapes

Complexity Group	Average Entropy
Simple	
Ordinary	2.174
Complex	2.074

Table 41 Average entropy in Japanese nighttime streetscapes

Complexity Group	Average Entropy
Simple	
Ordinary	1.951
Complex	

Table 42 Average entropy in all Algerian streetscapes (daytime and nighttime)

Complexity Group	Average Entropy
Simple	1.799
Ordinary	2.057
Complex	

Table 43 Average entropy in Algerian daytime streetscapes

Complexity Group	Average Entropy
Simple	1.825
Ordinary	2.072
Complex	

Table 44 Average entropy in Algerian nighttime streetscapes

Complexity Group	Average Entropy
Simple	1.73
Ordinary	2.035
Complex	

6.4 Summary

As analyzed in the previous chapter, Japanese streetscapes show higher entropy, especially in daytime, than Algerian streetscapes. The common concept is the inverse proportionality between the degree of complexity of a streetscape and the difference between classes in terms of size. The logic by which the composing classes are articulated seems to influence the degree of complexity of the resulting scene or streetscape.

Conclusion

Conclusion

This research is a comparative and explorative study about complexity, entropy and emergence within streetscape composition in two different urban morphological contexts, Algeria and Japan.

The first main phase of the study was based on the clustering of different randomly selected streetscapes from different sites in both contexts, Algeria and Japan. The evaluation of their degrees of complexity was done by 2 groups of subjects.

Different behavior analysis methods have been used throughout this comparative study, from cluster analysis to the factorial scoring of data. Even if the author could notice many interesting points by comparing the judgments of these 2 groups of subjects, the evaluation of the relationship between entropy and the complex composition of streetscapes based on their subjective evaluation of complexity would be a very difficult process because of the sensitivity of the concept of entropy.

Therefore, as a conclusion of Chapter 4, and for better conditions related to the experiment, the author opted for one homogeneous group of subjects, with a background in Architecture, and using a High definition screen for a better streetscapes presentation. A more simplified scoring scale, based on three categories of evaluation: simple, ordinary and complex helped in avoiding confusions for subjects.

The results of the analyses presented in Chapter 3 were quite meaningful. The research could figure out and confirm the hypotheses postulated in the early stages of the research, related to the increase of complexity from the smallest scale to the bigger one, that of the whole streetscape visual composition.

Compared to Japanese streetscapes, Algerian streetscapes dominate the simple

the complex groups.

The Application of nearest neighbor method in Chapter 5 and Shannon's model in Chapter 6 always showed that entropy in Japanese streetscapes is higher than in Algerian ones. The estimation of entropy in the lower scale is based on pixel intensities and seems to be directly proportional to complexity. In the higher scale, complexity increases when the classes that compose the street scene are close or similar in size. Complexity is then inversely proportional to the difference between classes in terms of size.

This research explored emergence via the concept of entropy by analyzing the streetscape in lower and higher scales. Complexity on the small scale of a pixel leads to the emergence of more complex patterns on a higher scale, the one of the classes for example.

This research is still in its early stages. Futures researches will aim to study the nature and characteristics of the classes composing urban scenes. What kind of classes are they? And how do human cognition deal with them?

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