Methodological Study on Structured Landscape Assessment for Landscape Planning Based on Visual Components

視覚的構成要素に基づく景観計画のための構造化された景観評価手法に関する方法論的研究

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

By

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SAITAMA UNIVERSITY

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Submitted to the Course of Environmental Science and Infrastructure Engineering in the

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Affectionally Dedicated

To

My Beloved Husband

And

Three Sons

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ABSTRACT

This study was conducted with the objective of finding out the perceivable effect of figures and backgrounds of the residential streetscapes, and their connections on visual complexity. The visual complexity depends on the amount of information a viewer can observe from visible area. The information includes a number of visual elements along the streetscapes, and their diversity and inter-connections. The aim of this research was to analyze the structural hierarchical visual complexity of the streetscapes, caused by varied spatial arrangement and numerous spatial connections of the perceivable visual elements. The visual elements of 70 residential streetscapes from urbanization controlled, medium urbanized and highly urbanized areas at the vicinity of Saitama University, Japan, were classified into figures and backgrounds using human perception of 20 subjects. The identified figures and backgrounds were arranged in a taxonomic diagram representing their connections. These taxonomic diagrams reflect the structural hierarchical visual complexity. Finally, taxonomic entropy was applied to statistically analyze the structural hierarchical visual complexity. When the taxonomic diagram is vertically and horizontally lengthy and the arrangement of the elements of taxonomic diagram is irregular, the complexity becomes high depicting a large number of figures whose spatial connections impart high visual complexity to the streetscapes.

Keywords: structural hierarchical visual complexity, figures and backgrounds, taxonomic diagrams, taxonomic entropy, urbanization

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CHAPTER ONE

INTRODUCTION

1.1 Background

Streets are important elements of a city, and, especially, residential streetscapes are important places to perceive and appreciate the quality of life of the residents. Street is a narrow and linear urban space lined by buildings, which is used for movement and other activities. The street, frontage of residential buildings along the street, commercial sign boards, skyline, street pavement, lighting, vegetation and etc. are all important parts of a street's visual elements. These visual elements are cumulatively responsible for the visual complexity of the streetscape. Visual complexity is an important phenomenon in landscape planning to create a pleasant environment to the people live in the place and for the visitors. Therefore understanding and measuring the visual complexity is very important in landscape and urban planning.

Definition of complexity differs from the subject it uses. There should be two or more components, to have a complexity. Similarly, the Oxford Dictionary defines something as "complex" if it is "made of (usually several) closely connected parts". Intuitively then, a system would be more complex if more parts could be distinguished, and if more connections between them existed. Therefore complexity has two aspects; distinction and connection. The aspects of distinction and connection determine two dimensions characterizing complexity. Distinction corresponds to variety, to heterogeneity, to the fact that different parts of the complex behave differently. Connection corresponds to constraint, to redundancy, to the fact that different parts are not independent, but that the knowledge of one part allows the determination of features of the other parts. Distinction leads in the limit to disorder, chaos or entropy. Complexity can only exist if both aspects are present: neither perfect disorder (which can be described statistically through the law of large numbers), nor perfect order (which can be described by traditional deterministic methods) are complex. It thus can be said to be situated in between order and disorder, or, using a recently fashionable expression, "on the edge of chaos" (Heylighen, 1996).

Visual complexity is traditionally defined as the level of features contained within a place or an image. It varies with the number of visual elements present in the visible area, and the diversity of the elements and their arrangement in space (location and orientation). In environmental psychology, visual complexity is related to the involvement component, which translates into enquiring "how much there is to see in a visual array?", and to the concept of affordance that refers to what a perceived scene has to offer as far as the perceiver is concerned (Kaplan, 1988). Complexity is broadly of four categories; (i) structural complexity, based on spatial dimensions of objects; (ii) functional complexity, based on temporal dimension of objects; (iii) structured hierarchical complexity, based on spatial scale of the objects and (iv) functional hierarchical complexity, based on temporal scale of the objects (Heylighen, 1996). Complexity is regarded as an important variable of formal aesthetics (Berlyne, 1974). Berlyne contends that the complexity of a pattern increases with increasing number of independently selected elements it contains. Thus, complexity can be defined in many ways, and measuring complexity is important for the identity of a landscape and for maintaining appropriate complexity among visual elements to ensure proper balance between nature and the manmade landscapes.

This research is a novel approach to study the variation in visual complexity, which depends on the spatial arrangement and the spatial connections of perceivable visual elements along the streetscapes. For this analysis, two approaches were applied; the Gestalt's concept of figure and background and the taxonomic entropy which have never being used in literature to measure the visual complexity.

1.2 Research Strategy

There are many methods in literature to measure visual complexity, some of them being statistical approaches and some manual approaches. Most of them measure complexity, based on the number or the appearance of the visual elements. The method proposed here is different from the existing ones in two ways: first, this study measures structural hierarchical visual complexity, not the simple structural visual complexity, which- most of the past researchers used to measure; second, in measuring the structural hierarchical visual complexity, two technique, which are new to the visual complexity measurement were applied, namely Gestalt's figure and background concept and the taxonomic entropy. The spatial arrangement and the spatial connections of visual elements along the streetscape are responsible for the structural hierarchical visual complexity. Visual elements could be classified into figures and backgrounds, based on the Gestalt's theory. One visual element may contain more than one figure or background. Using cues of differentiating figures and backgrounds, the perceivable figures and backgrounds in main visual elements can be identified. The sequence of arrangement of these figures and backgrounds and their mutual connections can be visualized through taxonomic diagrams. The taxonomic diagrams represent the structural hierarchical visual complexity. This is a novel approach for measuring visual complexity. The hypothesis applied for this research is that, when the spatial arrangement and the spatial connections of the figures and backgrounds along streetscape become complex, the visual complexity becomes high; therefore, visual complexity can be measured by analyzing the taxonomic diagrams of figures and backgrounds. For this analysis, taxonomic entropy was applied. Thus, for this research an attempt was made to introduce a new method for measuring structural hierarchical visual complexity by using Gestalt's explanation on the figure and background and the taxonomic entropy.

Besides, measuring structural hierarchical visual complexity is important in setting landscape planning regulations. Since structural hierarchical visual complexity properly represent the human perception of the visual elements, the visual complexity value given through this measurement expresses about the actual condition of the visual complexity of the landscape. Therefore, having structural hierarchical visual complexity values to different landscape types is helpful in preparing best and balanced landscape planning's for different landscape types in the future as well as it is helpful to rebuild the existing landscape to match with the human perception.

1.3 Importance of the study

Human has a limit of acceptance of visual complexity. Berlyne, 1971 researched on this and he has found that when the visual complexity increase gradually, the preference or pleasure created by the scene decrease gradually. Figure 1.1 displays this relationship.

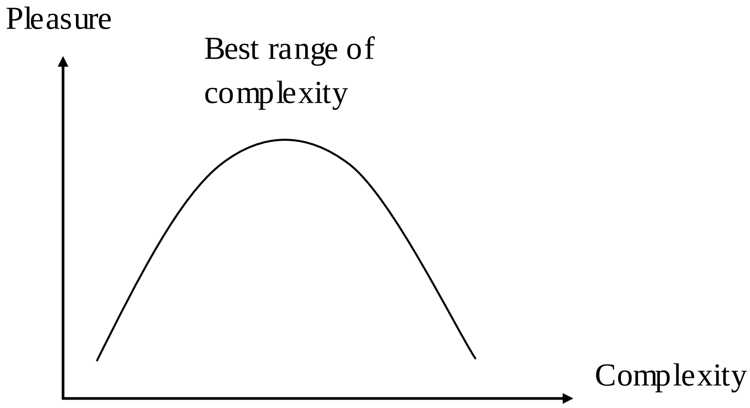


Figure 1.1: Relationship between Complexity and Pleasure

Viewers have a range of complexity that will give a maximum pleasure by viewing the scene. When the complexity is below this level or over this level, the curiosity to see the scene becomes decrease. Therefore, it is important to plan the landscapes to lie within this range of pleasurable complexity. To find out this complexity level, there should be a proper analysis method. Thus through this research a new approach is introduced to find out this best complexity levels in different landscapes.

Therefore this research is unique and important, since this study introduced new approaches to measure the structural hierarchical visual complexity which is more important than just simple visual complexity and the values obtained through this method are very important in setting landscape planning regulations.

CHAPTER 2

LITERATURE REVIEW

2.1 Complexity

There has been a lot of research on complexity and complex systems. However, there is no agreement over the formulation of the notion of complexity in the science(s) of complexity. Complexity is very difficult to define. The dozens of definitions that have been offered all fall short in one respect or another. Moreover, these definitions are applicable to the domain the researches are dealing with. However in any domain, in order to have a complexity, there should be at least two aspects to be satisfied; they are distinction and connection. Distinction implies the system should have at least two components and connections imply these two parts should join in such a way that it is difficult to separate them.

Thus complexity increases when the variety (distinction), and dependency (connection) of parts or aspects increase, and this in several dimensions. These include at least the ordinary 3 dimensions of spatial, geometrical structure, the dimension of spatial scale, the dimension of time or dynamics, and the dimension of temporal or dynamical scale. In order to show that complexity has increased overall, it suffices to show, that - all other things being equal - variety and/or connection have increased in at least one dimension (Havel, 1995).

The process of increase of variety may be called differentiation, the process of increase in the number or strength of connections may be called integration. The complexity produced by differentiation and integration in the spatial dimension may be called "structural", in the temporal dimension "functional", in the spatial scale dimension "structural hierarchical", and in the temporal scale dimension "functional hierarchical".

It may still be objected that distinction and connection are in general not given, objective properties. Variety and constraint will depend upon what is distinguished by the observer, and in realistically complex systems determining what to distinguish is a far from trivial matter. What the observer does is picking up those distinctions which are somehow the most important, creating high-level classes of similar phenomena, and neglecting the differences which exist between the members of those classes. Depending on which distinctions the observer makes, he or she may see their variety and dependency (and thus the complexity of the model) to be larger or smaller, and this will also determine whether the complexity is seen to increase or decrease (Heylighen, 1996).

2.1.1 Visual complexity

Visual complexity is traditionally defined as the level of features contained within a place or an image. It is based on the number of visual elements present in the visibility area, diversity of the elements and the arrangement of them in the space (location and orientation). 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 that refers to what a perceived scene has to offer as far as the perceiver is concerned (Kaplan, 1988). Complexity has been regarded as an important variable of formal aesthetics (e.g. Berlyne, 1974, 1977). Berlyne (1974) stated that the complexity of a pattern increases with the increasing number of independently selected elements it contains. Complexity perceived by each individual depends on the way he or she perceptually organizes the scene: "The collative variables are actually subjective, in the sense that they depend on the relations between physical and statistical properties of stimulus objects and processes within the organism. A pattern can be more novel, complex, or ambiguous for one person than for another or, for the same person, at one time than at another. Nevertheless, many experiments, using rating scales and other techniques, have confirmed that collative properties and subjective informational variables tend, as one would expect, to vary concomitantly with the corresponding objective measures of classical information theory" (Berlyne, 1974b).

Thus complexity can be defined in many ways and measuring complexity is important for the identity of the landscape and to maintain an appropriate complexity among landscapes to have a proper balance between nature and the manmade landscapes.

2.2 Diversity

Defining diversity is also a difficult task just similar with complexity. Diversity is explained in many ways by many scientists. Collins dictionary (1991), defines diversity is the state or quality of being different or varied. In another definition diversity explains as the relation that holds between two entities when and only when they are not identical or the property of being numerically distinct. In biology diversity defines as a composite measure of richness and evenness and can be computed in a variety of forms (e.g., Shannon and Weaver 1949, Simpson 1949), depending on the relative emphasis placed on these two components. Pyron (1972), explained diversity as the degree of uncertainty within a given enclosing space while Kuiper (1998) explained the diversity of landscape components as the expression of vertical relationships between land use and abiotic features.

2.2.1 Visual diversity

Visual diversity is the degree of diversity sense by the landscape users and the visitors to the landscape. Visual diversity is a commonly regulated design principle in promoting visual diversity, avoiding monotony, avoiding chaos, or a combination of all three. (Duerksen and Goebel, 1999; Lightner, 1993). The physical condition of the landscape is not always visible to the viewers. They want to see the relation between the beauty of the landscape and its richness in terms of bio-ecological factors. It gives a visual quality to the landscape. If there is no diversity, the landscape is completely identical. An identical space is tedious to the landscape users and to the viewers. If the landscape is completely diverse in nature, it moreover makes a hectic view to the users. Thus there should be a good interaction between diversity and the similarity of landscape to make it a pleasurable place to the users and the visitors to the place.

In this regard, measuring diversity unit by unit is not important. The main aim is to measure diversity of the landscape features that are visually important for the landscape viewers. Visual diversity is a subjective phenomenon. Feeling of visual diversity changes person to person. For one person a specific landscape feels as a highly diverse environment while another may explain it as a good combination of diversity and similarity. Hence the definition and the measurement of visual diversity ought to be carried out with a good concern.

2.3 Difference between complexity and diversity

Diversity considers about one aspect; it is the variety. To have diversity the elements should be different to each other. However complexity needs to satisfy at least two aspects; variety and connections. It implies that complexity is more advanced than the diversity.

In landscape assessments, there are lots of methods to measure both diversity and complexity. Some researchers have applied same technique to measure both diversity and complexity. Since diversity and complexity show a significant difference, the use of same method to measure both diversity and complexity is not successful, because the methods applied to measure diversity only considers about one aspect, that is variety, therefore applying same method to measure complexity will neglect the other important aspect of complexity that is connections.

Therefore through this research, a new approach has been introduced to measure the complexity in proper way by measuring both aspects; variety and connections.

2.4 Methods applied in literature to measure diversity

For better understanding of the uniqueness of the present research, following two chapters discuss the available diversity and complexity measuring techniques. Getting an idea about the available techniques will be helpful to understand the originality of the present study.

Carranza, et.al. (2007), analyzed the landscape diversity using Reny's generalized entropy function. In order to demonstrate its application they analyzed recent historic landscape diversity changes focusing on the evolution of boundaries between patches in the town of Isernia (central Italy). For this purpose they used three 1:25,000 land cover/vegetation raster maps (1954, 1981 and 1992) to find out the changes in landscape diversity by measuring the variation in the extension of boundary types between adjacent land cover categories (patches) from 1954 to 1992. To do this, Renyi's diversity curves for each year were built and compared. The major advantage in applying the Renyi's generalized parametric diversity function to analyze landscape changes in time is that diversity profiles do not display a single index. In fact, a family of indexes is shown.

Thus in this research the main idea was to measure the diversity changes through measuring the variation in the extension of landscape boundaries. In other words it measured the change of quantity of different landscape types during specific time period.

Another diversity measuring technique is the use of fractals. Fractals can be used to describe the spatial patterns in the variety of landscape level applications (Burrough, 1986; O'Neill, et.al. 1988; De Cola, 1989). Fractals hove been used recently to describe spatial patterns in many iandscape-leve1 applications. One such application has been to measure the geometric complexity of landscape features. Olsen, et.al. (1993), applied a modified fractal dimension as a measure of distribution of landscape diversity in a classified GIS image. The resulting modified fractal dimension calculation consistently describes diversity for the landscape, accounting not only for patch shape, but also for patch juxtaposition and evenness.

In this research also the fractals were used to measure the physical attributes of the landscape. It doesn't measure the connections among the physical attributes.

Rocchini, et.al. (2012) proposed a GRASS GIS based approach to measure the landscape diversity. It has been demonstrated that the relation between species and landscape diversity measured from remotely sensed data or land use maps varies with scale. However, Free and Open Source tools (allowing an access to the source code) for assessing landscape diversity at different spatial scales are still lacking today. In their research they aim at: i) providing a theoretical background of the mostly used diversity indices stemmed from information theory that are commonly applied to quantify landscape diversity from remotely sensed data and ii) proposing a free and robust Open Source tool (r.diversity) with its source code for calculating diversity indices (and allowing an easy potential implementation of new metrics by multiple contributors globally) at different spatial scales from remotely-sensed imagery or land use maps, running under the widely used Open Source program GRASS GIS. They says r.diversity will be a valuable tool for calculating landscape diversity in an Open

Source space given the availability of multiple indices at multiple spatial scales with the possibility to create new indices directly reusing the code.

In this study also they discussed only about the variety aspect.

Gunger (2013) conducted a research to measure the plant species diversity in Turkey Kazdagi national park. He has highlighted three main concepts in biodiversity: genetic diversity, species diversity and ecosystem diversity. In his research he measured species diversity in mountain ecosystems or alpine regions above the timberline, which is rich in terms of plant compositions and plant species diversity. Richness and evenness are two main factors in measuring the diversity of a habitat. Richness takes into account individual species, while evenness contributes towards the relative abundance of each species. According to the results of this study, 52% of the total endemic plant taxonomy of the Kazdağı National Park is determined in the alpine regions and therefore the alpine zones, with their rich endemic and rare plant species, are important from the aspect of biodiversity and species conservation. In addition, this study describes the relation between environmental factors and plant species diversity and evenness.

However this research is also dealing with only the variety aspect. They were no measurements on the connections among different species.

Some researchers applied diversity indices commonly use in biodiversity to measure landscape diversity. A diversity index is a quantitative measure that reflects how many different types (such as species) there are in a dataset, and simultaneously takes into account how evenly the basic entities (such as individuals) are distributed among those types. The value of a diversity index increases both when the number of types increases and when evenness increases. For a given number of types, the value of a diversity index is maximized when all types are equally abundant (Hill, 1973).

Landscape diversity indices continue to be employed by landscape ecologists to describe the composition of a landscape using a single number (e.g. Turner, 1990; Rey-Benayas & Pope, 1995; Riitters et al., 1995). Positive relationships between indices of species and landscape diversity have been noted by many researchers like Noderhaug, Ihse, & Pedersen (2000), Pino, Roda, Ribas, & Pons (2000). Stamps III (2003), in his study “Advances in visual diversity and entropy” introduced the applicability of Shannon’s entropy to measure the visual diversity. He addressed three questions in his study; (a) how to measure it? (b) what is the function between visual diversity and pleasure?, and (c) is the function between visual diversity and pleasure the same for different kinds of stimuli? To find the solutions for these questions he applied Shannon's entropy.

This equation originally created as a measure of physical disorder, entropy was reinvented in 1949 as a measure of disorder in information (Shannon, 1949; Shannon and Weaver, 1998). Entropy is zero if everything is the same and entropy is maximized if each thing is different. Because total sameness is uniformity, and each thing being unique is the maximum possible amount of diversity, entropy should be a strong candidate as a physical measure of subjective impressions of diversity. The basic equation for entropy is:

$$H = -\sum_{i=1}^{n} \mathrm{Pi} \log \mathrm{Pi} \qquad \text{Eqn 01}$$

Where Pi is the probability of i^{th} visual element, n is the total types of visual elements and H is the entropy value.

To check the applicability of entropy to measure diversity, he used computer simulations with 5 different factors and their levels. Figure 2.1 displays the used factors and their levels.

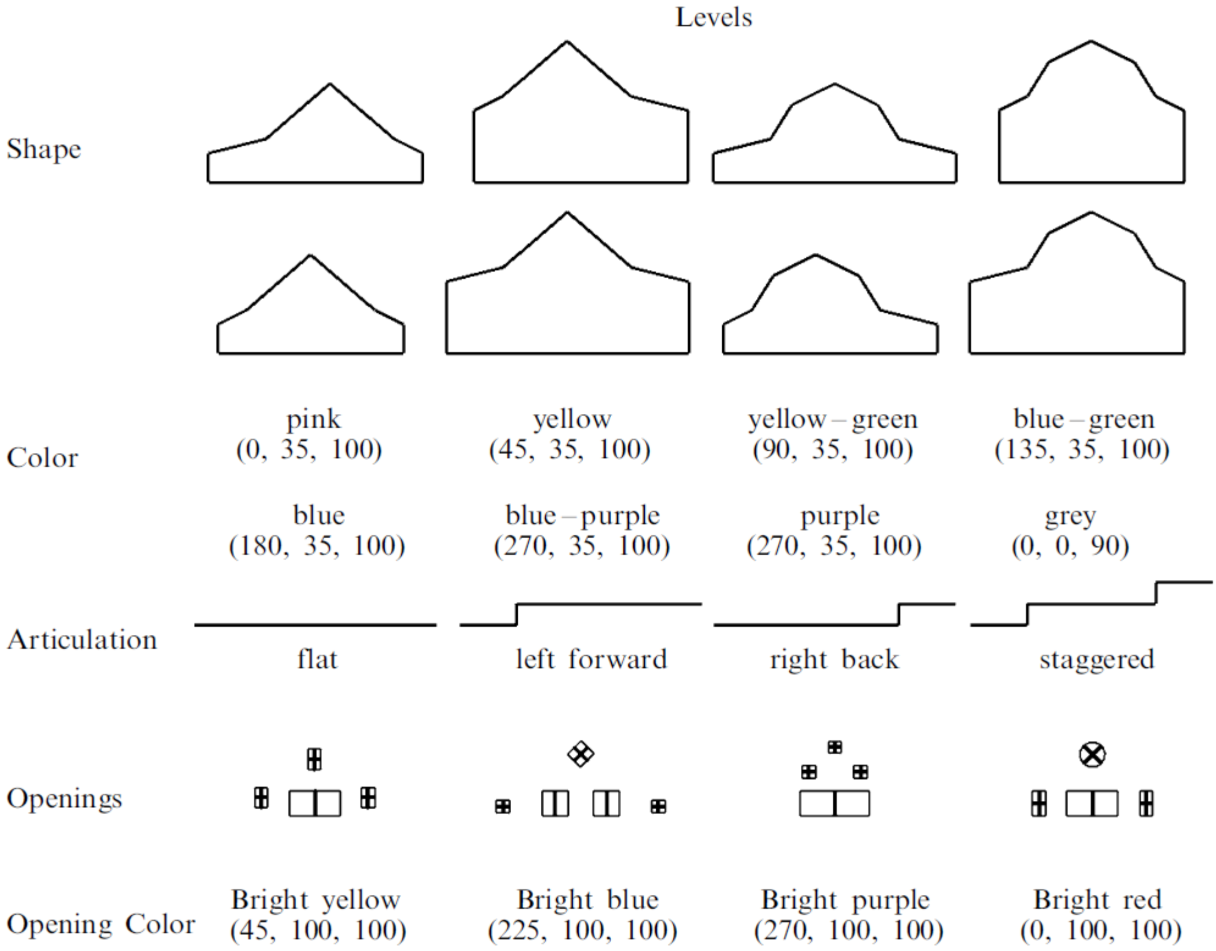


Figure 2.1: Factors and Their Levels Applied to Measure Visual Diversity

Using a group of subjects he analyzed the simulated images with these factors and levels. Then he found out the entropy values for least diversity and highest diversity. Figure 2.2 and 2.3 display the images with least diversity and highest diversity.

Figure 2.2: Image with Least Diversity. Entropy: 0.0

Figure 2.3: Image with Highest Diversity. Entropy: 12

Stamps III finally concluded that the Shannon's entropy can be applied successfully to measure the visual diversity of landscapes. After his experiment, many researchers followed his findings and applied entropy to find out the diversity as well as complexity of landscapes.

However, Dusek and Popelkova (2012), explained the limitations of applying Shannon's entropy to measure the landscape diversity. In his study, "Theoretical View of the Shannon's Index in the Evaluation of Landscape Diversity" he stated that, accurate evaluation of landscape diversity from Shannon's entropy is rather complicated. The aim of the article is (i) to take a closer look at the theoretical origin of the formula that stems from the principles of the calculation of information entropy and (ii) to draw attention to several issues connected to the Shannon index application in landscape diversity assessment. Numeric value of the Shannon's index depends on applied logarithm base that is not precisely specified by the formula. Presenting the resulting Shannon index value without stating the logarithm base is not very suitable. Nevertheless, a bigger problem is the dependence of the resulting Shannon's diversity index value on two parameters, namely the number of studied categories and evenness of spatial distribution of individual categories. The resulting value may be identical for different types of the division of the study area. Therefore, the number of categories and the evenness of spatial distribution need to be taken into consideration in the very assessment of the Shannon index result. The number of categories could also be presented along with the resulting Shannon's index value. A major drawback of the Shannon index is its inability to express spatial distribution of patches within the area; it only presents the total extent of each category. Out of existing modifications of the index that try to take spatial distribution into consideration, the most convenient is the coefficient of the distance between the extent of identical and different categories. Based on arguments deriving from theoretical basis of the Shannon index formula and its practical application, a new view of landscape diversity maximum is presented. The application of the Shannon index disregards the fact that the original relation required for entropy calculation presupposes independence of the existing state (e.g. land cover categories in case of landscape assessment). With regard to the fact that commonly defined categories of patches are independent; the index calculation should make use of the relation considering conditional probabilities of the occurrence of a certain category.

The conclusion comes from the Shannon's entropy for this study is, it is also a measure of variety only. It doesn't address the aspect; connections. Therefore, having above limitations and neglecting the connections aspect are major drawbacks of this equation to apply in measuring visual complexity in landscapes.

Another interesting study was conducted by Nassauer (1988). In his research conducted in the PO Valley region in Italy, found the correlation between the beauty of a landscape and its richness in bio-ecological terms. For this experiment he applied only the subjective analysis techniques. For example, he found out the elements which visually characterize the landscape, amongst which are hedges, springs, rows of poplars and willows, are not only leftovers from the traditional rural landscape giving beauty to the surrounding, but also provide important habitats which can contribute to the heterogeneity and therefore the ecological quality of the agricultural land.

Space syntax theory was also applied by many researchers to measure landscape diversity. One such experiment was conducted by Tucker,et.al. (2005). In his study he used space syntax method to analyze the visual diversity on streetscapes. By considering the open spaces generated by the existence of an interdependent built boundary extending in scale from the individual house through to the streets that form cities, space syntax attempts to explain human behavior as it occurs in those spaces. Describing the visual character of a streetscape through analysis of its spatial configuration might then provide an objective measure within a planning field that is dominated by qualitative methods.

2.5 Methods applied in literature to measure complexity

Section 2.4 discussed briefly about the past researches on diversity assessment of landscapes. This section explains about some common complexity measurement techniques applied in the literature.

In streetscapes, the interest and preference of pedestrians is shown to heavily depend on the perceived complexity (Kaplan, 1972). Specifically, pedestrians are apt to prefer streets perceived as high in complexity. Streetscape complexity is also found to influence driving behavior and performance (Jahn, et.al, 2005). Therefore proper measurement and quantification of the visual complexity is beneficial for the urban life of a city.

There are a number of methods to measure the visual complexity. One popular method is the use of fractal dimension. Section 2.4 explained the use of same method to measure diversity as well. This parameter describes how the patterns occurring at different magnifications combine to build the resulting fractal shape (Mandelbrot, 1977). For Euclidean shapes, dimension is described by familiar integer values - for a smooth line (containing no fractal structure) fractal dimension has a value of one, whilst for a completely filled area (again containing no fractal structure) its value is two. For the repeating patterns of a fractal line, fractal dimension lies between one and two and, as the complexity and richness of the repeating structure increases, its value moves closer to two (Mandelbrot, 1977). However, this method also considers only one aspect of complexity, that is variety.

Another interesting research was conducted by Attneave (1957). He showed that for scenes containing abstract shapes, certain visual characteristics (which he named symmetry, curvedness, angular variation, etc) was related to the perception of visual complexity. By combining these characteristics into a single equation, Attneave created an objective measure which was correlated with human judgments on visual complexity. Again attneave's attempt was limited to one of the aspects of complexity that is variety.

Another way of measuring complexity is the use of spatial frequency. It is reported that the amplitude of high-frequency components must be preserved for complex objects to be recognized (Campbell, 1968). Similarly, specific relationships among frequency components in the phase spectrum are crucial for visual recognition of complex scenes (Piotrowski & Campbell, 1981). Based on the characteristics of spatial-frequency, Nasanen et al. (1993) derived a complexity measure defined as the product between the effective image area and median frequency of the Fourier spectrum. Chikhman et al. (2012) used the components of this measure to analyze complexity in hieroglyphs and contour images. These methods did not address the connections among visual attributes. Thus they are having shortcomings in measuring complexity.

Some researchers have shown the presence of image edges is related to visual complexity. This inspired a simple and efficient measure known as perimeter detection. The measurement consists of counting the number of pixels which form image edges. This procedure can be easily applied on real-world scenes by using edge-detection algorithms (Forsythe, et.al, 2003).

Rosenholtz et al. (2005) proposed a framework called feature congestion to measure visual clutter, a concept closely related to complexity. Within this framework, several image characteristics such as contrast, color and orientation are combined into a vector space. Clutter is then determined by the covariance of the space calculated at each location of the image.

Another visual complexity measurement method was based on the idea of computing visual complexity according to the definitions of information theory (Donderi, 2006). An example of information based measure is the size in bytes of the image digital file created according to coding standards such as JPEG and TIFF. Theoretically, file size should increase as the amount of information increases.

Some researchers applied statistical approaches like Shannon's entropy to measure visual complexity (Rosenholtz & Nakano, 2007) after it was introduced to landscape assessments by Stamps III in 2003. However applying Shannon's entropy is questionable after showing the problems associated with the applicability of this equation by some researchers.

Another interesting approach was undertaken by Elsheshtawy (1997). He used a manual approach to segment meaningful elements of street houses such as windows, doorways and overall volumes of facades. Complexity was then measured based on the number and variety of those elements. Cooper (2003) also used a manual technique to segment street skylines. Then, he used fractal dimension to assess the complexity of these skylines.

Chipman (1977) adopted a different approach to measure visual complexity. In a series of seven experiments she explored the determinants of the perceived complexity of visual patterns. She used a series of 45 stimuli from a 6 x 6 black and white square matrix. Each stimulus contained 12 black squares. Some of the stimuli were randomly created, whereas other was created by the author by arranging the black squares to form a variety of patterns and symmetries. The subjective complexity of each of the stimulus was gathered by means of verbally expressed scores. Each participant was asked to estimate the complexity of a sample of the stimuli while computer programs calculated a series of complexity measures for each stimulus. These measures included the number of corners, (perimeter) 2/area, horizontal symmetry, diagonal symmetry, opposition symmetry (opposite colors), repetitions, and rotations. The results reveal that there are two important components in relation to the subjective determination of the visual complexity of a stimulus. The first one was the number of corners. The second one related with symmetry, rotation, and the repetition of motifs. Although she found that there are different determinants which affect the visual complexity, she had not addressed one of the most important aspects in complexity, which is connection among different sections.

Another important study was conducted by Rump (1968). He empirically examined intercorrelations among the different aspects of visual complexity. He compared people's preference for stimuli varying in asymmetry, multiplicity, and heterogeneity, using different materials for each test, designed to vary in only one of the dimensions. He registered the preference scores awarded to the stimuli by group of subjects and found that there was no correlation between the three scores. That is, people that preferred asymmetrical figures did not necessarily prefer pictures with many elements, nor figures with different elements. The author interpreted these results as an indication that a general concept of complexity is meaningless. Instead, researchers should specify the specific dimension of complexity manipulated in the study. Moreover, Rump (1968) suggested that people's assessment of the complexity of an image may differ depending on the feature they focus on primarily. Thus the conclusion which can be obtained through this research is the complexity varies incident to incident. From only one method it is difficult to measure all the aspects of complexity and it is impossible to introduce one method to match with all the requirements or all the aspects related with complexity.

2.6 Conclusions obtained from the past researches for the new study

Section 2.4 and 2.5 explained in detail about the available methods to measure visual complexity or visual diversity. However, none of the above methods address the most important aspects of visual complexity together; they are the variety and connections. It is useless to measure complexity using a technique without ways to measure both these aspects. It is because to have a complexity both these aspects must be satisfied and to measure the complexity, at least both these aspects must be measured.

However, in literature there was no any method to address these two important aspects together. Therefore the results obtained through the available methods are partially correct and they are not giving values to the true complexity.

Therefore the conclusions obtained through available researches and the landscape regulations created based on these results may contain shortcomings and they will not create a pleasant environment to the human. It is because the real or perceivable visual complexity was not representing by above complexity measurement methods.

Thus the prime objective of the proposed study is to introduce a new method which can address the both important aspects of complexity at the same time. Further this new approach basically based on the subjective judgments on their environment. Thus it represents the real visible complexity in the environment.

Therefore for this task, none of the above research techniques applied. Instead two new approaches introduced. First approach is Gestalt’s figure and background classification to identify the visual elements which are responsible for the visual complexity and to identify the sequence of the complexity created by them or in other words to measure the variety and connections aspects of complexity. Second approach is the taxonomic entropy to give a numerical value to both variety and connections among visual elements identified by the subjects.

Next sections explain about the Gestalt’s figure and background concept and the taxonomic indices.

2.7 Figure and background concept

Elements are perceived as either figures (distinct elements of focus) or ground (the background or landscape on which the figures rest). This concept was identified and explained by the Gestalt. In Gestalt psychology it is known as identifying a figure from background. It is a type of perceptual grouping which is a vital necessity for recognizing objects through vision (Schactar, et.al. 2011). To identify an element as a figure or a background is based on many cues all of which are of a probabilistic nature; they are size of elements, shape of the element, movement of elements, color, edge assignment and the distance. Any visual element can be grouped into figures and backgrounds. One element may contain more than one figure and one background. Subjects perceive visual elements as figures using above explained cues. Since this research basically based on the intensive field surveys, it is important to apply the above cues in identifying figures and backgrounds to find out the structural hierarchical visual complexity along streetscapes. Figure 2.4 gives a simple example of figure and background.

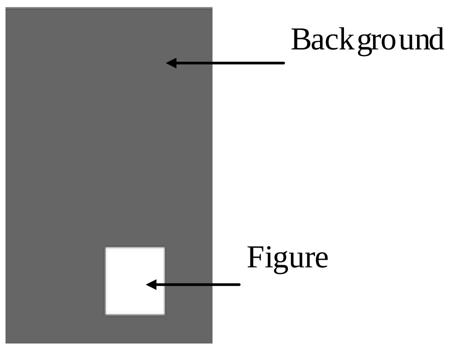


Figure 2.4: A Simple Sketch of Figure and Background

One of the most famous examples of figure and background concept is the faces–vase drawing that Danish psychologist Edgar Rubin described. Figure 2.5 displays this famous example.

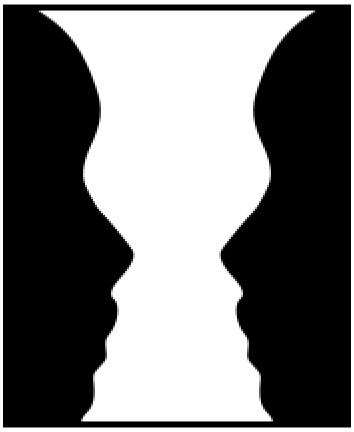


Figure 2.5: Faces-vase Drawing

This drawing exemplifies one of the key aspects of figure–ground organization, edge-assignment and its effect on shape perception. Notice in the faces/vase drawing, the perceived shape depends critically on the direction in which the border (edge) between the black and white regions is assigned. If the two curvy edges between the black and white regions are assigned inward then the central white region is seen as a vase shape in front of a black background. No faces are perceived in this case. On the other hand, if the edges are assigned outwards, then the two black profile faces are perceived on a white background and no vase shape is perceived. The human visual system will then settle on either of the interpretations of the Rubin vase and alternate between them. Functional brain imaging shows that when people see the Rubin image as a face, there is activity in the temporal lobe, specifically in the face-selective region (Schactar, et.al. 2011).

Visual perception is a subjective phenomenon, thus figure ground perception is also changing person to person. In this context, figure background identification and classification should be carried out with a good attention.

2.7.1 Methods to differentiate figures and backgrounds

There are lots of methods in literature to identify figures and backgrounds in natural images. Some common methods are explained in this section.

Chen and Chan (2012), in their study; "adaptive figure ground classification" propose an adaptive figure-ground classification algorithm to automatically extract a foreground region using a user-provided bounding-box. The image is first over-segmented with an adaptive mean-shift algorithm, from which background and foreground priors are estimated. The remaining patches are iteratively assigned based on their instances to the priors, with the foreground prior being updated online. A large set of candidate segmentations are obtained by changing the initial foreground prior. The best candidate is determined by a score function that evaluates the segmentation quality. Rather than using a single distance function or score function, they generated multiple hypothesis segmentations from different combinations of distance measures and score functions. The final segmentation is then automatically obtained with a voting or weighted combination scheme from the multiple hypotheses. Experiments indicate that their method performs at or above the current state-of-the-art on several datasets, with particular success on challenging scenes that contain irregular or multiple-connected foregrounds. In addition, this improvement in accuracy is achieved with low computational cost. Figure 2.6 displays an example of their method.

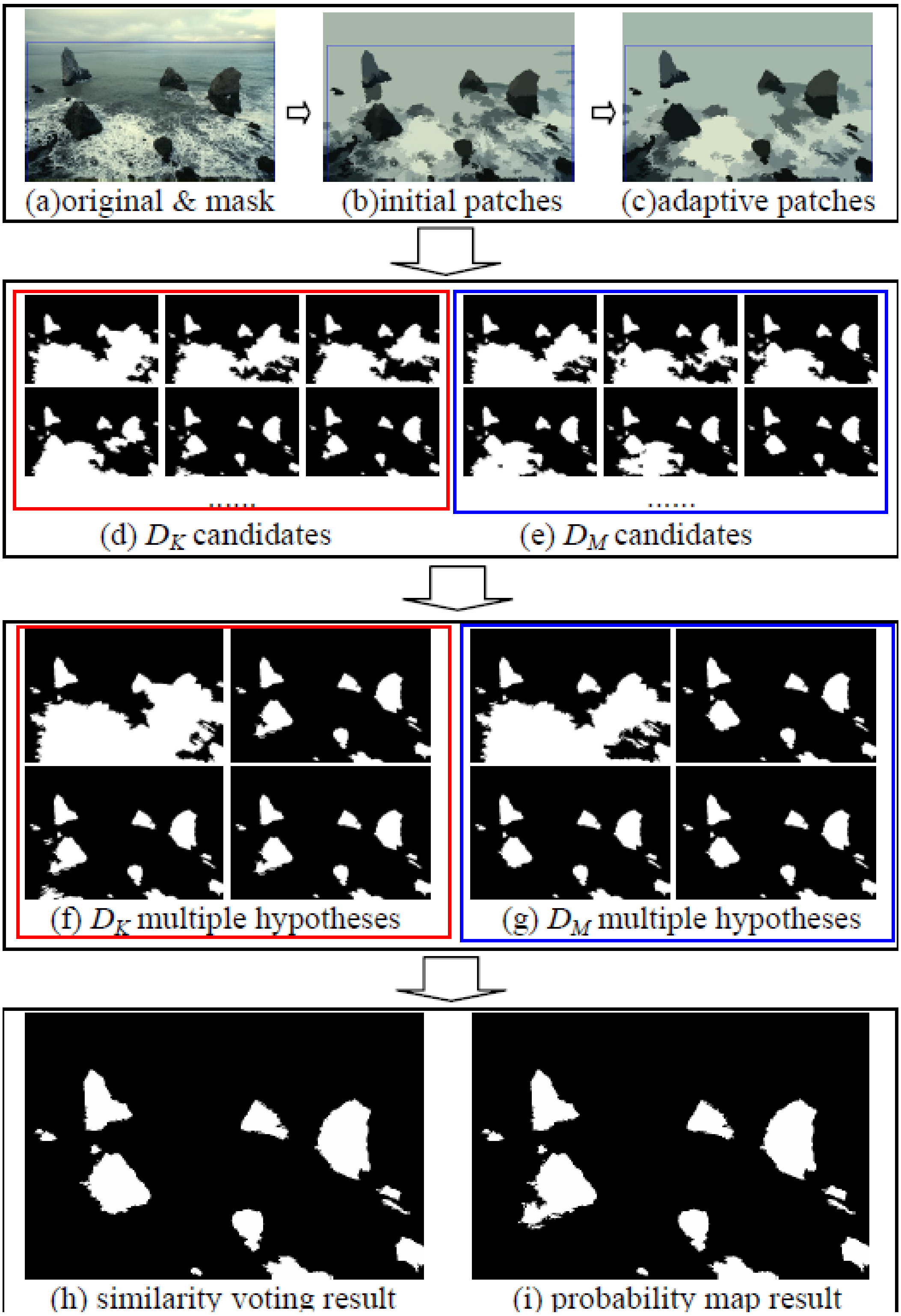


Figure 2.6: Figure-Ground Classification Method Introduced by Chen and Chan

Through this method, most highlighted figures could be separated easily. However from this method it is difficult to have a finer detailed figure and background classification. Further, this will not represent the sequential view of the human.

Human brain sees some elements in a sequence. Brain cannot see all the elements at once. It sees most highlighted figures first, and then goes for next elements. It is a sequential view. However, this method does not represent this sequential visual perception.

Another interesting figure ground classification approach was undertaken by Ren, et.al. (2012). In this paper, they developed a computational model for figure/ground assignment in complex natural scenes. They utilized a large dataset of images annotated with human-marked segmentations and figure/ground labels for training and quantitative evaluation. They operationalized the concept of *familiar configuration* by constructing prototypical local shapes, i.e. *shapemes*, from image data. Shapemes automatically encode mid-level visual cues to figure/ground assignment such as convexity and parallelism. Based on the shapeme representation, they trained a logistic classifier to locally predict figure/ground labels. they also considered a global model using a *conditional random field* (CRF) to enforce global figure/ground consistency at T-junctions. They used loopy belief propagation to perform approximate inference on this model and learn maximum likelihood parameters from ground-truth labels. They found that the local shapeme model achieves an accuracy of 64% in predicting the correct figural assignment. This compares favorably to previous studies using classical figure/ground cues. They evaluated the global model using either a set of contours extracted from a low-level edge detector or the set of contours given by human segmentations. The global CRF model significantly improves the performance over the local model, most notably when using human-marked boundaries (78%). These promising experimental results show that this is a feasible approach to bottom-up figure/ground assignment in natural images. Figure 2.7 displays the method they applied to extract figures and backgrounds.

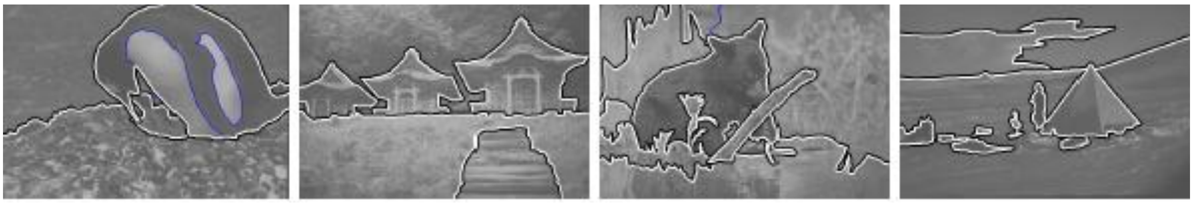


Figure 2.7: Examples from the Figure-Ground Classification of Natural Scenes

In this experiment, each image was first segmented by a human subject; then two human subjects assigned figure/ground labels to each boundary in the segmentation. Here the white boundary indicates the figure side and black the ground side. Blue boundaries indicate contours labeled by subjects as not having a clear figure/ground assignment (e.g. surface markings).

In this experiment also the finer figure –ground classification is impossible and there is no sequential analysis of figure-ground.

A good research was conducted by Fowlkes, et.al. (2007). The title of the research is "Local figure–ground cues are valid for natural images" and in this study they experimented on how much information about figure–ground assignment is available from locally computed cues? Using a large collection of natural images, in which neighboring regions were assigned a figure–ground relation by human observers, they quantified the extent to which figural regions locally tend to be smaller, more convex, and lie below ground regions. Their results suggested that these Gestalt cues are ecologically valid, and they quantified their relative power. They have also developed a simple bottom–up computational model of figure–ground assignment that takes image contours as input. Using parameters fit to natural image statistics, the model is capable of matching human-level performance when scene context limited. Figure 2.8 displays the method they adapted in their study.

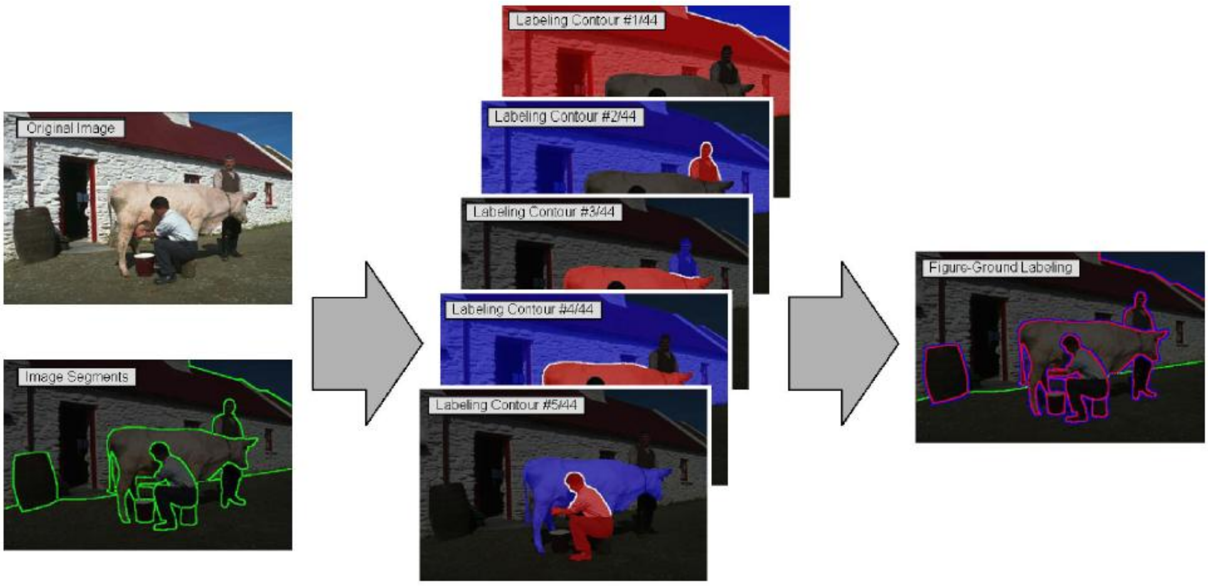


Figure 2.8: Acquiring figure–ground labels.

Human subjects labeled each contour in an image, indicating to which region it "belongs". Starting from a segmentation of the original image (left), subjects were presented with a sequence of highlighted contours corresponding to each pair of neighboring regions (center). The subject indicated which of the two regions the figural element was. The reported figural region is displayed here with a red tint, ground with a blue tint. Subjects also had the option of attributing a boundary to a change in surface albedo or a discontinuity in the surface normal. Such a boundary, exemplified by the corner between the building and earth, marked in green, was seen as belonging to both segments. Once all the contours had been labeled, the subject was presented with the final labeling (right) and given the opportunity to fix any mistakes.

All most all past researches introduced computer generated models to extract figures and backgrounds. Computer models are time saving and easy to use. However they accuracy of these models are not up to the level of expectation. Further they are not representing the real human perception. It is very difficult to build models to exactly represent the human perception. For general researches these models can be applied. However for a fine study it is better to go for the real human perception. Therefore in this present study real human perception was utilized to identify the figures and backgrounds in landscapes.

Next section explains about the next new approach applied in the present study; that is taxonomic indices.

2.8 Taxonomic indices

Taxonomic indices are introduced by ecologists by incorporating information about the degree of ecological similarity among species in a community (Ricotta, 2003). A community composed of species that are distantly related taxonomically or that have diverse ecological roles and characteristics is intuitively more diverse than a community composed of similar or near-similar species. Therefore valuable indices of diversity should account for differences related to functional type or morphology, taxonomic relatedness amongst species or genetic distances, because ecological differences between taxa are believed to be reflected in each of these (Warwick, 1995). Because taxonomic relatedness is most commonly used to determine the dissimilarity or distance between species, these indices of diversity are generally referred to as taxonomic diversity indices (Rachelle, 2004).

Rao (1982) was the first researcher introduced a taxonomic index incorporating ecological dissimilarity. It is Quadratic entropy; which can be defined as the mean difference between two individuals chosen randomly from a community. The equation is given below (eqn 02).

$$Q = 2\sum_{i>j=1}^{s} \text{dij Pi Pj} \qquad \text{eqn 02}$$

Where d_{ij} is dissimilarity between i^{th} and j^{th} species, s is the total number of species, Pi and Pj are the proportions of i^{th} and j^{th} species in a community.

Quadratic entropy calculation requires predefined matrix of distances that reflect the dissimilarity among all species and defines diversity as the product of the relative proportions of each species in a pair multiplied by the distance between them that are then summed for all possible species pairs (Rachelle, 2004).

Shimatani (2001) investigated the statistical properties of quadratic entropy and its behavior in environmental assessment using a distance matrix based first on taxonomic distances and second on genetic distances. She determined that quadratic entropy is the sum of Simpson indices over all taxonomic levels and found that the quadratic entropy uncovered significant differences among differently managed forest plots whereas Simpson index did not. It was found that the additional information about the community could be gained by examining individual components of quadratic entropy. Thus she introduced a new equation based on the above theories. Equation 03 is the one introduced by Shimatani.

$$Q^{+} = 2/s(s-1)\sum_{i>j} d_{ij} \qquad \text{eqn 03}$$

Where s is the number of species and d_{ij} is the distance between species i and species j.

Warwick and Clarke (1998) introduced two taxonomic diversity indices representing distribution of abundances amongst species and the taxonomic relatedness. First index is taxonomic diversity (Δ) is the average taxonomic distance between any two organisms chosen at random from a sample. Figure 2.9 gives the taxonomic diagram which they used to develop the equations and equation 04 is the taxonomic diversity index.

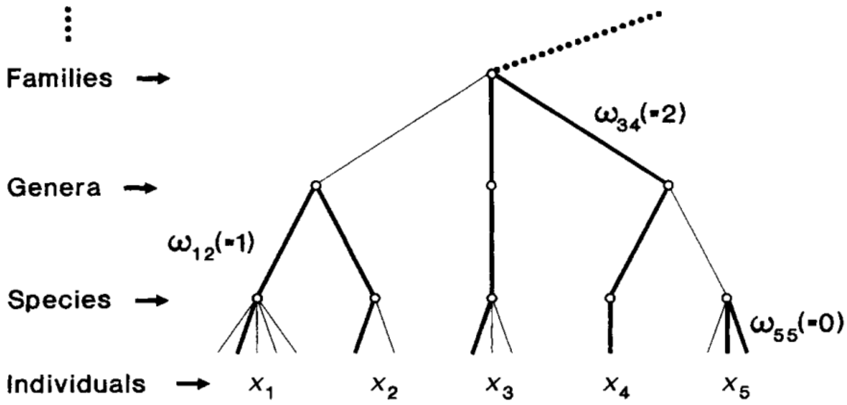


Figure 2.9: Part of a Taxonomic Classification

$$\Delta = [\sum\sum_{i<j}\omega_{ij}x_ix_j]/[n(n-1)/2] \qquad \text{eqn 04}$$

Where x_i (1,……s) denotes the abundance of the i^{th} species, $n(=\sum_i x_i)$ is the total number of individuals in the sample and ω_{ij} is the distinctness weight given to the path length linking species i and j in the hierarchical classification.

Second index is the taxonomic distinctness index (Δ^*) is the average path length between any two randomly chosen individuals, conditional on them being different species. Equation 05 displays the taxonomic distinctness index.

$$\Delta^* = [\sum\sum_{i<j}\omega_{ij}x_ix_j]/ [\sum\sum_{i<j}x_ix_j] \qquad \text{eqn 05}$$

Unlike Δ, the expression of Δ^* is invariant to a scale change in x. so that it could incorporate straightforwardly cases where the data are not counted individually, but for total biomass of each species. Further Δ^* can be explained as a measure of pure taxonomic relatedness while Δ mixes taxonomic relatedness with the evenness properties of the abundance distribution. Figure 2.10 displays some of the taxonomic diagrams with the Δ^* values. Highly complex diagrams have a higher taxonomic distinctness index value.

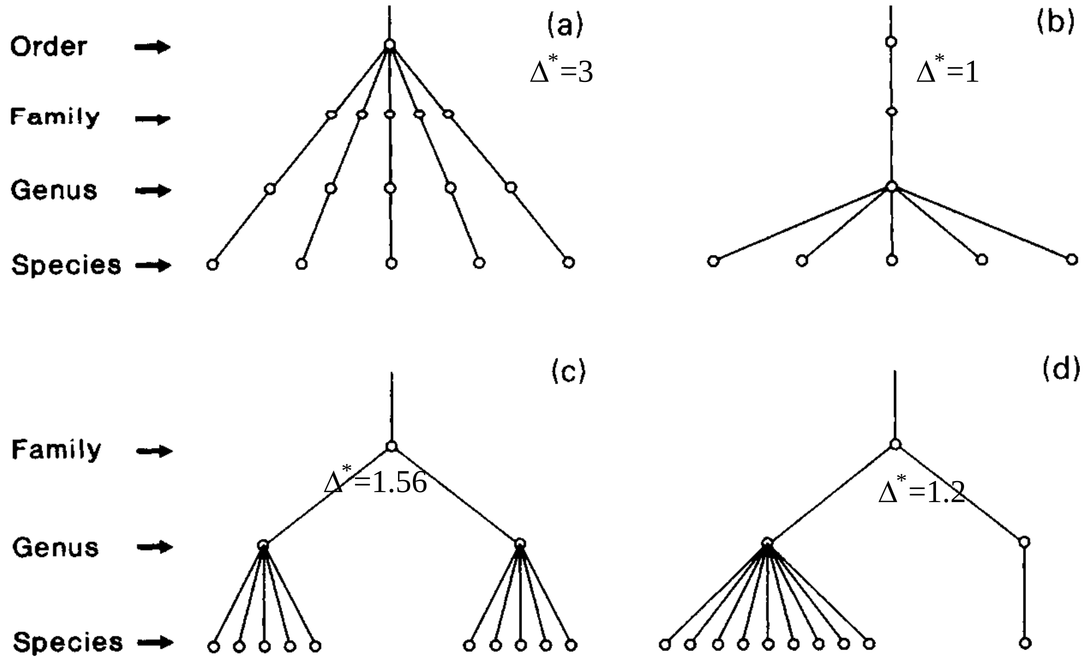


Figure 2.10: Different Types of Taxonomic Diagrams with Δ^* values

The index of taxonomic entropy, introduced by Ricotta and Avena (2003), associates taxonomic distance to a single species, whereas, other popular indices use pair-wise comparisons for the calculations. Pair wise comparison is more accurate when all the species end up in the same level. Equation 06 displays the taxonomic entropy equation.

$$H = -\sum p_i \log_2 k_i \qquad \text{eqn 06}$$

Where, H is taxonomic entropy, p_i the probability of i^{th} species and k_i the taxonomic distinctness of i^{th} species.

Taxonomic entropy is computed to the same way as the Shannon entropy is, that is as the negative sum of the proportions of each species multiplied by the logarithm of taxonomic distinctness.

This equation is useful because like the species relative proportions, the taxonomic distinctness values are transformed to a finite probability space meaning that the taxonomic distinctness values are proportions whose sum equals 1. As a result of this, the approach used to assign the pair wise distances will not have an unduly large effect on the resulting value of taxonomic diversity (Rachelle, 2004).

Quadratic entropy, the equation introduced by Shimatani and the equations introduced by Warwick and Clarke are all required pair wise comparisons of taxonomic distinctness. However, taxonomic entropy uses taxonomic distinctness of single species. For the best results of the pair wise comparisons, the taxonomic diagrams should be symmetrical or the species in the taxonomic diagrams should be in a same level. Therefore, the use of those equations is not appropriate in all situations. However, the taxonomic equation can be used for even symmetrical or asymmetrical taxonomic diagrams.

All the above taxonomic indices were tested during the present study using trial experiments to choose the best equation to match with the landscape visual complexity measurement using taxonomic diagrams of figure and backgrounds.

CHAPTER 03

THEORETICAL FRAMEWORK

3.1 Objective

The research was undertaken to achieve two objectives.

1. To develop a method to analyze the structural hierarchical visual complexity in residential streetscapes, which was not addressed in the past and which is very important in setting landscape regulations, than just the general visual complexity.
2. To assess the applicability of new method in streetscape planning and designs

3.2 Hypothesis

The hypothesis applied for this research is that, when the spatial arrangement (variety) and the spatial connections (dependency) of the figures and backgrounds along streetscape become complex, the perceivable visual amount becomes high increasing the structural hierarchical visual complexity. Therefore, structural hierarchical visual complexity can be measured by analyzing the taxonomic diagrams which represent the variety and dependency of perceivable visual elements along streetscapes.

3.3 Approach

Structural hierarchical visual complexity measurement needs to satisfy at least two aspects of visual complexity; they are the differentiation and connections. To measure these two aspects, Gestalt's explanations on figure and background identification and the taxonomic entropy were selected. The process of increase of visual elements is called differentiation, which is similar to the increase of the number of figures and backgrounds consist in the root visual element when dividing it into children figures and backgrounds. The process of increase in the number or strength of connections is called integration which is similar to the progressive division of root visual element into children figures and backgrounds.

Thus division of figures and backgrounds of a root element into children elements follows a kind of hierarchy. It can be represented using a tree classification. However, it is important to note that the representation of visual elements in a residential streetscape as a tree classification system is not an attempt to explain the streetscape visual elements follows a tree system. This tree classification system represents the differentiation and integration of visual elements resulted from the figure and background classification to find out the structural hierarchical visual complexity of the residential streetscapes. Showing the children figures and backgrounds of a root visual element in a tree classification system is a simplest way to represent their physical relationships and the connections between them. Further it is very helpful to find out the structural hierarchical visual complexity of the streetscapes. In this research the structural, functional, and functional hierarchical complexities are not going to measure. The Gestalt's figure and background concept was used in this research to measure the structural hierarchical visual complexity.

3.3.1 Applicability of taxonomic diagrams

A taxonomic diagram *t* is a finite nonempty set of elements; one of these elements is called the root. The remaining elements, if any, are partitioned into taxonomic diagram, which are called the branches of *t*. figure 3.1 displays an example of a taxonomic diagram.

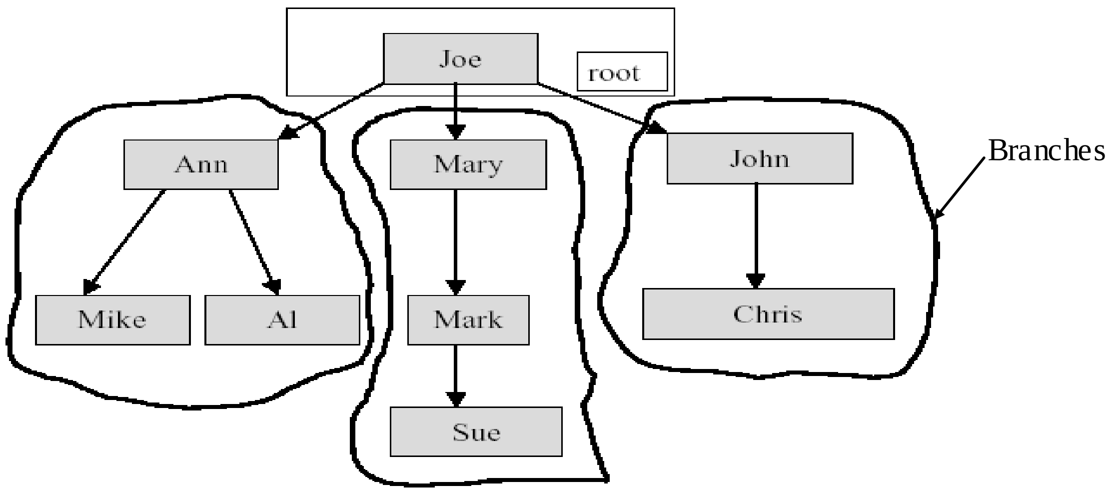


Figure 3.1: A Sample Taxonomic Diagram

The element at the top of the hierarchy is the **root**. Elements next in the hierarchy are the **children** of the root. Elements next in the hierarchy are the **grandchildren** of the root, and so on. Elements at the lowest level of the hierarchy are the **leaves**. Those root, children, grandchildren and leaves are called nodes. Root is at level 1 and its children are at level 2. The line connecting the levels is called edge. Figure 3.2 displays the common nomenclature of a taxonomic diagram.

Height = depth = number of levels

Nodes

Edge

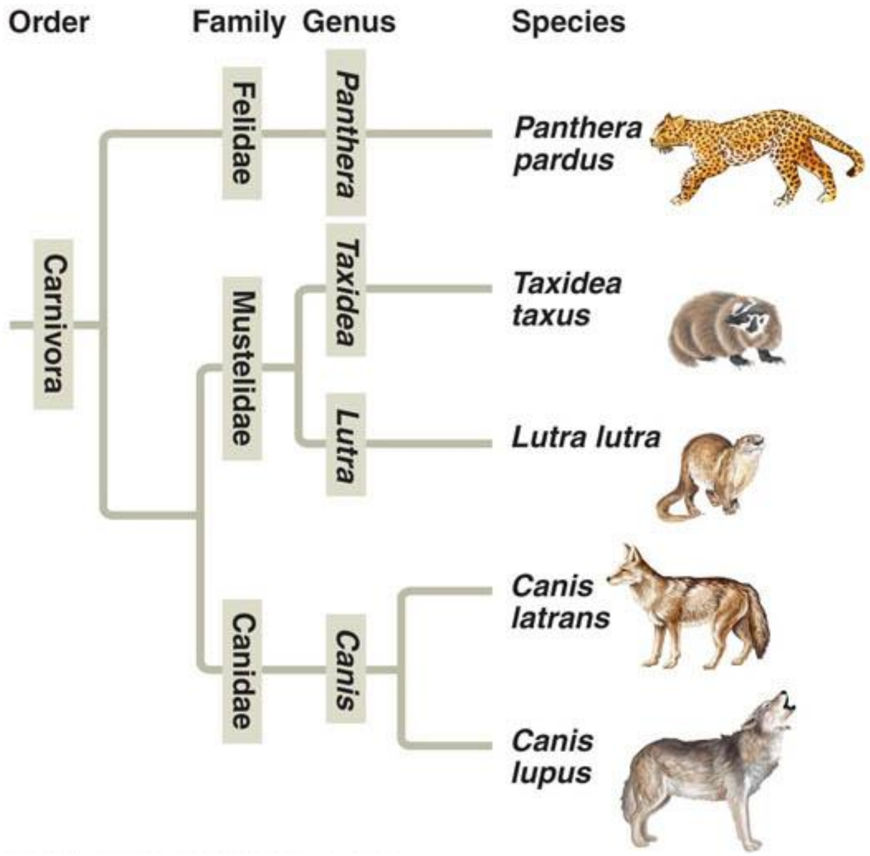


Figure 3.2: Common Nomenclature of a Tree

Similar taxonomic diagrams can be developed in landscape planning and architecture as well. For example, a house can be divided into different layers as in figure 3.3.

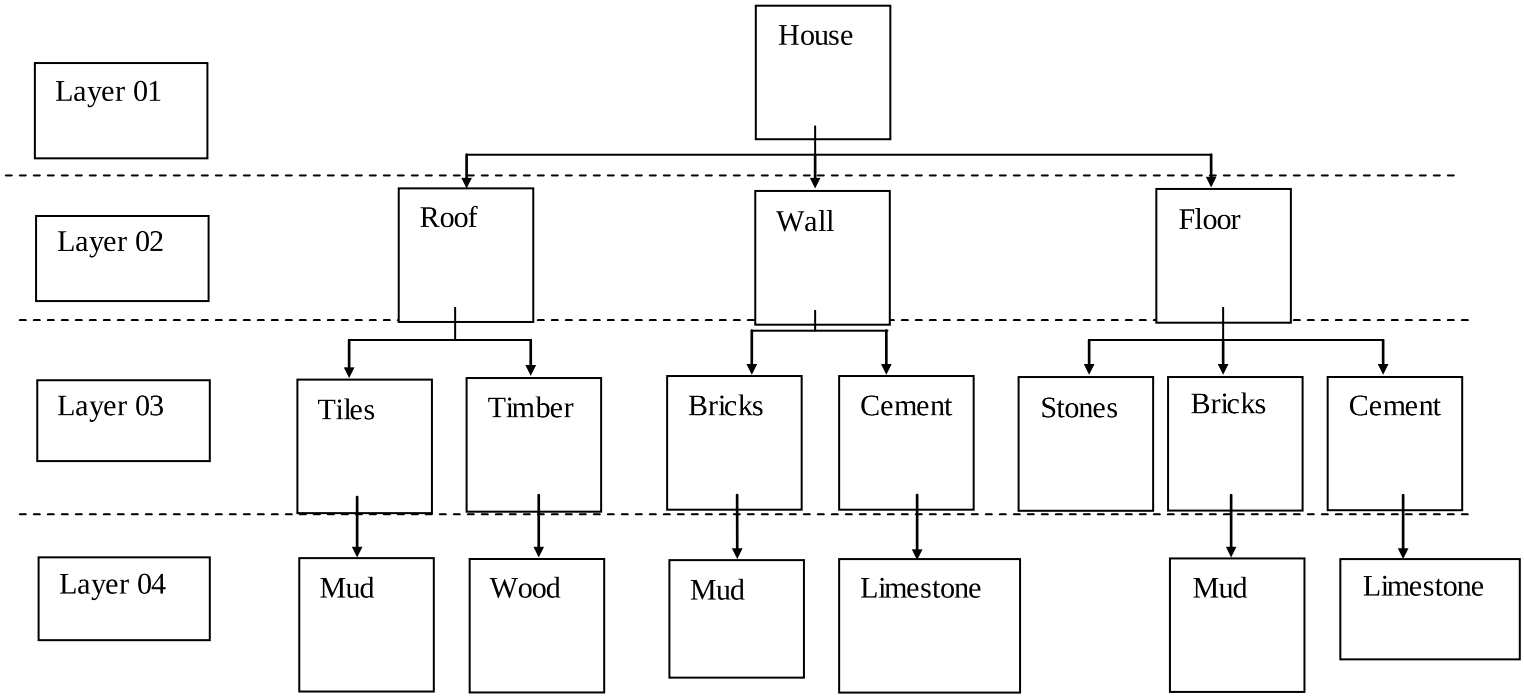


Figure 3.3: A Taxonomic Diagram for a House

Thus the house can be broadly subdivided into roof, wall and floor. Then roof can be subdivided into tiles and timber. Wall into bricks and cement and floor subdivide into stones, bricks and cement. Then each of these elements could be subdivided into mud, wood and limestone. In other words, mud, wood and limestone made the tiles, timber and cement which are helpful to build the house. Tiles, timber, cement, bricks and stones are used to build the roof, walls and the floor of the house. By combining all these together the final house unit built up. Thus the house is a complex unit with different types of elements and their interactions. Thus the house displays a structural hierarchical complexity. If the taxonomy has a higher number of levels and a higher number of nodes, then the structural hierarchical complexity becomes higher.

Similar patterns exist in the landscape as well. For example, residential streetscapes have different kinds of elements, such as houses, vegetation, utilities, billboards, and etc. All these units are made up of subunits. In other words, many subunits interconnect each other to make a major unit in the streetscape. Thus taxonomic diagrams can be developed to display the subunits and their interactions. In this research interaction means the physical connections between sub units. The activities in the buildings were not considered, since the measurements are undertaken to measure the perceived visual complexity.

Present research mainly focuses on the visual complexity available in streetscapes. Visual complexity means the complexity perceived by the people who travel along the street. The travelers will not notice or perceive all the subunits which are contributed to build the major units along the streetscape. While travelling they will perceive the dominant visual elements or the most eye catching elements and their subunits only.

Thus these eye catching elements are the main figures on the streetscape. Gestalt explained about the figure and background identification using some cues. Travelers along the streetscape also perceive figures and backgrounds with the help of these cues in visual perception. These are the size of elements, shape of the element, movement of elements, color, edge assignment and the distance. Inside one main figure, there will be sub figures and backgrounds. Consequently, it is possible to build taxonomic diagrams of figures and backgrounds of a main visual element along the streetscape. Therefore, for identification of figures and backgrounds along the residential streetscapes, the Gestalt explanations on figure and background was used.

Then taxonomic indices were selected for the statistical valuation of the taxonomic diagrams. For this several taxonomic indices were tested using trial experiments. Explanation about the applicability of taxonomic indices to the present research has explained in following sections.

3.3.2 Applicability of taxonomic indices

The concept applied in this research is similar to the taxonomic relatedness concept in biodiversity. If a main visual element has many sub-visual elements (variety) with connections (dependency), then the structural hierarchical visual complexity of the main visual element becomes high. This similarity can be further explained using an example.

Example: Visualize a pond consisting of different types of fish species, each taxonomically different from the other. The biodiversity of the pond is measured by using the taxonomic diagram of these fish species. Similarly, a house in a streetscape is a pool of sub-visual elements with connections. The structural hierarchical visual complexity of the house can be measured by using the taxonomic diagram of the variety and the dependency. By way of further elaboration, the taxonomic diagrams of these two examples are given in figures 3.4 and 3.5.

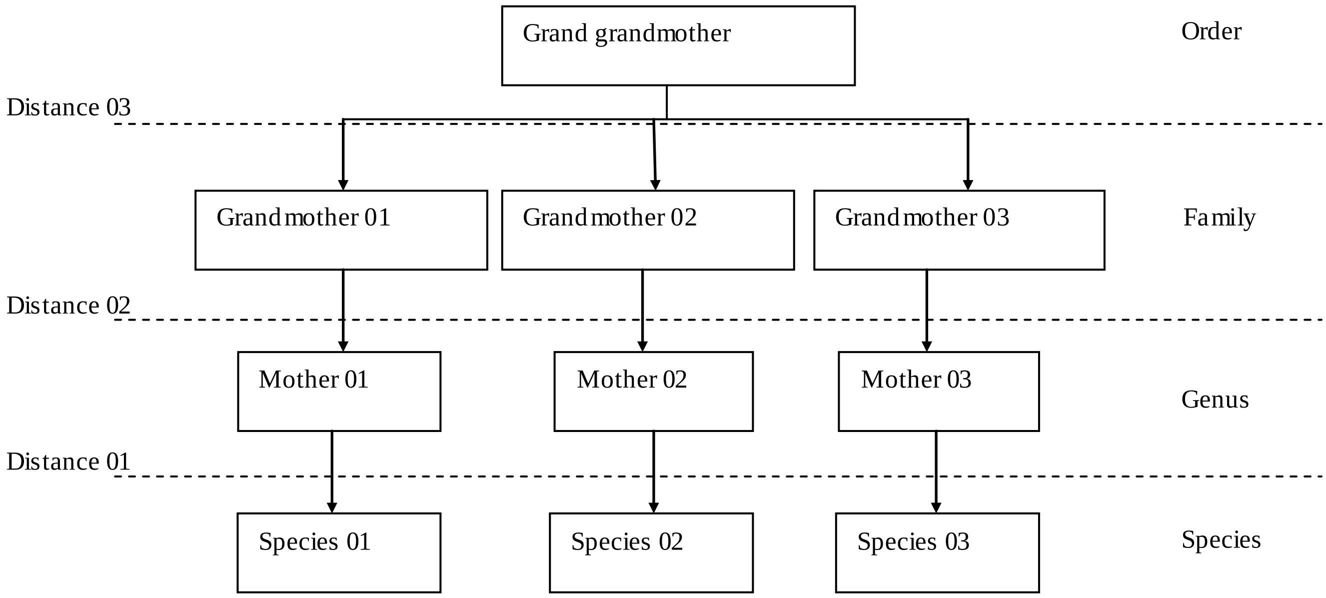


Figure 3.4: The Taxonomic Diagram of Biodiversity

The taxonomic diversity is calculated by using the probability of different types of species and the total distance between the species and their grand grandmother. Hence, for diversity calculation, only the probabilities and the distances were applied. Other information is immaterial for the calculation.

Similarly, for structural hierarchical visual complexity analysis by using taxonomic diagrams, the probabilities of each type of branches in the taxonomic diagram and the total distance from the end figure to the main visual element were taken into account. In biodiversity assessment, the probability of the species is taken into account, and in structural hierarchical visual complexity analysis, the probability of each type of branches is taken into account. Besides, in visual complexity analysis, the same end visual elements will not reappear to get their probabilities as they do in biodiversity assessment. Therefore, different types of branches were considered as one indicator of the structural hierarchical visual complexity.

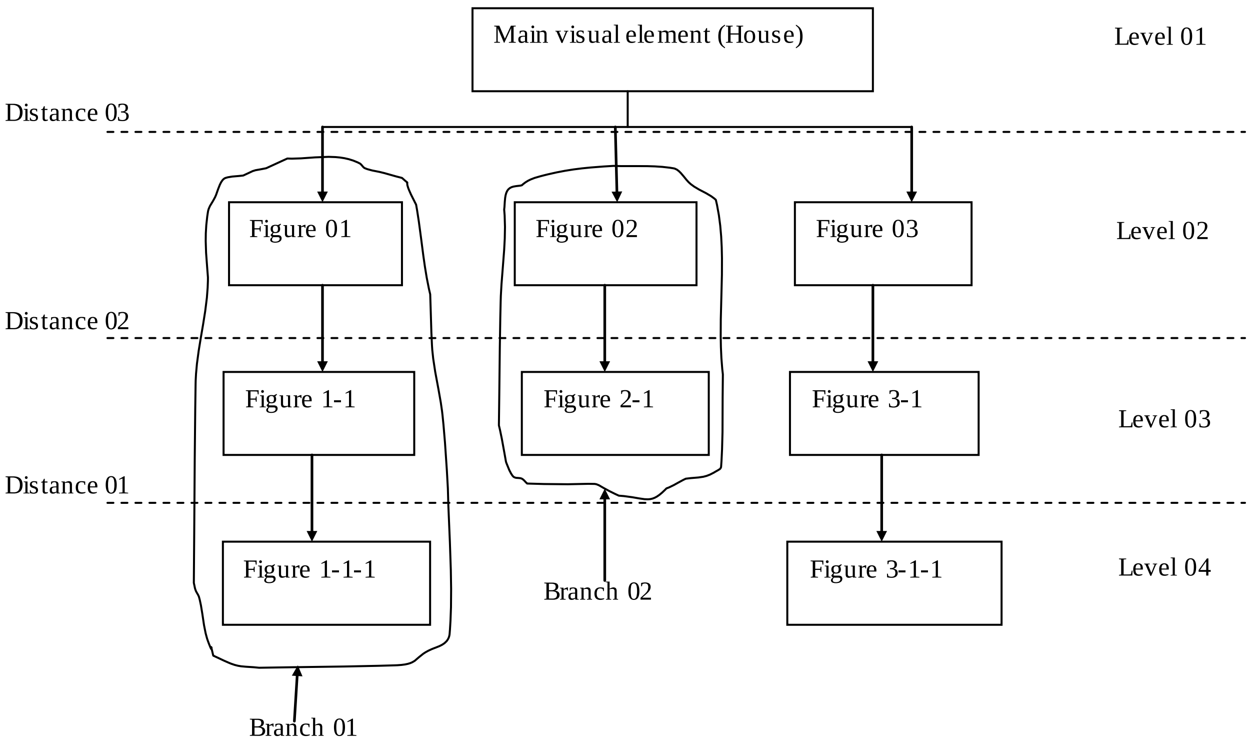


Figure 3.5: The Taxonomic Diagram of Visual Complexity

There are several taxonomic diversity indices, among which taxonomic distinctness index, taxonomic entropy and quadratic entropy are widely used in biodiversity assessment and detailed explanations about then have given under literature review section. For data analysis in this research, taxonomic entropy (equation 07) was finally selected after reviewing and trial applications of the available taxonomic diversity indices.

$$H = -\sum p_i \log_2 k_i \qquad \text{eqn 07}$$

Where, H is taxonomic entropy, p_i the probability of i^{th} species and k_i the taxonomic distinctness of i^{th} species.

3.4 Originality of the research

The research is very novel to the landscape and urban planning arena. Since the main focus is on the study of structural hierarchical visual complexity on streetscapes, the research completely included the new information to this study field. The main new things achieved through this study could be listed as follows.

- This is the first study on the structural hierarchical visual complexity on landscape (invisible structure)
- The study addressed both essential aspects of visual complexity; that is variety and dependency
- This is the first attempt to apply figure and background concept to represent the order of the visual perception on landscapes
- This is the first study to display the order of the visual perception associated with variety and dependency of the perceivable visual amount as a taxonomic diagram (invisible structure associated with visual perception)
- The most important point is this study successfully applied an objective analysis method which is new to landscape studies, to measure the structural hierarchical visual complexity on streetscapes (Taxonomic Entropy)

CHAPTER 04

METHODOLOGY

4.1 Study area

The research was conducted in the urban residential areas around the Saitama University in Japan. Figure 4.1 shows the study area.

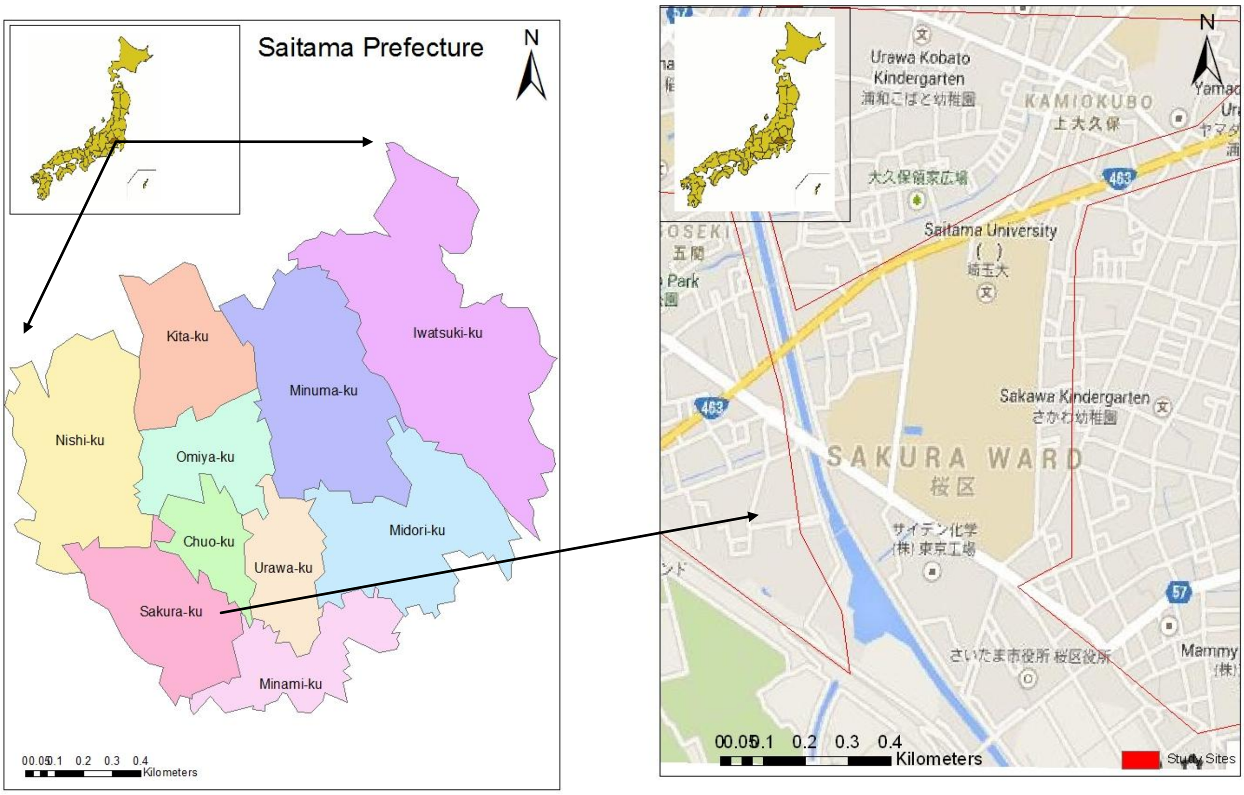


Figure 4.1: The study area

4.2 Method

The method has two main sections to achieve two objectives.

1. Section one - Method to find out a new way to analyze structural hierarchical visual complexity.

2. Section two - Method to check the sensitivity of the newly introduced method.

4.3 Section one of the Method

First section of the method followed here is described under four sections: (i) preparation of perspective views of the streetscapes, (ii) analysis of the perspective views, (iii) arrangement of the data and (iv) data analysis.

4.3.1 Preparation of perspective views

For the present research, 70 urban residential streetscapes were selected from the vicinity of the Saitama University. Each streetscape was around 200 m in length. The streetscapes were comprised of largely two story single family residential units. Occasionally one story and three or more story single family buildings were positioned in the study area. Auxiliary, in some streetscapes, housing complexes could be seen. The houses were built very near to the street line with a very small open space in front of the houses. Most of the time, this small open space is used as a parking place for the vehicles. Along the streetscape parking lots, home gardens, small retail shops and rarely religious places could be observed.

The streetscapes were grouped into streetscapes in urbanization controlled areas, streetscapes in medium urbanized areas and streetscapes in highly urbanized areas, based on the number of buildings within approximately 200 m distance along the streetscape. The selected streetscapes had approximately similar plot sizes. If the streetscape had fewer than 15 buildings on both sides, near the street line within 200m distance, it was classified as urbanization controlled streetscape. Streetscapes with building density of over 30 buildings within 200 m distance were classified as highly urbanized streetscapes and those with15-30 buildings as medium urbanized streetscapes. Finally, 20 streetscapes in urbanization controlled areas, 20 streetscapes in highly urbanized areas and 30 streetscapes in medium urbanized areas were selected for further analysis. Both forward and backward perspective views of the streetscapes were used for the analysis. Figure 4.2 display some of the example sites obtained from Google Earth images to show the building density along streetscapes.

(a) Urbanization Controlled Areas

(b) Medium Urbanized Areas

(f) H

(c) Highly Urbanized Areas

Figure 4.2: Different Sites Selected for the Study

4.3.2 Analysis of perspective views

The forward and backward perspective views of the selected streetscapes were analyzed with the help of a group of subjects, comprising 20 subjects of different nationalities from the Saitama University. The perspective views from five viewpoints, along each residential streetscape, were shown to them. Figure 4.3 displays 10 perspective views of one residential streetscape in forward and backward directions. They were asked to select a few major visual elements from each viewpoint in the first round. To facilitate their choice, a list of common major visual elements of residential streetscapes was provided to them. The list included 11 visual elements: street, the sky, utility, houses, property boundaries, garbage places, retail shops, open lands, vending machines, street mirrors, sign boards and the vegetation. Generally each subject selected 1-5 major visual elements from each viewpoint. Then they were asked to identify and make notes, to the extent they could, on the sub-figures and the backgrounds for each major visual element. Thereafter, they gave their explanations for the visual elements of five randomly selected viewpoints along the streetscape, following a similar procedure for all selected 70 residential streetscapes.

(a) Perspective Views of Forward Direction

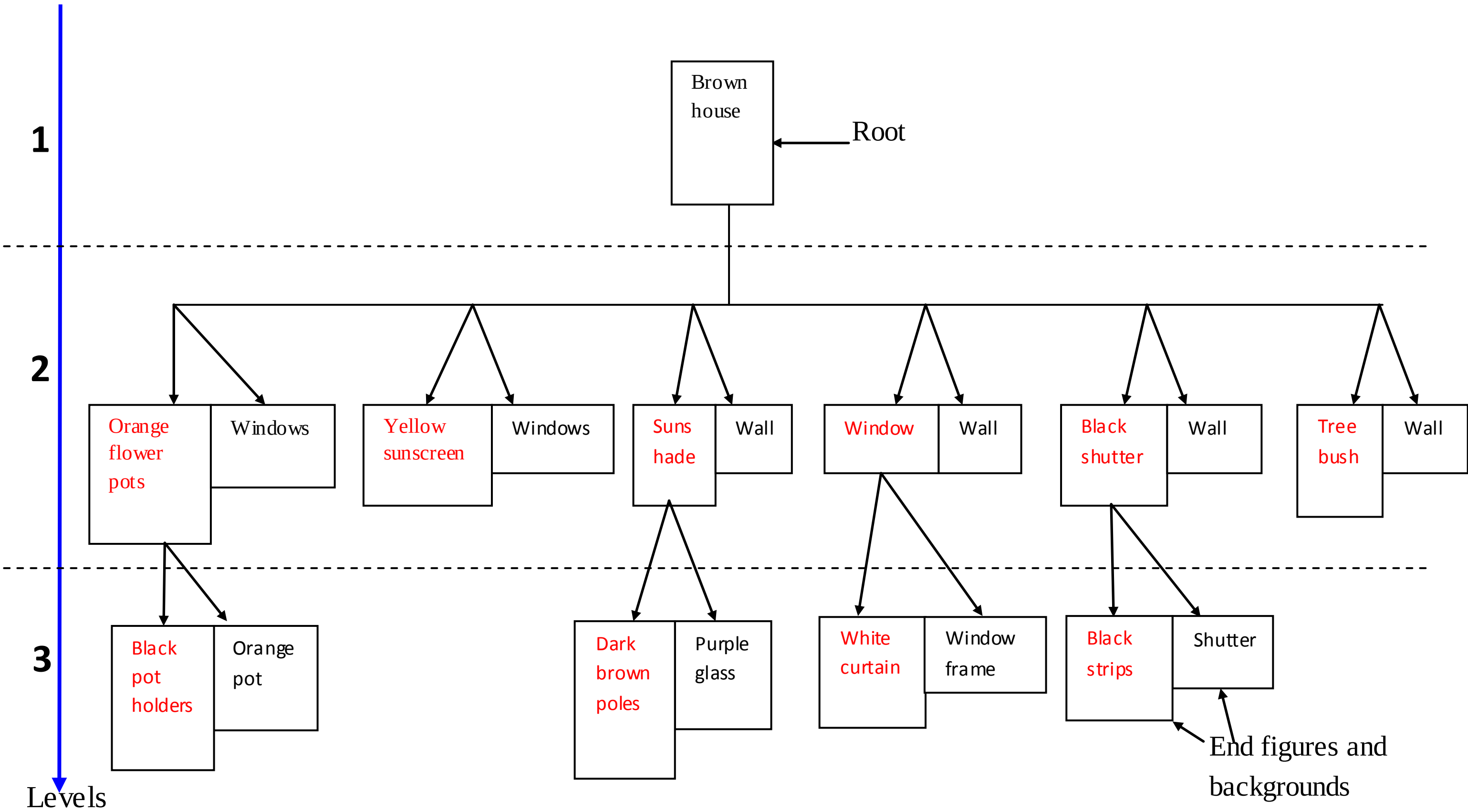
(b) Perspective Views of Backward Direction

Figure 4.3: Forward and Backward Views from 5 Viewpoints along a Residential Streetscape

4.3.3 The data arrangement

The subjects identified figures and backgrounds based on the cues of perception, size of elements, shape of the elements, movement of elements, color, edge assignment and the distance. Usually they explained about the figure elements standing against monotonous background. The detailed explanations of figures and backgrounds, given by the 20 subjects, were analyzed individually, based on the knowledge of the streetscapes, acquired by personally visiting the streetscapes. A major visual element may contain more than one figure and a background. After classifying the figures and backgrounds for each major visual element of the 20 subjects, the probabilities of highlighting visual elements as figures or backgrounds were calculated. Basically the subjects explained about the figure element, since they are the eye catching elements in the view. Therefore the probability of mentioning an object as a figure was considered to identify the figures and backgrounds in the view. If the probability of an element being classified as a figure was higher than 75%, then that visual element was classified as a figure element, and if less than 75%, then the element was classified as a background element. With the help of probability values, the figures and the backgrounds were classified and arranged as taxonomic diagrams for statistical analysis. A sample of the taxonomic diagram of figures and backgrounds, created for a major visual element, is given in figure 4.4. Labels with red letters are figures and those with black letters are the corresponding backgrounds.

(a) A Main visual element selected by subjects



(b) Taxonomic diagram drawn to the main visual element

Figure 4.4: A Sample of (a) a Main Visual Element Selected by Subjects and (b) Taxonomic Diagram Drawn to the Main Visual Element

4.3.4 Data analysis

The data was analyzed to determine the structured hierarchical visual complexity of each residential streetscape. For this analysis, taxonomic entropy (equation 08) was applied. A detailed explanation about the taxonomic entropy and other indices were given under literature review and theoretical framework sections.

Taxonomic entropy is computed to the same way as the Shannon entropy is, that is as the negative sum of the proportions of each species multiplied by the logarithm of taxonomic distinctness. For this research, the original equation was slightly modified to match with the objective of present research. Figure 4.5 shows the measurement taken from the streetscape taxonomic diagrams for index calculation. In streetscape taxonomic diagrams two features are available; figures which are similar to the species in biodiversity and the backgrounds, which are similar to the habitat in biodiversity. Since figures are the most important contributor for the streetscape visual complexity, they were selected for the taxonomic entropy calculation of the streetscape.

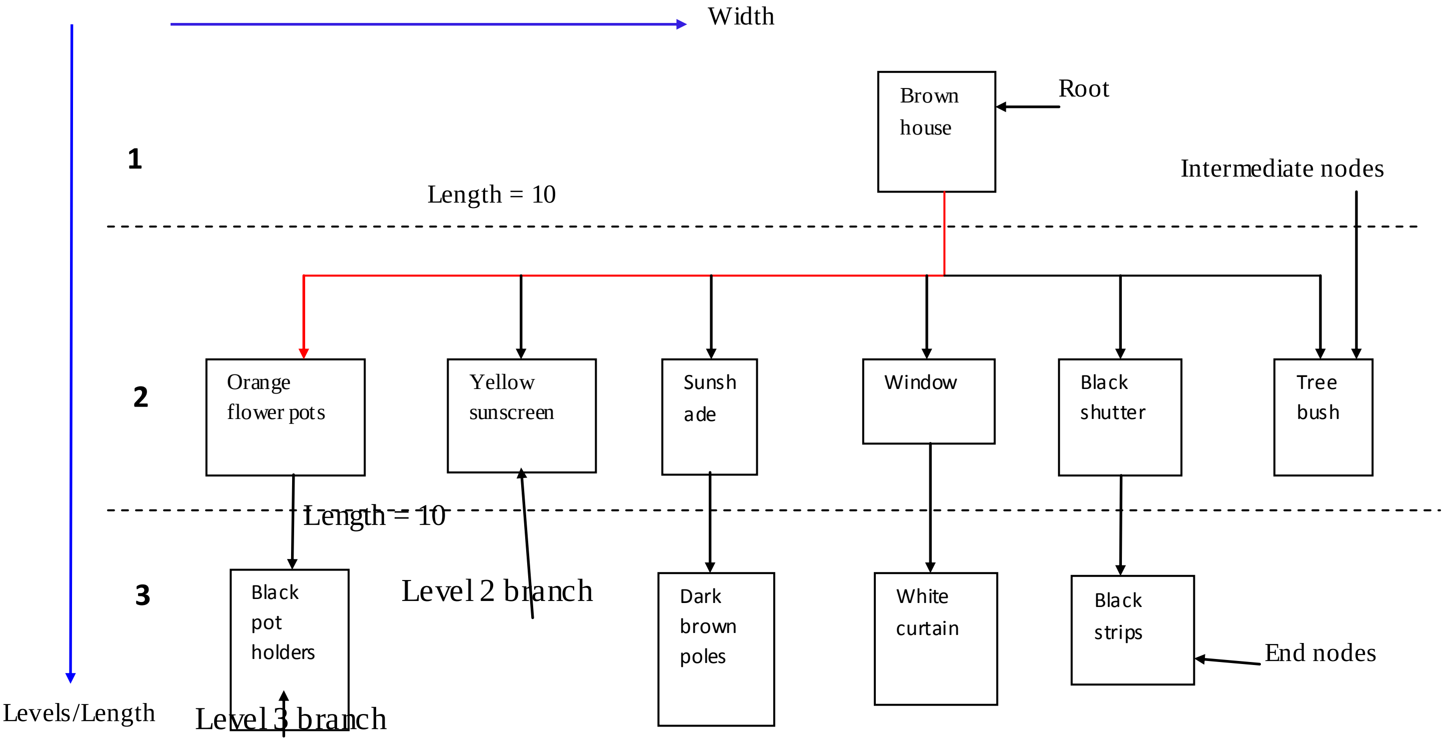


Figure 4.5: Streetscape Taxonomic Diagram

Taxonomic diagram has different types of branches, such as two-level branches, three-level branches and so on. The complexity of taxonomic diagram varies, depending on the number and length of the branches. Accordingly, the complexity was computed using the number of branches and their total length. Equation

$$H = \sum p_i \log_2 k_i \qquad \text{eqn 08}$$

Where, p_i refers to the probability of i^{th} branch and k_i to its total length. For length calculation, value 10 was given to the length between two levels to avoid errors in applying logarithmic values in the equation. Thus, the total length of a branch with two levels is 10 and that of a branch with three levels 20. Because the logarithmic values are non-negative, it is not necessary to get the negative sum as explained in the original equation.

4.4 Section two of the method

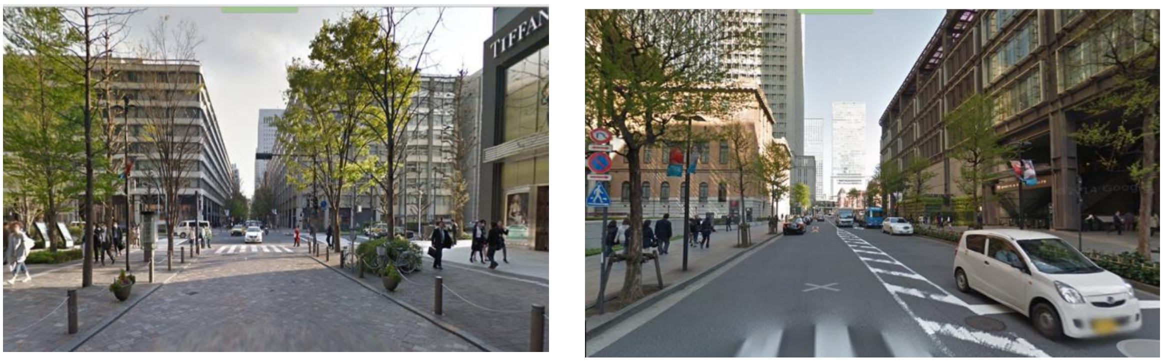
This section started after fully completed the first section. The main idea of this section is to check the validity and the sensitivity of the set method to measure the structural hierarchical visual complexity.

Section two was undertaken mainly on commercial streetscapes in Japan. For the study the streetscapes of Omiya, Urawa, Kita Urawa, Akihabara and Marunouchi business areas were selected. The perspective views and individual building views of the streetscapes were taken during field visits to the selected areas. Figure 4.6 displays some of the views obtained during field visits.

(a)Views from Kita Urawa

(b) Views from Omiya

(c) Views from Akihabara



(d) Views from Marunouchi

Figure 4.6: Some of the Perspective Views taken during Field Visits

The perspective views and perpendicular views of the streetscapes and commercial buildings were modified using Photoshop software to change several characters of the buildings and streetscapes. The changes were made up by changing, the color, building height, and thickness of window panels, changing window designs, changing design of buildings, removing and adding some visual elements to the buildings. Figure 4.7 displays some of the examples for this method.

(a) Make Building Appearance Simple by Removing Some Visual Elements

(b) Change of Color

Figure 4.7: The Original Views and Modified Views of Streetscapes

After modifications were done to the photographs, the taxonomic diagrams and the taxonomic entropy were calculated for the original image and for the modified image. This procedure was undertaken for more than 20 streetscape views.

CHAPTER 05

RESULTS AND DISCUSSION

5.1 Identification of visual elements

The residential streetscapes were classified into three groups-streetscapes in urbanization controlled areas, streetscapes in the highly urbanized areas and the streetscapes in medium urbanized areas- based on the urbanization level near the street line. Basically, the subjects tended to select the objects from the perspective views, based on the cues explained by Gestalt: the size, shape, color, edge assignment and the distance of objects. Therefore, their major selections for further classification were the houses visible near the street line, the sign boards, street signs, retail shops, vending machines, property boundaries, and the decoratively cut vegetation stretches. From each view point subjects were asked to select one to five visual elements. Twenty subjects selected the most prominent elements with the help of Gestalt's explanations. After their selections, the probabilities were counted to judge the final major visual elements from each view viewpoint. Figure 5.1 displays one viewpoint of a streetscape and figure 5.2 displays 5 major visual elements selected by 20 subjects. Table 5.1 displays the probability of mentioning each major visual element by 20 subjects.

Figure 5.1: One Viewpoint along a Residential Streetscape

(1) (2) (3) (4) (5)

Figure 5.2: Five Major Visual Elements Selected by 20 Subjects

Table 5.1: Probability of Mentioning Each Major Visual Element

Visual element	Probability	Percentage %
1	8	80
2	10	100
3	9	90
4	10	100
5	2	20

According to the probability percentages, the visual element (5) got the least percentage. It was less than 70%. Therefore the visual number (5) did not use for the further analysis. Other four visual elements obtained higher probabilities. Therefore from the above viewpoint only four visual elements were selected for further analysis. Similar procedure was applied to all viewpoints at the 80 residential streetscapes.

Typically where the urbanization level is high near the street line, of the subjects will have plenty of visual elements to choose. High urbanized residential streetscapes are normally characterized by diverse elements of human requirements, therefore, to cater to their day–to-day requirements, retail shops, vending machines and some other business places like laundries, saloons, etc. spring up among the houses. Thus, the variation of the streetscape becomes high and the subjects have a variety of elements to choose. Therefore, during the perspective view analysis stage, the subjects selected up to five visual elements from each viewpoint along high density streetscapes. However, from urbanization controlled streetscapes, the selections were fewer and in some viewpoints, there were no major visual elements for further classification. Generally, humans can memorize up to five objects at a time. Therefore, the selection of visual elements was limited to a maximum of five objects from one viewpoint.

Visual perception differs from person to person; therefore, a single person's perception of figures and backgrounds will not be adequate for reliable and accurate analysis. For that reason, in this study, the perceptions of 20 people were used to identify the figures and the backgrounds. The subjects were selected representing different nationalities to remove the biasness of visual perception. The probability of identifying an object as a figure or a background by 20 persons was used in differentiating the available visual elements into figures and backgrounds. After the selection of major visual elements, the sub visual elements or figures and backgrounds of major visual elements were identified by the subjects. In this step also the probability percentages were counted to select the figures and backgrounds. Figure 5.3 displays two major visual elements and table 5.2 and table 5.3 display the figures and backgrounds identified by subjects and their probabilities.

(1)

(2)

Figure 5.3: Two Major Visual Elements

Table 5.2: Identified Figures and Backgrounds and their Probability Percentages for Major Element (1)

Figure	Background	Probability Percentage
Orange flower pots	Windows	100
Black pot holders	Orange pot	100
Yellow sunscreen	Windows	100
sunshade	House wall	100

Dark brown poles	Purple glass	100
Red strips	gate	50
White car	Surrounding	80
Black glass	White car	80
headlights	car	100
windows	wall	80
White curtain	Window frame	100
Black shutter	wall	80
Black strips	shutter	70
Tree bush	wall	80

Table 5.3: Identified Figures and Backgrounds and their Probability Percentages for Major Element (2)

Figure	Background	Probability Percentage
White window	wall	100
White strips	glass	100
White window frame	wall	100
White goods	glass	100
window	wall	100
Black glass	White frame	80
White shutter	wall	100
Vertical strip	shutter	100
Horizontal lines	shutter	80
Exhaust fan outlet	wall	80
Sunshade	wall	80
bulbs	Sunshade	100

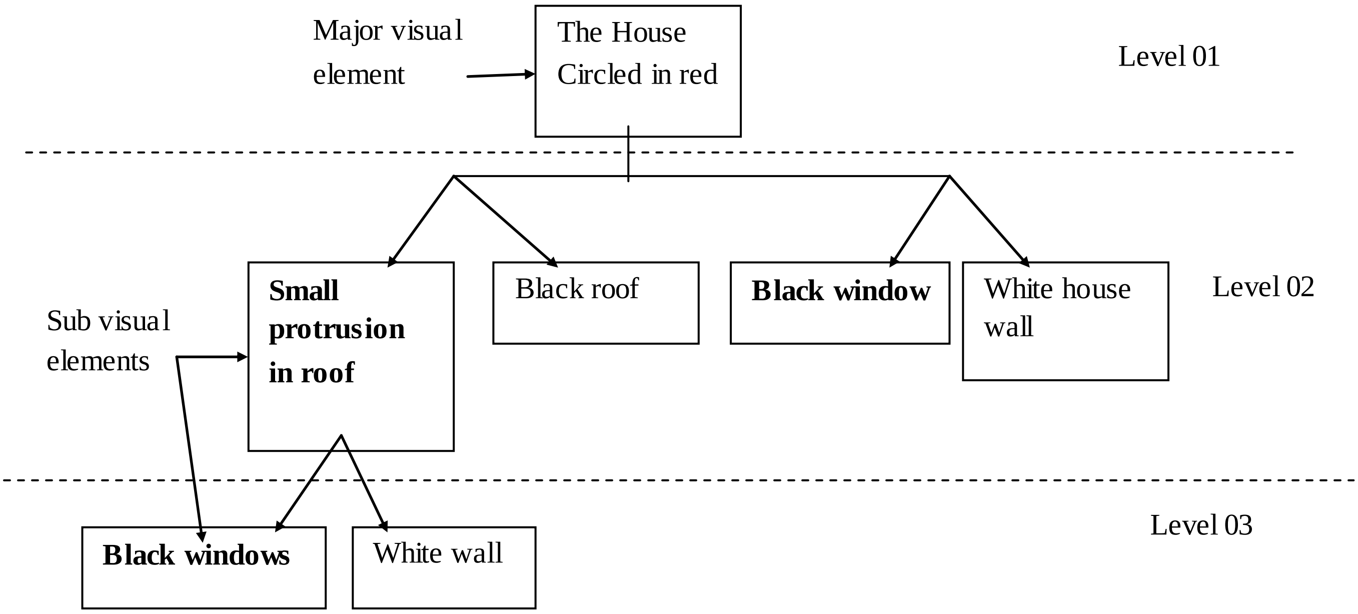
window	**wall**	**80**
Silver strips	**glass**	**100**
Bamboo	**wall**	**100**
Name board	**window**	**80**
Black letters	**Light pink area**	**100**
White bag	**wall**	**100**
Green water hose	**wall**	**80**
Orange pots	**wall**	**100**
Black pot holder	**wall**	**100**
pots	**wall**	**100**
White name tags	**pots**	**80**
Black letters	**White area**	**70**
Black box	**wall**	**60**
White tape	**Black box**	**100**
Orange pot	**wall**	**60**

Considering the probability values the figures and backgrounds of the major visual element were selected. If the probability is higher than 75 percent, those figures and backgrounds were selected for the further analysis.

5.2 Drawing taxonomic diagrams

One more important point is that the selected major visual elements in highly urbanized streetscapes can possibly be further classified into a large number of figures and backgrounds. Since highly urbanized streetscapes associate with diverse human activities, sub-visual elements used in improving the attractiveness of the houses and small scale business places are varied. A visual element is a pool of figures and backgrounds (variety), which display a spatial hierarchy and varied spatial connections (dependency). Owing to differences in variety and dependency, the visual elements get varied attractions. If an element has lots of figures and backgrounds and a number of spatial connections, that element becomes prominent in the view. Therefore, the subjects could easily select such elements from the streetscape view and identify many sub-figures and backgrounds in them. To find the variety and the dependency available within a major visual element, taxonomic diagrams can be utilized. The taxonomic diagram of major visual elements, with a large number of sub-visual elements and spatial connections, becomes large in both vertical and horizontal directions. Consequently, the taxonomic diagram drawn for major visual elements in highly urbanized streetscapes was lengthy up to six levels and wide with more than 10 branches. In contrast, the taxonomic diagram of the urbanization controlled streetscapes had few levels and fewer than five branches. Urbanization controlled streetscapes had fewer human activities, but other activities like home gardening, paddy cultivations, parking lots etc. are more; therefore, the availability of attractive visual elements was very little. Figures 5.4, 5.5 and 5.6 depict the taxonomic diagrams drawn for a major visual element of, respectively, urbanization controlled and highly urbanized residential streetscape views. Bold labels refer to the figures in the taxonomic diagrams.

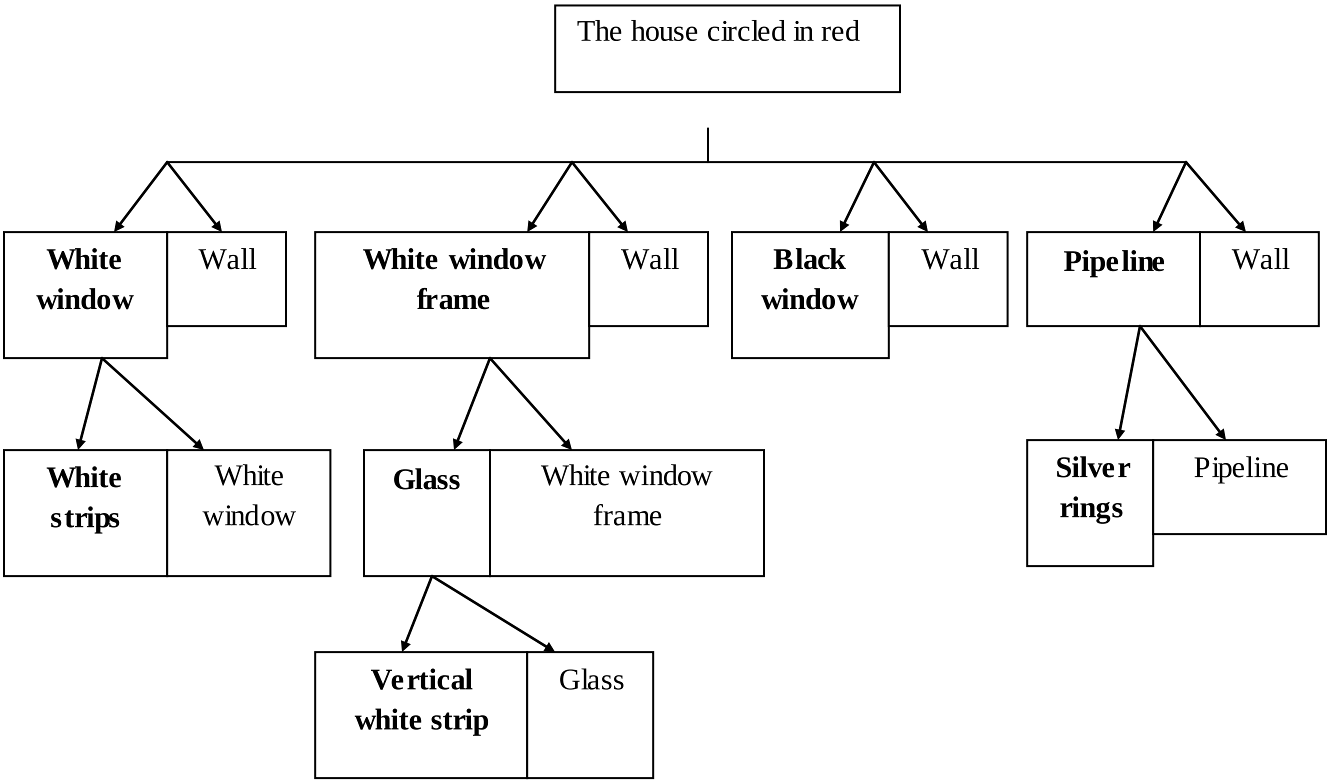
(a) Selected main visual element



(b) Taxonomic diagram drawn to the main visual element

Figure 5.4: A Perspective View of Urbanization Controlled Streetscape and the Taxonomic Diagram Drawn for one of its Major Visual Elements

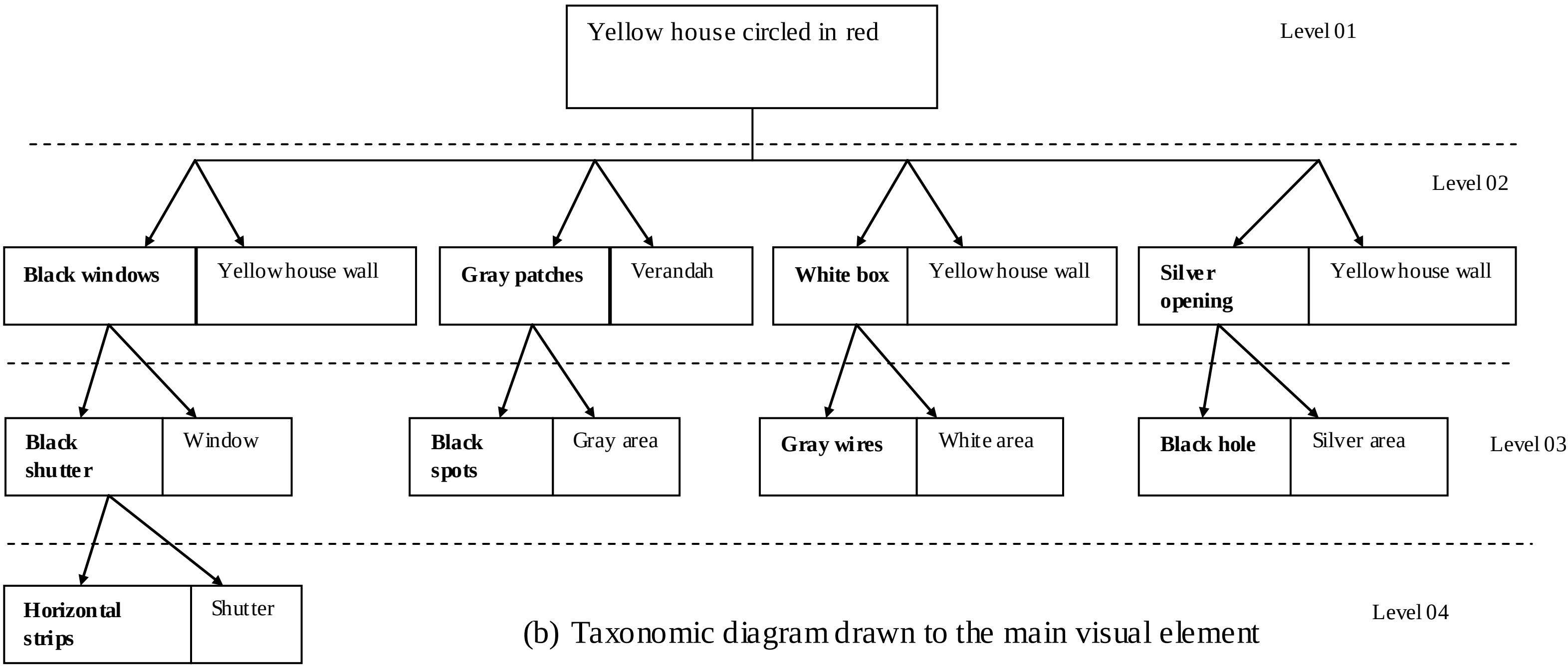
(a) Selected Main Visual Element



(b) Taxonomic Diagram Drawn to the Main Visual Element

Figure 5.5: A Perspective View of Medium Urbanization Streetscape and the Taxonomic Diagram Drawn for one of its Major Visual Elements

(a) Selected main visual element



(b) Taxonomic diagram drawn to the main visual element

Figure 5.6: A Perspective View of a Highly Urbanized Streetscape and a Section of the Taxonomic Diagram of One of its Major Visual Elements

By just looking at the taxonomic diagrams of urbanization controlled, medium and highly urbanized streetscapes, it is possible to get an idea of the variety and dependency of the visual elements that contribute to the variations in structural hierarchical visual complexity of the streetscapes.

5.3 Taxonomic entropy calculation

But, what is additionally required is a concrete method to measure the visual complexity objectively. To meet this requirement, taxonomic entropy was utilized. Taxonomic entropy gives a numerical value to the structural hierarchical visual complexity, based on the length and the width of the taxonomic diagram. When the taxonomic diagram has a large number of branches and levels, the taxonomic entropy becomes high and vice versa. Taxonomic entropy is widely applied in biodiversity assessment to measure taxonomic diversity of the species.

Taxonomic entropy is a new approach in landscape and urban planning. The present research is the first attempt to use taxonomic entropy in measuring the structural hierarchical visual complexity of streetscapes. Besides, utilizing taxonomic diagram is a novel concept to show the variety and the dependency of visual elements.

After identifying the sub-visual elements of a major visual element in urbanization controlled, medium and highly urbanized perspective views, they were arranged in terms of their taxonomic diagrams. This is followed by calculation of the taxonomic entropy, separately for each taxonomic diagram. Consequently, for highly urbanized streetscapes, a maximum of five taxonomic diagrams were drawn and as many taxonomic entropy values obtained for each viewpoint. Accordingly, for one highly urbanized streetscape, 25 taxonomic diagrams were drawn for 5 viewpoints. By summing up the figures in each level in all 25 taxonomic diagrams, a final taxonomic diagram was created. For the final taxonomic diagram, the taxonomic entropy calculation was undertaken with the help of Excel. Similar calculations were made for the forward and backward directions of the all 70 streetscapes. Figure 5.7 display 5 perspective views of 5 viewpoints along a urbanization controlled streetscape for forward direction and table 5.4 displays the entropy calculation using Excel. Figure 5.8 display the backward direction of the same streetscape and the table 5.5 display the entropy calculation for backwards direction.

(1)

(2)

(3)

(4)

(5)

Figure 5.7: Forward Perspective Views of a Urbanization Controlled Streetscape

Table 5.4: Forward Direction Taxonomic Entropy Calculation

Viewpoint	Level	No. of Branches	Probability(pi)	Total Length(ki)	ln ki	pi ln ki
1	2	31	0.62	10	2.302585	1.427603
	3	8	0.16	20	2.995732	0.479317
	4	8	0.16	30	3.401197	0.544192
	5	2	0.04	40	3.688879	0.147555
	6	1	0.02	50	3.912023	0.07824
	Total Branches	50			Entropy	2.676907
2						
	2	14	0.777778	10	2.302585	1.7909
	3	2	0.111111	20	2.995732	0.332859
	4	1	0.055556	30	3.401197	0.188955
	5	1	0.055556	40	3.688879	0.204938
	Total Branches	18			Entropy	2.517652
3						
	2	13	0.764706	10	2.302585	1.7608
	3	3	0.176471	20	2.995732	0.528659
	4	1	0.058824	30	3.401197	0.20007
	Total Branches	17			Entropy	2.489529
4						
	2	18	0.782609	10	2.302585	1.802023
	3	3	0.130435	20	2.995732	0.390748
	4	1	0.043478	30	3.401197	0.147878
	5	1	0.043478	40	3.688879	0.160386
	Total Branches	23			Entropy	2.501035
5						
	2	16	0.842105	10	2.302585	1.939019
	3	1	0.052632	20	2.995732	0.15767
	4	1	0.052632	30	3.401197	0.17901
	5	1	0.052632	40	3.688879	0.194152
	Total Branches	19			Entropy	2.469851
Forward Entropy	2.530995					

(1)

(2)

(3)

(4)

(5)

Figure 5.8: Backward Perspective Views of a Urbanization Controlled Streetscape

Table 5.5: Backward Direction Taxonomic Entropy Calculation

Viewpoint	Level	No. of Branches	Probability(pi)	Total Length (ki)	ln ki	pi ln ki
1	2	7	0.636364	10	2.302585	1.465281
	3	3	0.272727	20	2.995732	0.817018
	4	1	0.090909	30	3.401197	0.3092
	Total Branches	11			**Entropy**	2.591499
2						
	2	6	0.666667	10	2.302585	1.535057
	3	2	0.222222	20	2.995732	0.665718
	4	1	0.111111	30	3.401197	0.377911
	Total Branches	9			**Entropy**	2.578686
3						
	2	9	0.692308	10	2.302585	1.594097
	3	3	0.230769	20	2.995732	0.691323
	4	1	0.076923	30	3.401197	0.261631
	Total Branches	13			**Entropy**	2.547051
4						
	2	13	0.8125	10	2.302585	1.87085
	3	2	0.125	20	2.995732	0.374467
	4	1	0.0625	30	3.401197	0.212575
	Total Branches	16			**Entropy**	2.457892
5						
	2	13	0.866667	10	2.302585	1.995574
	3	1	0.066667	20	2.995732	0.199715
	4	1	0.066667	30	3.401197	0.226746
	Total Branches	15			**Entropy**	2.422036
Backward Entropy	**2.519433**					

Similar calculations were done for medium urbanized and highly urbanized streetscapes as well. The resulted taxonomic entropy values for forward and backward directions for all three groups of streetscapes are given in figure 5.9, 5.10 and 5.11.

Figure 5.9: Forward and Backward Taxonomic Entropy Values for 20 Urbanization Controlled Streetscapes

The taxonomic entropy values ranged between 2.36 and 2.62 for urbanization controlled streetscapes.

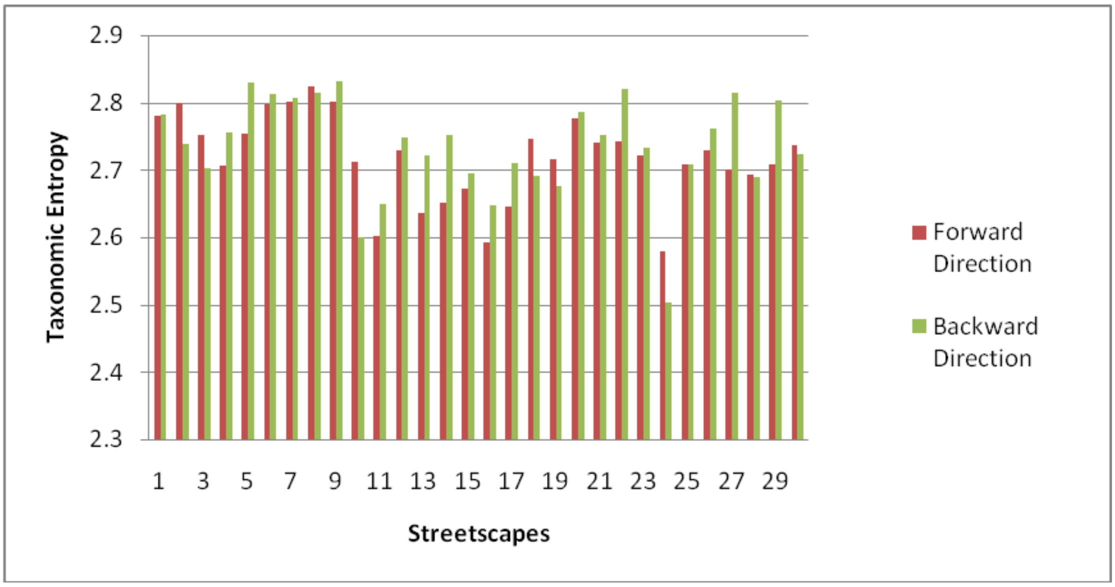


Figure 5.10: Forward and Backward Taxonomic Entropy Values for 30 Medium Urbanized Streetscapes

The entropy values ranged between 2.5 to 2.83 in medium urbanized streetscapes.

Figure 5.11: Forward and Backward Taxonomic Entropy Values for 20 Highly Urbanized Streetscapes

The entropy values ranged between 2.75 and 2.97 for highly urbanized streetscapes.

The entropy values ranges for forward and backward directions of streetscapes did not show a significant difference. In some streetscapes there were differences in values; however as a whole the forward and backward directions displayed similar taxonomic entropy values.

For clear understanding of the taxonomic entropy value ranges figure 5.12 and figure 5.13 displays a comparison of value ranges among three streetscape groups.

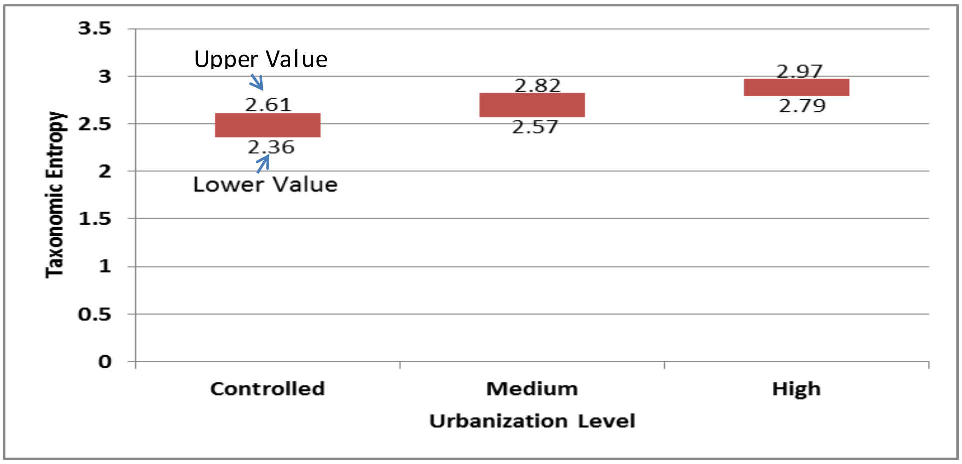


Figure 5.12: Taxonomic Entropy Values of Urbanization Controlled, Medium and Highly Urbanized Streetscapes in Forward Direction

The taxonomic entropy is an indication of the structural hierarchical visual complexity of the streetscape. The forward taxonomic entropy ranged between 2.36 and 2.61 for urbanization controlled streetscapes, 2.57 and 2.82 for medium urbanized streetscapes and 2.79 and 2.97 for highly urbanized streetscapes. Principally, the forward streetscape taxonomic entropy ranged between 2.3 to 2.6 for urbanization controlled streetscapes, 2.6 to 2.8 for medium urbanized streetscapes and 2.8 to 3.0 for highly urbanized streetscapes.

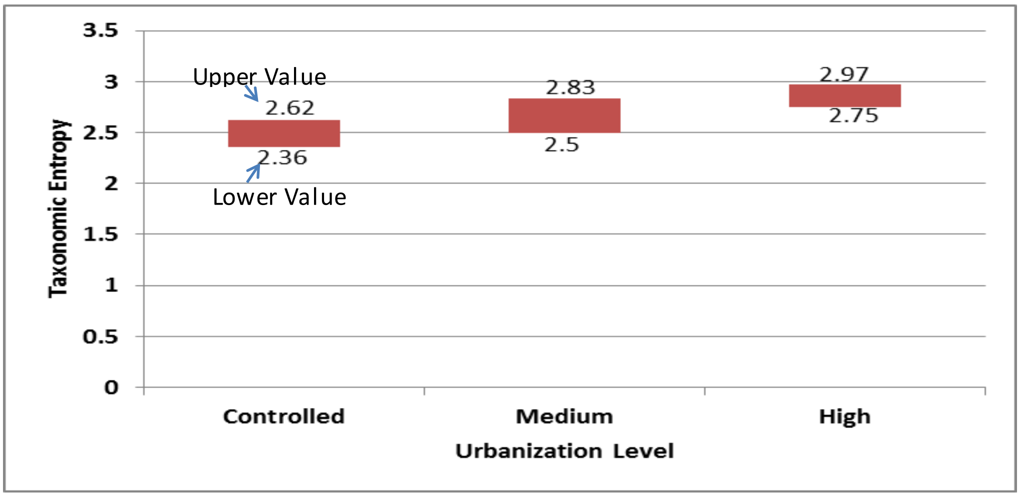


Figure 5.13: Taxonomic Entropy Values of Urbanization Controlled, Medium and Highly Urbanized Streetscapes in Backward Direction

According to the calculations, the backward taxonomic entropy values ranged between 2.36 to 2.62 for urbanization controlled streetscapes, 2.5 to 2.83 for medium urbanized streetscapes and 2.75 to 2.97 for highly urbanized streetscapes. Over all, the range of backward direction taxonomic entropy values is comparable with that of the forward direction entropy values.

From this figure it can be seen that the ranges of forward and backward entropy values comparable but for minor variations in some streetscapes in both directions. The entropy values displayed significant differences with the building density of the streetscapes.

5.4 Statistical verification of the relationships

To statistically test the differences of taxonomic entropy values for forward and backward directions and the different urbanization levels in the streetscapes, a two factor factorial ANOVA test was undertaken. The results of the ANOVA test are given in the table 5.6 and table 5.7.

Table 5.6: ANOVA Two-Factor With Replication for Three Streetscape Groups

SUMMARY	Low Density	Medium Density	High Density	Total
forward				
Count	20	20	20	60
Sum	49.74765119	54.49762523	57.79405293	162.0393293
Average	2.487382559	2.724881262	2.889702647	2.700655489
Variance	0.00658072	0.00504318	0.003287509	0.032534541
backward				
Count	20	20	20	60
Sum	49.50228627	54.7496232	57.42477294	161.6766824
Average	2.475114313	2.73748116	2.871238647	2.694611373
Variance	0.004395004	0.004398335	0.00316665	0.031381682
Total				
Count	40	40	40	
Sum	99.24993745	109.2472484	115.2188259	
Average	2.481248436	2.731181211	2.880470647	
Variance	0.00538574	0.004640419	0.003231749	

Table 5.7: ANOVA Table

Source of Variation	SS	df	MS	F	P-value	F crit
Forward and Backward	0.00109594	1	0.00109594	0.244707797	0.621778384	3.92433
Urbanization	3.255094677	2	1.627547338	**363.4081251**	**0.000000000**	**3.075853**
Interaction	0.005405926	2	0.002702963	0.603533091	0.54861395	3.075853
Within	0.510556544	114	0.004478566			
Total	3.772153087	119				

The results of the ANOVA test displayed that there is no significant difference (p value 0.62>0.05 and F value less than F critical) in the taxonomic entropy values for forward and backward directions of the streetscapes. The p value for urbanization level is less than 0.05 (0.000) and F value is greater than F critical value; consequently, there is a significant difference of the taxonomic entropy based on the urbanization level of streetscapes. The interaction between two directions and the urbanization level did not show any significant difference.

Thus the taxonomic entropy values for forward and backward directions are similar to each other. Therefore based on the moving direction along the streetscape, the subjects did not feel much difference in perceived visual complexity.

However, based on the urbanization level, there is a significant difference of the feeling of visual complexity. Highly urbanized streetscapes displayed a higher complexity and the urbanization controlled streetscapes displayed the lowest visual complexity.

Figure 5.14 displays perspective views of the lowest taxonomic entropy streetscape and figure 5.15 displays perspective views of the highest taxonomic entropy streetscape of the study area.

Figure 5.14: Perspective Views of Lowest Taxonomic Entropy Streetscape

Figure 5.15: Perspective Views of Highest Taxonomic Entropy Streetscape

In general, urban planning area can be classified into urbanization area (medium urbanized and highly urbanized) and the urbanization controlled area. The streetscapes in high building density areas can be considered as an urbanization area. Urbanization area associates with abundance of other visual elements like vegetation, boundaries of the properties, adornments on the buildings, and color variations.

Therefore more buildings entail with more visual elements. Therefore, in urbanization areas the taxonomic entropy became high. The low density streetscapes in urbanization controlled area showed lowest taxonomic entropy. These streetscapes are monotonous and they have very low amount of urban elements, therefore the taxonomic entropy became low.

In general, from the tested streetscapes, the streetscapes in the urbanization areas (medium urbanized and highly urbanized) displayed high taxonomic entropy values while the streetscapes in the urbanization controlled areas displayed lower taxonomic entropy values.

From the outcome of this research, it can be concluded that based on the availability of landscape features along the streetscapes, the taxonomic entropy differs. Higher urbanization means higher number of figures and backgrounds and their connections. Therefore the structured hierarchical visual complexity of the streetscapes in the urbanization areas increases. Urbanization controlled areas has lower number of attractive figures and backgrounds and their connections, therefore the structured hierarchical visual complexity becomes lower.

5.5 Sensitivity analysis of the taxonomic entropy using commercial streetscape views

The next section of the study was to analyze the sensitivity of the set method. To check the sensitivity, commercial streetscapes were selected. Modifications for the streetscapes and for the buildings were undertaken using Photoshop software. Modifications were done in several ways.

5.5.1 Change of design

The designs of the buildings and the streetscapes were done in this section. For example, from some buildings, the available window shapes were replaced by another shape windows, the square shaped buildings were changed to rectangular shaped buildings. When the design changes, some of the visual elements removed from the scene, while some of the visual elements added to the scene. In some cases, the amounts of visual elements keep unchanged.

Through this modification the taxonomic diagram changed in several ways, such as the length of the taxonomic diagram changed when the number of visual elements changed, the shape of the diagram changed when the design changed, etc. The changes made to the streetscape affected the visual perception. When the visual perception changed, the amount and the order of perceiving elements changed. It caused to change the taxonomic diagram. When the taxonomic diagram changed, the taxonomic entropy value changed accordingly. Figures 5.16 and 5.17displays the original condition of a house and its taxonomic diagram while figures 5.18 and 5.19 displays the design changed house and its taxonomic diagram for clear understanding of this section.

Figure 5.16: Original View of a House

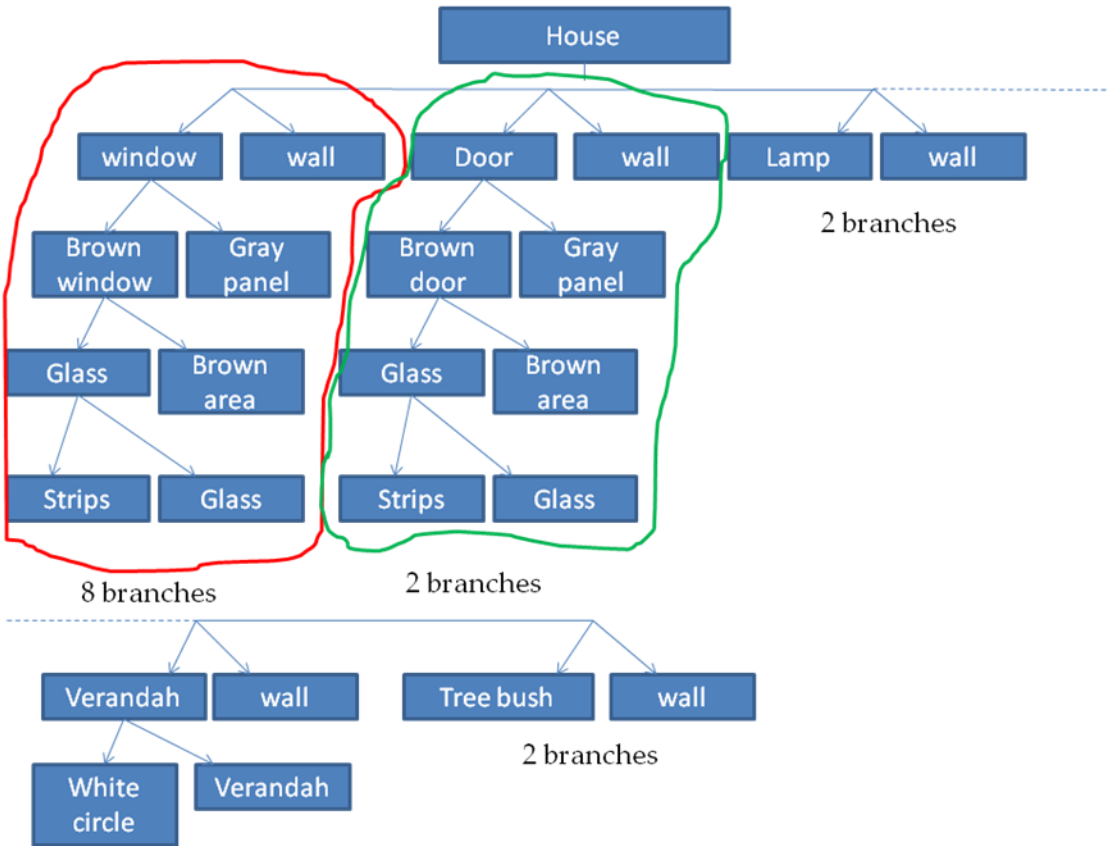


Figure 5.17: The Original Taxonomic Diagram.

The taxonomic diagram consisted of 10 level 5 branches, 1 level 3 branches and 4 level 2 branches. Using the number of branches the taxonomic entropy was calculated in Excel. Table 5.8 displays the taxonomic entropy calculation procedure for this house.

Table 5.8: Taxonomic Entropy Calculation in Excel

Level	No. of branches	Probability(pi)	Total length(ki)	ln ki	pi ln ki
2	4	0.266667	10	2.302585	0.614023
3	1	0.066667	20	2.995732	0.199715
5	10	0.666667	40	3.688879	2.459253
Sum	15			**Taxonomic entropy**	**3.272991**

The taxonomic entropy value for the original view was 3.27. After that, the calculations were done for the modified view of the same house.

Figure 5.18: Design Changed House

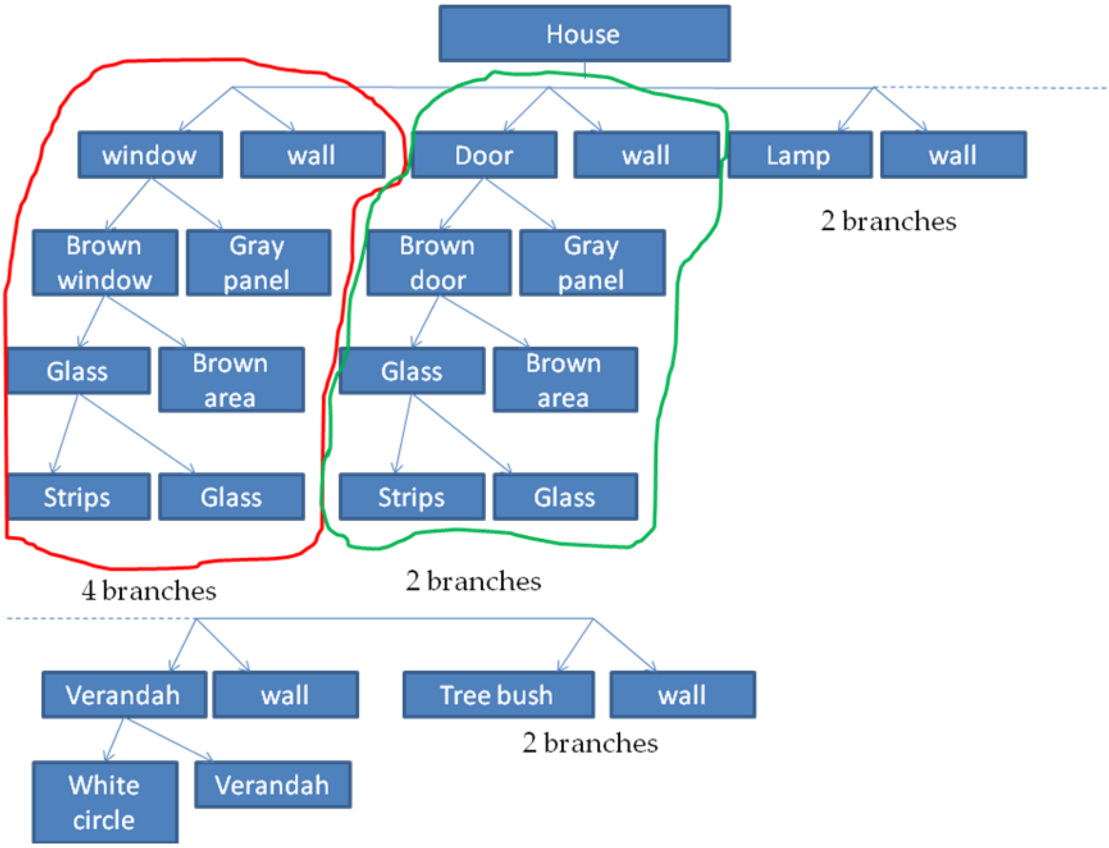


Figure 5.19: New Taxonomic Diagram

After modifying the design of the house, the shape of the taxonomic diagram changed. The new diagram had 6 level 5 branches, 1 level 3 branch and 4 level 2 branches. The table 5.9 displays the new taxonomic entropy calculation for the new diagram.

Table 5.9: Taxonomic Entropy Calculation for the New Diagram

Level	**No. of branches**	**Probability(pi)**	**Total length(ki)**	**ln ki**	**pi ln ki**
2	4	0.363636	10	2.302585	0.837304
3	1	0.090909	20	2.995732	0.272339
5	6	0.545455	40	3.688879	2.012116
Sum	11			**Taxonomic entropy**	**3.121759**

According to the results, when the building design changed, the taxonomic entropy value reduced from 3.27 to 3.12. When the design changed, the visual perception changed. It affected to change the order of visual perception and to change the shape of the taxonomic diagram. Therefore ultimately, the taxonomic entropy changed.

5.5.2 Change of the Color

Similar situations occur when any change was undertaken to the streetscapes. Figure 5.20 to 5.24 display another example of streetscape change by changing the color of building.

Figure 5.20: Original View of a Housing Complex

The taxonomic diagrams were drawn separately for the first floor and the ground floor of the housing complex since the building is large and having multiple taxonomic entropy values increase the accuracy of the analysis. Figure 5.21 displays the taxonomic diagram for the upper floor of the building.

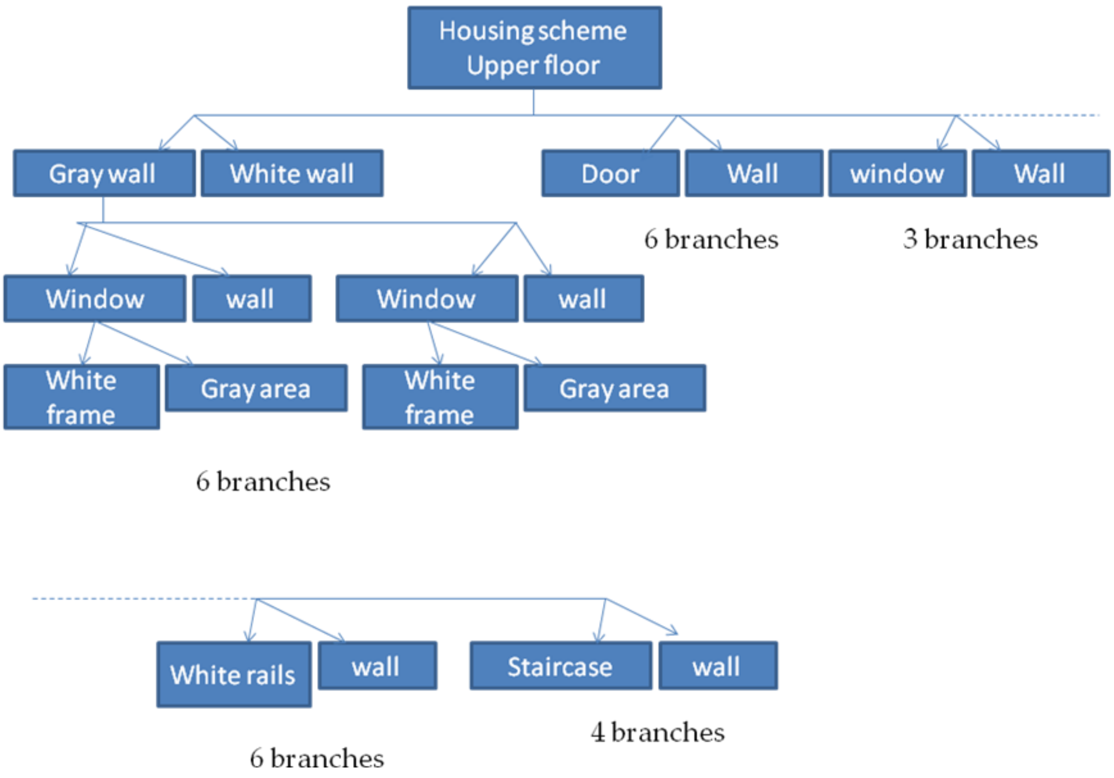


Figure 5.21: Taxonomic Diagram for the Upper Floor of the Housing Scheme

The taxonomic entropy value for the upper floor was 2.56. Figure 5.22 displays the taxonomic diagram for the ground floor of the building.

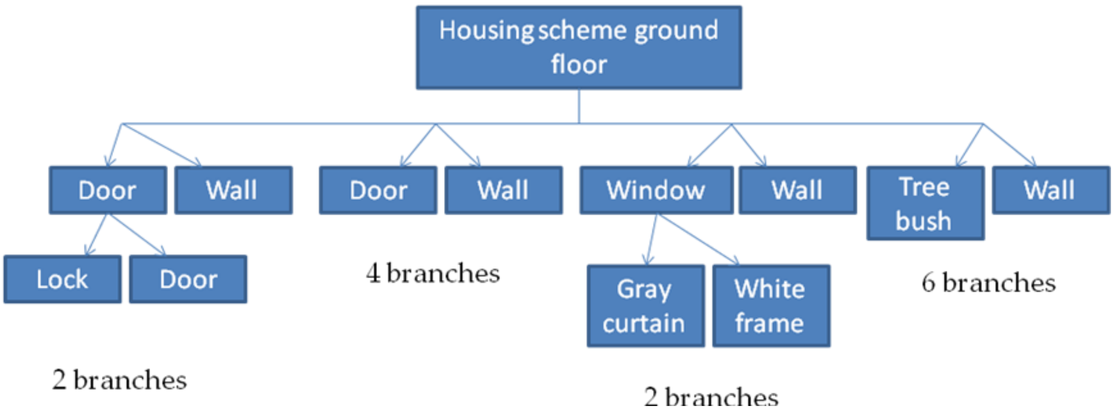


Figure 5.22: Taxonomic Diagram for the Ground Floor

The taxonomic entropy value for the ground floor was 2.5. The average entropy for the housing scheme was 2.53.

The next step was changing the color of the houses of the housing scheme. Each house was painted in different colors. When color changed the visual perception changed causing to change the order of perception of visual elements changed. It caused to change the taxonomic diagram. Figure 5.23 displays the color changed view of the same building.

Figure 5.23: Color Changed Housing Scheme

Figures 5.24 and 5.25 display the taxonomic diagrams drawn to the brown color house of the scheme.

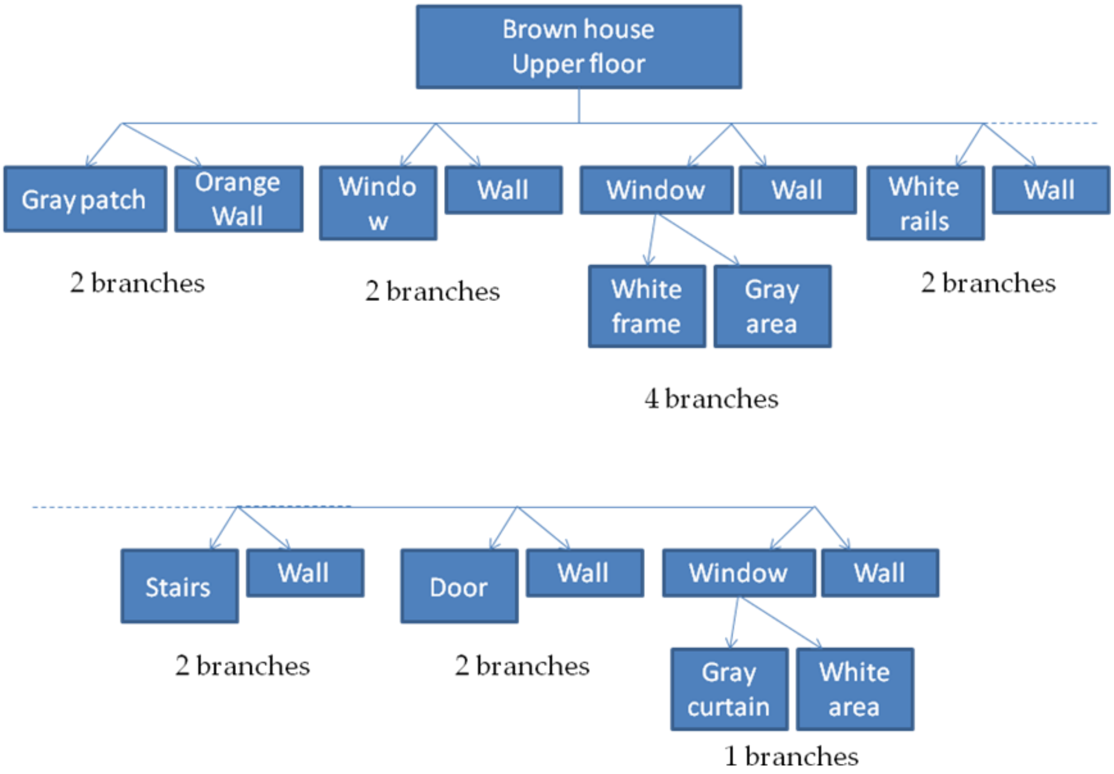


Figure 5.24: Taxonomic Diagram for the Upper Floor of the Brown Color House

The taxonomic entropy value for the upper floor was 2.64.

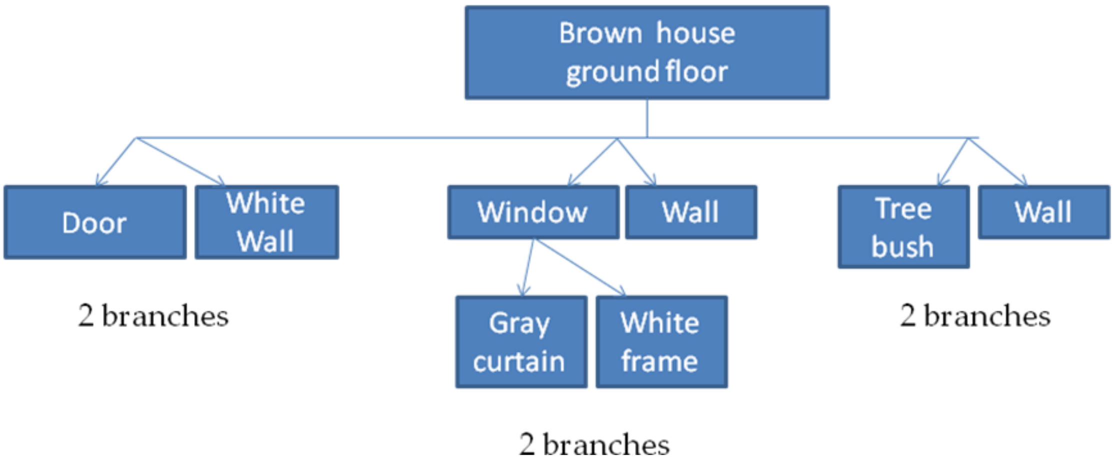


Figure 5.25: Taxonomic Diagram for the Ground Floor of the Brown Color House

The taxonomic entropy value was 2.58 for the ground floor. Same procedure was undertaken for the rest of the houses of the scheme and the taxonomic entropy values were obtained. Finally the average of all these entropy values was taken as the average taxonomic entropy for the building. It was 2.56. When the color of the housing scheme changed, the taxonomic entropy value changed from 2.53 to 2.56. A slight increase of the value could be observed. It was mainly because with the visual perception change with the color change.

5.5.3 Make buildings simple

In this modification, the complex buildings were converted into simple buildings by removing some visual elements which are not necessary for the building. Figure 5.26 and 5.27 display an example for this modification.

Figure 5.26: The Original View of the Buildings

Figure 5.27: The Simplified Building View

When the building was converted to a simple design, some of the visual elements removed from the view and some of the visual elements were added to the view. Therefore the taxonomic diagram was changed and the taxonomic entropy value changed. In this example, the taxonomic entropy value changed from 2.98 to 2.83 after making the building simple.

Similar condition occur when any modification is undertaken to the streetscape views such as, changing thickness of visual elements, change heights of buildings, change design of visual elements, etc.

Therefore, using this new method it is very easy and accurate to measure the structural hierarchical visual complexity changes with the changes of the landscape. Therefore, this new method is very useful for the architectural designers and landscape planners in their careers.

CHAPTER 06

CONCLUSIONS

This research was undertaken to measure the structural hierarchical visual complexity of residential streetscapes. To achieve this objective, two novel approaches for landscape planning were used: (i) the figure and background classification of visual elements and (ii) taxonomic entropy analysis.

Figure and background classification technique was applied to find out the distinction and the connections among the visual elements of the streetscapes. The structural hierarchical visual complexity increases when the variety (distinction) and the dependency (connections) increase. Drawing taxonomic diagrams, to depict the identified distinctions and connections between the figures and backgrounds is another novel approach applied for this research. As the variety and the connections among the visual elements in the streetscape increase, accordingly, by looking at the taxonomic diagrams of the streetscape elements, it was clear to get an idea about the streetscape structural hierarchical visual complexity.

To prove the structural hierarchical visual complexity reflected by the variations in the size of the taxonomic diagram, the taxonomic entropy was utilized. Taxonomic entropy gives a numerical value reflecting the variety and the connections between the elements in the taxonomic diagram. In consequence when the taxonomic diagram is vertically and horizontally lengthy, the taxonomic entropy increases. When the taxonomic diagram is small in both directions, the taxonomic entropy becomes small. Therefore taxonomic entropy calculation is a prolific effort to display the structural hierarchical visual complexity numerically.

According to the calculations, 70 residential streetscapes located in the Saitama city, Japan, displayed taxonomic entropy in between 2.3 and 3.0. These 70 residential streetscapes grouped into 20 streetscapes in highly urbanized areas, 30 streetscapes in medium urbanized areas and 20 streetscapes in urbanization controlled areas based on the building density. Based on the urbanization level the taxonomic entropy differed.

Consequently, the highly urbanized streetscapes obtained values in between 2.8 to 3.0, medium urbanized streetscapes obtained 2.6 to 2.8 taxonomic entropy values and the urbanization controlled residential streetscapes obtained values in between 2.3 to 2.6.

Counting figures and backgrounds perceived by the observer is a little bit difficult task. Visual perception varies person to person; therefore more observers and careful classification are needed for better classification of figures and backgrounds. This section was the most critical in this research and it consumed a lot of time.

Taxonomic entropy calculation primarily based on the subjective analysis of figures and backgrounds. Therefore the value may change based on the variation in human perception and based on the counting method of figures and backgrounds.

The results obtained through taxonomic entropy were statistically tested using two factor factorial ANOVA test. ANOVA test proves that there is no significant variation in the structural hierarchical visual complexity in the forward and backward directions of the tested streetscapes (p value > 0.05). However, based on the availability of streetscape features, the structural hierarchical visual complexity showed a significant variation (p value < 0.05).

Taxonomic entropy represents the visual complexity level of streetscapes. It depends on the perceivable figures and backgrounds. Hence this value is very useful for urban planners and architectural planners in designing streetscapes and building facades. Further this research method is useful in setting up landscape regulations. Once the taxonomic entropy values for best landscape types of different landscapes are identified, those values can be applied to evaluate the landscape complexity of existing landscapes as well as to build the new landscapes to match with the human perception.

Taxonomic entropy best represents the structural hierarchical visual complexity. Taxonomic entropy gives values based on both variety and dependency. It depends on the taxonomic diagram. Taxonomic diagram represents the order of human visual perception of figures and backgrounds. Therefore, taxonomic diagram is sensitive to the visual perception changes. Taxonomic diagram changes when the amount of perceivable visual information changes. Perceivable visual information changes with the landscape design changes. Therefore Landscape changes cause to change the visual perception and it causes to change the taxonomic entropy.

RECOMMENDATIONS

This research introduced two new approaches to landscape planning; those are the use of figures and backgrounds to identify the visual complexity and the use of taxonomic entropy to give a numeric value to the visual complexity.

The study was conducted in residential streetscapes in Saitama city. Although the obtained values displayed good variations to identify the visual complexity differences, it is not appropriate to come to the conclusions just only with one test site research. Therefore it is better to conduct the same study in different residential areas in different districts in Japan and come to the conclusions.

The next important thing is, the research should be carried out in different landscape types other than residential areas to identify the taxonomic value changes with the landscape type. It will be very useful in setting up landscape regulations in future.

For the study, only twenty subjects were selected. However, if the number of subjects increased, the accuracy of the research will be higher.

REFERENCES

1. Attneave, F (1957). Physical determinants of the judged complexity of shapes. Journal of Experimental Psychology 53: 221–227.

2. Berlyne, D. E (1971). Aesthetics and psychobiology. New York: McGraw-Hill.

3. Berlyne, D. E (1974). Studies in the New Experimental Aesthetics. New York: Wiley.

4. Berlyne, D. E (1977). The new experimental aesthetics and environmental psychology. In P. Suedfeld, J. A. Russell, L. M. Ward, F. Szigeti & G. Davis, (Eds), The Behavioral Basis of Design, Book 2, Proceedings, EDRA 7. Vancouver: McGraw Hill, 13-22.

5. Burrough. P. A (1986). Principies of Geographic information Systems for Earth Resources Assessment, Clarendon Press, Oxford, U.K., 193p.

6. Campbell, F., Robson, J (1968). Application of Fourier analysis to the visibility of gratings. Journal of Physiology 197.

7. Carranza, S., Romano, A., Arnold, E.N., Sotgiu, G (2007). Biogeography and evolution of European cave salamanders, Hydromantes (Urodela: Plethodontidae), inferred from mtDNA sequences. J. Biogeogr. 35 (4), 724–738.

8. Chen, Y., Chan, A.B (2012). Adaptive figure-ground classification. Peking university, China

9. Chikhman, V., Bondarko, V., Danilova, M., Goluzina, A., Shelepin, Y (2012). Complexity of images: experimental and computational estimates compared. Perception 41: 631–647.

10. Chipman, S.F (1977). Complexity and structure in visual patterns. Journal of Experimental Psychology. 106: 269-301.

11. Cooper, J (2003). Fractal assessment of street-level skylines: a possible means of assessing and comparing character. Urban Morphology 7: 73–82.

12. De Cola, L (1989). Fractal analysis of a classified Landsat scene. Photogrammetric Engineering and Remote Sensing, 55(5), 601-610.

13. Donderi, D (2006). An information theory analysis of visual complexity and dissimilarity. Perception 35: 823–835.

14. Duerksen, C.J., Goebel, R.M (1999). Aesthetics, community character, and the law. American Planning Association, Service Report Number 489–490.

15. Dušek, R., Popelková, R (2012): Theoretical view of the Shannon Index in the evaluation of landscape diversity AUC Geographica, 47, No. 2, pp. 5–13

16. Elsheshtawy, Y (1997). Urban complexity: Toward the measurements of the physical complexity of streetscapes. Journal of Architectural and Planning Research 14: 301–316.

17. Forsythe, A., Sheehy, N., Sawey, M (2003). Measuring icon complexity: An automated analysis. Behavior Research Methods 35: 334–342.

18. Fowlkes, C.C., Martin, D.R., Malik, J (2007). Local figure-ground cues are valid for natural images. Journal of Vision 7(8):2, 1–9

19. Gunger, B.S (2013). A study on relations between soil and plant species in Alpine zone at Kazdagi national park, Turkey. Pakistan Journal of Botany, 45(6): 1981-1987

20. HarperCollins Publishers 1991, 1994, 1998, 2000, 2003

21. Havel I (1995): "Scale Dimensions in Nature", International Journal of General Systems 23 (2), p. 303-332.

22. Heylighen, F (1996). What is complexity? Principia Cybernetica Web. http://pespmc1.vub.ac.be/complexi.html

23. Hill, M. O (1973). "Diversity and evenness: a unifying notation and its consequences". Ecology 54: 427–432

24. Jahn, G., Oehme, A., Krems, J., Gelau, C (2005). Peripheral detection as a workload measure in driving: Effects of traffic complexity and route guidance system use in a driving study. Transportation Research Part F 8255–275

25. Kaplan, R., Kaplan, S., and Ryan, R (1998). With People in Mind: Design and Management of Everyday Nature. Island Press, Washington, DC.

26. Kaplan, S., Kaplan, R., Wendt, J. S (1972). Rated preference and complexity for natural and urban visual material. Perception & Psychophysics, 12: 334-356.

27. Kuiper, J (1998). Landscape quality based upon diversity, coherence and continuity. Landscape planning at different planning-levels in the River area of The Netherlands, Landscape-and-urban-planning, Vol. 43, No. 1-3, pp. 91-104.

28. Lightner, B.C (1993). Survey of design review practices. Planning Advisory Service Memo January 1993. American Planning Association, Chicago.

29. Mandelbrot, B.B (1977). The fractal geometry of nature, W.H. Freeman and Company, (New York).

30. Nasanen, R., Kukkonen, H., Rovamo, J (1993). Spatial integration of band-pass filtered patterns in noise. Vision Research 33: 903–911.

31. Nassauer, J. I (1988). The aesthetics of horticulture: Neatness as a form of care. Hortscience 23: 973–977.Netherlands.

32. Noderhaug, A., Ihse, M., & Pedersen, O (2000). Biotope patterns and abundance of meadow plant species in a Norwegian rural landscape. Landscape Ecology, 15, 201–218.

33. O'Neill, R.V., Krummel, J.R., Gardner, R.H., Sugihara, G., Jackson, B., DeAngelis, D.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W., Dale, V.H. and Graham, R.L (1988). Indices of landscape pattern. Landsc. Ecol. l(3): 153-162

34. Olsen, A., Arnqvist, A., Hammar, M. Normark, S (1993). Environmental regulation of curli production in Escherichia coli. Infect.Agents Dis 2:272-274
35. Pino, J., Roda, F., Ribas, J., & Pons, X (2000). Landscape structure and bird species richness: implications for conservation in rural areas between natural parks. Landscape and Urban Planning, 49, 35–48.

36. Piotrowski, L., Campbell, F (1981). A demonstration of the visual importance and exibility of spatial-frequency amplitude and phase. Perception 11: 337–346.

37. Pyron, B (1972). Form and diversity in human habitats: judgmental and attitude responses. Environment and Behavior, 4(1), 87-120.

38. Rachelle, E.D., Madhur, A (2004). From traditional diversity indices to taxonomic diversity indices. International Journal of Ecology and Environmental Sciences 30: 85-92

39. Rao, C.R (1982). Diversity and dissimilarity coefficients: A unified approach. Theoretical Population Biology 21: 24-43

40. Ren, X., Fowlkes, C.C., Malik, J (2012). Figure/ground assignment in natural images. University of California, Berkeley.

41. Rényi, A (1961). "On measures of information and entropy" (PDF). Proceedings of the fourth Berkeley Symposium on Mathematics, Statistics and Probability 1960. pp. 547–561.

42. Rey-Benayas, J. M., & Pope, K. O (1995). Landscape ecology and diversity patterns in the seasonal tropics from Landsat TM imagery. Ecological Applications, 5, 386–394.

43. Ricotta, C., Avena, G.C (2003). An information theoretical measure of taxonomic diversity. Acta Biotheorica 51(1):35-41.

44. Riitters, K. H., O' Neill, R. V, Hunsaker, C. T., Wickham, J. D., Yankee, D. H., Timmins, S. P., Jones, K. B., & Jackson, B. L (1995). A factor analysis of landscape pattern and structure metrics. Landscape Ecology, 10, 23–39.

45. Rocchini, D., Neteler, M (2012). Let the four freedoms paradigm apply to ecology. **Trends in Ecology & Evolution**, 27: 310–311

46. Rosenholtz, R., Li, Y., Mansfield, J., Jin, Z (2005). Feature congestion, a measure of display clutter. ACM Special Interest Group on Computer Human Interaction 761–770.

47. Rosenholtz, R., Li, Y., Nakano, L (2007). Measuring visual clutter. Journal of Vision 7: 1–22.

48. Schacter, L.D., Gilbert, D.T., Wegner, D.M. (2011). "Psychology (2nd ed.)." New York, NY: Worth Publishers

49. Shannon CE, Weaver W (1949). The Mathematical Theory of Communication. University of Illions Press, Urbana, USA

50. Shannon, C., Weaver, W (1998) The Mathematical Theory of Communication, Urbana and Chicago, IL: University of Illinois Press

51. Shimatani, K (2001). On the measurement of species diversity incorporating species differences. Oikos 93: 135-147

52. Simpson E. H (1949). Measurement of diversity. Nature, 163: 688

53. Stamps III, A.E (2003). Advances in visual diversity and entropy. Environment and Planning B: Planning and Design 2003. 30: 449-463

54. Tucker, C., Ostwald, M., Chalup, S., Marshall, J (2005). A method for the visual analysis of the streetscape. Paper presented at the Space Syntax 5th International Symposium, Delft.

55. Turner, M. G (1990). Spatial and temporal analysis of landscape patterns. Landscape Ecology, 4, 21–30.

56. Warwick, R. M., Clarke, K. R (1995). New 'biodiversity' measures reveal a decrease in taxonomic distinctness with increasing stress. Mar Ecol Prog Ser 129:301-305

57. Warwick, R. M., Clarke, K. R (1998). Taxonomic distinctness and environmental assessment. Journal of Applied Ecology 35: 532-543

ANNEXURE

Annex A

Examples of Protocol Questioning Pattern for the Streetscape Survey

Sample 01:

1. What is the most prominent visual element at this viewpoint?
    a. Blue color vending machine
2. What qualities of the surroundings made you feel it as the prominent element?
    a. Surrounding is a mixture of tree bushes, gray short boundary wall and gray house. Thus the blue box appeared as the prominent element in dull color surrounding.
3. What can you see on the vending machine?
    a. White color letters

Sample 2:

1. What is the most prominent visual element at this viewpoint?
    a. The brown color house
2. What are the things surrounding it?
    a. sky
3. Can you please explain more about the house?
    a. It has a dark brown roof
    b. Side wall has 4 large windows and 6 small windows
    c. Some water pipes can be seen along the wall
4. Can you explain more about windows?
    a. Windows have dark brown frames and plain glasses
    b. Some windows have white curtains

Sample 03:

1. What is the most prominent element at this viewpoint?
    a. Two color house
2. What are the things surrounding it?
    a. The sky
3. Can you please explain more about the house?
    a. It is a two story house
    b. The house has two colors, gray and brown
4. What section of the house is more beautiful?
    a. The brown section
5. Please explain more about that part of the house?
    a. Brown wall has a brick pattern
    b. White lines separate the bricks on the wall
    c. Dark brown bricks could be seen in some places

    d. Two types of windows are there, Upper story has long windows, lower story has medium size windows

6. Can you please explain more about windows?
    a. Upper windows have a white color frame and a plain glass
    b. Plain glasses divided into sections by a white panel
    c. Lower window divided into two sections by white frame
7. Can you please explain about the gray color part of the house?
    a. It also has a brick structure on the wall
    b. Black lines separated the bricks
    c. White pipelines can be seen on the wall
    d. Upper story has 3 big windows and lower story has a big window and two small windows
8. Can you please explain about windows?
    a. Windows have white frame and plain glasses
    b. Behind the glass, white curtains can be seen
9. Can you explain about the roof?
    a. The roof is a dark gray color
    b. Surface has small openings
    c. The surface is corrugated

Annex B

Survey of Streetscape Analysis

The purpose of the survey: to identify the figures and backgrounds surrounding the streets.

Definition for Figure and Background:

Elements are perceived as either figures (distinct elements of focus) or ground (the background or landscape on which the figures rest).

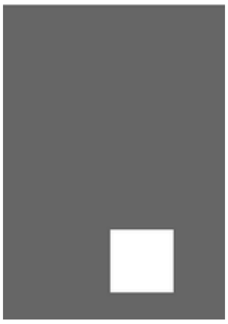


Figure: White box

Background: Dark gray area

1. Figure 1: black lines

   Background 1: white surrounding

   Figure 2: white boxes

   Background 2: black surrounding

2. Figure 1: white rectangle

   Background 1: black surrounding

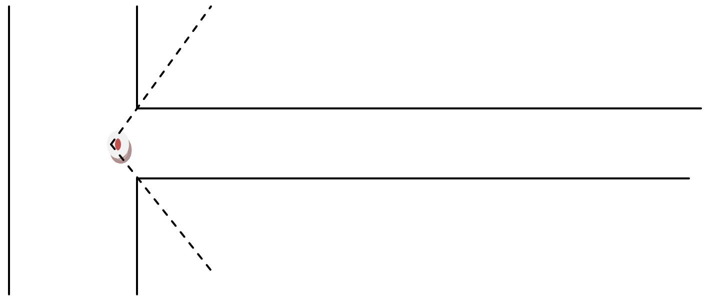
   Figure 2: black lines

   Background 2: white surrounding

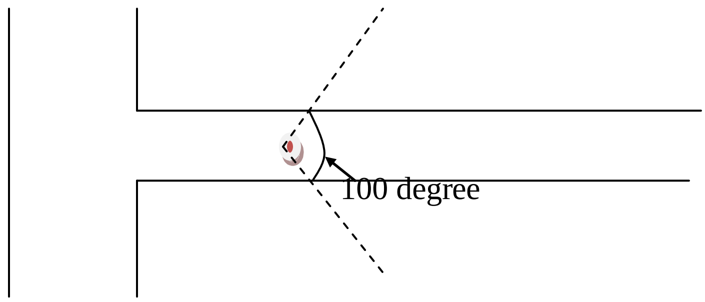
Similar classifications are expected from you during the survey.

Instructions for the viewer

1. Please use both the video recorder and the IC recorder given to you
2. Please start the streetscape viewing little bit away from the street junction. Please note the sketch below.

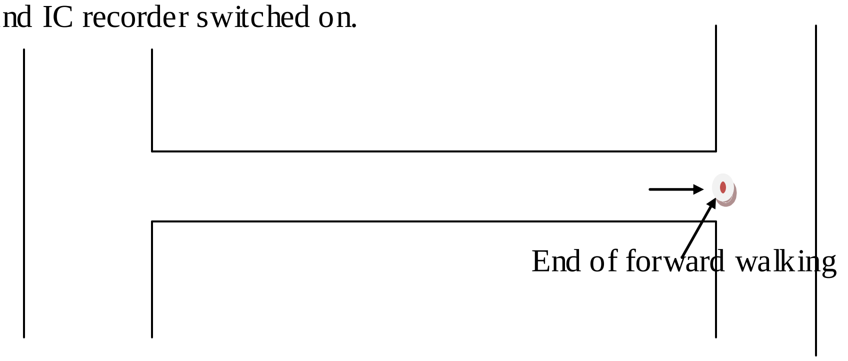


3. When you start walking, please switch on both the video recorder and the IC recorder.
4. Please try to keep head looking forward within 100 degree viewing angle.

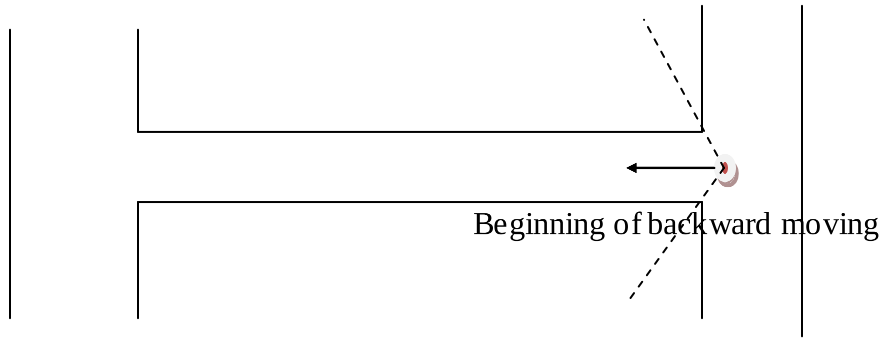


5. Please see the streetscape elements on either side of you and in front of you while you are walking forward along the street. The streetscape elements include the things on the street, the things on either side of the street, including buildings, utility, signboards and etc. and the things extending towards the sky. You have to select the prominent elements, considering all these sections.
6. Please don't look back while walking, note only the visual elements in front of you and either side of you.
7. You may perceive the visual elements near to the street or far away from the street
8. Please stop at the places the instructor says to you. Please answer the questions asked by the instructor at these points. A separate sheet is given to you explaining you about the example questions.

9. When you explain about the visual elements, please try to explain in detail as much as possible. A sample explanation is given on a separate sheet.
10. When you are explaining about a visual element, please stop walking. After finishing explanation start walking again. It will prevent missing of some visual elements from your eyesight.
11. Please walk until you meet the end junction of the street while keeping video recorder and IC recorder switched on.



12. At the end point of the street please switch off both the video recorder and the IC recorder.
13. After having some rest, please follow the same procedure for backward movement of the same street.



14. If you have any questions or unclear explanations about the survey, please feel free to contact me while doing the survey. I will be with you until you finish the survey.

Thank you very much for your kind corporation by spending your valuable time with me on streets to succeed my Doctoral Degree Research.