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Research

Cognitive-Mathematical Approaches for Evaluating Architectural Contextual Fit

Abstract. The main goal of this study is to apply a scientific quantitative approach to the investigation of contextual fit. This is approached mathematically within the framework of cognitive science and research on categorization and prototypes. Two experiments investigated two leading mathematical-cognitive approaches for explaining people's judgment of contextual fit of a new building with an architectural/urban context: prototype approach and feature frequency approach. The basic concept is that people represent the built environment via architectural prototypes and/or frequencies of encountered architectural features. In the first experiment, a group of twelve participants performed rank order tasks on artificially created architectural patterns, for the purpose of psychological scaling. Perceptual distances among all patterns were mathematically determined. In the second experiment, three groups of architectural patterns were constructed to represent assumed architectural contexts. The prototype of each context was mathematically determined according to prototype cognitive model, and based on the distances calculated in the first experiment. Fifty-six students participated in the main experiment, in which they rank ordered a group of fifteen architectural patterns in terms of contextual fit to each of the three architectural contexts. Participants' rank order data of the fifteen patterns were regressed on both the perceptual distances from prototypes, and numbers of features shared with each architectural context. Results indicated that both prototype and feature frequency approaches significantly accounted for important portions of participants' judgments. However, participants tended to prefer one approach to the other according to context composition. Results have implications for both research on utilizing cognitive-mathematical models in architectural research and on urban design guidelines and control.

Introduction

This study is based on the premise that understanding people's responses to architectural contexts requires knowing how they mentally represent the diverse forms of the experienced built environment as quantifiable images, which may be referred to as indices of contextual fit. The main goal of this study is to apply a scientific approach to the investigation of contextual fit. Investigating the contextual fit in the study is approached mathematically within the framework of cognitive science and research on categorization and prototypes. The basic assumption of the study is that people represent the diverse forms of the experienced built environment as abstract images, which account for the variation in its previously experienced exemplars and features. These abstract images could be either

internally created mathematical averages of previous experiences in the form of prototypes, or a summation of the total frequency of shared features. The direct objective of this study is to evaluate the hypothesis that people mentally represent an architectural/urban context (group of architectural elevations) in the form of a prototype and/or a feature frequency image, according to which they judge the belongingness of novel (infill) patterns to that specific architectural /urban context.

The need for this research

There has been a growing public dissatisfaction with the visual impact of environment in the past few decades [Sanoff 1991]. Accordingly, many countries began developing and applying new legislations that require solid assessment of environmental aesthetics. Research indicated that the public aesthetic dissatisfaction with their environments is associated with the differences between professionals and the public in their environmental judgments and preferences [Canter 1969; Groat 1982; Groat 1984]. It is also argued that this dissatisfaction is a result of the lack of empirical studies that validate urban design controls [Stamps 1995]. Developing public policies for aesthetic controls requires community support by involving people in shaping their visual environment [Sanoff 1991]. In this context, Stamps [1995] suggested “conducting scientific experiments on public preferences before the regulations are implemented”. Along this line, Stamps [2000] has conducted a considerable number of empirical studies and experiments in an attempt to apply a logical solid theory of environmental aesthetics, which also proposed to measure aesthetic impact. Within this context, the present study investigates another approach to evaluate architectural contextual fit quantitatively based on people’s perceptions.

Architecture influences the perception, memory, and clarity of the images that people form about their environments. Within this context, environmental ambiguity and imageability can be better understood by the perception of contextual fit. The discussion of contextual fit has traditionally ranged from philosophical perspectives to physical design tactics and cues. Harrison and Howard [1980] considered the physical components of the environment necessary to evoke strong images in observers. Appearance, which is an important aspect of the physical components, included shape, pattern, form, color, size, material, and design (pattern).

Theoretical background

Pattern recognition theories

Our environmental knowledge develops both from the regularities in the environment and the difference between the distinctive examples and the knowledge structure [Purcell & Nasar 1992]. Several psychological theories and models, including quantitative ones, have been explored to explain our understanding of the environment. Categorization and prototypicality studies have provided us with many of these models. Most theories of categorization are based on the idea that all instances of a category share something in common and that this “something”, however defined, is necessary for a particular instance to belong to a category [Kumatsu 1992]. Many of the previous theories followed one of two major streams: template-matching and feature analysis [Gibson 1969; Neisser 1967; Reed 1972; Reed 1978]. Feature analysis proposes that the process of pattern recognition includes decomposing the pattern into its constituent features and comparing these features with the stored ones. Template matching proposes that “an unknown pattern is represented

as an unanalyzed whole and is identified based on its degree of overlap with various standards” [Reed 1978: 139]. Feature analysis theory is generally more flexible than template matching theory, though it has the problem of configuration. For example, the same features could be used to construct many unrecognized and even scrambled patterns. On the other hand, one major problem of template matching theory is its incapacity to account for pattern variability and transformation. In response to the above criticisms of both theories, and based on the logic of exemplar variety and associated typicality, a prototype theory evolved.

The basic idea of the prototype theory is that the variety in exemplar differences from the generic knowledge creates experiences that vary in consistency with the knowledge structure. According to Rosch and Mervis [1975], members of a category regarded as typical shared more features with other members of the category than with non-typical members. In other words, examples that are consistent with the knowledge structure are judged as typical of knowledge structure. These typical examples were termed “good examples” by Rosch and Mervis [1975] and by Purcell [1984, 1986]. Prototype theory assumes that people establish a “virtual” member to represent the average member of a certain category. Using random configurations of dots, Posner and Keele [1968] demonstrated that participants abstract category prototypes and subsequently use them for classifying novel patterns. They found that the patterns most distant from the prototype were the most difficult to recognize. To account for these data, a prototype distance model was proposed by Posner [1969]. According to Posner’s model, when a series of similar visual stimuli are experienced, a prototype is created at the point in the multidimensional similarity structure that represents the greatest similarity to all stimuli. Using geometric forms which were systematic analytic transformations of a prototype, Franks and Bransford [1971] demonstrated that participants could construct a prototype to represent the central tendency of patterns. Their experiment consisted of an acquisition phase and a recognition phase. During the acquisition phase, participants were exposed to a subset of the instances of a pattern that varied in their transformational distance from the prototype. The recognition phase consisted of the prototype and a subset of the instances of a pattern that varied in their transformational distance from the prototype. Recognition ratings were found inversely related to an item’s transformational distance from the prototype, with the prototype receiving the highest recognition rating. This study was further developed by Abu-Obeid and Tassinari [1993] using schematic architectural patterns. However the psychological distances among these patterns were empirically determined according to the model of Posner [1969]. The findings of Abu-Obeid and Tassinari confirmed the earlier findings of Franks and Bransford, as people’s recognition of novel architectural patterns was found to be an inverse function of the transformational distances from prototypical elevations.

Previous studies have also compared the feature and prototype models as explanatory accounts of people’s patterns recognition. Generally speaking, these studies demonstrated that people tend to follow prototype models when recognizing human faces, while they tend to follow feature frequency model when recognizing geometric patterns. Using schematic human faces, Reed [1972] found that more study participants used prototype strategy than feature frequency strategy in their judgments. Neumann [1977] found that people follow a feature frequency approach when processing geometric patterns, yet follow a prototype approach when processing human faces.

Levels of affect and other types of experience were found to be associated with the levels of typicality to the knowledge structure of the encountered examples [Mandler 1984; Purcell 1984]. Purcell [1986] reported the occurrence of an affective response when there is a discrepancy between a current instance of a church building and its typical examples in memory. Purcell & Nasar [1992] related typicality to style and associated typicality with the experience of familiarity. Typical examples are judged as familiar, while examples that are discrepant from the knowledge structure are judged as atypical and experienced as unfamiliar.

Method

Previous studies on pattern recognition investigated two leading and competing approaches, which were argued to provide an explanation for people's recognition of novel patterns: 1) the prototype approach and 2) the feature frequency approach. The experiments reported below were conducted to determine whether people represent a group of related architectural forms (e.g., architectural context: street façade) via architectural prototypes and/or frequencies of encountered architectural features when judging an added infill, or judging the fit of a new building to an old context.

Study scheme

By manipulating specific design variables, a total set of artificial architectural patterns was to be created for use as architectural stimuli.

The study had to introduce hypothetical architectural contexts by creating examples of street façades, which were to be constructed from previously created set of architectural patterns. Cognitively speaking, these street façades were to be used as reference learning patterns.

A subgroup of architectural patterns was to be selected from the previously created total set of architectural patterns. This subgroup was to be introduced as possible infill to the street façades. Cognitively speaking, these infill patterns were to be used as reference recognition patterns.

A prototype pattern had to be identified for each street façade. This was achieved by applying multidimensional scaling experiments, through which dissimilarity judgments among all patterns of the previously created total set of patterns were transformed into perceptual (dissimilarity) distances. A prototype of a street façade is the pattern which has the least accumulated perceptual (dissimilarity) distance from all other patterns in the façade.

Prototype theory argues that the fit of any recognition (infill) pattern with the street façade is judged as a function of its perceptual distance from the prototype of that façade. This distance should be identified using multidimensional scaling.

In addition to its distance from prototype, each recognition pattern has a number of shared features with the patterns of the street façade (feature frequency). The feature frequency theory argues that any novel pattern is judged in its fit with the street façade, according to its accumulated number of shared features with all patterns of the street façade (feature frequency).

Fig. 1. Alternatives based on number of masses and proportions

In a recognition experiment, subjects were to judge a group of recognition patterns in terms of their fit with a street façade. Their judgments were to be statistically tested as a function of the patterns' distances from prototype and/or their features frequencies.

Stimulus material: contextual cues and design variables

Visual properties of buildings are to be addressed as the contextual variables in this study. According to Habe [1989], more than 98% of design controls are on visual properties of buildings. In a study by Groat [1983], she specified space, massing and style as aspects of design strategy according to which architects may fit the new to the old. In another study, Groat [1988] investigated the design attributes of contextual compatibility. She found that the façade components had the strongest effect on compatibility judgment. Bentley et al. [1985] suggested several contextual cues, such as windows, doors, and wall details as reference variables for contextual fit. Generally speaking, previous studies indicate that judgments of buildings are related primarily to building façades. Stamps [1995] presented a method to validate contextual urban design principles as a design control. In his study, Stamps identified two reference design variables: scale and character, according to which a new building could be matched with a group of older ones.

Fig. 2. Alternatives based on window form

In another study on preferences for residential façades, Stamps [1999] identified three factors of architectural façades: surface complexity, silhouette complexity, and façade articulation.

The present study builds upon the previously mentioned reference variables. Given the sheer number of possible combinations, it would be complicated to manipulate a large number of design elements in a single study systematically. Consequently, this study used simple artificial architectural elevations that were varied systematically by manipulating three design elements. In addition to proportion, this study identified the number of masses and the form of windows as contextual design variables. The elevations created were the result of applying combined transformational possibilities to the three design elements: 1) the number of masses (two possibilities – fig. 1); 2) the proportion of masses (two possibilities – fig. 1); and 3) the form of windows (nine possibilities – fig. 2), making a total set of thirty-six alternative elevations (2x2x9). The final set of all elevations was drawn with simple rendering as shown in Appendix I.

Experiment 1: stimuli scaling

The main objective of this experiment was to determine the perceptual distances of dissimilarities among all the stimuli which were to be used as part of the independent variables in Experiment 2.

Participants

Twelve undergraduate university students (seven males and five females) volunteered to participate. The participants were neither architecture nor art majors.

Procedure

Participants, one at a time, were presented with the stimuli, which consisted in the total set of thirty-six patterns. They were asked to rank order the total set of patterns in terms of similarity to a single reference pattern, which was to be randomly chosen from the total set and rotated for each trial by the experimenter. The participant rank ordered all the elevations of the total set in terms of similarity using a rotating reference technique. In each trial, the individual reference pattern was selected by the experimenter and was recorded in a matrix of rank decisions taken by the participant. Then, the participant rank ordered the rest of the total set (35 patterns) in terms of similarity to the single reference pattern. This was considered as one trial (ranking task). A total rotation of thirty-six reference patterns produced a matrix of ranks (36x36) for each participant. To complete this matrix, each individual had to participate in thirty-six trials. The order of presenting the reference patterns was randomized between participants. The order of distributing the to-be-ranked patterns in front of the participants was randomized both within and between participants. The experimental session took approximately ninety minutes per participant.

Analysis and results

The resulting data of experiment 1, hereafter referred to as proximity data, were in the form of square asymmetric matrices of dissimilarities between patterns of the total set. Each matrix represented the responses of one participant. A multidimensional scaling analysis was applied to the collected data in the total set of patterns (thirty-six) to determine the relative perceptual dissimilarity distances among all the patterns in the set. The thirty-six patterns of the total set were spatially conceptualized as scattered along a visual space, which

has a specific number of visual dimensions. Each pattern was represented by a projection on each visual dimension (a detailed mathematical explanation is provided in Appendix II). The number of dimensions for the total set of patterns was determined according to the lowest badness-of-fit (the best model fit) criterion. Scree analyses were performed and showed that a space of four-dimensional solution best fit the patterns, which was adopted as a reference scale for the main experiment (Experiment 2).

The first objective of the above analyses was to measure the perceptual (dissimilarity) distances among all patterns, which represent the levels of their dissimilarities. Determining such distances would facilitate determining the central representation (prototype) of any selected group (category) of elevations from within the total set. It would also facilitate determining the closeness of each recognition elevation to the prototype. Calculation of all possible distances between all patterns for the total set (thirty-six patterns) was performed using the Euclidean distance model. The final product of these calculations was a matrix comprised of all possible Euclidean distances between all patterns, which resulted in 630 possible distances.

Experiment 2 (Main Experiment)

The purpose of this experiment is to evaluate the hypothesis that people mentally represent a group of architectural elevations (architectural/urban context, street façade) in the form of a prototype and/or a feature frequency image, according to which they judge the belongingness of other novel (infill) patterns to the context.

Research participants

Fifty-six undergraduate university students (thirty males and twenty-six females) participated in this experiment. None of the participants were students of architecture or of art majors.

Stimulus material

Context groups (architectural contexts of street façades): Three groups (GA, GB & GC) of the previously created architectural elevations were constructed as reference architectural/urban contexts (street façades). Each group was composed of five different elevations to represent a selected portion of an assumed street façade, which in its turn represented an architectural context (fig. 2). The reason for using three context groups in the experiment instead of only one group was to investigate and reveal any effect of specific group compositions. A prototype pattern was determined to represent each of the three context groups. The selection of this prototype was based on the previously mentioned principle of central tendency [Posner 1969; Posner & Keele 1968]. In mathematical terms, the prototype pattern was selected as having the least accumulated perceptual dissimilarity distances from all of the five elevations of its associated context group. The perceptual distances were calculated according to the Euclidean distance model. To find this prototype, the total set of thirty-six patterns was subject to mathematical evaluation, through which the pattern having the least sum of the distances from its associated context group (five patterns) was to be specified as the group prototype. These distances were previously determined as a result of experiment 1. The mathematical calculation of prototypes revealed the existence of multiple prototypes for all groups. To make the study less complex, only one of these prototypes was selected for each context group for further analysis. This was done in a follow up session to experiment 1. Each participant in

experiment 1 was invited again to this session and was presented with all prototypes for each context group separately. The participant was then asked to select only one prototype that he/she thought was the most representative of its context group. The most frequently selected prototype by participants for each context group was then used in the main experiment as the main prototype of its context group (fig. 3).

Fig. 3. The three context groups of patterns, which represent street façades (architectural contexts)

Fig. 4. The selected prototypes for the three context groups (S6 is the prototype for Group A, S27 is the prototype for Group B, and S30 is the prototype for Group C)

Infill group: A group of fifteen patterns (architectural elevations) was selected by the experimenter as an infill group. Each of these patterns was considered as a possible new addition to each of the context groups (street façades). The infill patterns were rank ordered by each participant according to their fit with each one of the context groups (street façades). The selection of the infill group took into consideration the diversity of elevation compositions and design features and the diversity of psychological distances from reference groups' prototypes. The three selected prototypes were included in the infill patterns group (Table 1).

Infill Pattern	Pr: Perceptual Distances from Prototype			Fr: Feature Frequencies (Total Number of Shared Features with Context Group)		
	Group A	Group B	Group C	Group A	Group B	Group C
S1	0.14	2.57	0.80	17	0	4
S2	0.02	2.69	0.92	17	2	8
S4	0.28	2.99	1.22	15	0	6
S6*	0.00	2.77	0.94	17	0	4
S12	0.07	2.78	1.01	2	2	2
S19	1.02	1.69	0.08	2	13	11
S21	1.02	1.69	0.08	2	13	11
S22	1.23	1.48	0.29	0	13	14
S25	2.61	0.10	1.67	0	17	9
S27**	2.71	0.00	1.77	0	15	9
S30 ***	0.94	1.77	0.00	12	3	8
S31	1.27	1.44	0.33	10	3	8
S34	2.53	0.18	1.59	10	7	6
S35	2.63	0.08	1.69	10	7	6
S36	2.55	0.16	1.61	5	5	6

* prototype of group A   ** prototype of group B   *** prototype of group C

Table1. Independent variables: Values of perceptual distances from prototypes and total frequencies for all recognition stimuli on three context groups

Independent variables

Each of the infill patterns was assigned two mathematical values in relation to each reference group:

- Its calculated perceptual distance from the context group prototype. This is according to the Euclidean distance model.
- The total frequencies of shared features with the patterns of each of the context groups.

These two values were considered as two independent variables in the analysis to follow. By considering the three context groups, six mathematical values (2x3) were then to be assigned for each infill pattern (Table 1).

Dependent measure

The fifteen infill patterns were rank ordered in terms of fit with each of the three context groups. The study considered that the primary goal of each participant's ranking is to select the infill pattern with the best fit (rank 1). Then percentages of the number of participants assigning rank 1 for each infill pattern were treated as dependent measures. In other words, for each infill pattern, there was a percentage of participants who considered it the best contextual fit with the context group. This percentage was calculated and treated as a dependent measure for that infill pattern and in reference to a specific context group. By considering the three context groups, each infill pattern should have three dependent measures (Table 2).

Infill Patterns	Percentage of Frequency of Best Rank (1) for Each Infill Pattern		
	Group A	Group B	Group C
S1	19.6	1.8	1.8
S2	12.5	1.8	1.8
S4	23.2	1.8	5.4
S6*	30.4	0	3.6
S12	3.6	7.1	1.8
S19	1.8	0	12.5
S21	0	0	5.4
S22	0	0	10.7
S25	1.8	33.9	0
S27**	1.8	44.6	1.8
S30***	3.6	0	33.9
S31	1.8	0	21.4
S34	0	0	0
S35	0	5.4	0
S36	0	5.4	0

* prototype of group A   ** prototype of group B   *** prototype of group C

Table 2. Dependent measures: Percentages of frequencies for rank one (best contextual fit)

Procedure

Participants, one at a time, were presented with only one reference group of stimuli (five patterns), which were assumed to represent a portion of a street façade and were to be used as a reference group in a recognition task. With each of the three context groups, the participant was simultaneously presented with a series of fifteen infill patterns that were to be rank ordered in terms of the best fit with the presented context group. The subject was asked to assume that the presented group of infill patterns was going to be rank ordered in terms of its contextual fit with the presented street façade (context group), where rank 1 in the evaluation scale represented the best contextual fit with the context group, and rank fifteen represented the lowest contextual fit with the context group. The rank ordering task was performed by each participant for each of the three context groups. This means forty-five (15x3) ranking judgments were made by each participant. The order of presenting the fifteen infill patterns with each reference group was randomized among the participants, and the order of presenting the context groups to the participants was rotated among the participants. The experimental session took approximately forty-five minutes per participant.

Analysis and results

Both simple and multiple linear regression analyses were applied to the percentages of best rank (rank 1) for infill patterns as related to both distances from prototypes and feature

frequencies on each of the three context groups (GA, GB & GC). Data and analyses were characterized as follows (Table 3):

	Regression Models According to Context Groups & Independent Variables Included in Each Model								
	Group A			Group B			Group C		
	Mod.1 <i>Pr-a</i> , <i>Fr-a</i>	Mod.2 <i>Pr-a</i>	Mod.3 <i>Fr-a</i>	Mod.1 <i>Pr-b</i> , <i>Fr-b</i>	Mod.2 <i>Pr-b</i>	Mod.3 <i>Fr-b</i>	Mod.1 <i>Pr-c</i> , <i>Fr-c</i>	Mod.2 <i>Pr-c</i>	Mod.3 <i>Fr-c</i>
R	0.816	0.674	0.740	0.607	0.525	0.571	0.729	0.729	0.310
R²	0.666	0.454	0.548	0.369	0.276	0.326	0.531	0.531	0.096
Adjusted R²	0.610	0.412	0.513	0.263	0.220	0.275	0.453	0.495	0.027
Model Sig.	0.001*	0.006*	0.002*	0.063	0.044*	0.026*	0.011*	0.002*	0.261
Pr Sig.	0.062			0.388			0.006*		
Fr Sig.	0.017*			0.209			0.993		
B Coef. Pr	-3.709	-6.254		-3.212	-6.279		-10.79	-10.78	
B Coef. Fr	0.795		1.098	0.899		1.290	-0.006		0.957

*significant (p<0.05)

Table 3. Regression analysis for percentages of rank 1 rates

Dependent measures of the study were the percentages of first ranks for the fifteen infill patterns for each context group and for the fifty-six participants.

Independent variables of the study were two:

1. Dissimilarity distance between each infill pattern and the prototype of each context group (*Pr*);
2. The frequency of shared features between each infill pattern and each context group (*Fr*).

Regression analysis included three models:

1. Model 1 is a multiple regression, which included the two independent variables (*Pr* & *Fr*);
2. Model 2 is a simple regression, which only included the independent variable (*Pr*);
3. Model 3 is a simple regression, which only included the independent variable (*Fr*).

The results demonstrated the following:

In the case of context group A (GA):

- Multiple regression model 1, which included both independent variables (*Pr-a* & *Fr-a*) turned out to be highly significant: (p=0.001). $R^2 = 0.666$;
- Simple regression model 2, which only included (*Pr-a*) was found statistically highly significant: (p= 0.006). $R^2 = 0.454$;
- Simple regression model 3, which only included (*Fr-a*) was found statistically highly significant: (p= 0.001). $R^2 = 0.548$.

In the case of context group B (GB):

- Multiple regression model 1, which included both independent variables (*Pr-b* & *Fr-b*) turned out to be almost significant: ($p=0.063$). $R^2 = 0.0.369$;
- Simple regression model 2, which only included (*Pr-b*) was found statistically significant: ($p=0.044$). $R^2 = 0.276$;
- Simple regression model 3, which only included (*Fr-b*) was found statistically significant: ($p=0.026$). $R^2 = 0.326$.

In the case of context group C (GC):

- Multiple regression model 1, which included both independent variables (*Pr-c* & *Fr-c*) turned out to be significant: ($p=0.011$). $R^2 = 0.531$;
- Simple regression model 2, which only included (*Pr-c*) was found statistically highly significant: ($p=0.002$). $R^2 = 0.531$;
- Simple regression model 3, which only included (*Fr-c*) was found statistically not significant: ($p=0.261$). $R^2 = 0.096$.

Discussion

A general reading of the results shows the following:

- The two independent variables (*Pr* & *Fr*) explained considerable percentages of the data variance for the three street façades;
- There is an insignificant improvement in the model performance when the two independent variables are included as compared to only including one of them, except for the case of context group C;
- Regression and significance values for different regression models slightly vary across the three street façades, except for the case of context group C.

The results indicate that either distance from prototype or feature frequency accounted for a significant portion of participants' judgments of best contextual fit for the infill patterns. It seems that both strategies are probably followed by people in judging contextual fit. Regression analysis demonstrated that in the case of prototype approach, the more the infill patterns were distant from the prototype, the less the participants judged them to belong to the context groups. This finding is in support of previous studies on prototype approach [Posner 1969; Franks & Bransford 1971; Abu-Obeid & Tassinary 1993]. In the case of feature frequency approach, the more features infill patterns shared with the context groups, the more the participants judged them to belong to the context groups. This finding is in support of previous studies on feature frequency approach [Reed 1972; Neumann 1977]. This tells us that what the participants had learned about architectural contexts was not limited to the specific instances of the context group. It seems that the participants acquired general information about the whole group during scrutinizing. This general information appears to be represented by both the group's prototype and an accumulation of features. Moreover, the multiple regression models seem to be performing a little better than the simple regression models as they have higher R^2 values, except for street Group C, in which multiple regression model and prototype model (*Pr-c*) have the same R^2 value and the prototype model is higher in significance. In the case of group C, R^2 value for *Pr* (distance from prototype) was significantly higher than that of *Fr* (feature frequency). As a matter of fact, the simple regression model for feature frequency (*Fr-c*) was

not statistically significant ($p=0.261$). It seemed that participants tend to favor a distance from prototype strategy when referring to context C. This may reinforce the probability that participants employ double strategies in their judgments of some street contexts (as in the case of groups A and B) and employ prototype strategy in others (as in the case of group C). Looking at the composition of the three street groups, we notice that groups A and B are more harmonious in terms of proportion than street group C, which has the two height proportions. It is possible that the greater variety in height caused participants to employ the prototype strategy rather than the double strategy. Further research on this point may reveal a clear justification.

This study has a number of limitations that should be addressed before concluding the discussion, and these are:

1. The study stimuli were not realistic. They were two-dimensional and included a limited number of design variables;
2. The participants had a relatively short time to learn architectural street façades as architectural contexts (learning groups: A, B, and C). In real life, people require much more time and repeated experiences to establish stable (constant) images of architectural contexts in their real environments.

Accordingly, future research is recommended to address the above limitations. Other, more realistic stimuli with a larger number of variables (including textures, light qualities, colors and architectural details) are recommended for future studies. Also recommended is an investigation of such stimuli as being learned frequently by study participants, to make sure they establish stable images of architectural context. Finally, further research needs to be undertaken on the effect of context composition on which strategy is adopted by perceivers in contextual fit.

The importance of this research for architectural practice and research comes from the following:

- It is an attempt to further develop scientific and quantitative studies in architectural research;
- It involves people in shaping their visual environment;
- It can be used to develop public policies for aesthetic controls by conducting scientific experiments on public preferences before the regulations are implemented.

Appendix I

Patterns: S1-S18

Patterns: S19-S36

Appendix II

A. The central tendency of a prototype of any chosen category can be determined by measuring the similarity between the prototype and the other categories. Shepard [1962] proposed a method of transforming similarity measures into distance measures, which was modified later by Kruskal [1964]. Shepard proposed that similarity and distance could be related such that the greater the similarity between two stimuli, the smaller the distance between them in a multi-dimensional space. The exact metric can be found empirically for any set of stimuli:

If we have a set of N patterns, then, $N(N-1)/2$ similarity measurements data are needed for the scaling algorithm. By taking advantage of the constraints inherent in the data, ordinal scale similarity data can be converted into ratio scale distance measurements. The Shepard-Kruskal distance algorithm follows the Minkowski r -metric as follows:

$$d_{ij} = \left\{ \sum_{m=1}^d (x_{im} - x_{jm})^r \right\}^{1/r}$$

where:

d_{ij} = distance between stimuli i and j ;

m = subscript for orthogonal axis of the space ($m = 1, 2, \dots, d$);

X_{im} = projection of stimuli i on dimension m ;

X_{jm} = projection of stimuli j on dimension m ;

r = number of model dimensions which best fit the data.

The two most popular values of r are: $r = 1$, for the city block model, and $r = 2$, for the Euclidean model. The city block model is applicable when the stimuli differ with respect to an obvious and compelling dimension. The Euclidean model is applicable when there is no dominant single dimension, which means that r -value can be 2, 3, or more. Stimulus X_i can be spatially represented within a three-dimensional space by the projections (X_{i1} , X_{i2} , X_{i3}). The distance between the two stimuli X_{i1} and X_{j1} on dimension-1 can be identified as $(X_{j1} - X_{i1})$. The distance between these two stimuli on dimensions (1 & 2) can be determined according to the following formula: $((X_{j1} - X_{i1})^2 + (X_{j2} - X_{i2})^2)^{1/2}$

B. In our study, the calculations were based on the previously mentioned Shepard-Kruskal distance algorithm, and following Minkowski r -metric as follows:

m = subscript for orthogonal axis of the space ($m = 1, 2, 3, 4$);

X_{im} = projection of stimuli i on dimension m :

$$X_i = (X_{i1}, X_{i2}, X_{i3}, X_{i4});$$

X_{jm} = projection of stimuli j on dimension m :

$$X_j = (X_{j1}, X_{j2}, X_{j3}, X_{j4});$$

$r = 4$ (four-dimensional solution).

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