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Quantifying the Qualitative Design Aspects

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Architecture is a mixture of art and technique. This implies that the architect deals not only with engineering aspects that can be easily quantified and thereafter processed, but deals with aesthetics as well which is in first place qualitative and therefore rather difficult to estimate and numerically represent. As an example, in such cases, these 'qualitative quantities' are expressed in linguistic form which should be somehow expressed in numerical form in order to treat such data by powerful and conclusive numerical analysis methods. Expressions such as: bright colour, light room, large space are some of these examples. These expressions are fuzzy concepts whose actual interpretation is hidden and all of them together attach a qualitative value to a certain space. To deal with such information the emerging technologies of the last decade can provide an important aid. One of them is the soft computing technology that can deal with such soft data. In this paper, based on the case studies, we explain the potential of using soft computing techniques.
Keywords: *Qualitative design data; information processing; soft computing; knowledge modeling; neuro-fuzzy network*

Introduction

The information that the architects deal with is in more often qualitative rater than quantitative. This already indicates some difficulty that may emerge while trying to process the information from this domain. To obtain numerical data is essential for processing and therefore, for exact sciences like pure engineering sciences it occurs quite natural to deal with numerical data, while in soft sciences, like architecture, this may not seem so natural due to the qualitative aspects of its data. Expressions such as: bright color, light room, large space are some of these examples. To deal with such information the emerging technologies of the last decade can provide an important aid. Such as, for example, the soft computing (Jang, et al 1997; Kaynak, et al 1998; Chen et al 1999; Azvine, et al 2000;). The tools for data analysis in soft computing are mainly referred to as neuro-fuzzy systems involving fuzzy logic and neural networks. With these tools it is feasible to discover the most important aspects that determine the quality of a space and, thereafter, to define exactly the shape of a function of one fuzzy concept to the other.

The data used in this paper is obtained from an extensive inquiry based on a questionnaire regarding four different underground stations in the Netherlands, which is processed by soft computing techniques. After information processing, knowledge is modeled where the relationship between various design aspects is provided. In total there are 43 design aspects that are considered, which are directly related to comfort and safety of these particular stations. It is important to mention that for underground stations the aspects of comfort and safety are those that eventually determine the quality of a space. The following section provides a quick scan of aspects that were dealt with in the questionnaire. Thereafter, a brief introduction of soft computing techniques applied in this research for knowledge modeling is provided. Finally, the knowledge elicitation from the knowledge is done

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through systematic introduction of 'new' cases to the network.

The comfort and safety aspects for underground stations

Two most important psychological aspects, for underground spaces, are the safety and comfort. Various authors dealt with these aspects (Passini,1992; Voordt and Wegen, 1990; Korz et al, 1998; Fisher and Nasar, 1992; OT 99), but rarely these two were mentioned together. Yet, both of them are crucial for integral space perception. A person may feel comfortable but not safe and also the other way round. It is rather artificial to separate them, since certain dimensions may be important for both of them. For example, orientation in underground space may influence a feeling of comfort but may affect safety as well. The determinants which are identified to be related to comfort are given in table 1 and those related to safety are presented in table 2 (Durmisevic et al 2001) (tables 1 & 2).

Data obtained from four underground stations being Beurs, Blaak, Rijswijk and Wilhelminaplein were used for knowledge modeling. Knowledge was modeled separately for each station, meaning that there were in the end 4 knowledge models. Rijswijk and Wilhelminaplein stations are linear stations, where platforms are present only on one level, while the other two stations are complex stations where more levels are present, meaning that there are also the exchange areas. As it has been earlier mentioned, the questionnaire dealt with aspects mentioned in table 1 and table 2 so that the comparison between stations could be made on some common issues. Although it is important to mention that there were 7 questions less for linear stations since these stations do not have an exchange area.

From 27th May till 30th May 2000, one thousand of questionnaires were handed out on each one of these stations to the passengers visiting the station. In a 6 week period around 210 questionnaires per station

Table 1. Aspects related to comfort (28 aspects).

Attractiveness	***Wayfinding***	***Daylight***	***Physiological***
color	*to the station*	*pleasantness*	*noise*
material	*in station*	*orientation*	*temperature winter*
spatial proportions	*placement signs*		*temperature summer*
furniture	*number of signs*		*draft entrance*
maintenance			*draft platforms*
spaciousness entrance			*draft exchange areas*
spaciousness train platform			*ventilation entrance*
spaciousness metro pl.			*ventilation platforms*
platform length			
platform width			
platform height			
pleasantness entrance			
pleasantness train platform			
pleasantness metro pl.			

Table 2: Aspects related to safety (15 aspects).

Overview	***Escape***	***Lighting***	***Presence of people***	***Safety surrounding***
entrance	*possibilities*	*entrance*	*public control*	*safety in surrounding*
train pl.	*distances*	*train pl.*	*few people daytime*	
metro pl.		*metro pl.*	*few people night*	
exchange area		*exchange area*		
	dark areas			

were returned completed. Some cases were immediately excluded since they failed the control question which was asked in a questionnaire in order to improve reliability of the outcomes, which eventually left about 200 cases that could be used for knowledge models.

Knowledge modeling by soft computing (neuro-fuzzy network)

*I*n the last decade, there has been a rapidly growing interest in the application of neurally inspired computing techniques. The essential thrust for this development was the anticipation of more effective use of brain-like information processing methods alongside with their rapid developments. The most commonly cited examples of brain-like information processing activities are ability to learn and generalize from experience, ability to process information, which may be incomplete or even partly erroneous, ability to process information rapidly and ability to adapt solutions over time to compensate for changing circumstances. Such information processing capabilities are commonly referred to soft computing activities. Soft computing is an innovative approach to constructing computationally intelligent systems. It is an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision (Zadeh, 1994). In plain terms, it is the processing of uncertain information with the methods, methodologies, and paradigms of artificial neural networks, fuzzy logic and evolutionary algorithms. In this research we made use some properties of neural network and fuzzy logic creating in such way a hybrid network, here coined as neuro-fuzzy network.

Fuzzy logic is based on the concept of fuzzy sets (Zadeh, 1973). A fuzzy set is a generalization of a classical set in the sense that memberships are graded between 0 and 1. In this case, if x is a variable over a domain of discourse U, and X is a fuzzy set over U, then $m_x(x)$ is defined as the degree of membership of x in X. A system of fuzzy sets over a domain can form a fuzzy partition of the domain.

Since, by means of fuzzy logic, even the linguistic terms are converted to numeric values, symbolic computation in an artificially intelligent environment is replaced by numerical computation and symbolic computation, inevitable in a conventional expert system domain, is avoided. Due to multi-valued logical properties of fuzzy logic, while extrapolations in the knowledge domain are made, the uncertainties of the input information are also taken care of precisely in the way as human does at any moment in a complex decision-making situation. In a complex environment, in place of one complex knowledge model structure, several knowledge models can be established in their individual structure and their outcomes can be constructively combined for a final decision-making in any complexity, by means of gating network. More information regarding such possibility can be found in earlier publication by the authors of this paper (Ciftcioglu et al, 2001a).

Artificial neural networks (ANN), or connectionist systems, are finding applications in almost all branches of science and engineering. An ANN consists of highly interconnected simple processing units called neurons. A major concern in the development of a neural network is determining an appropriate set of weights that make it perform the desired function. This is accomplished by means of special algorithms, which are called training algorithms.

In the actual implementation, the neural network used is a radial basis functions (RBF) network (Broomhead and Lowe, 1988) trained with a particular algorithm known as orthogonal least squares (OLS) (Chen et al, 1991), so that the inherent structure of the information at hand is kept intact. By this algorithm, the fuzzy associations between input and these spaces are establish. The relation matrix R, which is transparent to the user and embedded in the neural net structure itself is obtained by training. Referring this, the considerations leading to the equivalence of the RBF networks and the fuzzy logic structure play the essential role (Jang and Sun, 1993). By means of implementing fuzzy modeling through RBF network,

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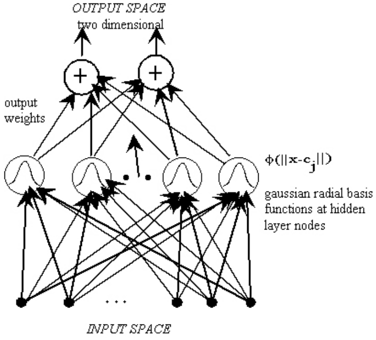

Figure 1: Radial basis function network for knowledge modeling

the model is established by training the data at hand, avoiding subjective membership functions to be prescribed in advance. Especially, in the case of high dimensionality of the input space, such prescription of fuzzy membership functions would be a formidable task and that is the case in the present research (fig1).

The equivalence of neural networks and fuzzy logic applications is well established. However, the effectiveness of either method is still dependent on the application itself. Each method has its strong merits. However, in general, best performance is obtained when both methods are used in hybrid form. Especially neural system can cope with complex systems while it is relatively difficult for fuzzy systems. On the contrary, it is easier to deal with linguistic variables by fuzzy systems. By combining the two, a neuro-fuzzy network is modeled, meaning that in first place it is a neural network type of systems which simply uses the fuzzy logic properties in order to represent the linguistic values. By means of neuro-fuzzy network a knowledge model is created. Creating a knowledge model means that the input information regarding aspects that explain comfort and safety is provided and output information is provided as well, which is actual assessment of comfort and safety. This information is provided through questionnaire. Knowledge model is established through interrelation of input and output space for each case introduced to the model. The soft computing techniques are suitable for such type of information processing. Training and testing of a knowledge model is given in figure 2 and represents the data obtained from station Blaak.

The knowledge elicitation

Having modeled the knowledge, one of the methods to extract the knowledge can be by well-known technique of sensitivity analysis (Saltelli et al, 2000). In such way, the relative dependency of the input variables on comfort and safety can be identified by where basically the gradients of comfort and safety with respect to each variable in the input space is

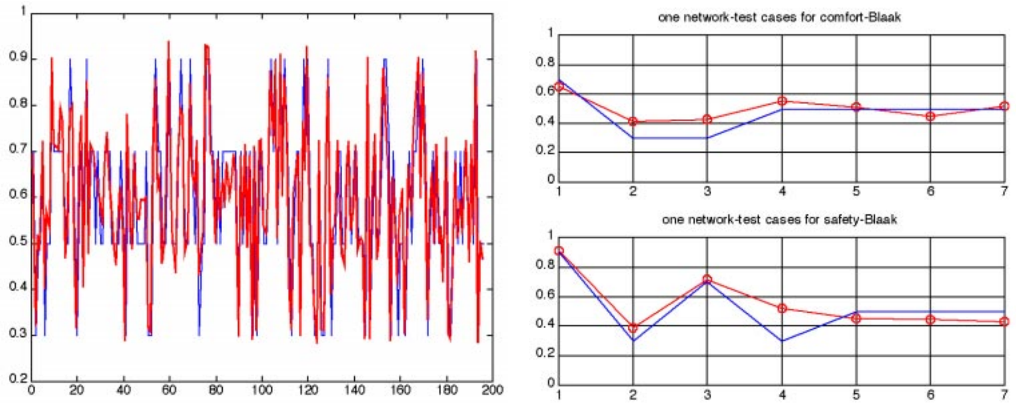

Figure 2: (figure left) Network training for 196 cases with 43 inputs and 2 outputs with 90 receptive fields Broken lines represent the knowledge model response to the training data after training. Continuous lines represent the actual knowledge used for modeling. (figure right) Test results of the network performance for comfort and safety. Line with circles represents the estimated value by the network, while the other line is the actual value

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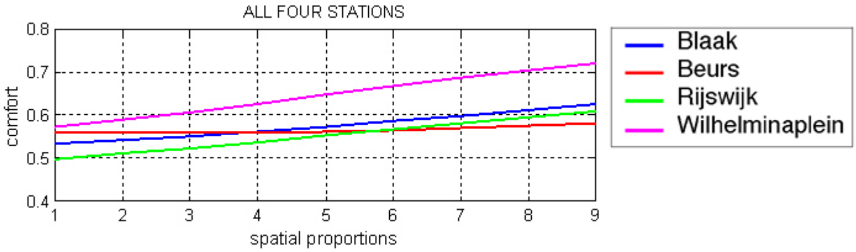

Figure 3. Functional relationship of variable 'spatial proportions' to variable 'comfort' and 'safety'

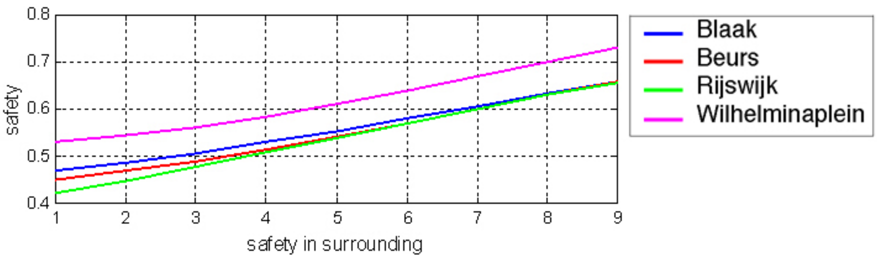

Figure 4. Functional relationship of variable 'safety in surrounding' to variables 'comfort' and 'safety'

computed. This has been already published by the authors (Ciftcioglu et al, 2001a). Another method is to find out the functional relationship of one fuzzy concept to the other. The experiment was done in the following way. Having modeled the knowledge, the inputs per variable for all input training sets were set to the same value, beginning with 0.1 value. All those input training sets modified, formed a new test set, where after each testing the results are recorded in a file. The result represents the mean for both comfort and safety estimations. The experiment was repeated with input values set to 0.2, 0.3 … till 0.9 and was done for all four stations. For illustration of results, two variables are given in relation to comfort (figure 3) and safety (figure 4).

With such method, an actual functional relationship of one fuzzy concept to the other is precisely given. This method confirmed the results obtained by sensitivity analysis in a sense that as a slope becomes steeper, indicating a significant change with changed values, the safety/comfort variables are more sensitive to that particular aspect. These results are important for the following reasons. Firstly, if any of these stations were to be reconstructed, out of this model, knowledge can be obtained regarding problematic aspects. An indication could be obtained immediately showing the effect of improvement. Secondly, this knowledge model provides an indication of amount of intervention and suitability of an aspect for an improvement or in other words it shows the effect of a change.

Conclusions

The linguistic quantities, that are present in architectural design, were expressed in numerical form by means of a questionnaire for treatment by powerful and conclusive numerical analysis methods. This paper explained the soft computing method used for knowledge modeling of four underground stations. It was mentioned that one way for knowledge

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extraction was by means of sensitivity analysis. Other way was through discovery of functional relationships between various fuzzy concepts in the input space to the fuzzy concepts in the output space. This paper presented a very powerful technique for an automated structural knowledge modeling related to soft data in architectural design.

References

Azvine, B., Azarmi, N. and Nauck, D. D.: 2000, Intelligent systems and soft computing : prospects, tools and applications. Springer, Berlin

Broomhead, D.S. and Lowe, D.: 1988, Multivariable Function Interpolation and Adaptive Networks, Complex Systems, 21, pp.321-355

Chen S, C.F.N. Cowan and Grant, P. M.: 1991, Orthogonal Least Squares Algorithm for Radial Basis Function Networks, IEEE Trans. on Neural Networks, Vol.2, No.2, March

Chen, G., Ying, M. and Cai, K. Y.: 1999, ed. Fuzzy logic and soft computing. Kluwer Academic, Boston

Ciftcioglu, Ö., Durmisevic, S. and Sariyildiz, S.: 2001a, Multiresolutional information fusion for building technology, Conference Proceedings of EuropIA'8, 25-27 April 2001, Delft, The Netherlands

Ciftcioglu, Ö., Durmisevic, S. and Sariyildiz, S.: 2001b, Knowledge management by information mining, Conference Proceedings of CAAD Futures, 8-11 July 2001, The Netherlands, TU Eindhoven

Durmisevic, S., Ciftcioglu, Ö. and Sariyildiz, S.: 2001, Knowledge modeling by AI for underground space environment, Conference Proceedings of EuropIA'8, 25-27 April 2001, Delft, The Netherlands

Fisher, B. S. and Nasar, J. L.: 1992, Fear of Crime in Relation to Three Exterior Site Features: Prospect, Refuge and Escape. Environment and Behavior. Volume 24, number 1, January. Sage Periodical Press, London

Jang J.-S.R. and Sun C.-T.: 1993, Functional equivalence between radial Basis Function networks and fuzzy inference systems, IEEE Trans. on Neural networks, Vol.4, No.1, p.156

Jang, J. S. R., Sun, C. T. and Mizutani, E.:1997, Neuro-fuzzy and soft computing; a computational approach to learning and machine intelligence. Prentice Hall, Upper Saddle River

Kaynak, O.: 1998, ed. et al., Computational intelligence: soft computing and fuzzy-neuro integration with applications. Springer, Berlin

Korz, S., Aarts, H., Luten, I., Lugtmeijer, E.: 1998, Hoe Dieper hoe Gevoeliger. Collaboration of TU Eindhoven, TU Delft and Eysink Smeets & Etman, The Netherlands

Opperwal, H. and Timmermans, H. (1999). Modeling Consumer Perception of Public Space in Shopping Centers. Environment and Behavior. Volume 31, number 1, January. Sage Periodical Press, London

Passini, R.: 1992, Wayfinding in Architecture. Environmental Design Series 4, second edition. Van Nostrand Reinhold, New York

Saltelli A., Chan K. and Scott E. M., (Eds.): 2000, Sensitivity Analysis, Chichester:Wiley

Voordt, van der D. J. M. and Wegen, van H. B. R.: 1990, Sociaal Veilig Ontwerpen; Checklist ten Behoefte van het Ontwikkelen en Toetsen van (plannen voor) de Gebouwde Omgeving. Publikatieburo Bouwkunde, Delft

Zadeh, L.A.: 1973, Outline of a new approach to the analysis of complex systems and decision processes, IEEE Trans. Systems, Man, and Cybernetics, Vol. SMC-3, No.1, January

Zadeh L.A..: 1994, Fuzzy logic, neural network, and soft computing, Commu. ACM, Vol.37