ARCHITECTURAL DESIGN KNOWLEDGE MODELING

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Abstract: We have presented an approach for automated knowledge modelling and re-use in design through the development of an algorithm that operates in conjunction with the machine learning technique. The approach presented has the advantage that such automated knowledge modelling system works in conjunction with the problem-solving process as the knowledge representation is in an embedded/distributed structural form with fast response. The model has the features of an artificial intelligence (AI) system. The AI approach adapted belongs to the methodology of soft computing and it is most convenient to retain the knowledge from architectural data, for instance, that are rather soft as well. Through the use of domain specific knowledge a designer determines attribute values based on dependency among the design variables to support the design development process. The present research is carried out in relation to the determination of the architectural design quality of underground stations in the Netherlands. The methodology employed is a multivariable functional approximation structured in a neuro-fuzzy knowledge representation form. The paper deals with the details of the novel design knowledge modelling and highlights its important merits for architectural design.

Keywords: Knowledge Modelling, Machine Learning, Architectural Design, Orthogonal Least Squares, Radial Basis Functions Network

1 Introduction

With the advances in software technology, computer became indispensable partner of a design process. It can be of help in various ways depending on the nature of the design task. For knowledge intensive design tasks, it is essential that computer retain experiential knowledge repositories to provide the means to support a design activity. A desirable approach for this issue might be the active use of existing and updated knowledge gained before and during the design respectively. Desirably problem solving and learning should operate simultaneously and provide feedback to each other where computer may play an essential role through the provision of a dynamic source of design experience. This requires the use of machine learning techniques in the design activities. To integrate computer into design effectively special methods are required. These methods are presently in the course of development and they are collectively referred to as knowledge discovery and data mining [Han, Kamber 01; Cios et al.; Witten, Frank 00; Bramer 99; Fayyad et al 96]. They already belong to their respective emerging technologies. For machine learning, information should be transformed in a form convenient for this type of learning. There are several methods for this. For a particular machine learning task some suitable transform methods can be used [Haffey and Duffy 00]. Among others, the outstanding ones stepwise implemented in this work are as follows. The first step is abstraction. Abstraction is involved with the generation of a new version of a concept
with less detail than the original. The second step is association. Association is the determination of relationships or correlation among given entities or descriptions based on logical, causal or circumstantial observed relationships. Third step is classification. Classification determines a specific description that may be a key component or components of a design based on the design information subjected to the preceding steps above. Fourth step is clustering. Clustering involves the grouping of the design information based on the similarity of some criteria. The fifth step is derivation. Derivation is the process of deriving a piece of knowledge that is based on the existing or during these steps attained knowledge, through a level of dependency. The sixth step is generalisation. Generalisation provides a clear description within a set of final design solutions. This description may be in the form of knowledge model so that the description characterises all of the design solutions based on the design information of concern used.

In this work, we present an approach that attempts to address the task of knowledge modelling by machine learning methods. The approach presented has the advantage that such automated knowledge discovery/acquisition and modelling system works in conjunction with the problem-solving process as the knowledge representation is performed in an embedded (distributed) structural form with fast response. The structure has the features of an artificial intelligence (AI) system due to its relevance to fuzzy logic. The set of data is from an architectural design is considered where data itself are essentially qualitative. To deal with such data, methods which to some extend emulate human information processing should be invoked. The main feature of this type of processing is the imprecision of the information similar to the imprecise information that we normally deal with in a real life. This pervasive imprecision of real life information is remarkably well processed by human. Qualitative or linguistic information belongs to this category. For traditional information processing methods such a task is referred to as ill-defined, since the available methods are not suitable to tackle. The AI approach adopted belongs to an emerging intelligent technology known as soft computing and it is most convenient for modelling knowledge gained from soft data.

2. Knowledge modelling

The mathematical model employed is a multivariable functional approximation structured in a neuro-fuzzy knowledge representation form. The advantage of such a structure is that the knowledge can effectively be modelled by such a system with appropriate learning strategy. The neuro-fuzzy structures are well-known and used in engineering and applied sciences since it is especially suitable for data from exact sciences. In contrast to that, the data, from soft sciences, including also architectural data are mostly linguistic and intuitive rather than exact. Therefore, representation of this information in such a structural form requires a careful attention and design-dependent innovative solutions. The vagueness is not the only characterisation of the architectural data. Next to this, the volume and diversity of the data even for a specific design task are large so that to represent the domain knowledge already poses the problem of complexity. Therefore, a kind of automated structural knowledge representation/modelling with adequate domain representation and fast response is imperative. Traditionally, the methods dealing with data use various techniques, which are mostly analytical. Among these, mention may be made to statistical (probabilistic) analyses, principal
component (clustering) analysis, trend (time series) analysis and so on. However, referring to the complexity mentioned above, such analyses are not fully adequate for the purpose. This is because the available data compared to the complexity of the design parameters are usually much less than what is actually needed not to mention the soft nature of data. In this respect, the approach employed presents novelties in two aspects. Firstly, considering the linguistic nature of the architectural data, fuzzy logic techniques are invoked. Secondly, knowledge is modelled by machine learning methods so that the complex data is structured automatically without use of domain knowledge explicitly. Domain knowledge plays important role in providing the underlying information, which is subject to modelling. Such a model is supposed to be generic and robust enough for design in the domain of concern. For this a particular purpose regularisation process is devised by this research.

The multivariable functional approximation adapted for knowledge modelling uses radial basis functions and is implemented in a form similar to artificial neural network structure. This structure is known as radial basis functions (RBF) networks as shown in Figure 1.

![Radial basis function network for knowledge modelling](image)

**Figure 1: Radial basis function network for knowledge modelling**

Such a form, is compatible with a fuzzy logic structure as the radial basis functions play the role of fuzzy membership functions [Cios et al. 98] and the output is a fuzzy decision-making based on the soft (fuzzy) architectural design data. In particular, the machine learning method used is orthogonal least squares (OLS) method [Chen et al. 91], which is the essential requirement to use for machine learning in this particular knowledge modelling research. The multivariable functional approximation with OLS algorithm with particular implementation is briefly described below. For sake of simplicity in representation and description, a single function is considered so that the network has one output for each multivariable input. For this case the output is given by

\[
    f(x) = w_0 + \sum_{j=1}^{N} w_j \phi_j(\|x - e_j\|)
\]

(1)
where \( x \in \mathbb{R}^p \) is the input vector; \( w_i \), output weight; \( \phi(.) \), basis function; \( N \), the number of multivariate input sets, i.e., input patterns. Essentially, RBF network is the generalisation of the linear regression model
\[
d(t) = \sum_{i=1}^{N} \theta_i r_i(t) + \varepsilon(t)
\]
corresponding to the preceding equation. The desired output, \( r_i(t) \) are the regressors which are some fixed functions of \( x(t) \). If the model is right, then \( \varepsilon \) is not correlated with the regressors.

For a set of input-output pairs, this model, in matrix form can be expressed as \( \mathbf{d} = \mathbf{R} \theta + \mathbf{E} \) where \( \mathbf{d} \) is the desired output vector; \( \mathbf{R} \) is the regression matrix that consists of regressor vectors \( r_i \), each of which has dimension of M; \( \theta \) is the parameter vector; \( \mathbf{E} \) is the error vector. The regressor vectors \( r_i \) form a set of basis vectors, and the least squares estimation of \( \theta \) provides that \( \mathbf{R}\theta \) is the projection of \( \mathbf{d} \) onto the space spanned by these vectors. The OLS method makes orthogonal decomposition of the \( \mathbf{R} \) matrix of the form
\[
\begin{bmatrix}
1 & a_{12} & \cdots & a_{1M} \\
0 & 1 & \cdots & a_{2M} \\
0 & 0 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 1
\end{bmatrix}_{M \times M}
\]
and \( \mathbf{W} \) is an \( N \times M \) matrix with orthogonal columns such that
\[
\mathbf{W}^T \mathbf{W} = \mathbf{H}, \quad \mathbf{H} = \begin{bmatrix}
h_1 & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & h_M
\end{bmatrix}_{M \times M}
\]
\( \mathbf{H} \) is a diagonal matrix with dimension of \( M \times M \). With the definitions \( \mathbf{W} = \mathbf{R} \mathbf{A}^{-1}, \quad \mathbf{q} = \mathbf{A} \theta \)
the matrix equation \( \mathbf{d} = \mathbf{R} \theta + \mathbf{E} \) in this case takes the form \( \mathbf{d} = \mathbf{W} \mathbf{q} + \mathbf{E} \), which has the solution for the estimation of the transformed parameter vector \( \mathbf{q} \) and weights ( \( \theta \) ) of the RBF network as
\[
\mathbf{q} = \mathbf{H}^{-1} \mathbf{W}^T \mathbf{d} \quad \text{or} \quad q = \frac{w_i^T d}{w_i^T w_i}, \quad i = 1, \ldots, M
\]
\( \theta = \mathbf{A}^{-1} \mathbf{q} \)\( \quad \) (6)
In terms of energy transmitted from input to the output, we can write the following algebraic energy balance equation for zero-mean output vector:
\[
d^T d = \sum_{i=1}^{M} q_i^2 w_i^T w_i + E^T E
\]
Normalising by \( \mathbf{d}^T \mathbf{d} \) we obtain
The relative energy contribution from each hidden node, i.e. from each regressor to the output becomes
\[ z_i = \frac{q_i^* w_i^T w_i}{d_i^T d} \quad i = 1, \ldots, M \quad (9) \]

Generally, in data based modelling, the learning should not be exhaustive to tend the model error virtually to zero. This is because in this case the generalisation capability of the model degrades. This phenomenon is known as bias-variance dilemma [Haykin 00]. To circumvent this problem, the method of regularisation is used [Bouman 98]. In the case of OLS method, regularisation can be applied by considering the error term as \( E^T E + \lambda q_i q_i \) where \( \lambda \) is the regularisation parameter. With regularisation consideration (7) takes the form [Chen et al. 96].

\[ \frac{E^T E}{d_i^T d} + \lambda q_i q_i = 1 - \sum_{i=1}^{M} q_i^* (w_i^T w_i + \lambda)/(d_i^T d) \quad (10) \]

where for \( \lambda = 0 \), equation reduces to eq.6. In place of using the regularisation parameter \( \lambda \), we write the matrix equation 6 in a partition form as

\[
\begin{bmatrix}
\theta_1 \\
\theta_2
\end{bmatrix} =
\begin{bmatrix}
A_{11} & A_{12} \\
A_{21} & A_{22}
\end{bmatrix} \begin{bmatrix}
q_1 \\
q_2
\end{bmatrix}
\quad \text{or} \quad
\begin{bmatrix}
\theta_1 \\
\theta_2
\end{bmatrix} =
\begin{bmatrix}
A_{11} & A_{12} & q_1 \\
A_{21} & A_{22} & q_2
\end{bmatrix}
\]
\quad (11)

If we consider only the parameters defined by \( \theta_1 \) in the model, which means a restricted number of basis functions \( (P) \) in place of total number of input patterns \( N \) and compute it by \( \theta_1 = A_{11} q_1 \) then the energy balance equation defined by (8) becomes

\[ \frac{E^T E}{d_i^T d} + \sum_{i=1}^{N} q_i^2 = 1 - \sum_{i=1}^{P} q_i^* (w_i^T w_i + \lambda)/(d_i^T d) \quad (12) \]

where the second term plays the role of regularisation term in (10). Note that, in the OLS algorithm, initially, we consider as much nodes as the number of input set of data where each set forms a pattern and the length of this pattern vector determines the dimension of the input space of the RBF network \( (N=M) \). The energy contribution of nodes to balance equation 7 is given by (10). Since nodes following the \( P \)-th node have small contribution to the energy balance, the regularisation effect is heuristically justified. The degree of regularisation is handled simply by changing the number of hidden layer nodes. From knowledge modelling viewpoint equation 12, identified in this research, has outstanding importance and implication as explained below.

The regularisation is an important safeguard in machine learning. The appropriate value of regularisation parameter \( \lambda \) is dependent on the underlying system that generates the training data and the choice of basis function \( \phi(.) \). For a set of soft data being considered in this research, to determine an appropriate value for \( \lambda \) is not an easy task. Added to this, in the case
where regularisation is omitted the number of hidden layer nodes parameter becomes an issue and a considerable research regarding this parameter appeared in the literature [Gomm, Yu 00; Chen et al 91; Zhu, Billings 96; Musavi et al 92]. Still this issue is very much application dependent without any proper formulation. From the knowledge-modelling viewpoint, without regularisation to judge about the generalisation capability of the model becomes difficult. However, tuning the regularisation by the number of hidden layer nodes releases the need of determining strict number of nodes in the model as with regularisation the model becomes rather insensitive to the number of nodes parameter in a wide range. In other words, the generalisation capability of the knowledge model is ensured in a wide range of this very parameter. Therefore, the OLS algorithm with regularisation as described in this research generates a robust model. This model is equivalent to a fuzzy system, where basis functions play the role of fuzzy membership functions associated with fuzzy IF-THEN rules in this equivalent knowledge model. In fuzzy systems, generally regularisation is avoided [Yen, Wang 99] and determination of fuzzy basis functions is carried out by two-pass OLS algorithm [Setnes 99].

It is interesting to note that, in RBF network model, the nodes also play the role of cluster centres in the input space. The selection of nodes in the OLS algorithm implies appropriate selection of the clusters representing the information at the input space of the knowledge model.

The knowledge model generated involves the information transformation steps mention in the introduction. These are namely abstraction, association, classification, clustering, derivation and generalisation. One of the important advantages having such analytical knowledge model is the possibility of deriving further important knowledge from the model itself. One example in this research is the derivation of the dependency of a design parameter as a function of user’s perception, which is not directly measurable or attainable. This could be obtained simply by elaboration after the model having been established. Sensitivity analysis based on the model is another important design knowledge worth to mention which is a concern of derivation.

In this work, the design information provided to RBF network at input is basically linguistic and qualitative. In basic mathematical terms, if we assume that the input vector x(t) represents a n-dimensional vector of real-valued fuzzy membership grades: x(t) ∈ [0,1]^n, then, the output y(t) of the model represents an m-dimensional vector of corresponding real-valued membership grades, y(t) ∈ [0,1]^m. This structure actually performs a non-linear mapping from an n-dimensional hyper-cube I^n = [0,1]^n to an m-dimensional hyper-cube I^m = [0,1]^m:

\[ x(t) \in [0,1]^n \rightarrow y(t) \in [0,1]^m \]

In the actual implementation, x_i(t) (i=1,2,….n) in x(t) represents the degree to which an input fuzzy variable x_i'(t) belongs to a fuzzy set, while y_j(t) (j=1,2,…,m) in y(t) represents a degree to which an output fuzzy variable y_j'(t) belongs to a fuzzy set.

4. Case study - Blaak station in the Netherlands

As a case study of design knowledge modelling, a set of underground building design data was used. Data are obtained for Blaak station, in the Netherlands. Blaak is relatively new station,
which was finalised in the mid 90's. It is an important exchange station, which is situated in the centre of Rotterdam and is located in the area with mixed functions such as living, business and schools. It is at the same time a tram, metro and a train station (figure 2). Tram station is situated on a ground level. Metro platforms are one level below ground (at approximately -7m) and train platforms are two levels below ground (at approximately -14 meters). Main entrance to the station is representative, with a lot of daylight mainly coming from a glass structure, which reaches even the train platforms at 14 meters below ground.

The purpose of the study was to find out what users’ perception is with regard to this station with main accent on their perception of public safety and comfort at the station. For that reason it was necessary to develop a questionnaire. A pre study was done, where all the variables of safety and comfort were grouped [Durmisevic et al. 01]. Based on their classification, a questionnaire was designed. From 27th May till 30th May 2000, one thousand of questionnaires were handed out at random to the passengers visiting the station and in a 6 weeks period 219 questionnaires 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. Final amount of cases that could be used for the neural
network training was 203. A decision was made to use 196 cases for the training and 7 arbitrary cases were left aside for the test purpose. The knowledge model outcome is designed as the evaluation of comfort and safety aspects of the stations. Based on test results it could be concluded that the network performance was satisfactory. The training results are provided in figure 3. In both cases the number of hidden layer nodes was set to 90 (P=90). A dashed line with circles represents the networks estimation, while a solid line represents the real outcome. Note that the difference is due to regularisation to enhance the generalisation capacity of the network.

Figure 2: Machine learning results (true data set with its estimation by the knowledge model) by regularised orthogonal least squares where outcome represents comfort aspects (a) and safety aspects (b) of design, respectively. Note that the difference plays the role of regularisation to enhance the generalisation ability of the model

Figure 4: Network performance tested for the comfort and safety aspects respectively for seven cases. With regularisation mean square error = 1.06E-1

As it has been earlier mentioned, seven test cases were used for performance testing, and these cases are presented in the figure 3 which shows the validation of the network performance for P=90. In both cases a dashed line represents network prediction, while the solid line
represents what the outcome actually should be. The repetition of the same analysis with the number of hidden layer nodes between 70 and 100 did not show any significant difference between the results. This is due to regularisation implemented in this research for the robustness of the knowledge model. The same analysis without regularisation is given in figure 5. The degradation in estimations in figure 5 is also noticeable by visual inspection following the comparison of figures 4 and 5 together.

Figure 5: Network performance tested for the comfort and safety aspects respectively for seven cases. Without regularisation mean square error is 1.85E-1

The method of knowledge modelling presented is generic enough to generate knowledge model in a general sense using any domain information. In this way, another interesting application in architectural design is the information ordering where the design information is distributed to actors in different volumes, as they needed avoiding redundancy in information release. In such application, the knowledge model formation remains the same as presented, while only the domain information becomes different.

5. Conclusions

The paper deals with a novel design knowledge modelling and highlights its important merits for architectural design. It also gives indications, implications and potential of the approach for design where design data is qualitative so that such a design task is generally ill defined for traditional design analysis methods in use. For the modelling task, soft computing methods are invoked, which are closely related to artificial intelligence methodologies. In particular, for machine learning task, the OLS algorithm used in a particular form shown to play the role of regularisation that it is a safeguard of robust modelling. The research is carried out in relation to
the determination of the architectural design quality of underground stations in the Netherlands. Some quantities involved in the research are safety, comfort, illumination, volume and so on. The model has more than 40 variables representing knowledge gathered through comprehensive public inquiries through a series of questions in a printed form. The test results from the knowledge model were found to be satisfactory to describe the architectural quality of the stations in a perspective, which is an important issue in decision-making for the architectural design quality determination.

6. References

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