

AN APPROACH TO THE DEVELOPMENT OF COMMONSENSE KNOWLEDGE MODELLING SYSTEMS FOR LAND SELECTION

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Abstract

The land use methods which are ergonomically and environmentally appropriate are determined first and foremost by characteristics and location. For instance, land selection in architectural construction domain is considered as an area in land use methods, which involves commonsense knowledge of architects. This is because land selection criteria are very personal and there is no theory behind how it should be done. Sometime, there are too many redundancies in the process selection of lands.

In this paper we present an approach to modeling commonsense knowledge in a sub field of architecture domain of land selection to come up with land classifications as psychological, physical and social events. This gives three-phase knowledge modeling approach for modeling commonsense knowledge in, which enables holistic approach for land selection.

At the initial stage commonsense knowledge is converted into a questionnaire. Removing dependencies among the questions are modeled using principal component analysis. Classification of the knowledge is processed through fuzzy logic module, which is constructed on the basis of principal components. Further explanations for classified knowledge are derived by expert system technology. This paper describes one such approach using classification of human constituents in Ayurvedic medicine. Evaluation of the system has shown 77% accuracy.

Key words: land selection, land classification, commonsense knowledge modeling systems, Fuzzy logic, principal component analysis

1. Introduction

Knowledge is the fundamental resource that enhances to function intelligently. Knowledge can be defined into two types such as explicit and implicit. Commonsense knowledge is one type of in implicit knowledge as defined by Bellman R.E, Zadeh (1970), Richards D, Bush (2003) and Coppin (2003). Explicit knowledge can be presented formally and capable of effective (fast and good quality) communication of data to the user where as implicit knowledge can be represented in informal way and further modelling needed for gaining effective communication.

Developments in land use, especially in agriculture, transportation and urbanization, have led to a continuous decline in biodiversity due to habitat alteration, loss and isolation. Many species were not able to adapt to these changes and their numbers declined or they disappeared as discussed by Saunders (1991). Spatial planning can play a role in the preservation of biodiversity by selecting reserve networks. The effectiveness of selecting reserve networks in human dominated landscapes depends on the extent to which the spatial claims and suitability of the land for competing land use are included as suggested by Van Buuren, M. and Kerkstra (1993). The land selection problem has drawn increasing interest in conservation planning. Enlargement of existing sites or addition of new sites may enhance biodiversity. The available space in these landscapes to enlarge habitat patches and add new habitat close to existing habitat is often limited due to competing land uses. We defined a problem of selecting land that both enhance biodiversity and minimize the disadvantages for the competing land uses. Therefore, we developed a commonsense knowledge modelling system in terms of selecting lands in three ecological innovations: psychological, physical and social.

In this paper we present an approach to modelling commonsense knowledge in land selection restructuring to analyze three ecological innovations effectively. This gives three-phase knowledge modelling approach for modelling commonsense knowledge in land selection, which enables holistic approach for land use. At the initial stage principal component analysis has been used to model refinement. Modelling commonsense knowledge in term of classification has been done using fuzzy logic at the second stage. The final stage of modelling commonsense knowledge has been conducted using expert system technology, which enables reasoning ability.

2. Methodology

Our framework for modelling of commonsense knowledge has been developed on the basis of three-phases mentioned above. As such the framework enables PC analysis, Knowledge classification and intelligent Reasoning using the expert system technology as suggested by Mendis (2007).

In this sense, the framework comes out as a hybrid intelligent system by integrating the techniques described as given below. The entire system can be seen as a fuzzy-expert system. Figure 1 shows the top-level architecture of the framework. It consists of a user Interface, Inference engine, knowledge base, fuzzy logic module, principal component analyzer and a database.

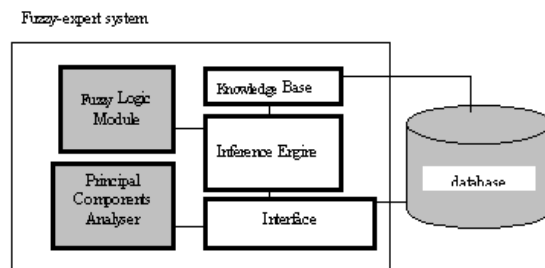


Figure 1. Top-level Architecture of the system

2.1 User Interface

The interface of the fuzzy-expert system supports the user interaction with the entire system. It gives direct access to the database while the expert system is accessed through the inference engine. Access to principle component analyzer is also provided via the interface. Both ordinary users and the developers can access the system subject to various levels of authentication.

2.2 Knowledge Base

The knowledge base contains the domain knowledge useful for problem solving. The knowledge is represented as a set of fuzzy rules of a particular domain. Knowledge base of the system has been constructed by using the fuzzy rules generated by the fuzzy logic module. The development of the knowledge base has been done using the FLEX expert system shell tool kit as suggested by Dave (2000). Since FLEX consists of a powerful inference engine, it is easy to use this in a development environment

2.3 Database

Database consists of domain knowledge in the original form. According to our approach, tacit knowledge of the domain is stored in the database. Further, domain knowledge has been stored in the form of a questionnaire. The result obtained by analysing the questionnaire is also stored in the database. More importantly, derived principle components are also stored in the database. This has been developed using MS-Access. Questions are evaluated using Likert scale methodology. This module can be directly accessed through the interface without going through the expert system.

2.4 Fuzzy Logic Module

The Fuzzy logic module has been implemented to further analyze the results from the principle component analysis. It fuzzifies the commonsense knowledge in a manner that can be used in the knowledge base. This is the key module in the proposed framework. This has been written using Visual Basic. This module can be delivered as an added feature for standard expert system shells to model the tacit knowledge. At present this module works with FLEX expert system shell.

2.5 Inference Engine

The inference engine carries out the reasoning whereby the expert system reaches a solution. This is the inference engine of the FLEX expert system shell. Since this is built in to the system there are no development activities with regard to this component in the system. Note that inference engine has nothing to do with the modelling of commonsense knowledge but it runs the expert system.

2.6 Principal Component Analyser

This module reads from database and gets collected data and feeds into statistical package SPSS the statistical tool suggested by Matei (1997). It analyses data with the support from SPSS and sends extracted principle component into database. This is a necessary input for fuzzyfication of the tacit knowledge so as to suit the knowledge base.

2.7 Algorithm for Modelling Tacit Knowledge

Based on our research, the algorithm emerged for modeling the tacit knowledge is given in Figure 2 as suggested by Mendis (2007).

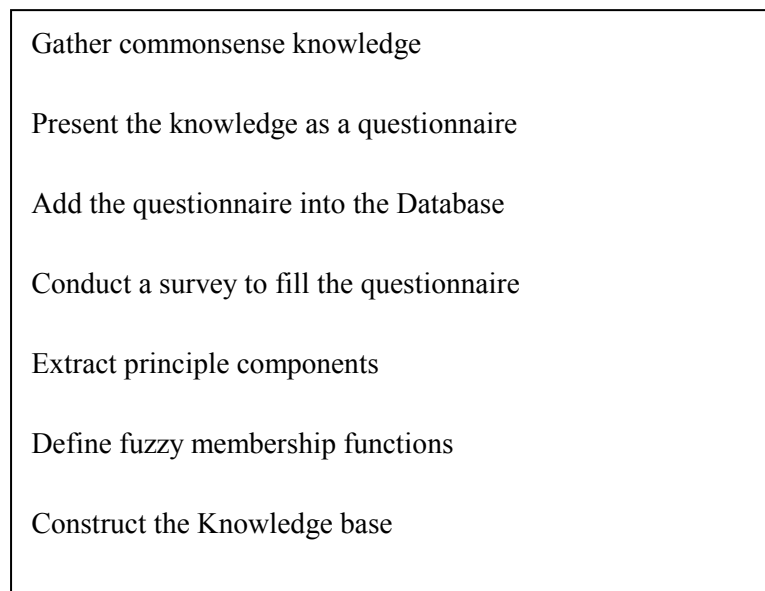


Figure 2. Algorithm for modeling tacit knowledge

3. Commonsense Knowledge modelling systems for land selection

We postulate a new approach enhancing the ability of modelling commonsense knowledge for analysis of ecological innovations in relation to land selection. Here we have addressed problems of data collections, information analysis and forecasting in land selection as suggested by Zoysa (2003). The process of the new approach is given in the following steps. It has been proposed a framework for modelling tacit knowledge. The framework has been designed as a three-phase knowledge modelling approach as suggested by Mendis (2007). The related design underlies the following steps.

5.1 Removing dependencies

We begin with the fact that an analysis of land selection. Three ecological innovations are in the focus of the analysis: psychological, physical and social play a critical role in land selection. It is thus addressed in the first phase of three-phase commonsense knowledge modeling approach. In the first phase, commonsense knowledge about interviews is mapped into a questionnaire consisted 30 no. of questions classified into physical, psychological and physical. As such, questionnaire based on interviews is considered as the input for the system.

ID	Question	Marks Range	Marks
5	Unique geomorphologic feature should be perceive	1-6	6
6	Surface feature such as rock faces	1_6	3
7	surface feature such as steep slopes	1-6	5
8	Rare historic features should be perceive	1-6	1
9	Rare and unique plants should be conserved	1-6	1
10	Plant communities should be perceive	1-6	2
11	Habitable animals should be conserved	1-6	3
14	veryfertile soil	1-6	1

Figure 3.A part of questions in the Questionnaire for modeling commonsense knowledge

The approach begins by acquiring commonsense knowledge. This can be done as an interview between domain experts and the knowledge engineer. Using the interviewing process between expert and knowledge engineer, tacit knowledge has been acquired and mapped in to a questionnaire based on Likert scale technology.

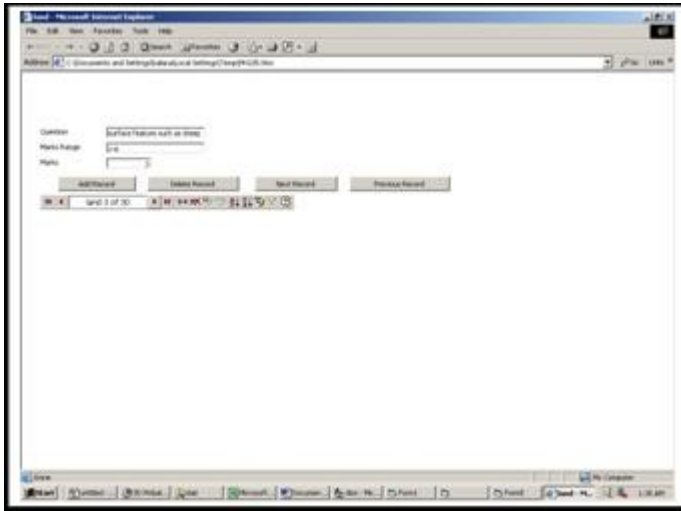


Figure 4. Questionnaire for window

Removing of dependencies in the questions that are constructed in qualitative approach on the basis of tacit knowledge has been a key concern of the approach. Principal Component Analysis (PCA) is used as the first step towards the removal of dependencies. It has been identified 15 numbers of principal components as described in figure 5.

Component Matrix						
	Component					
	1	2	3	4	5	6
VAR00001	-.208	.344	-.365	-.395	.485	-.234
VAR00002	-.472	.569	.143	-.247	-.212	.371
VAR00003	-.372	.607	-3.444E-03	.524	.218	-.247
VAR00004	.174	-.863	-.160	-.343	-1.486E-02	.251

Figure 5. Principal components matrix

5.2 Knowledge classification in land selection

The questionnaire should be classified for the purpose of analysis of ecological innovations in land selection. However, Principal components alone could not give a statistically significant classification for the commonsense knowledge gathered through the questionnaire. We have used

Fuzzy logic in Artificial Intelligence to fine-tune the derived answers by principle components analysis.

Ecological innovative in land selection can be computed into three categories as psychological, physical and social. The percentages of these components are shown below. Note that the Membership functions for ecological innovative, have been constructed in fuzzy logic module using the out puts of principle component analyzer.

- **Membership function for classifying physical innovative in land selection**

Boundary values of membership function have been constructed using the output of the principal component analysis.

$$\sum_{i=1}^{15} \sum_{j=1}^8 a_{ji} = 3.474936 \quad (1) \quad \therefore X_U = 6 \sum_{i=1}^{15} \sum_{j=1}^8 a_{ji} = 20.06002 \quad (2)$$

Here X_L denotes lower bound value at the minimum level of evaluation scale (Does not apply) in the questionnaire. X_U denotes upper bound value at the maximum level of evaluation scale (Applies most) in the questionnaire

$$V(X) = \begin{cases} 0 & X \leq X_L \\ (X - X_L) / (X_U - X_L) & X_L < X < X_U \\ 1 & X > X_U \end{cases}$$

$V(x)$ denotes membership function for classifying physical innovative.

- **Membership function for classifying psychological innovative in land selection**

Boundary values of membership function have been constructed using the output of the principal component analysis.

$$\sum_{i=1}^{15} \sum_{j=1}^8 a_{ji} = 94.63854 \quad (3) \quad \therefore X_U = 6 \sum_{i=1}^{15} \sum_{j=1}^8 a_{ji} = 544.6385 \quad (4)$$

Here X_L denotes lower bound value at the minimum level of evaluation scale (Does not apply) in the questionnaire. X_U denotes upper bound value at the maximum level of evaluation scale (Applies most) in the questionnaire

$$V(X) = \begin{cases} 0 & X \leq X_L \\ (X-X_L)/(X_U-X_L) & X_L < X < X_U \\ 1 & > X_U \end{cases}$$

$V(x)$ denotes membership function for classifying psychological innovative.

- **Membership function for classifying social innovative in land selection**

Boundary values of membership function have been constructed using the output of the principal component analysis.

$$\sum_{i=1}^{15} \sum_{j=1}^8 a_{ji} = 5.989302 \quad (5)$$

$$\therefore X_U = 6 \sum_{i=1}^{15} \sum_{j=1}^8 a_{ji} = 35.5006382$$

(6)

Here X_L denotes lower bound value at the minimum level of evaluation scale (Does not apply) in the questionnaire. X_U denotes upper bound value at the maximum level of evaluation scale (Applies most) in the questionnaire

$$V(X) = \begin{cases} 0 & X \leq X_L \\ (X-X_L)/(X_U-X_L) & X_L < X < X_U \\ 1 & > X_U \end{cases}$$

$V(x)$ denotes membership function for classifying psychological innovative.

5.3 Reasoning

Explanations for output generated by the fuzzy logic module have been processed using fuzzy rules in the knowledge base of the expert system (see Figure. 6).

So following fuzzy rules can be illustrated for classifying land selection ecological innovative in to physical, psychological and social in term of percentage values

For physical innovative:

Rule 1: If $X \leq X_L$ then $V(X) = 0\%$

Rule 2: If $X_L < X < X_U$ then $V(X) = (X - X_L) / (X_U - X_L)\%$

Rule 3: If $X \geq X_U$ then $V(X) = 100\%$

For psychological innovative:

Rule 1: If $X \leq X_L$ then $V(X) = 0\%$

Rule 2: If $X_L < X < X_U$ then $V(X) = (X - X_L) / (X_U - X_L)\%$

Rule 3: If $X \geq X_U$ then $V(X) = 100\%$

For social innovative:

Rule 1: If $X \leq X_L$ then $V(X) = 0\%$

Rule 2: If $X_L < X < X_U$ then $V(X) = (X - X_L) / (X_U - X_L)\%$

Rule 3: If $X \geq X_U$ then $V(X) = 100\%$

Further reasoning process is generated through fuzzy rules in knowledge base constructed for each of selected land classification innovative such physical, psychological and social.

A part of fuzzy rules constructed in the knowledge base implemented by Flex Expert shell is shown as given below:

question p1

'select the nature of the physical feature';

choose one of evaluatesp1.

group evaluatesp1

soft_property, hard_property.

question p2

'what is the rate of the sun light';

choose one of evaluatesp2.

group evaluatesp2

large_amount, small_amount.

question p3

'what is the wind speed';

choose one of evaluatesp3.

group evaluatesp3

large_amount, small_amount.

question p4
 'what is the percentage of land use';
 choose one of evaluatesp4.
 group evaluatesp4
 highly_built, highly_unbuilt.

question p5
 'what is the effect of the rain';
 choose one of evaluatesp5.
 group evaluatesp5
 heavy_rain, soft_rain.

rule pp1
 if p1=soft_prperty then a1:=1
 end if.
 rule ppp1
 if pp1=hard_property then b1:=1
 end if.
 rule pp2
 if p2=large_amount then a2:=1
 end if.
 rule ppp2
 if p2=small_amount then b2:=1
 end if.
 rule pp3
 if p3=large_amount a3:=1
 end if.
 rule ppp3
 if p3=small_amount then b3:=1
 end if.

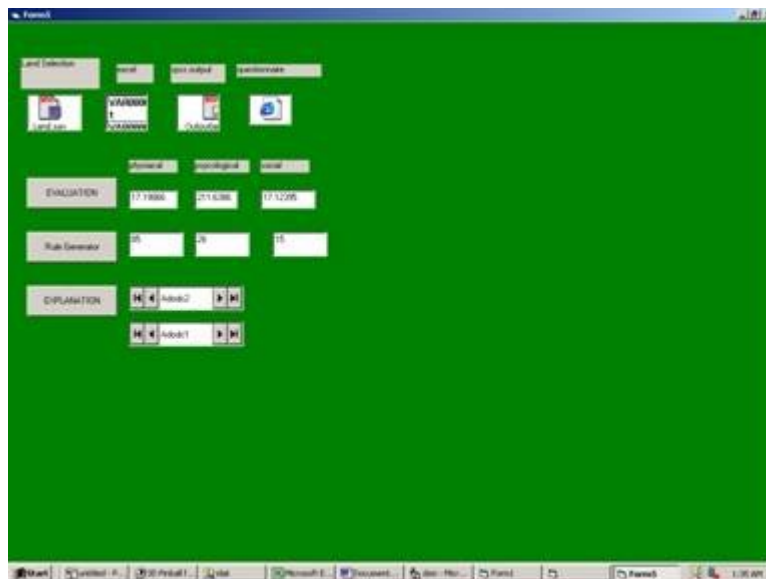


Figure 6. Results of the Analysis

6. Testing of a system on classification of human constituents in Ayurvedic Medicine

The expert system developed using the concept of classification of human constituents in Ayurvedic medicine as described by Tripathi (1978) and Dubey (1978) was tested with a sample of 30 persons of Ayurvedic experts and students (see Table 1).

Table 1. System testing: expert vs. system

vata	pitta	Kapha	Expert_decision
25.71	20.71	53.57	KV
32.95	23.86	43.18	VP
39.88	23.81	36.31	VP
27.65	46.1	26.24	KP
25.69	29.36	44.95	KV
33.58	24.09	42.34	KV
25.71	34.28	40	KP
32.21	31.54	36.24	KV
22.51	29.8	47.68	KP
20.37	30.56	49.07	PK
30.6	35.52	33.88	PK
29.71	17.39	52.9	KV
41.07	10.71	48.21	KV
34.5	32.16	33.33	KV
23.46	28.57	47.96	PK
35.27	30.77	33.97	KV

42.36	36.11	21.53	VP
23.01	35.71	41.27	PK
47.94	19.86	32.19	KV
14.03	35.96	50	PK
19.15	36.88	43.97	PK
22.46	25.36	52.17	PK
40.47	26.78	32.74	PK
30.28	29.58	40.14	KV
12.71	44.92	42.37	PK
11.18	40	48.82	PK
11.24	40.24	48.52	PK
23.44	26.9	49.66	PK
17.09	36.75	46.15	KV
33.09	30.15	36.76	KV

The evaluation was conducted to see how far the answers generated by the system matches with the identification by Ayurvedic experts and the students. Further, the system's ability to fine-tune the answers was also tested. It has been investigated that 23 (77%) of conclusions matches with the system and expert (see Table 2), which leads to determine the accuracy of the system.

Table 2. Compression of conclusions: expert v. system

vata	Pitta	kapha	Expert_decision	conclusion
25.71	20.71	53.57	KV	matched

33.58	24.09	42.34	KV	matched
25.71	34.28	40	KP	Matched
32.21	31.54	36.24	KV	Matched
22.51	29.8	47.68	KP	Matched
20.37	30.56	49.07	PK	Matched
30.6	35.52	33.88	PK	Matched
29.71	17.39	52.9	KV	Matched
41.07	10.71	48.21	KV	Matched
34.5	32.16	33.33	KV	Matched
23.46	28.57	47.96	PK	Matched
35.27	30.77	33.97	KV	Matched
23.01	35.71	41.27	PK	Matched
47.94	19.86	32.19	KV	Matched
14.03	35.96	50	PK	Matched
19.15	36.88	43.97	PK	Matched
22.46	25.36	52.17	PK	Matched
30.28	29.58	40.14	KV	Matched
12.71	44.92	42.37	PK	Matched
11.18	40	48.82	PK	Matched
11.24	40.24	48.52	PK	Matched
23.44	26.9	49.66	PK	Matched
33.09	30.15	36.76	KV	Matched

7. Conclusion

The system has been used for commonsense knowledge reasoning in the domain of architecture. For instance, land selection in architectural construction domain is considered as an area, which involves commonsense knowledge of architects. This is because land selection criteria are very personal and there is no theory behind how it should be done. Sometime, there are too many redundancies in the process selection of lands. In view of this, our framework has been applied to model commonsense knowledge in a sub field of architecture domain of land selection to come up with land classifications as psychological, physical and social events.

Since the framework has been developed as a system that can be linked up with any expert system shell, the end result can be delivered as a commercial product. At present expert system shells do not provide mechanisms for modelling of tacit knowledge. Since we have developed our framework in association with FLEX expert system shell, we have already shown that the framework can be linked up with expert system shells.

With the use of Ayurvedic domain we have demonstrated how our approach works in practice. We have also explained how the framework can be used to model any domain, for example, disaster management, concerning commonsense knowledge. At present the fuzzy-expert system that emerged from our research in modeling of Ayurvedic domain used at the System has been evaluated in faculties of Indigenous Medicine, University of Colombo and University of Kelaniya, Sri Lanka. This has gained an accuracy of 77%. Both Ayurvedic consultants and Ayurvedic medical students use this expert system. Therefore, we conclude that our framework can be used as a generic approach to develop fuzzy experts systems for reasoning in domains with common sense knowledge.

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