Visualisation of Fuzzy Decision Support Information: A Case Study

Ross Brown and Binh Pham
Faculty of Information Technology
Queensland University of Technology
Brisbane, GPO Box 2434, Australia

***Abstract*—Present fuzzy system visualisations while being useful, have been ad hoc in nature. In this paper we present a new integrated task-oriented approach to the visualisation of fuzzy logic systems. In addition, this approach is incorporated into an agent-based software architecture to guide the user through the process of developing a fuzzy logic system visualisation. A case study then illustrates a structured walk through of the new approach with an electricity spot price prediction application.**

***Index Terms*—Fuzzy Systems, Intelligent Systems, Visualization, Decision Support Systems.**

I. Introduction

Fuzzy logic systems fuzzify data to facilitate computations with imprecise quantities [18]. This approach has enabled the development of systems to model the imprecise rules used by human experts for decision support and control systems and for applications involving fuzzy sets for handling the inherent imprecision in measured data [1]. As is the case with any processing of data, there is the need to visualise the results to harness human capabilities in the area of pattern recognition, from both design and user perspectives.

However, most of the present visualisation of fuzzy data has been ad hoc in nature, and has not sought to encompass an integrated view of fuzzy data visualisation. Present work has concentrated on the visualisation of certain aspects of fuzzy data and systems, concentrated mainly from a design perspective [2-5, 9, 12]. Furthermore, except in the case of Lowe et al. [9], most of the work has not sought to enhance the understanding of the internal model processes in the fuzzy system, as an aid for the user in understanding the process behind the results being viewed. The goal for this paper is to draw from our previous work [13] and apply a general framework to the visualisation of fuzzy implication, in order to make apparent the meaning of internal processes.

Just such an approach will seek to make clear some inherent information or knowledge from the data, rather than just showing patterns in the data for the user to interpret.

Secondly, the approach will seek to provide a method for guiding the user through the visualisation process, by identifying relevant techniques and explicitly demonstrating a way to apply these techniques. This is expected to have applications in decision support scenarios, where the user requires further insight into the conclusion reached by the system, and requires a task-oriented viewing of the data in the system.

Paradoxically we wish to make clear the fuzziness of the data, while most existing visualisation systems seek to be unambiguous in their representations, as the data underlying the image is considered to be crisp in nature [15]. In this application area the motivation is to make explicit the levels of imprecision in the data, by using possibly visually ambiguous stimuli to directly map the imprecise nature of the underlying data. This mapping of visual uncertainty to the uncertainty level of the decision being made is presented as a useful metaphor to aid the user in how much they should trust the results of the system.

Fuzzy data is imprecise in its nature and is often represented by terms and by distributions of data over an interval, and not crisp points [1]. There are issues with the fuzzy data that is being analysed. What type of data is being analysed–discrete, continuous, textual, images, volumetric? How does the system handle the imprecision? Does it use fuzzy sets, rough sets, fuzzy rules, filtering, theory of evidence, probabilistic calculus? Furthermore, what is the nature of the fuzziness, that is, how precise is the system? All these issues require considerable thought in the application of visualisation techniques.

Therefore, to visualise such data the user needs to find a mapping between the imprecision and some form of visual representation, which directly shows to the viewer the fuzziness of the data. In addition, relationships between components of the system need to be analysed, especially the relationships between various data in the system and the relationship between the data and the task being performed.

The structure of the paper is broken up into two main sections. First, a new approach for the visualisation of data is presented. In particular, we describe an architecture for an agent-based system that incorporates this approach to facilitate the effective visualisation of imprecise data.

The paper then concludes with a case study illustrating the application of this approach to the visualisation of results obtained from a fuzzy logic model of electricity spot market prices.

II. Visualising Imprecise Data

Successful visualisation of data is facilitated by the correct choice of visual features to illustrate the magnitude of data dimensions. The visual features are often chosen based upon their ability to act as a visual signal of inherent patterns within the data. These visual features are then organised into higher representations such as 2D/3D graphs for the same purpose

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[15]. A number of techniques have further developed these representations for the visualisation of various components of fuzzy systems: *parallel axes* [5], *fuzzy rule surfaces* [11], *dimensionality reduction* [2], *fuzzy cognitive maps* [4], *membership visualisations of fuzzy c-means* [3] and *believability visualisations* [9].

These techniques are useful, especially for designers of fuzzy systems. However, they still lack an integrating framework to apply them in a coherent manner for a particular visualisation task. Therefore, in the next section we develop an appropriate framework for such an approach.

A. A Task-Oriented Approach to Visualising Imprecise Data

We use the main points of the data and task ontology developed by Pham and Brown as an approach to the visualisation of imprecise decision support data [13]. The framework highlights a number of relationships that must be analysed in order to create a visualisation that is suitable for the task at hand. We concentrate on the following for this application:

- data to data relationships–effects on the data in the system as it undergoes transformations from one space to another, for example, data fusion.
- data interpretation–approaches to interpreting different features or events, for example, how great a change in a scalar value is marked by the visualisation.
- data to task relationships–how the visualisation to be used, for example, what-if scenarios.

1) Data to data relationships

Data fusion becomes an issue when the data requires a consistent representation and consistent mapping to visual features. The variables may be in different numerical spaces with either real or discrete values being used. This requires appropriate data space normalisation in order to create a visually informative and numerically correct visualisation.

2) Data Interpretation

Data interpretation is the actual process of response to the features within the data. Once a representation has been chosen for the data, the interpretation then has to be carried out. For example, a change in data can be interpreted as either being positive or negative to the visualisation task, and as such needs to be mapped appropriately to visual features to facilitate the interpretation of the data. This also includes dynamic effects, and is again strongly related to the task at hand.

Secondly, the fuzzy nature of the data is an issue with regards to its visualisation. The system may be quite imprecise, even to the level of rough sets [16], or may move towards being a nearly crisp system. The internals of the system may combine data at various levels of precision, which needs to be considered when interpreting the values and mapping them to an appropriate visualisation.

3) Data to Task Relationships

This is especially important, as the tasks carried out by the user will strongly influence the presentation of the data. The nature of the usage falls into two main categories: *user* and *designer*.

The user of the system, in general, will be wanting information as to the reliability of the results, as has been explored with anaesthetic decision support systems [9]. This approach is for decision support, while other systems such as clustering, what-if, simulation and predictive systems will require visualisations of multidimensional clusters and comparisons of potential solutions.

Design tasks require the visualisation of the internals of a fuzzy system for verification and analysis. This includes the structure of the rules, clustering effects, contributions of the rules during operation and the effects of different operators.

We believe that such data analysis and mapping of visualisation tasks to techniques would be best carried out within an intelligent agent software framework. We detail an appropriate architecture in the next section.

B. An Agent-based Visualisation Architecture

The task to technique to data mapping is performed by a visualisation agent that guides the user to appropriate techniques for visualisation, according to the task and data involved. An agent is a

> *computational entity such as a software program or a robot that can be viewed as perceiving and acting upon its environment and that is autonomous in that its behaviour at least partially depends on its own experience* [17].

This quotation contains the main reasoning for the adoption of an agent-based architecture for the software. Firstly, the approach needs an intelligent module to communicate with the other agents contained in the newly developed framework by Pham and Brown [13], so an ability to interact with a data processing agent is required.

Secondly, the experience modelling provides a system that modifies its behaviour based upon user preferences selected in previous iterations. This facilitates user profiling and adaption of internal knowledge.

Finally, its autonomous nature removes much of the overhead for a user seeking to use a visualisation tool, as the agent is able to effectively extract visualisation requirements.

There are many systems and approaches to visualisation which have used hard rules gleaned from years of research and application experience, but few, if any, use intelligent agents to facilitate modification to user preferences [8, 15]. In particular, to our knowledge, none have been developed for visualisation of fuzzy/imprecise data.

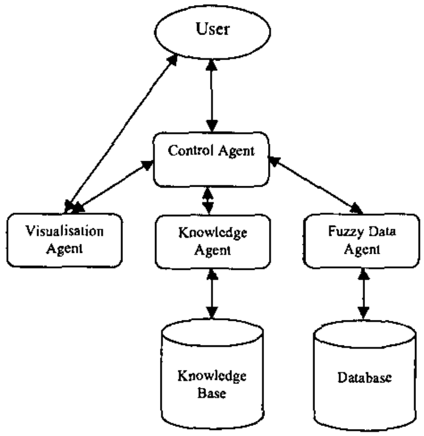

Fig. 1 Flow diagram for the Visualisation Support System Architecture showing the major components of the system.

The *Visualisation Support System* architecture is made up of a number of key components, as illustrated in Fig. 1:

- *control agent*–gains information from the other agents within the visualisation system, including the user, and initiates appropriate requests;
- *knowledge agent*–gleaned from expert knowledge about the visualisation of fuzzy system information, using an expert system;
- *visualisation agent*–provides visualisation and rendering services;
- *fuzzy data agent*–serves data from the fuzzy system in appropriate formats for the requested visualisations.

This agent works in three major stages, gaining data regarding the nature of the following:

- *tasks*– depending on the context of the visualisation task an appropriate visualisation is shown;
- *techniques*–chosen to maximise the potential understanding of the data;
- *attributes*–chosen to enhance the visualisation according to expert opinions, including interactive components to allow the viewer to modify the visualisation in an exploratory manner.

The visualisation presented for the task may be drawn from the different visualisation tasks, techniques and attributes in their appropriate application areas. This information would be drawn from the knowledge base, abstractly represented as a *Visualisation Task Network* (VTN), contains the relationships between different components that control the traversal of the data structure, and interactions with users. Furthermore, this task network is updated to accommodate new information from the user via different links and weightings being applied to the visualisation task structure. The task structure is organised according to the diagram in Fig. 2.

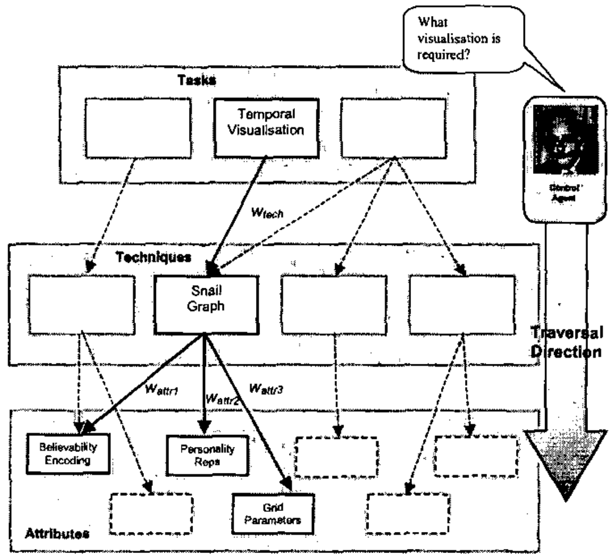

Fig. 2 Illustration of Visualisation Task Network, with example visualisation path in bold.

Each component of the data structure encodes necessary information about the particular task. The task nodes contain information about the type of task being performed, such as its type (what if, simulation, animation) and the pointers to appropriate techniques. The technique nodes contain information about the actual visualisation technique used, including pointers to appropriate methods to be invoked and pointers to appropriate attributes. The attribute nodes contain information about the attributes of the visualisation, such as: data formats, colour, glyph information, grid spacings, viewing angles, interactive parameters etc. Each link has associated weights that support the adaptive capabilities of the knowledge base.

This VTN is incorporated into an expert system that asks appropriate questions about the visualisation task to be performed. An expert system will be used due to the applicability of knowledge-based systems to this application domain, particularly as the rules for the appropriate representation of data in a visualisation can be expressed relatively easily as rules. In addition, expert system approaches allow for user modelling and modification of the relationships between components of the knowledge base [7].

The previously shown questions are encoded in the decision tree and enable the traversal of the visualisation task structure to choose appropriate techniques for the visualisation. First, the system may analyse the data and present a potential first solution based upon statistical characteristics of the data. The system then commences the interaction with the user of the system. The control agent by interacting with the knowledge agent, traverses the VTN.

An example of a higher-level question is: 'Is the visualisation task a *time-based* visualisation?' At this stage examples are shown to the user to aid their choice in what direction to take. Note that the task may have one or more appropriate techniques, which may be presented at once. The system then may seek to refine the visualisation with queries or presentations of choices regarding attributes. For example, a number of colour scales may be selected and proposed according to the knowledge base. The system then prompts the user to choose a particular colour scale that is most useful.

Furthermore, the visualisation agent collaborates with the data agent to format the data in an appropriate fashion for the visualisation.

Both these areas need to allow for visualisation with modification of parameters in a meaningful manner, especially in a dynamic environment. This is the domain of the knowledge agent within the system. The knowledge agent has the capacity to modify the visualisation task data structure and the decision tree according to the previous history of usage by the users. For the visualisation task structure there are weights allocated to the links as well as the ability to add/delete the links. This enables the visualisation agent to modify its internal state and approach facilitate user modelling.

III. ELECTRICITY SPOT PRICE PREDICTION CASE STUDY

Using the above approach, we have chosen to perform a case study with a fuzzy system developed to model spot prices on the Australian electricity market [10]. The case study is in two major parts. The first part details background information, to provide a basis for the application of our approach. The second section describes a mock up of the major components of the system as a walk-through, in order to illustrate the expected functionality of an implementation.

A. Description of the Fuzzy System

This case study covers the visualisation of data from a fuzzy model developed to predict electricity prices. These newly developed markets seek to improve the efficiency of monopolistic supply systems by incorporating a free market approach to the selling of electrical power. The newly developed model simulates spot prices that occur within these electricity markets. This is marketed on what is called the *Spot Market*–the market for uncontracted electricity. Various contracts within this market are negotiated which seek to maximise the profit for any buyer or seller of electricity.

For each contract a strike price is negotiated where if a particular threshold is exceeded then one party has to compensate the other party in the agreement. These thresholds can be organised in three ways:

- *one way*: seller repays buyer when price goes above strike price;
- *two way*: seller repays buyer when price goes above strike price or buyer repays seller when the price is below the strike price (in other words a fixed price);
- *ceil floor*: uses an upper and lower threshold to allow the price to fluctuate between two values before repayment has to occur.

The fuzzy model fuzzifies the estimation of the spot price trends to then quantify the potential risk involved in purchasing at that price. The fuzzy model thus ameliorates the uncertainty involved in trend prediction of spot prices. The system uses linguistic variables and fuzzy filters to fuzzify the trend prediction.

People respond to the value of the data based upon an internal model of the expected value of imperfect information. According to this line of thought, risk takers respond to low value data and conservative people respond to high quality data. Contract seekers are thus categorised as *very conservative*, *conservative*, *neutral* and *risk-seeking*. The trends are approximated by a linear regression model, using a pair of upper and lower margins. These margins are fuzzified so that the terms correspond to a proportion of spot prices which are within the boundaries of the linear model, as shown in TABLE 1.

This is fuzzified by using the membership function filter specified in Fig. 3. The narrower the filter the more accurate the value generated, but the less one is able to trust the trend estimation. The filter is asymmetric due to the larger deviation of spot prices above the main trend line.

TABLE 1 TABLE OF RISK TAKING ATTITUDES AND MARGIN PERCENTAGES

Category	Margin Percentage
Risk-seeking	70%
Neutral	80%
Conservative	90%
Very Conservative	95%

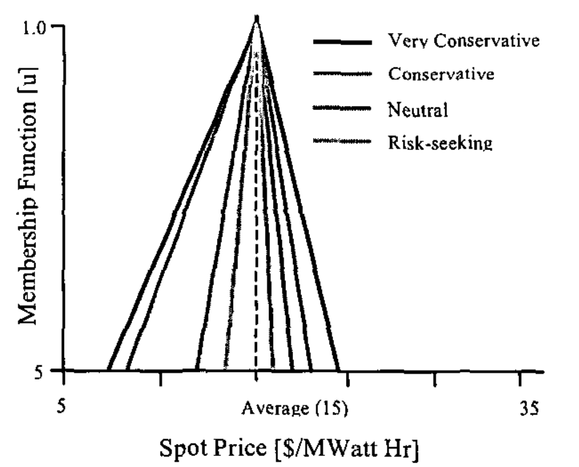

Fig. 3 Illustration of the membership function used to fuzzify the spot price [10].

These are then used in a fuzzy scheme to estimate the trend in spot prices, based upon the previous four weeks of data. The schemes were tested with max, min and weighted-sum techniques. With the min value corresponding to risk-taking people, max value corresponding to risk-averse people and weighted-sum corresponding to risk-neutral people.

Additional estimates of costs incurred by the system are generated by the model, including estimates of costs incurred when the spot prices are above and below the estimated trends. Risk estimates are also made for each personality type modelled in the system.

B. Application of the Approach

From the previous description, a number of data to task relationship points can be noted about the application area:

1. There are a number of levels within which to view the data. Either as an iconic trend indicator or a temporal trail from the past to the present (to show model history), or as a statistically rich visualisation in a graphic form [6].
2. The believability of the data needs to be indicated on the visualisation [14].
3. Other supporting data needs to be shown for cost risk analysis.
4. Comparisons need to be made for differing personality types.

These issues inspire questions the system can ask a user to help guide the visualisation, via the internal knowledge representation for the domain of spot price visualisation.

We now describe a mock up example containing a visualisation of spot price trends. The visualisation can take place at a number of levels, *iconic*, *temporal* and *statistical*, in a similar manner to a other visualisation systems [6].

The iconic representation is a simple indicator of the predicted trend and a believability value encoded as a colour. This provides a high level indicator of the predicted value provided by the system.

If the user requires more information about the temporal history of the system, then they may require a more detailed visualisation of the system. This is provided as a temporal display, with status information over a period of time.

The final visualisation is more statistical in nature incorporating cost/risk calculation values and more detailed information of the state of the spot market and prediction values.

The control agent commences the session by querying the user about the visualisation task, the first level of the VTN. This dialog box forms the basis of the interactions performed between the user and the system. A general mock up of this dialog box is presented here in Fig. 4.

For this case study, the user has requested a temporal visualisation of the spot price estimates. The system has responded with a selection of techniques, which are available from its knowledge base (Fig. 4). The choice favoured by the system has been highlighted. The user is then asked to choose the technique or accept the recommendation of the system.

Here, we assume the user chooses the recommended Snail technique. The snail temporal visualisation is essentially a metaphor of a snail, crawling across the screen. The head of the snail indicates the predicted value for the next time interval. The snail trail presents a temporal visualisation of the previous accuracy of the model to indicate believability over time for the predicted values. Finally, the costs and estimated risk values can be displayed as a glyph above the present value of the estimate. This involves the use of a histogram, colour coded to match the believability of the projected costs. However, these statistics are not shown in as much detail as those displayed in the low-level statistics visualisation.

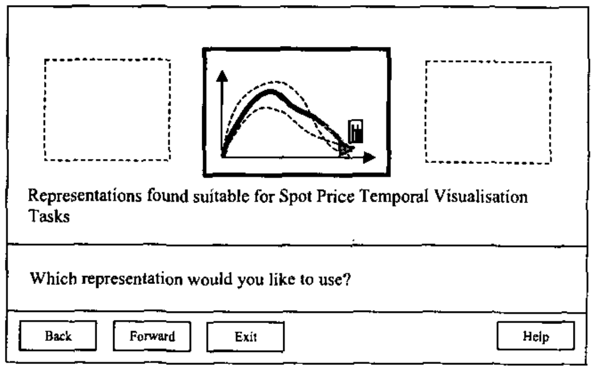

Fig. 4 Illustration of the general layout of the Control Agent dialog box.

The agent then traverses the VTN to the attribute level for the Snail visualisation technique. Each of these attributes has a number of parameters which can modified under the direction of the visualisation system. Due to lack of space, we will only cover the risk personality visualisation parameters.

The risk personality of the visualisation seeks to give a picture of the performance of the modelling of different risk personalities. A number of options are available to the user at this stage:

- number of risk profiles presented–one or more can be presented to the user on the graph.
- method for multiple personality representation–using blurring or dashed and full lines to have only one or several highlighted at once.
- features for different personalities–with colours either provided by the expert systems or with the choice of the user, or even luminance levels.

The user is therefore queried by the system to ascertain the appropriate techniques and parameters for this visualisation. The user is presented with a query about the presentation of multiple risk personalities, which the user has chosen previously. The system presents the options available regarding multiple personalities on the snail graph. In this case the user chooses to have the personality of interest represented as a bold line, with the others represented as dashed lines (refer to Fig. 5).

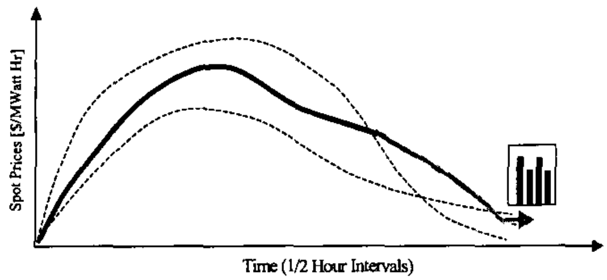

Fig. 5 Illustration of choosing a method of representing multiple risk personalities for the temporal visualisation. This illustration also shows the glyph used as a representation of summary cost risk statistics at this point in time. The believability of the predictions is presented as a luminance value superimposed onto the previous 4 predicted values.

This paper has only presented a small section of the potential interactions between the user and the envisaged system. In a real scenario, additional questions are asked about the attributes of the visualisation, such as the use of a grid on the graph, labelling and techniques for visualising personality types. For expert users, interactive techniques will be used to allow the user to not only select, but actually construct the visualisation.

The user is then presented with the final visualisation. At any stage the user may accept the default values offered by the agent, or may simply let the agent create a visualisation for the task specified in an autonomous manner. In addition the user may go back and modify any of the parameters within the visualisation to their satisfaction. Furthermore, the visualisation may contain interactive parameters, to allow exploratory what-if modifications by the user.

The information gleaned from this session is used to update the weightings on the links. If the user chooses an option not specified in the VTN, then the agent creates a new link with an appropriate weighting on the linkage. This facilitates the user profiling process and as such enables the software to adapt itself to the idiosyncratic preferences of each user of the system.

IV. Conclusion

In this paper we have presented a new intelligent and task-oriented approach to the visualisation of fuzzy system information. The approach integrates techniques already developed for the visualisation of fuzzy system data into a coherent approach for developing visualisations.

Furthermore, we have incorporated this approach into an agent-based visualisation software architecture, which uses a Visualisation Task Network and Expert System to guide the user through the visualisation process.

We have illustrated this approach using a case study of electricity spot prices. It was shown that this method facilitates the development of appropriate temporal visualisations by the user. Such an approach can then be applied to more complex multivariate visualisations in other application areas.

Future work includes the implementation and testing of the Visualisation Support System architecture for a number of application areas.

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