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Interpolative Fuzzy Reasoning and Fuzzy Automata in Kansei Technology

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Abstract

Application of interpolative fuzzy reasoning and fuzzy automata in Kansei Technology gives a simple way for adding user adaptivity to emotion-based selection systems (like interactive furniture selection based on human feelings in our case). One way of handling user adaptivity in emotion-based systems is a kind of combination of existing (off-line collected) human opinions in the function of the approximated similarity to the actual user opinions. This method has two main tasks, namely approximating the similarities of the actual user opinions to the off-line collected ones, and the next is to combine these off-line collected opinions in the function of the corresponding approximated similarities to get the approximated actual user opinions. In this paper we suggest to apply fuzzy automata and interpolative fuzzy reasoning for a simple way of solving these tasks.

Keywords: Kansei technology; interpolative fuzzy reasoning; fuzzy automata.

1 Introduction

One of the key goals of the emotion-based "Kansei" selection systems is to build the Kansei user model, the relation of the user emotion related requests (like "friendly" or "convenient") and the physical parameters characterising the objects to be selected. One of the main difficulties of building this relation is the highly user dependent interpretation of the physical meanings of the same emotional word. In most cases the same emotional word for different users covers very different physical interpretations. The first systems applied the Kansei technology were unable to handle this problem. They had only one fixed Kansei user model, generated off-line, based on a wide user inquiry, as a statistical average of the different answers [1,2]. Nowadays were are a lot of work related to the on-line user adaptivity of the Kansei user model. Some of these works applying learning methods to modify a global user model based on the on-line interventions, or interactions of the actual user [3,4,5]. We think, that there are some chance of having situations, there modifying only a small region of the user model (as a part of the on-line adaptation) can lead to incoherence (in sense of the consistency, or locality of the modification) of the user model.

Solving the problem of the probable occasional incoherence, in this paper we suggest to implement user adaptivity in the Kansei user model as an on-line variable combination of some fixed existing (off-line collected) user models.

This combination could be done globally in the manner of "more similar the actual user to one of the existing user models, more similar must be the actual user model to that user model".

Supposing, that all the off-line collected user models are appropriate, and the combination is affecting coherently the entire user model, we hope, – that the global combinations of the valid user models are also valid user models – that we can avoid the above mentioned accidental incoherence.

2 The adaptive Kansei user model

Having a set of valid off-line collected user models, the main idea of the proposed adaptive Kansei user model generation is to generate the actual user model as a combination of the existing models in the following manner: "More similar the actual user to one of the existing user models, more similar must be the actual user model to that user model".

This goal is twofold. First we have to approximate the similarities of the actual user and the existing user opinions, and than we have to combine the existing models based on these similarities.

For the first task we suggest to adapt a *fuzzy automata*. Its actual state (actual similarities, see fig.1.) is a set of similarity values, the actual approximated similarities of the actual user and the existing user opinions (Kansei descriptor sets on fig.1.). The state-transitions of the fuzzy automata are driven by fuzzy reasoning (Fuzzy state transition rulebase on fig.1.) as a decision based on the previous actual state (similarities) and the similarities of an editing actual user opinion to the existing user opinions (Similarity calculations on fig.1.). Practically the modification of the actual similarities is done during the editing state of the selection system (which could be invoked any time of the selection process). This case the actual user can modify the actual similarities (state) by giving his/her opinions related to the actual object (Edited furniture on fig.1.), and based on the similarities of this opinion to the existing user opinions (Similarity calculations on fig.1.), and based on the previous state, the state transition Fuzzy reasoning calculates the new actual state (similarities).

The rulebase applied for the state-transitions of the fuzzy automata (rules for interpolative fuzzy reasoning) for the i[th] state S_i (R_{Ai}): (1)

```
If  Si=One    And
    SSi=One   Then Si=One

If  Si=Zero   And
    SSi=Zero  Then Si=Zero

If  Si=Zero   And
    Sk=One    And
    SSi=One   And
    SSk=One   Then Si=Zero

If  Si=One    And
    SSi=Zero  And
    SSk=Zero  Then Si=One

If  Si=Zero   And
    Sk=Zero   And
    SSi=One   And
    SSk=Zero  Then Si=One
```

where SS_i is the calculated similarity of the actual user opinion to the i[th] existing user opinion, $k \in [1, N], k \neq i$.

The structure of the state-transition rules is similar for all the states. The reason of the interpolative way of fuzzy reasoning is the incompleteness of state-transition rulebase [6].

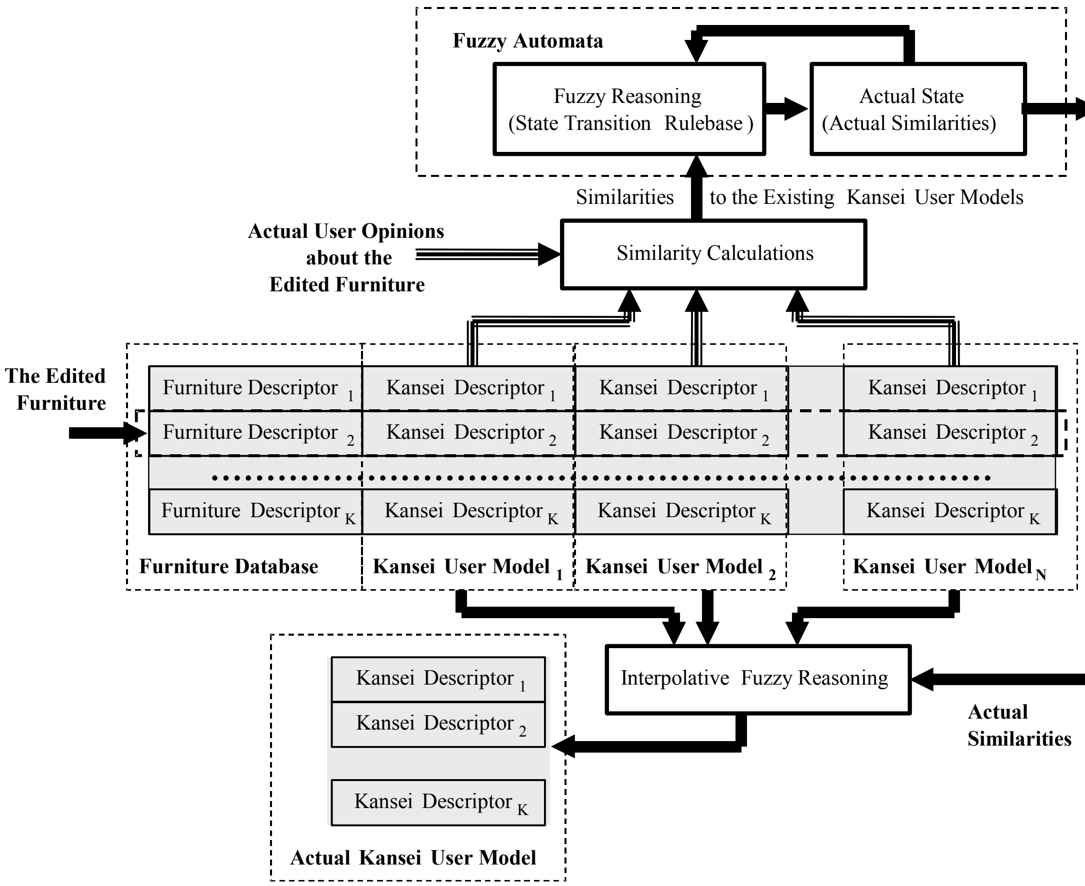


Fig.1. Structure of the proposed adaptive Kansei user model generation

For the second task, for the combination of the existing Kansei user models based on the actual similarities, we suggest to apply interpolative fuzzy reasoning.

Having all the off-line collected user models (and supposing that they are appropriate), we try to generate the actual Kansei user model as a combination of them (in a function of the corresponding actual similarities) (see fig.1.).

Hoping, that if the combination is affecting coherently the entire user model, we will get a valid user model from their combination too (avoiding the accidental incoherence).

The simplest way for such a combination is the application of the interpolative fuzzy reasoning [7]. The main idea of the proposed adaptive Kansei user model generation is - "More similar the actual user to one of the existing user models, more similar must be the actual user model to that user model" - can be directly translated to an interpolative fuzzy rulebase. (Applying interpolative fuzzy reasoning the completeness off the fuzzy rulebase is not necessary.)

The rulebase applied for the interpolative fuzzy reasoning to combine the existing user models (sets of Kansei descriptors on fig.1.) in a function of the corresponding similarities is the following: (2)

If S_1=One **And** S_2=Zero **And** ... **And** U_N=Zero **Then** KD=KD_1
If S_1=Zero **And** S_2=One **And** ... **And** U_N=Zero **Then** KD=KD_2
...
If S_1=Zero **And** S_2=Zero **And** ... **And** U_N=One **Then** KD=KD_N

for all the Kansei descriptors in a user model, where KD_i is the set of Kansei descriptors in the i^{th} user model, and KD is the set of Kansei descriptors of the actual Kansei user model we are searching for.

Comments: instead of interpolative fuzzy reasoning a kind of weighted average (where the weights are functions of the corresponding similarities) is also applicable (even it is not so flexible in some cases).

The goal of the actual Kansei user model modifications from the actual user side is to tune the system to be closer to his/her opinions. Practically the system is starting from an initial stage (where the similarities to the existing models are equal), and in the case the user is disagree with the evaluation of the actual object (furniture) given by the system, he/she has the possibility to modify the actual user model by giving his/her opinions. In most cases the given opinions are related to one or a few Kansei descriptors of the edited object (furniture in our case). But because of the proposed structure, all the changes are done globally (all the Kansei descriptors of an existing user model has the same weights "globally" in the actual model – not only the descriptor weights related directly to the given user opinion are "locally" modified). We hope that this kind of adaptation strategy keeps the actual user model coherent. E.g. if one of the users have exactly the same opinions as one of the existing user model (even his opinions were given through some of the Kansei parameters only), than (after a few modification, detection steps) as the best fitting existing user model, the system will use it exactly.

2 The user adaptive furniture selection

As an example of the proposed adaptive Kansei user model structure, a Kansei furniture selection system was developed (see fig.2.).

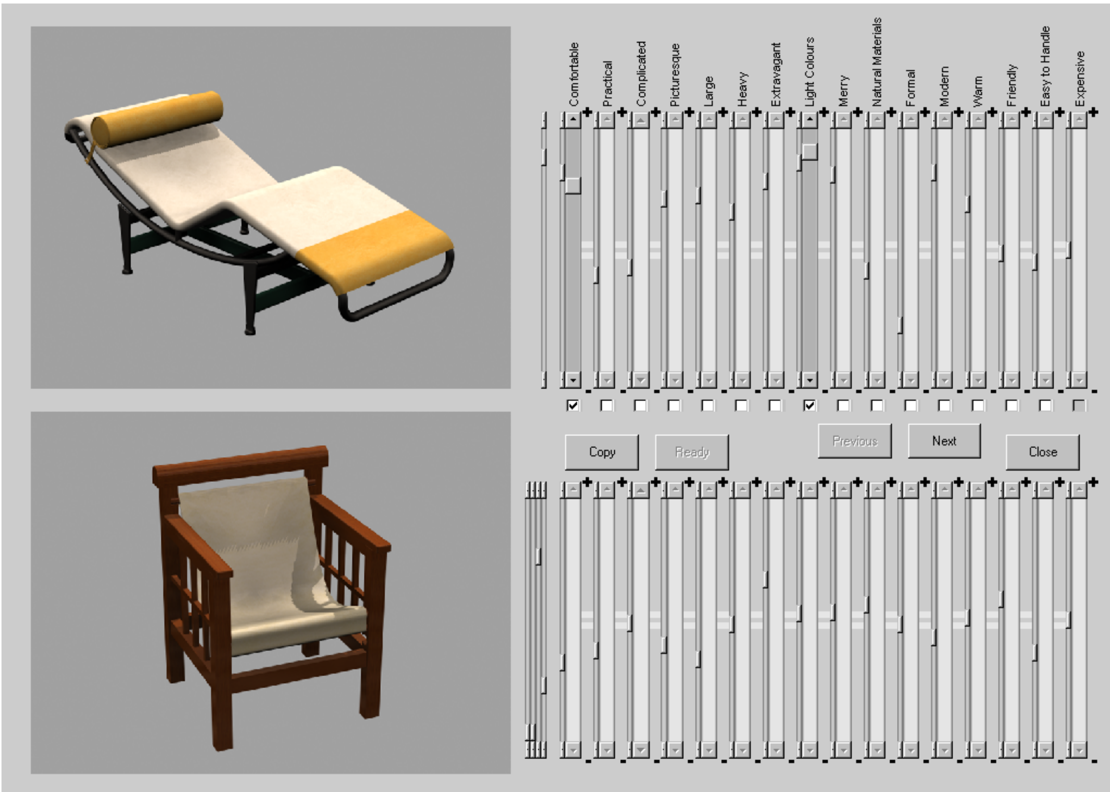


Fig.2. Screenshot of the furniture selection system

The goal of the selection system is to aid furniture (chair) selection by giving the chance to the user to express his/her requirements through emotional (Kansei) levels. The set of handled emotions is fixed to 16 emotional words related to chairs. The user is giving the requirements by selecting some of the emotional words and adjusting the corresponding sliders. On the sliders the "+", "0", "-" symbols are appearing only, to inspire the user to give his/her feelings in a scaleless manner (see fig.2.).

As a response of the user intervention, the best fitting chair is appearing in the working window. The same time the system gives all the Kansei values (16 in our case) related to the furniture on screen, fetched from the actual Kansei user model. These values are appearing the same manner, on sliders (side by the user sliders, see fig.2.), as the user was giving his/her requirements. This method inspires the user to make modifications in more/less, small/big differences manner – relative to the furniture on screen.

2.1 The Kansei user models

The existing Kansei user models were generated based on questionnaires. Some persons (four in our case) were asked to give their opinions about chair pictures. The inquired persons had to make a partial ordering of a set of pictures of 43 different chairs. For each emotional (Kansei) attributes in the questionnaire, the inquired persons were first asked to make a rough order of the pictures into seven groups: very ~, ~, a little bit ~, ?, a little bit not ~, not ~, very not ~ - where ~ is the actual Kansei attribute. Than he/she was asked to partially order the pictures of the same groups. (Partially ordering was meant as ordering in the case of the pictures are distinguishable in respect to the Kansei attribute, and signing equality, if they are indistinguishable.)

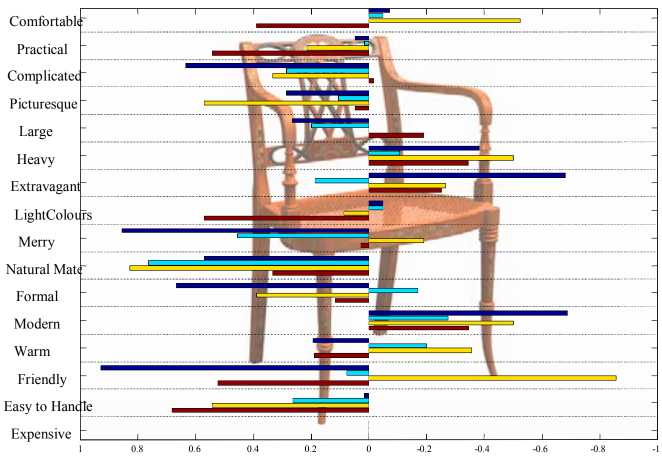


Fig.3. Different user opinions about the same furniture

The answers than translated to real values of the [-1,1] interval, according to equal width of the seven attribute group, and equal distances of the elements of the same group in the manner of partial ordering (equal values for the indistinguishable ones). These values are forming the Kansei descriptors. The Fuzziness of the Kansei descriptors are characterised by constant scaling function [8] (like similar isosceles triangle shaped fuzzy sets). All of these values for all the emotional attributes are forming the Kansei user model.

As we had a sample application only, there were a small query made, only four persons were asked about their opinions. As a result we get four existing Kansei user models. See an example of the different ranking of the same chair with respect to 16 different Kansei attribute of four persons we asked on fig.3.

2.2 The selection system

According to the proposed structure on fig.1., our system has four Kansei user model (four set of Kansei descriptors - values characterising the human feelings related to the database elements) and a set of furniture descriptor – picture, or CAD description of a furniture (picture in our case).

The actual Kansei user model is generated as the combination of the existing Kansei user models based on the actual similarities, by interpolative fuzzy reasoning (as it is proposed in section 2., using the rulebase (2)).

The initial value of the actual similarities (initial state of the fuzzy automata) is a vector of 0.5.

The actual selection is done by a selection engine (fig.4.). The task of the selection engine is to select the furniture descriptors from the furniture database which have the closest actual Kansei descriptor to the user requirements. The similarities are calculated as distances in Euclidean sense. Having a user selection command, the best fitting (closest) furniture is put on screen. Than the user can use the Next (Previous backward) button to view the next best fitting furniture (fig.2.).

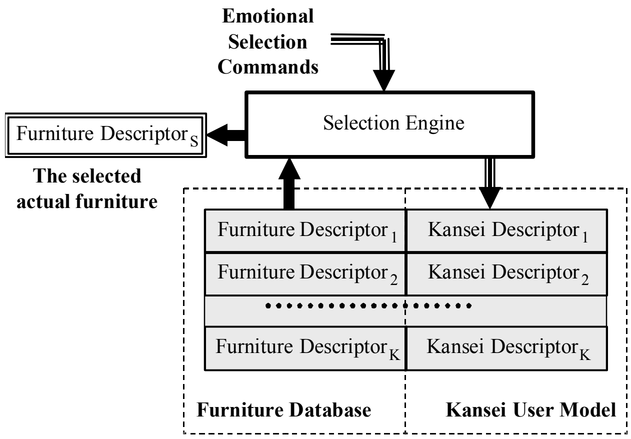


Fig.4. The selection engine

The same time as the furniture appearing on the screen, the system shows its Kansei descriptors (fetched from the actual Kansei user model). These values are appearing the same manner, on sliders (side by the user sliders, see fig.2.), as the user was giving his/her requirements.

In the case the user is disagree with the evaluation given by the system, he/she can give his/her opinions by copying the actual furniture to the editing window (bottom of the screen on fig.2.) and adjusting some of the bottom sliders. Pressing the Ready button, the system recalculates the actual similarities (as it was introduced in the 2. section)

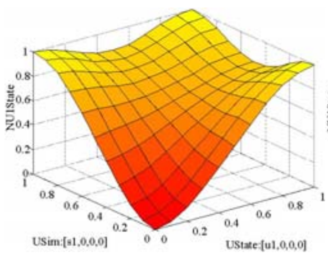
The similarities (SS_i) of the given user opinions and the ith existing Kansei user model is calculated using the following formula (applying functions of the Fuzzy c-Means fuzzy clustering algorithm [9]):

$$SS_i = \frac{1}{\sum_{j=1}^{N} \left(\frac{d_i}{d_j} \right)^{\frac{2}{m-1}}}$$

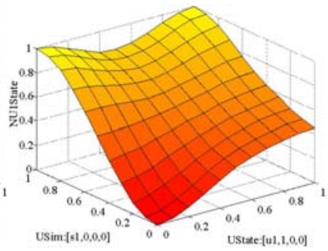
where $d_k = \|\mathbf{x} - \mathbf{v}_k\|$, the distance (measure of dissimilarity) of the user opinions (Kansai descriptors) $\mathbf{x}$ and the Kansei descriptors of the edited furniture in the kth existing Kansei user model $\mathbf{v}_k$, m is a weighting exponent (usually m=2).

The fuzzy automata (as it is proposed in section 2.) using the rulebase (1). Its initial state (initial value of the actual similarities) is a vector of 0.5.

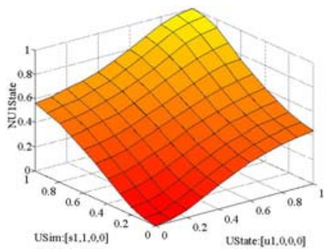
Corresponding to the rulebase (1), some of the state-transition surfaces of the fuzzy automata are shown on fig.5.



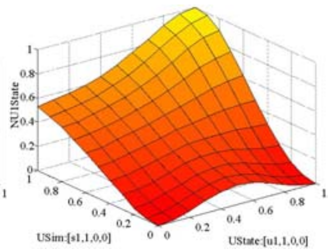
S_{k-1}=0, SS_k=0, $\forall k \neq i$



S_{k-1}=0, SS_k=1, $\exists k \neq i$



S_{k-1}=1, SS_k=0, $\exists k \neq i$



S_{k-1}=1, SS_k=1, $\exists k \neq i$

Fig.5. Some ith state-transition surfaces of the fuzzy automata $S_i(SS_i, S_{i-1})$

3 Experiences

Checking the efficiency of the proposed structure, as it deals with emotional parameters, is not easy.

At least for checking the ability of approximating the user opinions, we made a test user model set. These user models are containing only one Kansei descriptor and one furniture. By the first user model, this furniture is very not ~, by the second a little bit not ~, by the third a little bit ~, by the fourth very ~. Running the actual user opinions through all the universe [-1,1], as a step function (repeating the same requirements 10 times, than jump), we got the actual Kansei user model as shown on fig.6. The notation of the figure is the following: KVUi is the ith user model (only one Kansei descriptor), Si is the ith element of the state vector (actual level of similarity to the ith user model), Ureq. is the user requirement, and SysApprox is the actual Kansei user model (only one Kansei descriptor).

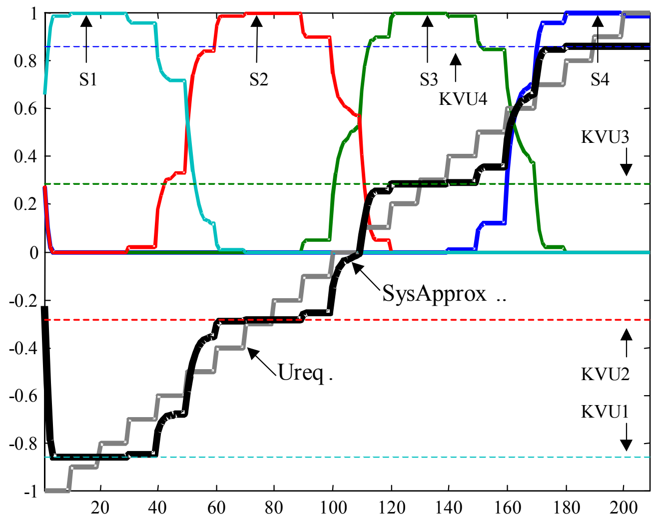


Fig.6. Test user model set, step user requirements.

For testing the robustness of the system against random noise, we used the above introduced test user model set. This case the input actual user opinions was a constant value superimposed with random noise. The actual Kansei user model we got this case is shown on fig.7. (The notation of the figure is the same as fig.6.)

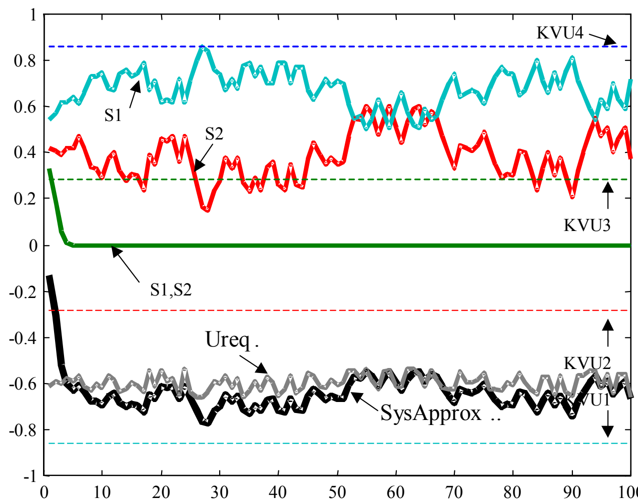


Fig.7. Test user model set, constant noisy user requirements.

Repeating the first test (step function actual user opinions), using the real Kansei user model set, we got the result shown on fig.8. (The notation of the figure is the same as fig.6.)

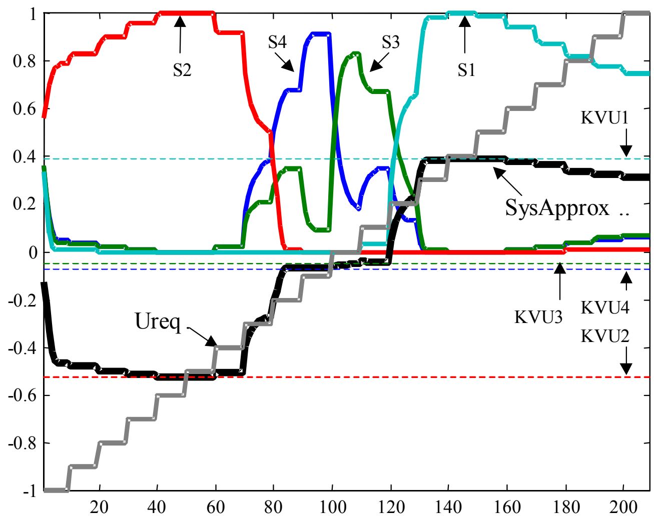


Fig.8. The selection engine

4 Conclusion

The main benefit of the proposed structure is to give a simple way for adding user adaptivity to emotion-based selection systems. Having different existing Kansei user models, it achieves user adaptivity simply by combining them (in interpolative manner) in the approximated best fitted way to the actual user. The proposed structure can handle many different user model parallel, even if they are in contradiction with each other. The system will combine the user models in the manner: "More similar the actual user to one of the existing user models, more similar must be the actual user model in use to that user model".

Basically the "adaptive knowledge" of the system related to the actual user is not a new adapted user model, but a set of approximated similarities, the similarities of the actual user to the existing user models.

We hope, this kind of structure, the global similarity based combination of existing user models, is able to avoid incoherence could caused by step by step partial modifications of the user model.

Because of the interpolative properties of the user model combination, the proposed system is unable to follow user requirements outside the area covered by the existing user models (see e.g. on fig.8.). In other words, the system cannot go beyond its existing "knowledge". The only solution of this problem is extending the number and the variety of the existing user models. The goal is to cover the state space by user models as much as it is possible (e.g. collecting the different opinion sets of different typical user types, or user clusters, as deep as possible).

Adopting interpolative fuzzy reasoning for user model combination, and fuzzy automata for user similarity approximation makes the proposed structure very flexible, simple to build, and easily adjustable.

5 Acknowledgement

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