Model Reduction in User Adaptive Emotion-based Selection Systems

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Abstract: *A simple way of implementing user adaptivity in emotion-based selection systems is the adaptation of behaviour-based control structures [6], [7]. In this case the user adaptation itself is handled as a kind of adaptive fusion of existing (collected off-line) human opinions (emotional models). Beyond the difficulties of collecting emotional models related to a set of objects from numerous individuals, these systems are also faced with the problem of economical model storage. For tackling the problem of model storage, the adaptation of HOSVD (High Order Singular Value Decomposition) based model reduction [10], [11] is proposed, as a kind of model pre-processing and handling method.*

Keywords: *Emotion-based systems, Singular Value Decomposition, interpolative fuzzy reasoning, fuzzy automata.*

1 Introduction

One of the key goals of the emotion-based selection systems is to build an emotional user model, being 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 many cases the same emotional word for different users covers quite different physical interpretations. The first systems applying the emotion-based structures were unable to handle this problem. They had only one fixed emotional user model, generated off-line, based on a wide user inquiry, as a statistical average of the different answers [1], [2]. Currently there is a lot of work related to the online user adaptivity of the emotional user model. Some of this work applies learning methods to modify a global user model based on the on-line interventions, or interactions of the actual user [3], [4], [5]. Another view of online user adaptivity of the emotional user model – based on behaviour-based control structures – is introduced in [6], [7] as on-line variable combination of some fixed existing (off-line collected) models. In this case the user adaptation itself is handled as a kind of adaptive fusion of existing emotional models in the manner of "the more similar the actual user to one of the existing emotional model, the more similar must be the actual emotional model to that model". In other words, instead of identifying the actual emotional model itself, the user is classified in the manner of existing emotional models (or user types).

The main benefit of this view is quick convergence, as in the most cases the problem of user classification related to some existing emotional models is much simpler than the identification of the complicated emotional model itself. The ability of proper depiction of user emotion is highly dependent on the number and diversity of existing emotional models available in the system. The implementation difficulties of these structures, beyond the problems of collecting emotional models related to a set of objects from numerous individuals, are the problems of economical model storage. For tackling the problem of model handling, in this paper an efficient technique of model storage and retrieval based on the adaptation of HOSVD (High Order Singular Value Decomposition) based model reduction [10], [11] is suggested.

In the following, section two will give a brief introduction to the structure of the user model based on the adaptive fusion of existing emotional models and section three will discuss the adaptation of Higher Order SVD (HOSVD) [10], [11] based model reduction techniques, with the main steps of the emotional model adaptation executed directly on the reduced form of the model.

2 The adaptive emotional user model

In behaviour-based control systems, the actual behaviour of the system is formed as one of the existing system behaviours (which best fits the actual situation), or a kind of fusion of the known behaviours appearing to be the most appropriate to handle the actual situation (see e.g. on fig.1.). Turning this structure to adaptive emotion based systems, the actual user model can be formed as a fusion of the known emotional models appearing to be the most appropriate to fit the taste of the actual user - interpreting the situation, or environment adaptivity of the behavioural-based control structures as user adaptivity.

Having a set of valid emotional user models collected off-line, the actual user model can be generated in the manner of: "the more similar the actual user to one of the existing user models, the more similar the actual user model must be to that user model".

This task is twofold. First the similarities of the actual user opinions and the existing user models have to be approximated and than in a corresponding manner the existing models have to be fused to form the actual user model.

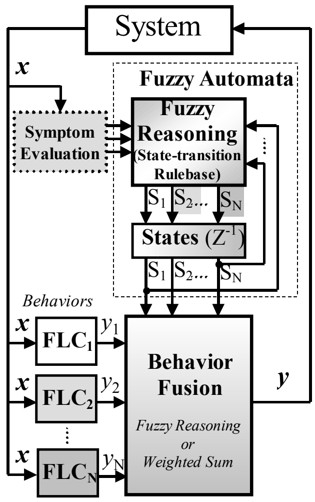


Fig. 1. The proposed behaviour-based control structure.

2.1 The emotional model

As a sample emotional model structure for the rest of the paper, the emotional model can be simply described as values of emotions related to physical objects in the form of a matrix $E_{i,j}$, where $i \in [1, I]$ is the object identifier (e.g. the index of the physical description of the object) and $j \in [1, J]$ is the emotion identifier (e.g. *Nice*, *Convenient*, *Friendly*, etc.). (See e.g. on fig.2.) The emotional model generation can be based on questionnaires of individuals or groups representing the possible user clusters (each person, or group has a separate model).

Emotion identifier *(Nice, Convenient, Friendly, etc.)*

Object id.	1	2	3	………	J
1	$E_{1,1}$	$E_{1,2}$	$E_{1,3}$		$E_{1,J}$
2	$E_{2,1}$	$E_{2,2}$	$E_{2,3}$		$E_{2,J}$
3	$E_{3,1}$	$E_{3,2}$	$E_{3,3}$		$E_{3,J}$
⋮				⋱	
I	$E_{I,1}$	$E_{I,2}$	$E_{I,3}$		$E_{I,J}$

Fig. 2. A simple emotional model structure

2.2 The structure of the adaptive model

The task of forming the adaptive emotional model is twofold. First the similarities of the actual user and the existing emotional models have to be approximated in an iterative manner based on user feedback, and then the existing models as a function of the corresponding similarities are fused to form the actual user model. For the first iterative approximation task, in [6], [7] the adaptation of *fuzzy automata* is suggested. In this case the actual state of the automaton is a set of similarity values (actual similarities, see fig.3.), the iteratively approximated similarities of the user opinions and the existing emotional models (emotional descriptor sets on fig.3.). The state-transitions of the fuzzy automata are driven by fuzzy reasoning (Fuzzy state transition rulebase on fig.3.), as a decision based on the previous actual state (the previous iteration step of the approximation) and the similarities of the user opinions (user feedback) to the existing emotional models. In practice the automata is starting from an initial state (e.g. all the similarities are equal to 0.5), and during the events of the user feedback (giving his/her opinions related to an "edited object" – see fig.3.) the actual similarities are recalculated.

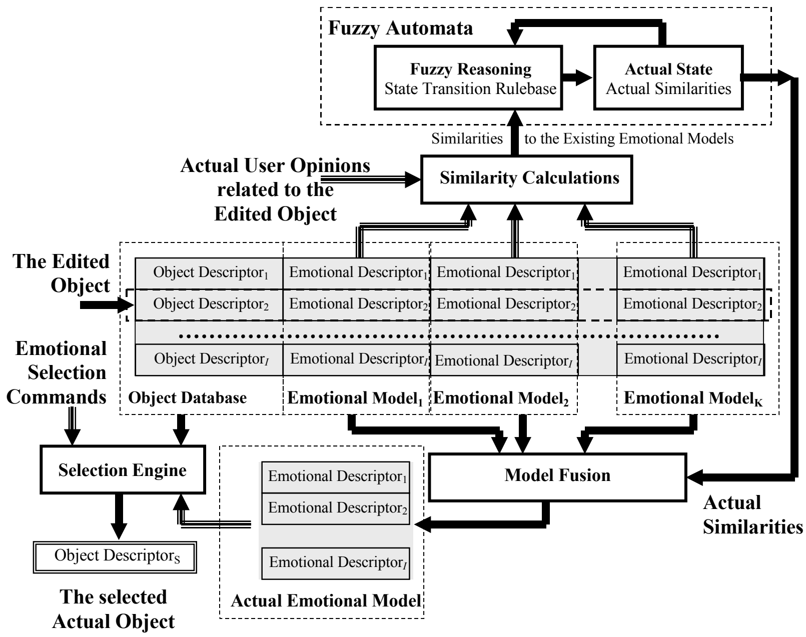


Fig. 3. The structure of the iterative emotional user model adaptation (in an object selection application)

For the second task of forming the adaptive emotional model, for the emotional model fusing, in [6], [7] the adaptation of *interpolative fuzzy reasoning*, or where there is no need for higher flexibility simply the *weighted sum* is suggested. The task of the emotional model fusion is to form the actual emotional model from the

existing emotional models in the function of their corresponding necessities, approximated by the fuzzy automata in the form of the state vector.
The function suggested for the emotional model fusion is simply the following:

$$E_{i,j} = \frac{\sum_{k=1}^{K} w_k \cdot E_{i,j,k}}{\sum_{k=1}^{K} w_k}, \ \forall i \in [1, I], \ \forall j \in [1, J], \ w_k = S_k, \ \forall k \in [1, N], \qquad (1)$$

where $E_{i,j}$ is the matrix of the actual emotional model, $E_{i,j,k}$ is the tensor of the all existing emotional models, $i \in [1, I]$ is the object identifier, $j \in [1, J]$ is the emotion identifier, $k \in [1, N]$ is the model identifier, $w_k = S_k$ is the k^{th} model weight, S_k is the k^{th} state variable of the state vector **S** and N is the number of the models (or state variables).

2.3 The steps of emotional model adaptation

The goal of the actual emotional user model modifications from the user side is to tune the model to be closer to his/her opinions. Starting from an initial stage (e.g. where the similarities to the existing models are equal) in the events of user interaction – user feedback, opinions given related to the evaluation of an object presented by the system – first the approximated similarities of the user opinions related to the existing emotional models (state vector) are recalculated, then the actual model is reformed. (In other words, the state vector is the actual view of the system related to the actual user in the space of the emotional models.) This means that the actual model is always changing in the manner of the model fusion, not only in parts affected directly by the user interaction. (In most cases, the opinions given by the user are related to one or a few emotional descriptors of the object.)
In case of an object selection application, the steps of emotional model adaptation could be the following:

1. The user states his/her requirements in the form of emotional values (levels).
2. As an answer, the system orders Objects Identifiers, in the accordance with the similarity between the user requirements given and the object related emotional values (fetched from the actual emotional model), and presenting the results together with its emotional values to the user.
3. The user can select some object, and give his/her opinions (in the form of some emotional values) related to the selected object in contrast to the evaluation of the system. (See e.g. fig.4.)
4. Getting the user feedback, the system first calculates the similarities of the existing emotional models and the emotional values given by the user. (See e.g. fig.5.) Having these similarities and the previous state, the system recalculates its state (modifies its view, related to the actual user).
5. Based on the new state, the new actual model is fused from the existing emotional models.

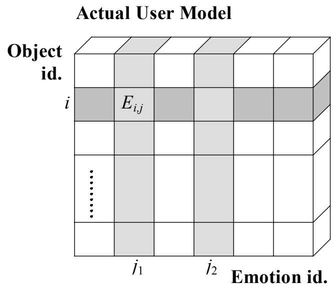
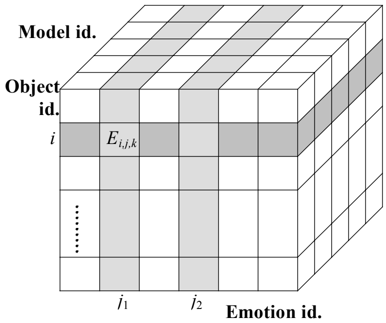


Fig. 4. User feedback, e.g. object i is selected, and opinions as emotional values related to j_1 and j_2 are given.



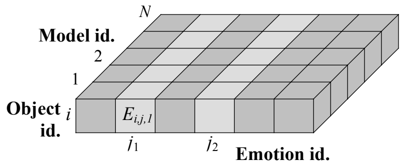


Fig.5. User feedback, e.g. similarities of the user opinions given as emotional values related to j_1 and j_2 for the i^{th} object of the existing models.

3 Emotional model reduction

Most cases the main implementation difficulties of the emotional systems are to collect relevant emotional related information, e.g. by organising wide queries and asking numerous individuals to fill in questionnaires. Moreover, in case of adaptive emotional models based on model fusion, not only a kind of "average" model is stored – as the adaptability of the structure is highly depending on the number and diversity of the stored emotional models – but we store as many as collected, or as many as are be able to stored in the system.

For retaining the benefits of the model fusion based adaptive emotional model structures, and maintaining the overall low computational resource demand, in this paper the adoption of Higher Order SVD [10], [11] based model reduction technique is suggested. In the following the Higher Order SVD reduction method, and the main steps of the emotional model adaptation executed directly on the reduced form of the model will be briefly introduced.

3.1 Singular Value Decomposition (SVD) based reduction

The key idea of using SVD in model reduction is that the singular values can be applied to decompose a given model and indicate the degree of significance of the decomposed parts. Reduction is conceptually obtained by the truncation of those parts, which have weak or no contribution at all to the model, according to the assigned singular values.

Singular Value Decomposition:
Every matrix $\mathbf{B} \in \Re^{I_1 \times I_2}$ can be written as the product

$$\mathbf{B} = \mathbf{U}_1 \cdot \mathbf{B}^d \cdot \mathbf{U}_2^{\mathrm{T}} \qquad (2)$$

where matrices $\mathbf{U}_1$ and $\mathbf{U}_2$ are orthogonal, and diagonal matrix $\mathbf{B}^d$ contains the singular values in decreasing magnitude.

Exact, non-exact SVD reduction:
Assume a matrix $\mathbf{B} \in \Re^{I_1 \times I_2}$. The exact reduced form $\mathbf{B} = \mathbf{U}_1 \cdot \mathbf{B}^r \cdot \mathbf{U}_2^{\mathrm{T}}$, where "$r$" denotes "reduced", is defined by matrix $\mathbf{B}^r \in \Re^{I_1 \times I_2}$ and basis matrices $\mathbf{U}_n \in \Re^{I_n \times I_n^r}$, $\forall n : I_n^r \le I_n$ which are the result of the SVD, where only zero singular values and the corresponding singular vectors are discarded ($\mathbf{B}^d = \mathbf{O}$):

$$\mathbf{B} = [\mathbf{U}_1^r \mid \mathbf{U}_1^d] \cdot \begin{bmatrix} \mathbf{B}^r & \mathbf{O} \\ \mathbf{O} & \mathbf{B}^d \end{bmatrix} \cdot [\mathbf{U}_2^r \mid \mathbf{U}_2^d]^{\mathrm{T}} = \mathbf{U}_1^r \cdot \mathbf{B}^r \cdot \mathbf{U}_2^{r\,\mathrm{T}} \qquad (3)$$

where matrix $\mathbf{O}$ contains zero elements, matrices $\mathbf{U}_1$ and $\mathbf{U}_2$ are orthogonal, and diagonal matrix $\mathbf{B}^r$ contains the singular values in decreasing magnitude.
The non-exact reduced form $\hat{\mathbf{B}} = \mathbf{U}_1^r \cdot \mathbf{B}^r \cdot \mathbf{U}_2^{r\,\mathrm{T}}$ is obtained if not only zero singular values and the corresponding singular vectors are discarded ($\mathbf{B}^d \ne \mathbf{O}$).

3.2 Higher Order SVD (HOSVD) based reduction

The Higher Order SVD is a multi-dimensional extension of the SVD, proposed and applied for fuzzy rule base complexity reduction e.g. in [10], [12].

Definitions:

N-mode matrix of tensor A:
Assume an N^{th} order tensor $A \in \Re^{I_1 \times I_2 \times \ldots \times I_N}$. The n-mode matrix $A_{(n)} \in \Re^{I_n \times J}$, $J = \prod_k I_l$ contains all the vectors in the n^{th} dimension of tensor A. The ordering of the vectors is arbitrary, this ordering shall, however, be consistently used later on. $(\mathbf{A}_{(n)})_j$ is called an j^{th} n-mode vector. Note that any matrix of which the columns are given by n-mode vectors $(\mathbf{A}_{(n)})_j$ can evidently restored to the A tensor form.

N-mode matrix-tensor product:

The n-mode product of tensor $A \in \Re^{I_1 \times I_2 \times \ldots \times I_N}$ by a matrix $\mathbf{U} \in \Re^{J \times I_n}$, denoted by $A \times_n \mathbf{U}$ is an $(I_1 \times I_2 \times \ldots \times I_{n-1} \times J \times I_{n+1} \times \ldots \times I_N)$-tensor of which the entries are given by $A \times_n \mathbf{U} = B$, where $B_{(n)} = \mathbf{U} \cdot A_{(n)}$. Let $A \times_1 \mathbf{U}_1 \times_2 \mathbf{U}_2 \ldots \times_N \mathbf{U}_N$ be noted for brevity as $A \overset{N}{\underset{n=1}{\otimes}} \mathbf{U}_n$.

N^th Order SVD or HOSVD:

Every tensor $A \in \Re^{I_1 \times I_2 \times \ldots \times I_N}$ can be written as the product $A = S \overset{N}{\underset{n=1}{\otimes}} \mathbf{U}_n$, in which $\mathbf{U}_n = [\mathbf{u}_{1,n} \quad \mathbf{u}_{2,n} \quad \ldots \quad \mathbf{u}_{I_N,n}]$ is a unitary $(I_N \times I_N)$-matrix called n-mode singular matrix. Tensor $S \in \Re^{I_1 \times I_2 \times \ldots \times I_N}$ of which the subtensors $S_{i_n=\alpha}$ have the properties of all-orthogonality (two subtensors $S_{i_n=\alpha}$ and $S_{i_n=\beta}$ are orthogonal for all possible values of n, α and β, when $\alpha \neq \beta$) and ordering: $\left\| S_{i_n=1} \right\| \geq \left\| S_{i_n=2} \right\| \geq \ldots \geq \left\| S_{i_n=I_n} \right\| \geq 0$ for all possible values of n.

See the detailed discussion and notation of matrix SVD and Higher Order SVD (HOSVD) in [12].

Exact, non-exact HOSVD reduction:

Assume an N^{th} order tensor $B \in \Re^{I_1 \times I_2 \times \ldots \times I_N}$. The exact reduced form $B = B^r \overset{N}{\underset{n=1}{\otimes}} \mathbf{U}_n$, where "*r*" denotes "reduced", is defined by tensor $B^r \in \Re^{I_1^r \times I_2^r \times \ldots \times I_N^r}$ and basis matrices $\mathbf{U}_n \in \Re^{I_n \times I_n^r}$, $\forall n : I_n^r \leq I_n$, which are the result of HOSVD, where only zero singular values and the corresponding singular vectors are discarded.

The non-exact reduced form $\hat{B} = B^r \overset{N}{\underset{n=1}{\otimes}} \mathbf{U}_n$, is obtained if not only zero singular values and the corresponding singular vectors are discarded.

3.3 Adaptation applying the reduced model

For retaining the benefits of the HOSVD based model reduction technique in the model fusion based adaptive emotional model structures, maintaining the overall low computational resource demand, all the steps of the emotional model adaptation must be able to be executed on the reduced form of the model directly (without extending the data to its original size).

The reduced emotional model

In the case where the existing emotional models can be characterised by a three dimensional tensor, e.g. as it is in the case of this paper's example (1), the size of the emotional models description can be simply reduced by the HOSVD reduction technique:

$$E = E^r \overset{3}{\underset{n=1}{\otimes}} \mathbf{U}_n = \left(\left(E^r \times_3 \mathbf{U}_3 \right) \times_2 \mathbf{U}_2 \right) \times_1 \mathbf{U}_1 \tag{4}$$

where $E \in \Re^{I \times J \times N}$ is the tensor of the all existing emotional models, $E^r \in \Re^{I^r \times J^r \times N^r}$ is the tensor of the reduced model, $\mathbf{U}_1 \in \Re^{I \times I^r}$, $\mathbf{U}_2 \in \Re^{J \times J^r}$, $\mathbf{U}_3 \in \Re^{N \times N^r}$ are the basis matrices of the object identifier, emotion identifier and model identifier respectively (see e.g. on fig. 6.).
Depending on the demands of the implementation limitations and the maximum permitted error bound, both exact and non-exact reduction could be applied.

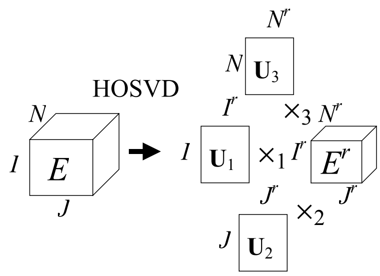


Fig. 6. Emotional model reduction.

The storage gain of the model reduction:
Applying the model reduction, instead of the whole model tensor $E \in \Re^{I \times J \times N}$, the reduced model tensor $E^r \in \Re^{I^r \times J^r \times N^r}$ and the three basis matrices $\mathbf{U}_1 \in \Re^{I \times I^r}$, $\mathbf{U}_2 \in \Re^{J \times J^r}$ and $\mathbf{U}_3 \in \Re^{N \times N^r}$ are stored. The reciprocal storage gain of the model compression can be estimated by the following formula:

$$\frac{1}{\mathrm{G_M}} = \frac{\|E^r\| + \|\mathbf{U}_1\| + \|\mathbf{U}_2\| + \|\mathbf{U}_3\|}{\|E\|} = \frac{I^r \cdot J^r \cdot N^r + I \cdot I^r + J \cdot J^r + N \cdot N^r}{I \cdot J \cdot N}. \quad (5)$$

Model Fusion:
The function (1) suggested for the emotional model fusion can be simply rewritten in the following N-mode matrix-tensor product form:

$$\mathbf{E} = E \times_3 \mathbf{w} \quad (6)$$

where $\mathbf{E}$ is the matrix of the actual emotional model, $E \in \Re^{I \times J \times N}$ is the tensor of the all existing emotional models and $\mathbf{w} = [w_1, w_2, ..., w_N]$ is the model weight vector ($w_k = S_k$ is the k^{th} model weight).
For performing all the operations on the reduced model, applying (4), equation (6) can be rewritten to the following form:

$$\mathbf{E} = E \times_3 \mathbf{w} = \left(\left(E^r \times_3 (\mathbf{w} \cdot \mathbf{U}_3)\right) \times_2 \mathbf{U}_2\right) \times_1 \mathbf{U}_1 = \mathbf{U}_1 \cdot \mathbf{E}^r \cdot \mathbf{U}_2^{\mathrm{T}} \quad (7)$$

where $\mathbf{E}^r = E^r \times_3 (\mathbf{w} \cdot \mathbf{U}_3)$ is the matrix of the reduced actual emotional model (see e.g. on fig. 7.).

According to (7), during the intermediate steps of the model fusion, an additional temporary storage area at least of size $\min\left(I \cdot J^r, I^r \cdot J\right)$ is also required.

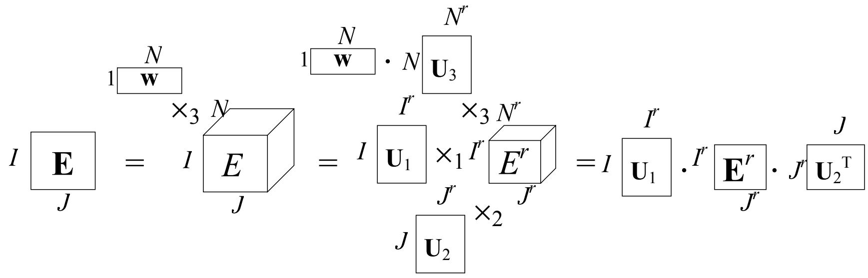


Fig.7. Emotional model fusion.

One object selection

According to the 4th step of the emotional model adaptation (introduced in section 2.3.); getting the user feedback, the system has to calculates the similarities of all the existing emotional models and the feedback emotional values given by the user. To perform these calculations, all the emotional values of all the existing models related to a selected object are required (see e.g. fig.5.).

For presenting these values directly from the reduced form of the models the following calculation is suitable:

$$\mathbf{E}_i = \left(\left(E^r \times_3 \mathbf{U}_3\right) \times_2 \mathbf{U}_2\right) \times_1 \mathbf{U}_{1i} = \left(\left(E^r \times_1 \mathbf{U}_{1i}\right) \times_2 \mathbf{U}_2\right) \times_3 \mathbf{U}_3 \qquad (8)$$

where $\mathbf{E}_i \in \Re^{J \times N}$ is the matrix of all existing emotional values related to the i^{th} object, $i \in [1, I]$ is the object identifier and $\mathbf{U}_{1i} \in \Re^{I^r}$ is the i^{th} row of the object identifier basis matrix (see e.g. on fig. 8.).

According to (8), during the intermediate steps of the object selection, an additional temporary storage area at least of size $\min\left(J \cdot N^r, J^r \cdot N\right)$ is also required.

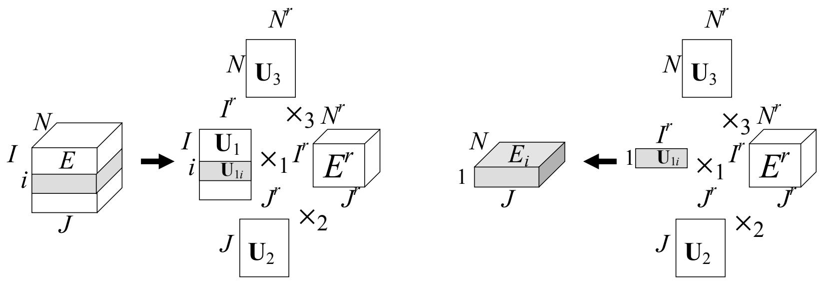


Fig.8. All emotional values related to an object.

3.4 The estimated storage gain of the model reduction technique:

Summing up the additional temporary storage requirements of the calculations (7), (8) to the needs of the reduced model storage, based on (5), the estimated reciprocal storage gain of the model compression can be characterised by the following formula:

$$\frac{1}{\mathrm{G}}=\frac{1}{\mathrm{G_M}}+\frac{\max\left(\min\left(I\cdot J^r, I^r\cdot J\right), \min\left(J\cdot N^r, J^r\cdot N\right)\right)}{I\cdot J\cdot N}=$$

$$=\frac{I^r\cdot J^r\cdot N^r+I\cdot I^r+J\cdot J^r+N\cdot N^r+\max\left(\min\left(I\cdot J^r, I^r\cdot J\right), \min\left(J\cdot N^r, J^r\cdot N\right)\right)}{I\cdot J\cdot N},$$

where I, J, N are respectively the number of objects, emotion and model identifiers, and I^r, J^r, N^r are the dimensions of the reduced model tensor $E^r \in \Re^{I^r\times J^r\times N^r}$.

Disregarding the additional calculation demands of the structure, a storage gain could be achieved only in the case, if

$$I\cdot J\cdot N > I^r\cdot J^r\cdot N^r+I\cdot I^r+J\cdot J^r+N\cdot N^r+\max\left(\min\left(I\cdot J^r, I^r\cdot J\right), \min\left(J\cdot N^r, J^r\cdot N\right)\right).$$

This inequality also forms the upper plausible bound of the minimal HOSVD model reduction needed.

Depending on the demands of the concrete application, if this inequality cannot be fulfilled, e.g. higher level of reduction can not achieved because of the maximum permitted error bound of the emotional model, the proposed model reduction technique is not suitable for lowering the computational resource demands of the model fusion based adaptive emotional model structures. (For details related to the error bounds of the non-exact HOSVD reduction see [11], [12].)

4 Conclusion

The main benefit of the application of behaviour-based control structures in interactive emotion-based selection systems is introducing a simple technique for handling user adaptivity. In this case the user adaptation itself is handled as a kind of adaptive fusion of existing (collected off-line) human opinions (emotional models) models in the approximated best fitting way to the actual user taste. In case of online applications this adaptive structure also has the benefit of relatively quick iterative adaptation as the system tries to identifies the actual user in the space of the existing models, based on a series of user interactions (feedback), not the – usually much more complicated – actual model itself. In most cases the main implementation difficulties for emotional systems are to collect relevant emotional related information, e.g. by organising wide queries and asking numerous individuals to fill in questionnaires. Moreover, in case of adaptive emotional models based on model fusion, not only a kind of "average" model is stored – as the adaptability of the structure is highly depending on the number and diversity of the stored emotional models – but as many as collected, or as many as are able to be stored in the system. For retaining the benefits of the model fusion based adaptive emotional model structures, and maintaining the overall low computational resource demand, the adoption of Higher Order SVD (HOSVD) [10], [11] based model reduction techniques together with the main steps of the emotional model adaptation executed directly on the reduced form of the model, as a kind of model pre-processing and handling method, was introduced in this paper. As an application guideline, for checking the plausibility of the proposed technique, the required minimal HOSVD model reduction, was also investigated.

Acknowledgements

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