

Remind Me: An Adaptive Recommendation-Based Simulation of Biographic Associations

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ABSTRACT

Classical reminiscence therapy has been shown to effectively enhance the stability of memory and identity in people with dementia. Typically, reminiscence therapy uses biography artifacts like photos and personal items and objects. Today, many of these artifacts are from the digital realm providing new options to adapt or even improve the purely analog therapy. In this work we propose a method to enhance reminiscence therapy by computer simulated biographic associations. Our approach provides assistance for associative reasoning on affective stimuli and thus enables access to biographic content so that no deliberate search is required. We develop a recommender model for mapping mental states to biographic content based on similarity. The system dynamically adapts its state and the depicted digital artifacts to the responses of the user. It is a first step towards an immersive reminiscence therapy which will incorporate associated stimuli on multiple channels to increase effectiveness. A preliminary study showed encouraging results concerning the usability of the system.

Author Keywords

Elderly people; dementia; reminiscence therapy; computer-mediated health promotion; immersion;

ACM Classification Keywords

H.5.m Information Interfaces and Presentation (e.g. HCI); Miscellaneous

INTRODUCTION

In 2030, the number of people living with dementia is estimated to be 65.7 million worldwide, doubling every 20 years [17]. Thus, the improvement of the effectiveness of interventions that meet the needs for people with dementia is considered a major issue [14]. A major symptom of dementia is the development of multiple cognitive deficits that manifest by

the impairment of memory and disturbance of executive functioning, like abstracting and sequencing [2]. Reminiscence therapy is one of the most popular interventions in dementia care for tackling these symptoms. It is highly rated by caregivers and participants [20]. Also, it has been shown to be a promising intervention for improving the sense of integrity and ameliorate depression in people with dementia [9, 7, 20]. In reminiscence therapy, participants are encouraged to reflect on past experiences with the aid of familiar stimuli from the past, like photographs. In the future items with a dominant visual or auditive aspect will be represented mainly in the digital realm and the number of these items will increase to a great extent. Yet, to our knowledge, technical support for improving the effectiveness of reminiscence therapy is very limited.

To address the challenge of increasing the effectiveness of reminiscence therapy, we present a system that aims to increase immersion on biographic relevant stimuli by simulating associative reasoning on a huge set of personal stimuli. This approach contrasts to traditional methods, where associative reasoning is only supported externally by the caregiver and the directly tangible stimuli. A major aspect of reminiscence therapy is the personal interaction of the caregiver with the participant. Thus, we set high priority on not changing this setting, in order to maintain the effective treatment factors of reminiscence therapy. Our system is designed to facilitate personal interaction during the intervention, not to replace it. Furthermore, the requirement of technical expertise for setup or operation is a major obstacle for the use of information technology devices by caregivers [11]. To that effect we use mobile touch devices that allow low threshold usage in face-to-face or group settings.

The two contributions of this work are as follows: we provide a system, (1) for increasing immersion in reminiscence therapy by simulating association and (2) for enabling automated accessibility of biographic stimuli where no deliberate semantic reasoning is required.

RELATED WORK

Technical approaches that aim to support reminiscence focus on displaying stimuli that are linked by a fixed definition and have to be selected manually. In the CIRCA project [1, 3] a system is developed that allows structured browsing through multimedia archive designed to support communication and

reminiscence. Hereby the focus is not on adapting content to implicit user behavior. In this context it was found that the use of touch screen interfaces seems to encourage users with dementia to use the system and provides a supportive interaction environment [4].

In [5] and [19] multimedia presentation tools for a set of historic stimuli that also allow the storage of personal data are presented. A framework for interaction with 3D reconstructions of familiar environments is introduced in [6]. Several systems have been proposed that aim to compensate for memory deficits during reminiscence therapy by providing material that has recently been recorded [10, 12, 21]. In [16] a system to support reminiscence in everyday life is presented. A review of information technology aided reminiscence therapy outlines its potential but also a lack of knowledge about the type and content that is beneficial to people at different stages of dementia [11]. To date, assisted selection of stimuli to enhance reminiscence has not been well addressed.

There are two elements that distinguish our work from previous approaches for information technology aided reminiscence therapy. First, our implementation aims to simulate, and thereby stimulate impaired association processes. Second, our implementation gives automated access to stimuli without requiring manual preselection.

OUR PROPOSAL

Our conceptual goal is to facilitate association processes by the simulation of semantic association. Therefore, we propose a system that iteratively aims to activate mental entities that are specified by two conditions: first, the history of previously activated mental entities and second the currently predominant pattern of change between these entity sets. Here the set of currently activated mental entities models the content a user is conscious of. While the pattern of change models the predominant emotional mindset of the user. We propose to simulate this association model by applying an adaptive semantic recommender system to emotion triggering stimuli. Hereby the user navigates through a directed, weighted, complete graph of emotional relevant stimuli. The weights of this graph model the association strength by which two stimuli are linked to each other. They are simultaneously adapted during the navigation through this graph in the following way: first, a set of semantic similarity measures is evaluated. Second the set of these similarity measures is weighted according to their currently estimated relevance.

SYSTEM PROCESS

Our system aims to recommend biographic stimuli that are similar to previously selected content in terms of the currently predominant mental state of the user. This recommendation task presents two technical challenges: first, a model for mapping mental states to similarity of biographic content has to be defined and second, this model has to adapt to the response of the user to the recommended content. Usability for dementia patients was of high priority in the design of our system. Therefore, user interaction is restricted to a simple affectively motivated selection task, where no explicit reasoning is required. The implementation we propose could run on a tablet

or smartphone device for a low threshold usage in clinical and care settings. The process of the system, outlined in Figure 1, is structured as follows: initially a set of static distance measures is evaluated on semantic annotated stimuli. An iterative selection task is presented to the user, where several stimuli that are similar to previous selections are recommended. This similarity term is defined by a weighted sum of the static distance measures. Hereby the weights are updated according to the selection behavior of the user.

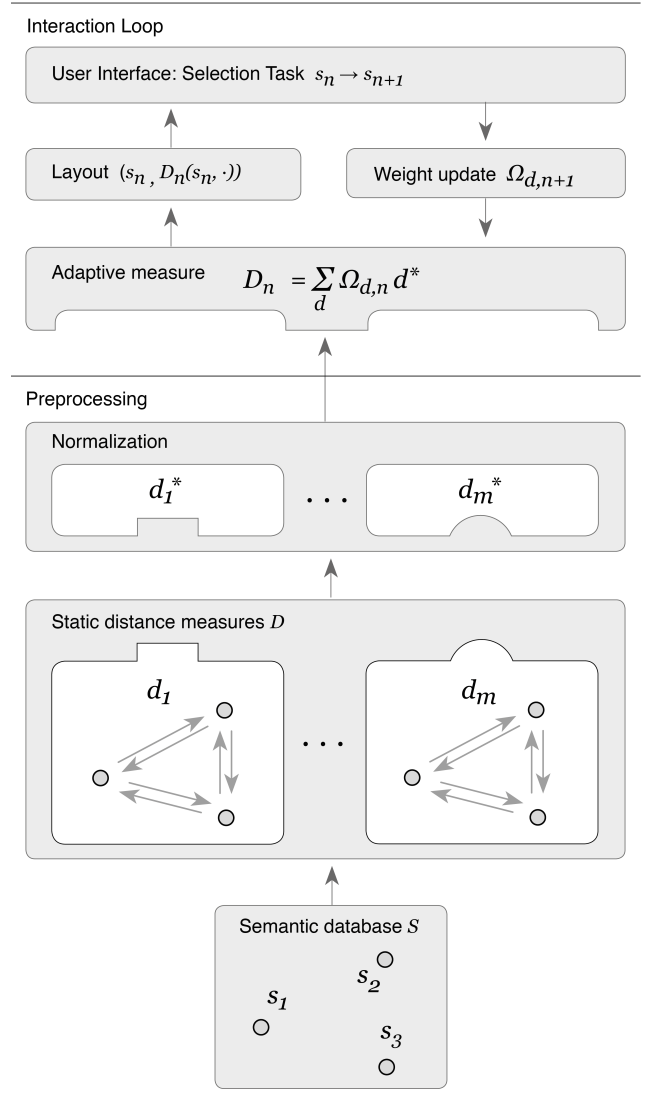


Figure 1. Illustration of the system process. First normalized semantic distance measures are initialized and second an adaptive distance measure is iteratively updated by evaluating user behavior.

Semantic Database

We denote S as the set of stimuli represented in the system. For our demonstration we restricted stimuli to images. These images can either be added and semantically annotated at runtime or be loaded from a database.

Static Distance Measures

A set of semantically motivated distance measures D on the stimuli set S has to be selected. Each of these distance measures models a semantic aspect of non-similarity of two stimuli. These aspects, and hence the measures in D remain static throughout the procedure. For a valid distance measure, we only require non-negativity and coincidence.

For our implementation we chose three distance measures that aim to encode different types of memory cues.

1. For modeling interpersonal memory cues we define a distance measure that relates to the persons that are contained in an image. Therefore, we call P the set of persons that appear at least in one image. Each image is mapped to the set of persons appearing in it by the mapping $p : S \rightarrow \mathcal{P}(P)$, where $\mathcal{P}(P)$ indicates the power set of P . First a binary distance measure $d_p : S^2 \rightarrow [0, 1]$, indicating the amount of overlap of appearing and not appearing persons. For two images $s_1, s_2 \in S$ the person distance is defined as

$$d_p(s_1, s_2) := 1 - \frac{|R(s_1, s_2)|}{|P|}$$

whereas R denotes the set of persons that either appear on both images s_1 and s_2 or on none of them:

$$R(s_1, s_2) := \{\varphi \in P : (\varphi \in p(s_1) \wedge \varphi \in p(s_2)) \vee (\varphi \notin p(s_1) \wedge \varphi \notin p(s_2))\}$$

For a survey of binary distance measures see [8].

2. For modeling situational memory cues we define a geographical and a temporal distance measure in the canonical way. Therefore, we assume that each image is mapped to the geographical location of its content, i.e. to its latitude and longitude values by the mapping $g : S \rightarrow \mathbb{R}^2$. For approximating the geographical distance measure $d_g : S^2 \rightarrow \mathbb{R}_0^+$ we use the Haversine formula for great-circle distances between two points [18].
3. For modeling temporal memory cues we assume that each image is mapped to the date and time of its content $t : S \rightarrow \mathbb{R}$, presupposing the existence of a reasonable date mapping over \mathbb{R} . For the temporal distance measure $d_t : S^2 \rightarrow \mathbb{R}_0^+$ the Euclidean distance is used.

For our system we define the set of static distance measures as $D := \{d_p, d_g, d_t\}$.

Normalization

The value range and spread of the above defined distance measures may vary to a great extent. In order to combine the different distance measures, they are normalized in two steps. First a z-score transformation is applied to allow the relative comparison of the selected measures. Therefore, for each distance measure $d \in D$ and each stimulus $s \in S$ the distance to a neighbor $\xi \in S$ is considered as a random variable $d(s, \cdot) : S \rightarrow \mathbb{R}$. The z-score transformation is applied on each random variable $d(s, \cdot)$, aligning the standard deviation and center. The resulting standardized random variable

is denoted by $z_{d,s}$. Second, in order to increase the significance of further distance measures for small and large outliers a quasi homogeneous transformation is applied. For an overview on homogeneous coordinates see, for example, [13]. This transformation is defined as the first coordinate of the intersection of the line between the origin and the point $z_{d,s}(\eta)$ and the unit circle. Thus, in total for a given neighbor $\xi \in S$ of the stimulus s and a distance measure $d \in D$ the normalized distance function $d^* : S^2 \rightarrow [-1, 1]$ is defined as $d^*(s, \xi) := z_{d,s}(\xi)(z_{d,s}(\xi)^2 + 1)^{-\frac{1}{2}}$. Figure 2 informally illustrates the described normalization process.

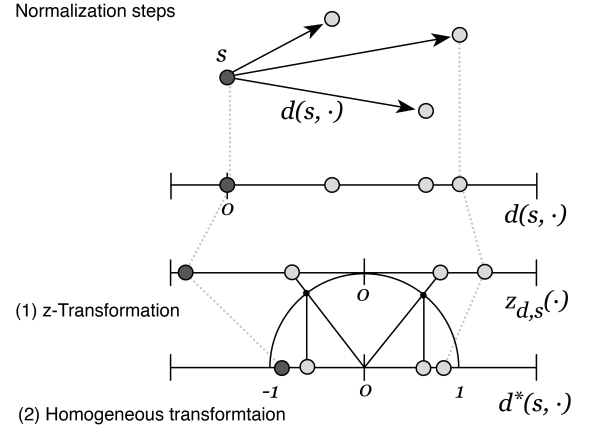


Figure 2. Informal illustration of the normalization process. For the neighbor distances of each stimulus first a z-transformation and second a quasi homogeneous transformation is applied.

Adaptive Measure

To traverse through the image graph the system recommends images in the order of their distance to the current node within the graph, where this distance adapts to the recent choices of the user. For a given iteration step $n \in \mathbb{N}$ we define this adaptive distance measure $D_n : S^2 \rightarrow \mathbb{R}$ as a weighted sum of the static distance measures, as $D_n(s_1, s_2) := \sum_{d \in D} \Omega_{d,n} d^*(s_1, s_2)$, where $\Omega_{d,n}$ denotes the weights that are adapted to the traversal behavior. During the traversal of the graph, indicated by the sequence of stimuli $(s_0, \dots, s_n) \in S^n$ the weights $\Omega_{d,n}$ are defined as the arithmetic mean of $N \in \mathbb{N}$ weight components $\omega_{d,\eta} \in [0, 1]$, so that $\Omega_{d,n} = \frac{1}{N} \sum_{\eta=\max(0, n-N)}^n \omega_{d,\eta}$. For an iteration step $\eta \in \{1, \dots, n\}$ the weight components $\omega_{d,\eta} \in [0, 1]$ model the prediction value of the distance measure d in contrast to the other competing distance measures. That prediction value shall be high if the chosen stimuli is close to the previous stimulus in terms of the distance measure d .

Weight Update

The weight components are defined as the relative difference between the differently measured distances of two subsequent stimuli as follows: for each distance measure $d \in D$ and each iteration step $\eta \in \{0, \dots, n\}$ we define the distance between the currently and the previously selected stimulus

as $\Delta_d(\eta) := d(\eta - 1, \eta)$. The unnormalized weight components $\tilde{\omega}_{d,\eta}$ are now defined with inverted fraction of these values $\tilde{\omega}_{d,\eta} := \frac{\sum_{\bar{a} \in D} \Delta_{\bar{a}}(\eta)}{\Delta_d(\eta)}$. Here the weight components themselves are defined as the normalization of their counterparts $\omega_{d,\eta} := \frac{\tilde{\omega}_{d,\eta}}{\sum_{\bar{a} \in D} \tilde{\omega}_{\bar{a},\eta}}$. Thereby it is assured that $\sum_{d \in D} \omega_{d,\eta} = \sum_{d \in D} \tilde{\omega}_{d,\eta} = 1$. For practical reasons we initially chose an even distribution for the start configuration $\eta \leq N$. For computing one iteration of the interaction loop only the weights have to be updated. This is done in constant time, since only a direct comparison of two stimuli has to be evaluated. Thus, no interference during the interaction with the system is expected.

User-Interface

For the touch user-interface the currently selected stimulus is displayed together with the closest neighbors in terms of the measure D_n . The selected image is prominently displayed on the left and the recommended images are placed in two rows on its right hand side. Hereby the proximity and opacity of the unselected images decreases by their adaptive distance to the selected image. The layout is smoothly updated when one of the recommended images is selected. The selected image takes the position of the focused image, and its closest neighbors in terms of D_{n+1} get recommended, as illustrated in figure 3. Emphasis was put on a low threshold for the usage within the therapeutic setting for people with dementia and caregivers. Touch devices with a low interaction complexity seem to be suitable for that purpose [4].

PRESTUDY

To pre-evaluate the usability of our system we conducted a user study with 15 participants (13 males and 2 females) between the ages of 20 and 60. Participants included students and academic staff. For practicability, only the the person and location measures were used and for the calculation of the weights, N was set to 3. The stimulus set for the study contained 18 images. These images were composed of 18 backgrounds showing 3 different cities and portraits of 9 persons in the foreground. Each image shows one to three persons.

Procedure

First the participants were given an introduction to the system. Then they were given the task to interact with the system for 5 minutes and to switch between a person and a location based selection every 1 to 5 selections. Afterwards the participants completed a questionnaire measuring the intuitive usability of the system. The questionnaire consisted of the QUESI [15] and two questions to be evaluated in what extent the recommended images matched their expectations in terms of person or location cues. A five point Likert scale from very negative (1) to very positive (5) was used.

Results

The results of the pre-study are encouraging: the QUESI overall score of intuitive use was 4.19 with standard deviation 1.05. The matching of the recommendations to expectations for person cues was rated on average by 3.67 with standard

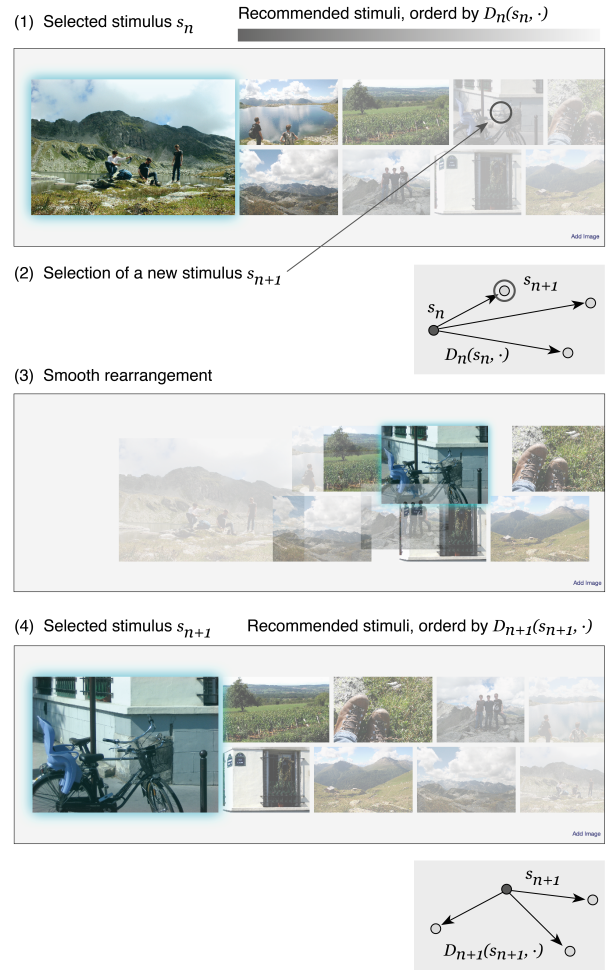


Figure 3. Illustration of the layout for one interaction iteration. The selected image is displayed large, whereas the recommended images are displayed on its right-hand side, ordered and blurred ascending by their adaptive distance to the selected image (1). When a new image is selected (2) the layout is smoothly updated (3) and the adaptive distance measure is updated (4).

deviation 1.11. Whereas for location cues the matching was rated on average by 4.33 with standard deviation 0.90.

CONCLUSION

In this work we proposed a new approach for increasing the effect of reminiscence therapy, by computing semantic similarities to automatically suggest related biographic stimuli (images). A first preliminary study shows encouraging results concerning the system effectiveness. One important part of our future work is to conduct a similar evaluation with patients at different stages of dementia and practitioners. Our second prototype will include additional modalities (audio, video) and further semantic similarity measures, such as inferring user's preferences from viewing duration.

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PREPRINT

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