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A PROBABILISTIC APPROACH FOR EXTRACTING DESIGN PREFERENCES FROM DESIGN TEAM DISCUSSION

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ABSTRACT

During the formative stage of the design cycle, teams engage in a variety of tasks to arrive at a design, including selecting among design alternatives. A key notion in design alternative selection is that of "preference" in which a designer assigns priorities to a set of design choices. This paper presents a preliminary approach for extracting a projection of aggregated design team preferences from design team discussion. This approach further takes into consideration how the design preferences of a team can evolve over time as the team changes its priorities based on new design information. Two initial models are given for representing the most probable and preferred design alternative from the transcriptions of design team discussion, and for predicting how preferences might change from one time interval to the next. These models are applied to an illustrative, real-world case example.

Key words: design preferences, concept selection, design process

INTRODUCTION

One way of thinking about the early stages of design is as a process of generating and selecting solutions to meet requirements. During design selection, multiple criteria may be considered, and if any of these criteria are at odds, decision makers may need to make trade-offs among several design alternatives. The process of making trade-offs involves evaluation and comparison of design alternatives. Methods for formalizing design trade-offs include utility theory originally developed by von Neumann and Morgenstern [1-6] and the Method of Imprecision (MoI) developed by Otto, Antonsson,

and Wood [7, 8]. Both of these methods are based on the designers' preferences for multiple criteria of a set of design alternatives. A key notion in design alternative selection is that of "preference" in which a designer assigns priorities to a set of design choices. This paper examines three aspects of preferences in design teams: design preference extraction from a group and understanding preference evolution over the life of a project, and presents a case example to illustrate its approaches. In theory, the method described in this paper may be applied to any selection problem in which all design alternatives are known a priori. It is envisioned that the method will be of value in real world engineering design situations where it is important to have to understand a design team's preferences.

Preference Extraction

In formal design approaches, accurately modeling the strength of preferences is very important in the design decision making process. One common way to determine a designer's preference is to explicitly ask them via surveys or questionnaires. The lottery method [9] is a classical way to elicit preferences in a quantitative way in which alternatives are preferentially scaled from 0 to 1 based on a questionnaire. In order to ensure the consistency among the preferences, pair-wise comparisons are made to determine the relative performance of the alternatives in terms of each individual criterion. This approach is often used in the Analytical Hierarchy Process (AHP) [10] as a decision making support tool. Other quantitative pair-wise comparison approaches include: Wang [11], who employs a fuzzy preference relationship to discriminate three preference models for design

evaluation, and Li and Jin [12] who apply this fuzzy preference relationship to select alternatives. All of these methods rely on directly asking designers for their preferences, or assuming some value for them.

Another, lower overhead approach is to extract preferences from a designer's actions. Collaborative filtering [13] is based on the assumption that individuals with similar profiles gravitate to the same choices. Collaborative filtering has been used in many commercial applications, particularly in sales and marketing. However, collaborative filtering requires a relatively large number of individual opinions to be effective, more than is typically on a small design team.

This paper proposes a new approach to extract preferences from the transcribed discussion of design teams. It assumes that designers' preferences are somewhat related to what designers discuss during the design process, and this kind of relationship can be modeled in probabilistic ways.

Group Preference Aggregation

Designer preferences are often considered for a whole team rather than the individual member alone, and several approaches exist to aggregate group preferences. Arrow's Theorem [14, 15] demonstrates that there is no guarantee of consistency in a group. It is reasonable that the team members may have different preferences, and it is more important to consider the group preference rather than the individual preferences for the group design. Keeney uses cardinal utility functions to accumulate group preferences [16], while Bask and Saaty [17] apply Analytical Hierarchy Process and pair-wise approach to aggregate the group preferences, assuming each group member's opinion is equally important. Jabeur, Martel et al.[18], and See and Lewis [19] go one step further and assume unequal weights on the preferences of the group members, although this sometimes requires prior knowledge of weighting factors, such as a member's technical expertise. This paper takes a different approach that does not require prior knowledge of an individual's background or ways to formulate unequal weights. Instead, the preferences of a team are considered from the point of view of group discussion, and group preferences are extracted directly from the text analysis of a single transcript of the design team's discussion. The approach described in this paper represents group preference without aggregation of the individual preferences of a group. Instead, the group preferences are extracted from the discussion as if the group is a single entity.

Design Preference Evolution

Much past research in modeling design preferences has focused on representing preferences at a single point in time. In practice, these trade-offs may be iterative as teams better understand their objectives and criteria, as requirements and constraints change, or as teams gain new information about their design, so the cumulative preference of the design team may change over time. Consequently, the design process can be described from the perspective of preference evolution.

Several researchers have examined the design process over time through surveys [20], coding of design journals [21], "story telling" [22], word frequencies and information certainty analysis [23]. This study describes the design process in terms of the preference evolution which is extracted from the analysis of the designers' transcribed discussion.

METHODOLOGY

The basic method is as follows:

1. Word occurrences of all design alternatives in the transcript of designers' discussion are collected. The collection of the word occurrences is called utterance data. In this step, the variations of the specific terms to represent the same alternative are also determined and collected.

2. A *preference transition model* is built to describe the relationship between preferences of two consecutive time intervals, along with an *utterance-preference model* to describe the relationship between what designers say and what designers prefer in the same time interval. The parameters of the two models are unknown.

3. Reasonable initial values are arbitrarily assigned to the parameters of these two models.

4. Both models are applied to the transcriptions to predict preferences. The preference data will be used to describe the evolution of preferences over the design process.

5. The parameters of these two models are updated using the Expectation-Maximum (EM) algorithm [24] on the predicted preference data and the given utterance data.

6. Steps 4 and 5 are repeated until there is convergence. Parameters converge because the EM algorithm is guaranteed to improve Probability of the occurrences of the utterance data at each iteration [25].

Assumptions

This study makes five simplifying assumptions as follows:

Assumption 1: It is assumed that the group discussion is a reasonable reflection of group preference. During the design process, what designers say to each other generally corresponds with what they think. This is also an implicit assumption of protocol studies of designers [26].

Assumption 2: It is assumed that all major design alternatives for a concept selection problem are largely known a priori. While this is probably not true for many early stage design problems, it is a reasonable assumption for a large-scale system re-design problem because they generally limit the number of design alternatives under consideration to ones that have been used in the past.

Assumption 3: It is assumed that an entire discussion can be divided into several time intervals during which the designers' preference are unchanged. The change of the preferences can only occur between consecutive time intervals.

Assumption 4: It is assumed that designers tend to talk more about the design alternative they choose. Within the same interval, how often designers mention (utter) the alternatives depends on what they think. The relationship between what is

thought and said is probabilistic in the sense that the more an alternative is preferred in the discussion, the more likely this alternative will be uttered by the design team as a whole.

Assumption 5: It is assumed that what designers think in current time interval is affected by what they thought in the previous time interval. This relationship can also be represented in probabilistic way.

Notation

N: total number of alternatives in the studied design selection problem

T: total number of time intervals over the whole design process

i, j: the index to represent different time intervals in the design process

m, n, k: the index to represent different alternatives in the studied design selection problem

r: the index to represent the different iterations of the calculation process

a_m: the mth alternative of of the studied design selection problem in the design process

A: the set of all alternatives, i.e. A={ $a_1, a_2, ..., a_N$ }

π_i: the alternative which designers prefer to all other alternatives in Time Interval i, i.e., the most-preferred alternative in Time Interval i

ε_i: the alternative which designers utter at sometime during Time Interval i of the design process

σ_i: the sequence of the utterances of design alternatives in Time Interval i. e.g., if in Time Interval 2, the design alternatives are uttered as $a_2, a_2, a_1, a_1, a_1, a_2, a_3, a_1, a_1, a_3$ in the designers' transcribed discussion, then $\sigma_2 = \{ a_2, a_2, a_1, a_1, a_1, a_2, a_3, a_1, a_1, a_3 \}$

P($\pi_i = a_m$) : the probability that designers prefer Alternative a_m to all other alternatives (i.e., Alternative a_m is most preferred) in Time Interval i. If the preference value of Alternative a_m in Time Interval i is represented by $\mu_i(a_m)$ on a scale from zero to one, then $\pi_i = a_m$ is equivalent to $\mu_i(a_m) \geq \mu_i(a_n)$ for all $1 \leq n \leq N$

P($\pi_i = a_m \mid \pi_j = a_n$) : the probability that designers prefer Alternative a_m to all other alternatives in Time Interval i, given that designers prefer Alternative a_n to all other alternatives in Time Interval j

P($\varepsilon_i = a_m$) : the probability that Alternative a_m is uttered in Time Interval i

P($\varepsilon_i = a_m \mid \pi_j = a_n$) : the probability that Alternative a_m is uttered in Time Interval i given the condition that Alternative a_n is preferred the most in Time Interval j

Utterance Data Collection

In this preliminary study, the alternatives are represented by nouns or noun phrases in the discussion. The appearance of

any noun of interest or direct variation of it is considered an occurrence of a design alternative. For example, if a product design team were considering power sources for a consumer electronics product, the design alternative might be "NiCad battery", and "Nickel Cadmium battery" would also be considered an instance of the same term. The best way to represent a design alternative linguistically is still an ongoing and unresolved area of research [27].

In addition, because the discussions were largely at a high, system level, discussion did not go too far down in hierarchical detail, and a major simplifying assumption was made that all discussions about a design alternative did not need to go down or up levels of meaning. The weightings of the uttered alternatives can be determined from the frequencies of the uttered alternatives [23], the lexically related words [28, 29], and the appraisals [30] of the alternatives in the discussion.

Preference Transition Model

This model relates the design team's preference in the current time interval to that in the next time interval. Individual designers may have different preferences, but in this model, only the accumulative group preferences are considered.

In one time interval, it is assumed that there is an alternative which the team prefers the most, called the *most-preferred alternative*, and the remaining alternatives are the *less-preferred alternatives*. In the case when several preferences equally "most preferred", any one can be chosen arbitrarily as the most-preferred one and the others are regarded as less-preferred. The probability of one alternative to be most-preferred is the *most-preferred probability* of this alternative. From one interval time to the next consecutive time interval, the most-preferred alternative is either kept the same or changed to a different one. The transition relationship depends on the preference strengths of the most-preferred alternative and the less-preferred alternatives. In this study, a simple relationship is used that all less-preferred alternative in the current time interval are equally likely to become the most-preferred alternative in the next time interval. In mathematical terms, the model can be expressed as in Equation (1).

$$P(\pi_{i+1} = a_n \mid \pi_i = a_m) = \begin{cases} p & when \ n = m \\ \dfrac{1-p}{N-1} & when \ n \neq m \end{cases} \quad (1)$$

where $0 \leq p \leq 1$ is an hidden parameter, which means the probability that the most-preferred alternative is kept unchanged from one time interval to the next consecutive one. The bigger p is, the more consistent the preferences are over the design process; and the smaller p is, the more frequently the preferences are changed.

Utterance-Preference Model

This model relates the team's preference to the utterances of the alternatives in the same time interval. In other words, it

tries to approximate what designers think with what designers say.

An alternative can be uttered in the discussion transcript in two ways, positive or negative. When an utterance of an alternative has no negative words (e.g. "no," "not," "hardly") nearby in the transcript, then this utterance of the alternative is regarded as positive, otherwise negative. To simplify things, negative utterances are ignored and only positive utterances are considered. The influence of negative utterances will be considered in the further research. Similarly, this utterance-preference relationship should also be a function of the preference strengths of the most-preferred alternative and the less-preferred alternatives. This study uses a simple model that the less-preferred alternatives are equally likely to be uttered by designers in the same time interval. In equation form:

$$P(\varepsilon_i = a_n \mid \pi_i = a_m) = \begin{cases} q & when \ n = m \\ \dfrac{1-q}{N-1} & when \ n \neq m \end{cases} \quad (2)$$

where $0 \leq q \leq 1$ is an hidden parameter, which means the probability that the most-preferred alternative is to be uttered positively in the discussion. In the protocol studies of designers [31], it is assumed that what designers say generally corresponds with what they think. In this study, it is assumed that designers say what they think in most cases. i.e., $q > \dfrac{1-q}{N-1}$. It denotes that the reasonable value range for q is $\dfrac{1}{N} < q \leq 1$.

Preference Calculation

The preferences of the design alternatives in the design process may change over time during the discussion of the design team. One of the objectives in this paper is to extract the preference evolution over the whole process. Although the preference value of each alternative cannot be acquired from the method proposed in this paper, the probability of each design alternative to be most-preferred can be calculated.

The challenge: given the utterance data about the design alternatives and the most-preferred probabilities of the design alternatives in the current time interval, what are the most-preferred probabilities of the design alternatives in the next time interval?

By Law of total probability,

$$P(\pi_i = a_k \mid \sigma_i, \sigma_{i-1}, \sigma_{i-2}, ..., \sigma_1) = \sum_{1 \leq m \leq N} P(\pi_i = a_k \mid \sigma_i, \sigma_{i-1}, ..., \sigma_1, \ \pi_{i-1} = a_m) P(\pi_{i-1} = a_m \mid \sigma_{i-1}, \sigma_{i-2}, ..., \sigma_1) \quad (3)$$

By Bayes Theorem,

$$P(\pi_i = a_k \mid \sigma_i, \sigma_{i-1}, ..., \sigma_1, \ \pi_{i-1} = a_m) =$$

$$\frac{P(\sigma_i \mid \pi_i = a_K, \sigma_{i-1}, ..., \sigma_1, \pi_{i-1} = a_m) P(\pi_i = a_K \mid \sigma_{i-1}, ..., \sigma_1, \pi_{i-1} = a_m)}{\sum_{1 \leq n \leq N} P(\sigma_i \mid \pi_i = a_n, \sigma_{i-1}, ..., \sigma_1, \ \pi_{i-1} = a_m) P(\pi_i = a_n \mid \sigma_{i-1}, ..., \sigma_1, \pi_{i-1} = a_m)} \quad (4)$$

Equation (4) can be simplified into Equation (5) because the utterance data in the current time interval are independent of the utterances in the historical time intervals while given the preference in the current time interval, and the preference in the current time interval is independent of the utterance data in the historical time intervals while given the preference in the latest previous time interval.

$$P(\pi_i = a_k \mid \sigma_i, \sigma_{i-1}, ..., \sigma_1, \ \pi_{i-1} = a_m) =$$

$$\frac{P(\sigma_i \mid \pi_i = a_k) P(\pi_i = a_k \mid \pi_{i-1} = a_m)}{\sum_{1 \leq n \leq N} P(\sigma_i \mid \pi_i = a_n) P(\pi_i = a_n \mid \pi_{i-1} = a_m)} \quad (5)$$

Substituting Equation (5) back into Equation (3) gives the following two equations ((6) and (7)).

When $i \geq 2$,

$$P(\pi_i = a_k \mid \sigma_i, \sigma_{i-1}, \sigma_{i-2}, ..., \sigma_1) =$$

$$\sum_{1 \leq m \leq N} \frac{P(\sigma_i \mid \pi_i = a_k) P(\pi_i = a_k \mid \pi_{i-1} = a_m)}{\sum_{1 \leq n \leq N} P(\sigma_i \mid \pi_i = a_n) P(\pi_i = a_n \mid \pi_{i-1} = a_m)} P(\pi_{i-1} = a_m \mid \sigma_{i-1}, \sigma_{i-2}, ..., \sigma_1) \quad (6)$$

When $i = 1$,

$$P(\pi_1 = a_k \mid \sigma_1) =$$

$$\sum_{1 \leq m \leq N} \frac{P(\sigma_1 \mid \pi_1 = a_k) P(\pi_1 = a_k \mid \pi_0 = a_m)}{\sum_{1 \leq n \leq N} P(\sigma_1 \mid \pi_1 = a_n) P(\pi_i = a_n \mid \pi_0 = a_m)} P(\pi_0 = a_m) \quad (7)$$

Suppose the design alternatives are uttered w_i times in the ith time interval, as $a_i^{(1)}, a_i^{(2)}, a_i^{(3)}, ..., a_i^{(w_i)}$, which are all in Alternative Set A. Assume that the utterances of alternatives in one time interval strongly depend on designers' preference, and the utterances of design alternatives are indifferent of each other given the strong dependence on preferences, then

$$P(\sigma_i \mid \pi_i = a_k) = \prod_{u=1}^{w_i} P(\varepsilon_i = a_i^{(u)} \mid \pi_i = a_k) \quad (8)$$

Equations (6), (7) and (8) recursively calculate the preference in the next time interval from the preference in the current time interval. In order to make the recursion work, two pieces of information should be given.

1. The initial most-preferred probabilities of all alternatives before the first time interval.
2. The parameters of Preference Transition Model and Utterance-Preference Model. i.e. Parameters p and q.

The first one can be resolved by doing surveys on designers before the start of the design process, or by collecting the preference information from the previous design process, or by analysis of the previous preferences of alternatives for design of similar products. In this study, all alternatives are initiated with uniform alternative distribution, which gives an unbiased starting point. i.e.,

$$P(\pi_0 = a_k) = \frac{1}{N}, \quad k = 1, 2, ..., N \tag{9}$$

This equation means that before the discussion of the design process, all alternatives have the equal probabilities to be most preferred.

Regarding the parameters of two key models, they are not as easy to acquire as the initial most-preferred probabilities of alternatives. In this paper, an EM algorithm is applied to searching the parameters of Preference Transition Model and Utterance-Preference Model.

Estimation of Hidden Parameters

If Preference Transition Model and Utterance-Preference Model are known, it is feasible to calculate the most-preferred probabilities for each design alternative in each time interval and then to plot the preference evolution over the whole design process. But the problem is that initially the parameters of these two models are unknown. In this situation, utterance data are observable but preference data are unobservable, and the models are incomplete because of the hidden parameters. An Expectation-Maximization (EM) algorithm [24] is often used in statistics for finding maximum likelihood estimates of parameters in probabilistic models, where the model depends on unobserved hidden variables. In this study, it can be applied to seek the values of the two hidden parameters of the two models.

An EM algorithm has two steps, the E-step and the M-step. The E-step estimates the unobservable data. It can be accomplished by Equations (6) and (7). The M-Step computes the maximum likelihood estimates of the parameters by maximizing the expected likelihood found on the E step. In this study, it corresponds to estimating the values of p and q which make the utterance sample of the design alternatives occur in the discussion with the maximal likelihood.

From Equation (1), it is known that $P(\pi_{i+1}=a_k|\pi_i=a_k)$ is independent of k and i. It means that no matter what time interval it is in, no matter which alternative designers prefer the most in the previous time interval, designers have a fixed probability to keep the most-preferred alternative unchanged.

By the maximum likelihood [32], $P(\pi_{i+1}=a_k|\pi_i=a_k)$ can be estimated as

$$P(\pi_{i+1}=a_k|\pi_i=a_k) =$$

$$\frac{\sum_{1 \le i \le T-1} \sum_{1 \le m \le N} C(\pi_{i+1}=a_m, \pi_i=a_m)}{\sum_{1 \le i \le T-1} \sum_{1 \le n \le N} \sum_{1 \le m \le N} C(\pi_{i+1}=a_n, \pi_i=a_m)} \tag{10}$$

where $C(\pi_{i+1}=a_n, \pi_i=a_m)$ is a fractional count that counts the cases that a_n is most-preferred in the current time interval while a_m is most-preferred in the previous time interval. $C(\pi_{i+1}=a_n, \pi_i=a_m)$ can be calculated as follows.

$$C(\pi_{i+1}=a_n, \pi_i=a_m) =$$
$$P(\pi_{i+1}=a_n|\sigma_{i+1}, \sigma_i, ..., \sigma_1) P(\pi_i=a_m|\sigma_i, \sigma_{i-1}, ..., \sigma_1) \tag{11}$$

The fractional counts are fractional numbers, and they are not the same as the normal counting numbers, which are integers. But the values of fractional counts have the proportional relationship with the integral numbers which count the cases when $\pi_{i+1}=a_n$ and $\pi_i=a_m$, so fractional counts can be used in Equation (10) to estimate of Parameter p.

Similarly, from Equation (2), $P(\varepsilon_i=a_k|\pi_i=a_k)$ is independent of i and k. It means that in a certain time interval, designers have a fixed probability to utter the same alternative as the one they prefer the most.

By the maximum likelihood, $P(\varepsilon_i=a_k|\pi_i=a_k)$ can be estimated as

$$P(\varepsilon_i=a_k|\pi_i=a_k) =$$

$$\frac{\sum_{1 \le i \le T} \sum_{1 \le m \le N} C(\varepsilon_i=a_m, \pi_i=a_m)}{\sum_{1 \le i \le T} \sum_{1 \le n \le N} \sum_{1 \le m \le N} C(\varepsilon_i=a_n, \pi_i=a_m)} \tag{12}$$

where $C(\varepsilon_i=a_n, \pi_i=a_m)$ is also a fractional count, which counts the number of cases that a_n is uttered while a_m is most-preferred in the same time interval. It can be calculated as follows.

$$C(\varepsilon_i=a_n, \pi_i=a_m) =$$
$$C(\varepsilon_i=a_n) P(\pi_i=a_m|\sigma_i, \sigma_{i-1}, ..., \sigma_1) \tag{13}$$

where $C(\varepsilon_i=a_n)$ is the number of utterances of Alternative a_n in the time interval i.

Equations (12) and (13) calculate q based on the samples of alternative utterances and preferences. When using the above procedure to calculate q, it should be noted that the value of q should be more than 1/N.

Because the EM algorithm is guaranteed to improve the probability of the sample of alternative occurrences at each iteration, p and q will converge to values which try to maximize this probability [25]. These converged values can be regarded as the parameters for Preference Transition Model and

Utterance-Preference Model. The shortcoming of EM algorithm is that it may converge to a local optimum. Multiple initial estimates can be used to avoid being trapped in a local optima. Simulated annealing can be combine with EM algorithm to overcome the local optima problem [33, 34].

Time Intervals

In this study, it is assumed that designers do not change their preferences on design alternatives in one time interval. Preferences can only be changed at the transitions between time intervals. Based on the designers' transcribed discussion, there are several ways to determine time intervals.

1. Collect all transitional words (e.g., "but", "however," "while") in the transcript, and divide the transcript into varying time intervals with these transition words.
2. Collect all key design alternative occurrences from the transcript of designers' discussion, and time-stamp all collected words. Big time gaps between the key alternative words mark the separations of time intervals.
3. Set up a fixed word frequency. The process is divided into time intervals in which there are equal numbers of word utterances of key alternatives.
4. Make a fixed time interval in which the alternative words are neither too many nor too few.

Although Methods 3 and 4 are not as accurate as Methods 1 and 2, they are more direct to implement. In this preliminary study, Method 4 is chosen to specify the time intervals in the design process.

CASE STUDY

Case Background

The above methods are applied to a real-world design team working on the design of a large-scale system architecture problem in an industry setting. The design team was composed of approximately 15 experienced scientists and engineers of different disciplines working together in a collocated, highly concurrent setting. The team had worked together on several similar projects in the past. This study focuses on the audio recorded utterances of one member of the team, as he described his design decision-making process in detail to a novice member of his team. The project took place over three 3-hour sessions. This 9 hour recording was transcribed into a text document of approximate 28,000 words. All data was time coded. In the transcript, the primary team member talked nearly 85% of the time, and four other members made up the remainder. In the project, the team aimed to make decisions on two component selection problems, and each component selection problem has three alternative candidates. These three design alternatives were known a priori because the design problem relied heavily on previous system designs. This is common design practice particularly in aerospace mission design [35]. For example, standard alternatives for types of propulsion are chemical, electric, and thermal. To achieve the

mission goals, the designer responsible for propulsion must make trade-offs among the different propulsion types and, at the same time, consider the configuration of specific propulsion design. This approach to design decision-making applies to most other space subsystems as well. In the project described in this case study, designers attempted to solve two component selection problems, each with three alternative candidates. This paper focuses primarily on the first session of the first component selection problem.

Data Collection and Method Implementation

The transcript in the first session was input as the raw data in this paper. The utterances of the three alternatives (represented by a_1, a_2, and a_3) for the first selection problem were collected in intervals of 10 minutes, as shown in Table 1.

TABLE 1 SAMPLE DATA: UTTERANCES OF ALTERNATIVES

Alternative / Interval	a_1	a_2	a_3
1	0	9	3
2	2	9	7
3	0	1	0
4	0	4	9
5	0	0	6
6	1	3	0
7	0	1	2
8	1	0	2
9	0	1	8
10	0	0	1
11	1	0	2
12	0	0	5

Initially, we can give any values to p and q if $0<p<1$ and $1/3<q<1$ are met. And the values will be updated in the later iterations. To distinguish p and q in different iterations, let p_r, q_r be the variables of p and q in the rth iteration. In this example, initial values are randomly chosen as $p_1=0.5$ and $q_1=0.4$. And the initial most-preferred probabilities of the alternatives all equal 1/3:

$$P(\pi_0 = a_1) = P(\pi_0 = a_2) = P(\pi_0 = a_3) = \frac{1}{3} \qquad (14)$$

In the first time interval of the transcript, there were no utterances of a_1, while 9 times of a_2, and 3 times of a_3. By Equation (8)

$$P(\sigma_1 \mid \pi_1 = a_1) = (q_1)^0 (\frac{1-q_1}{2})^9 (\frac{1-q_1}{2})^3 = 5.3144^{-07} \qquad (15)$$

$$P(\sigma_1 \mid \pi_1 = a_2) = (\frac{1-q_1}{2})^0 (q_1)^9 (\frac{1-q_1}{2})^3 = 7.0779^{-06} \qquad (16)$$

$$P(\sigma_1 \mid \pi_1 = a_3) = (\frac{1-q_1}{2})^0 (\frac{1-q_1}{2})^9 (q_1)^3 = 1.2597^{-06} \qquad (17)$$

These three values are not the normalized probabilities. Every value only has meanings when comparing with each other.

Substituting values from (15-17) into Equation (7) gives

$$P(\pi_1 = a_1 \mid \sigma_1) = 0.0663$$
$$P(\pi_1 = a_2 \mid \sigma_1) = 0.7798$$
$$P(\pi_1 = a_3 \mid \sigma_1) = 0.1539$$

The most-preferred probabilities in later time intervals can be calculated recursively by Equations (6) and (8). The probability values in different time intervals are listed in Table 2, in the first iteration with $p_1 = 0.5$ and $q_1 = 0.4$.

TABLE 2 MOST-PREFERRED PROBABILITIES OF DESIGN ALTERNATIVES (THE FIRST ITERATION)

Interval i	a_1	a_2	a_3
1	0.0663	0.7798	0.1539
2	0.0574	0.6829	0.2597
3	0.2328	0.4878	0.2795
4	0.0579	0.2179	0.7242
5	0.0934	0.112	0.7946
6	0.2481	0.4419	0.3099
7	0.2309	0.3514	0.4177
8	0.2993	0.2508	0.4498
9	0.0835	0.1058	0.8107
10	0.2367	0.2418	0.5215
11	0.2971	0.2267	0.4763
12	0.1595	0.1497	0.6909

Parameters p_r and q_r would be updated by Equations (10) and (12) with the fractional counts calculated from Equations (11) and (13) in the previous iteration.

After updating the parameters, the new most-preferred probabilities of alternatives are re-calculated according to Equations (6), (7) and (8). The above procure is iterated until converged.

Results and Discussion

Table 3 shows the iterative results of p_r and q_r. It shows that p_r converges to 0.716 after 5 iterations, while q_r converges to 0.672 after 7 iterations. In the experiment, several initial estimates for p and q are tried, and all of them are converged to the same values.

TABLE 3 ITERATIVE VALUES OF PARAMETERS

Iteration	p_r	q_r
1	0.4	0.5
2	0.564	0.418
3	0.694	0.546
4	0.714	0.644
5	0.716	0.668
6	0.716	0.671
7	0.716	0.672
8	0.716	0.672

Figure 1 shows the probabilistic preference evolution of three alternatives when the converged parameters are applied to Preference Transition Model and Utterance-Preference Model. The solid line with square dots stands for the evolution of probabilities that Alternative a_2 is most preferred, the dotted line with triangle dots stands for the evolution of probabilities that Alternative a_3 is most preferred, and the broken line with circle dots stands for the evolution of probabilities that Alternative a_1 is most preferred. In terms of preferences, Figure 1 suggests that Alternative a_2 and a_3 dominate and that these two alternatives alternate with each other during the design process. This conjecture from the chart is validated by a qualitative reading of the original transcript.
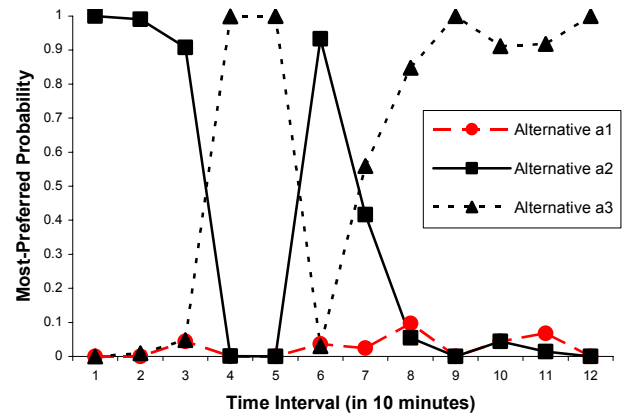

FIGURE 1 DESIGN PROCESS EVOLUTION: MOST-PREFERRED PROBABILITIES OF THE THREE ALTERNATIVES

Design sensitivity. Since the converged values of p and q are estimated with EM algorithm, they might vary from the true values. Let $\hat{p}$, $\hat{q}$ be the converged values of p and q, and suppose p, q are in the range with $\hat{p}$, $\hat{q}$ shifting 10%. The evolutions of the most-preferred probabilities for the cases when p or/and q are underestimated/overestimated are plotted as shown in Figures 2-4. The gaps between the uppermost lines and the lowermost lines give the true value ranges that alternatives are most preferred. In this example, qualitatively speaking, the true values of p and q are in close ranges of the converged p and q. Therefore, the most-preferred probabilities of design alternatives calculated based on $\hat{p}$, $\hat{q}$ can approximately describe the preferences over the design process.
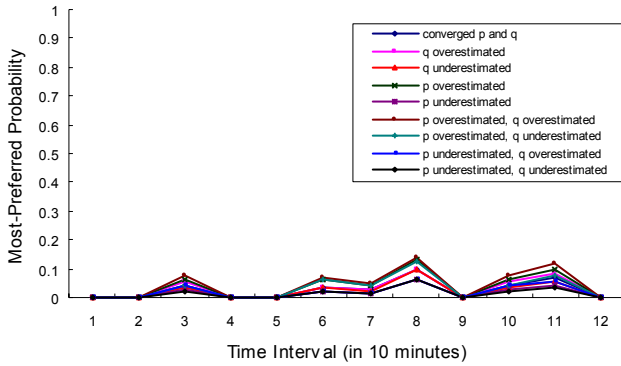
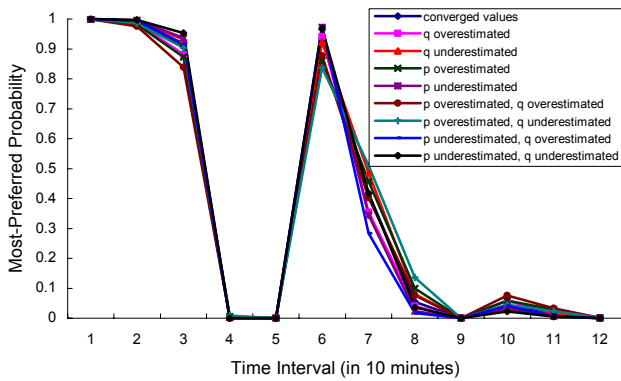**FIGURE 2 MOST-PREFERRED PROBABILITY RANGES OF ALTERNATIVES A_1**

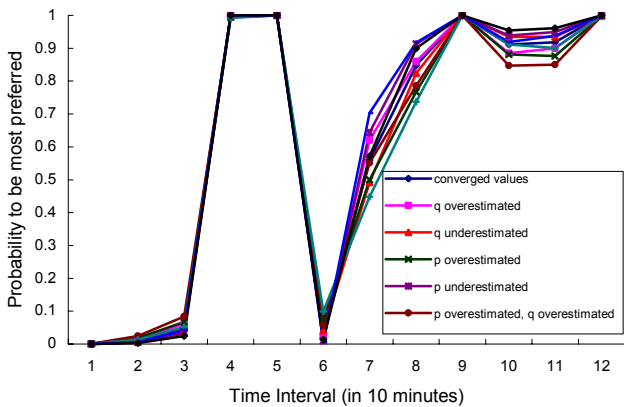**FIGURE 3 MOST-PREFERRED PROBABILITY RANGES OF ALTERNATIVES A_2**

FIGURE 4 MOST-PREFERRED PROBABILITY RANGES OF ALTERNATIVES A_3

CONCLUSIONS AND FUTURE RESEARCH

The methodology presented in this paper suggests a probabilistic way to describe the preferences in the design process and model the design selection process through preference evolution. The method may lead to a novel way to understand the nature of design choices over time. The results of applying the methodology to the case study are consistent with the qualitative reading of the design transcript. It was expected that design alternative choices would oscillate in a large-scale system design problem, and this was true for the component selection problem which was chosen for the case study in this paper. Qualitative readings are not a rigorous way of verifying the preference probabilities. Future work will focus on experiments to validate more accurately these findings.

This preliminary research models design preference evolution using a probabilistic approach. The methodology in this paper shows a method for modeling the relationship between the preferences observed in two consecutive time intervals and the relationship between a design team's utterances and their possible preferences. There are several directions which could be done in the future to improve the models as well as the methodology.

In this study, fixed time intervals were specified as the simplest, preliminary way to test the approach. This fixed time interval was chosen such that neither too many nor too few key alternative words. The biggest risk of this approach is that there may be too many key alternative words in some intervals, and too few in others. Another potential problem of this approach to selecting time intervals is that the preference transition may happen in a time interval, not between two time intervals. This would make the model not consistent with the real design process. This was not a problem for the case study described in this paper as the design team was very intensively concentrated, and the session chosen was not very long. However, for a more complicated and longer design process, fixed time intervals may be insufficient. Future work would involve other approaches to specifying the time intervals such as combining the first and the second methods discussed in the "Time Interval" section. Transitional words and long time gaps between utterances of alternatives could be taken as indicators as the separators of the time intervals.

In the case study, all design alternatives are considered at the embodiment level, but the method can be extended to the design alternatives at a different level such as the functional or the behavior level. In practice, this may somewhat complex, as design alternatives may be considered at different levels throughout during design team discussion. Levels of granularity in design alternatives should be considered in the future via linguistic analysis.

This study directly associates design choices of the design alternatives with the utterances of the alternatives in the discussion. However, the unambiguous identification of a design concept or alternative in text is an open area of research in linguistic. There are several papers related to the association of the design concept, such as concept formation as knowledge accumulation [27], linguistic application to engineering notes

[36], text analysis for constructing design representations [37]. Simple word frequency may be useful for some cases, but not for others. A more accurate language model for the elicitation of preferences will be developed. Actually, some utterances of alternatives occur in negative context, such as negative adverbs "no", "not", "hardly", or negative adjectives "bad", "ridiculous", "impracticable". In the further research, the influences and weightings of the negative utterances should also be included. In addition to considering word frequency as a weighting factor for design alternative collection, appraisals [30] for the design alternatives will also be quantified to give weightings on the design alternatives. For example, the appraisal word "great" on an alternative in the contextual discussion will give more weighting on that alternative than the appraisal word "good". And during the design process, different designers may use different words to represent the same or the similar meanings. The degree of similarity of different words or phrases should also be considered. The lexical relationships among the key words will be built and the semantic analysis will be employed to extract the information. The lexical relationships are being used include: synonymy, antonymy, hypernymy, hyponymy, meronymy, holonymy, troponymy [28, 38].

This study assumes a simple preference transition model and a simple utterance-preference model, the parameters of which are constant. But intuitively, the probabilities of preference transitions and utterance representations of preferences could be different in different time intervals depending on such factors as the preference strengths of different alternatives and etc. The expressions of the key two models can be represented in more detailed and complicated way in the future.

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