

Swarm-Optimization-Based Affective Product Design Illustrated by a Pen Case-Study

Arvind Mohais, Alexander Nikov, Ashok Sahai, and Selahattin Nesil

Abstract—An optimization approach for suggesting product design parameters based on emotive responses is proposed that combines Kansei techniques and particle swarm optimization algorithm (PSO). The approach involves designing a Kansei survey for collecting data on customers' affective responses to various aspects of a product, using several exemplars of the product. After information gathering, the PSO algorithm is employed to build a prediction binary linear model that aggregates the survey data. Subsequently, another binary linear model links product design parameters to the outputs of the first model to establish mathematical connections between the subjective impression of a product (Kansei) and its properties. This approach is illustrated by a case study for pen design. Three PSO neighborhood configurations are tested, and the results yield insight into the nature of the optimization function. Experimental work in implementing the proposed approach was able to suggest customers' preferences for pen design attributes that would be considered optimal by all of those surveyed. They can be used for improvement and development of new future products.

Keywords—Affective design, neighborhood configurations, particle swarm optimization.

I. INTRODUCTION

MODERN competitive computer-oriented product development makes products functionally equivalent and therefore hard to distinguish between for customers [22]. They make their purchasing decisions by highly subjective criteria. For increasing product competitiveness, one possible solution is to capture the customer's feelings regarding products and translate these affective aspects into concrete design parameters.

Affective design attempts to define the subjective emotive relationships between consumers and products and to explore the affective properties that products intend to communicate through their physical attributes [2], [3], [20]. It aims to deliver approaches able to elicit maximum psychophysiological pleasure from consumers, targeting all of their

senses.

Kansei Engineering is used for supporting affective product design. Kansei presents “a total concept of intuition, preference, subjectivity, sensation, perception, cognition” [24]. It helps to identify customer needs and their importance, as well as to conduct benchmarking and to connect the customer needs mathematically to the technical characteristics of the product. [4], [12], [22]. Kansei engineering software like KESo [27] can be used to collect Kansei data.

Examples of Kansei engineering studies are: on the affective impact of soaps; on ergonomic properties of cellular phones; on subjective impression of web pages and steering wheels; on warning signs, remote controls, car dashboards, couches, toothbrushes, interface design [26]; on car interior [6] and profiles [10]; on rocker switches for work-vehicles [23].

Statistical methods like regression analysis, as well other methods like fuzzy sets [13], rule-based inference models [25], neural networks [7], [11], data mining [5], evolutionary computation [1], [24] are used to give a mathematical connection between customer emotions mapped through Kansei words and the product properties.

Quite often in Kansei engineering fitness functions turn out to be highly multi-modal. Therefore, swarm intelligence algorithms [15] are rather the most appropriate for these types of modeling. The first such study [21] applies particle swarm optimization (PSO) to analyze customers' affective responses with regard to products, and use the results to propose design properties that embody those responses. The current paper continues our study [21] by experimenting with different PSO configurations for determining an optimal Kansei model and using it for suggesting product design attributes. An illustration of approach will be presented in a case study of pen design.

II. APPROACH FOR SWARM-OPTIMIZATION-BASED AFFECTIVE PRODUCT DESIGN

An approach suggesting product design parameters based on emotive responses is proposed. It combines Kansei techniques and the particle swarm optimization algorithm. The approach involves designing a Kansei survey for collecting data on customers' affective responses to various aspects of a product. After information collection the particle swarm optimization algorithm is employed for analysis of the data to establish mathematical connections between the subjective impression of a product (Kansei) and its properties. A

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prediction Kansei model is built to capture how a certain product is perceived by a customer group. This information can be used for improvement and development of new products. Fig. 1 presents the steps of the approach proposed.

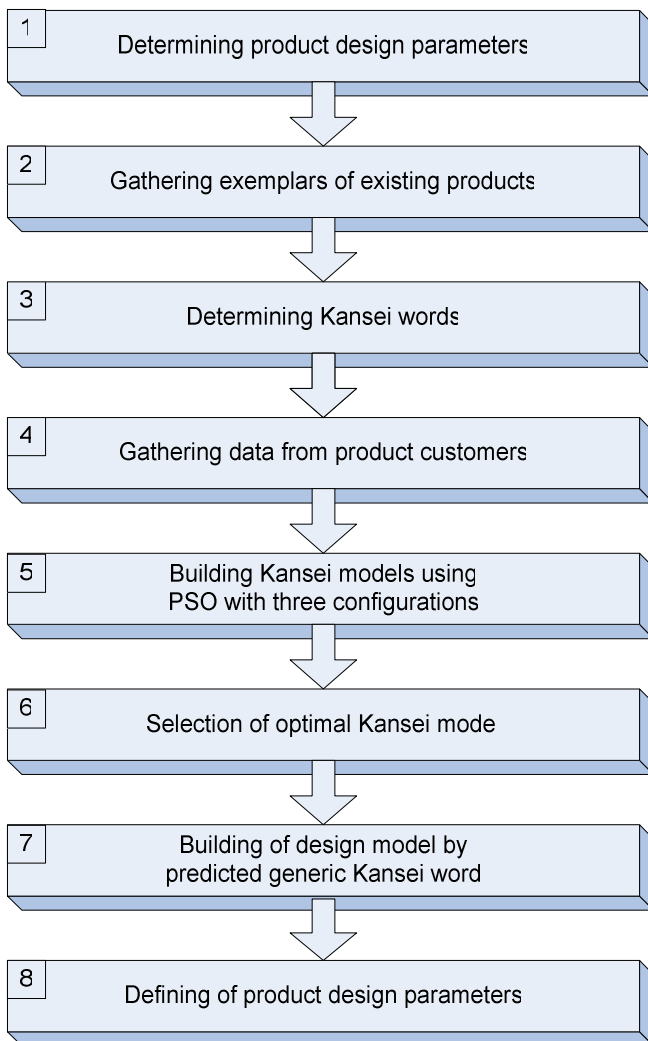


Fig. 1 Affective design steps

A. Description of Affective Design Steps 1-4

Steps 1 to 4 constitute the overall collection of data from potential users or customers of the product of interest.

At *step 1*, concrete characteristics of the product (*design parameters*) that can be manipulated in its fabrication are determined. For example, if the product under consideration is a computer mouse, then possible design parameters could be, the size of the mouse, the number of buttons on it, its color and whether it is wired or wireless. On the survey form issued to respondents, these design parameters are used as questionnaire items.

Step 2 involves gathering several exemplars of the physical product to be assessed. The exemplars should cover a wide variety of what exists. They are given to respondents of the survey so that they can record their feelings about each of the exemplars.

At *step 3*, Kansei words are selected for inclusion on the survey questionnaire. These are words that capture a particular feeling about the product. For example, again considering a computer mouse, a few Kansei words might be: *comfortable*, *attractive*, *hi-tech-looking*, *smooth*, and *easy-to-use*. These Kansei words will be the basis for semantic differential scaled questionnaire items [19]. Respondents are asked to assign a rating to each such word from some minimum to some maximum value. For example, *easy-to-use* may be rated from 1 to 5, where 1 means “*very difficult to use*”, and 5 means “*very easy to use*”. One of the Kansei questionnaire items is expected to ask for a rating of the overall suitability of the product being evaluated.

Step 4 is the delivery of the exemplar items and the questionnaire survey to selected respondents so that data can be collected.

B. Particle Swarm Optimization Algorithm (PSO)

Before describing steps 5 to 8, it is necessary to introduce the particle swarm optimization algorithm and its variants. PSO is inspired by social interactions [8], [9]. Given an optimization function $f: R^n \rightarrow R$, (where R is the set of real numbers), a PSO manipulates a set of candidate solutions by moving them through the search space, based on information that they exchange amongst themselves. This information flow is based on a *neighborhood structure*, which is a pattern of interconnection amongst the particles that is independent of their positions in the search space. Such a structure defines a set of neighbors for each particle.

Primarily, each particle contains information about its current location in the search space and also its current velocity vector. In an iterative fashion, each particle is moved to a new position that is calculated by adding its velocity vector to its current position. Velocity vectors are updated by incorporating information from the particle’s memory of its previous best visited location in the search space as well as similar memories from its neighbors.

The varieties of PSOs considered in this paper are based on two factors, the first is the kind of velocity update equation used, and the second is the kind of neighborhood configuration.

Many PSO researchers use standard neighborhoods in their work, these are usually the ring or the *global neighborhoods (GBest)*. It has been shown that random neighborhoods can produce better results on some problems [17], [18], and so random neighborhoods will be considered in this paper. Random neighborhood configurations link particles to randomly selected neighbors at initialization time.

Most PSO research uses a velocity update equation based on the *constriction factor* constant [3]. The *fully-informed particle swarm (FIPS)* [14]-[16] uses a different velocity update equation that incorporates information from all of a particle’s neighbors instead of just the best one. FIPS is important in work that focuses on neighborhood configurations. Here, when FIPS is used, each neighbor’s contribution is equally weighted. In this paper, both constriction factor and FIPS velocity update equations are used.

Several types of neighborhood dynamism exist. The one that will be used in this paper is called *re-structuring*. It is a complete set of changes in the links between particles, amounting to a re-initialization of the random neighborhood graph, with the same graph parameters.

The re-structuring operator is applied probabilistically at the end of each PSO iteration according to the parameter *dynamism probability* P_d . A linearly decreasing scheme will be used for this parameter. At the start of the PSO it will be assigned a value of 1.0 and will be uniformly decremented at each iteration, in such a way that it reaches a value of 0.0 at the last iteration. PSO experiments will be allowed to run for a fixed number of function evaluations, and hence a fixed and therefore known number of iterations.

C. Description of Affective Design Steps 5-8.

This section describes the steps involved in taking the Kansei survey data and creating a model that suggests design choices that would perhaps embody characteristics that are appealing to the customers who were originally surveyed.

Step 5 uses particle swarm optimization to build *Kansei model* that aggregates respondents' emotional feedback. This model should match as closely as possible the participants' rating of the overall suitability of the products (high level generic Kansei word).

In order to use PSO for the creation of such a model an optimization function is defined. The Kansei surveys are based on questionnaire items that ask the respondent to select from a set of semantic differential levels [19]. For example, a questionnaire item may ask that the weight of a product be rated from 1 (very light) to 5 (very heavy), in whole integer steps. One criticism for example may be that a rating of 5 does not necessarily mean that the product is 5 times heavier than one with a rating of 1. Another example of a questionnaire item may be to identify the color of a product using codes 1 to 5, where each code represents a different color. In such a case, there is no notion of scale whatsoever.

Therefore for each such questionnaire item, instead of using a single variable that can have a value from 1 to 5, it would be better to use 5 binary variables. Thus if a questionnaire item, A_i , can take values of 1,2,3,4 or 5, then this will be encoded using 5 binary variables, $A_{i1}, A_{i2}, A_{i3}, A_{i4}, A_{i5}$. If A_i is assigned a value of 3 say, then A_{i3} will be assigned a value of 1, and all of the other binary variables will be assigned values of 0.

Using the above method for encoding the survey data, an attempt will be made to devise a linear weighted model that can predict a user's rating of the overall suitability of a particular exemplar of the product based on his or her ratings of the low level Kansei words. The *Kansei model* is given by the following equation:

$$P_K(x_1, x_2, \dots, x_n) = w_0 + w_1 x_1 + w_2 x_2 + \dots + w_n x_n$$

\hat{y} is a prediction function that takes as arguments a user's ratings, for a particular exemplar of product, of the low level Kansei words x_1, x_2, \dots , (except generic Kansei word). It is expected that with appropriate w values, \hat{y} can predict the user's rating of the overall suitability.

Such a model is sought because it is conjectured that, in terms of a linear relationship between the generic Kansei word and the low level Kansei words, users may not actually accurately aggregate their feelings to respond to that question. It would be desirable to have a simple linear relationship for the purposes of this exploratory research, thus PSO is being used to create such a model.

The optimization function that will be given to the PSO will therefore be taken to be the average relative mean squared error (RMSE) of the prediction of Kansei model induced by a set of weights over the entire sample responses collected in the survey. This is given by the equation below where \hat{y}_{ij} is the response to the j Kansei word question for the i data vector and y_{ij} is the response to the suitability question for that same vector.

$$f(w_0, w_1, \dots, w_n) = \frac{1}{m} \sum_{i=1}^m \left(\frac{w_0 + (\sum_{j=1}^n w_j \cdot x_{ij}) - y_{iz}}{y_{iz}} \right)^2$$

The PSO algorithm will perform differently on this optimization function depending on the neighborhood parameters used. At step 5 the following three methods are used:

1. A FIPS-based PSO with a set of size (n) and connectivity (k) parameters of the neighborhood graph structure;
2. A constriction factor-based PSO, with the same set of neighborhood parameters, as above;
3. A global best PSO (GBest) using the constriction factor with several options for the number of nodes in the neighborhood graph structure.

At step 6 the best result coming out of all of the tests in step 5 is selected. The weights of the PSO particle that produced the smallest RMSE are put into P_K , and this is the *optimal Kansei model*.

At step 7 by optimal Kansei model is generated a suitability prediction for each of the data vectors collected from the survey. These predictions are then used as targets for the linear *design model*:

$$P_D(x_1, x_2, \dots, x_m) = w_0 + w_1 x_1 + w_2 x_2 + \dots + w_m x_m$$

\hat{y} is a prediction function that takes as arguments a user's ratings of the design parameters x_1, x_2, \dots, x for a particular exemplar of product. As before, it is expected that with appropriate w values, \hat{y} can predict the output of \hat{y} for rating from the same data vector.

At step 8 is taken the result of the PSO optimization \hat{y} and interpreted the weights of the best particle so as to suggest choices for the design parameters. The maximum weight associated to a binary variable for a given design parameter suggests the choice for that design parameter.

III. CASE STUDY

A. Data Collection

The approach proposed is illustrated by a real-world design example using a Kansei survey on pens, conducted at Fatih

University, Istanbul. The design parameters determined at step 1 as well as their rating levels are given in Table I. 13 pens (cf. Fig. 2) were chosen as exemplars at step 2, to be used in conjunction with the survey questionnaire.

TABLE I
PEN DESIGN PARAMETERS

Design parameter number	Pen design parameter	Pen design parameter values
1.	Pen length	[1] short [2] average [3] long
2.	Pen volume	[1] thin [2] average [3] fat
3.	Pen color	[1] mixed color [2] white [3] blue [4] green [5] yellow
4.	Pen form	[1] completely straight [2] almost straight [3] semi-curved [4] moderately curved [5] very curved



Fig. 2 Exemplars of pens used in the case study

The Kansei words selected at step 3, as well as their rating levels are given in Table II. At step 4 are collected data from 49 student respondents, resulting in 637 data vectors.

TABLE II
SEMANTIC DIFFERENTIAL KANSEI WORDS

Number	Kansei words	
1.	Unimposing	Imposing
2.	Cool Feel	Warm Feel
2.	Conservative	Modern
4.	Ugly	Beautiful
5.	Unpleasant	Pleasant
6	Low quality	High quality
7.	Feminine	Masculine
8	Hard to write	Easy to write
9.	Bad Design	Good Design
10.	Unfit for FU students	Fit for FU students

B. Data Processing and Analysis

Various particle swarm configurations were tested at step 5 in an attempt to determine the best setting (amongst the parameters investigated) for the problem of predicting the

product suitability based on affective responses.

Two general PSO classes were used: the fully informed particle swarm (FIPS) and the constriction-factor PSO. For each of these, different random dynamic neighborhood parameters were used. The size and connectivity parameters are: $n=\{20,30,40,50,60,70,80,90,10$ and $k=\{1,2,3,4,5,6,7,8,9,1$.

Neighborhood re-structuring was used with a linearly decreasing dynamism probability of $P_{dyn}=1.0$ at the start down to $P_{dyn}=0.0$ at the final iteration. Each configuration was tested in 100 trials, each of which was allowed to run for 20000 function evaluations.

Initial exploratory experiments showed that multiple runs of the PSO would find similar small RMSE values, but using drastically different sets of weight. The situation was such that under these circumstances it was impossible to interpret the weights in any consistent way. As a result, it was decided to use expert-assigned initial weights.

At the end of each PSO run, the global best result was collected. The results from the 100 trials executed for each configuration were used to find the 95% confidence interval of the mean value of the best possible result using that configuration.

TABLE III
KANSEI MODELS FOR THREE PSO CONFIGURATIONS

FIPS									
Kansei words	1	2	3	4	5	6	7	8	9
Preferred level	4	1	2	5	1	5	4	5	3
RMSE	0.20241								
Constriction Factor									
Kansei words	1	2	3	4	5	6	7	8	9
Preferred level	4	1	2	5	1	5	4	5	3
RMSE	0.20278								
GBest									
Kansei words	1	2	3	4	5	6	7	8	9
Preferred level	5	1	2	5	1	5	4	4	3
RMSE	0.20247								

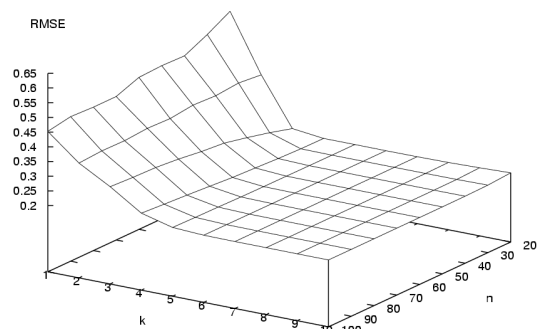


Fig. 3 Variations of RMSE in relation to neighborhood parameters n and k for FIPS

When a particular PSO configuration is run several times, the RMSE value tends to be roughly the same. This was evidenced by the small error values for the 100 runs. However the individual weights for the 46 coordinates of the search space can be quite different. This leads to the problem of interpretation of the best solution found by the PSO at the end

of a run. Two approaches were considered to deal with this problem. The first is to look at the relative ordering of the weights, specifically, it was assumed that a larger weight assigned to one of the binary variables associated with a particular question was indicative of that response level being more important. The second approach was to assume the same meaning with respect to the weight with the largest absolute value.

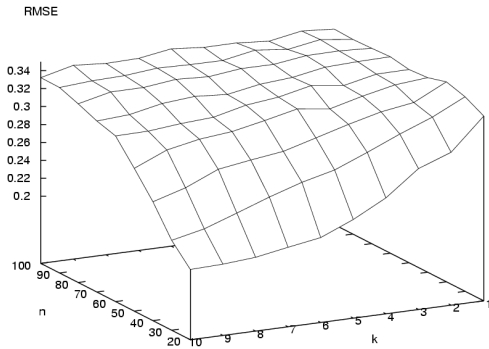


Fig. 4 Variations of RMSE in relation to neighborhood parameters n and k for constriction factor PSO

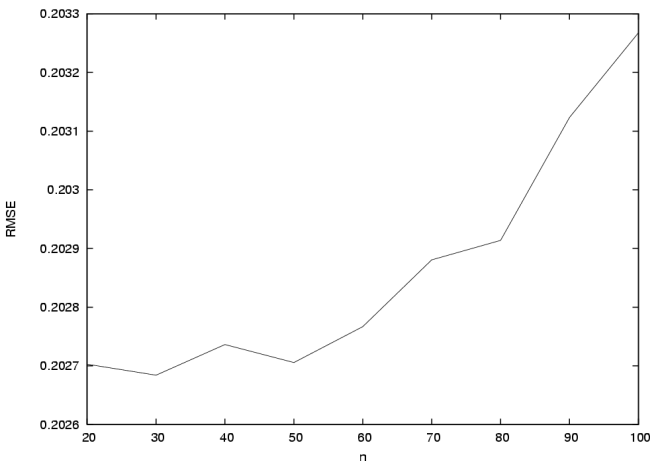


Fig. 5 Variations of RMSE in relation to neighborhood parameter n for GBest

Using this interpretation, Table III shows the questions used in the PSO experiments and the desired levels that obtained the maximum weight. The information in this table was taken for one of the FIPS runs with $n=40$, $k=8$, one of the constriction factor runs with $n=20$, $k=10$, and one of the GBest runs with $n=30$.

The best RMSE results in each method were comparable, there was no clear winner. However, looking at Figs. 3, 4 and 5, it becomes clear that FIPS is the more robust method (*step 6*). This is because there is a larger set of neighborhood graph settings that allow a FIPS-based PSO to find the optimal RMSE as compared to the other methods. Thus, for the second set of experiments FIPS is used. Another important observation is that simply the fact that GBest was able to find the optimum consistently is indicative of the nature of the

optimization function. GBest is considered a poor choice of neighborhood configuration because it tends to cause premature convergence of the algorithm. In light of this, it would appear that the choice of expert initialization of the weights for the model creates an effect whereby the PSO now seems to be searching a function landscape with far fewer local optima, perhaps even a uni-modal landscape.

Once the a set of weights were found that minimized the relative mean square error between the predicted suitability and actual suitability responses, this new prediction was taken as an ‘improved’ suitability response that is assumed to be a better aggregation of respondents emotions than what they actually put down on the survey form. This improved response was then used as a target and at *step 7* were found the weights for the design parameters that would now predict the improved response. Since the FIPS method was the most robust in the first experiment, a sample run from one of the best neighborhood configurations ($n=40$, $k=8$) was used to generate predicted values that would be used at *step 7*.

The fitting of the binary design properties to the predicted generic Kansei word yielded the results shown in Table IV. Based on these results the most important pen design parameters for Fatih University students seemed to be long curved pen with average volume and mixed mostly blue color. This fits also with the logo color of university. Those considered of students to be of less importance is thin straight pen with average volume and white color. These results are close to [21] but still different.

TABLE IV
DESIGN PARAMETERS DETERMINED BY PSO WITH FIPS CONFIGURATION

Length	Value	Volume	Value
short	-0.212	thin	0.191
average	-0.169	average	0.321
long	-0.092	fat	0.238
Color	Value	Form	Value
mixed colors	0.455	completely straight	0.148
white	0.177	almost straight	0.209
blue	0.448	semi-curved	0.223
green	0.322	moderately curved	0.279
yellow	0.194	very curved	0.424

RSME=0.0767

IV. CONCLUSION

A particle-swarm-optimization-(PSO)-based approach for affective product design has been proposed. The most popular swarm intelligence method, namely the particle swarm optimization algorithm, was used to model the relationship between Kansei words and product design parameters. It is a simple, feasible and versatile approach determining the combination of product parameters that could result in designs taking into account customer emotions. A model evolved by the particle swarm algorithm suggests product design properties. Depending on these values, relevant product designs could be proposed.

For illustrating and validating the PSO-based approach a case study of pens was carried out. Relevant Kansei words, product design properties and exemplar pens were defined.

PSO was first used to generate a linear model that predicts users' perceptions of the overall suitability of various products. It was found that the search space of this problem was highly multi-modal and in order to get consistent and reasonable results, it was necessary to seed the initial particle position vectors with values based on expert opinion. Three general types of neighborhood configurations were used for the PSO experiments. It was found that it was possible to tweak each method to obtain comparable best results. However, the fully informed particle swarm proved to be the most robust option, in the sense that many graph settings for this scheme were able to find the optimal result. The predictions of the optimal linear Kansei model were then used as targets for a second linear model that sought to fit the design parameters to the predicted suitability values. This model generated suggestions that were plausible.

There are some lines of further research that have arisen out of this paper. First, in terms of computational intelligence and particle swarm optimization, it is curious that the expert initialization of the weights causes the PSO to consistently find similar solutions since it is known that PSO is usually not affected by initial weights. A careful study of this phenomenon should be performed to gain more knowledge into the PSO's behavior with respect to the type of function defined in the paper. Second, in terms of Kansei engineering, the effect of using different expert initial weights should also be studied. Also, attempts must be made to make the process independent of human input into the search algorithms.

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