A Tunable Swarm-Optimization-Based Approach for Affective Product Design

ARVIND MOHAIS, ALEXANDER NIKOV, ASHOK SAHAI
Department of Mathematics and Computer Science
University of the West Indies
St. Augustine
TRINIDAD AND TOBAGO (W.I.)

http://sta.uwi.edu/~anikov

Abstract: - An approach for affective product design using a hybrid of tunable particle swarm optimization (PSO) and Kansei engineering is proposed. Customers' emotive responses to a product are collected using a questionnaire designed on Kansei engineering principles. They are used to create models which can suggest design parameters for the product that may implicitly embody customers' emotional preferences. These models are created by PSO algorithms, tuned to use the best possible velocity update equation and neighborhood configuration. Results of a pen case study are compared by means of the relative mean squared error with respect to the difference between predicted and known target values. Secondary differentiation of performance is obtained using the statistical measure of the coefficient of variance.

Key-Words: - Emotive Design, Product Design, Particle Swarm Optimization, Neighborhood Configurations

1 Introduction

The affective product design is aimed at determining the relationships between consumers and products and to define the emotive properties that products intend to communicate through their physical attributes [4], [7], [13]. Kansei Engineering techniques support affective product design by linking the customer needs mathematically to the technical characteristics of the product [7], [13]. For mathematically connecting customer emotions mapped through Kansei words and the product properties methods like data mining [4], regression analysis, neural networks [6], evolutionary computation [1] and fuzzy sets [8] are used.

The fitness functions in Kansei engineering are often highly multi-modal. Therefore, swarm intelligence algorithms [5] [4] are appropriate for these types of modeling. The first such studies [14] and [11] applied particle swarm optimization (PSO) to analyze customers' affective responses with regard to products, and use the results to propose relevant product design parameters. Here we continue our studies [14] and [11] by tuning different PSO configurations for determining an optimal Kansei model based on the most robust PSO neighborhood configuration. This approach will be applied in a case study of pen design.

2 A Tunable Swarm Optimization – Based Approach for Affective Product Design

The following steps of affective product design are proposed:

1. Determine product design parameters.
2. Gather exemplars of existing products.
3. Determine Kansei words.
4. Gather data from product customers.
5. Build Kansei model by PSO tuning.
6. Select the optimal Kansei model based on the most robust PSO neighborhood configuration.
7. Build a design model by the predicted generic Kansei word.
8. Define the product design parameters.

Data is collected by a questionnaire that is completed by potential clients of the product under consideration. The questionnaire contains three sections, first a set of feelings-based items, second, a set of product design parameter items and finally a single item that asks the respondent to judge the overall suitability of a product specimen. Each respondent is provided with multiple specimens of the product under consideration and for each, he/she is required to respond to all items on the questionnaire. Binary variable encodings are used to represent the responses to each pseudo-scaled questionnaire rating item. For example, if a questionnaire item, A, can take values of 1,2,…,n, then this would be encoded using n binary variables, $A_1, A_2, \ldots, A_n$. If a respondent assigned a value of j to item A, then A_j would be assigned a value of 1, and all of the other binary variables would be assigned values of 0.

Once this data has been collected, Particle Swarm Optimization (PSO) [5] is used in two phases in an attempt to build a model that can suggest design characteristics of the product that would be emotionally pleasing to clients.

In the *first phase*, PSO is used to build a linear model that links the respondents' impressions of overall suitability of the sample products to their emotive responses to items in the first part of the questionnaire. The model is intended to be able to predict how a respondent will judge overall suitability based on given emotive responses to the product. Inevitably the model will not perfectly match the data collected, however it is assumed that the model may be taken as a preferred measure of users' assessments of overall suitability, instead of their actual responses. In the *second PSO phase* another linear model is created that links the data on design characteristics with the output of the model from the first phase. The coefficients resulting from this model are then used to suggest values for each design parameter.

Particle Swarm Optimization is a sub-field of Evolutionary Computation that borrows ideas from natural social interactions in animal and human beings and adapts them for the purpose of solving optimization problems [5]. The PSO algorithm takes a set of candidate solutions to a problem and moves them through the search space R^n of the optimization problem. Each particle changes its direction of movement based on the exchange of information with neighboring particles. The determination of neighborhoods is independent of particles' positions in the search space, instead it is imposed by a directed graph structure.

Many variations on the basic PSO algorithm exist, and in this paper two parameters of the algorithm will be manipulated and studied. The first is the velocity update equation. Much PSO research employs the constriction factor velocity update equation [2], but recently there has been increased focus on the Fully-Informed Particle Swarm (FIPS) approach [9]. It uses information from all members in a particle's neighborhood when updating the velocity, in contrast to the canonical constriction factor approach in which only the best performing neighbor is considered.

The second aspect of the PSO algorithm that is systematically varied is the neighborhood interconnection structure. This paper uses randomly generated neighborhoods [12] of varying size (n) and out-going connectivity (k). It also uses a linearly decreasing probability of total neighborhood re-structuring [10]; an operation that completely re-arranges the connecting directed edges between particles that dictate neighborhoods.

The first PSO phase attempts to create a model

$$p_K(x_1, x_2, \ldots, x_n) = w_0 + w_1 x_1 + w_2 x_2 + \cdots + w_n x_n$$

That can predict a respondent's suitability rating for a product given the emotive responses $x_1, x_2, \ldots, x_n$. Determining the w_i coefficients is the goal of the PSO application in this phase. In order to accomplish this, the PSO is programmed to optimize the following function:

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

Here x_{ij} is the response to the j^{th} emotive questionnaire item for the i^{th} data vector and x_{is} is the response to the suitability question for that same vector. The calculation used to evaluate (1) is the equation for the average relative mean squared error (RMSE) of the prediction with respect to the actual target value.

In the first phase, PSOs optimize this function many times, using different algorithm parameter values. The 'tuning' of the algorithm is based on determining the best PSO parameters for solving this particular problem. Using the model arising from the best-performing PSO configuration, the second phase is performed. Its predictions are targets for the second linear model:

$$p_D(x_1, x_2, \ldots, x_m) = w_0 + w_1 x_1 + w_2 x_2 + \cdots + w_m x_m,$$

where $x_1, x_2, \ldots, x_m$ are responses to the design attributes items on the questionnaire, and w_i are the weights to be determined by the PSO. p_D is expected to predict the output of the p_K selected from the first phase. The weights are then used to suggest choices for the product design parameters. Further details of this algorithm can be found in [14].

The PSO is subject to some stochastic instability inasmuch as it uses (uniform) pseudo-random numbers in its optimization algorithm. A scale-invariant/ dimensionless measure of this stochastic instability is provided by the "coefficient of variation" (C.V.=standard deviation / mean) of the relative mean squared errors (RMSE) over the 1000 runs of PSO. The optimization criterion RMSE (unlike MSE usually employed in similar papers in the literature) is also a scale-invariant/dimensionless measure of the solution at hand. This concept of RMSE is frequently applied in the analogous area of statistical estimation to determine the most desirable robust method amongst the ones competing [3]. The coefficient of variance would furthermore assist with differentiation in the situation observed in [11] where it was found that for the FIPS settings, there were many neighborhood configurations that were similar in terms of the mean RMSEs.

3 Case Study

The tunable PSO two-phase approach to affective product design is illustrated by a real-world example involving pens as the product. Survey data was collect at Fatih University, Istanbul, Turkey. Students were asked questions, structured as outlined in the previous section, about their emotive impressions of 13 different pens. There were 49 respondents, thus resulting in 637 data vectors.

For the tuning of the PSO, several neighborhood configurations were studied. Each configuration was employed with the canonical constriction factor PSO as well as with a FIPS-based PSO. The neighborhood parameters are: $n \in \{20,30,\ldots,100\}$, and $k \in \{1,2,\ldots,10\}$. Total re-structuring was employed as a form of neighborhood dynamism. It was used with a linearly decreasing probability of application from 1.0 down to 0.0 over the course of the algorithm run. Each run was terminated after 20000 function evaluations, and each complete PSO setting was run 1000 times in order to obtain statistically reliable results. As noted in [11], it was necessary to initialize the PSO particles within a Gaussian neighborhood of expert-assigned initial values in order to obtain consistent weight rankings, before proceeding to the second phase.

Figures 1 and 2 show the results obtained when the FIPS-based PSO was used. In fig.1 the mean RMSE over 1000 trials is plotted, and in fig. 2 the coefficient of variance is shown. Both plots share the same characteristic shape. The area of good results occurs between k=6 and k=10 for all values of n.

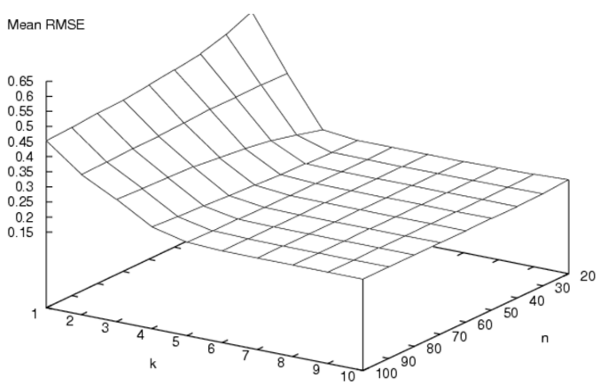

Fig. 1. Mean RMSE in relation to n and k for FIPS

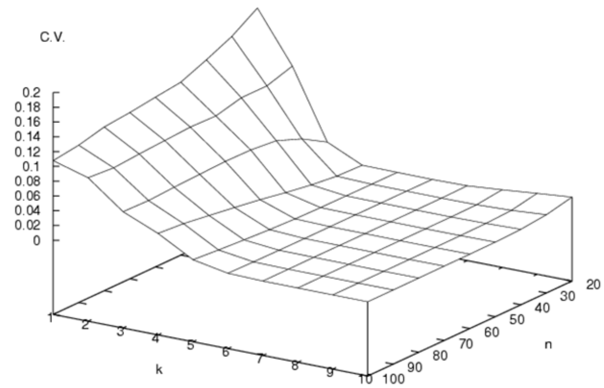

Fig. 2. C.V. in relation to n and k for FIPS

Figures 3 and 4 show the results obtained when the canonical constriction factor PSO was used. In this case, the plots are dissimilar in shape. The RMSE plot slopes downward as n decreases and k increases. However, the coefficient of variance plot slopes slightly downwards as k increases, although there is a sharp drop in the region near k=1, and n=20.

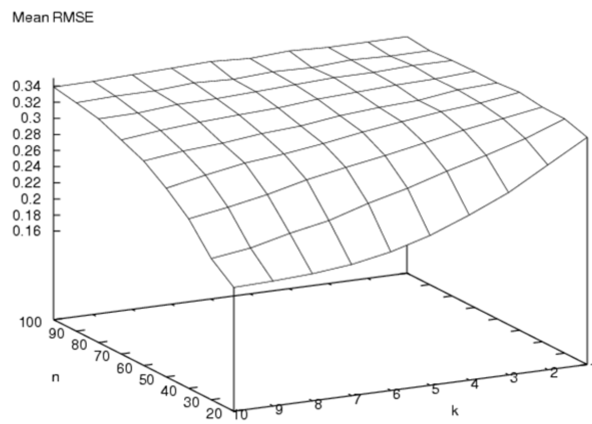

Fig. 3. Mean RMSE in relation to n and k for constriction factor PSO

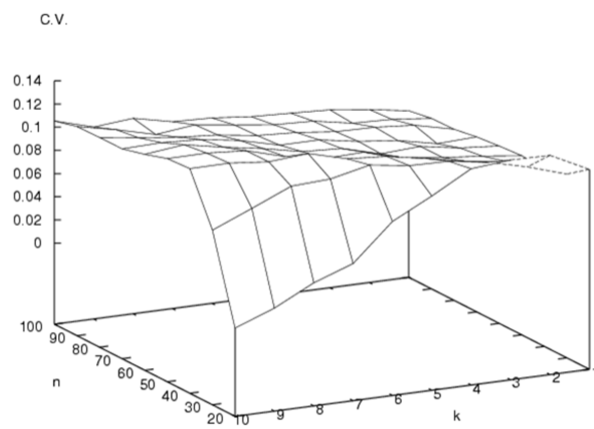

Fig. 4. C.V. in relation to n and k for constriction factor PSO

The FIPS results show that for a given value of n, the value of k that produces the smallest RMSE also produces the smallest C.V. For the constriction factor PSO, other than for n=20,30, this pattern did not hold. In fact the values of k that produced the smallest RMSE and C.V., were on opposite extremities. These k values are given in Table 1.

Table 1. k values producing the smallest mean RMSE and C.V. for different values of n.

FIPS									
n	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
k (min. mean)	6	7	8	8	9	9	9	10	10
k (min. c.v.)	6	7	8	8	9	9	9	10	10
Constriction Factor									
n	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
k (min. mean)	10	10	10	10	10	10	10	10	10
k (min. c.v.)	10	10	1	1	1	2	1	1	1

Figures 5 and 6 show the variation in C.V. with respect to k for different levels of n. For the FIPS-based PSO there is a region around k=6 and k=9 where the minimum C.V. values can be found. At k=4, there is a clear correlation between increasing n and increasing C.V. For the constriction factor PSO, there is no apparent new information to be gleaned from the plots.

Figures 7 and 8 localize in the (Mean RMSE, C.V.)-plane the (n,k) points that produced the smallest Mean RMSEs within each level of n. In the case of FIPS, one outlier is omitted in order to better display the points on the plot. These figures emphasize the fact that the FIPS algorithm vastly out-performed the constriction factor PSO. This is clear by a comparison of the scales of the axes of these plots.

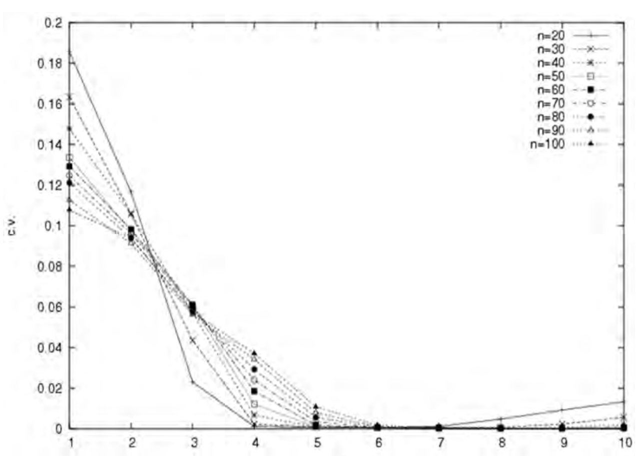

Fig.5. FIPS: Variations of C.V. with respect to k for different levels of n.

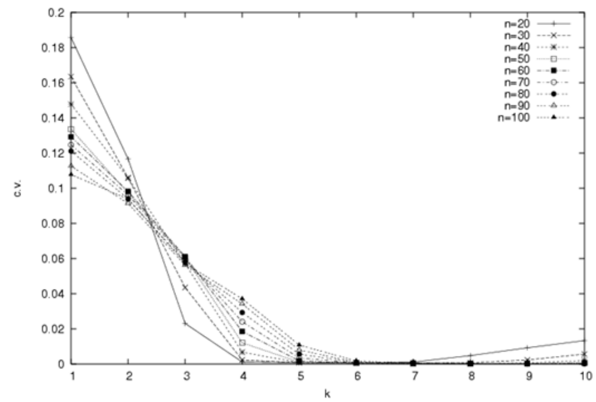

Fig. 6. Constriction factor: Variations of C.V. with respect to k for different levels of n.

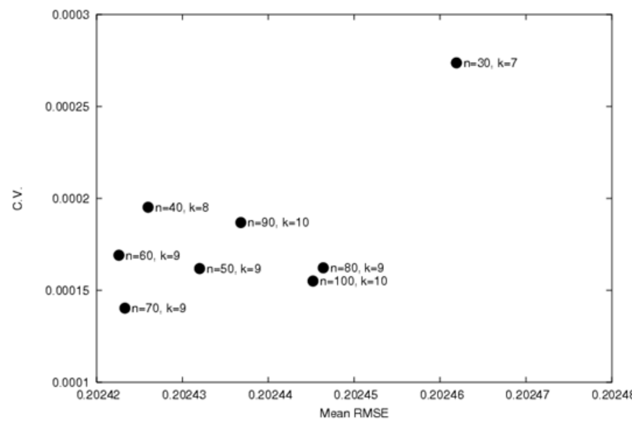

Fig. 7. Lowest RMSE and corresponding C.V. for different n values for FIPS

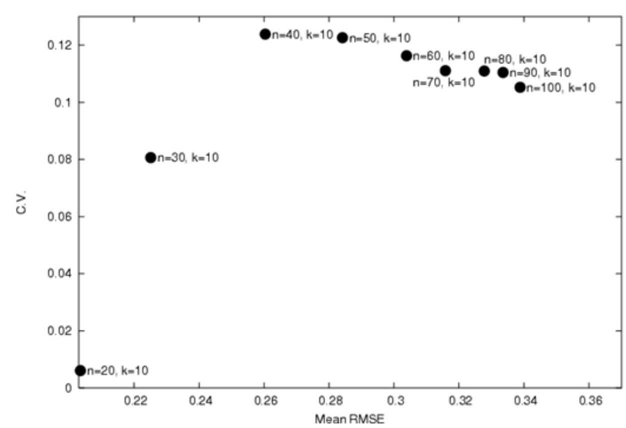

Fig. 8. Lowest RMSE and corresponding C.V. for different n values for constriction factor

The best-performing FIPS configuration in terms of mean RMSE was at n=70, k=9. The predictions of the model created by this setting were used as targets for the second PSO phase. The same configuration was arbitrarily used to run the second phase optimization.

The model produced by the second phase of PSO suggested design parameters that were essentially the same as in our previous study (cf. Table 2). The only difference was that the proposed pen color is now ``blue'' in [11] it was ``mixed color''. This development is not troubling since in both cases the weights associated with each of these options are quite similar.

Table 2. Design Parameters Determined by PSO with FIPS Configuration

Length	Value	Volume	Value
short	0.018	thin	0.240
average	-0.0233	average	0.370
long	0.151	fat	0.235
Color	**Value**	**Form**	**Value**
mixed colors	0.515	completely straight	0.114
white	0.253	almost straight	0.294
blue	0.562	semi-curved	0.304
green	0.334	moderately curved	0.197
yellow	0.201	very curved	0.746

4 Conclusions

This paper expanded on previous research concerning the application of a hybrid approach that combines Particle Swarm Optimization and Kansei Engineering, to the problem of affective product design [11], [14]. Key improvements were the use of significantly more experimental trial runs, 1000 instead of 100, and the use of the statistical measure of the coefficient of variance to identify stable neighborhood configurations, in what would otherwise appear as similar performance results.

One important observation arising out of the calculation of the C.V. is that although the best constriction factor configuration was able to perform comparably to that of FIPS, the stability of the performance was not at all the same. The best constriction setting had a C.V. on the order of 1% whereas that of FIPS was on the order of 0.1%. The FIPS algorithm is also better behaved in the sense that for a given n, values of k that produce the smallest mean RMSEs also produce the smallest C.V. This was not the case for most of the constriction factor settings.

Future research in this area could involve the application of PSO to train neural networks that embody the models required in both phases in place of the simple linear models now in use.

References:

[1] J. Ängeslevä, Evolutionary computation in creative design, in *Computer Related Design*, 2001, Royal College of Art, UK.

[2] M. Clerc, and J. Kennedy, The Particle Swarm - Explosion, Stability, and Convergence in a Multi-dimensional Complex Space, *IEEE Trans. on Evolutionary Comp.*, Vol. 6, No. 1, 2002 pp. 58-73.

[3] D. Glotsos, J. Tohka, J. Soukka, J.T. Soini, and U. Ruotsalainen, Robust Estimation of Bioaffinity Assay Fluorescence Signals, *IEEE Trans. on Information Technology in Biomedicine*, Vol. 10, No. 4, 2006, pp.733-739.

[4] J. Jiao, Y. Zhang, and M. Helander, A Kansei mining system for affective design, *Expert Systems with Applications*, Vol. 30, No. 4, 2006, pp. 658-673.

[5] J. Kennedy, and R. Eberhart, Particle swarm optimization, in *Proc. IEEE Int. Conference on Neural Networks*, IEEE Press, 1995, pp.1942-1948.

[6] H. Lai, Y. Lin, and C. Yeh, Form design of product image using grey relational analysis and neural network models, *Computers & Operations Research*, Vol. 32, No. 10, 2005, pp. 2689-2711.

[7] S. H. Lee, A. Harada, and P. J. Stappers, Pleasure with Products: Design based on Kansei, in Ch. 16 of *Pleasure with Products: beyond usability*, by W. S. Green (Ed.), Taylor and Francis, 2000, pp. 219-230.

[8] Y. Lin, H. Lai, and C. Yeh, Consumer-oriented product form design based on fuzzy logic: A case study of mobile phones, *Int. J. of Industrial Ergonomics*, Vol. 37, No. 6, 2007, pp. 531-543.

[9] R. Mendes, J. Kennedy, and J. Neves, The fully informed particle swarm: Simpler, maybe better, *IEEE Transactions on Evolutionary Computation*, Vol. 8, No. 3, 2004, pp. 204-210.

[10] A. Mohais, R. Mendes, C. Ward, and C. Posthoff, Neighborhood Restructuring in Particle Swarm Optimization, in *Proc. Australian Conference on Artificial Intelligence*, 2005, Springer, Berlin, pp.776-785.

[11] A. Mohais, A. Nikov, A. Sahai, and S. Nesil, Swarm-optimization-based affective product design illust-rated by a pen case-study, 4th Int. Conference on Computational Intelligence, ICCI'07, Berlin, *Proc. of the World Academy of Science, Engineering and Tech.*, Vol. 23, 2007 pp. 239-244.

[12] A. Mohais, C. Ward, and C. Posthoff, Randomized directed neighborhoods with edge migration in particle swarm optimization, in *Proc. Con-gress on Evolutionary Comp.*, 2004, Vol. 1, pp. 548-555.

[13] M. Nagamachi, Kansei engineering as a powerful consumer-oriented technology for product development, *Applied Ergonomics*, Vol. 33, No. 3, 2002, pp. 289-294.

[14] A. Nikov, A. Mohais, and S. Nesil, Emotive design by swarm-intelligence-modelling, in *Proc. 9th Int. Symposium, TECHNOMAT, Materials, Methods and Technology*, 2007, Bulgaria, pp. 204-214.