ADDING IMPLICIT MEASUREMENT METHODS TO INTERACTIVE OPTIMIZATIONS IN INDUSTRIAL DESIGN - A CONCEPT, FIRST TESTS, AND COMPARISON USING TWO SIMPLE CASE STUDIES

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ABSTRACT

In this article, a new approach to interactive optimization in industrial design is presented in which, for the first time, implicit preference acquisition methods are integrated. Suitable methods for preference acquisition will be selected, adapted and combined with an own PSO-inspired algorithm. The application of implicit preferences as well as the combined application of implicit and explicit preferences in an interactive optimization represents the main novelty of this contribution since this has not yet been carried out according to the current state of knowledge.Two case studies will be used to test this new approach with regard to convergence and acceptance, and a comparison will be made between the three different kind of optimization (implicit, explicit as well as a combination of both) in terms of their results.

Keywords: Interactive Optimization, Implicit Measures, Industrial design, Optimisation, Crowdsourcing

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Cite this article: Wiesner, M., Petrow, A., Vajna, S. (2019) 'Adding Implicit Measurement Methods to Interactive Optimizations in Industrial Design - A Concept, First Tests, and Comparison Using Two Simple Case Studies', in *Proceedings of the 22nd International Conference on Engineering Design (ICED19),* Delft, The Netherlands, 5-8 August 2019. DOI:10.1017/dsi.2019.251

1 INTRODUCTION

The human capacity for creativity, i.e. the ability to create something new that is original and usable (Mark A. Runco, Garrett J. Jaeger 2012), is undisputed. However, for good reasons, especially in technical questions, this outstanding ability is in many cases supplemented by far-reaching optimization strategies when detailing a product. The motivation for this is to find an optimum, especially for complex and strongly connected problems (Krettek, 2012), and to investigate the solution space to an extent that is impossible or only achievable with enormous effort for the individual. In comparison, the area of industrial design, in particular the formgiving process, is still almost exclusively dependent on the individual's ability to explore the solution space exploratively and intuitively (Nordin, 2015). This paper article is not intended to question the basic approach of industrial design, but to put optimization methods to the test in the phase of detailing a design project, which are meant to provide fine adjustments to clearly defined design problems. In addition, the opportunity will be taken to close the gap between industrial designers and users through a user-oriented approach. This can be motivated by mass customization strategies or by the need to avoid risks in product design, especially during market introduction (Kohler, 2003). Although industrial designers have a high level of education and qualification to understand The needs of customers, identify trends and make innovative proposals, differences can occur between the product perceptions of designers and users (Petiot *et al.*) . From the authors' point of view, it is not enough to use rating scales to ask users directly about their preferences. Rather, custom-made methods should be used to get a comprehensive picture of their preferences, especially since users are often unable to formulate their needs for product appearance (semantics) and aesthetics (Zeh, 2010), and in some cases these are even unconscious.

2 ANALYSIS OF THE STATE OF RESEARCH

From the motivational introduction we can extract two goals. First the selection of an efficient and sensitive preference acquisition method set which is combinable in an efficient way with optimizations and second examination of applicability of Interactive optimizations to complement the industrial design process. For both of these goals a brief outline of current research will be given below.

2.1 Current state and own preparatory work for preference assessment

In the literature, a variety of methods are known to assess design preferences (Greb *et al.*, 2016; Carbon, 2018). In own preliminary work an extensive collection of methods and a collection of relevant attributes was prepared and structured in five groups (sensory acquisition, questioning, choice experiments, observation and computational methods) (Wiesner and Vajna, 2018). Choice experiments, as one part of these method groups, seem to be particularly close to real purchase decisions (Wiesner and Vajna, 2018). Additionally implicit methods seem to be interesting as complementary means to capture what subjects cannot articulate, or to conceal due to social desirability or deliberately indicated otherwise. This point can also easily be deduced on the basis of current hierarchical aesthetic theories (Leder *et al.*, 2004; Norman, 2005; Zeh, 2010; Graf and Landwehr, 2015). These distinguish between automatically processed levels of perception (implicit) and reflectively processed perception levels (explicit). It is worth covering both types, since the implicit levels guide consumer decisions in many areas and these are less manipulable in a survey due to social desirability effects (Greenwald *et al.*, 2008) and since they are based on partly different design characteristics (Ulrich, 2011).

2.2 Current state of research on interactive optimization

After a review of the literature, it becomes clear that this paper is by far not the first to deal with user-based optimizations. An often-used keyword for this type of optimization is interactive evolutionary computation (IEC). According to Takagi, this is a category of methods where the user plays the role of the evaluator in an evolutionary process (Takagi, 2001) (Petiot *et al.*). The approach of IECs has already been used in the context of product design for eyeglass frames (Yanagisawa and Fukuda, 2004), car's silhouettes (Cluzel *et al.*, 2010), Cola bottles (Kelly, 2008) , truss stuctures (Felkner *et al.*, 2015), and html style sheets (Takagi, 2001).

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2.3 Identified research gap and research questions

From this analysis, a research gap can be identified as the Necessity to define a kind of user integration that is sensitive enough and comprehensive enough for all phases of the perceptual process and to integrate this into interactive optimizations. The application of implicit preferences as well as the combined application of implicit and explicit preferences in an interactive optimization represents the novelty of this contribution besides the custom-made algorithm, since this has not yet been carried out according to the current state of knowledge.

In the first research question of this contribution, an answer will be given to the extent to which implicit and explicit design preferences differ in their results in optimizations and to what extent there is an added value in integrating these implicit measurement methods into interactive optimizations.

In the second research question, an answer will be given to the extent to which optimization algorithms, in which implicit measurement methods are used in addition to explicit preference decisions of users, can converge with computer-aided design solutions.

3 NEW APPROACH OF INTERACTIVE OPTIMIZATIONS IN INDUSTRIAL DESIGN

Our new approach consists of two components. Firstly, the selection and adaptation of an algorithm and secondly, the use of a preference acquisition method supplemented by implicit methods.

3.1 Selection and Adaptation of an algorithm to the specific problem

The method used for the optimization of the evaluated representations is a population-based metaheuristic inspired by the particle swarm optimization (PSO) (Poli *et al.*, 2007). A PSO inspired algorithm is used because this type of algorithm needs less evaluations compared to Genetic Algorithms and converges quickly (Felkner *et al.*, 2015; Hassan *et al.*). The convergence speed and the amount of evaluations is of particular interest, since user fatigue is the biggest problem in such interactive optimizations (Takagi, 2001). Using a PSO inspired metaheuristic algorithm, convergence speed can be controlled by parameters in the algorithm's formula. Each representation or particle *k* has its current values x^k and vector of motion v^k. The next values x^k_{new} are calculated as follows:

$$x^k_{new} = x^k + v^k$$

The vector of motion is calculated by two parts, the movement from the previous position and the influence of the other particles.

$$v^k = \omega_p (x^k - x^k_{prev}) + \omega_o \vartheta^k$$

The two parts are weighted by $\omega_p = 0.05$ for the influence of the previous movement $(x^k - x^k_{prev})$ and $\omega_o = 0.4$ for the influence of the swarm defined by ϑ^k.

$$\vartheta^k = \sum_{j=1}^{n_x} (x^j - x^k) \max(0.5\varrho^{k,j}, 1.5\varrho^{k,j})$$

Since the swarm is fully connected each particle is influenced by all other particles. The intensity $\varrho^{k,j}$ how much the particle x^k is attracted or rejected by x^j depends on the difference in their objectives. If the other particle is worse, it is rejected itself and attracted elsewhere. In case of a rejection the influence will be decreased by 50% and increased by 50% otherwise. The influence is calculated as the following:

$$\varrho^{k,j} = \frac{o^j - o^k}{\sqrt[2]{\sum_{l=1}^{n_x} (o^l - o^k)^2}}$$

Since the search space (valid values for the position of the particle) is restricted a constraint handling technique is needed in case particles are leaving the search space. The constraints in this case are box-constraints. Hereby each parameter of a particle can be handled separately. In case a parameter is updated to a value outside the restricted search space this parameter will be modified. The violation by this parameter is reduced by half and applied to the boundaries towards the feasible search space.

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3.2 Selection and customization of preference acquisition methods for implicit and explicit preferences

In order to be able to integrate both types of preference acquisition (implicit and explicit) comparably in one procedure and still create a user interface in which all variants are clearly perceivable and easy to process for the user, only two stimuli pictures should each be presented in a paired comparison. This is an easier task to perform for the user compared to the fitness assignment of individuals within an entire generation, which seems to be common within interactive optimizations (Takagi, 2001). Furthermore there is already an application in which implicit and explicit preference determination have already been successfully combined in such a pair comparison (Carbon *et al.*, 2018). Paired comparisons are sensitive enough even for small perceptual differences between stimuli and offer a better sensitivity than rating scales in detecting differences (Eisenberg and Dirks, 1995) (Carbon *et al.*, 2018). In addition to the objectives of sensitivity, the objectives of efficiency and acceptance should not be neglected in the final selection of the method. Thus, according to Carbon, measurement methods capturing implicit attitudes differ very strongly in their effort (Carbon, 2018).

3.2.1 Selection of the implicit preference acquisition method

The Single Category Implicit Association Test (SC-IAT) (Karpinski and Steinman, 2006) (Greenwald *et al.*, 1998) and the Affect Misattribution Procedure (AMP) (Payne *et al.*, 2005) have proved to be applicable implicit preference acquisition methods in own preliminary work (Wiesner and Vajna, 2018). The contribution quoted above (Carbon *et al.*, 2018) can be used to extract another conceivable method called backward masking procedure, which can also be directly combined with paired comparisons. However, IAT is omitted due to the high expenditure of time, AMP is omitted due to partly low user acceptance in own observations with 20 test persons (this problem arose in particular with elderly persons) so that the choice falls on the backward masking procedure. Interestingly enough, the IAT test was rated as at least okay by seniors as well as by students, sometimes even as very easy.

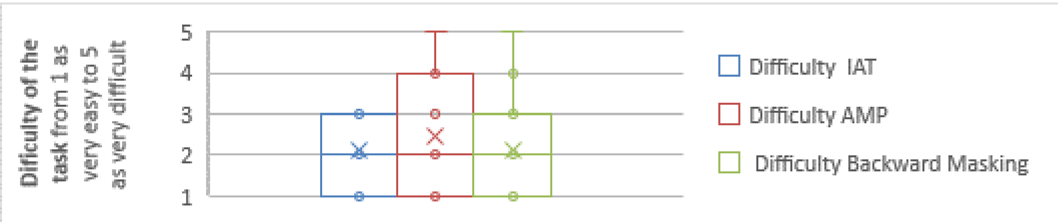

Figure 1. Subjectively perceived difficulty for IAT, AMP and Backward Masking

Backward masking occurs when the visibility of one stimulus, called the target, is reduced by the presence of another stimulus, called the mask (Breitmeyer and Ogmen, 2000). There are different types of masking. In the following we would like to deal only with masking by noise. In backward masking by noise, the mask typically consists of random dot noise that overlaps the target (Neath and Surprenant, 2007) This noise effectively prevents the after-effect of the stimulus (Liss, 1968) and can therefore be used to keep the presentation time so short that one can assume that the user reaction is based on implicit processes (Turvey, 1973).

3.2.2 Customization of the choosen implicit preference acquisition method

In an initial pretest with scientists from the chair of the author, it turned out that it could potentially be afflicted with perception problems to transfer the backward-masking technique to paired comparisons without further adjustments. In particular, it can happen that the test persons can only pay attention to one of the images during the short-term presentation. Our approach to the improvement of this situation is to direct the respondents' attention from one stimulus to another. This means to first fade in a fixation cross and then to present the stimuli image on one side and only when the first image is already covered with the mask to direct the attention of the user with a fixation cross to the other side followed by the stimuli image and the noise. In a survey with eleven test persons based on this, many of them found the simultaneous perception to be "difficult" and some test persons stated that they could only have paid attention to one of the pictures. In comparison, the changed (time-staggered) approach was assessed as "easy" task (see Figure 2).

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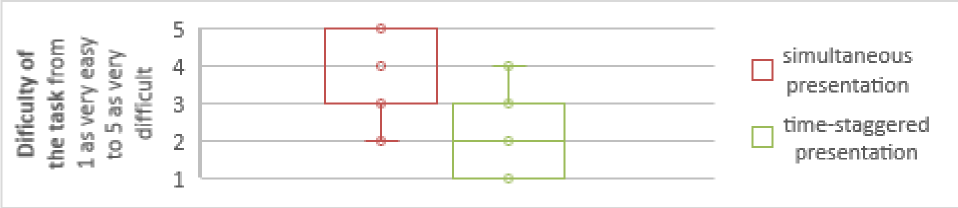

Figure 2. Subjectively perceived difficulty of simultaneous and time-staggered presentation of the stimuli images

4 CASE STUDY ON THE VISUAL BALANCE OF BASIC SHAPES

The visual balance can be regarded as one of the important aesthetic attributes of several authors (Hekkert and Leder, 2008; Ellis, 1993). The phenomenon of visual balance is also known as white space or reversed coded, also called instability (Berlyne, 1971).

4.1 Optimization model and user interface

Within the phenomenon of visual balance, this special case study deals with the balance of two objects to each other and to the ground surface. The motivation to treat such a case study comes from the design study of one of the authors in which exactly this task had to be done manually and obviously the need to find a design task with few parameters in order to test the optimization system for the first time. In this example, the designs are created by two parameters based on definitions in the Cascading Style Sheets (CSS), which are common within web pages to manipulate the visual appearance. The variation of CSS definitions for web pages could be a typical design task, although the case study itself is much simpler and more generic. For the stimuli presentation a web page with CSS definitions is created and the aspects in which CSS is to be optimized are defined as variables. Basically, all other parameters of a CSS definition can be adjusted by such an optimization. The implementation in a web app is based on the Django framework (djangoproject.com). Figure 3 shows the evaluation page.

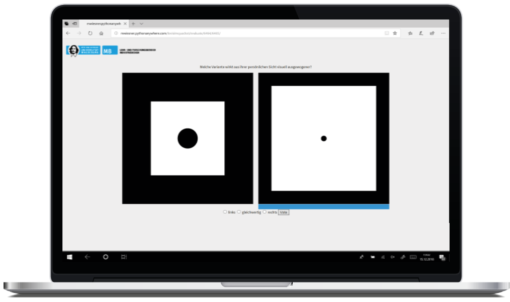

Figure 3. Evaluation page of the web app for the case study visual balance of basic shapes

4.2 Convergence test

As discussed in section 2.3, the introduction of an implicit preference acquisition method is a novelty in interactive optimizations and it cannot be assumed that an optimization with unknown input really converges. Furthermore, the self developed algorithm has to be checked for convergence too.

While typically the fitness function can be used as a convergence criterion (Takagi, 2001), this approach does not apply to the dichotomous evaluation of paired comparison. Consequently, it had to be reconsidered how convergence can be proven. A first test case to measure this is to record the changes of each individual from generation to generation. The individuals here correspond to the five individual particles in the PSO optimization that move in the parameter space based on the user preferences. Test criterion for convergence in this case is to check whether this change gradually becomes smaller, i.e. whether figuratively speaking the individual particle has found a position within the swarm from which it moves only minimally away. Firstly convergence is shown for one proband and one parameter in Figure 4 (border size of the square).

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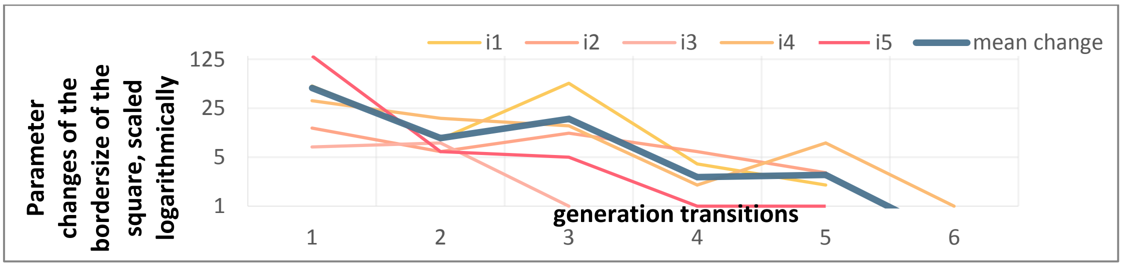

Figure 4. Parameter changes of each individual design (i1 - i5), scaled logarithmically, for one proband between seven generations for the optimization based on the combination of explicit and implicit preferences as specific example of a parameter progression

In all three optimization types implicit, explicit and the combination of both, a reduction of change can be found over the generations (see Figure 5) which can be interpreted as convergence for at least the individual particles of the optimizations, i.e. the single individual designs. The most stable convergence characteristics are also observed in the first case study with the least fluctuating curve and the lowest average change values at the end of the optimization.

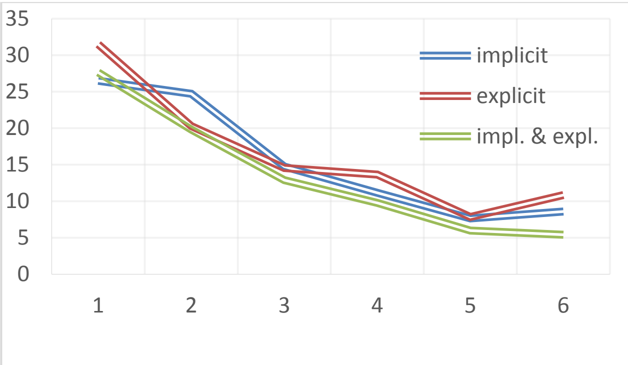

Figure 5. Mean parameter changes of all probands of all parameters for the three types of optimization

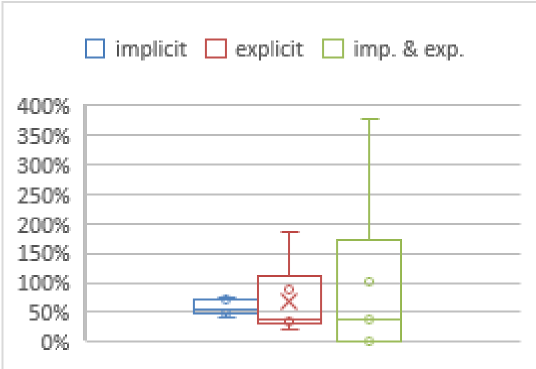

Figure 6. Mean relative variance s² for all probands and individuals shown for all three types of optimization in the last generation

In addition to the first test, we checked for the mean relative variance s² for all datasets (probands and individuals) in the last generation in reference to the start parameters. We found out that this variance remains relatively constant. There is only a small decrease, which could conservatively be interpreted as an indicator for an only slight convergence with regard to a global optimum. Interestingly the decrease (53 %) that is still the highest can be shown for the implicit optimization while the decrease for explicit (33%) and in particular for the combination of both methods is quite low (17 %) and widely scattered.

4.2.1 *Subjective impression of convergence and subjective accuracy of convergence*

In addition to the data-based test for convergence, a subjective test is also carried out to check whether the test persons feel convergence and whether it is developing in the right direction subjectively.

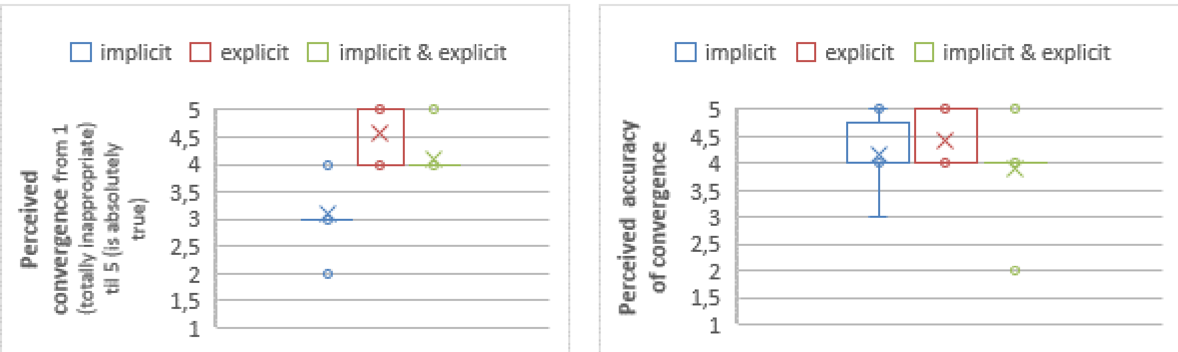

Figure 7. Subjective impression of convergence and subjective accuracy of convergence on the types of optimization

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The results show that the highest subjective perceived convergence and perceived accuracy of the convergence can be achieved for the optimization based on explicit evaluations as appropriate between rather accurate (4) and is absolutely true (5) for optimization on the basis of implicit evaluations. The subjectively perceived convergence is on average only indicated as "neither right nor wrong" while the direction of convergence is indicated as rather correct. The optimization based on the method set (implicit and explicit) is stated for both questions as rather correct (4).

4.3 Results and differences between the three types of optimization

In the following, the differences between implicit and explicit optimization as well as the combination of both will be shown in scatter plots of the last (7th) generation. The dots represent all solutions which are shown here in the three-dimensional space of fitness value and the two geometry parameters (bordersize and circlesize).

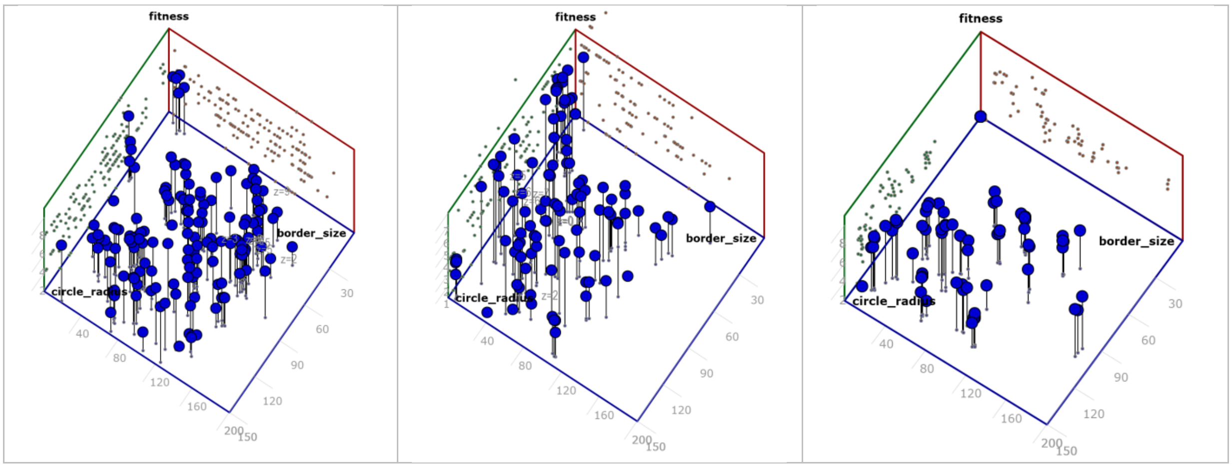

Figure 8. Results of different types of optimizations implicit (left) explicit (middle) and the combination of both (right) in a 3-dimensional scatterplot

Based on the optimization of several optimizations with 5 individuals per test person each, a lot of datasets were generated. Much larger amount of individual good designs than one might have imagined were created. The vast majority of these designs have their justification, but subsequently there is a need to find designs that a majority can evaluate as visually balanced. Therefore, a survey with given designs out of the last generation of all types of optimization with the same preference acquisition method (implicit and explicit) is placed on the same web app to choose the best design in each category of preference acquisition based on the same participants of the optimizations.

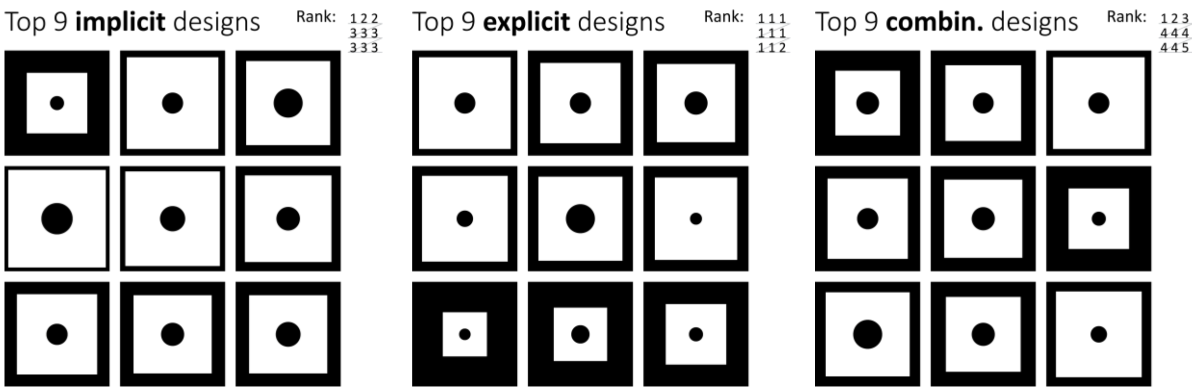

Figure 9. Presentation of the top designs out the three types of optimization

Overall, one can see in this presentation (Figure 9) that the results differ between implicit and explicit preference acquisition. Interestingly, a variety of different designs were given first place in the explicit preference listing and the variance s² is also higher here, so that one could suppose carelessly that aspects of taste may seem to play a stronger role in explicit than in implicit assessment.

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5 CASE STUDY FOR THE OPTIMIZATION OF PERSONAL SIGNIFICANCE OF VEHICLE FRONTS

In addition to the relatively theoretical example, a more typical example from automotive design will be used to illustrate the usefulness of such a tool and to query another attribute from the field of product semantics. The attribute to be considered in this case study is the degree of personal significance which means the correspondence of a vehicle design with one's own personality. Such a question, which deals with the relation to self-understanding and thus falls within the field of product semantics, can be regarded as an important factor in the purchase decision (Schwemmle, 2016).

5.1 Vector-based model generation

The approach in this case is to be as close as possible to the practice of the designers, as far as it is possible with the same simplistic optimization interface. The model was therefore created based on common vector graphic software and then exported as a Scalable Vector Graphics File (SVG). Within the SVG file, three points (A, B and C see Figure 10) of the headlights were parameterized as variables in order to make them controllable for the algorithm.

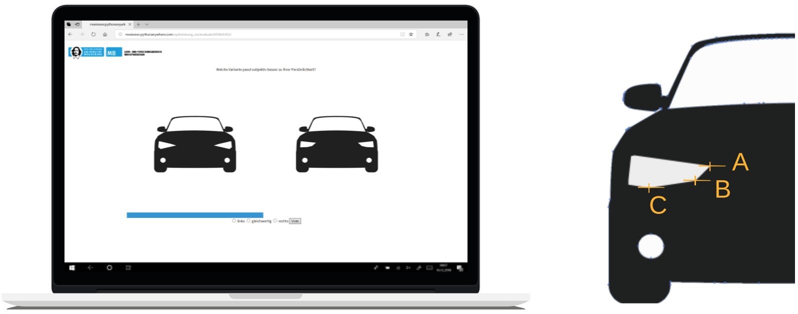

Figure 10. Evaluation page of the second case study and underlying vector model

5.2 Convergence test

Also in the second case study,convergence is evaluated in a data-based analysis with eleven subjects for all three types of optimization. By analyzing the average change of the geometry parameters (Figure 11) it is observed that of all three types of optimization, one based on the combination of both detection methods most stable converges followed by optimization based on explicit detection. According to this analysis method a convergence can be observed.

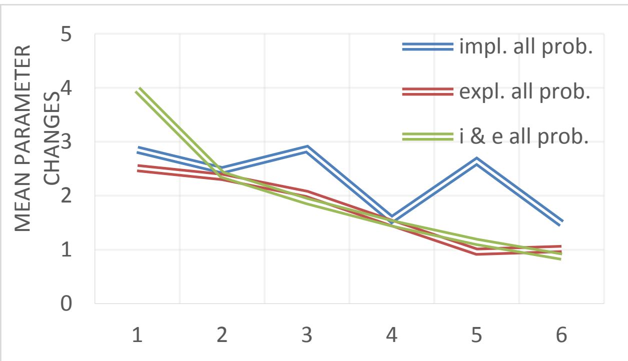

Figure 11. Mean parameter changes of all probands of all parameters for the three types of optimization

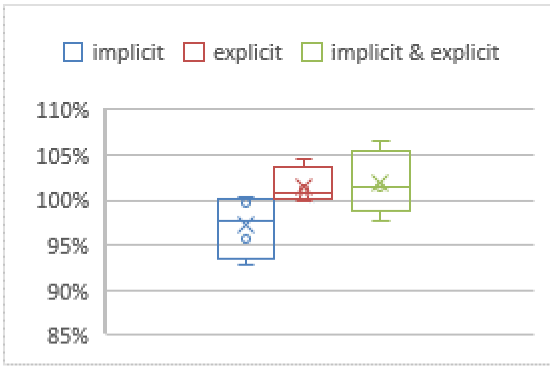

Figure 12. Mean relative variance s² in % for all probands and individuals in the last generation

In figure 12 it shall be analysed whether the individual optimization results are aligned between different probands and whether these differences between the designs of the first and last generation decrease. The percentage value thus refers to the difference to the similarity of first and last generation across all probands. This result does not come as a surprise with the specific question of personalisation of vehicle design.

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6 SUMMARY AND OUTLOOK

In this article, a new approach to interactive optimization is presented for the first time and details of its design are explained. The convergence properties are presented on the basis of two case studies. In all three types of optimization (implicit, explicit as well as the combination of both), the solutions converge except for the second test scenario in the second case study for variance across multiple subjects. The implicit optimization seems to converge somewhat more unsteadily, but the overall variance is even the lowest in the last generation in both case studies. For further investigations with significantly more test persons it might be interesting whether the variance of implicit optimizations is generally lower than with explicit optimizations for different test persons and for which design dimensions (here e.g. personal meaning) one cannot assume a general optimum. As shown in section 4.3 both optimization methods differ from each other in their results so that neither type (implicit or explicit) could replace the other, and our hypothesis is that the combination of both provides a more comprehensive picture of consumers preferences and the most continuous convergence rate. However, with this combined optimization there are still large differences in the overall variance across all test persons, which must be investigated further. This contribution is only the start of many further research activities in this environment. It is certainly worthwhile to optimize the defined parameters of the own PSO-inspired algorithm in detail. Also in preference acquisition there are some parameters that can be further analyzed and potentially be adjusted. Furthermore an abort criterion based on convergence shall be defined in order to avoid too short optimization runs without convergence and on the other hand to avoid an unnecessarily tedious burden for the test persons. Since it is planned to continue working on the combination of implicit and explicit preference detection methods within interactive optimization, such an optimization should be tested in the next step on the basis of multi-criteria algorithms. In addition to the optimization of 2D geometries, it is also planned to optimize 3D CAD models in further case studies. Finally, the integration of such interactive optimization strategies regarding aesthetic and product-semantic specific criteria in combination with classical technology-driven optimizations such as stiffness seems to be another interesting research topic. It will also be interesting to investigate in which applications such an optimization approach is worthwhile. It is conceivable, for example, that customers could iteratively design their own products according to their preferences (keyword mass customization) or that these optimizations are used for very specific and tricky design problems that are difficult to overlook and strongly networked.

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