Automated design of vehicle silhouettes using genetic algorithms and statistical analysis

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Shrnutí
Tento článek popisuje metodu automatického návrhu siluety vozu. V průběhu historie vzniklo mnoho automobilů jejichž rysy jsou do značné míry podobné. Tyto rysy (siluety) můžeme extrahovat pomocí statistické metody analýzy hlavních komponent a použít je pro návrh nové siluety, která je dále optimalizována pomocí genetických algoritmů. Proces optimalizace zohledňuje zadané fyzikální parametry jako je objem prostoru pro motor, zavazadla a pasažéry. Výsledek produkovaný algoritem pak slouží jako inspirace pro člověka-designéra a může být zobecněn na vybraný typ produktu.

Klíčová slova:
návrh automobilů, styling automobilů, produktový design, styling, PCA (analýza hlavních komponent), genetické algoritmy, vývoj a návrh produktu

Abstract
This paper describes a method for the automatic design of vehicle silhouettes. Over the years many different vehicles have been created, but most of them share similar features. We can extract these features through statistical analysis (principal component analysis) and use them in creating the shape of a vehicle’s silhouette. To produce the new original silhouettes we utilize an optimization method (a genetic algorithm) which fits the new silhouette to the prescribed physical conditions, e.g. space for the engine, space for the passengers etc. This algorithm serves as a source of inspiration for human designers and can be generalized to produce many kinds of products.

Keywords
vehicle design, vehicle styling, product design, styling, PCA (principal component analysis), genetic algorithms, Design and Product Development

1. Introduction and problem statement:

This paper focuses on the use of computational mathematics to create a valuable contribution to vehicle design and styling. The strong design potential of the computer was considered with interest in the 60s (Alexander, 1964). Alexander observes that although many design tasks have a lot of variables (product
requirements), there is only one ideal solution. The quantity of the variables (product requirements) is a problem that a human designer overcomes through personal experience and habits. Of course, it is not feasible to check all the possibilities, and this is why the best solution will never be found. Therefore the author suggests using a computer in a specific way. It is clear that the role of the computer is important, and this was true even in 60s. It is not a question of whether to use a computer or not. The point of Alexander’s ideas rests in the question of what to use it for. He noted that there are some common tasks that a computer is ideal at dealing with, but nobody uses it.

Problems like these exist in computational aesthetics, and this topic still gives rise to animated discussions about aesthetics and its possible computability. In the 70s Stiny and Gips (Stiny et al., 1972) brought Shape Grammars into the discussion. They used a logical structure of rules to define how new artwork, such as a painting or sculpture will look. Stiny and Gips have many followers. Seth Orsborn et al. are known in the field of vehicle design and styling. Firstly they defined how principal component analysis (PCA) can be used for evaluating product shapes and the relationships between them (Orsborn et al., 2008, Identifying Product Shape Relationships Using Principal Component Analysis). Later they employed the shape grammars to build orthogonal views of vehicles (Orsborn et al., 2008, Automating the Creation of Shape Grammar Rules) and they also developed a method for quantifying the customer’s aesthetic form preference (Orsborn et al., 2009). The computer as a tool for designers can be used in the sense of Computer Aided Styling (CAS), for example 3D applications in combination with marketing research tools (Lin-Lin et al., 2007), or enhancing 3D modeling using tools for extracting curves from sketches (Kara et al., 2006) (Lin et al., 2004). Thus the computer can contribute to creating an idea or new design.

This paper provides a contribution to the realization of the idea. Every new product has many predecessors and the designer makes choices as to which features of the predecessors will influence his new product. It is not possible for the human designer to extract all these features in an exact way, even if the number of the chosen samples (inspirations) is significantly reduced. Our main goal, presented in this paper, is to develop a methodology for the exact consideration of inspirations for a new design and to verify it with a working example.

2. Analysis of the stated problem

The design process for a new product involves taking the product's history into account. The designer faces the problem of selecting suitable features of its predecessor and integrating them into the new composition. We propose a novel method, based on principal component analysis and genetic algorithms, for an algorithmic treatment of such tasks. A proper understanding of the algorithm requires us to state our interpretation of the design process and define the opportunities for its computational improvement. For the sake of simplicity, we describe the design process as a sequence of objectives, which we will also use as a basis for prescribing suitable conditions of the algorithm.

2.1 Design process without any algorithm:

1. A human designer considers his inspiration (consciously or not) and defines the vehicle shape by free hand (applying some features of predecessors into the new design).
2. The shape is fitted to the correct dimensions with respect to the product’s architecture (Chin, 2004). The architecture can be represented by simple shapes defining its volumes and spaces (a package).
3. Design finishing using an arbitrary method.

2.2 Design process including an algorithm:
1. Defining the product (a package) architecture. Collecting samples of the product’s predecessors.
2. Running the algorithm and determining a new silhouette in the correct scale.
3. Design finishing using an arbitrary method.

2.3 Vehicle silhouettes, extracting of a silhouette:
The majority of a vehicle’s visual aspects can be seen from a side view, where the silhouette plays the key role. Dealing only with one silhouette, represented by a curve, reduces the complex design task to a simple form and allows us to start to develop an effective algorithm.

The design style of vehicles can be divided into two basic categories, evolutionary and revolutionary (Tumminelli, 2006). Those two kinds can by ramified by different approaches as rational or emotional.

The problem of classifying the design style is in fact more complex, but for this paper it is important to describe only evolutionary and revolutionary kinds.

- **Evolutionary design:** A designer considers obligatory needs (utility, ergonomics, economy, ecology, aesthetic, etc.) and aims to achieve an original and aesthetically well balanced product. Every new design carefully adapts features of all its predecessors in history. For an example see Figure 1.

*Figure 1:* Example of evolutionary design.
*Obrázek 1:* Příklad evolučního návrhu.
● **Revolutionary design:** A designer also considers all the needs relating to the essence of the product. A deep rethinking can give rise to fundamental innovations and originality of design. The predecessors are chosen arbitrarily by a designer. For an example see Figure 2.

**Figure 2:** Example of revolutionary design.

**Obrázek 2:** Příklad revolučního návrhu.

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3. **Statistical analysis of silhouette curves**

Several methods can be used to analytically describe a plane curve. The popular methods include description by Bezier curves, by splines or by a series of space coordinates connected by straight lines. We approximate our curves by the continuous connection of linear vectors (see the example in Figure 3), where each vector contains two real-valued components (increments on the perpendicular axis of the plane). For instance, if we have one hundred vectors we have two hundred real numbers which define a curve in the plane. From the statistical point of view, these points form a random vector with two hundred dimensions. The components of the random vector are not independent, but they have some strong correlation between each other. The highest correlation is between components which define close plane vectors of the curve.

**Figure 3:** Example of used method of statistical analysis of vehicle silhouette.

**Obrázek 3:** Příklad použité metody statistické analýzy siluety vozidla.
Not all the possible curves in the plane look like vehicle silhouettes. The key idea is to define a few real vehicle silhouettes and find correlations between their vector descriptions. Afterwards, the subclass of all the curves which have similar correlations to real vehicles is considered to be the set of all the possible vehicle designs.

Principal component analysis (PCA) is a convenient statistical method for describing a set of vectors with given correlations. It identifies linear combinations of the vector components where the obtained outcomes have the highest variance. The obtained linear combinations are called principal components and they are, in fact, transformations of the initial space into the space with the new basis. In general, the method gives the same number of components as the initial space has, but most of them have very small variance and therefore they can be omitted without substantial loss of information. Each of these principal components is independent and uncorrelated with each other. This lets us set the most significant components to arbitrary values, neglecting the unimportant components, and by inverse transformation obtain a vector from the initial space with similar correlations to the original elements.

Mathematically speaking, the linear combinations are represented by the eigenvectors of the covariance matrix and the variances of their transformations are their related eigenvalues.

Let us denote a matrix of the original data as $X$, where its rows are particular elements $x_i$ and columns are their components. The vector $\mu_X$ represents a mean of each column in matrix $X$.

Matrix $B = X - \mu_X$ is then a normalized data matrix and $v_i$ are its eigenvectors with corresponding eigenvalues $\lambda_i$. If the eigenvalue $\lambda_i$ is greater than 1, we consider the eigenvector $v_i$ to be the significant principle component. Matrix $W$ composed of the significant components is the transformation matrix and its transposed matrix $W^T$ represents the inverse transformation.

Now, if we have some element $x_{orig}$ from the original space, we can transform it into the new space by $x_{transf} = (x_{orig} - \mu_X) \cdot W$. Conversely, an element $y_{transf}$ from the principal component space can be transformed to the original space by $y_{orig} = y_{transf} \cdot W^T + \mu_X$. For more details about the PCA method see (Johnson, 2007).

3.1 Algorithm for identifying an appropriate vehicle silhouette

The subspace of all curves which look like vehicle silhouettes is described by several real numbers related to the principal components. Now, the main question is how to choose a curve which satisfies our prescribed constraints. The constraints include smoothness of the curve, adhering to required dimensions, etc. Most of these requirements have a strong nonlinear character and therefore it is nearly impossible to obtain an accurate solution. A class of algorithms capable of giving sufficiently good solutions are soft computing methods. These methods are usually based on some heuristics and artificial intelligence approaches. We selected a genetic algorithm designed for searching for numerical vectors with predefined properties.
The main idea of the genetic algorithms is based on Charles Darwin’s theory of evolution. This theory states that a population of some species is adapted to its environment by producing new better individuals. The more adapted the parents are, the better offspring they can produce. Thus the genetic algorithms try to mimic this evolutionary process and use it for solving computationally complex problems. At the beginning, the algorithm creates a set of random candidate solutions (population of species), and by choosing a pair of high quality individuals (parents) it produces new solutions (offspring). If the new offspring is better than some individual in the current population, then the old one is deleted and replaced by this newly produced solution. The algorithm repeatedly produces new individuals and thereby the population improves with each iteration. The final solution is the best individual discovered during the whole algorithm run. The genetic algorithms have many variations and for a more precise description see (Yang, 2008).

3.2 Utilized algorithm
The initial step of the whole procedure is to create a few vehicle silhouettes and compute all the necessary parameters using the PCA method. The set of all the silhouettes will serve as a database for new vehicle designs. Our implementation approximates each of these silhouettes with one hundred real vectors (similar to Figure 3) and the sequence $x_i$ is obtained from the components of these vectors. Then the matrix $X$ is constructed by putting all the vectors $x_i$ into separate rows. Finally, the matrix $W$ of $n$ principal components is computed using a PCA algorithm for the created matrix $X$.

Now the aim of the algorithm is to find the curve which is as close as possible to the predefined package and which has similar properties to the cars in the database. This can be achieved by the aforementioned genetic algorithm used in the space of principal components. At the beginning, a few initial curves are randomly created and then the new curves are produced by one-point genetic crossover (combination of random parts of two selected curves) (Yang, 2008). The mutation is performed with the probability at 0.05 such that one of the principal components is randomly changed to a new value.

All these operations are carried out in the space of principal components, i.e. the curve is represented only by $n$ numbers and for verifying its quality it is necessary to transform it back to the initial space. The transformed curve is obtained by multiplying the principal components by $W^T$ and its fitness can be computed by comparison with the defined package. We use the Hausdorff metric for quantifying the proximity between the curve and the package, defined as a maximum of Euclidean distances between each point of the curve and the package. The other important conditions, laid down on the curve, are that none of its points can be inside the package (see Figure 4) and also its smoothness should be sufficiently low (minimum number of points of inflection). The objective is therefore to minimize a linear combination of the Hausdorff distance, the number of points inside the package and the number of points of inflection.

The algorithm ends when the quality of the best curve is satisfactory or when a predefined number of iterations is reached.

The following pseudocode describes the algorithm:

$X = $ matrix of approximated silhouettes (one row is one silhouette).
$W = $ computed matrix of principal components by PCA algorithm from $X$.
$n = $ the number of the principal components
$population = $ set of 70 randomly created real vectors of length $n$
while termination is not met
    $parents = $ select two vectors from the population
offspring = crossover the parents and produce one new vector
with low probability mutate the offspring
new_silhouette = \hat{W} * offspring
compute the fitness of the new_silhouette (proximity + inside
points + smoothness)
if the fitness is better than some other member in the
population, then replace it.
End while
4. Experiments
We conducted several experiments belonging to two categories with different objectives. The first category contains experiments on the evolutionary method of design, and the second category on the revolutionary method. The evolutionary experiments compared two different brands of standard vehicles on the same package. We took ten samples from both brands and let the algorithm evolve a new design for each brand separately. Unfortunately, the obtained results did not meet our expectations. They did look different for each brand, but did not have the appropriate quality of a standard vehicle design. The results of experiments from this category are not intended to cover the history of the predecessors, but rather only some chosen samples.

The experiments from this category can briefly be described as follows:

- We take ten different vehicles into account (chosen silhouettes) and these vehicles form a group of the initial patterns for our experiment.
- We create a package (the physical conditions) and ran the algorithm (PCA + genetic algorithm).
- The obtained curve is finished using standard designing procedure.

Description:
The first step of the algorithm is to choose the set of predecessors and convert them to the same scale and form suitable for the algorithm. The chosen samples are shown in Figure 5; these vehicles are mainly experimental and innovative cars developed in the recent past.
The package, describing the physical conditions for the new design, is shown on the left side of Figure 6. It is represented by a poly-line and graphically specifies a space for passengers, an engine, a trunk etc. The algorithm finds nine principal components of the initial samples, and by setting them to the new values it creates a new curve displayed on the right side of Figure 6.
Each particular algorithm run can produce a different curve, and a few samples are shown in Figure 7. A human designer has a few computed results and he can select the one which inspires him the most. In simple terms, these results represent the initial samples melted down according to the dimensions of the defined package. We selected one most inspiring result (result 7 in Figure 7) and continued manually with the sketching and designing in 3D software.

**Figure 7:** Examples of vehicle silhouettes generated by different algorithms

**Obrázek 7:** Příklad siluet vozidel vygenerovaných různými algoritmy

Figure 8 shows the sketch made on the basis of result 7 with an LCD tablet. Although the curve on the back side runs unexpectedly far from the package, it was also an inspiration for us and we used it for presentation of a trailer concept behind the vehicle.

The next step after making the sketch was to model the vehicle in 3D. Figure 9 shows a visualization of the experimental vehicle for individual urban mobility and it represents the final result of our experiment.
Figure 8: Sketch inspired by the algorithm’s curve
Obrázek 8: Skica inspirovaná produktem algoritmu

Figure 9: Final design - virtual 3D model to scale
Obrázek 9: Výsledný design – virtuální 3D model v měřítku
**Figure 10:** The left side shows a comparison between the predefined package, automatically generated curve and the created sketch. The right side represents a comparison of the package, the generated curve and the final design.

**Obrázek 10:** Na levé straně je vidět porovnání mezi předdefinovanou obálkou, automaticky vygenerovanou siluetou a náčrtem vozidla. Na pravé straně obrázku je srovnání obálky, vygenerované siluety a konečným uspořádáním vozidla.

The experiment has three phases described graphically in Figure 11. The first phase translates predecessors’ features to the innovative shape. In the second phase we (human designers) choose the most suitable silhouette and create sketches, which are usually at the beginning of the design process. The last part represents an arbitrary kind of finalization; in our case it is the creation of a 3D model.

**Figure 11:** Graphical representation of different phases of design process.
**Obrázek 11:** Grafické znázornění různých fází postupu návrhu.

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**5 Conclusions and further research:**

This paper deals with the process of evolving a new vehicle design. Our main objective was to answer the question of how exactly to consider inspirations for a new design and obtain useful shapes - vehicle silhouettes that serve as a source inspiration for human designers. The proposed method is part of the creative work and provides original results arising from two main aspects:

1. What is known about the product’s look (considering the history and predecessors)
2. What new conditions have to be met (defining a package)
A human designer usually starts with new ideas on a blank sheet of paper. His inspiration comes from the depth of his mind and it makes the development process subconscious. The method we presented in this paper contributes to the process of designing a new product usually handled by a human designer. Using the algorithm leads us through a conscious process to new original silhouettes, which are statistically influenced by the character of their predecessors. The obtained results provide inspiring patterns to help the human designer with innovative design.

Future research will focus on the process of obtaining samples. We envisage having an application with automatic image recognition, where the user just uploads his data (as bitmap images) and the algorithm automatically processes their features and evolves a new vehicle silhouette. Further progress can be made in incorporation of other analyzed features, such as window shapes etc. We have been thinking about 3D applications, but this needs a huge database with accurate data. Since we have developed a method for analyzing a given set of samples, there is still a big challenge to find out how to obtain samples and how to consider the quality and suitability of results.

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References:


HEURISTIC STATISTICAL GENERATION OF GRAPHICAL CURVES

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Abstract: This article presents an algorithm that generates graphical curves with properties corresponding to a given set of patterns. The algorithm statistically extracts features from the sample curves and combine them to get the new curve with a new innovative style. The algorithm has very general nature and can be utilized for any kind of continuous curves. We demonstrate its functionality through designing new car silhouettes based on a set of a few common contemporary automobiles. The main tool for the initial statistical exploration is the principal component analysis and the creation logic of the new curves is controlled by a sequence of tabu search methods.

Keywords: heuristic design, tabu search, principal component analysis, graphical curves

1 Introduction

The main purpose of our algorithm is to bring innovative ideas into the designing shapes of new products. When the classical designer creates new product shape (a car, a teapot, a furniture, etc.) he has to take into account various important aspects. Among the most significant aspects are the fulfillment of the product functionality and innovative attractiveness of its visual design. The former is highly individual for each product and cannot be generalized, but the latter usually comes from the historical evolution of similar products and can be automatized by our presented algorithm.

Automatization of designing process has been previously studied from several perspectives. One important way of automatic design is by fulfilling some prescribed physical requirements (e.g. optimal wing shape by evolutionary algorithms [1]) but this way requires detailed insight into the designed product and create its parametrization. Another way is focused on designing visual aspects without consideration of any physical constraints. Among these algorithms, which serve as a new source of inspiration, can be, for example, put a work incorporating genetic algorithms [3] or shape grammar [4] or their combination [5]. Our presented algorithm can be also viewed as an approximation algorithm and therefore it can be compared with some traditional methods like Bézier curves or NURBS [2]. But the main difference is that the algorithm proposed here produces only curves with required shape characteristics, in contrary to the traditional methods which generate curves with no explicit relationship to the designed products.

The article is organized as follows. The second section sketches the main idea of the algorithm and the further sections three explains how the main utilized theoretical tools work (PCA and tabu search). The more detailed description of the algorithm is in the section four and its demonstrated experiment shows the section five.

2 Algorithm Outline

To generate the graphical curves we need to determine which features the new curve has to have. Not every curve can represent a vehicle (or any other designed product) and therefore we need to explore only a small subset of all the possible curves. Thus the first step in the algorithm is to extract important features from the products with similar shapes to allow us to deal only with the curves which look like a vehicle (or any other designed product). Very general way for solving this task is to use multivariate statistical method known as principal component analysis (PCA). As same as all the other statistical methods, the PCA processes a numerical dataset and therefore we need to transform the graphical curves into it. So every curve from the set of similar shapes is approximated by the same given number of small linear vectors (see example in Figure 1), and therefore we can create a dataset with rows representing the particular curve and columns representing the relative coordinates of the computed vectors.
The obtained dataset will have many dimensions (columns) and the PCA method allows further transformation from this high dimensional space to the space with much lower number of dimensions. Every curve from the given set can be therefore represented by only a few numerical values and its graphical form can be easily obtained by an inverse transformation. The generation of new curves is then provided by finding new values for these few parameters and the subsequent inverse transformation assures that the outcome curve has similar look like the initial set.

Usually a classical designer does not create a new product shape without defining any prior physical requirements (height, length, rough proportions, ...). For this reason our algorithm lets the designers define a set of points which the new curve should go through. This allows roughly shaped the required outcome and the algorithm therefore only fills the gaps between the defined points.

To obtain the course between each consecutive pair of the defined points, the algorithm splits the whole curve into corresponding subparts and computes them independently. The algorithm then only needs to find a suitable curve which starts and ends in the defined points and by sequential computation of all the separated parts it produces the whole new curve. The finding of a suitable curves which connect the defined points are performed by tabu search algorithm in the space of principal components obtained by the PCA method. After the initial random guess of these components the tabu search optimizes them in such a way that the inverse transformation (the graphical representation) fulfills the connection criterion.

3 The main tools in the algorithm

3.1 Principal Component Analysis (PCA)

The Principal Component Analysis is one of the main tools used in multivariate statistical analysis. Its fundamental intention is to uncover hidden relations in the given dataset and thereby significantly reduce the dimension of the explored problem. Mathematically speaking, the PCA is an orthogonal linear transformation such that the new coordinate system reflects magnitude of the variance in the data. The new coordinates are called the principal components and the projection with the greatest variance lies on the first of them, the second greatest variance is projected on the second principal components and so forth. The number of principal components is the same as the number of dimension in the original data, but by omitting the new axes with the lowest projected variance, the dimension of the new space can be reduced without significant loss of information. For the dataset represented by a matrix $D_{m \times n}$ ($m$ samples with $n$ values), the PCA computes the transformation matrix $A_{k \times n}$ ($k$ principal components) which can be used to transform a sample $c_{n \times 1}$ to the vector $v_{k \times 1}$. The inverse transformation is computed by the inverse transformation matrix $A^{-1}$.

$$
\begin{align*}
v_{k \times 1} &= A_{k \times n} \cdot c_{n \times 1} \\
c_{n \times 1} &= A^{-1}_{n \times k} \cdot v_{k \times 1}
\end{align*}
$$

The PCA method is explained in the most of the multivariate statistics textbook (for instance in [6]) and the reader is referred there for more detailed description.

The most important feature of PCA for our algorithm is that it can allow us to describe the graphical curve (divided into a set of many linear vectors) by a small number of new principal components. The transformation itself therefore contains the general shape properties of the given graphical samples encoded into the transformation matrix $A$.

3.2 Tabu search

Whereas the PCA provides a method for drawing a curve from a few given numbers (the principal components), the Tabu search algorithm is used for finding those values which lead to the most suitable curve. The Tabu search algorithm was created by F. Glover and is detailed described in [7]. It belongs to the class of metaheuristic algorithms and therefore its main purpose is to iteratively explore the space of all possible solutions and try to
find the best possible one. The algorithm starts with randomly generated solution and evaluation its quality by an objective function. In our implementation the objective function takes the values of principal components and by inverse PCA transformation computes the corresponding graphical curve. Then, the objective value is the Euclidean distance between its end point and the required one. If the computed objective value is not within the given tolerance then the algorithm evaluates a few other curves with slightly modified principal components (neighbourhood of the current solution) and the best one is taken as a next starting solution. The algorithm stops either after predefined number of iterations or if the solution reaches the desired quality.

The main reason for incorporating the Tabu search into our algorithm is that the curves are deformed continuously with respect to their principal components and therefore the local search algorithms, like Tabu search, is effectively able to find the suitable solution.

4 The algorithm description

A brief outline of the presented algorithm is described in the section 2 and this section extends it to more accurate form. The first part of the procedure consists of the analytic extracting important features form the initial samples. The given curves are approximated by constant number of linear vectors and flowingly processed by the PCA method. Thereafter the splitting points are computed. These points can be modified by a designer to influence the final shape of the designed curve. Although they can be generally chosen arbitrarily, it is wise to use some traceable way. One such way is described by Pseudocode 1

Pseudocode 1: the heuristics for obtaining the splitting points

1. create a dataset from the whole graphical curves
2. compute PCA of the dataset and obtain the transformation matrix $A$
3. denote one of the sample curve as $c_1$ and compute its projection $v_1 = A \cdot c_1$
4. multiply the first principal component (the highest variability) of $v$ by -1 and compute the corresponding curve $c_2 = A^{-1} \cdot v_2$
5. compute Euclidean distances for all corresponding points between curves $c_1$ and $c_2$
6. find $k$ splitting points (local extremes or points of inflection) of the computed distance function

The splitting points obtained by the aforementioned heuristics are the points which maintains the roughest shape of the curve. The course of the curve between these points can be found by heuristics described in the following Pseudocode 2

Pseudocode 2: for each consecutive pair of the splitting points $p_n, p_{n+1}$ do

1. compute $\Delta x_{n,n+1}, \Delta y_{n,n+1}$ - the distances between the coordinates of $p_n$ and $p_{n+1}$
2. create a dataset $D_{n,n+1}$ from the initial sample curves by considering only the parts between $p_n$ and $p_{n+1}$
3. perform the principal component analysis on the $D_{n,n+1}$ and compute the transformation matrix $A_{n,n+1}$
4. $\max_i, \min_i = \text{maximal} (\text{minimal})$ values of the principal component $i$ among all the initial samples
5. randomly generate vector $v$ (the values for all the principal components) from the uniform distribution $U(\alpha \cdot \min_i, \alpha \cdot \max_i)$

6. by the inverse PCA transformation compute its corresponding curve $C = A^{-1} \cdot v$

7. compute the distances $\Delta x_C$, $\Delta y_C$

8. if $\sqrt{(\Delta x_C - \Delta x_{n,n_1})^2 + (\Delta y_C - \Delta y_{n,n_1})^2} < \varepsilon$ stop the algorithm and return $C$

9. generate a set of neighbors for the vector $v$ by small modification of its components

10. select acceptable vector $v_j$ with the smallest value of $\sqrt{(\Delta x_{C_j} - \Delta x_{n,n_1})^2 + (\Delta y_{C_j} - \Delta y_{n,n_1})^2}$

11. $C = C_j$, $v = v_j$ and update the tabu list by $v_j$

12. go to step 8

The steps 8-12 describe standard tabu search algorithm with maintaining usual tabu list. There can be used any other optimization heuristics instead of the tabu search, but the important is to use only local search, not the global one, to preserve features included in the actual curve.

The parameter $\alpha$ used in the step 5 controls the innovativeness of the designed curve. The value $\alpha = 1$ causes generation of the curve within the boundaries given by the initial samples. But higher values (e.g. $\alpha = 1.5$) allows the principal components to exceed the initial boundaries and therefore it allows higher variation in the curve design. It must be said that too high values give rise to undesired shapes which are too far away from the intended goals. Our recommendation is to use the values $\alpha \in (0.5, 1.5)$.

5 Experiment and discussion

The algorithm was tested by designing car silhouettes based on a set of 10 automobiles of the similar types (shown in Figure 5). Each silhouette was approximated by 100 vectors.

![Figure 5: The sample curves.](image)
The computed results have several important features and interpretations. The most obvious feature is its ability to combine shape of various initial silhouettes and therefore it is able to produce a kind of average vehicle. The principal components of the new curve determine its analogy with the initial samples and particularly the first components play the most dominant roles in the forming of the shape. At the first sight, the Figure 6-a looks like one of the initial samples, but in fact, it is not one of them and it only shares the values of the principal components and therefore the correlations arisen from the inverse transformation.

By moving some of the controlled points far from the usual position we can obtain new curves with preservation of the relationships given by the initial samples. In other words, it answers the question – how would the car silhouette evolves, if the designer's requirements be significantly changed. The Figures 6-b,c,d show silhouettes of such vehicles and represent the innovativeness brought by statistical analysis. All these effects can be combined by simultaneous moving the controlled points to get the final shape of required quality. An illustration of a simple vehicle with new features arisen from the algorithm is shown in Figure 7 and for better impression it is completed by an undercarriage and wheels.

6 Conclusion

This paper presents a simple method for creating graphical curves. The general class of the curve is defined only by a given set of samples and consequent designer’s requirements are tailored by controlling positions of a few splitting points. The algorithm does not need any prior parametrization of the curves, because it extracts all the necessary information by the principal component analysis.

The algorithm is demonstrated on the example of designing vehicle silhouettes and it successfully shows its ability to produce new curves with required properties. The utilization for this algorithm can be either in bringing new ideas by randomization of the designing process or in modification of current shapes by unusual requirements. Many designers faces to tasks that are based on the adapting their curves to the new demands or to the actual trends and the presented algorithm is able to encompass these needs by a few simple steps. Due to the tabu search operates in the space of principal components, it is ensured that the final curve will always have similar features like the initial sample set and therefore they will be from the same class. This feature makes
the greatest difference with respect to the traditional methods for generating curves (Bézier curves, splines, NURBS, ...).

Our example was based on 10 similar sample curves and further extension of this initial set would bring new possibilities. For instance, the initial sample curves can be selected from wider range of vehicle silhouettes (not only one kind of vehicles) and therefore the matrix $A$ obtained by PCA analysis would contain information about more general class of vehicles and consequently newly produced curves would not be so similar to each other but rather more heterogeneous.

Moreover, incorporation of actual trends could be easily done by adding new trendy curves among the initial classical samples and all of the consequent computations naturally encompass it. The algorithm also allows straightforward extension for 3D applications. Other possible implementation areas can be addressed to off-line recognition of noisy shapes (e.g. handwriting text or image reconstructions). Investigation of these possibilities will be the subjects of the further research, as well as determination of the limitations and extensions for the proposed designing application.

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References


Developing of the manipulative sketch generator for the product design

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Abstract: The parametric sketch manipulator, presented in this paper, provides solution for decision making in the process of evaluating a new design concept alternatives. This helping tool for designers is based on statistical analysis of the predecessors and takes in to account a physical conditions prescribed by designer. Pictorial representation of the output is not only a source of inspiration for further designer’s work, but can be even used as pre-sketched draft, dedicated for manual retouching by designer. The wide scope of this article is computer aided methods of dealing with formal-aesthetic tasks.

Keywords: product language, design, styling, formal-aesthetic tasks, computer aided styling (CAS), design and product development, design reasoning, inspiration, active appearance model (AAM), principal component analysis (PCA), genetic algorithms

1. Introduction

According to conceptual model of the Offenbach theory of product language [4], which was originally presented by Gros, product language (sensual functions of the product) can be distinguish to semantic and and formal aesthetic functions. Design can be understood as dealing with formal-aesthetic tasks. Depend on the kind of dealing; we can distinguish it in conceptual and stylistic ways.

One of the first efforts in this field was developing and using shape grammars [5] influenced also fine arts and it is also dealing with aesthetic aspects [6]. Shape Grammars are formalism provides base for many later investigations and practicing in exploring product language in brand identity defining [7].

Shape of the composed solution is usual, but not always strictly rectilinear. It can be also represented by cubic Bézier curves to achieve freeform shapes [11] dedicated to organic product forms. Exploring of rules for shape grammars can begin with investigation how sketches arises [8,9]. Authors accomplish an empirical study of guiding principles in sketching to obtain guidelines leads to shape grammar rules. First they concerned on participant’s design movements to gain sequence of the sketch transformations. Secondly they clustered sketches form each participants into design families, represents alternatives with different features and

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finally they got and tested seven general rules (like outline transformation, structure transformation, substitution of the element, etc). Research proved ability to describe shape transformations along sketching process and shows, how this can be used by designer while exploring new ideas through shapes [9,12]. Those methods, based on shape grammars, may serve for conceptual design purposes, if it is able to produce results through design families (to provide new design language possibilities). On the other side, there are methods dealing with pure style. The stylistic approach are mainly part of the field called computer aided styling (CAS) or computer aided aesthetic design (CAAD) which is often beside of computer aided design (CAD) as tool for implementing aesthetic aspects into modeling while creating 3D geometry [14]. It assumes a few conditions as formalization of verbal terms [15], which enables facilitating automatic optimization of modeling procedures by global shape modeling modifiers. Finally we can conclude, that there are methods provides tool for decision making in design process or optimizing product’s features.

2. Problem statement

Methods, using shape grammars, are based on composition of pictorial fragments; therefore we can see it closer to the conceptual formal-aesthetic approach then only styling. This statement seems to be promoted by Prats: “If the previous set of transformations is replaced by a different set of transformations, then a new design family is formed.” [10]. Later efforts in automated creating shape grammar rules [3] shows using statistical analysis (principal component analysis - PCA) to describe features of the predecessors. Anyway the output has finally typical set of lines and arcs, which could be handled by mentioned cubic Bézier curves [11] to obtain smoother results. The idea of having natural smooth curves leads us to employ PCA’s strong potential in dealing with exact shapes and using genetic algorithms to obtain smoothed silhouettes [13]. The solution like this is characterized by noticeable distance from result of the algorithm to the final product. Motivation for the research presented in this paper was to shrink this gap by creating free form shape and texture generator (sketch generator). Design tasks are often ill-structured and catching the best solution is tough decision making problem. Our goal is to provide contribution into solving of the formal-aesthetic tasks between computer aided styling and decision making methods.

3. Shape and texture generator (method)

Shape and texture generator is considering predecessors described by initial set of curves and manually created sketches. The first step in our algorithm is to generate vehicle silhouettes suitable for further processing. The silhouette must fulfill several constraints required by designers. Firstly, it has to preserve features from the initial set of curves (see Figure 1) and secondly, it has to respect desired physical proportions.

Fig. 1. Initial set of curves.
A designer can determine these proportions by drawing a few rectilinear shape (package) which will be contained entirely inside the final shape and the generated curve will embrace them as close as possible (see Figure 2).

![Figure 2](image2.png)

**Fig. 2.** Prescribed physical conditions (package – red line, solution – black line).

The silhouette is represented by a fixed number of straight line segments interconnected into one continuous curve. We divide the curve on 100 segments, to ensure smooth appearance of the silhouettes. The relative coordinates of the entire curve in the initial set form a statistical dataset representing features of the designed shapes. Further computation of the principal component method reduces this high dimensional space to only a few components, and allows us to deal with much lower complexity. The aim of this part of the algorithm is to produce a silhouette bounded by the given rectangular boxes. For this reason, we use heuristic optimization technique, called genetic algorithm, which find the best curve complying with these requirements. The genetic algorithm operates in the space of principal components and by systematic examination of various possibilities it iteratively searches for the curve with the highest quality. During each iteration, there are chosen several new values the principal components and corresponding silhouettes is computed by inverse PCA transformation. The quality of a curve is thereafter obtained by determining the highest distance between the curve and the required rectangular boxes. The curve with the smallest distance is the resulted silhouette. For exhausting description of this method, with an illustrative example, see [13]. The second step of the algorithm is generating the most suitable sketch for already existing silhouette. If we want to consider the texture as a sketch, it has to be generate from already existed sketches due to its strictly limitation to given silhouette.

![Figure 3](image3.png)

**Fig. 3.** Initial set of sketches.

For possibility of the designer to generate different sketches for given silhouette is the process of making sketches controlled only by the value of few certain parameters. As in input for already existing silhouette is used significant point representation of the shape with relatively entered positions. Each point shows significant location of the contour. Final sketch is represented by the model. For the process of making the model is used method called Active Appearance Model (AAM) [16]. This method requires training set of the sketches with geometric information for the description of their contour. The AAM method with using the principals of PCA makes the model of the sketch that only by changing values of limited
number of parameters generates different representations of the model. For itself generating of the texture is used pre-trained AAM model to which is given entered shape. The AAM model is a combination of the shape model and texture model and by changing the value of parameters is also changed the final shape and texture in the same time. That is way is the generated shape replaced by input shape. After this is the final texture generated only in the entered shape.

4. Results and working examples (manipulating)
For generating new sketches can be used two different ways. The first way is manual setting of the values of each parameters of the model of the sketch. Each parameter influences certain properties of the sketch. These properties come out with the basics of PCA, where each property represents certain components and parameters are ordered by the size of these components. The second way of generating sketches is automatically generate sketches and the core of this method is randomly setting of the value of certain parameters in given extent of the sizes of the components.

![Fig. 4. Interface of manipulative sketch generator.](image)

![Fig. 5. Results examples.](image)
5. Discussion - critical conclusions
The contribution of this method can be evaluated from stylistic perspective of the industrial design. Main theme to discuss seems to be a measure of the computational aesthetics’ contribution. However some efforts arose to support aesthetics in design process [1], we suppose that the major benefit consist in decision making process rather than improving aesthetic values. Our method is closer to the shape grammars perspective of generating alternatives and for that we can say: “the grammar alone cannot guarantee aesthetic results” [2]. Also the considering of predecessors by algorithm does not make any new aesthetic value initially, but it requires human act of understanding if the results match some context or not.

A particular problem in technical way of our method inheres in generating inside shapes. There is not robust solution, how to define correct relationships between each shape. Some issues reside also in the second part of generating sketch texture, which now requires manual selections of significant points of the shapes. Another issue and maybe the biggest one is the resolution of the sketch in term of quantity of shape information. Our method is accurate enough for the presented rough sketches, but it is not well suited for high detailed ones. Nevertheless described issues can be objective for further research.

6. Conclusions - summary
The algorithm implemented in Python programming language uses principal component method (PCA) for processing entered vector data that carry information about the shape of the sample products. To obtain a result that best fits to the specified parameters is necessary to find out suitable solution that follows accurate standards in a multidimensional space of principal components. For this purpose we used optimization metaheuristic that due to iterative steps in artificial evolution choose the best features and after a few tens of iterations finds desired solution. Solution obtained by this algorithm defines the shape of the new automatic design that becomes an input variable for the design of its bitmap fill (textures). For designing this kind of texture is used statistical method known from computer vision field as Active Appearance Model (AAM) that was adjusted for our purpose just to take only shape results from previous process that influence the final bitmap information. The process of analyzing input data (training bitmaps) was again based on the principal component method (PCA) but in this case was an analyzed object bitmap (hand-drawn sketches) divided by triangulation network. A new representation of texture in a specified shape we generated either randomly setting of values of principal component or their conscious modification.

We provided contribution in solving of the formal-aesthetic tasks between computer aided styling and decision making methods, by development of presented manipulative sketch generator. The motivation for using this tool should consist in its strength in complex problem solving.

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