CAPTURING USER AESTHETIC DESIGN PREFERENCES DURING MULTI-OBJECTIVE ROOF TRUSS OPTIMIZATION

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ABSTRACT

To facilitate the conceptual design of large-span roof truss systems, multi-objective optimization algorithms offer engineers a choice of potential design alternatives that meet rigorous standards in terms of allowable weight and deflection. Often, these algorithms operate independently of the designer until selection of a final alternative. However, incorporating a user's aesthetic design preferences into roof truss optimization may improve the process by capitalizing on a human user's ability to visually assess design effectiveness and by making the system more responsive to the needs of the designer. The current research effort develops a mechanism for capturing a user's aesthetic design preferences so that these preferences may be embedded into the optimization process. Development of the mechanism includes selecting a set of features to uniquely identify the aesthetic characteristics of a truss; choosing a clustering mechanism to perceive similarities between trusses and simplify the user input process; and creating an algorithm to extrapolate previous user evaluations into predictions of future preference.

KEY WORDS

multi-objective optimization, truss design, aesthetic preferences, user interaction, neural networks.

INTRODUCTION

Automated systems for large-span roof truss optimization seek to provide engineers with the flexibility to consider multiple alternatives during conceptual design while simultaneously ensuring that these alternatives remain structurally rigorous. This investigation extends previous work on multi-objective roof truss optimization to include the aesthetic design preferences of a human user. The overall design methodology uses an implicit redundant representation (IRR) genetic algorithm (GA) to simultaneously optimize truss topology, geometry, and member shape. While minimizing truss weight and mid-span deflection, the IRR GA generates designs in a sparsely defined search space.

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Although easily quantified, structural performance is not the only requirement placed upon large-span roof truss systems during the conceptual design phase. Constraints such as conformance to the architectural program, constructability, and overall economic feasibility may play equally important roles in selecting the final design. However, although such intangible criteria are often apparent to a human user based upon visual inspection of the design alternatives, formulating these constraints in terms accessible to the GA is mathematically intractable.

Teaching GAs to recognize these "intuitive" constraints would establish their efficacy for use in conceptual design. Not only would GAs be able to aid engineers by rapidly generating and identifying optimal structural solutions, they would also have the ability to autonomously assess the practicality of these solutions. Moreover, if feedback from a designer could provide information about practicality and aesthetic desirability, the GA could use this information to perform a user-guided exploration of the search space.

This paper will detail the development of soft-computing methods to capture a human user's aesthetic design preferences for incorporation into multi-objective optimization of large-span roof trusses. This research effort created a preference-recognition mechanism from the results of investigations into feature identification, classification mechanisms, and preference detection.

REVIEW OF RELATED LITERATURE

In recent years, researchers in various fields have made a concerted effort to engage the human designer during the automated design process. In multi-objective optimization problems, utility functions have been used to estimate a user's preferences and converge on a single solution most likely to meet these preferences (Al-alwani et al. 1993; Malakooti and Al-alwani 2002). Users evaluate pairs of similar solutions to help identify the boundaries of acceptable and unacceptable designs (Yang and Sen 1996). Utility functions are most often used to make decisions in terms of *trade-offs* between problem objectives (Al-alwani et al. 1993; Malakooti and Al-alwani 2002; Yang and Sen 1996)—that is, to determine the sacrifices in one objective a user is willing to make to improve performance for a second objective.

The current research, however, seeks to model a user's *aesthetic* preferences, and to use this information to encourage the development of more pleasing design alternatives while still fully satisfying structural performance criteria. Moreover, the goal is to present the designer with a range of equally viable truss alternatives, from which the most appropriate may be selected, rather than contract a multi-objective problem into a single proposed design. The search for appropriate tools, therefore, focused on examining previous efforts in interactive evolutionary computing (IEC).

Similar to the idea of weighted objectives used in utility functions, Furuta et al. (1995) created a GA to assess the fitness of trussed bridges based upon a designer's aesthetic preferences. These preferences were reflected in a-priori weight assignments to the variables of formative beauty, balance, and slenderness of the truss (Furuta et al. 1995). This work, like many others, considered only the satisfaction of aesthetic criteria, rather than overall structural performance.

While Furuta et al. (1995) collected user preference information before beginning the GA, many other studies interactively incorporate user preference throughout the simulation. Takagi (1998) provides a good summary of current IEC methods. Previous applications include computer graphics (Sims 1993; Graf and Banzhaf 1995) and automobile design (Petiot and Grognet 2002; Yanagisawa and Fukada 2004). In some cases, a CAD, or CAD-like, environment is used to create a range of products, from simple geometric shapes like cups or vases, to more complex entities, such as automobiles (Adelson 1998; Smyth and Wallace 2000).

Interactive GAs are popular tools for allowing users to guide design evolution. The interactive GA replaces the mathematical fitness function with human judgment (Takagi 1998). In most cases, this means users directly select the phenotypes to become parents of the next generation (Sims 1993; Smyth and Wallace 2000; Graf and Banzhaf 1995). The evolution is considered complete when the user is satisfied with the current design.

Other methods learn a user's design preferences in order to speed convergence towards an acceptable solution. This learning may take the form of rule-based expert systems (Adelson 1998) or rough set approximations of a user's "favored" features (Yanagisawa and Fukada 2003; Yanagisawa and Fukada 2004; Yanagisawa and Fukada 2005). Neural networks have also been used to estimate a user's design preference, such as in the Chikata et al. (1998) effort to capture user evaluations of concrete retaining walls.

FEATURE IDENTIFICATION

Humans have the ability to visually distinguish one truss design from another. The intuitive judgments they make about the practicality or aesthetic desirability of a given design rely upon these visual distinctions. A set of quantifiable truss characteristics must exist to translate human perception into decision criteria transparent to a computer algorithm. Therefore, the first task in capturing a user's design preferences was to create a characteristic feature vector to describe the aesthetic appearance of a given truss.

The characteristic feature vector will serve as input for the classification and preference detection mechanisms and represents the most fundamental "picture" of the truss available to the computer program. In creating such a feature vector, it is important to determine what features most strongly impact truss appearance and to effectively formulate mathematical measures of these features. This investigation explored twenty potential features, which varied from simple, geometric properties to more abstract measurements intended to capture truss behavior.

It was desirable to isolate truss characteristics that were invariant to population changes, since the IRR GA creates design alternatives through random processes and because a user's needs may change for a given application. The test populations used to determine the most effective truss features varied both in size and complexity and were created using the topology generator described in Agarwal and Raich (2005). All trusses had a 22.86-meter (75-foot) span and a maximum height of 7.62 meters (25 feet). Population sizes varied between 25 and 100 trusses, and trusses within these populations contained between 25 and 100 structural members. Each proposed characteristic was evaluated for its effect on five different test populations.

The one-dimensional (1D) Kohonen self-organizing map (KSOM) was selected as the major tool for creating feature maps of the test populations. The KSOM is an unsupervised neural network that projects an incoming signal onto a discrete, topographic map, which is usually one- or two-dimensional (Haykin 1999). The use of KSOMs to identify relationships between data has been well established (Kohonen 1988; Schyns 1991; Taner et al. 2001). Obayashi et al. (2005) use KSOMs to visualize tradeoff information in large dimension multi-objective optimization classifications.

The 1D KSOM performed separate trials for each of the proposed truss descriptors. Trusses similar to each other in terms of a given feature activated the same output neuron of the KSOM and were therefore placed in the same category. The effectiveness of these categories in capturing the aesthetic variations within a population then determined the effectiveness of the proposed feature. The KSOM used in this application contained a maximum of nine output neurons.

Feature maps output by the KSOM were subjectively evaluated based upon their ability to visually partition the truss population, to determine whether the groups created in response to the feature inputs made significant distinctions between trusses. The averages and standard deviations for the KSOM groups were also calculated. Characteristics with large standard deviations or closely spaced averages were undesirable, since they indicated that no real order within the characteristic was being mapped by the KSOM. Similarly, the distribution of group averages was considered to ensure that no single truss group dominated the map. Such "super groups" would have illustrated an insufficient amount of information in the input.

Additionally, three-dimensional plots were created to study the clustering behavior of the KSOM. These plots helped illustrate whether groups identified by the KSOM were easily distinguishable from each other and contained closely spaced members. The plots also explored distribution of groups in feature-space, which indicated how much variation existed within the truss populations. Clearly, features resulting in little or no variation within a population would be unsuccessful at distinguishing differences between trusses. To create these plots, feature sets of successfully performing characteristics were outlined. Three characteristics were assigned to each feature set, and each of these characteristics formed an ordinate by which an individual truss could be assigned a place in three-dimensional feature space.

Based upon comparisons of the above data for all truss populations, the nine most significant descriptors of truss behavior were selected for inclusion in the characteristic feature vector. When combined into feature sets, these characteristics were able to represent fundamental ideas about the general shape, simplicity, and chord shape of a truss. Table 1 summarizes these sets and their constituent features.

Table 1: Summary of Feature Sets for Truss Discretization

General Shape	**Simplicity**	**Chord Shape**
Maximum truss height	Number of members	Top chord direction changes
Mid-span clearance	Number of joints	Top chord flatness
Truss depth	Average joint connectivity	Bottom chord flatness

The feature map generated by the 1D KSOM for the complete feature vector is shown in Figure 1 for a population of 50 trusses containing a maximum of 50 members per truss. Trusses in groups 8 and 9 tend to be the simplest in the population, while the map as a whole reflects variations in height among all designs. More sharply arched trusses, such as those in group 7, have also been successfully separated from flatter designs, as in group 1.

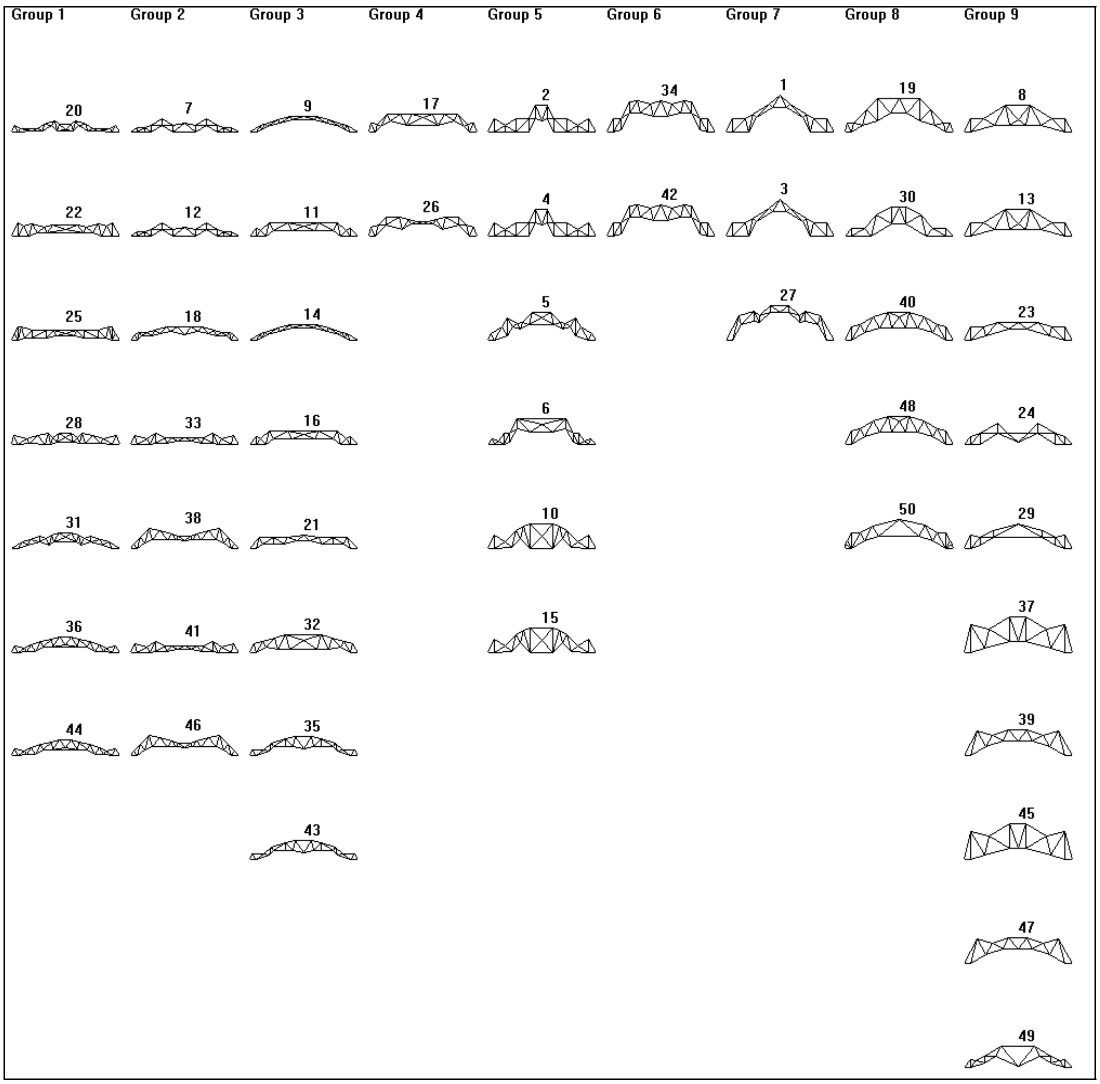

Figure 1: Feature Map for Sample Population Using Final Characteristic Feature Vector

CLASSIFICATION MECHANISM

In the feature identification investigation, a Kohonen's self-organizing map was used to visualize similarities between trusses with respect to a given feature. The KSOM is frequently used to simplify relationships between complex, multi-dimensional data, as in Obayashi et al. (2005). Such applications often use an extensive KSOM network, with individual neurons for each data point. On a smaller scale, however, the KSOM may also be used to create clusters of related designs, and it was this ability that first suggested the KSOM for the present application.

IEC approaches that require a user to directly assess the fitness of each individual in the population create a "physical and psychological" burden on the user (Takagi and Ohya 1996). Previous studies have suggested that human users tend to naturally categorize a population of objects into similar groups before assessing fitness (Ohsaki and Takagi 1998) and that allowing users to evaluate solutions on a group basis, rather than individually, is an effective way of reducing fatigue (Takagi and Ohya 1996). Therefore, it was thought that a KSOM or other unsupervised clustering technique could simplify the input procedure for determining a user's aesthetic design preferences. Having users select preferences for groups of similar truss designs reduces the number of evaluations a user must make while simultaneously increasing the information available to form judgments about a user's future preferences.

Since the population of truss designs will vary with each application of the IRR GA, it was important to determine a mechanism capable of independently detecting similarities between trusses. The KSOM was considered, with both one and two-dimensional neuron arrays, as well as the classical k-means and nearest neighbor clustering algorithms. These algorithms were used to create clustering maps of five truss populations to ensure that the final algorithm remained effective regardless of variations in population size or complexity.

Two performance measures examined whether the classifications proposed by any, or all, of these methods would be considered "good" by a human user. First, similarity matrices were created to compare the unique topologies of two truss populations. Entries in these matrices expressed the degree of similarity (on a 1 to 4 scale) perceived between truss pairs. The proposed classifications were graded on how closely group members aligned with these judgments. Points were awarded whenever similar trusses were grouped together or dissimilar trusses were separated; conversely, points were subtracted when similar trusses were separated or dissimilar trusses grouped. Additionally, results from a survey of nine volunteers were used to create a "composite" classification for two truss populations. A Rand Index indicated how often a clustering map agreed with the composite map.

The second goal of this investigation was to determine which clustering method would best classify an arbitrary population. The sum-of-squares error was used to determine the efficiency of a proposed classification by indicating how tightly clustered proposed truss groups were. While not an absolute indicator of within-group truss similarity, the SSE is a useful tool for determining relative similarities between the different clustering methods.

Another method for exploring the numerical performance of the unsupervised clustering methods was to examine the distribution of standard deviations across the populations. Proposed maps that had many features with small standard deviations were considered highly performing. However, the number of single topology groups in a clustering map was also taken into account, since the practice of not grouping trusses artificially inflates the number of small standard deviations in the population and should not be uniformly rewarded. In some cases, it is important to isolate trusses that truly diverge from other designs in the populations. However, an excess number of single topology groups indicates a *failure* of the clustering map to correctly subdivide the truss population into groups of *similar design*.

Variations in the size and complexity of the populations lead to variations in the advantageousness of one or the other methods. However, the preponderance of evidence suggested the one-dimensional Kohonen self-organizing map as the most effective classification method. The 1D KSOM method most clearly reflected human judgments about truss placement as measured through the similarity matrices and the Rand Index. The 1D KSOM also showed a consistently strong performance in terms of numerical efficiency. The SSE values for this method are low across the board and a minimum of single topology groups are created.

PREFERENCE DETECTION

By categorizing the trusses according to perceived similarities in their characteristic feature vectors, the 1D KSOM arranges potential designs and allows users to select the most pleasing groups. This selection process allows for a user's likes and dislikes to be recorded for a given population. However, the IRR GA creates many potential truss populations in the search for optimal designs. Therefore, it is crucial to convert information about what designs a users has selected using the 1D KSOM into a prediction of what designs a user will like from a *previously unexplored* population.

The characteristic feature vector remains the most effective source of information from which to make these predictions. The vectors for trusses selected by the user will be compared to the vectors of trusses the user has never examined. The KSOM was considered as a predictive mechanism, as were the rough set reduct (RSR) techniques outlined in Yanagisawa and Fukada (2003; 2004; 2005) and a back-propagation neural network (BPNN).

Identifying a method for predicting a user's preferences required performance evaluations on several levels. Judgments need to account not just for which method was the most numerically efficient but also which method's results most coincided with human intuition. Before a prediction method could be incorporated into the dynamically changing populations of the IRR GA, its ability to identify user preferences in a static setting had to be established.

To accomplish this goal, two types of preference trials were conducted: the input reproduction trials and the preference detection trials. These trials made use of the "original set" truss populations previously generated using the algorithm described in Agarwal and Raich (2005). Additional "preference set" population were created to provide the same variations in size and complexity. The preference set populations were used only in the preference detection trials.

In the input reproduction trials, the user selected desirable topologies from among the original set truss populations. These preferences were presented as input for all of the preference detection techniques. Once this data had been adequately analyzed, the algorithms were asked to extrapolate the user's preferences to a second population. The key element of the input reproduction trials was that the *original set* of populations was presented to the algorithms a second time, rather than presenting a new population. Therefore, each of the prediction algorithms were asked to identify preferences they had already seen. The purpose of these trials was to *reproduce* the user's inputs. Success at this task was viewed as critical to a method's ability to identify and distinguish between trusses using the characteristic feature vector.

As in the input reproduction trials, the preference detection trials began by presenting the user's selections from the original population set to the prediction algorithms. Once again, the different methods predicted a user's preferences in a second population based upon preferences previously explored. In this instance, however, predictions were drawn from the *preference set* populations. Therefore, the goal of this analysis was to extrapolate a user's selections in the original set to topologies they were likely to prefer in the preference set. Before presenting the preference set topologies to the prediction algorithms, these topologies were labeled as being preferred, acceptable, or unacceptable to the user.

The input reproduction and preference detection trials were used to verify different aspects of the prediction algorithms' performance: whether or not the inputs were correctly analyzed, and whether or not predictions based on these analyses were accurate. In order to answer these questions from a numerical standpoint, both trials used a sum-of-squares error (SSE) to quantify the distance between the originally selected topologies and those predicted by the proposed algorithms. Additionally, percentages were calculated to determine prediction accuracy. Percentages attempted to account for how often a topology was predicted that a user did not like as well as whether or not a user's preferences were fully predicted.

Results for both the input reproduction and preference detection trials indicated that both the KSOM and BPNN algorithms outperform RSR. The KSOM also appears to perform slightly better than the BPNN during preference detection. However, the ability of any of these methods to accurately and consistently predict a user's preferences was not established by the initial trials. For all methods, predictions during the preference detection trials were below 50% for two of the five populations tested. Moreover, although RSR sometimes failed to learn a user's preferences, this algorithm made some important predictions missed by the KSOM and BPNN.

Therefore, in order to improve overall accuracy and capitalize on the RSR method's ability to identify a user's "favored" features, a hybrid back-propagation with rough set reduct (BP-RSR) method was developed. The BP-RSR screens user selections in an attempt to determine the characteristics that distinguish an individual design from all other selected trusses. If the distinguishing features of a design diverge significantly from other designs in its assigned group, then the design is eliminated from the user's selections. The remaining designs were used to create a training set for a BPNN.

When asked to identify user selections among the preference set, the BP-RSR showed increased overall prediction accuracy. Moreover, the BP-RSR greatly increased prediction performance for those populations where the KSOM and BPNN struggled. In cases where it did not have the highest percentage of acceptable topologies, BP-RSR offered comparable results to most of the other methods. Therefore, the BP-RSR algorithm was identified as being an acceptably accurate method for detecting a user's preferences within a population.

CONCLUSIONS

This paper developed soft-computing methods for capturing a user's aesthetic design preferences for large-span roof trusses. Before being implemented in a multi-objective optimization algorithm, techniques for describing and predicting these preferences had to be defined.

Twenty potential features were evaluated based upon their ability to visually partition truss populations of varying size and complexity. These features represented geometric as well as behavioral properties of the individual trusses they were used to describe. The nine most effective features became part of a characteristic feature that described basic information about the simplicity, general shape, and chord shape of a potential truss design.

Both classic and heuristic unsupervised clustering algorithms were considered for the task of classifying a population of potential truss designs based upon this feature vector. The 1D KSOM best matched judgments made by human users. Numerically, the KSOM formed tight groups, as described by the sum-of-squares error and a comparison of standard deviations, with relatively few single-topology clusters.

Using the KSOM, truss designs are placed into groups according to perceived similarities in their characteristic feature vectors. A designer is selects design preferences from among the proposed truss groups, and these selections provide feedback about a user's likes and dislikes in the present population. Different mechanisms were examined to convert this input into predictions of a user's likes and dislikes in *future* populations.

The characteristic feature vectors of both selected and unselected designs formed the basis for predicting future preferences. After an initial investigation failed to provide sufficiently accurate results, a hybrid back-propagation with rough set reduct (BP-RSR) algorithm was developed. The BP-RSR algorithm relies on rough set reduct to strategically reduce user selections that vary significantly from the population as a whole as well as corresponding group members. Once inputs are analyzed for consistency, a back propagation neural network is trained to recognize the user's preferences. Overall, the BP-RSR outperformed all other preference algorithms considered in this study and proved to be an effective method for predicting user preferences.

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