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Kansei clustering for emotional design using a combined design structure matrix

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ABSTRACT

Consumers' emotional requirements, or so-called Kansei needs, have become one of the most important concerns in designing a product. Conventionally, Kansei engineering has been widely used to co-relate these requirements with product parameters. However, a typical Kansei engineering approach relies heavily on the intuition of the person who uses the method in clustering the Kansei adjectives, who may be the engineer or designer. As a result, the selection of Kansei adjectives may not be consistent with the consumers' opinions. In order to obtain a consumer-consistent result, all of the collected Kansei adjectives (usually hundreds) need to be evaluated by every survey participant, which is impractical in most design cases. Therefore, a Kansei clustering method based on a design structure matrix (DSM) is proposed in this work. The method breaks the Kansei adjectives up into a number of subsets so that each participant deals with only a portion of the words collected. Pearson correlations are used to establish the distances among the Kansei adjectives. The subsets are then integrated by merging the identical correlation pairs for an overall Kansei clustering result. The details of the proposed approach are presented and illustrated using a case study on wireless battery drills. The case study reveals that the proposed method is promising in handling Kansei adjective clustering problems.

Relevance to industry: This study presents a generic method to deal with consumers' Kansei requirements for emotional design in new product development. It appears that the proposed method can be utilized to capture and analyze consumers' Kansei needs as well as to facilitate decision making in practical industrial design cases.

1. Introduction

It is well-known that a successful product is one that has the highest quality, the lowest cost, and the shortest time-to-market. This has been widely advocated by most product manufacturers in their new product development (NPD) endeavors. On top of this, in recent years, product design and development has shifted its emphasis to the experiences gained from users' interaction with products (Norman, 2008). The studies of users' experiences (or user-centered design) may tackle different problems in various perspectives. In this regard, the Kansei engineering approach (Nagamachi, 1995, 1999, 2002, 2008; Nagamachi et al., 2006) is considered to be the most reliable and useful methodology to handle consumers' emotional requirements (Chen et al., 2008). It has been successfully applied in various design domains, such as domestic commodities (Hsiao et al., 2010), interior decorating (Hsiao and Tsai, 2005), seat comfort (Goonetilleke, 1998; Goonetilleke and Song, 2001), machine tools (Mondragón et al., 2005), home appliances (Demirtas et al., 2009), and trade show booth (Huang et al., 2011).

A conventional approach to studying Kansei involves the following nine consecutive steps (Grimsæth, 2005): (1) collecting as many Kansei adjectives as possible from various sources (about 300–500 Kansei adjectives for a product); (2) pre-processing/clustering the collected Kansei adjectives in such a way that a small number of Kansei adjectives can be used to represent the whole unit (about 25–30 clustered Kansei adjectives); (3) collecting product samples; (4) listing product attributes and attribute variables; (5) surveying and evaluating representative products using the clustered Kansei adjectives; (6) representing the survey results in a proper format; (7) identifying the correlations among the Kansei adjectives using factor analysis (FA), followed by a cluster analysis to further cluster the Kansei adjectives; (8) identifying the correlations between the clustered Kansei adjectives and the product attributes, using such methods as quantification theory type I or cross tabs analysis; and (9) presenting the results, using such tools as bar and/or radar charts to interpret, explain, and check the results. Although relatively less studied, the first two steps deserve more in-depth investigation, because the results obtained from the early steps may significantly affect the later steps.

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Based on the literature, it appears that the semantic differential (SD) method (Osgood, 1962; Osgood et al., 1967) has been widely adopted by most conventional approaches in studying Kansei adjectives, such as car wheel hub study (Luo et al., 2012), ladies' dress shoes design (Au and Goonetilleke, 2007), and customer preferences on real estate (Llinares and Page, 2011). Osgood postulated that any two concepts can be differentiated semantically by a set of a limited number of antonym scales. Following Osgood's idea of the SD method, Nagamachi (1999) suggested that any two products can be differentiated semantically by a set of a limited number of emotional antonym scales (Kansei adjectives). Therefore, choosing the antonym scales (Kansei adjectives) is of great importance to the success of Kansei engineering implementations. A typical Kansei engineering approach collects as many Kansei adjectives as possible from customers. However, it depends on the user(s) of the method to decide how the Kansei adjectives should be pre-clustered (Step 2). The question is how to justify that a set of much fewer selected Kansei adjectives can be used to represent the whole meaning of all of the Kansei adjectives collected from the customers. For example, a case study from Grimsæth's work (2005) shows that two words "freedom and comfort" were reduced to one, "freedom," by the researcher's subjective judgments. However, to other researchers, "freedom" might lead to "comfort," but "comfort" does not necessarily refer only to "freedom." The elimination of "comfort" is debatable. Therefore, this work proposes a Kansei clustering method to deal with such problems.

A large number of data clustering methods have been proposed to date. These methods can be categorized into two major categories, namely hierarchical methods and partitional methods (Xu and Wunsch, 2008). Hierarchical methods group data with a sequence of nested partitions, either in a bottom-up or top-down manner. Partitional methods organize data sets into clusters, while maximizing or minimizing a pre-specified criterion function without any hierarchical structure. Some representative hierarchical clustering algorithms are average linkage clustering for shape similarity (Rodrigo et al., 2012); balanced iterative reducing and clustering using hierarchies (BIRCH) for clustering very large numerical data sets in Euclidean spaces (Zhang et al., 1996; Gan et al., 2007); clustering using representatives (CURE), which can identify non-spherical shapes in large databases with a wide variance in size (Guha et al., 2001); Chameleon, a two-phase agglomerative hierarchical clustering algorithm (Karypis et al., 1999); DISMEA, a divisive hierarchical clustering algorithm that uses the k-means algorithm to subdivide a cluster into two (Späth, 1980); and so on. Hierarchical clustering methods are able to break data objects up into several levels of nested partitions (or a tree of clusters). Despite the many advantages, the weaknesses of hierarchical clustering methods make them unsuitable to cluster Kansei data. For instance, deploying Kansei adjectives hierarchically may ignore relatively weak connections among Kansei clusters, which might result in an unreliable clustering solution.

On the other hand, partitional clustering methods aim to organize data sets into many clusters while maximizing or minimizing a pre-specified criterion function without any hierarchical structure (Xu and Wunsch, 2008). Typical partitional clustering algorithms include the standard k-means, which works best on data that contains spherical clusters (Macqueen, 1967); variations of k-means, which improve some aspects of the standard k-means (Likas et al., 2003; Kaufman and Rousseeuw, 1990); and a mixture density-based clustering method in which each data object is assumed to be generated from one of the k underlying probability distributions (Law et al., 2004). Additional clustering algorithms include the graph theory-based clustering method, which treats clusters as highly connected subgraphs and uses a minimum weight cut procedure to identify the subgraphs recursively (Hartuv and Shamir, 2000; Shamir and Tsur, 2007); fuzzy c-means, in which the object can belong to all of the clusters with a certain degree of membership (Bezdek, 1981; Zhou and Schaefer, 2009); the constrained agglomerative algorithm, which is a combination of hierarchical and partitional methods (Zhao and Karypis, 2005); search techniques-based clustering methods (Hall et al., 1999; Brown and Huntley, 1992; Al-Sultan, 1995); and so on.

Unfortunately, partitional clustering methods are not suitable for handling Kansei clustering problems either. This is mainly due to three reasons. First, Kansei adjectives are vague to be manipulated using existing partitional clustering algorithms. Guha and Munagala (2009) suggested clustering uncertain data using approximation algorithms. Nonetheless, Kansei data cannot be easily represented using probability distributions. Second, the meaning or mapping of the Kansei adjectives may not be a continuous region, which might hinder the use of partitional methods. Third, although fuzzy clustering algorithms are capable of dealing with vague data such as Kansei, it may be difficult to define a membership function for each Kansei adjective. In summary, the existing data clustering methods and algorithms are not fully capable of handling the Kansei adjective clustering problems. A new clustering method is thus needed.

The design/dependency structure matrix (DSM) proposed by Steward in the 1980s has a distinct advantage in showing the information cycles or connections among all units in a system in a visual and traceable way (Steward, 1981). Each unit in a DSM is assigned to a row and a corresponding column of the matrix. The off-diagonal entries correspond to the information dependencies between two units (Jiao et al., 2004). In this sense, an entry below the diagonal stands for a feed-forward information flow while that above the diagonal indicates a feedback information flow. By changing the sequence of units in a DSM, it is possible to identify loops or iterated connections among units. More specifically, a DSM is rearranged into a lower triangular form, and iterations located along the diagonal line can be minimized. For example, it is possible to trace forward manually until a unit is encountered twice. All units between the first and second occurrence of the unit constitute a loop and should be placed together. This process is known as partitioning a DSM. A number of DSM partitioning algorithms have been proposed, for example, binary matrix algebra (Warfield, 1973), the powers of adjacency matrix method (Gebala and Eppinger, 1991), a loop tracing procedure (Steward, 1981), and a triangularization algorithm (Kusiak and Wang, 1993), to name a few. These algorithms are rather similar in a sense. The major difference among them lies in how the iterations are identified. In addition to binary entries, numerical entries have been adopted in DSMs to offer more information about the units so that more complex situations can be handled. For example, repeat probabilities incurred (Smith and Eppinger, 1997) and two-dimensional variables (Yassine et al., 1999) make use of single or multiple numerical entries to measure the strengths of the unit dependencies in a DSM. Nonetheless, the lower triangular form is not suitable for dealing with Kansei clustering problems, because a Kansei DSM is symmetrical and heavy weighted units should be placed close and along the diagonal. In addition, conventional partitioning algorithms are capable of handling a single DSM only. Therefore, a method to establish relationships among multiple DSMs so as to enable a holistic analysis on a combined DSM is required. Accordingly, a new DSM partitioning method, DSM for Kansei partitioning, is proposed in this work.

The proposed Kansei clustering method uses a complete set of Kansei adjectives during a product evaluation. In order to facilitate the evaluation, the set is divided into several Kansei subsets. Then, a combined DSM is built accordingly. Subsequently, the DSM is partitioned, which results in clusters of Kansei adjectives based on the customers' viewpoints. Thereby, a smaller number of Kansei