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Interdependency between Average Novelty, Individual Average Novelty, and Variety

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Abstract

Idea generation is an important part of the engineering design process, and therefore significant research efforts have focused on developing methods to support designers in generating ideas. A key factor is the measurement of ideation effectiveness. The effectiveness of idea generation methods can be measured using metrics such as novelty, variety, quantity, and quality. Average novelty of a set of ideas is also used as one of the ideation metrics. However, the interdependency between average novelty and variety has been given little attention. An investigation of the interdependency between these metrics is important to enhance our understanding of the metrics of ideation, and thereby to develop methods for improving ideation effectiveness. This article examines the interdependency between average novelty and variety. In addition, the metric ‘individual average novelty’ has been introduced, and the interdependency between ‘individual average novelty’ and variety has been investigated.

Keywords: conceptual design, evaluation, average novelty, individual average novelty, variety

1. Introduction

Developing useful and innovative solutions is the primary aim of engineering design. The engineering design process covers a range of stages from the identification of a need to a stage, where a solution is completely described such that the solution can be produced and implemented to fulfill the need. The conceptual design phase at the front end of this process, is one of the most important phases. In this phase, requirements are identified, principles of solutions are developed and the best candidate solution is selected for its further development (Pahl and Beitz, 1996). The cost incurred in this phase is relatively small compared to that in later phases (Berliner and Brimson, 1988), and this phase provides maximum scope for most striking improvements (French, 1999; Terwiesch and Ulrich, 2009).

A greater number of alternative solutions helps to produce a higher quality design when the solutions are evaluated timely (Fricke, 1996). Dylla (1991) has shown a positive correlation between the amount of design space considered during idea generation and the quality of final design. This correlation is seen up to a certain number of ideas. Design space is a space that includes all possible options to a given problem (Ullman, 2010). Design space is not fully known. Several studies have been carried out in the area of ideation. These studies are aimed at: (1) understanding the cognitive processes during idea generation (Finke et al., 1996; Nijstad et al., 2002; Linsey et al., 2008); and (2) evaluating different idea generation methods

(Goldschmidt et al., 2011; Hernandez et al., 2010; Shah et al., 2003; Linsey, 2007). The idea generation methods can be evaluated through process-based and/or outcome-based approaches. Process-based approaches are difficult due to the inherent complexity of examining cognitive processes responsible for creative thought. In addition, the process-based approaches are time-consuming. Due to this, outcome-based evaluation approaches are frequently used (Shah et al., 2003). In outcome-based approaches, the designs/outcomes produced by designers during ideation are evaluated. Idea generation methods can be evaluated for their effectiveness by comparing their outcomes based on predefined metrics (Shah et al., 2003).

Shah et al. (2003) developed four key metrics for evaluating a designer's exploration and expansion of design space. The four metrics are: novelty, variety, quality, and quantity of designs. Several design ideation studies have used all or some of these four metrics (e.g. Wilson et al., 2010; Hernandez et al., 2010; Chan et al., 2011; Viswanathan et al., 2011; Viswanathan and Linsey, 2013). While the work of Shah et al. (2003) in the area of design ideation metrics is foundational, they have not examined the interdependencies between these metrics.

The mean of novelty scores of ideas in a set (i.e. Average Novelty) has also been used in some ideation studies (Wilson et al., 2010; Hernandez et al., 2010; Chan et al., 2011; Srinivasan et al., 2010). As explained further in this paper, there appears to be a correlation between the Average Novelty (AN) of a given set of ideas and the variety of that set. Shah et al. (2003) and many of the studies that have computed AN and variety, have not examined the interdependency between AN and variety (e.g. Wilson et al., 2010; Hernandez et al., 2010; Chan et al., 2011; Srinivasan et al., 2011). An investigation of the interdependency between these metrics is important to enhance our understanding of the metrics of ideation. Consequently, this improved understanding can help in developing effective idea generation methods. An idea generation method is considered effective if the method helps to improve the outcomes based on predefined metrics (Shah et al., 2003). An in-depth understanding of such metrics is important in identifying ways to increase scores of these metrics, and thereby in developing idea generation methods that employ those ways. Furthermore, this in-depth understanding can help in focussing on appropriate metrics in developing idea generation methods. Our work presented in this paper fills the above-mentioned gaps found in the current literature regarding the interdependency between AN and variety. In this paper, we define the interdependency between AN and variety as a correlation between them. This research aims at examining:

- the interdependency between Average Novelty (AN) and variety; and
- the interdependency between Individual Average Novelty (IAN) and variety.

In this research, we have introduced the metric IAN. The metric IAN can help design researchers to save their time and effort in evaluating idea generation methods and also to develop effective idea generation methods. The metrics AN and IAN are explained further in this paper. In order to examine these above interdependencies, we used Shah et al.'s (2003) metrics, novelty and variety.

This paper is structured as follows. Section 2 presents related research on ideation metrics. Section 3 details the research methods used in this work. Section 4 explains AN and IAN. The interdependencies between IAN and variety, and between AN and variety are investigated in Sections 5 and 6, respectively. Finally, Section 7 discusses the findings of our research. This section also explains how the findings of our research (i.e. the metric IAN and interdependency between AN/IAN and variety) can help design researchers to save their time and effort in evaluating idea generation methods, and also to develop effective idea generation methods.

2. Background literature

This section presents relevant research on ideation metrics, in particular, Shah et al.'s (2003) four ideation metrics - quantity, quality, novelty, and variety. Effectiveness of idea generation methods can be evaluated by using such ideation metrics. For example, Charyton et al. (2011) used such ideation metrics to assess the tool 'Creative Engineering Design Assessment'. Kudrowitz and Wallace (2010) developed a method to evaluate a large quantity of product ideas using such metrics. Jensen et al. (2009) used ideation metrics to evaluate a suite of concept generation techniques (e.g. modified 6-3-5, design by analogy technique, etc.). Using the metric quantity, Yang (2009) examined concept generation via brainstorming, morphology charts and sketching. Some studies have used metrics of ideation in investigating characteristics of concept generation process. Nagai et al. (2009) analyzed the characteristics of the concept generation in the design process in comparison with the linguistic interpretation process. They evaluated the design outcomes from the viewpoint of practicality (e.g. if the idea was feasible) and originality (e.g. if the idea was novel). Dahl and Moreau (2002) used ideation metrics to examine cognitive processes in the creation of product concepts. Recently, Linsey et al. (2011) and Linsey et al. (2010) used ideation metrics to evaluate concept generation methods (e.g. brainsketching, gallery, C-sketch, etc.), and to study design fixation.

2.1. Quantity

Quantity is the total number of ideas produced (Lamm and Trommsdorff, 1973, Shah et al., 2003). MacCrimmon and Wagner (1994) state that the quantity of generated ideas is a commonly agreed upon metric. The quantity is a metric that applies to a set of ideas. Classical literature in psychometric psychology uses the term fluency as quantity (Torrance, 1964). According to Osborn (1953) quantity breeds quality in ideation and early ideas are unlikely to be of higher quality during an ideation session. The rationale for the measure quantity is that generating a large number of ideas enhances the chance of better ideas (Osborn, 1953; Kumar et al., 1991; Basadur and Thompson, 1986). However, this is applicable under certain conditions (e.g. generating a large number of ideas with timely evaluation).

2.2. Quality

Quality is a measure of the feasibility of an idea and how closely it satisfies the design specifications (Shah et al., 2003). In engineering design, this metric is required because an engineering idea needs to be feasible and practical (Charyton et al., 2011). According to Lamm and Trommsdorff (1973), quality of an idea is effectiveness (the ability of an idea to fulfil the given requirements) plus feasibility (i.e., extent to which an idea can be implemented under the constraints of reality). According to Linsey (2007), quality is synonymous to technical feasibility or implementability. Dean et al. (2006) suggested workability (acceptability plus implementability), relevance (applicability plus effectiveness), and specificity (completeness) as sub-dimensions of quality. Girotra et al. (2010) compared the quality of best ideas generated in two group structures - (1) group works together in time and space, and (2) the hybrid structure (group members first work independently and then work together). They found that the quality of the best ideas generated by the hybrid structure is higher than that generated by the group working together. Goldschmidt and Tassa (2005) found that the ideas of higher quality are ones that are built on earlier ideas. According to Reinig et al. (2007), majority of good quality ideas are generated somewhere in the middle part of an ideation session.

2.3. Novelty

Novelty is an important ideation metric (Dahl and Moreau, 2002). According to Shah et al. (2003), novelty is a measure of how unusual or unexpected an idea is as compared to other

ideas including those from other individuals. This suggests that uncommon ideas are likely to be seen as novel. In terms of a design space, novelty is a measure of whether the exploration of ideas occurred in areas of the design space that are well-travelled or little-travelled (Nelson et al., 2009). In a design space, novel ideas occupy points that are not initially perceived (Shah et al., 2003). An agent generates a novel outcome when it is not identical to any existing outcome(s) (Sarkar, 2007). Lopez-Mesa and Vidal (2006) and Linsey (2007) employ ‘infrequency’ as a measure of novelty. Shah et al. (2003) classified novelty into three different types, namely personal novelty (the outcomes of an individual are new according to that individual), societal novelty (a product or idea is new to all people in a particular society), and historical novelty (a product or idea is the first of its kind in the history of all societies and civilizations).

There are several methods of novelty assessment. To assess novelty of a product, Sarkar (2007) suggests the use of experienced designers having knowledge of the domain(s) of the product whose novelty is to be assessed. Amabile (1996) also suggests the use of experts to assess novelty. Chakrabarti and Khadilkar (2003) developed a method to assess novelty of a product by assessing its similarity or difference with existing products as reference. Sarkar and Chakrabarti (2011) developed a method to assess novelty of a product at various degrees: very high, high, medium, or low. The method uses function–behavior–structure (FBS) and SAPPPhIRE (state change, action, parts, phenomenon, input, organs, and effect) models together. The FBS model is used first for determining novelty followed by the use of SAPPPhIRE model to assess the relative degree of novelty.

In their foundational work on design ideation metrics, Shah et al. (2003) proposed the following two approaches to measure novelty. (1) The first approach uses ‘*a priori*’ perspective. In this approach, the universe of ideas for comparison is obtained by defining what is usual or expected, preferably before analysing any data. This helps to avoid bias, which can be due to personal preferences in obtaining the universe of ideas. Researchers can involve experts in obtaining the universe of ideas for comparison in order to further reduce bias. (2) The second approach uses ‘*a posteriori*’ perspective. In this approach, ideas generated by all participants from all methods are collected. Then, the key attributes of these ideas (e.g. motion type, propulsion, etc.) are identified. This is followed by the identification of different ways in which each of those attributes is satisfied (e.g. the attribute ‘motion type’ can be satisfied by using different ways such as rotation, oscillation, sliding, etc.). Then one can count how many instances of each solution method occur in the entire collection of ideas. If the count is lower (i.e. the less a characteristic is found), the novelty is higher.

Shah et al. (2003) have explained in detail the procedure to measure novelty of an idea. The problem is first decomposed into its key functions or characteristics. Each generated idea is analysed by first identifying which functions it satisfies and also by describing how it fulfils these functions at levels/stages such as conceptual level and/or embodiment level. Each description is then graded for novelty according to one of the two above approaches (i.e. *a priori* or *posteriori*). The overall novelty of each idea can be computed from the following equation (1).

$$N = \sum_{j=1}^m f_j \sum_{k=1}^q S_{N_{jk}} p_k \quad (1)$$

N is the overall novelty score for the idea having m functions or attributes and q levels. Weights (f_j) are assigned depending on the importance of each function. The assignment of these weights depends on the judgement of researchers, and therefore some subjectivity is present in this

metric. Each function can be addressed at the conceptual and/or embodiment level and weights (p_k) are assigned according to the level's importance. The upper levels are assigned higher values of p_k than lower levels.

The calculation of S_N depends on the approach chosen. For the first approach (*a priori*) a universe of ideas for comparison is subjectively defined for each function or attribute, and at each level. A novelty score S_N is assigned to each idea in this universe. In order to evaluate the function and level of an idea, a closest match is found. For the second approach (i.e. *a posteriori*), S_N is calculated from the following equation (2).

$$S_{Njk} = \frac{T_{jk} - C_{jk}}{T_{jk}} \times 10 \quad (2)$$

Where T_{jk} is the total number of ideas produced for function (or key attribute) j and level k , and C_{jk} is the number of ideas in T_{jk} that match the current idea being evaluated. Multiplying by 10 normalizes the expression. Shah et al. (2003) have explained the procedure of calculating S_N scores with an example.

2.4. Variety

Jansson and Smith (1991) explain variety as the flexibility of generating a range of ideas. A low flexibility indicates a narrow range of generated ideas, while a high flexibility shows a broadly searched idea space. To estimate variety, Sarkar and Chakrabarti (2008) compare the number of similar ideas to those with less similarity. "Variety is a measure of the explored solution space during the idea generation process" Shah et al. (2003). The metric variety indicates "how well one has explored the design space". The variety of a set of similar ideas is low. Generating a large number of ideas that are very similar to each other does not guarantee an effective idea generation. In an idea generation process, variety indicates the number of categories of ideas that one can imagine.

Shah et al. (2003) have also proposed a procedure to estimate variety of a set of ideas. For measuring variety, one examines how each function is satisfied. Ideas are gathered based on how different two ideas are from each other. The use of a different physical principle to satisfy the same function implies that two ideas are very different. In contrast, if two ideas differ only in some secondary construction level detail (e.g. a dimension value), the ideas are slightly different. The variety is calculated from equation (3).

$$V = \sum_{j=1}^m f_j \sum_{k=1}^4 S_k b_k / T \quad (3)$$

Where V is the variety score, b_k is the number of branches at level k , m is the total number of functions, T is total number of ideas, and S_k is the score for level k (four scores 10, 6, 3, and 1 are assigned for physical principle, working principle, embodiment, and detail levels, respectively). For greater variety, branches at upper levels (physical principle differences) should get higher rating than the number of branches at lower levels. The number of branches is based on how ideas fulfil each function (e.g. at the highest level, ideas are differentiated by different physical principles used to satisfy a given function).

A recent study carried out by Oman et al. (2013) compared different metrics of ideation. This study found that Shah et al.'s (2003) metrics are extensively used. The metric novelty measures the quality or usefulness of the design space exploration that the variety quantifies (Nelson et al, 2009). The metric novelty applies to a single idea, and the metric variety applies to a set of

ideas (Shah et al, 2003). The metrics AN (novelty scores are estimated by comparing ideas with other ideas including those from other individuals) and IAN (novelty scores are estimated by comparing individual's ideas with other ideas generated by the individual) apply to a set of ideas. The metrics AN and IAN are explained further in Section 4.

2.5. Interdependency between AN/IAN and variety

The measurement of ideation effectiveness is important in developing methods to support designers in generating ideas (Shah et al., 2003). Ideation metrics play a key role in measuring ideation effectiveness. An investigation of the interdependency between ideation metrics is important to enhance our understanding of such metrics, and thereby to develop methods for improving ideation effectiveness. The investigation of interdependency between AN/IAN and variety has been given little attention. We could find only two studies that have checked and found a positive correlation between AN and variety (Kurtoglu et al., 2009; Srinivasan et al., 2010). However, these studies have not used Shah et al.'s (2003) metrics, novelty and variety, which are prolific within the design research community. Furthermore, these studies have not discussed the correlation between AN and variety, and have not examined the correlation between IAN and variety.

3. Research method

We have introduced the metric IAN because this metric can help design researchers to save their time and effort in evaluating idea generation methods and also to develop effective idea generation methods. In addition, this metric appears to have a link with the metric 'variety'. We have distinguished between IAN and AN. AN of a set of ideas generated by an individual is computed by using the novelty scores of ideas in that set and these novelty scores are estimated *by comparing each of those ideas with other ideas including those from other individuals*. On the other hand, IAN of a given set is computed by using novelty scores of ideas in that set and these novelty scores are estimated *by comparing each of those ideas with other ideas in that given set*. The implications of AN and IAN are elaborated further in Section 7.

In order to examine these above interdependencies, we used Shah et al.'s (2003) metrics, novelty and variety, because these metrics have been used prolifically in the literature (Lopez-Mesa and Thompson 2006; Nelson et al. 2009; Verhaegen et al., 2012; Srivathsavai et al. 2010). A recent comprehensive study on ideation metrics also found that Shah et al.'s metrics have been used extensively (Oman et al., 2013).

By using equations (1) and (2), we developed an equation to compute the IAN of a set of ideas for a single function and one level (i.e. level of physical principles). Therefore, for a single function and one level, the collection of empirical data was not required to investigate the interdependency between IAN and variety. We used the data from the empirical study of Shah et al. (2003), which is secondary data (i.e. data not collected by us), for investigating the interdependency: (1) between AN and variety; and (2) also between IAN and variety. This secondary data was useful as our aim was only to check if there is a correlation between AN/IAN and variety, and helped to save time and effort by avoiding the collection of primary data (i.e. data collected by us).

4. Average Novelty (AN) and Individual Average Novelty (IAN)

Novelty of an idea is a measure of how unusual or unexpected an idea is as compared to other ideas including those from other individuals. In this section, we explain AN and IAN. Consider for example a design ideation experiment involving three designers (D_x , D_y , and D_z). Suppose that they have generated some ideas individually to satisfy a given function. Figure 1 illustrates

the sets of ideas generated by the three designers to satisfy the given function. For example, the set 'x' consists of three ideas ($x_1, x_2,$ and x_3) generated by the designer D_x . The set 'e' consists of five ideas ($e_1, e_2, e_3, e_4,$ and e_5) that existed even before the experiment to satisfy that given function. The set 'u' includes all the ideas generated by the three designers plus the ideas in set 'e'. We call the set 'u' as the universe of ideas for the ideation experiment that is exemplified.

As shown in Figure 1, the *novelty score* of idea ' x_1 ' as computed by comparing it with other ideas from the universe of ideas is denoted as N_{x_1} . Similarly, N_{y_2} is the novelty score of idea ' y_2 ', and N_{z_5} is the novelty score of the idea ' z_5 '. *Average novelty* $AN_{(set-x)}$ of the set 'x' is $(N_{x_1}+N_{x_2}+N_{x_3})/3$. Similarly, the average novelty $AN_{(set-y)}$ of the set 'y' is $(N_{y_1}+N_{y_2}+N_{y_3}+N_{y_4})/4$, and the average novelty $AN_{(set-z)}$ of set 'z' is $(N_{z_1}+N_{z_2}+N_{z_3}+N_{z_4}+N_{z_5})/5$.

The novelty of the idea ' x_1 ' can also be computed by comparing it with other ideas from the set 'x'. We denote this novelty as IN_{x_1} . We call IN_{x_1} as '*individual novelty*' score of idea ' x_1 ' (see Figure 1). We call the average novelty of set 'x', computed by using 'individual novelty' scores $IN_{x_1}, IN_{x_2},$ and IN_{x_3} , as *Individual Average Novelty* of set 'x' and denote it by $IAN_{(set-x)}$. Therefore, $IAN_{(set-x)}$ is $(IN_{x_1} + IN_{x_2} + IN_{x_3})/3$. Similarly, $IAN_{(set-y)}$ is $(IN_{y_1} + IN_{y_2} + IN_{y_3} + IN_{y_4})/4$.

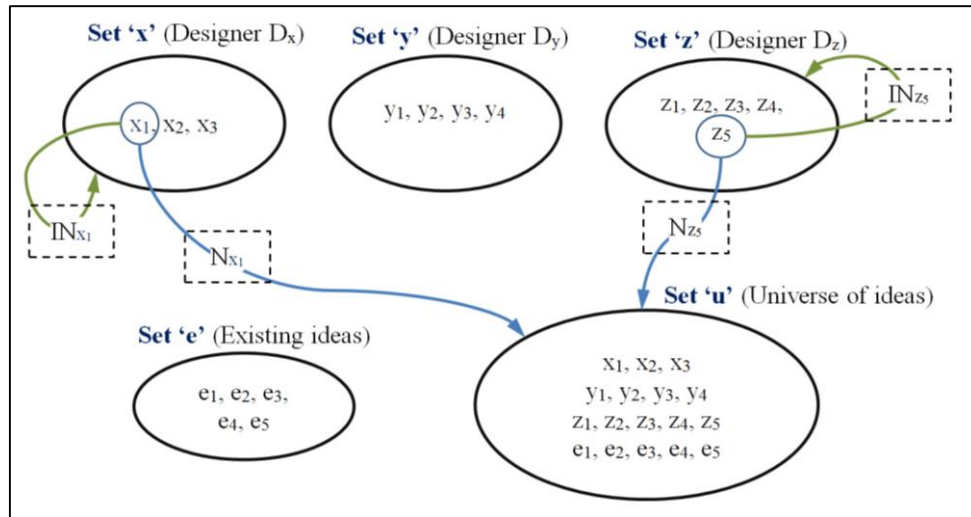


Figure 1 Illustration of different types of sets and novelty score of an idea





5. IAN and variety

For a single function and one level, we developed an equation for IAN because this equation can be used to compute IAN scores without the need of empirical data. In this section, the development of this equation is explained. Understanding gained through this equation is useful in developing effective idea generation methods. These implications are elaborated in Section 7.

We explain the interdependency between IAN and variety for a single function and one level (i.e. the level of physical principles). Consider for example a set 'y' of ideas ($y_1, y_2, y_3 \dots y_t$) generated by a designer to satisfy one function. The IAN of the set 'y' - that is $IAN_{(set-y)}$ - can be computed by using '*individual novelty*' scores of ideas and total number of ideas (T) in that set. Suppose that the total number of physical principles used in the set of T ideas is n (see Table 1). One physical principle is used to satisfy the single function. There can be differences in ideas at the embodiment and detail level; however for simplification we will not consider these levels. As shown in Table 1, the number of ideas that have used the third physical principle (i.e. PP₃) is C_3 . In this table, the values of C_j are organized in descending order. This is illustrated by using the coloured horizontal bars in this table.

From equation (1), for a single function and for one level (i.e. level of physical principles), the ‘individual novelty’ score of idea y_1 (computed by comparing this idea with other ideas in the set ‘y’) is found as follows: $IN_{y_1} = f_1 S_N = S_N$, because $f_1 = 1$ for a single function. Where $S_N = [10*(T-C_j)]/T$. Suppose that the idea y_1 uses the physical principle PP_3 . The number of ideas using the PP_3 is C_3 . Therefore, for the idea y_1 , the S_N score is $[10*(T-C_3)]/T$, which is its ‘individual novelty’ score as well. Therefore, the ‘individual novelty’ scores of ideas using physical principles in the lower rows of this Table 1 will be relatively higher.

Table 1 Calculation of C_j and S_N for ‘individual novelty’ scores

Physical Principle (PP)	C_j	S_N
PP ₁	 C_1	$[10*(T-C_1)]/T$
PP ₂	 C_2	$[10*(T-C_2)]/T$
PP ₃	 C_3	$[10*(T-C_3)]/T$
...
PP _n	 C_n	$[10*(T-C_n)]/T$

$IAN_{(set-y)}$ can be computed as follows.

$$IAN_{(set-y)} = \frac{(S_N \text{ score for the idea } y_1) + (S_N \text{ score for the idea } y_2) + \dots + (S_N \text{ score for the idea } y_t)}{T} \quad (4)$$

The numerator on the right hand side of the above equation (4) is the addition of S_N scores of T ideas. The number of ideas using the PP_1 is C_1 , using the PP_2 is C_2 , and so on. Therefore, in this numerator, S_N score for PP_1 will be counted C_1 times, S_N score for PP_2 will be counted C_2 times, and so on. Using this information, equation (4) reduces to:

$$IAN_{(set-y)} = \frac{C_1(S_N \text{ score for } PP_1) + C_2(S_N \text{ score for } PP_2) + \dots + C_n(S_N \text{ score for } PP_n)}{T}$$

Considering the fact that $C_1 + C_2 + C_3 + \dots + C_n = T$, and substituting S_N scores for different physical principles, the above equation reduces to:

$$IAN_{(set-y)} = \frac{10 [T^2 - (C_1^2 + C_2^2 + \dots + C_n^2)]}{T^2}$$

Taking into account the standard deviation (σ) of the data set ($C_1, C_2, C_3 \dots C_n$) of the values of C_j , the above equation reduces to:

$$IAN_{(set-y)} = 10(n - 1) \left(\frac{1}{n} - \frac{\sigma^2}{T^2} \right). \quad (5)$$

We introduced standard deviation (σ) because it makes the equation for IAN concise, and helps to discuss implications of IAN . These implications are discussed further in the paper. For a single function and one level (i.e. the level of physical principles), the IAN of a set of ideas thus depends on the number of physical principles used (n), the standard deviation (σ) of the data set of the values of C_j , and the total number of ideas generated (T). The standard deviation (σ) is relevant for a single function and one level. In the case of multiple functions and levels,

equation (1) needs to be used to compute IAN score of a set of ideas. This is because in such a case, the values of f_j depend on the problem at hand.

In order to illustrate the variation of the IAN with the values of n and σ for a given T , we now compute the values of IAN for a set of 10 ideas (i.e. $T = 10$). In this case, for nine physical principles (i.e. $n = 9$), there is one data set of the values of C_j - that is - (2, 1, 1, 1, 1, 1, 1, 1, 1). The standard deviation of this data set is 0.33. Therefore, from equation (5), for $n = 9$ and $\sigma = 0.33$, the IAN score is 8.8. For eight physical principles ($n = 8$), there are two data sets of the values of C_j : (3, 1, 1, 1, 1, 1, 1, 1) and (2, 2, 1, 1, 1, 1, 1, 1). For the first data set of C_j , the standard deviation is 0.71 and for second set it is 0.46. The IAN scores for $n = 8$ and $\sigma = 0.71$ is 8.41, and for $n = 8$ and $\sigma = 0.46$ it is 8.60. Similarly, we computed IAN scores for the set of 10 ideas for different values of n and the possible data sets of the values of C_j . The result is presented in Figure 2.

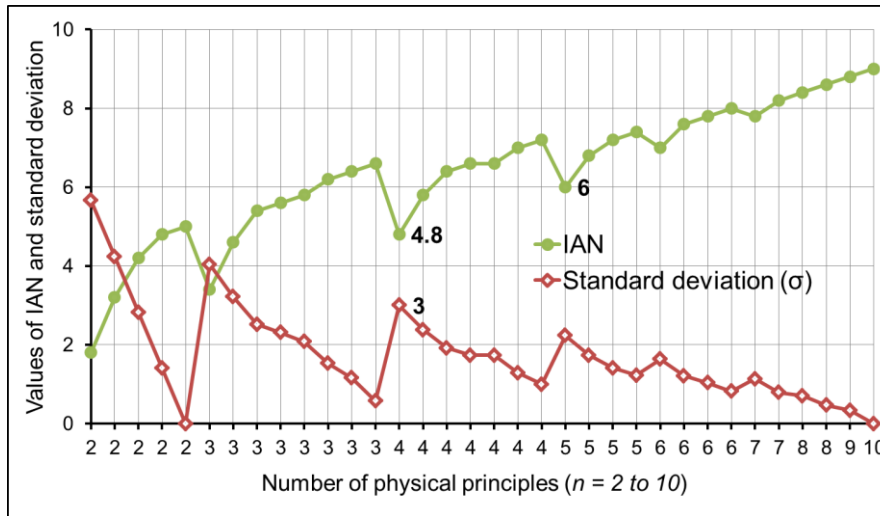


Figure 2 IAN and standard deviation for $T = 10$ and $n = 2$ to 10 (one function and one level)

From Figure 2, we can note that for given T and n , the IAN score increases with the decrease in σ . The lowest possible score of IAN for given T and n is obtained when the value of σ for that n is highest. For example, in the case of $n = 4$, the standard deviation for the lowest IAN score is 3, and the corresponding IAN score is 4.8 (see Figure 2). We compared the lowest possible score of IAN for $n+1$ and that for n . The value of σ is highest for a given n and T when one of the physical principles has $[T - (n - 1)]$ number of ideas and each of the remaining physical principles has one idea. Using this information we found that when $T > n$, the lowest possible IAN score for $(n+1)$ is higher than that for n because $[(\text{lowest possible IAN score for } n+1) - (\text{lowest possible IAN score for } n)] > 0$ as per the following equation:

$$(\text{lowest possible IAN score for } n+1) - (\text{lowest possible IAN score for } n) = \frac{20 \times (T - n)}{T^2}. \quad (6)$$

For example, $(\text{lowest possible IAN score for 5 physical principles}) - (\text{lowest possible IAN score for 4 physical principles}) = 20 \times (10 - 4) / 10^2$ which is 1.2 (see Figure 2). The above discussion shows that for a given T , increasing the number of physical principles and decreasing the standard deviation of the data set of the values of C_j prove effective idea generation in terms of the IAN score for a single function and one level. The implications of this finding have been discussed in Section 7. In particular, we have explained its relevance in developing effective idea generation methods.

From equation (3), variety of a set of T ideas for one function and one level (i.e. level of physical principles) can be computed from the equation: $V = (f_j * S_1 * b_1) / T = (1 * 10 * n) / T$. Where $f_j = 1$ for one function, $S_1 = 10$ for the level of physical principles, and $b_1 = n$ (number of physical principles).

For the above example of a set of 10 ideas ($T = 10$) generated by a designer, variety is computed from the equation $V = (10 * n) / 10 = n$. This means that for a given T , variety of a set of ideas for one level (i.e. level of physical principles) and a single function is proportional to the number of physical principles. Figure 3 shows the scatterplot of IAN and variety for the above example ($T = 10$). We also conducted a correlation study. The Pearson's correlation coefficient between the IAN and variety is strong (0.84). The relevance of this correlation is explained in Section 7.

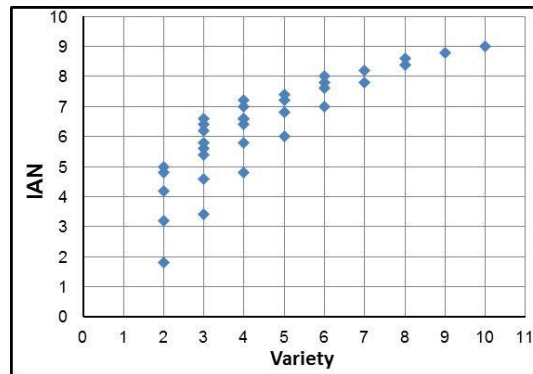


Figure 3 Scatterplot of IAN vs. variety for one function and one level (Correlation coefficient = 0.84)

6. AN and variety

The AN of a given set is computed by using the novelty scores of ideas in that set and these novelty scores are estimated by comparing each of those ideas with other ideas in the universe of ideas. Thus, in estimating AN of a set of ideas, ideas from the universe of ideas need to be considered. Therefore, empirical data needs to be used in estimating AN. We used data from the empirical study of Shah et al. (2003) to check if there is a correlation between AN and variety of a set of ideas.

Shah et al. (2003) have illustrated the procedure to compute the novelty score of an idea with the help of a design problem used in a student design competition. The design aimed at building a device using fixed set of materials and powered by a given volume of pressurized air. The device that travelled the longest distance from the starting position was considered as a winner. In total, there were 46 ideas. Figure 4 shows some ideas.

From equation (1), Shah et al. (2003) computed the novelty score of each of the 46 ideas. They computed the novelty scores for the following four functions or characteristics: (1) propulsion/thrust method (jet, sail, etc.); (2) medium of travel (air, land, water). (3) motion of device (rolling, sliding, tumbling, etc.), and (4) number of pieces into which the device separated in operation.

Using 46 ideas from Shah et al.'s (2003) study, we created 14 sets of ideas (set-1 to set-14). The rationale behind the creation of these 14 sets is as follows. The intention in creating the 14 sets was to examine the correlation between AN and variety (i.e. to check if values of variety scores increase with increase in AN scores for a given design problem). In order to check if variety scores increase with increase in AN scores, there is a need of different values of AN scores and associated variety scores for a given design problem. In other words, to examine this correlation, for a given design problem, we need to have different sets of ideas having different

values of AN scores and associated variety scores. Using these values of AN and variety scores, the correlation between AN and variety can be examined. Using this rationale, we created the abovementioned 14 sets to gain different values of AN scores and associated variety scores. Using these AN and variety scores, we examined the correlation between them by computing the Pearson's correlation coefficient.

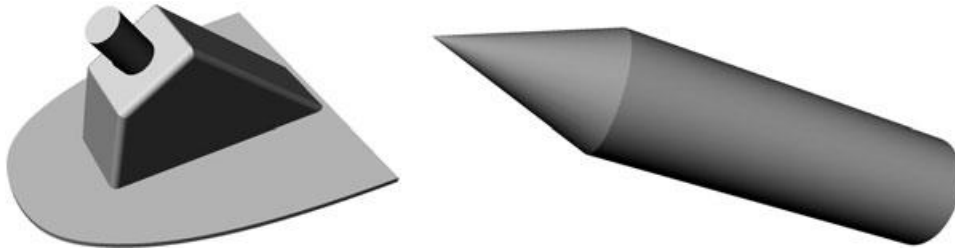


Figure 4 Three design ideas from the 46 ideas (adapted from Shah et al., 2003)

From equation (3), we computed the variety score of each of the 14 sets. For example, the set-7 employed four ways for the propulsion/thrust method. Therefore, the number of branches for this function is four. Similarly, we identified the number of branches for the remaining functions or characteristics ('medium of travel' - 2 branches, 'motion of device' - 2 branches, and 'number of pieces into which the device separated in operation' - 2 branches). As mentioned above, these characteristics are used by Shah et al. (2003) in computing novelty scores of 46 ideas. Figure 5 shows the genealogy trees for four functions or characteristics in the case of the set-7.

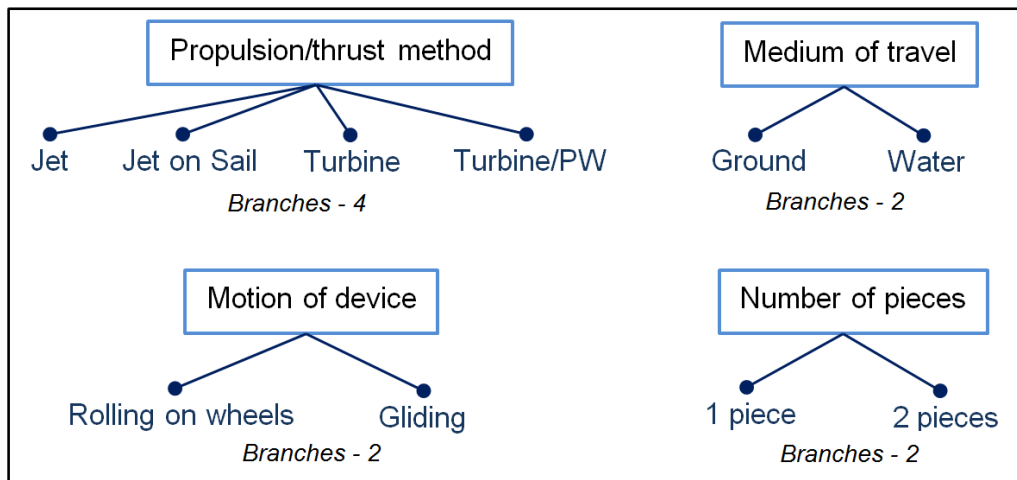


Figure 5 Genealogy trees for four functions or characteristics in the case of set-7 (at conceptual level)

We used the following values for f_j : $f_1 = 0.35$, $f_2 = 0.35$, $f_3 = 0.2$, and $f_4 = 0.1$ (these values have been used by Shah et al. (2003) in computing the novelty scores of 46 ideas). Then, the variety score of the set-7, consisting of 12 ideas, is calculated from equation (3) as follows: variety score (set-7) = $(f_1S_1b_1 + f_2S_1b_1 + f_3S_1b_1 + f_4S_1b_1)/12 = (0.35*10*4 + 0.35*10*2 + 0.2*10*2 + 0.1*10*2)/12 = 2.25$. Similarly, we calculated variety scores of all the 14 sets. Shah et al. (2003) have not computed variety scores in their study regarding 46 ideas. In order to compute the AN scores of each of these sets we used the novelty scores (*a posteriori*) of 46 ideas as computed by Shah et al. (2003). Figure 6 shows the scatterplot of AN vs. variety for the 14 sets. The Pearson's correlation coefficient between the AN and variety (0.79) is fairly strong ($p < 0.01$). In Section 7, we have explained the relevance of this correlation.

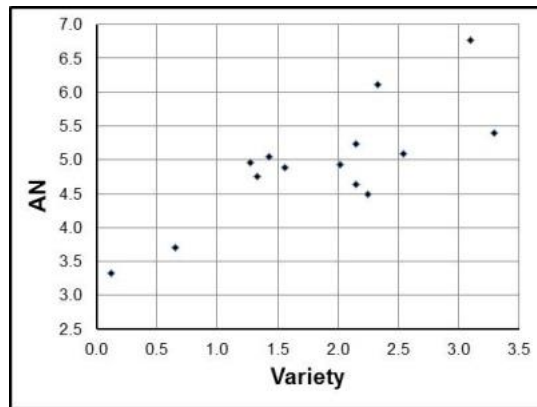


Figure 6 Scatterplot of AN vs. variety - Correlation coefficient = 0.79

In Section 5, for a single function and one level we examined the correlation between IAN and variety based on the equation we developed for IAN. The availability of 14 sets of ideas provided us an opportunity to examine correlation between IAN and variety based on empirical data as well. We computed IAN scores for the 14 sets of ideas. The Pearson's correlation coefficient between the IAN and variety (0.78) is fairly strong ($p < 0.01$). Figure 7 shows the scatterplot of IAN vs. variety for the 14 sets.

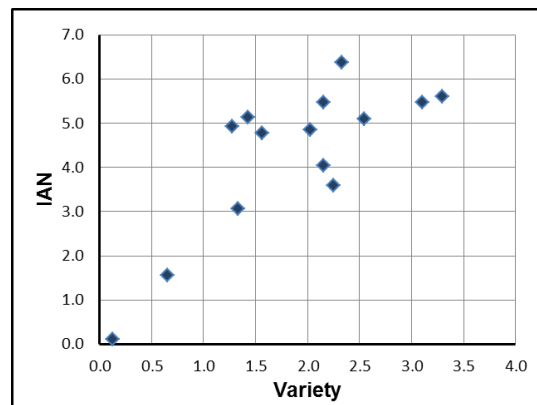


Figure 7 Scatterplot of IAN vs. variety - Correlation coefficient = 0.78

7. Summary of findings and discussion

The measurement of ideation effectiveness is important in developing methods to support designers in generating ideas. The work of Shah et al. (2003) in the area of design ideation metrics is foundational. However, they have not examined the interdependency between AN and variety. Furthermore, the interdependency between these metrics has not been examined in other studies using Shah et al.'s (2003) metrics. An investigation of the interdependency between these metrics is important to enhance our understanding of the metrics of ideation, and thereby to develop methods for improving ideation effectiveness.

Our study provides valuable insights into the interdependency between AN/IAN and variety, and their implications are discussed further in this section. We introduced IAN, and investigated the interdependency between IAN and variety. For this purpose, we used Shah et al.'s (2003) metrics, novelty and variety.

7.1. IAN and variety

We found correlation between IAN and variety based on the equation we developed for IAN (Section 5), and also by using empirical data (Section 6). The insights gained through our study allowed us to explain the interdependency between IAN and variety. Variety is computed from the genealogy tree of a set of ideas. There is an increase in the variety score of a set of ideas with the increase in the number of branches in the genealogy tree. An increase in the number of branches in the genealogy tree also increases the 'individual novelty' scores of ideas and thereby the IAN score of the set of ideas. This explains why there is a correlation or interdependency between IAN and variety.

The interdependency between IAN and variety can also be explained by using the meanings of variety, 'individual novelty' and IAN. Variety of a set is the degree to which the ideas in the set are dissimilar from the set's other ideas. This suggests that the variety of a set of similar ideas is low. 'Individual novelty' score of an idea generated by an individual is a measure of how unusual or unexpected that idea is as compared to other ideas generated by that individual. This suggests that the 'individual novelty' scores of ideas in a set of similar ideas are low, and thereby the IAN of that set is low. The variety score of a set of similar ideas is also low. Our findings regarding the correlation between IAN and variety (based on the IAN equation and empirical data) plus the above explanation of the interdependency grounded in the meanings of IAN and variety suggest that IAN of a set of ideas indicates variety of that set.

7.2. AN and variety

Based on the empirical data, we found a correlation between AN and variety (Section 6). The correlation or interdependency between AN and variety can be explained as follows. The AN of a given set is computed by using the novelty scores of ideas in that set and these novelty scores are estimated by comparing each of those ideas with other ideas in the universe of ideas. While we cannot control the ideas in the universe of ideas, designers will generate several ideas to satisfy a given function by using physical principles which are frequently seen in the universe of ideas. A reason for this can be that the designers are probably aware of the use of physical principles that are employed in commercially available products for satisfying the given function, and are therefore likely to generate several ideas using these physical principles. Therefore, these physical principles are likely to be frequently seen in the universe of ideas. The designers can generate ideas by employing an increased number of physical principles. If a designer generates ideas using greater number of physical principles, he/she is likely to use the physical principles which are not frequently seen in the universe of ideas. This can enhance the AN score of a set of ideas generated by using a greater number of physical principles. From equation (3), a greater number of physical principles used helps to increase the variety of the set of ideas. Therefore an increase in the AN of a set of ideas enhances the variety of that set.

7.3. Implications

The research findings regarding IAN and its interdependency with variety can help: (1) design researchers to save their time and effort by using IAN score as an indication of variety score, and (2) in developing effective idea generation methods for improving IAN scores. These implications are discussed in the paragraphs that follow.

Our above-mentioned explanation that IAN indicates variety (Section 7.1) can be useful for design researchers undertaking ideation studies (e.g. studies to evaluate idea generation methods). Design researchers can compute the IAN score of a set of ideas instead of its variety score if time and resources do not allow them to compute the variety score. As novelty is considered as an important component of creativity (Chakrabarti, 2009; Linsey et al., 2008),

novelty of ideas is generally computed in ideation studies. The procedure of computing 'individual novelty' score of an idea is the same as that used for computing the novelty score except for the fact that these procedures use different sets of ideas as a reference to compare the given idea with other ideas in the reference set. Computation of novelty score involves using the universe of ideas as a reference set, and the computation of 'individual novelty' score involves using an individual's set of ideas as a reference set. Using the same procedure of computing novelty scores to compute 'individual novelty' scores can help researchers to accelerate their process of computing 'individual novelty' scores and thereby the IAN score of a set of ideas. Computing variety score requires constructing a genealogy tree of a set of ideas, and this can be a time-consuming task. Therefore, researchers can save their time by computing IAN score of a set of ideas instead of its variety score, and this IAN score can be used as an indication of the variety score.

In Section 5, we developed equations (5) and (6), and using these equations we showed that for a given number of ideas (T), increasing the number of physical principles and decreasing the standard deviation of the data set of counts of ideas that use different physical principles (i.e. data set of values of C_j) prove effective idea generation in terms of the IAN score for a single function and one level. For a given number of ideas, paying equal attention to the physical principles used in generating ideas (i.e. generating equal number of ideas for the physical principles used) helps to decrease the standard deviation of the data set of the value of C_j , and thereby helps to increase IAN score. This finding can be used in developing effective idea generation methods in terms of enhancing IAN score. According to Shah et al. (2003) an idea generation method is considered effective if the method helps to improve the outcomes based on predefined metrics. An in-depth understanding of such metrics is important to identify ways to increase scores of these metrics, and thereby to develop idea generation methods that employ those ways. The abovementioned finding of our research regarding IAN can be used in developing idea generation methods to enhance IAN scores for a single function and one level. For example, a method can ask a designer to generate a certain number of ideas, and prompt him/her to increase the number of physical principles used and to pay equal attention to these physical principles. This increases the IAN score. This is applicable for a single function and one level (i.e. level of physical principles). There are many design problems aimed at fulfilling a single function (e.g. a problem to crack nuts, a problem to open tin cans, etc.). Furthermore, the level of physical principles is crucial in idea generation.

In general, the development of idea generation methods is aimed at improving their performance based on some metrics. In this process, focussing on appropriate metrics is important. The finding regarding the correlation between AN and variety can be useful in this process. In the development of idea generation methods aimed at enhancing novelty and variety scores, researchers can focus more on enhancing novelty scores of ideas because: (1) increasing novelty scores increases AN and variety scores as there is a positive correlation between AN and variety, and (2) as novelty is an important component of creativity, novelty of ideas is generally computed in ideation studies. Thus, between the metrics novelty and variety, focussing more on novelty can help to appropriately direct efforts in the development of idea generation methods.

7.4 Limitations and further work

Our research findings are applicable to Shah et al.'s (2003) metrics, namely novelty and variety. It would be interesting to undertake further research using other methods to assess novelty and variety, for example, methods developed by Sarkar and Chakrabarti (2008, 2011).

The work reported in this paper is about the interdependency between average novelty, 'individual average novelty' and variety. The work is thus limited to the metrics - novelty and

variety. Further work is required to explore the interdependency between all the four key metrics - novelty, variety, quantity, and quality. An investigation of the underlying reasons behind this interdependency (if any) can enhance our understanding of each of these metrics. Such an understanding could lead to ways for increasing scores of these metrics.

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