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Uncertainty in Communication with a Sketch

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Abstract

Sketches are one of the main tools for the communication of design ideas during the conceptual phase of the design process. In design communication, one of the major problems is the uncertainty associated with imprecisely defined sketches. There is a need to understand the uncertainty in the communication with sketches. This motivated the formulation of the research question: can uncertainty in communication with a sketch be quantified? To answer the research question, three specific aims were developed, namely, (1) determine the ranking of the features in a sketch, (2) determine the probability of importance of the features in a sketch, and (3) quantify the uncertainty of a sketch using Shannon's normalized entropy. This paper demonstrates the effective use of the established framework for the quantification of uncertainty and contributes to the improvement of design communication with a sketch.

Keywords: uncertainty quantification, sketches, design communication, Shannon's entropy

1. Introduction

Sketches play a vital role in the development of the conceptual design phase, as they are the main tools for the communication of concepts and ideas during this phase of the design process (Chandrasegaran et al. 2013; Dym 2006; Pache 2005). This is evident as sketches are considered as elements of the language of design (Bucciarelli 2002), and more specifically a visual element of the language of design (Maier, Eckert, and Clarkson 2005). They are used to communicate the physical nature of an entity conceived in imagination (McGown, Green, and Rodgers 1998). Do (Do 2005) described the important role of sketches in visualizing spatial arrangements whereas Zeng et al. (Zeng et al. 2004) reported the advantage of sketches in visualizing ideas. Sketches are used to create interaction between depictive and descriptive data and relate the concepts of function and structure (Tseng and Ball, 2010). Furthermore, sketches convey specific meanings based on their autonomous properties, which emerge from the interpretation of the relationship between their elements (Goldschmidt 2003). The fact that sketches could be created quickly and easily makes them a great medium for exploring and solving design problems (Häggman et al. 2015). Ultimately, sketches allow the quick communication of new design ideas by enabling the transmission and understanding of the design intent of a new product through the interpretation of its composing elements.

In some instances, sketches can be simply defined as hand written drawings on a piece of paper, whose purpose is to describe something inexact, provisional or missing in a quick, informal, and imprecise way (Eckert et al. 2012). Based on a perceptual approach, sketches are defined as cognitive vehicles used by designers to realize their mental representations (Bucciarelli 2002). Sketches are made of embodying elements, such as, icons and shapes. These elements have a geometrical meaning and hold determined

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spatial relationships between them. The elements enable them to depict objects and, thus, represent objects within specific categories or domains (Eckert, Clarkson, and Zanker 2004).

As a result of their imprecise and informal nature, sketches are inherently ambiguous. Ambiguity causes difficulty of sketch recognition (Alvarado 2011). Among the causes for ambiguity, authors such as Blackwell mentioned that the ambiguity in sketches is related to their semantic load, i.e. the less semantic load sketches have, the more ambiguous they will be (Blackwell et al. 2008). Sketches play a major role in the communication of new ideas in the design of products i.e. design communication (Stacey and Eckert 2003). Thus, ambiguity is of major concern in design communication as it affects the capability of sketches to communicate their design intent, hindering their interpretation, and thus making them uncertain (Crilly et al. 2008). This is especially an issue of great impact in visuospatial design fields such as architecture and mechanical design; where sketches are widely used (Stacey and Eckert 2003). However, note that uncertainties of sketches can be regarded as positive attributes for the design community. The inherent uncertainty of sketches in the conceptual design stage plays a significant role by creating an opportunity for designers to generate and expand creative ideas (Menezes and Lawson 2006; Atilola, Tomko, and Linsey 2016). This has inspired expert designers and increased possible design alternatives in the conceptual design stage (Tseng and Ball 2011).

The presence of uncertainty in sketches is a topic of great concern (Stacey, Eckert, and McFadzean 1999). Uncertainty in sketches may arise from lack of clarity, lack of information, unpredictability, and vagueness (Tseng and Ball 2011). Bucciarelli (Bucciarelli 2002) mentions that the meaning of sketches relies not only on their visible features but also on the context and design intention. It should be noted that the communication of a design content could be affected by uncertainty in a sketch (Demirezen 2012). Thus, managing uncertainty in the communication with sketches has become a major topic in design communication (Stacey, Eckert, and McFadzean 1999). Lovett et al. (Lovett, Dehgnani, and Forbus 2007) referred to the lack of straight lines or clear corners in a sketch as noise. On the other hand, Alvarado (Alvarado 2011) presented a detailed analysis of noise and methods of handling noise in hand drawn sketches. In this study, noise in sketches, such as non-straight lines and non-joining corners, was categorized as signal-level noise and description level variation.

Whereas there is substantial literature on functional product features, there is limited literature on form features related to aesthetics (Jagtap and Jagtap 2015). The form features or form concepts are externally visible constructs akin to sketches. Often, later in the concept generation phase, form concepts need to be developed and presented to consumers to elicit feedback that can be used to inform further development of the concepts (Häggman et al. 2015). An automated multi-agent system was used to automatically generate product form concepts based on consumer form preferences (Orsborn and Cagan 2009). Using designers' opinions and the shape grammar method to express those opinions, Prats et al. (Prats et al. 2004) were able to determine the most important, and less important form features that define the sketch of a product. Other researchers (Sagan and Yang 2012) compared the importance of aesthetics versus accuracy in sketch interpretations and they determined that the accuracy of a sketch is more important. Lovett et al. (Lovett, Dehgnani, and Forbus 2007) reported that expressions (spatial representations of sketches) should be ranked first by their predicates and then by their edges. In case of predicates defining attributes receive the highest ranking followed by anchoring relations. On the other hand, in edge ranking external edges are the most important and receive the highest ranking. Zeng et al. (Zeng et al. 2004) categorize the information contained in a sketch as geometry, text, and gesture. They developed a mathematical model to represent the hierarchy structure (tree) of a sketch. This mathematical approach was shown to be a more effective hierarchical representation of a sketch than the set theory, which lacks a robust definition of levels of abstraction of objects. More recently, the concept of design hierarchy was used to determine the importance of the constituent components of mechanical devices such as wind turbines, in order to determine their evolution and future development trends (Huenteler et al. 2016). In design hierarchy, the notion of service characteristics was used to formulate an analysis tool to generate the hierarchy of the components. Recently, Hyun et al. (Hyun, Lee, and Kim 2015) quantified novel design elements in a car such as: front bumper, side silhouette, and side front fender. They showed that ranking these externally visible novel elements in a hierarchy of order of importance was crucial in evaluating design changes, synthesizing design alternatives, and redesigning. In their most recent paper, Hyun et al. (Hyun et al. 2015) used this method again to form a hierarchy of the top five visually significant car design elements. Clearly, their hierarchy had inherent uncertainty due to the fact that it is based on a subject's eye movement and the length of time spent on the design elements. Nahm et al. (Nahm, Ishikawa, and Inoue 2013) formulated a ranking of importance, or a hierarchy, of customer requirements based on customer preference rating and customer satisfaction rating. This hierarchy exhibited elements of uncertainty in its formulation due to the fact that it relied on incomplete or uncertain perceptions.

The shape of an object is represented by its external boundaries or contour. Since contours are single-closed lines which sometimes do not have holes or internal details, these lines can be parametrized by using arc lengths (Belongie, Malik, and Puzicha 2002). A shape descriptor is a set of numbers produced to describe the mathematical signature of a shape. A good descriptor is able to describe mathematically any shape feature according to the human perception or according to task-specific requirements (Yang et al. 2008). Shape descriptors, such as histograms, have been widely used for representing, analyzing and characterizing 2D and 3D shapes. The main advantage of using histograms on shape characterization is that they mathematically represent probability density distribution of the underlying random variable (Feng et al. 2008). Desirable characteristics of a shape descriptor are low computation complexity (Zhang and Lu 2004), compactness, simplicity, and robustness (Yang et al. 2008). In general, shape representation and description techniques fall into three main classes of methods depending on where the shape features are extracted (Daliri and Torre 2008; Yang et al. 2008). The first class is called contour-based method, and it uses only the shape contour information to describe the object, whereas the second class includes the region-based methods and uses the shape interior information to characterize the object. In the third class, which is referred to as skeleton-based methods, the features are extracted from internal axis of the shape (Sá Junior and Backes 2015). In the shape representation and description techniques the topic of free-hand sketch recognition has recently received a lot of attention. Vashisht et al. (Vashisht, Choudhury, and Prasad 2012) proposed a sketch recognition system that utilized human perceptual rules as a guide for recognition and for the constraints in the language. Li et al. (Li et al. 2015) recently proposed a star graph representation, that captures both the local features and holistic structure, and a multiple kernel feature learning framework for free-hand sketch recognition.

Rigau et al. (Rigau, Feixas, and Sbert 2008) measured the structure and hierarchy of an image, and quantified an image's capacity to be ordered. They proposed an informational measure of aesthetics based on Shannon's information theory and Kolmogorov's complexity. Shannon's information theory has also been used in design theory and design communication (Maier, Eckert, and Clarkson 2005). It has been used by designers to define "artifacts" as transmitters of a message to their customers (Crilly, Maier, and Clarkson 2008). In the work of Khan and Angeles (Khan and Angeles 2007), Shannon's information theory was used to determine the complexity of design solutions and measure their diversity. This theory has also been used to model the communication channels of a sketch in order to determine its formality to embody and express meaning to designers (Eckert et al. 2012). Other authors (Hannah, Joshi, and Summers 2012) adapted Shannon's information theory to quantify the information content of sketches. The authors established that there is a need to know the type of information contained in a sketch.

2. Research Question

While sketches with high level of uncertainty reduce accurate information transmission, they can induce and facilitate increased creativity among the design team. It is important to note that depending on the design stage, its required level of ambiguity also varies. High level of ambiguity is desirable in sketches used during the early conceptual design stages to encourage creativity, whereas low ambiguity is preferable in sketches used during the later conceptual design stages, i.e. to elicit user preferences. Hence, it is essential to determine and optimize the level of ambiguity accordingly to achieve the desired outcome. Therefore, regardless of the design stage, there is a need for uncertainty quantification of a sketch to determine its level of uncertainty. There is also a need to quantify uncertainty in communication with sketches due to the following reasons:

- 96% of designers use sketches at the product development phase (Chandrasegaran et al. 2013; Pache 2005; Dym 2006), which accounts for 70% of the total product costs (Römer et al. 2001).
- Sketches improve the flow of the cognitive process among designers during the product development phase (Chandrasegaran et al. 2013).
- Sketches have been shown to reduce the time and cost of modelling and fabrication of new products (Orsborn, Cagan, and Boatwright 2009; Eckert et al. 2012; Hannah, Joshi, and Summers 2012).
- Unlike computer models, sketches maintain their provisional quality and promote the creative work of designers during the product development phase (Chandrasegaran et al. 2013).
- Form features or form concepts of a sketch are important for consumer evaluation of new designs (Jagtap and Jagtap 2015; Orsborn, Cagan, and Boatwright 2009; Prats et al. 2004; Sagan and Yang 2012; Lovett, Dehgnani, and Forbus 2007).

The aforementioned reasons serve as a motivation for the formulation of the research question: can uncertainty in communication with a sketch be quantified? To answer the research question, three specific aims were developed, namely, (1) determine the ranking of the features in a sketch, (2) determine the probability of importance of the features in a sketch, and (3) quantify the uncertainty of a sketch using Shannon's entropy.

3. Methodology

3.1. Ranking of Features

The ranking of the features of a sketch is a major focus in determining the uncertainty in communication with a sketch. The concept of nested hierarchy states that the hierarchy of the embodying components of a product can be determined by quantifying their pleiotropy score, based on the impact this components have towards the completion of the particular service characteristics of a product (Murmann and Frenken 2006). This gives rise to the concept of design hierarchy, which arises from the merger of the concept of dominant design and the concept of nested hierarchy. Design hierarchy allows to determine and prioritize the embodying components of a product based on the importance of each component on the completion of a products' particular functions, which are also referred to as service characteristics (Huenteler et al. 2016). Using visual significance hierarchy for unique design elements on externally visible design attributes such as those contained in a sketch, researches have been able to formulate a hierarchy of importance (Hyun, Lee, and Kim 2015).

Hence, given a sketch, the first step is to identify the features contained in the sketch. To identify the features in a sketch, the service characteristics are identified first. Then, the features are extracted based on the service characteristics (see Table 1). In this study, the service characteristics considered were energy, control and interface. The energy characteristic is the service characteristic responsible for supplying the energy required for the system to achieve its objective function. On the other hand, the control characteristic is responsible for controlling the performance of the system. The interface characteristic is an interaction between the system and the environment as well as among the components of the system.

After the features of a sketch have been identified, they will be ranked. The process to rank the identified features of a sketch starts with the refinement of the service characteristics based on the completion of the objective function of the sketch. For example, to refine the energy characteristic of a helicopter sketch, the type of flight the helicopter employs to achieve its objective function will be identified.

These main flight types, hover, lift and thrust, will be the refined energy service characteristics. The second step in ranking the features is construction of the service characteristics assessment matrix. This is performed by listing all the refined service characteristics in one column and each of the identified features in the preceding columns (see Table 2). The matrix then can be used to assess if the identified features in each column have an impact on each refined service characteristic. If the feature is determined to have an impact on the service characteristic, the intersection cell between both should be filled with an "X" mark. On the other hand, if a feature does not have an impact, the corresponding cell in the table will be filled with a "0". The X's of each feature in the table are finally added to provide the pleiotropy score of each feature. The pleiotropy score is the parameter that is used for ranking the features. The ranking of the feature was designated by the variable *i*. The procedure of using a hand-drawn or digitalized sketch as input to determine the features and their ranking is depicted in Fig. 1.

Table 1. Extracting features using service characteristics.

Service Characteristics	Features
Energy Characteristic	Feature # 1
	Feature # 2
Control Characteristic	Feature # 3
	Feature # 4
Interface Characteristic	Feature # 5
	Feature # n

Table 2. Functional Service Characteristics Assessment Matrix.

Service Characteristics		Feature Assembly	Feature # 1	Feature # 2	…	Feature # N
Energy Characteristics	Characteristic #1	×	0	×	…	0
	Characteristic #2	×	0	0	…	0
	Characteristic #n	×	0	0	…	0
Control Characteristics	Characteristic #1	×	×	0	…	0
	Characteristic #2	×	×	0	…	0
	Characteristic #n	×	×	0	…	0
Interface Characteristics	Characteristic #1	×	×	0	…	×
	Characteristic #2	×	0	0	…	×
	Characteristic #n	×	0	×	…	×
Pleiotropy		n	4	2	…	3
Feature Rank		-	1	3	…	2

It should be noted that features, other than the single first feature, can have the same rank. The number of features with a rank *i* were designated by the value k_i. For example, if the pleiotropy results in two features having rank 2, then $i = 2$ and $k_2 = 2$.

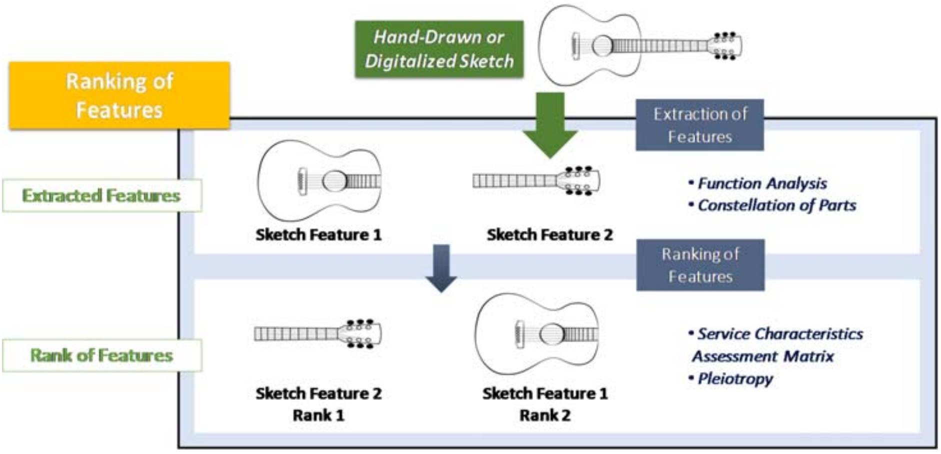

Fig. 1. Feature extraction and ranking.

3.2. Probability of Importance

The probability of importance is the key factor driving the level of uncertainty in a sketch, as it reflects not only the level of importance of each of the composing features, but links its importance to its level. In order to determine the probability of importance, it is necessary initially to determine the probability of likeliness (L_i) for the features in a sketch by comparing their "likeness" (Jupp and Gero 2004) with respect to the image of an actual mechanical component. Among several image attributes that can be used in the comparison, the proposed methodology focuses on the shape (contour) similarity measurement between the sketch feature and the image of actual mechanical component.

Several shape-matching methods are available to determine the similarity between two images. Among them, the Inner-Distance Shape Context (IDSC) proposed by Ling and Jacobs (Ling and Jacobs 2007) was selected and applied to the proposed methodology. IDSC is based on histogram shape descriptors (Belongie, Malik, and Puzicha 2002) which use the concept of inner-distance, i.e. the length of the shortest path between landmark points within a shape's profile, in order to create a mathematical signature of an object. Given a point, x_l, on the contour of the first shape and a point, y_j, on the contour of the second shape, the cost of matching of these two points, c_{lj}, is defined using a Chi-Square test statistic (Belongie, Malik, and Puzicha 2002; Ling and Jacobs 2007):

$$c_{\mathrm{lj}} = \frac{1}{2}\sum_{r=1}^{R} \frac{\left[h_l(r)-h_j(r)\right]^2}{h_l(r)+h_j(r)}, \qquad (1)$$

where r are the bins uniformly divided into log-polar spatial coordinates, $h_l(r)$ and $h_j(r)$ denote the R^{th}-bin normalized histogram at x_l and y_j, respectively.

In order to solve the matching problem and determine the pairwise correspondence of points x_l and y_j, a Dynamic Programming (DP) optimization procedure was used (Gorman, Mitchell, and Kuhl 1988). In summary, DP finds the pairwise of corresponding points x_l, y_j that minimizes the summation of the cost of matching of these points. Considering that the indexes of the points of shape y_j which correspond to the points of the shape x_l are the elements $\pi(l)$ of the vector π, the average cost of matching $\bar{C}(\pi)$ of the correspondent points x_l, $y_{\pi(l)}$ can be defined as,

$$\bar{C}(\pi) = \frac{\sum_{\mathrm{l}=1}^{N_{cp}} c(x_l, y_{\pi(l)})}{N_{cp}}, \qquad (2)$$

where N_{cp} is the number of pairwise corresponding points. In fact, Eq. (2) provides a probability number that measures the dissimilarity between two shapes with limits ranging from 0 (for identical shapes) to 1 (for extremely different shapes). Feng et al. (Feng et al. 2008) used a similar concept to define a discrepancy factor to compute the cost of matching between 3D shapes. Then, the complement of the average cost of matching, 1-$\bar{C}(\pi)$, is a probability number which accounts for the similarity, or the probability of likeliness, L_i, between the two shapes and is given by,

$$L_i \equiv 1 - \bar{C}(\pi) = 1 - \frac{\sum_{i=1}^{N_{cp}} c\left(x_i, y_{\pi_i}\right)}{N_{cp}}, \quad (3)$$

in which the value of the probability of likeliness is also contained in the range $0 < L_i < 1$.

This range was referred to as "probability of likeliness space." In order to calculate the probability of importance, p_i, the "probability of likeliness space" was mapped to the "probability of importance space". This mapping follows a set of rules based on the ranking of features and the principles of Shannon's information theory.

The rules presented below consider a sketch that has N total number of features ranked based on their importance from $i = 1$ to n, having k_i (number of features in each rank) and where $i = 1$ is given to the most important feature:

1. There will only be one most important feature in a sketch, i.e.,

$$k_1 = 1 \quad (4)$$

2. The summation of the probability of importance , p_i of all features is given by Shannon (Shannon 1948):

$$\sum_{i=1}^{n} k_i p_i = 1 \quad (5)$$

3. The probability of importance, p_1 of the most important feature in a sketch cannot be less than $1/N$, this is associated to the maximality property of Shannon's entropy (Aktunc 2008), and will have a maximum value of 1, i.e.,

$$\frac{1}{N} \leq p_1 \leq 1 \quad (6)$$

4. The probability of importance, p_i , of each of the ith ranked feature(s), where $2 \leq i \leq n-1$, is given by:

$$\left(\frac{1-\sum_{j=1}^{i-1} k_j p_j}{N-\sum_{j=1}^{i-1} k_j}\right) \leq p_i \leq \left(1 - \sum_{j=1}^{i-1} k_j p_j\right) \quad (7)$$

5. The probability of importance, p_n of each of the n^{th} ranked feature(s) is given by:

$$p_n = \frac{1-\sum_{i=1}^{n-1} k_i p_i}{k_n} \quad (8)$$

6. Probability of likeliness space, $0 < L_i < 1$, of the i^{th} ranked feature $(i = 1, 2, \ldots, n-1)$ shall be mapped to the probability of importance space, $p_{L_i} < p_i < p_{U_i}$, defined in Rule 3 and Rule 4, of the same feature according to a linear transformation given by:

$$p_i = (p_{U_i} - p_{L_i}) L_i + p_{L_i} \quad (9)$$

For example, the mapping function for the most important feature $(i = 1)$ will be,

$$p_1 = \left(\frac{N-1}{N}\right) L_1 + \frac{1}{N} \quad (10)$$

Note that the constrained probability space gets narrower as you go down the ranking. Using as input the features and their corresponding rankings, the procedure to calculate the probability of likeliness and consequently the probability of importance is depicted in Fig. 2.

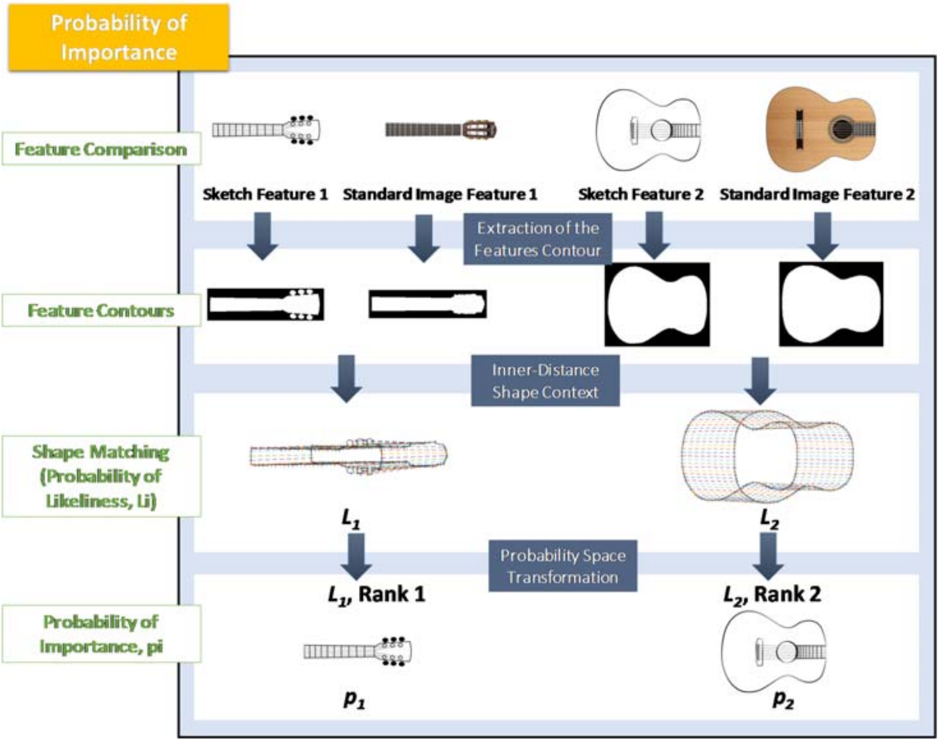

Fig. 2. Determining the probability of importance (*p_i*).

3.3. Quantification of Uncertainty

The entropy of the sketch was obtained using Shannon's communication theory (Baez, Fritz, and Leinster 2011).

$$H = -\sum_{i=1}^{n} k_i p_i \log_2 p_i . \qquad (11)$$

The uncertainty of a sketch, based on the normalized value of the entropy, where $0 \leq u \leq 1$, is given by (Masisi, Nelwamondo, and Marwala 2008):

$$u = \frac{H}{log_2(N)} . \qquad (12)$$

Hence, Eq. (12) is the quantification of the uncertainty of communication with a sketch (Cruz-Lozano et al. 2015; Ekwaro-Osire, Cruz-Lozano, and Endeshaw 2015; Cruz-Lozano, Alemayehu, and Ekwaro-Osire 2014). Using the probability of importance as an input, the uncertainty quantification can be performed as shown in Fig. 3.

The steps outlined in sections Ranking of Features, Probability of Importance, and Quantification of Uncertainty are used to construct the framework for the quantification of uncertainty of communication with a sketch as depicted in Fig. 4. As described in the prior paragraph, this framework is anchored to Shannon's information theory.

Using the framework in Fig. 4, Eq. (12) was used to generate Fig. 5 for a sketch with number of features of 2, 3, 4 and 5. From the results shown in Fig. 5, the following important aspects were identified. First, as the number of features that compose a sketch increases, its uncertainty level decreases.

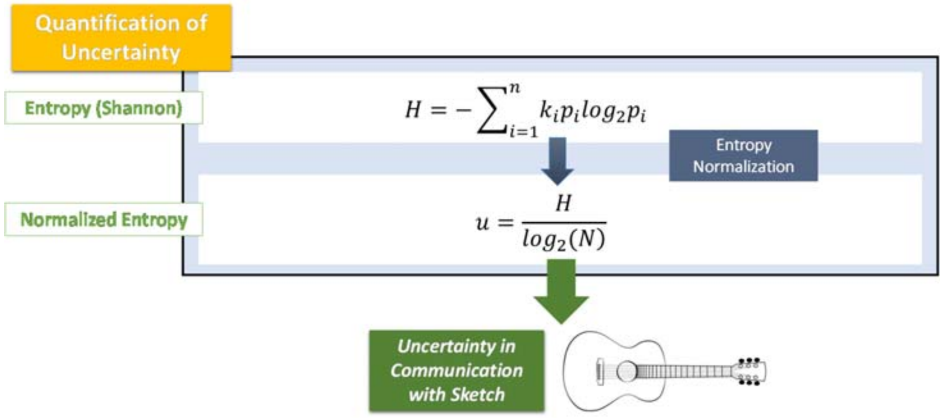

Fig. 3. Uncertainty quantification.

Thus, to reduce uncertainty in sketches with fewer features, the most important features should be drawn more accurately. Second, as p_1 goes to 1, the significance of its value to the actual uncertainty of a sketch decreases. This means, for sketches with well-drawn most important features, e.g. $p_1 \geq 0.95$, the improvement of the drawing of their other features will not have a considerable effect in the reduction of their uncertainty regardless of their total number of features. Hence, it is useful to pay attention to the quality of the drawing of the most important feature in any sketch. In addition, drawing the most important feature well avoids the need to improve other features in the sketch. Third, aspect comes from the fact that as the number of features in a sketch increases, the range of values that p_1 i.e. $1/N \leq p_1 \leq 1$, also increases. In the case of the present discussion, this aspect allowed us to focus on the idea of viewing a sketch as a graphic representation of a design, with the purpose of only communicating its design intent. Thus, it is possible to infer that a sketch needs to have only the necessary features to communicate its design intent and nothing more. So, sketches that need more features to be embodied will have a greater chance to be misunderstood from the start. Thus, not only the most important feature in the sketch should be drawn in the best way possible, but the number of its embodying features should be kept to a minimum.

4. RESULTS AND DISCUSSIONS

4.1. Ranking of Features

The framework presented in Fig. 4 is now applied on a sketch of a helicopter shown in Fig. 6. A helicopter is a type of aircraft whose main lift power is generated from a rotor with a vertical axis. Based on their service characteristics, helicopters have the following distinguishable features (see Table 3).

Rotor: its function is to create the lift and thrust power that allows the helicopter to lift its cargo (passengers or goods) and to fly forward. Tail: its function is to create thrust to control the helicopter's direction as well as to counteract the torque effect generated by the rotor. Cockpit: its function is to provide the space that allows the cargo to be transported. Landing Gear: its function is to support the weight of the helicopter in its non-flying stages, i.e. taking off and landing, and thus avoid its damage. The features identified in Table 3 were imported into the sketch to generate Fig. 7. The features in the figure are labeled as follows: landing gear (a), tail (b), cockpit (c), and rotor (d). The next step after identifying the features that constitute the sketch of a helicopter is to rank them. This task is done by assessing the identified features of the sketch, using the service characteristics assessment matrix for the sketch which is shown in Table 3.

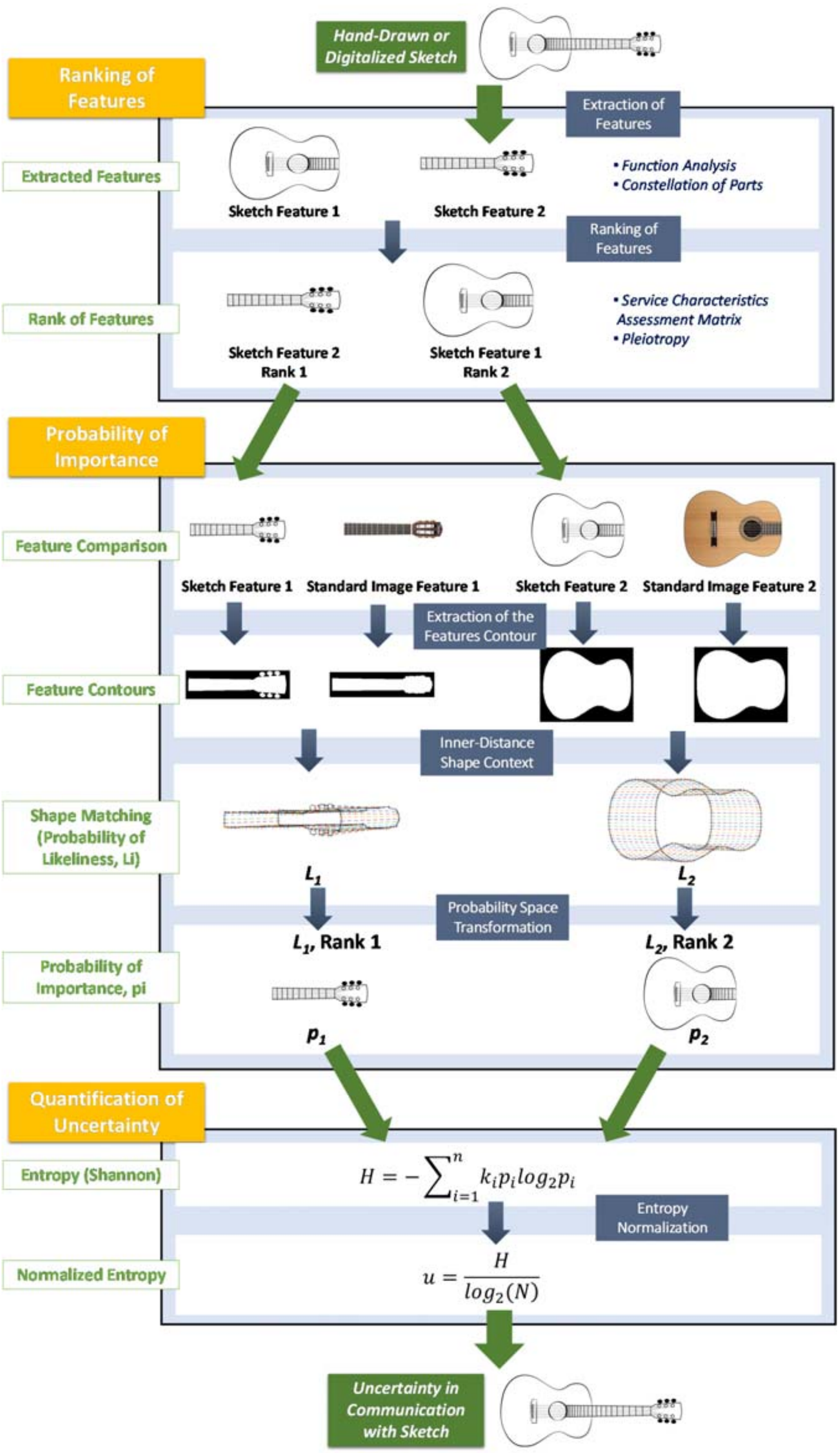

Fig. 4. Framework for the quantification of uncertainty in communication with a sketch.

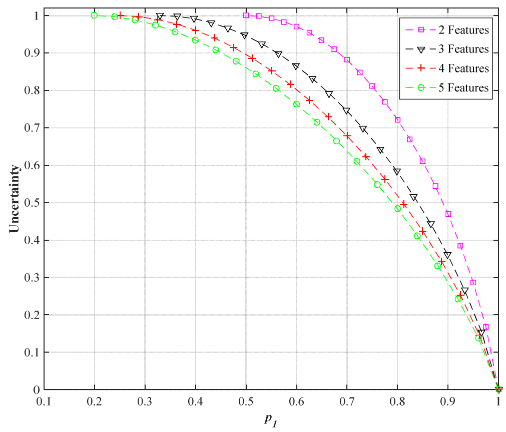

Fig. 5. Uncertainty as a function of the probability of importance value of the most important feature (p_1).

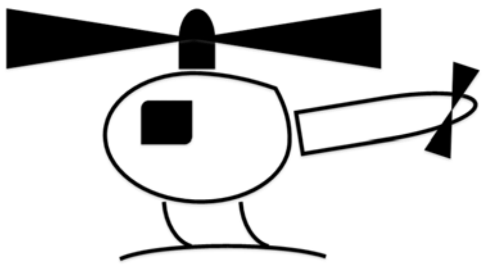

Fig. 6. Sketch of a helicopter.

Table 3. Features of helicopter sketch extracted using service characteristics.

Service Characteristics	Features
Energy Characteristic	Rotor
	Tail
Control Characteristic	Rotor
	Tail
Interface Characteristic	Landing Gear
	Rotor
	Tail
	Cockpit

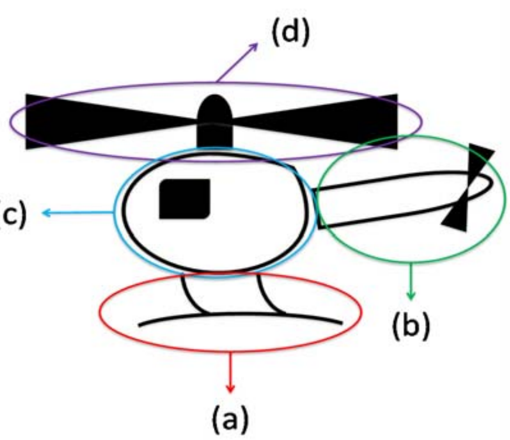

Fig. 7. Features of the helicopter sketch: (a) landing gear, (b) tail, (c) cockpit, and (d) rotor.

After the features of a sketch have been identified, they were ranked. The energy characteristic was refined to hover, lift and thrust. Similarly, the control service characteristic was refined as hover control, lift control, and thrust control. On the other hand, the interface service characteristic was refined to interface air, interface cargo, interface connector, and interface ground contact. The service characteristics assessment matrix was constructed (see Table 4).

Table 4. Service Characteristics Assessment Matrix for the Sketch of a Helicopter.

Function: Transport Cargo		Sketch	Features			
Service Characteristics		Helicopter	Landing Gear (a)	Tail (b)	Cockpit (c)	Rotor (d)
Energy Characteristic	Hover	×	0	0	0	×
	Thrust	×	0	×	0	×
	Lift	×	0	0	0	×
Control Characteristic	Hover Control	×	0	×	0	×
	Thrust Control	×	0	×	0	×
	Lift Control	×	0	×	0	×
Interface Characteristic	Interface Air	×	0	×	0	×
	Interface Connector	×	0	0	×	0
	Interface Cargo	×	0	0	×	0
	Interface Ground Contact	×	×	0	0	0
Pleiotropy		**10**	**1**	**5**	**2**	**7**
Feature Rank, *i*		**-**	**4**	**2**	**3**	**1**

The pleiotropy of the sketch is shown to have a value of 10 (see Table 4). The pleiotropies of the rotor, tail, cockpit, landing gear were 7, 5, 2 and 1, respectively. It is also observed that the pleiotropy of the rotor is much higher than that of the next pleiotropy, i.e. tail. This yielded the following ranking of the features of the helicopter sketch: rotor (Rank 1), tail (Rank 2), cockpit (Rank 3), and landing gear (Rank 4). Therefore, in the sketch (see Fig. 7), the rotor has the highest rank with a pleiotropy much higher than the second highest feature, i.e. tail. This implies that the rotor may play the most important role as the identifier of a sketch of a helicopter.

4.2. Probability of Importance

In order to determine the probability of importance, p_i, of each of the composing features of the sketch of a helicopter, "probability of importance" in the proposed framework (see Fig. 4) is developed. In this step, each feature of the sketch in Fig. 7 is now compared to the corresponding actual component of a helicopter using images of the same size and orientation (see Fig. 8). Through the use of IDSC and based on the overall matching cost C(π) of each pair of corresponding images in the figure, the probability of likeliness, L_i, for each of the features of the sketch was determined (Table 5).

The results obtained are shown in Table 5, where the values for the L_i's for the features of the sketch of a helicopter range from 64.84% to 76.67%. It can be observed that the probability of likeliness for the rotor is higher than the rest of the other features. This is due to the fact that unlike the tail feature, the sketch of the rotor based on its contour shape has the best match to the shape of its corresponding component. Thus, although not sufficient by itself, this results can initially serve as a clue to the possible level of uncertainty in the sketch. Therefore, in order to fully determine the level of uncertainty associated with the sketch of a helicopter, the application of the process for the transformation of the probability space and the resulting probability of importance (p_i) for each of the features was calculated.

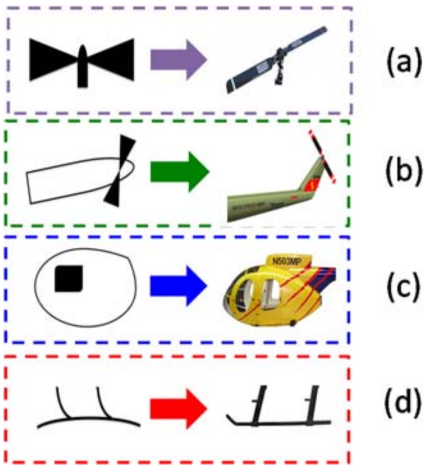

Fig. 8. Images to be compared (a) rotor, (b) tail (c) cockpit (d) landing gear.

Table 5. Probability of likeliness (L_i) for the features of the sketch of a helicopter.

Feature Assessed of Helicopter	Probability of Likeliness (L_i)
Rotor	76.67%
Tail	64.84%
Cockpit	69.17%
Landing Gear	69.92%

As shown in Eq. (4), the rotor is the only feature in the first rank, $k_1 = 1$. Following Eq. (6), the limits of the probability of importance are:

$$0.250 \leq p_1 \leq 1. \quad (13)$$

Next, using Eq. (9) the value of p_1 is determined to be 82.50%. Eq. (7) is used to determine the boundary values for the probability of importance, p_2, for the tail feature

$$0.0583 \leq p_2 \leq 0.1750. \quad (14)$$

Using Eq. (9), p_2 was determined to be 13.39%. Next, Eq. (7) was used again to determine the boundary values for the probability of importance, p_3, for the cockpit feature as

$$0.0205 \leq p_3 \leq 0.0411. \quad (15)$$

It can be observed that the probability space gets narrower with decreasing rank. This is due to a decrease in residual probability that occurs with decreasing rank.

Using Eq. (9) the value of p_3 was determined to be 3.47%. Finally, as the probability of importance, p_4, was calculated using Eq. (8) as 0.64%. Note that the sum of the probability of importance of the features is 100%. It should be noted that the probability of likeliness of the rotor was the highest (see Table 5), and after the transformation, its probability of importance remained the highest, and with a very significant difference from the other features e.g. the tail which the second highest ranking feature has a p_i of almost 65% less than the rotor. This fact, stems as a result of the highest ranking of the rotor among the features that compose the sketch of a helicopter, as well as to its highest L_i value with respect to the other features as well.

Hence, the rotor has the highest probability of importance of 82.50% while the landing gear has the lowest probability of importance of 0.64%. This shows that the rotor will play a crucial role in the reduction of uncertainty in the sketch. In other words, in order for the helicopter sketch to be interpreted correctly, more attention should be given to drawing the rotor.

4.3. Quantification of Uncertainty

In order to quantify the uncertainty associated with the sketch, first, the entropy, H, of the helicopter was determined to be 0.832 bits using Eq. (11). The uncertainty of the sketch, u, was then quantified to be 41.61% using Shannon's normalized entropy (Eq. (12)). This indicates that there is a 41.61% chance that the sketch will not be interpreted as a helicopter. In order to reduce this uncertainty, features with higher ranks (such as the rotor and the tail) should be revisited and redrawn accordingly. Redrawing of the high-ranked features may include changes such as orientation and detail.

5. Conclusion

The research question in this study was: can uncertainty in communication with a sketch be quantified? Indeed, it was shown that uncertainty in communication with a sketch could be quantified. To this effect, a framework based on Shannon's information theory was proposed for the quantification of uncertainty in communication with a sketch. In this study, the proposed framework was applied to a sketch of a helicopter. Using a service characteristics assessment matrix, four features were determined for the sketch. The features were rotor, tail, cockpit, and landing gear. The features were ranked as follows in descending order: rotor, tail, cockpit, and landing gear. This implies that the rotor may play the most important role as the identifier of a sketch of a helicopter. Furthermore, the rotor had the highest probability of importance of 82.50% while the landing gear has the lowest probability of importance of 0.64%. This shows that the rotor plays a crucial role in the reduction of uncertainty in the sketch. In other words, in order for the helicopter sketch to be interpreted readily, more attention should be given to drawing the rotor. In order to reduce this uncertainty, features with higher ranks (such as the rotor and the tail) should be revisited and redrawn accordingly. Redrawing of the high-ranked features may include changes such as orientation and detail.

High level of ambiguity is desirable in sketches used during the early conceptual design stages to encourage creativity, whereas low ambiguity is preferable in sketches used during the later conceptual design stages, i.e. to elicit user preferences. Hence, it is essential to determine and optimize the level of ambiguity accordingly to achieve the desired outcome. Uncertainty quantification presented in this paper can, thus, be used for determining the level of uncertainty regardless of the type of the sketch.

Future work will include improving the selection and matching of the standard image features to the sketched features. Furthermore, other shape matching methods will be explored. Additionally, a rigorous validation of the calculation of probability of importance will be pursued.

Appendix: Additional Example of Application of Framework

In this section, the development of a second case study using the proposed framework in Fig. 4 is presented. This with the goal of enabling the reader to have a better understanding of the application of the framework based on another application belonging to a different class. Thus, next the framework is applied to the sketch of a bicycle, a two wheeled steerable machine that is pedaled by a person, the bicycle rider, in order to propel it and thus achieve movement (Academic 2016). Therefore, based on its service characteristics, four features were identified in the sketch of a bicycle (see Fig. A1), namely: mounting system (saddle + frame), steering system (handlebar + fork + front wheel), power system (drivetrain), and rear wheel system (rear wheel). They were ranked, using its service characteristics and refined service characteristics namely steering, propulsion, interface rider, interface terrain, and interface connector, yielding the following results: rear wheel system (Rank 1), power system (Rank 2), steering system (Rank 3), and mounting system (Rank 4). Next, the L_i values for each feature were determined giving the following results: rear wheel system, $L_1 = 0.5786$; power system $L_2 = 0.7016$; steering system $L_3 = 0.6354$, and mounting system $L_4 = 0.8341$. This L_i values were later transformed into the following P_i values: $P_1 = 0.6839$, $P_2 = 0.2197$, $P_3 = 0.0884$, and P_4=0.008. Hence, ultimately yielding an uncertainty value u = 61.01 % for the sketch of a bicycle presented in Fig. A1.

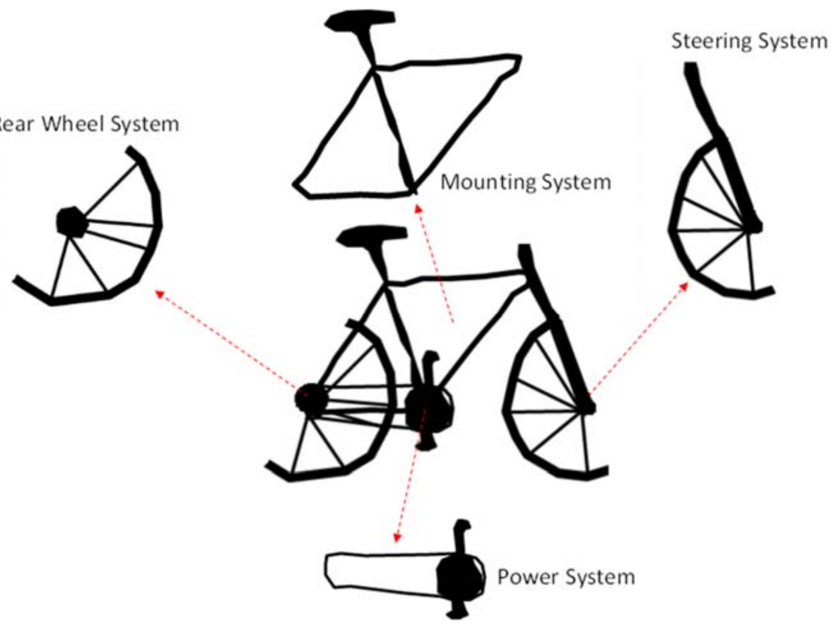

Fig. A1. Sketch of a bicycle and four main features: rear wheel, system, power system, steering system, and mounting system

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