Visual Information Vases: Towards a Framework for Transmedia Creative Inspiration

Britton Horn
PLAIT Research Group
Northeastern University
Boston, MA USA
bhorn@ccs.neu.edu

Gillian Smith
PLAIT Research Group
Northeastern University
Boston, MA USA
gillian@ccs.neu.edu

Rania Masri
College of Arts, Media and Design
Northeastern University
Boston, MA USA
rania@raniamasri.com

Janos Stone
College of Arts, Media and Design
Northeastern University
Boston, MA USA
j.stone@neu.edu

Abstract

Inspiration is an important aspect of human creativity and one that creative systems are only recently implementing. In this research, we describe and implement a transmedia creative inspiration model for generative art systems. Our implementation of this model is Visual Information Vases (VIV), an artificially intelligent ceramicist that creates 3D-printable vases using inspiration from a user-supplied image. VIV scores an image along four aesthetic measures—activity, warmth, weight, and hardness—by evaluating the image's color palette. VIV then attempts to create a vase with similar aesthetic measures through evolution. The resulting vases are diverse and functional creations. We hope that this model will allow future generative systems to create inspired artifacts from a wide variety of sources.

Introduction

In current models of creative AI systems, one under-explored aspect of creativity is inspiration: interpreting concepts from one medium and translating them into another. The analogical mapping of perceptions and concepts (Hofstadter and Mitchell 1994) is a critical step in human creativity since it allows people access to solutions or creations outside their current mental state through influence by some external source (Hadamard 1996). This method of inspiration is common in many areas and can produce novel results. Composers interviewed by McCutchan conveyed their inspiration came through channels including music, nature, and poetry. More technical fields also involve creative inspiration, including examples of animals and insects inspiring work in robotics (McCutchan 2003).

In Thrash and Elliot's conceptualization of inspiration, three commonalities arose from their readings on previous literature: Inspiration is *evoked*, involves *transcendence* and implies *motivation* (2003). In this paper, we describe a system that focuses on evocation of inspiration from a source domain and transcendence of that inspiration to create an artifact in an entirely different domain. We also believe motivation is a critical step in creativity, however one which is outside the scope of this paper.

A full computational model of inspiration is still a long way off, however we attempt to close this gap by modeling one piece of inspiration: cross-domain analogy mapping. In order to show this is a feasible construct for creative systems, we developed a framework for transmedia analogy mapping from color palettes of images to 3D printable vases using the four aesthetic measures activity, warmth, weight and hardness. These measures were chosen primarily because of their importance among sculptors we interviewed, as well as their history within color science (Eysenck 1941; Granger 1955; Ou et al. 2004). Our inspiration framework was derived to mimic a common creative process performed by many sculptors and artists—choosing a color from an image to be the basis of inspiration for a new piece. The artist must transfer her feelings about the color onto a completely different domain. The essence of the inspiration source is not lost, but expressed in the new domain using techniques available in the target domain.

Visual Information Vases (VIV) is an AI-based generative art system which uses our model of inspiration to produce 3D-printable vases with inspiration from 2D images uploaded by a user. Users interact with VIV online by uploading images, viewing results, and printing vases for everyday use. Our proof-of-concept implementation presented in this paper produces vases through evolution using the four aesthetic measures stated above as primary components of the fitness function. To our knowledge, this is the first instance of a system using evolution to create content optimized on aesthetic characteristics from an entirely different domain.

VIV analyzes the colors of a user's image to create a color palette from salient and dominant colors. Color palette analysis is performed to create an aesthetic profile for the image. VIV then uses an evolutionary algorithm to produce a vase with a similar profile to that of the user supplied image. The resulting vase can be printed from a myriad of materials and printers to produce a functional, decorative vase. Vases are described in a manner similar to that of Reed's while researching beauty as an aesthetic measure for evolutionary vase creation (2013).

The main contribution of this research is the implementation of a novel cross-domain inspiration framework which translates aesthetic qualities from color to vases. This framework resembles a small part of methods used by human artists to create content with external inspiration sources. While humans have successfully used this technique perhaps for centuries (Thrash and Elliot 2003), our goal is to show this is a viable form of inspiration in generative art systems through its implementation in VIV and the creation of usable, decorative vases.

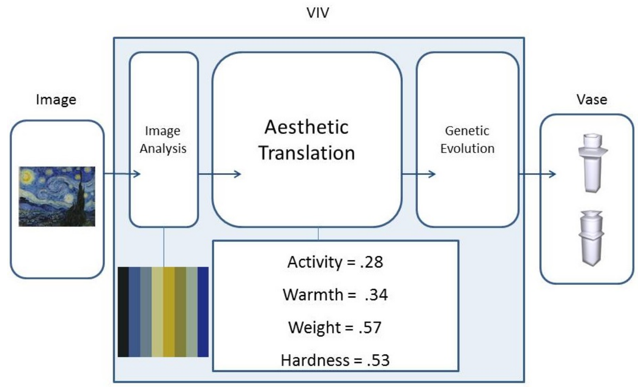

Figure 1: Design of the VIV system. The input image is analyzed and scored along the four aesthetic measures of activity, warmth, weight, and hardness. VIV's evolution component then evolves a vase to match the given aesthetic scores.

Related Work

Generative Art Systems

Existing generative art systems use a wide range of techniques. Some create content based solely on pre-programmed rules (Cope 1996; Krzeczkowska et al. 2010; McCorduck 1990; Norton, Heath, and Ventura 2013) while others use user input (Clune and Lipson 2011; Draves 2005; Machado and Cardoso 2000; Secretan et al. 2008) or external sources (Cook and Colton 2011; Smith et al. 2006). Systems that use external inputs could be seen as receiving inspiration from outside stimuli. However, existing systems using external inspiration directly map stimuli to generation rules (Cook and Colton 2011; Smith et al. 2006). Also, these systems gain their inspiration from a pre-defined domain and so their inspiration model is non-extensible. Our model of inspiration allows an artifact from a wider range of domains to be used as inspiration for another domain since it is the high-level aesthetic measures which translate knowledge rather than a direct mapping.

A popular fitness function in generative art systems is to have either an individual or larger audience choose their favorite artifact from a set of produced artwork. The system then generates future content using responses from users. This method can be seen in *Endless Forms* (Clune and Lipson 2011) and *Pic Breeder* (Secretan et al. 2008) where users choose their favorite item from a given set of produced content. These systems create the next generation of candidates which are variants of a user's choices. On a larger scale, *Electric Sheep* (Draves 2005) produces abstract art work to please a more global audience. When a computer goes to sleep, the Electric Sheep come on to create morphing abstract animations that can be voted up by users. More popular sheep live longer and thus allow the system to evolve its creations to the favorability of a large audience. VIV was not created with the intent of personalization. Rather than have a human intervene in each generation step, VIV generates vases using aesthetic metrics found to be important by subjects of a preliminary survey.

In the domain of vase generation, one previous system has created printable vases through evolution with aesthetic measures as fitness functions (Reed 2013). Reed's generation of vases based on Birkhoff's beauty metric (Birkhoff 2003) produced many interesting vases rated highly by viewers. This research differed from previous generative art research which focused on 2D abstract art by expanding the application of aesthetic measures to a functional and decorative 3D object. Birkhoff's metric was adapted to be suitable as a fitness function in an evolutionary algorithm to great success. VIV, in contrast, does not have one aesthetic score which she is trying to maximize each time. Instead, VIV generates vases using four aesthetic measures with scores varying between evolutionary runs based on user input.

Cross-Domain Inspiration

Cross-domain knowledge transfer as inspiration is a concept creative people have put to great use throughout history. Artists, scientists, and social leaders have gained inspiration from supernatural, internal (intrapsychic), and external (environmental) sources (Thrash and Elliot 2003). Creative computer systems, on the other hand, are only beginning to have the concept of inspiration incorporated into their makeup.

Research by Ranjan et al. (2013) had expert artists create paintings that were the artist's interpretation of one of a small set of instrumental music pieces. Results showed that people were able to correctly identify which painting went with a particular piece of music. The painters in this research did not convey which aspects of the music they were inspired by and they also did not state how they would manifest that inspiration into their painting. Similarly, viewers gave no indication of the features they found correlated between the two artistic mediums.

Similar research was conducted in the opposite direction–composers were asked to create music pieces using a square, lightning bolt, curved shape and an edgy shape as creative stimuli (Willmann 1944). This research showed composers are capable of interpreting an image, creating abstract concepts based on that image, then constructing those concepts within the domain of music. This is a complicated set of events which have yet to be implemented in computational systems. Our research attempts to close this gap by using consistent and limited aesthetic measures to demonstrate a

Figure 2: Two examples of VIV's color palette extraction and the resulting vases which correspond to a similar aesthetic profile. The left example is a warm, soft vase and the right is a cool, hard vase.

system can gather abstract characteristics from one domain and produce those concepts in a different domain with techniques unique to that domain.

One of the few generative systems that uses transmedia inspiration to create its content is *Game Blender* (Lopes and Yannakakis 2014). *Game Blender* uses conceptual blending as its means of cross-domain inspiration to create games. This crowdsourced, mixed-initiative system blends audio, narrative, ludus, and level architecture facets into a playable game. Blended creations consist of one artifact from each facet and can be controlled by the user through a number of parameters. Rather than a direct conceptual blending approach, VIV utilizes a mediation layer which performs analogy mapping from one domain to another. This is an attempt to move away from domain-specific blending approaches and towards an a more abstract methodology.

VIV

A diagram showing an overview of VIV's process is shown in Fig. 1. This section will detail the image analysis and vase generation portions of the system.

Image Analysis

VIV extracts a color palette of dominant and salient colors from the source image in the CIELAB color space. Dominant colors are chosen by selecting the average color from the most common bins in the image's color histogram. Colors are determined to be salient if they are at least two standard deviations from the mean color of an image (Huang, Liu, and Yu 2011). VIV then ranks salient colors according to dominance preventing tiny areas of a few pixels from making it into the color palette. Duplicates are removed using the current CIELAB distance function (Sharma, Wu, and Dalal 2005) and a final color palette is produced with a maximum of 8 dominant and salient colors each. An example color palette obtained from an image can be seen in Fig. 2.

Previous research by Ou et al. developed formulas to model single color emotion by having Chinese and English viewers rate individual colors along the aesthetic dimensions of activity, weight, warmth, and hardness (2004). We use these equations to determine scores for each color in an extracted color palette along the same four aesthetic dimensions. VIV then applies a weighted average of all colors from the dominant and salient color groups. The highest ranked colors from the dominant and salient groups are weighted at 75%. The remaining percentage is progressively halved until all colors are evaluated in the color palette. We use a weighted average rather than equal weights to allow for a more distinct aesthetic profile. We still use all colors in the color palette, although at reduced levels, since each color is a prominent color in the image and should have some effect on the overall analysis. The final aesthetic profile is then passed to an evolutionary algorithm which will use these scores in its fitness function. We acknowledge colors are a very small subset of information processed by human viewers of images and our color weighting is not necessarily human-like, however we feel this information is sufficient to demonstrate transmedia analogy mapping.

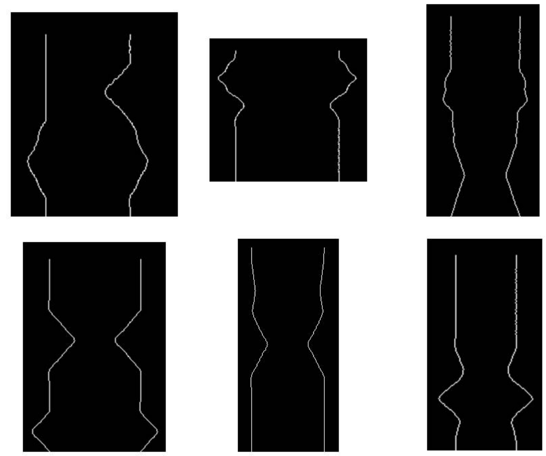

Figure 3: Example silhouettes of a variety of vases. Beziér curves for each side can be identical or unique. These curves are then interpolated around the center axis with a variable sampling rate.

Vase Depiction

Similar to Reed's work with vases, our vases are described as two Beziér curves interpolated around a center axis. The distance from each curve to the center axis may vary and be unique between curves. Also, the interpolation can be performed with a variable sampling rate, producing vases with triangular, square, or round bases and anything between. Each vase begins as a cylinder (two straight lines of equal distance to the center axis). Vase genetic data corresponds to a set of initial parameters (e.g. starting height, width, interpolation points, number of points per line) and a list of vase manipulations.

Vase manipulations in our initial implementation are only squeeze/pull and shorten. Each of these operations can be done on one or both sides of the vase. Even with these limited and simple manipulations, definite variation can be seen (see Fig. 3). The squeeze and pull manipulations are described using two numbers: size and depth. The size determines how drastic of an alteration occurs and the depth determines how many neighboring points are affected. This produces manipulations which can be smooth or jagged. Some constraints were placed on these alterations in order to maintain a functional and printable vase. For example, due to 3D printer constraints, a minimum wall width needed to be enforced so that the vase wouldn't break during the printing process. Vases with a minimum distance between curves below this threshold were considered non-viable and thrown out during evolution.

Data Collection

In order to determine which vase metrics contribute to each of our four aesthetic measures, we administered a web survey to both trained artists and novices. Recruitment was done through campus e-mails, social media posts and leveraging existing professional and artist contacts. There were 50 respondents of which 27 described themselves as artists with at least three years of experience. The remaining respondents labeled themselves as "hobbyists", "no experience" or did not complete demographic information. The survey was administered anonymously therefore no background verification was done on self-reported artistic experience. All demographic information was collected at the completion of the survey. This questionnaire design was modeled after previous research which attempted to model player preference in generated Mario levels (Shaker, Yannakakis, and Togelius 2013). We applied similar techniques replacing players' level preference along fun, challenge and frustration with respondent's assessment of vase activity, weight, warmth, and hardness in order to determine features associated with each dimension.

Survey respondents were given a series of randomly generated paired vases and asked to compare them along the four previously mentioned aesthetic dimensions in a four-alternative forced choice questionnaire. Responses included "both" and "neither". An example comparison can be seen in Fig. 4. Subjects were allowed to do as many comparisons as they desired before completing the survey and filling out demographic information. The least number of comparisons performed by a single respondent was 1 and the greatest was 30 (mean=8.58). Data is still being collected, but at the time of writing this paper, 430 comparisons had been obtained. Using these 430 comparisons, vases were ranked along each aesthetic dimension by number of votes using existing pairwise comparison techniques (Shaker, Yannakakis, and Togelius 2013). A winning vote garnered one point, each vase received half a point for a vote of "both", and losing or "neither" resulted in no points awarded. Once rankings had been determined, we then used Principal Component Analysis and Multiple Linear Regression to determine which vase metrics contributed to each aesthetic measure (Freedman 2009). One big advantage of using Multiple Linear Regression is that it creates a function which is human-readable and easily implemented in a computer system.

Feature Selection

We identified several metrics for evaluating the vases. Many more are possible but using previously applied vase metrics as a starting point, we compiled the following list:

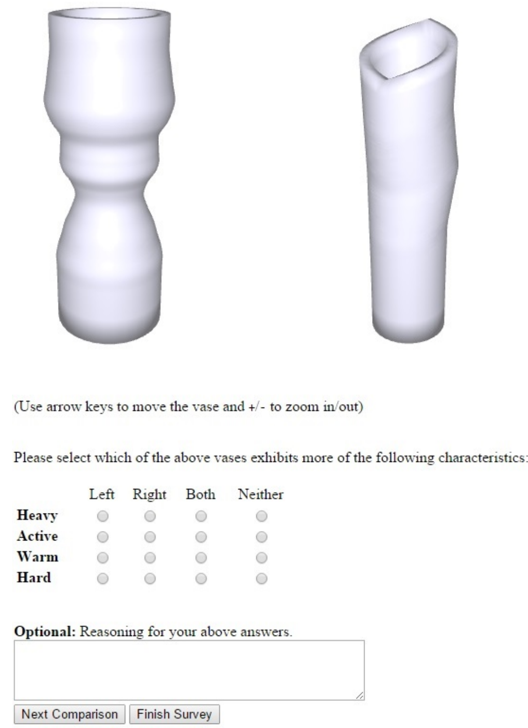

Figure 4: Example comparison from our four-alternative forced choice questionnaire.

- H — Height: In vases with a height difference between sides, the greater of the two is selected.
- W_{max} — Maximum width: Greatest total distance perpendicular from the center axis.
- W_{min} — Minimum width: Least total distance perpendicular from the center axis.
- I — Inflection points: Number of changes in slope along each side of the vase. Inflection points from each curve of the vase silhouette are added to obtain the total inflection points.
- Center of mass: x and y location of the center of mass of the 3D rendered vase. CoM_x denotes the x location and CoM_y denotes the y location.
- Linearity: Variance from a straight line between inflection points averaged along each side of the vase. A cylinder would have a linearity of 1.0 as the base and lip location count as inflection points and there is no variation between the two in the vertical direction.
- S — Sampling Rate: number of equidistant points around the unit circle which are used during interpolation. Can also be viewed as the number of points in the base.

We also included additional relational metrics which are the result of combining these:

- A — Asymmetry. Evaluated as $\frac{CoM_x}{W_{max}}$
- R_{min} — Minimum width to height ratio. $\frac{W_{min}}{Height}$

Figure 5: Printed vases created by VIV. The left and center vases were created with inspiration from the artwork in fig. 2 (first example) and the vase on the right is an attempt by VIV to make her most active vase.

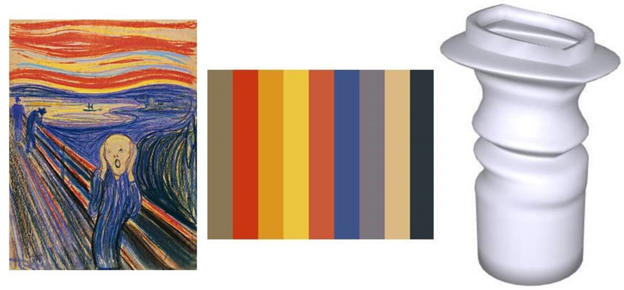

Figure 6: Depiction of the complete vase generation process using inspiration from one version of the famous *Scream* works by Edvard Munch.

- R_{max} — Maximum width to height ratio. $\frac{W_{max}}{Height}$

Principal Component Analysis of our survey data for activity yielded important vase metrics to be the number of inflection points, lateral asymmetry and a low number of interpolation points. Warmth was influenced by lateral symmetry and a higher number of interpolation points. The ratio of the location of the minimum and maximum widths to the vase height correlated with weight. Hardness was determined by a high ratio of maximum width to height, high center of gravity, and less interpolation points. Each of the vase metrics used are not direct inputs to the vase generation algorithm. Instead, they are tools for expression of aesthetic qualities interpreted from another domain.

Vase Generation

Each generated vase is given an aesthetic profile by the four equations below which was determined through Multiple Linear Regression of our survey data.

$$Activity = -0.2 * I + 2.3 * A - 0.002 * S + 0.5 \quad (1)$$

$$Warmth = -2.0 * A + 0.001 * S + 0.41 \quad (2)$$

$$Weight = 0.06 * R_{width} - 0.06 * R_{max} + 0.6 \quad (3)$$

$$\begin{aligned} Hardness = 0.2 * R_{max} - 1.8 * CoM_y \\ -0.2 * R_{min} - 0.01 * S + 1.6 \end{aligned} \quad (4)$$

The fitness function used during evolution is the Euclidian distance between an image's aesthetic profile and the generated vase's profile where evolution is trying to minimize this score.

Vase creation is done through genetic evolution of a population of 100 vases over 100 generations. We used 100 generations because this is the point where additional generations produced results which were no closer to an aesthetic profile than the current population. For each generation, there is a 10% elitism rate where vases are kept without change, 40% crossover rate, and 50% mutation rate.

Recall that vase representation is comprised of initial parameters including starting height, width, sampling rate, and points per line as well as a list of vase manipulations. Our crossover implementation involved choosing initial parameters from one parent or the other and combining manipulation lists. Manipulations lists could be combined in a couple of different ways. Most simply, the manipulations from the second parent could be appended to the first parent's list. Alternatively, for each list index, one manipulation was randomly chosen from a parent's list at that same index.

Mutations involved re-assigning one of the initial parameters to a different value, adding a manipulation to the manipulation list at a random index, randomly removing a mutation, or altering the size of a manipulation.

Results

The examples given in this paper show input from a variety of famous artworks (see Fig. 6) and the diverse vases created by VIV using each of these artworks as inspiration. There is great variety in input and output to the system yet VIV consistently creates vases with an aesthetic profile which reflects that of the inspiring work. Fig. 8 demonstrates a set of vases produced from the amateur photo in Fig. 7. VIV determined this image to be a light and soft image so the vases produced tended to be round with a high center of gravity.

Using a generative art system such as VIV coupled with modern 3D printing techniques, vases can be produced in a matter of hours which previously took expert artists weeks, if at all. Fig. 9 is an example which ceramicists we corresponded with stated would be extremely difficult for them to replicate because of the sharp edges throughout the internals of the vase.

Discussion

In order to prove our inspiration model, we set out to create a working generative art system with this model at its core. VIV has been used to create numerous distinct vases with various aesthetic profiles inspired by images ranging from some of the most famous paintings to amateur photos. While many may argue VIV is not truly creative since she neither possesses any type of novelty search nor a true understanding of her creations, we can see that cross-domain analogical inspiration is a viable model for generative art systems.

Our initial implementation uses the four aesthetic measures of activity, warmth, weight, and hardness as the inspiration channels between two dimensional images and 3D-printable vases. This model is not confined to our proof-

Figure 7: An example image and color palette extracted from an amateur photo.

Figure 8: A set of vases created with the image from Fig. 7 as inspiration. The image was viewed by VIV as soft and light therefore the vases produced had a high center of gravity and a round base.

of-concept, but extensible to other analogy mappings and domains. Our implementation has shown how a system can interpret aesthetic measures from one domain using techniques specific to that domain, create an analogous mapping to another domain, and produce content within the target domain using techniques separate from those of the source. Fig. 5 contains examples of VIV's final printed output.

Future Work

Color analysis is just one piece of information people take in when viewing art. In future implementations, a more robust image analysis which includes line, angle, feature, and object detection would be desirable as well as the extension of our single color affect analysis to color combinations. Just as human viewers take in a range of stimuli from artwork, we want VIV to mirror this in her analysis of images with a more in-depth interpretation.

We plan to conduct user studies in order to quantitatively determine if our resulting vases fit within acceptable bounds of the previously stated aesthetic measures for a large portion of human viewers rather than our initial face-value assessment. We envision this proceeding in two phases. For the first validation phase, we will give subjects a pool of vases with varying pre-defined aesthetic profiles and ask them to group together the vases they feel are most similar. If our vase profile equations are adequate, subjects should be able to organize vases by aesthetic profile. The second validation phase would extend this method to grouping vases by image. Because our inspiration model only uses an image's color palette rather than the image as a whole, this validation may be better suited to grouping by color palette rather than by original image.

Also, extension of these aesthetic measures to other researched methods would be beneficial. Birkhoff's beauty metric is an abstract aesthetic measure which could be incorporated since it perhaps is more easily studied in a broad range of domains rather than something such as warmth or hardness. As this measure has already been studied in both the domains of evolutionary vase creation and color science, its addition to our initial implementation would be rather straightforward. However, its use in domains where more granular aesthetic principles are hard to assess could be useful for future applications.

Conclusion

We have presented the detailed design of VIV and her use of a novel cross-domain inspiration framework. We demonstrated how VIV uses this framework to create vases with an aesthetic profile interpreted from a different domain. In this way, abstract artistic concepts can be gathered from one domain and manifested in another mirroring creative methods utilized by people. Generative art systems in parallel with new media technologies, allow for a wider range of artistic content to be produced by both humans and computers. Our hope is that this model of inspiration can be used to provide creative systems with the ability to translate high level knowledge between new domains and expand their expressive range as well as broaden people's creative potential.

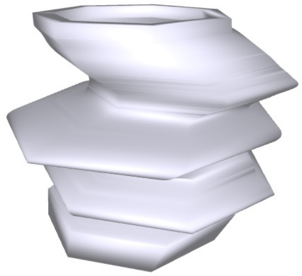

Figure 9: Example vase from VIV obtained when she tries to max out the activity measure. This vase was considered to be difficult to replicate by some ceramicists.

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