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Evolutionary Experiments in the Development of Typographical Posters

Keywords: Graphic Design; Poster Design; Evolutionary Design; User-Guided Evolution.

Abstract:

During the 19th century, the poster, driven by technological advancements, becomes the primary Graphic Design's medium for mass communication. However, these posters were not evolved by a graphic designer (in the current sense of profession), but by joint work between the printer and the client. Based on this production method, we present an evolutionary system to generate poster designs from a given text input. To assign the individuals' fitness we resort to a semi-autonomous scheme set by hardwired and user-guided measures. Three main aesthetics measures define the scheme: (1) Composition; (2) Design; and (3) Client satisfaction. In this paper, we will describe the system, and discuss its ability to interactively evolve the poster designs. We will also analyse the outcomes of the system in the development of typographic poster designs using a typographic superfamily, and the impact of the user criteria in the results.

1. INTRODUCTION

The poster is Graphic Design's (GD) "blank slate" — like the artistic "blank canvas." It is often the medium used by graphic designers to make self-reflective exercises or express concerns (Blauvelt 2011). It has always been considered one of the most important media to visual communication. Already in the Ancient times, posters were set in a certain location and were used to proclaim notices, news, political campaigns and advertising announcements to the passers-by (Hollis 1994; Meggs and Purvis 2012). This role was eventually supplanted with the democratisation of print and the consequent emergence of newspapers (Blauvelt 2011).

However, the earliest times of Industrial Revolution (England, c. 1760–1840) had a dramatic impact on typography and graphic arts (Carter et al. 2014). Over this period, the amount of energy generated by steam power increased a hundredfold. Electricity and gasoline-fuelled engines increased the productivity, new factory systems-based machine manufacturing systems and novel labour-division theories were developed, and new materials (e.g. iron and steel) became available. Thereby, people moved from the countryside to the cities lured by the employment in the factories, and cities grew rapidly. Therefore, buying power increased and stimulated the emergence of mass production (Meggs and Purvis 2012). Through this scenario of abundance, society saw an advertising explosion. Consequently, poster was reborn proclaiming the new emergent commercial contexts and reaching its high point at the end of the nineteenth-century as a result of the advances made in largescale reproductive technologies, such as the introduction of the silkscreen or the invention of colour lithography (Blauvelt 2011; Godlewsky 2008).

Similar to today, the technological innovations radically altered printing and stimulated a shift in GD's practice. Wood-type letterpress had become the key method of printing, enabling type founders to try every possible type design permutation (Carter et al. 2014; Lupton 2010). In these permutations: typographic proportions were distorted; new ways of decoration were developed (especially in serifs); the classic typographic shapes were changed, e.g. traditional body part of letters were embedded or engorged. These experiences led to the emergence of a new kind of typography (Lupton 2010; Bringhurst 2004). Furthermore, they also turned the poster into the key medium of communication at the time (Meggs and Purvis 2012). In this way, posters intrude throughout the cities' spaces, multiplying themselves over the sides of the buildings (Blauvelt 2011).

Contrary to the ancient types of posters — where a unique message was anchored to a precise location — the nineteenth century's poster emerged as a multiple reproductions' artefact. A paradigm which revolutionises graphic designers' mind-set about the creation of posters until now (Blauvelt 2011). However, the production of these posters, at the time, did not involve a graphic designer in their present-day sense. The poster was composed by a composer that — in consultation with the client — selected and composed the typography with the ornaments and the wood-engraved illustrations (Meggs and Purvis 2012).

Based on the operating mode of these print-houses, we develop a digital system to generate posters through a similar design process. To simulate this process, we use Evolutionary Computation (EC) paradigms. Like in the Victorian era print-houses, the poster is composed by a composer (i.e. the system) in consultation with the client (i.e. the user). Although it is still a work in progress, the system is already automatically generating posters from text strings. Beyond the description of the functional prototype of the system, in this paper, we also will contribute with: (1) a Genetic Algorithm (GA) wherein individuals are composed by text boxes; and (2) a set of measures for evaluating poster's graphical quality.

The remainder of this paper is organised as follows: Section 2 presents related work, considering applications of evolutionary techniques in domain of GD; Section

3 thoroughly describes the approach used in the development of the system; Section 4 presents the analysis of the experimental results; and finally, conclusions and future work are presented in Section 5.

2. RELATED WORK

Evolutionary Art (EA) systems have been around for some years — the idea was introduced in the 1980s (Dawkins 1986) — and since then has been used, over the last decades, to generate artistic imagery. Briefly, these systems produce graphic actions throughout an image (e.g. adjust the position of a graphical element or change its visual properties, such as colour, hue, transparency, etc.). Matthew Lewis (2007) gives a good overview on the subject. One of the fundamental issues of these systems is the development of the proper fitness assignment schemes. In the domain of visual arts, we found five essential approaches, that sometimes are combined amongst themselves: (1) Interactive Evolution (IE), i.e. the system allows the user to drive the evolution; (2) similarity based, i.e. the system evolves towards a specific image or images; (3) hardwired fitness functions; (4) machine learning approaches, i.e. the system learns how to evaluate aesthetics; and (5) co-evolutionary approaches, i.e. the system evolves its population interacting with another population (Machado, Romero, and Manaris 2008; Lewis 2007).

These systems, as mentioned above, encapsulate the basic set of actions that a graphic designer performs during his/her working hours. In this sense, they have an enormous potential to be a useful tool to graphic designers, especially the IE systems, which allow the designers' choices to drive the system (Anderson et al. 2008). However, graphic designers seldom use these systems. In most of the cases, designers do not have the necessary quantitative background to learn how to use an EA system; additionally, the developers of these systems often are not concerned about mass appeal, stability, or usability issues. In this sense, the use of evolution-based techniques to support GD processes still is not a very explored field.

In the fields related to GD, Type Design is the field most explored. Butterfield and Lewis (2000) developed a system to evolve the deformation of typefaces, using an IE. Michael Schmitz (2004) developed *GenoTyp*, a Flash-based program that allow users to experiment generating new typefaces through genetic rules. Martins et al. (2016) developed *Evotype*, a GA able to automatically generate alternative glyphs from scratch, using line-segments. Unemi and Soda (2003) built a prototype of a type design system for a Japanese Katakana alphabet. On the other hand, *The Alphabet Synthesis Machine* (Levin, Feinberg, and Curtis 2002) creates and evolves alphabets to an "imaginary civilisation." These abstract letter shapes are created from a physically based writing simulation, using a GA with a fitness function based on user inputs.

Although with less frequency, EC experiments are also developed to create content to use in GD artefacts, and / or to support the exploration in the earliest stages of a design process. Carnahan et al. (2005) developed a user-centred design process to create anthropomorphic pictorial symbols for visual communication (e.g. warning pictograms). Cunha et al. (2017) used GA with multiple populations to generate visual blenders, using as the basis the concepts of an angel, a pig and a cactus. Anderson et al. (2008) developed an IE system, the *EvoDesign*, to develop regular lattice tiles (e.g. to use in walls or floors). Oliver et al. (2002) proposed a method that creates and iteratively optimises the look of websites (i.e. text and background style) and the layout of a page (i.e. the position of the different elements on a page). Deniz Cem Önduygu developed *Gráphagos* (2010) an evolutionary approach to create GD's artefacts (e.g. a poster or a book cover). The system starts with a randomly generated design, composed of different visual elements (such as text, shapes, and images) from a given text string. At each run, the user selects the outputs he/she prefers. Denis Klein also noticed that IE methods streamline the GD process in its preliminary

stages. With this in mind, he developed the tool *Crossing, Mixing, Mutating* (2012). This tool generates variations of a template given by the user through the application of genetic operators; subsequently, this tool was updated and released by the studio Less (co-founded by Denis Klein and Lisa Reimann) as an Adobe InDesign plug-in named *Evolving Layout* (Less 2016).

Michael Schmitz (van Nes 2013, 165; Schmitz 2006) also explored the use of evolution paradigms in the development of dynamical graphic identities. Schmitz's *Evolving Logo* is system for the creation of generative visual identities, which uses an evolutionary algorithm to adjust itself to the institution's current state. This system allows the creation of different variations of the logo, through genetic operators (e.g. mutation and recombination). The logotype is evaluated in two ways: (1) the system compares candidate solutions' attributes with a set of variables which reflect the company's state; and (2) the company's employees occasionally choose their favourite logo. The *Evolving Logo* system was implemented in the Max Planck Institute of Molecular Cell Biology and Genetics (Dresden, Germany).

3. THE APPROACH

The main aim of this system is organising a set of text boxes in order to design a typographic poster. To achieve this, we implemented a GA to evolve and evaluate the candidate solutions which, in this case, are poster designs. As stated above, the system is projected to operate in a semi-autonomous way, using the data provided by the client (in this case, the user) to guide the evolutionary process.

Although the problem is similar to the traditional 2D bin packing problems, the traditional packaging algorithms (e.g. Button-Left Packaging, Jakobs 1996) are focused only on the solution of problems linked to the optimisation of the space, i.e. finding the best way to organise a set of shapes; accordingly, they are not being concerned with the visual appearance of the compositions. Furthermore, they work with shapes with the size already defined; however, in this case, besides the type-face positions and disposition, we will also evolve the text boxes' sizes. In this sense, the use of this kind of algorithms, in this context, is not workable. Therefore, we achieve the evolution of the rectangles by evolving parametric information of the text boxes' size (e.g. width and height) and adding visual information to the candidate solutions (i.e. text box font).

The system enables the user to guide the evolutionary process, i.e. the user can communicate his / her typographical preferences to the system. The communication is performed through the user's definition of the system's *visual parameters*. In the current state of the system it is possible to set the definition of the *horizontal motion*¹ and the *weight*² of the target font. The interaction with the system, currently, is made using the keyboard, and the user can see the target typeface in the system interface (presented in Figure 1). The current system's interface is only designed for exploration and debug; nonetheless, it already gives the necessary means to enable the user to communicate his/her desires to the system.

The posters are constructed in a modular grid of sixteen horizontal modules by twenty-four vertical modules in the same format as A series of ISO 216. While the system is generating posters, the user can improve the visual parameters (e.g. improve the horizontal movement) and, so, bring closer the current solution to his / her desired composition. Although the system stops at the end of each run, the user can continue running the algorithm until he / she feels satisfied with the outcome.

To generate poster designs, the system employs a GA to generate the first population of posters and, afterwards, evolve this population. The process begins with the generation of a population with randomly created individuals. Thereafter, the individuals are evaluated and, then, selected for recombination and mutation according to their fitness. The process is repeated until the system finds an individual with optimal

2. According to Bringhurst (2004, 332) the weight of a typeface is the "darkness [...] of a typeface, independent of its size."

^{1.} *Horizontal motion* is the horizontal proportion of the typographic composition. In this system, this variable influences the choice of the target typeface. In other words, the variable controls the condensed – extended property of the typeface. On the other hand, the higher is the variable's value, the more extended is the typeface (see Bringhurst 2004, 25).

Fig. 1. Snapshot of the temporary interface of the system. Poster content retrieved from the poster "Amerika is Devouring its Children" designed by Jay Belloi (1970).

AMERIKA	AMERIKA	AMERIK
IS	IS	IS
Devouring	devouring	devouring
ITS CHILDREN	its children	its
	THIN BLACK	SANS SERIF

fitness or a predefined number of generations is reached. Early experiments prove that the operations made by genetic operators were extremely destructive, leading to the creation of unstable populations. To solve this, we implemented an elitist approach — passing the best individual of each generation to the next generation. The dimension of the search space is reduced using a rectangular grid that constraints the coordinates and position of text boxes.

Each candidate solution's genotype is a sequence of a set of parameters, or genes, that encode a poster design (see Figure 2). The set (1) and (2) are the poster's grid and size, respectively. The set (3) encodes the text boxes: (a) and (b) are related to the text box size, and (c) to the typeface used in the text box. The set (4) stores the text boxes' content. The set (3) and (4) are organised in the same order. The posters' size and posters' grid are defined during the initialisation. The number of text box-es is also defined when the population is created. This number is defined by the number of text lines on the text file supplied by the user.

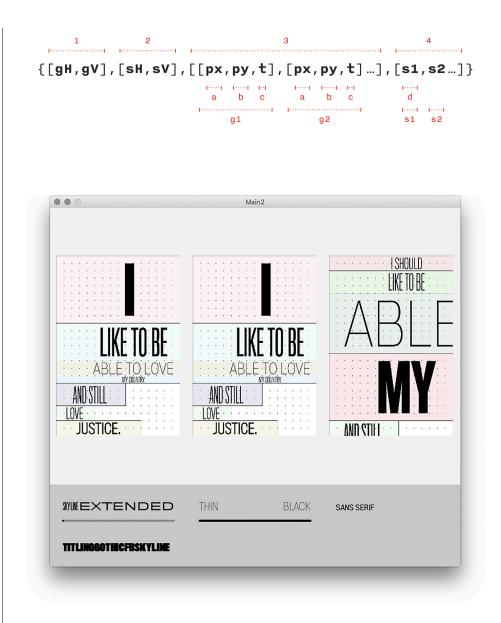
Typefaces are loaded into the system through a CSV file. Each typeface is imported with a set of constants (e.g. vertical ratio, horizontal ratio, serif type or weight). In the first experiments, multiple typefaces were loaded into the system; however, often the results were not satisfactory — the poster had a crude, unorganised and inconsistent appearance. In this sense, we decided only to load one typographic family at once.

The phenotypes consist in a graphic translation of the genotype, i.e. a poster created from the genotype encoded parameters. The expression process consists of drawing a set of text boxes — defined in genotype — and placing the text content aligned in the middle point of the box (see Figure 3).

The system is developed using Processing 3. The operating mode of the system is divided into two main modules: (1) *the Creator*, i.e. the module that implements a GA to create candidate solutions and employs the genetic operations (see subsection 3.1); and (2) *the Appraiser*, i.e. the module that implements the fitness' assignment and evaluates the candidate solutions (see subsection 3.2).

Fig. 2. Genotype encoding. The genotype is composed by a sequence of four set of parameters: (1) poster's grid; (2) poster's size; (3) text boxes' encoding; and (4): text boxes' contents. The third set (i.e. the text boxes' encoding) is a list with the attributes: (a) box's width; (b) box's height; and (c) used typeface; The text boxes' content (4) is organised in the same order of (3); for instance, the content of text box g1 is the string s1 and so on.

Fig. 3. Example of rendered phenotypes. The text boxes are presented in distinct colours. The points are the grid delimitation spaces. Original content by Albert Camus and published in the book *Resistance, Rebellion and Death: Essays* (1995).



3.1. The Creator

New candidate solutions are created throughout the evolutionary process by applying genetic operators. In this section, we describe the genetic operators designed to manipulate the representation proposed above, namely: initialisation, mutation, and crossover.

3.1.1. Initialisation

The first population is seeded with randomly generated genotypes. Each genotype is created through the reading of the given text file. For each line in the text file, the system creates a text box. To define the text boxes size and typography the system employs a set of methods to generate the text box's width, the text box height (or the leading between the words) and the used typeface. These methods are not completely stochastic and are dependent upon the input. The definition of the text box width is directly related to the string's length. This value is multiplied by a random float number (between 0.25 and 4) to generate less predictable compositions and to enable the application of different styled typefaces. Baseline leading (and, consequentially the text box height) is obtained by generating a random number between 1 and h/2, where h is the height of the poster. On the other hand, the text box's typeface is selected randomly from the set of the typefaces loaded in the system.

3.1.2. Recombination

For recombination, we implemented a *uniform crossover* method, i.e. to each position on the child's genotype, the parents' genetic material is exchanged with the same probability. The offspring is selected using Stochastic Universal Sampling. For each parent in the offspring, a second parent is randomly selected from the population and the genotype content is exchanged creating two children. Repeating this process, in the end, two distinct offspring are created and added to the population. The recombination operator only exchanges genetic content in the list of parameters that encode the text boxes (see Figure 2).

3.1.3. Mutation

Mutating a candidate solution involves stochastic modifications and/or the introduction of new genetic material in some parts of the genotype. The mutation, in this system, is designed to ensure that the search space is fully connected, i.e. to ensure that all the solutions are reachable from any starting point. Such as the recombination operator, this mutation operator only performs alterations in the list of parameters that encode the text boxes (see Figure 2). Besides that, the operator is designed to perform alterations in all the levels of this genotypes list; therefore, it performs mutations in the list sequence and in the values inside the list. This resulted in a total of seven mutation operators. The operation to be performed in each generation is chosen randomly by the system. Each operator has always the same probability of choice.

The developed mutation operators are as follows: (1) Independent Mutation, i.e. a method that flips each gene in the list and randomly changes its values. Each gene is flipped with a low probability; (2) Gene Mutation, i.e. an operator that randomly chooses a text box parameterisation and replaces it by a new one; (3) Gene's value Mutation, i.e. an operator that randomly selects a value in the genotype and replaces it by a new one; (4) Gene Swap Mutation, as the name indicates, this operator randomly selects two text boxes parameterisation and swaps them; (5) Value Swap Mutation, i.e. an operator that randomly selects two text boxes parameterisations and swaps one of their parameters. In the system's first versions, the population stabilised without reaching an optimal composition (e.g. a text box needed more than one grid width value, or the text box typeface was bigger than the available space). In this sense, we developed two more operators to accelerate the evolutionary process, they are: (6) Change Text Box Width, i.e. a function that flips each width parameterisation in the genotype and increases, keep, or decreases these values; and (7) Change Typeface, as the name indicates, that method flips each typeface parameterisation in the genotype and changes, or keeps, these values.

3.2. The Appraiser

The evaluation of results in an EA system is not an easy task. Since the aesthetical evaluations are subjective, typically, the systems use IE to evaluate the results (Lewis 2007); however, this can be a fatiguing task to the user. In this sense, autonomous evaluation approaches have been developed, such as, machine learning approaches (Baluja, Pomerleau, and Jochem 1994), hardwired fitness functions (Machado, Romero, and Manaris 2008), co-evolutionary approaches (Dorin 2004), or personalised fitness functions (Machado et al. 2016). These methods have proven to be useful tools to alleviate some of the burdens of coding the fitness function and automates some aspects in the IE.

Therefore, we developed a measure to evaluate a poster design process, combining hard-wired fitness assignment with user-guided evolution. The merit of each can-

didate is evaluated according to three main aspects: (1) merit of poster's composition; (2) merit of the poster's design; and (3) merit of the system's typography decisions in relation to the user's preferences. Each aspect has different weights in the fitness function. By empirical exploration, we defined the following weights: the composition measures are a third part of the total evaluation; the poster's "design" represents around 46.7% of the evaluation; the typographic evaluation is a fifth part of the evaluation.

3.2.1. Composition Measure

The composition of the poster is evaluated by the calculation of the similarity between the poster text boxes disposition, and the disposition of the target solution. The similarity, between the individuals, is calculated by subtracting the size (width and height) and comparing the area of the candidate solution to the best solution. In the end, this value is normalised between [-1,0].

3.2.2. Design Measure

We measure the "design" value of a poster calculating, for each text box, the distance between the textbox width and the width of text after rendering. In the end, the design value of all the text boxes is calculated and normalised between [-1,0].

Three measures are implemented to calculate the outcome's "design" value in this system: (1) *linear*, i.e. the value of distance does not alter if text width is bigger or smaller; (2) *non-linear*, i.e. the value of distance is bigger when the content is bigger than the text box; and (3) *truncate*, i.e. the value of distance is only calculated when the text width is bigger than the text box's width.

3.2.3. Client's Satisfaction / Typography Measure

As previously mentioned, it is possible for the user to define a set of graphics variables that will be used to evaluate the typographic decisions of the system. To give the system the ability to measure the typeface, each font is loaded with a set of constants that define its *horizontal motion* and its *weight*.

To evaluate the typeface choices, the candidate's solution typefaces are compared with the values inputted in the system by the user. The distance between the used typeface and the desired typeface is, then, normalised (as a value between [-1,0]) and encoded into the individual's fitness.

4. EXPERIMENTAL RESULTS

We conducted experiments to assess the adequacy of the EC System and to reply to our two main questions: (1) "Is the system able to create readable posters?"; and (2) "How do the user's preferences influence the evolution of the poster design?" To develop these experiments, we used the typographic superfamily *Titling Gothic FB*, published by Font Bureau (2005), and designed by David Berlow.

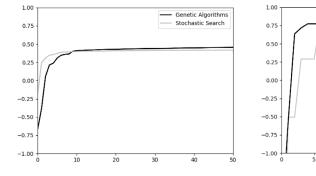
First, we assess the result of the GA compared with a simple Random Search Algorithm (RSA), i.e. for each generation, the system generates a random population and saves the best individual to the next generation. We conclude that the use of the GA presents a constant growth of the individual's fitness. On the other hand, the RSA, albeit sometimes produces good outcomes, the growth of the individual's fitness is inconstant, and its quality is only related with the system's capacity of to produce good random individuals (see Figure 4 and Figure 5).

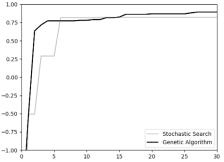
We also conclude that low mutation rates and high crossover rates enable the system to produce good solutions faster; however, the population stabilizes faster.

On the other hand, high mutation rates and low crossover rates allow a slower increase of the fitness of the population; nevertheless, the population is more diverse.

As we have seen in Figure 6, the system creates readable posters compositions. Although the evaluation of the quality of the GD artefacts is not easy and unanimous and should always be made by the user, the authors believe that the results, albeit with some limitations, are interesting.

As already explained, each aspect of the fitness function has a different weight. Although the client's satisfaction measure is only a fifth part of the fitness function, as we can see in Figure 6, the system chose to use fonts "closer" to the target typography. Therefore, although the visual parameters are not fundamental in the creation of readable poster compositions, they add value to the system in the user's point of view, and, so, are a fundamental part of the system. We define this value because, in the first experiments, the system often did stagnate without a perfect composition. This occurred because the target typeface was not allowing the system to compose (e.g. the target typeface was too wide for the available space).





WHAT, You don't Know Grapus?



Fig. 4. Comparison between the system's outcomes using a GA or a RSA. Left: Average of 25 runs' outcomes over generations; right: outcomes of one example run. System Setup: Number of generations: 50; Selective Pressure: 2; Mutation rate: 45%; Crossover rate: 55%; Target typeface: Titling Gothic FB Skyline Black (horizontal motion: 0 / weight: 1); Design measure: Truncate. Content: "What, You Don't Know Grapus?" retrieved from the Léo Favier's book cover with the same name (2014).

Fig. 5. Comparison between phenotypes generated by the system using a GA and a RSA. Left: phenotype of the best individual, in the end of an example run, using a GA; at Right: phenotype of the best individual, in the end of an example run, using a RSA. Using the same setup from experiments in Figure 4. Fig. 6. Selected poster designs generated using the system. The stop point is defined by the user. These posters are generated using the same setup as in Figure 4, except the target typeface (which is defined in in the image) and the content.



5. CONCLUSIONS AND FUTURE WORK

During the 19th century, the poster was reborn with the advertising's explosion. The wood-type letterpress became the key method of production printing enabling the appearance of the new typographic permutations. This led to the poster reaching its high point in the ends of the 19th century. However, back then, the creation of a poster did involve a graphic designer, in the profession's current sense. The posters were composed by a composer that — often in consultation with the client — selected and composed the typography with the ornaments and the illustrations.

Based upon this idea, we developed an evolutionary system for the automatic generation of poster designs. Although it is still a work in progress, the system already automatically generates posters. The system presents a semi-automatic fitness assignment scheme based on three main criteria: (1) the composition of the poster; (2) the design of the poster; and (3) the client's satisfaction with the typo-graphic decisions of the system. During the building of the system, we also developed: a representation that allows the definition of poster designs; the corresponding genetic operators; and an aesthetical measure to evaluate the generated poster designs. To keep the typography consistency of the poster, the system composes only with one typographic superfamily.

Future work will focus on: (1) increasing the number of parameters that the user can influence; (2) developing an interface that allows the user to step backwards one or more generations and reset the evolution to this point; (3) including illustrations in composition; and (4) developing a physical implementation of the system.

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