Using Genetic Programming for Making a New Evolutionary Artwork, Based on Human-Computer Interactions for Autism Rehabilitation

Seyed Muhammad Hossein Mousavi¹, Narges Aghsaghloo²

(1) mosavi.a.i.buali@gmail.com, h.mosavi93@basu.ac.ir (2) n.aghsaghloo@gmail.com

Abstract

In past two decades, a lot of mathematical problems have been solved by nature inspired algorithms like Genetic Algorithm (GA). But this mathematical structures could be colorful and beautiful like an artwork. Due to that Evolutionary Art (EA) was created and made a revolution in art, especially in visual art. Evolutionary Art (EA) is one of the most top topics in the field of Artificial Intelligence (AI) and computer science these days, and that is because of its nature inspired structure. Despite of its beauty in combining and shaping the colors, it could be used in medicine and rehabilitation. Autistic people need different methods of learnings and through evolutionary art, it is possible to learn and rehabilitate them. This paper first introduces an unsupervised evolutionary art structure or visual art using genetic algorithm and programming and two aesthetic measure as the fitness function (Global Contrast Factor and Information Theory). In the second step this visual artworks uses on 3 children with Autism Spectrum Disorder (ASD) to rehabilitate them. Positives and negatives results happened in the process, but more of them was successful. Results shows that, they have good react in bright and smooth colors and hate dark and sharp artworks. This subject is novel and hope to opens a way in human (autistic person)-computer rehabilitation era.

Keywords: Genetic Algorithm (GA), Evolutionary Art (EA), Artificial Intelligence (AI), Aesthetic Measure, Information Theory, Rehabilitation, Autism Spectrum Disorder (ASD)

1 Introduction

With the aid of Artificial Intelligence (AI) techniques, and especially computer vision branch in subset of image processing, ease of use enters our houses in last two decades. Using image processing techniques, entertainment, industry, medicine, engineering and more fields, had great changes and improvements. These improvements, leads us to better and easier life. One of the best improvements was using image processing in medicine science. It is possible to use image processing techniques in psychology for rehabilitation purposes. One of these techniques is Color Therapy [25] or Painting Therapy [25]. Using Evolutionary Computations (EC), it is possible to make nature inspired painting artworks, which is possible to use it for painting therapy. As autistic people needs different and unknown ways to learn and rehabilitate, using Evolutionary Art (EA) could be useful in this subject. This paper first pays to some of the important details, definitions and required informations for the title in section 1 and section 2, pays to some of the related works which is done by other researchers on this subject. Section 3 covers our proposed EA workflow using Genetic Algorithm (GA) and how to employing it for rehabilitation of Autistic Spectrum Disorder (ASD) children. Evaluations, validations and results are take place in section 4 and section 5 includes, the conclusion of the paper and some important suggestions for making this novel paper even better.

^{*} Corresponding author. Email address: mosavi.a.i.buali@gmail.com, Tel: +9809332892726

Definition 1.1. Evolutionary computations and algorithms

Evolutionary computation (EC) is a family of algorithms for global optimization inspired by biological evolution, and the subfield of artificial intelligence studying these algorithms. In other word, they are a group of population-based trial and error problem solvers with a meta-heuristic optimization character. In EC, an initial set of candidate solutions is generated and iteratively updated. Each new generation is produced by accidentally removing less wanted solutions, and introducing small random changes. In biological terminology, a population of solutions is subjected to natural selection (or artificial selection) and mutation. As a result, the population will step by step evolve to increase in fitness, in this case the chosen fitness function of the algorithm. Evolutionary computation techniques can generate highly optimized solutions in a wide range of problem settings, making them popular in computer science. Many variants and extensions exist, suited to more unique groups of problems and data structures. Evolutionary Algorithms (EA) form a subset of evolutionary computation in that they generally only involve techniques implementing mechanisms inspired by biological evolution such as reproduction, mutation, recombination, natural selection and survival of the fittest. Candidate solutions to the optimization problem play the role of individuals in a population, and the cost function determines the environment within which the solutions live. Evolution of the population then takes place after the repeated application of the above operators. In this process, there are two main forces that form the basis of evolutionary systems: Recombination and Mutation create the necessary diversity and thereby facilitate novelty, while selection acts as a force increasing quality [1] [2] [3] [4] [5].

Definition 1.2. Genetic algorithm and programming

Genetic algorithm (GA) is a meta-heuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms. Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems by relying on bio-inspired operators such as mutation, crossover and selection (as mentioned above) [6]. Genetic Programming (GP) is a technique where through computer programs are encoded as a set of genes that are then modified (evolved) using an evolutionary algorithm (often a genetic algorithm) – it is an application of (for example) genetic algorithms where the space of solutions consists of computer programs. The results are computer programs able to perform well in a predefined task. The methods used to encode a computer program in an artificial chromosome and to evaluate its fitness with respect to the predefined task are central in the GP technique and still the subject of active research [4] [7] [8].

Definition 1.3. Evolutionary art

Evolutionary Art (EA) is a branch of generative art that, the artist does not make the work of constructing the artwork, but except lets a system make the construction. In evolutionary art, initially generated art is put through an iterated process of selection and modification to arrive at a final product, where it is the artist who is the selective agent. It is a human-computer interaction that human orders and computer generates. In each iteration, 0human artist select the best artwork (among all computer generated artworks) which is made by the computer and computer make the next art or artwork according to selected artworks. Human artists use genetic algorithm to make the artwork usually (makes better artworks). With manipulating mutation, crossover, iteration and other factors, it is possible to make perfect image artwork from genetic algorithm. It is just about giving proper pattern to follow and having right knowledge in color ology and connection between colors and the rest is with the computer. We use evolutionary art in image processing, but it could be used in sound and signal processing and more other arts [9] [10] [11] [12].

Definition 1.4. Autism and autistic people

Autism is a developmental disorder characterized by troubles with social interaction and communication [13]. Often there is also restricted and repetitive behavior [13]. Parents usually notice signs in the first two or three years of their child's life [13] [14]. These signs often develop step by step, though some children with autism reach their developmental milestones at a normal pace and then worsen [15]. Autism is caused by a

combination of genetic and environmental factors [16]. Risk factors include certain infections along pregnancy such as rubella as well as valproic acid, alcohol, or cocaine use during pregnancy time [17]. Controversies surround other proposed environmental causes; for example the vaccine hypotheses, which have been disproven [18]. Autism affects information processing in the brain by altering how nerve cells and their synapses connect and organize; how this occurs is not well understood [19].

Definition 1.5. Autism rehabilitation or therapy

Autism therapies are interventions that attempt to lessen the deficits and problem behaviors associated with autism spectrum disorder (ASD) in order to increase the quality of life and functional independence of autistic individuals. Treatment is typically catered to person's needs. Treatments fall into two major categories: educational interventions and medical management. Training and support are also given to families of those with ASD [20]. Studies of interventions have some methodological problems that prevent definitive conclusions about efficacy [21]. Although many psychosocial interventions have some positive evidence, suggesting that some form of treatment is preferable to no treatment, the systematic reviews have reported that the quality of these studies has generally been poor, their clinical results are mostly tentative, and there is little evidence for the relative effectiveness of treatment options [22]. Intensive, sustained special education programs and behavior therapy early in life can help children with ASD acquire self-care, social, and job skills [20], and often can improve functioning, and decrease symptom severity and maladaptive behaviors [23]; claims that intervention by around age three years is crucial are not substantiated [24]. Available approaches include applied behavior analysis (ABA), developmental models, structured teaching, speech and language therapy, social skills therapy, and occupational therapy [20]. Figure 1 shows some of the autistic children and rehabilitating process for them in different way. As it is clear in Figure 1, autistic child paints 1 and 2 are so similar to proposed genetic art painting (generated by the computer) which is in sections 2 and 3.



Figure 1: Music therapy (a), Toy therapy (b), Color therapy (c), Music therapy (d), Toy therapy (e), Painting therapy (f), Painting therapy (g), Autistic child paint's-1 (h), Autistic child paint's-2 (i)

2 Related prior works

In the early 1990s, both Karl Sims and William Latham (with Stephen Todd) followed in the footsteps of scientist Richard Dawkins by mixing evolutionary methods and computer graphics to create artistic images of

great complexity [26] [27] [28] [29]. More recently, David Hart [30] has put significant effort into developing a collection of images with a very diverse visual appearance from the majority of expression-based, evolved imagery. His interest, in particular in gaining control over the evolving colors and shapes, is noteworthy. As such, his system's interface allows for extensive low-level tuning [29]. It can be interesting to note the similarities and differences in image galleries produced using various systems. Information about the precise function sets used to build genotypes is usually not available, but the characteristic results of different functions are sometimes evident. Some online examples include work by Bacon [31], Davidson [32], Kleiweg [33], Maxwell [34], Mills [35], and Saunders [36]. Specific additions to the function set or other system extensions push system results in specific (often new) directions: Ellingsen's distortion and iteration operators [37], Gerstmann's HDR mapping [38], or McAllister's evolved color palettes [39] provide a few visual samples. Some hybrid systems using expression images such as Baluja's [40], Greenfield's evaluations of expression evolution [41] [42] [43], and Machado's NEvAr system [44] could be mentioned too [29]. Also in autism rehabilitation some works were so valuable which is going to mentioned. For example in 2013, Wang, Michelle, and Denise Reid, used the virtual reality-cognitive rehabilitation approach to improve contextual processing in children with autism [45] or Boccanfuso, Laura, and Jason M. O'Kane made an adaptive robot design with hand and face tracking for use in autism therapy in 2011[46]. In 2014, Boucenna, Sofiane, et al, made a review on interactive technologies for autistic children [47]. Scassellati, Brian et al in 2012, discussed the past decade's work in Socially Assistive Robotics (SAR) systems designed for autism therapy by analyzing robot design decisions, human-robot interactions, and system evaluations [48]. Figure 2 represents, some of the prior related works done by other researchers in EA field.

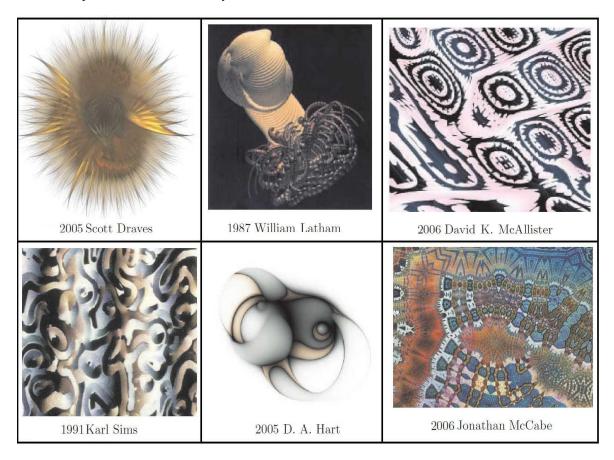


Figure 2: Some of the prior related works done by other researchers in EA field

3 Proposed unsupervised evolutionary artwork

This paper first introduces an unsupervised evolutionary art structure or visual art using genetic algorithm and programming and two aesthetic measure as the fitness function (Global Contrast Factor and Information Theory). In the second step this visual artworks uses on 3 autistics children to rehabilitate them. Java Programming language is used for implementation of the unsupervised EA structure.

Converting genotype to phenotype is done as follows. For a target phenotype image with a resolution (width, height) the function value (the genotype) for each (x, y) coordinate of the image will be calculated. The genotype is subject to crossover and mutation. The standard sub tree crossover and standard sub tree mutation is used. The resulting matrix of floating points is mapped onto an indexed colour table, and this results in a matrix of integers, where each integer refers to a colour index of the corresponding colour scheme. This way the coloring is independent of the double. The colour scheme is also part of the genotype, and subject to mutation and crossover. A mutation in the colour scheme could result in a completely different colored image, even if the expression remain unchanged. The resulting image is passed to the fitness function (aesthetic measures) for validation.

3.1. *Terminal and Function sets*

Some of the terminals and functions is used in the experiments. The terminals variables x and y refer to the (x, y) coordinate of image pixels. 'Width' and 'height' are variables that refer to the width and height of the image. The use of width and height is useful because we usually perform evolutionary computation using images with low resolution (for instance 250*250) and want to display the end result on a higher resolution. Also function sets are +, -, *, /, min, max, abs, neg, warp, sign, sqrt, pow, mdist, sin, cos, if marble/2, turbulence/2, plasma/2, moire/2, mandelbrot/2, complexiteratormap/2, chaoticdust/2 [27] [53] [54] [55]. We use them to make final phenotype result. Table 1 represents proposed EA parameters for GA. Figure 3 represents proposed GUI made by Matlab software. Figure 4 shows GA, GP and proposed EA cycle as flowchart. Figure 5 presents some of the evolutionary artworks, constructed using proposed unsupervised evolutionary art method.

Table 1: Proposed EA parameters using in GA

PARAMETERS	GA
·	
Number of Decision Variables	800
Size of Decision Variables Matrix	[1, 800]
Lower Bound of Variables	0
Upper Bound of Variables	5
Maximum Number of Iterations	700
Population Size	100
Crossover Percentage	0.6
Number of Offspring's (Parents)	75
Mutation Percentage	0.4
Number of Mutants	45
Mutation Rate	0.5
Selection Pressure	7
Terminal Sets	x, y, width, height and random
	constants
Function Sets	Refer to
Aesthetic measure or (fitness	Global Contrast Factor (GCF) and
function)	Information Theory (IT)
Phenotype Resolution	800*600 or 1920*1080

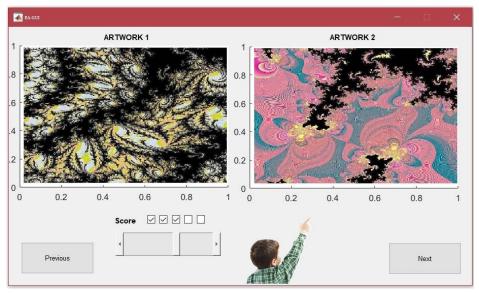


Figure 3: Proposed GUI made by Matlab software

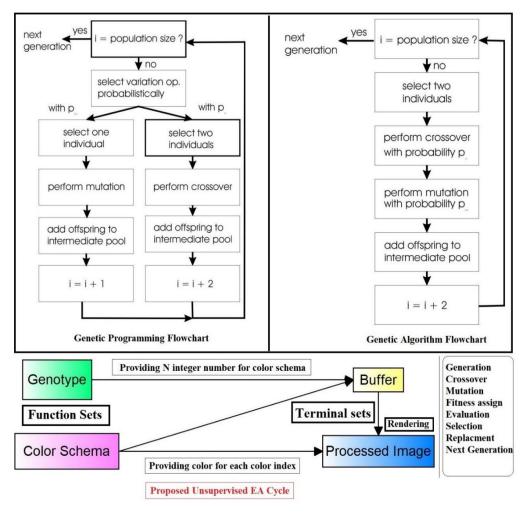


Figure 4: GA, GP and proposed EA cycle flowcharts

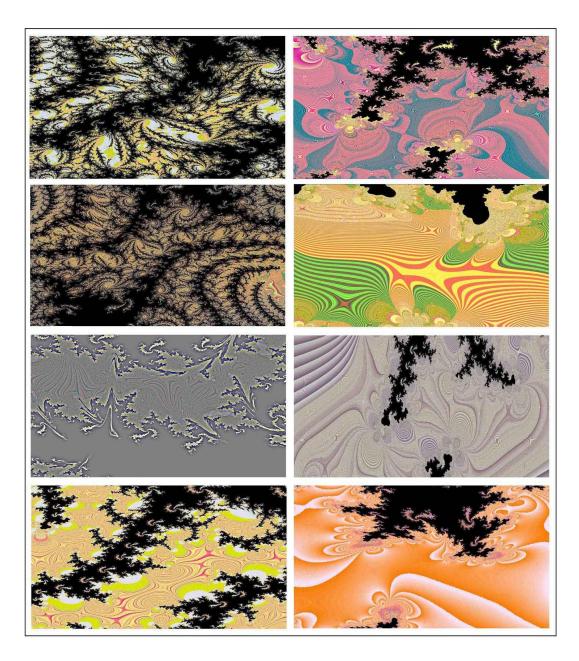


Figure 5: Some of the evolutionary artworks, constructed using proposed unsupervised evolutionary art method

4 Validation and results

4.1. Aesthetic measure (fitness function)

Functions that assign an aesthetic value to an object are typically called aesthetic measures. Aesthetic measures is used for validating proposed unsupervised EA structure as fitness function made by Genetic Algorithm (GA). First, the aesthetic measures that were used in the experiments will describe shortly. The aesthetic measures are Global Contrast Factor (GCF) [49] and Information Theory (IT) [50]. In the next

subsections a brief description of each aesthetic measures is given; more details can be found in the original papers.

4.2. Global Contrast Factor (GCF)

The Global Contrast Factor (GCF) is an aesthetic measure explained in [49] with details. Fundamentally, the GCF calculates contrast (difference in luminance or brightness) at different resolutions. Images that have little or less differences in luminance have low contrast and are considered 'boring', and thus have a less aesthetic value. Contrast is calculated by computing the (average) difference in luminance between two neighboring superpixels. Superpixels are rectangular blocks in the image. The average contrast for several resolutions is summed as:

$$M_{gcf}(I) = \sum_{k=1}^{10} w_k.contrast(n, p_k, r_k)$$
 (1)

Where r_k refers to the resolution of the superpixels, w_k refers to the weight of the contrast of the superpixels (the weight of the contrast differs per resolution) and p_k is a power factor. Both w and p were optimized using several experiments in [49].

4.3. Information Theory (IT)

There have been multiple attempts to use information theory to compute the aesthetic value of an object. For example [51] [52] describe a number of methods by Bense and Moles, and [50] describe a family of closely related aesthetic measures funded on Shannon entropy and Kolmogorov complexity. Our information theory aesthetic measure is an implementation of [50], whereby we have implemented the variant using Kolmogorov complexity using RGB entropy:

$$M_{it}(I) = \frac{NH_{max} - K}{NH_{max}} \tag{2}$$

Where N is the image size (the number of pixels) and H_{max} is a constant colour length code which is 30 in our case (since we use 30 bit colour; 10 bits for each R, G, B channel). K_{max} stands for Kolmogorov complexity of the image. Since Kolmogorov complexity can only be estimated, we (like [50]) use JPEG compression. In our implementation, we used a JPEG quality setting of 70%. For more details and for other variants of this aesthetic measure we refer to [50].

Due to compare the two different aesthetic measure, a number of experiments is done. 15 runs for each aesthetic measure is performed and collected the images of the 8 fittest individuals of each run. Next, we computed the aesthetic measure of those 5 individuals by the other aesthetic measures. From the 40 images of each experiment (15 runs, 8 fittest individuals) handpicked 8 images that were typical for that image set. Besides the aesthetic measure, all evolutionary parameters were the same for each run. It founded out that populations of around 100 usually tended to converge better for individuals and their offspring. For the genetic operators sub tree mutation (rate 0.5), sub tree crossover (rate 0.6) is used. Also roulette wheel selection for both parent selection and survivor selection is used. Next generation is selected based on bests from present and new individuals. All other parameters are based on Table 1. Figure 6 represents results from GCF and IT fitness progressions of 15 different runs and 5 generations. Also fitness range is considered between 0-0.5. The GCF computes and values contrast on various resolutions of an Image, and this results in images with a lot of contrast. Since contrast is calculated at different resolutions, the spread of contrast across different resolutions is rewarded. The information

theory aesthetic measure optimizes images that have a low JPEG compression ratio. Images evolved using this measure will have the trend to be relatively simple.

For presenting small statistical overview of a number of image properties which produced by aesthetic measure, calculation is as follow. For some images that is generated by the system, mean, maximum, and minimum for the image properties (hue, saturation, and brightness) for red, green and blue colors is calculated. All image properties and their statistics are described in Table 2. From the image statistics in Table 2 can conclude the Global Contrast Factor aesthetic measure ensures that its produced images have brightness values that maximize the contrast but in information theory it is not like that.

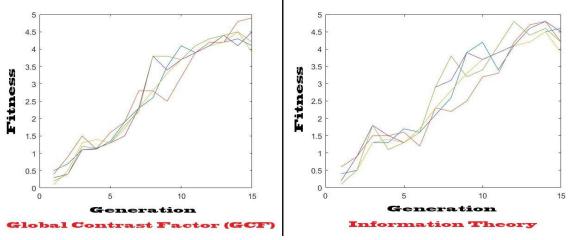


Figure 6: GCF and IT fitness progressions of 15 different runs and 5 generations using proposed method

Aesthetic Measure **GCF** IT Mean Hue 194 51 Min. Hue 29 78 Max. Hue 101 251 **Mean Saturation** 108 104 Min. Saturation 48 97 129 248 Max. Saturation 98 Mean Brightness 98 69 3 Min. Brightness Max. Brightness 110 187 Mean Red 150 210 98 Min. Red 52 197 246 Max. Red Mean Green 45 199 Min. Green 9 150 Max. Green 83 253 Mean Blue 74 124 Min. Blue 69 78

Table 2: Images statistic's per aesthetic measures

4.4. Therapy result

3 autistic subjects (2 male and 1 female) in 3 days get EA treatments. Results was different in each child (positives and negatives), but and the end proper patterns have founded for therapy. First subject was male and gets 29% treatments after 3 days and watching different EA. Child was attracted to smooth

201

Max. Blue

193

shapes, light colors with lowest EA complexity and vice versa. Second subject which was female had similar result pattern's to subject 1, but treatment estimation after day 3 was not satisfactory and just 12% (maybe because of girly nature of the subject). After having 2 subject (1 male and 1 female), we had the measures, but experiments should be done in the similar condition. Strangely third male subject had very good interests in colors and shape and returned 35% of therapy estimation after day 3. So all subjects (male or female) tend to smooth shapes, light colors and less shape complexity. More details about EA therapy placed in Table 3.

Table 3: Evolutionary art therapy results using proposed EA structure on 3 autistic subjects in 3 days with similar conditions

Day	Patient	Art work's colors	Art work's shape	Artwork complexity	Subject's emotion	Effect	Treatment Estimation	Therapy Estimation
1	Subject 1	Red-Black- White-Green	Sharp	80%	Fear	objection	-2%	-2%
	Male	Violet-White- Yellow- Orange	Sharp	70%	Surprise	Next artwork request	+7%	5%
		Black-White- Orange- Yellow	Smooth	50%	Joy	Next artwork request	+17%	22%
2	Subject 1 Male	Blue-Red- Yellow- Green	Smooth	65%	Neutral	Repeating autistic actions	+3%	25%
		White-Red- Yellow-Blue	Sharp	40%	Neutral	Next artwork request	+3%	28%
		Black-Green- Red-Violet	Smooth	90%	Surprise	Repeating autistic actions	-4	24%
3	Subject 1 Male	White- Yellow- Orange-Gray	Smooth	99%	Fear	Repeating autistic actions	-8	16%
		White- Yellow- Orange-Gray	Sharp	99%	Fear	objection	-10	10%
		White- Yellow- Orange-Gray	Smooth	30%	joy	Next artwork request	+19	29%
1	Subject 2	Red-Black- White-Green	Sharp	80%	Fear	objection	-3%	-3%
	Female	Violet-White- Yellow- Orange	Sharp	70%	Fear	objection	-3%	-6%
		Black-White- Orange- Yellow	Smooth	50%	Joy	Next artwork request	+10%	4%
2	Subject 2 Female	Blue-Red- Yellow- Green	Smooth	65%	joy	Next artwork request	+5%	9%
		White-Red- Yellow-Blue	Sharp	40%	Surprise	Next artwork request	+4%	13%
		Black-Green- Red-Violet	Smooth	90%	Surprise	Next artwork request	-1	14%

3	Subject 2 Female	White- Yellow- Orange-Gray	Smooth	99%	Fear	objection	-6	8%
		White- Yellow- Orange-Gray	Sharp	99%	Fear	objection	-8	0%
		White- Yellow- Orange-Gray	Smooth	30%	joy	Next artwork request	+12	12%
1	Subject 3 Male	Red-Black- White-Green	Sharp	80%	Neutral	Repeating autistic actions	0%	0%
		Violet-White- Yellow- Orange	Sharp	70%	Neutral	Next artwork request	+7%	7%
		Black-White- Orange- Yellow	Smooth	50%	Joy	Next artwork request	+10%	17%
2	Subject 3 Male	Blue-Red- Yellow- Green	Smooth	65%	Joy	Next artwork request	+8%	25%
		White-Red- Yellow-Blue	Sharp	40%	Neutral	Next artwork request	+5%	30%
		Black-Green- Red-Violet	Smooth	90%	Surprise	Repeating autistic actions	-1	29%
3	Subject 3 Male	White- Yellow- Orange-Gray	Smooth	99%	Surprise	Next artwork request	2	31%
		White- Yellow- Orange-Gray	Sharp	99%	Fear	Next artwork request	-2	29%
		White- Yellow- Orange-Gray	Smooth	30%	joy	Next artwork request	+16	35%

5 Conclusion

Using A.I, computer vision and especially image processing techniques had good effects in autism therapy in last two decades. Due to nature inspired evolutionary art structure's and with the aim of autistic people treatment, we made a new unsupervised evolutionary art structure which produces genetic inspired paintings and used it to autism therapy in this paper. Positives and negatives results had been shown in the 3 subjects (male and female). At the end proper pattern had been founded and last subject result's is prove to this claim. All of the subjects tend to smoother and lighter artworks with lowest complexity and vice versa. Having right knowledge, using proper tools and using discipline, it is possible to use image processing techniques like EA in different therapy and medicine fields. This paper was a new era to using EA in therapy and could be an open door in this area for other researcher. So it is suggested to use supervised EA for making even better approach. Even it is possible to change the evolutionary algorithm to algorithms such as PSO [56], ACO [57], DE [58], ICA [59], GGO [60] or Bat algorithm [61] to use other sides of the nature to make different and even better systems. Using this kind of systems as an assist or alternative automatic expert system is highly recommended (Autism therapy or different medicine and therapy fields).

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