

USING VISUAL EVOLUTIONARY ART BASED ON COLOR PATTERNS AND DEPTH ASSIST FOR AUTISM REHABILITATION

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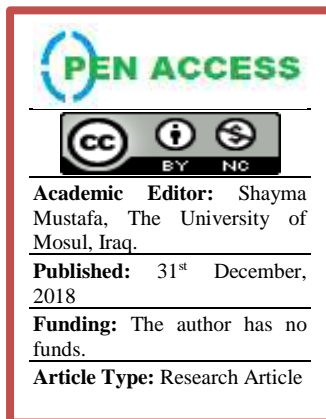
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ABSTRACT

It is possible to solve highly complicated mathematical problem using evolutionary nature inspired algorithms like Imperialist Competitive Algorithm (ICA). Despite of their capability to solve mathematical problems, they can be seen or hear as beautiful as the nature. For example, if an Evolutionary Algorithm (EA) appears in pixel and color, it looks like a visual artwork. Thus, they can be used in psychology and medical rehabilitation (like autism) purposes. This paper presents a method to show the ICA algorithm in colorful pixels to communicate with Autistic Spectrum Disorder (ASD) person for rehabilitation purposes. Moreover, depth image is used to calculate the distance between subject and sensor (Kinect V.2). Face detection employs Viola and Jones algorithm and face recognition uses SIFT features along with K-Nearest Neighbor (KNN) classifier for fast recognition. As there are no more than just 5 subjects, system works fast and precise using subject's pre-learned face images. System works in a communicative manner between computer and the subject (ASD person) along



with an autism psychologist to estimate the rehabilitation percentage (positive or negative) in each experiment on 5 ASD children. This communicative manner relation between human and computer is called, Human Computer Interaction (HCI). System performance is validated using 5 aesthetic measures as objective function for ICA. Proposed evolutionary art returned perfect results on making art works and also in validation part. System is tested with 5 aesthetic measures as fitness function. After finding proper pattern, it is possible to use this system in an applicable method even in real time systems.

Keywords : evolutionary algorithm; imperialist competitive algorithm; visual art work; Kinect V.2; autistic spectrum disorder; human computer interaction;

1. INTRODUCTION

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 these improvements was in medicine. It is possible to use image processing techniques in psychology for therapy and rehabilitation purposes. One of these techniques is Color Therapy or Painting Therapy [1]. Using Evolutionary Computations (EC), it is possible to make nature inspired painting artworks, which is possible to be employed in painting therapy. As autistic people need 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 information for the subject in section 1. Section 2, pays to some of the related works which is done by other researchers on this subject. Section 3 covers proposed EA workflow using Imperialist Competitive Algorithm (ICA) [15] and how to employing it for rehabilitation of Autistic Spectrum Disorder (ASD) children. Evaluations, validations and results are explained in section 4 and section 5 includes, the conclusion of the paper and some important suggestions for making this novel paper even better.

1.1 Autistic spectrum disorder

Autism is a developmental disorder characterized by troubles with social interaction and communication [2]. Often there is also restricted and repetitive behaviour [2]. Parents usually notice signs in the first two or three years of their child's life [2] [3]. These signs often develop step by step, though some children with autism reach their developmental signs at a normal step and then get worse [4]. Autism is caused by a combination of genetic and environmental factors [5]. Risk factors include certain infections along pregnancy such as rubella as well as valproic acid, alcohol, or cocaine use during pregnancy time [6]. Controversies surround other proposed environmental causes; for example, the vaccine hypotheses, which have been disproven [7]. Autism affects

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information processing in the brain by altering how nerve cells and their synapses connect and organize; how this occurs is not well understood [8].

1.2 Autism rehabilitation and therapy

Autism therapies are interventions that attempt to lessen the lack and problem behaviours associated with autism spectrum disorder (ASD) in order to increase the quality of life and functional independence of autistic persons. 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 [9]. Studies of interventions have some methodological problems that prevent definitive conclusions about efficacy [10]. 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 [11]. Intensive, sustained special education programs and behaviour therapy early in life can help children with ASD acquire self-care, social, and job skills [9], and often can improve functioning, and decrease symptom severity and maladaptive behaviours [12]; claims that intervention by around age three years is crucial are not substantiated [13]. Available approaches include applied behaviour analysis (ABA), developmental models, structured teaching, speech and language therapy, social skills therapy, and occupational therapy [9]. Figure 1 shows some of the autistic children and rehabilitating process in different ways. As it is clear in Figure 1, autistic child paints h and i are so similar to proposed ICA art painting (generated by the computer) which is described in sections 3. One of the most novel rehabilitation and learning methods for ASD people is Denver model [14].



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)

1.3 Depth images and sensors

Depth sensors are made to calculate the distance between sensor and the subject. Also they can be used to make 3-D model of the subject, just by watching at the subject. With these abilities, they can be useful to increase the accuracy of the recognition. Kinect is one of the most useful depth sensors to have. It is so much cheaper than other depth sensors and efficient. It can be used on Microsoft Xbox 360 (Kinect V.1) or Xbox one (Kinect V.2) consoles or be used as a developer device. Kinect 2.0 was released with Xbox One on November 22, 2013. Because of the lower price and high power to use, a lot of developers and researcher use it as a main depth device. It could record RGB and Depth video frames with 1920*1080 resolution for RGB images and 512*424 for Depth images on 30 fps. Also it is also capable to of working between 0.8-5.0 meter ranges [16]. An RGB-D image is simply a combination of an RGB (color) image and its corresponding depth image. A depth image is an image channel in which each pixel relates to a distance between the image plane and the corresponding object in the RGB image. It is also termed as 2.5D or Range image [17]. Figure 2 shows Kinect V.1 VS V.2 specifications.

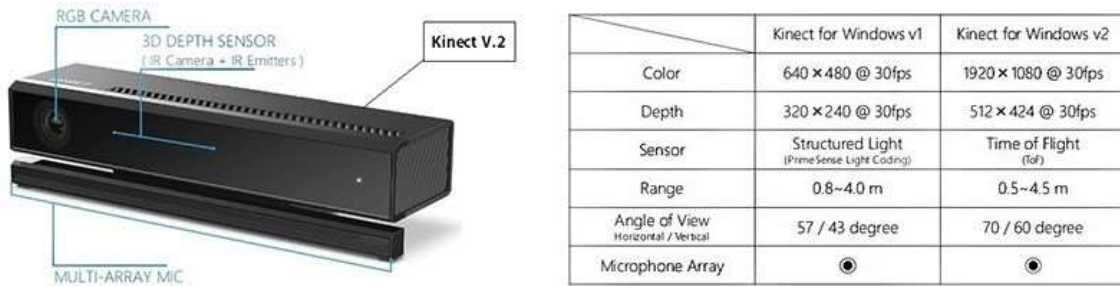


Figure. 2 Kinect version 1 versus version 2 specifications

1.4 Evolutionary computing 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 words, 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 [18-19].

1.5 Imperialist competitive algorithm

ICA algorithm proposed in 2007 by Atashpaz-Gargari, Esmail, and Caro Lucas, which was so extraordinary in solving mathematical problems and especially optimization ones [15]. In this algorithm, each individual is called country, which are colonies and imperialists. They will make an empire together. Inside each empire, competition for being imperialist is going on (assimilating (cross over here)) and outside of empires, empires themselves are trying to possess each other and weak empire will collapse. Moreover, there is a mutation called revolution happens in each generation on some of the countries, which could cause increasing or decreasing the power of that selected country. Finally in the best condition, just one empire remains (global maxima). Final cost function of the empires is based on total power of imperialist and colonies in each remained empire. Figure 3 represents ICA's flowchart and main stages of it [15]. The algorithm is used to generate the evolutionary artwork. Result is so similar to genetic algorithm artworks. For more information about ICA algorithm, please refer to [15]. Converting genotype (country here) to phenotype which is converting countries cost value to color in order to make final artwork is described in Section 3.

1.6 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, human artist selects 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 artwork. Human artists use evolutionary 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 evolutionary algorithm. It is just about giving proper pattern to follow and having right knowledge in colorology and connection between colors and the rest is with the computer. The evolutionary art is used in image processing, but it could be used in sound and signal processing and more other arts [20-21-22-23]. Figure 4 shows some of evolutionary artwork, generated by other researchers using genetic programming in different years.

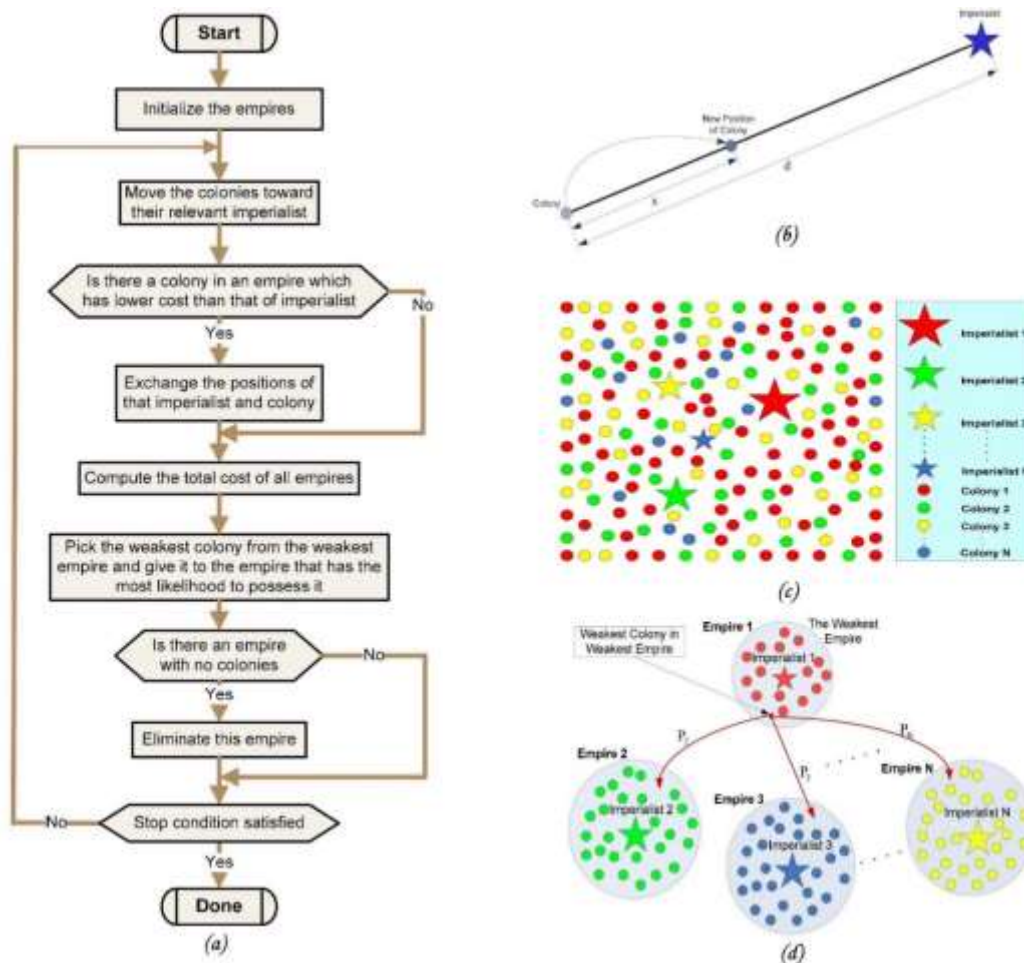


Figure. 3 (a). Flowchart of the ICA algorithm, (b). Moving colonies toward their relevant imperialist, (c). Generating the initial empires: The more colonies an imperialist possesses, the bigger is its relevant ★ mark, (d). Imperialistic competition. The more powerful an empire is, the more likely it will possess the weakest colony of the weakest empire [15].



Figure. 4 Some evolutionary artworks generated by other researcher’s methods

2. RELATED RESEARCH WORK

According to proposed subject dealing with both EA and autism rehabilitation is considered. Genetic algorithm is not used to generate the EA, but some of the mentionable research in this area will be described. Also the main purpose of the paper is autism rehabilitation using image processing techniques (here evolutionary art). So some of the famous researches on making evolutionary art are described in part 2.1, and some of the researches on autism rehabilitation are described in part 2.2; But using evolutionary art for autism rehabilitation is used for the first time in this paper, which is the limitation of previous researcher's research. As it mentioned earlier, and in Figure 1, autistic child paints h and i are so similar to proposed ICA art painting (generated by the computer). This make connection between ASD subject and computer.

2.1 Prior on making visual evolutionary art

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 [24] [25] [27]. Aneta Neumann and et al, used random walk algorithms for evolutionary image transition in 2017 [26]. In 2006, David Hart [28] 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 [27]. 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 [29], Davidson [30], Kleiweg [31], Maxwell [32], Mills [33], and Saunders [34]. Specific additions to the function set or other system extensions push system results in specific (often new) directions: Ellingsen's distortion and iteration operators [35], Gerstmann's HDR mapping [36], or McAllister's evolved color palettes [37] provide a few visual samples. Some hybrid systems using expression images such as Baluja's [38], Greenfield's evaluations of expression evolution [39] [40] [41], and Machado's NEvAr system [42] could be mentioned too [27]. Some of these works are shown in Figure 4.

2.2 Prior on using image processing for autism rehabilitation

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 [43] 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 [44]. In 2014, Boucenna, Sofiane, et al, made a review on interactive technologies for autistic children [45]. Scassellati, Brian et al in 2012, discussed the past decade's work in Socially Assistive Robotics (SAR) systems designed for autism therapy by analysing robot design decisions, human-robot interactions, and system evaluations [46]. Also [60] and [61] are valuable recent researches on using robotic for autism rehabilitation.

3. PROPOSED REHABILITATION METHOD

The paper introduces an unsupervised evolutionary art structure or visual art using ICA [15] algorithm and 5 aesthetic measures as the fitness function (Global Contrast Factor [53], Information Theory [54], Benford law [55], Ross & Ralph (bell curve) [56] and Machado & Cardoso [57]). In the second step this visual artwork uses on 5 autistics children to rehabilitate them.

3.1 Converting genotype to phenotype

Converting genotype (country) 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 (assimilation) and mutation (revolution) 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.

3.2 Data acquisition, human and face detection

System starts with accruing color and depth data from Kinect V.2 sensor and human detection using Viola and Jones algorithm [47] on depth image takes place. Depth sensor, sense the distance between the subject (autistic child) and sensor (Kinect V.2) and returned proper output based on subject's placement. If subject was in 2.5

meter distance from sensor, system says “please stop” and face detection using Viola and Jones algorithm [47] takes place on color data.

3.3 Face recognition, next artwork generation and rehabilitation

For face recognition purposes, Scale-Invariant Feature Transform (SIFT) [48] features are used. Due to low number of subject's (just 5), K-Nearest Neighbourhood (KNN) [49] classifier is employed or fast real time recognition. Now it is time to generate proposed ICA evolutionary art based on Table 1 parameters as default. For first time system used initial default parameters, but in next experiments, system uses pre-feedback data (psychologist's rehabilitation percentage value) to generate next art work and show it to the autistic subject. Psychologist estimates the rehabilitation progress and system save it for next experiment on present subject. This happens on all 5 subjects during experiments and recognizing subjects, takes place in face recognition stage (due to using related feedback data on each subject). Figure 5 represents the proposed EA rehabilitation method's flowchart for people with ASD. Some of the generated proposed ICA evolutionary art samples with different parameters and colors is presented in Figure 6. System is made by Matlab software and a screen shot of the GUI is presented in Figure 7. The process of converting genotype (country) to phenotype (pixel color) is presented in Figure 8.

3.4 Terminal and function sets

Some of the terminals and functions sets are used in the experiments. The terminal 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 the system 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 [50-51-52]. They used to make final phenotype result.

Table. 1 Proposed ICA evolutionary art parameters

PARAMETERS	ICA
Number of Decision Variables	700
Size of Decision Variables Matrix	[1, 700]
Lower Bound of Variables	0
Upper Bound of Variables	7
Maximum Number of Iterations	500
Population Size	150
Crossover (assimilation) Percentage	0.4
Mutation (revolution) Percentage	0.3
Number of Mutants	35
Mutation Rate	0.5
Selection Pressure	6
Terminal Sets	$x, y, \text{width, height}$ and random constants
Function Sets	Refer to
Aesthetic measure or (fitness function)	Benford law, Global Contrast Factor, Information Theory, Ross & Ralph (bell curve) and Machado & Cardoso
Phenotype Resolution	800*600 or 1920*1080

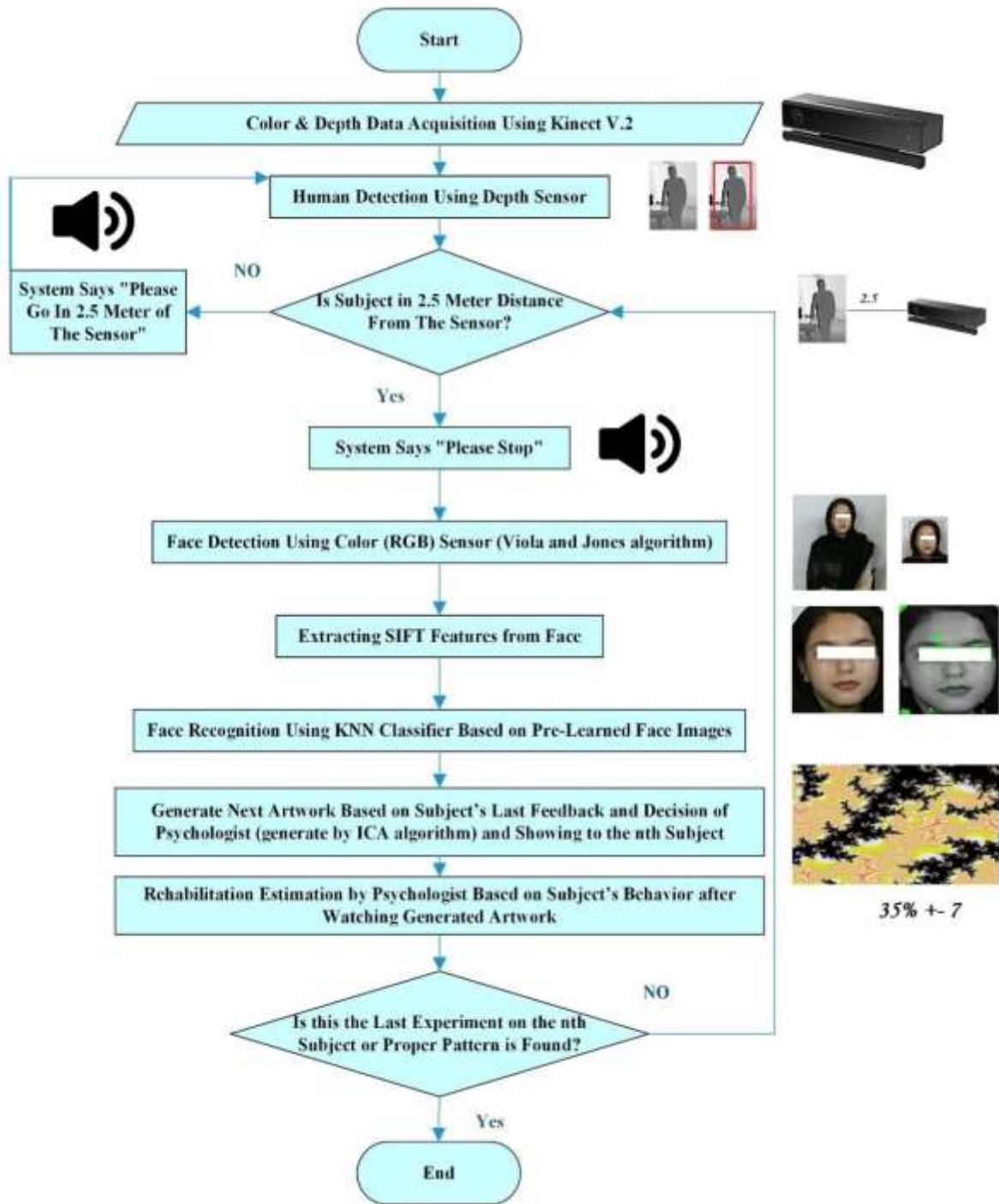


Figure. 5 Proposed EA rehabilitation method's flowchart

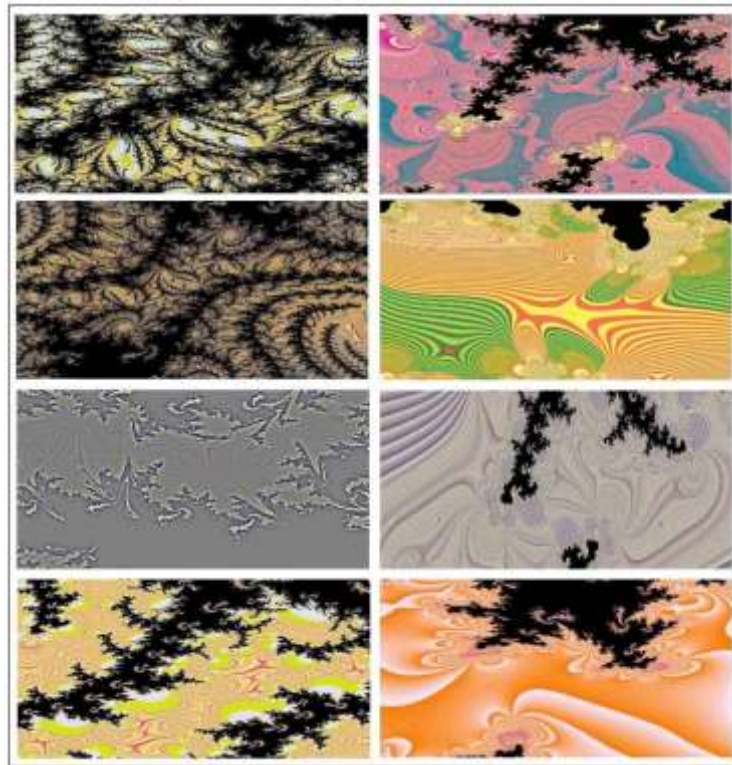


Figure. 6 Some of the generated proposed ICA evolutionary art samples with different parameters and colors

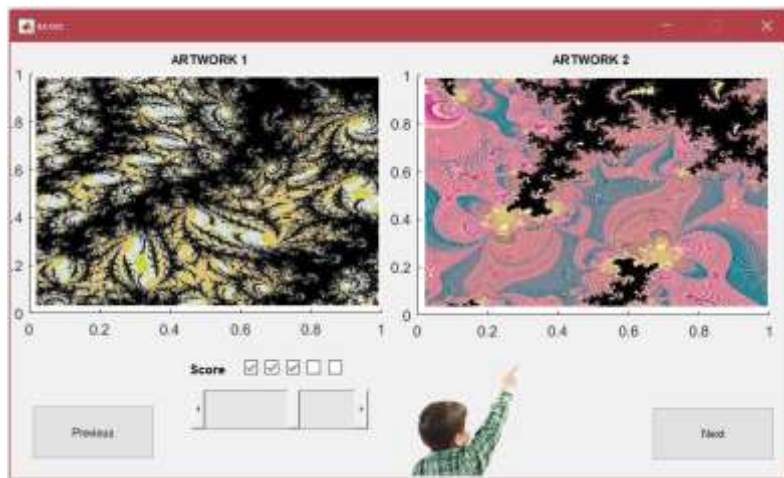


Figure. 7 A screenshot from proposed system's GUI



Figure. 8 The process of converting genotype (country) to phenotype (pixel color)

4. VALIDATION AND RESULTS

Validation section consists of two parts: validating of the proposed ICA evolutionary art using 5 standard and famous aesthetic measures as fitness functions and using proposed EA system on 5 autistic subjects in 5 days of experiments. Medical center gave access to 5 ASD child (2 male and 3 female), as 3 subjects are sufficient in this type of experiment, but having 5 subjects makes the research stronger. Aesthetic measures are selected based on popularity, usage and paper's need. These 5 aesthetic measures could cover almost all the aspect of a digital image as it is needed. Each aesthetic measure and its application is explained in next part of this section.

4.1 Aesthetic measures (objective function (fitness or cost))

Functions that assign an aesthetic value to an object are typically called aesthetic measures. Aesthetic measures are used for validating proposed unsupervised EA structure as fitness function made by ICA. The aesthetic measures that were used in the experiments will describe shortly in following subparts of this part. The aesthetic measures are Global Contrast Factor (GCF) [53], Information Theory (IT) [54], Benford law [55], Ross & Ralph (bell curve) [56] and Machado & Cardoso [57]. In the next subsections a brief description of each aesthetic measures is given; more details can be found in the original papers.

4.1.1 Global contrast factor

The Global Contrast Factor (GCF) is an aesthetic measure explained in [53] 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:

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

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 [53].

4.1.2 Information theory [54]

There have been multiple attempts to use information theory to compute the aesthetic value of an object. For example [58-59] describe a number of methods by Bense and Moles, and [54] describe a family of closely related aesthetic measures funded on Shannon entropy and Kolmogorov complexity. This aesthetic measure is an implementation of [54], whereby Kolmogorov complexity using RGB entropy is implemented using:

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

Where N is the image size (the number of pixels) and H_{max} is a constant colour length code which is 30 in this case (since 30 bit colour and 10 bits for each R, G, B channel are used). K_{max} stands for Kolmogorov complexity of the image. Since Kolmogorov complexity can only be estimated, proposed system (like [54]) uses JPEG compression. In proposed implementation, system used a JPEG quality setting of 70%. For more details and for other variants of this aesthetic measure please refer to [54].

4.1.3 Benford law [55]

Benford Law (or first-digit law) states that list of numbers obtained from real life (i.e. not created by man) are distributed in a specific, non-uniform way. The leading digit occurs one third of the time, the second digit occurs 17.6%, etc. Proposed system uses the Benford Law over the distribution of brightness of the pixels of an image. For more information on the equation, can refer to [55].

4.1.4 Ross & Ralph (bell curve)

This measure is based on the observation that many fine art painting exhibit functions over colour gradients that conform to a normal or bell curve distribution. The authors suggest that works of art should have a reasonable amount of changes in colour, but that the changes in colour should reflect a normal distribution (hence the name 'Bell Curve').

4.1.5 Machado & Cardoso

The aesthetic measure described in [57] builds on the relation between Image Complexity (IC) and Processing Complexity (PC). Images that are visually complex, but are processed easily have the highest aesthetic value. As an example, the authors refer to fractal images; they are visually complex, but can be described by a simple formula. The aesthetic measure M of an image I is defined as

$$MI = \frac{IC(I)}{PC(I)} \tag{3}$$

The Image Complexity can be regarded as the effort needed to compress an image, and is defined as

$$IC(I) = \frac{RMS(I)}{Comperession\ ratio(I)} \tag{4}$$

Where RMS refers to the difference between the original image and the compressed image, expressed as the root mean square. The compression ratio is the ratio between the original image size and the compressed image size.

Due to compare the 5 different aesthetic measures, 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, the aesthetic measure of those 5 individuals by other aesthetic measures is computed. 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. 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 9 represents results from Global Contrast Factor (GCF), Information Theory (IT), Benford law, Ross & Ralph and Machado & Cardoso fitness progressions of 15 different runs and 5 generations. Also fitness range is considered between 0-0.6.

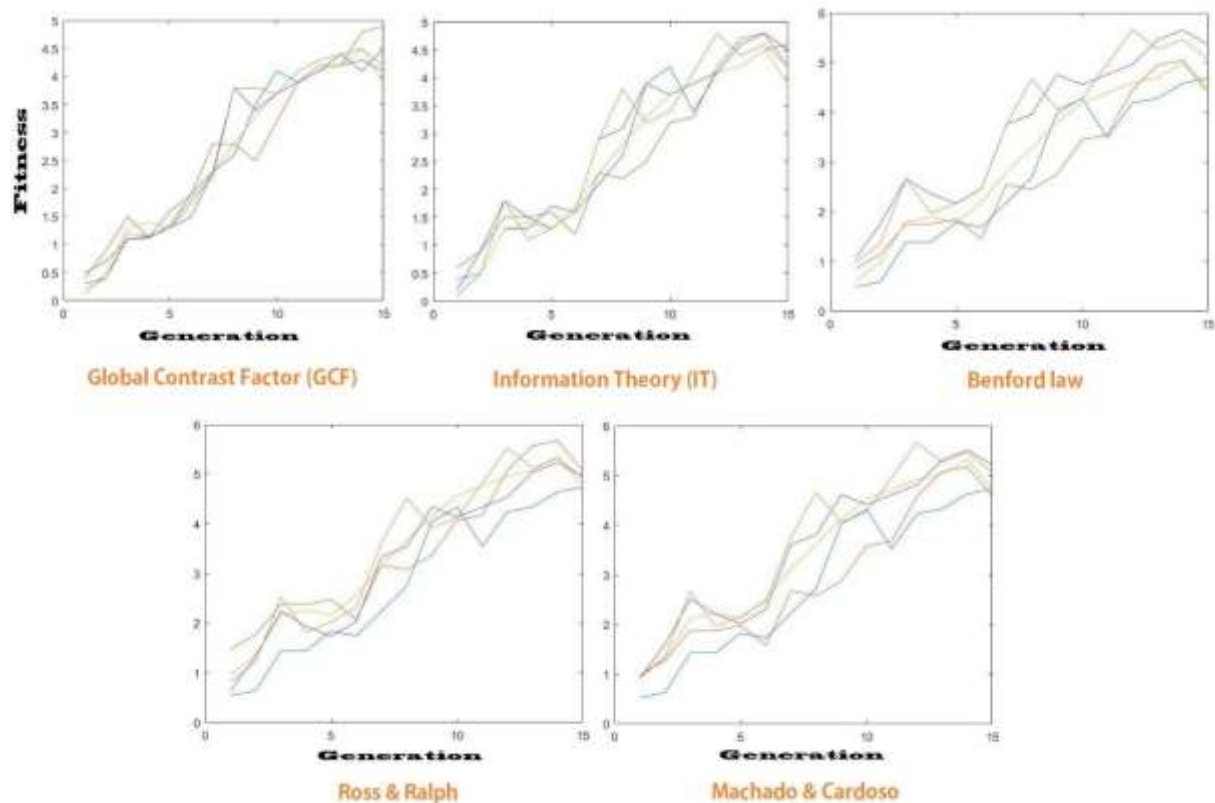


Figure. 9 Results of Global Contrast Factor (GCF), Information Theory (IT), Benford law, Ross & Ralph and Machado & Cardoso fitness progressions of 15 different runs and 5 generations

As Figure 9 represents, 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. The other fitness functions worked perfectly.

For presenting small statistical overview of a number of image properties which produced by aesthetic measures, 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. Also seems IT and Machado & Cardoso have similar characteristics.

Figure 10 shows experiment environment. Figure 11 represents subject’s average association in each meeting and Figure 12 represents Subject’s average distress rate in each meeting. More details about EA rehabilitation placed in Table 3.

Table 2. Images statistic’s per aesthetic measure

-	Aesthetic Measure				
	GCF	IT	Benford law	Ross & Ralph	Machado & Cardoso
Mean Hue	51	194	61	56	189
Min. Hue	29	78	39	34	73
Max. Hue	101	251	111	106	246
Mean Saturation	108	104	118	113	99
Min. Saturation	48	97	58	53	92
Max. Saturation	129	248	139	134	243
Mean Brightness	98	98	108	103	93
Min. Brightness	3	69	13	8	64
Max. Brightness	110	187	120	115	182
Mean Red	150	210	160	155	205
Min. Red	98	52	108	103	47
Max. Red	197	246	207	202	241
Mean Green	45	199	55	50	194
Min. Green	9	150	19	14	145
Max. Green	83	253	93	88	248
Mean Blue	74	124	75	133	119
Min. Blue	69	78	22	16	73
Max. Blue	201	193	73	121	188



Figure. 10 Experiment environment

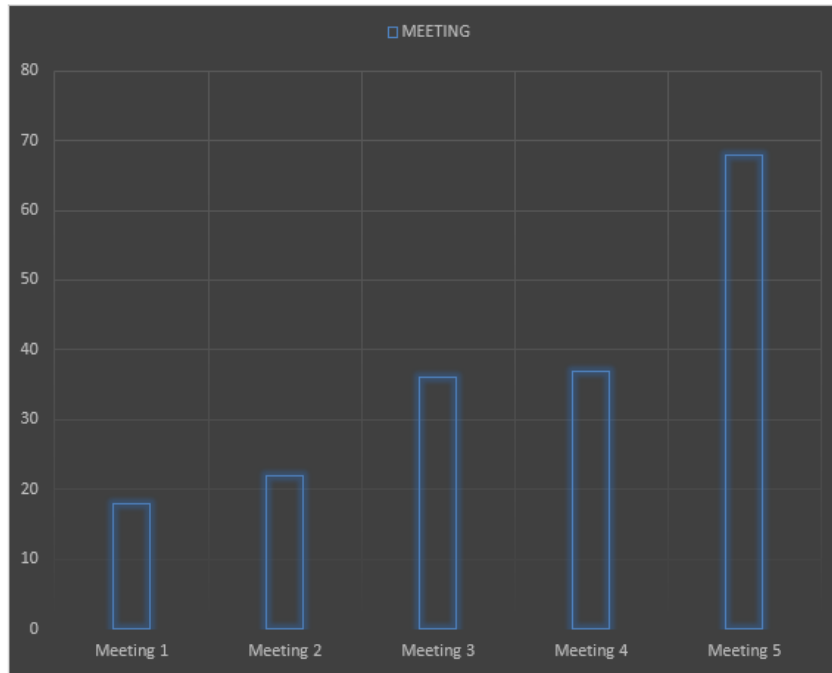


Figure. 11 Subject's average association in each meeting



Figure. 12 Subject's average distress rate in each meeting

Table. 3 Evolutionary art rehabilitation results using proposed EA structure on 5 autistic subjects in 5 days in similar conditions

Days	Patient	Art works colors	Art works shape	Artworks complexity	Subject's emotion	Effect	Treatment Estimation	Rehabilitation Estimation
1-5	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	+24%	29%
1-5	Subject 2 Female	Blue-Red-Yellow-Green	Smooth	65%	Neutral	Repeating autistic actions	+3%	3%
		White-Red-Yellow-Blue	Sharp	40%	Neutral	Next artwork request	+3%	6%
		Black-Green-Red-Violet	Smooth	90%	Surprise	Repeating autistic actions	+6%	12%
1-5	Subject 3 Male	White-Yellow-Orange-Gray	Smooth	99%	Fear	Repeating autistic actions	-8	-8%
		White-Yellow-Orange-Gray	Smooth	70%	Neutral	Next artwork request	+19	11%
		White-Yellow-Orange-Gray	Smooth	30%	joy	Next artwork request	+25	36%
1-5	Subject 4 Female	Red-Black-White-Green	Sharp	80%	Fear	objection	-3%	-3%
		Violet-White-Yellow-Orange	Sharp	70%	Fear	objection	+2%	-1%
		Black-White-Orange-Yellow	Smooth	50%	Joy	Next artwork request	+22%	21%
1-5	Subject 5 Female	Blue-Red-Yellow-Green	Smooth	65%	joy	Next artwork request	+5%	5%
		White-Red-Yellow-Blue	Sharp	40%	Surprise	Next artwork request	+13%	18%
		Black-Green-Red-Violet	Smooth	90%	Surprise	Next artwork request	+8%	26%

4.2 Therapy result

5 autistic subjects (2 male and 3 female) in 5 days get EA treatments. Results were different in each child (positives and negatives), but and the end proper patterns have founded for rehabilitation. First subject was male and gets 29% treatments after 5 days and watching different EAs. Child was attracted to smooth 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 5 was not satisfactory and just 12% (because of girly nature of the subject). After having 2 subjects (1 male and 1 female), there were 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 rehabilitation estimation after day 5. Subject 4 and 5 were female and got 21% and 26% rehabilitation estimation based on psychologist observation. So all subjects (male or female) tend to smooth shapes, light colors and less shape complexity.

5. CONCLUSION, DISCUSSION AND SUGGESTIONS

Using A.I, computer vision and especially image processing techniques had good effects in autism rehabilitation in last two decades. Due to nature inspired evolutionary art structure's and with the aim of autistic people treatment, a new unsupervised evolutionary art structure is made, which produces nature inspired paintings (based on ICA) and used it to autism rehabilitation in this paper. Positives and negatives results achieved from 5 subjects (male and female). Finally, proper pattern had been found. Third and fifth subjects' results are proof 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 rehabilitation and could be an open door in this area for other researcher. Also using depth image could make interactive systems smarter, like proposed system. Using this kind of systems as an assist or alternative automatic expert system is highly recommended (Autism rehabilitation or different medicine and therapy fields).

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