Calculate Patterns for Perceptual texture image Sign and mining

*Candidate Name: MrsPadmavathiMtech(Computer Science and engineering)*Email: rahulkarthik.j@gmail.com
Aditya institute of technology and management
Internal Guide Name: CH.Ramesh (phd)

ABSTRACT:

A Pattern-based approach to calculate from content-based image representation and mining is proposed here. We consider perceptual textured images and propose to model their patterns in content of host image by a set of features having a perceptual meaning and their application to pattern-based image mining. Here we use Techniques to find out the textual patterns are Histogram equalization-Redistributes the intensities of the image of the entire range of possible intensities (usually 256 gray-scale levels) and Un sharp masking-Subtracts smoothed image from the original image to emphasize intensity changes. The Proposed Measures will work on single host image to retrieve exact patterns from there. The set of computational measures proposed is applied to content-based image retrieval on a large image data set. Here the threshold value applied for find the exact pattern retrieval. And normalization is to reduce the duplication of pixel from the host image.

We have our unique work in this paper for sub image without any distortions though the selected part placed on third party editors. Normally third party editors or tools will have deferent representation mechanism of pictures. Here we proposed an open compatible and sink technique to have original pixel vector from the main and without any distortions sub image can be placed in synchronization with editors display environment.

Key Terms: *Histogram equalization, image intensity, image mining, unsharp masking, normalization***.**

INTRODUCTION:

Image mining is a nontrivial method to determine legitimate, novel, potentially useful, and ultimately clear knowledge from huge image sets or image databases. Image mining is not only a branch of data mining and knowledge discovery, but also an interdisciplinary research area which includes digital image dealing out, image understanding, database, and artificial intelligence and so on. Image mining deals with the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the image databases. The main obstacle to rapid progress in image mining research is the lack of considerate of the study issues mixed up in image mining. Presently, tools for mining images are few and require human intervention. Feature selection and extraction is the pre-processing step of Image Mining. In the process of image mining concept study is an important technique. In this paper framework of image mining based on concept of image patterns and image intensity is proposed.

It has widely studied as well as used within texture images while it acting a extremely vital task in human visual perception. Although there exist no precise and universal definition of texture, some perceptive concepts can be cleared about texture. Texture refers to the spatial distribution of grey-levels and can be defined as the deterministic or random repetition of one or quite a lot of primitives in an image. Micro textures refer to textures with small primitives while macro textures refer to textures with large primitives. Texture analysis techniques have been used in several domains such as classification, segmentation, and shape from texture and image retrieval. Texture analysis techniques can be divided into two main categories: spatial techniques and frequency-based techniques. In general, the frequency-based methods are based on the analysis of the haunted solidity function in the frequency-based domain. Such methods include the Fourier convert and the wavelet-based methods such as the Gabor representation. Spatial texture analysis methods can be categorized as statistical methods, structural methods, or hybrid methods. The majority of the existing methods applied on textures have many drawbacks. In fact, statistical methods appear to give healthier outcome in the case of micro textures while structural methods grant best results in the case of macro textures. The majority of the existing methods, whether they are statistical, structural or hybrid, have another drawback not less significant: the computational cost. In fact, most of these methods necessitate a very considerable computation cost. Reversely, the human visual perception seems to effort absolutely for about all types of textures. The differences between textures are usually easily visible for the human eye whereas the automatic processing of these textures is more complex. The reason for this variance between human vision and computational models proposed in literature is the information that the majority of computational methods use arithmetical features that have no perceptual meaning easily comprehensible by users.

//proposed work:

Image integration is challenge in the current image processing scenario. In this existing paper the pixels are compared with the 3 attributed metrics to have more brightened image . This is mainly because when ever the image is getting processed for more contrast(color- by enhancing G(Green) or gramma(symbol) values). This work will be done exclusively for sub images individually. But existing work is with the same scenario but for all the time it is for single image with n-1 pixcel pair correlation which is of time complex teqnique so we propose the new technique DII*F*TP(double integrated image for textual pattern.

DII*F*TP(double integrated image for textual pattern.): This algorithm is mainly proposed for time / repetitive pixel processing . Normally before processing the image the image is scanned and will chosen, similar image for integration for further processing. Once 2 images selected for the process, these will be scanned to retrieve similar pixel to ignore repetitive improvement of brightness. This shows our work for time reducing perspective of integration. Once indexing is done 2 images are integrated with similar pixels and starts correlation with again 3 attributed conditions.

Conditions: *Base pixel, threshold pixel, high pixel.*

Base pixel: Normally RGB values are below 50% with gamma as neutral(ignore condition)

Threshold pixel: with all RGB(128,128,128)(20) which is conditional values with gamma as neutral or fluctuated.

High pixel: the range would be more than (20) with gamma with fixed.

Normally when ever single image is started from processing , starting with the 0^{th} pixel will be correlated with the proceeding one to achieve the more bright single pixel to get the result as bright image than existing one. Overall preceding pixels will always be correlated to get better pixel quality results to consolidated quality image. The main usage of this technique is to reduce the time for sub image brightness improvement.

Attributed condition

Base Pixel:

Non constant $|R| < 128$ (Range 0 to 128)
$|G|<128$ (Range 0 to 128)
$|B|<128$ (Range 0 to 128)
γ = RAND (0-255)

Threshold pixel:

Constants $\int R \Leftarrow 128$
$\int G \Leftarrow 128$
$\int B \Leftarrow 128$
γ =RAND (0-255)

High Pixel:

$|R|>128$
$|G|>128$
$|B|>128$
$\gamma \Leftarrow 128$

Algorithm for DII*F*TP -> single image:

Input $\longrightarrow$ segment image I

Output ⟶ Pixel brightness improvement P_B (Pixel Brightness)

Initialization:

```
    Pixel count ⟵ 0
    Count ⟵ 0
    n ⟵number of pixels
    cat1, cat2 ⟵ category
    Category (P)
        Cat = 0
        BP (P)
        R ⟵ Pr
        G ⟵ Pg
        B ⟵ Pb
        Cat = 1
    TP (P)
        R ⟵ Pr
        G ⟵ Pg
        B ⟵ Pb
        Cat=2
    HP (P)
        R ⟵ Pr
        G ⟵ Pg
        B ⟵ Pb
        Cat = 3
    Loop:
        For each P in I
        PB ⇐ Correlate (P,P+1)
        Count ++
    End Loop

    Correlate (Pi, Pj)
    {
        Cat1 = Category (Pi)
        Cat2 = Category (Pj)
        Condition(Cat1 = 0 & Cat2 = 0)
    {
        Incr (Pi)
    }
    Condition (Cat1 = 0 & Cat2 = 1)
    {
        Incr (Pi)
        Incr (Pj)
    }
    Condition (Cat1 = 0 & Cat2 = 2)
    {
        Incr (Pi)
        Incr (Pj)

    }
    Condition (Cat1 = 1 & Cat2 =0 )
    {
        Incr (Pi)
        Incr (Pj)

    }
    Condition (Cat1 = 1 & Cat2 = 1)
    {
        Incr (Pi)
        Incr (Pj)

    }
    Condition (Cat1= 1 & Cat2 = 2)
    {
        Incr (Pi)
        Incr (Pj)

    }
    Condition (Cat1 = 2 & Cat2 = 0)
    {
        Incr (Pi)
        Incr (Pj)

    }
    Condition (Cat1 = 2 & Cat2 = 1)
    {
        Incr (Pi)
        Incr (Pj)

    }
    Condition (Cat1 = 2 & Cat2 = 2)
    {
        Incr (Pi)
        Incr (Pj)

    }
```

Algorithm for DII*F*TP -> double image integration

//

RELATED WORKS:

Here are a number of mechanisms available in literature on the subject of individual illustration observation since the previous studies completed by Bergen and Julesz *et al.* still, there are two main works that are strongly correlated to our work. The first work is done by Tamura *et al.* and the second work is done by Amadasun*et al.* Each of the two has proposed computational measures for a set of textural features. The work of Tamura *et al.* was based on the co-occurrence matrix and the work of Amadasun*et al.* was based on a variant of the co-occurrence matrix called NGTDM (neighborhood grey-tone difference matrix). The results obtained by both of them show good correspondence with human perception. Another work done by Ravishankar*et al.* in which the authors present what they call a texture naming system: they have made an attempt to determine the relevant dimensions of the texture, as in the case of color (RGB, HSI, etc). The objective that we follow in our work falls into this universal outline. We propose, however, a new method to estimate a set of perceptual textural features. The texture pattern model proposed is evaluated using a psychometric method (based on rank correlation) and originate to keep up a correspondence extremely fine to human judgments and outperforms related works. We apply the proposed perceptual model to texture pattern mining and show interesting results. Furthermore, to improve retrieval efficiency, we propose to use two representations: the original images representation and the exact pattern finding. By using of these two representations and the combination of their results are shown to improve performance in an important way.

TEXTURE PATTERN RETRIEVAL:

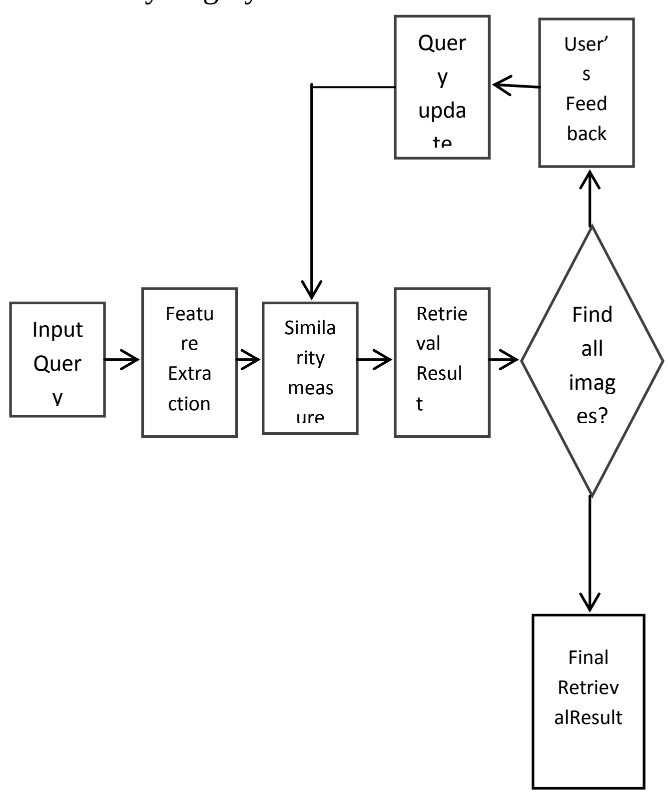
In Proposed system we retrieve exact pattern for texture images based on the threshold value. Here the patterns show exact reorganization for images. The pattern intensity also calculated by using the perceptual features. So we get sharp pattern images.

Relevance feedback is an interactive process that starts with normal CBIR. The user input a query, and then the system extracts the image feature and measure the distance with images in the database. An initial retrieval list is then generated. User can choose the relevant image to further refine the query, and this process can be iterated many times until the user find the desired images.

FEATURES FOR FINDING IMAGE INTENSITY:

Clumsiness:

Clumsinessis the mainly one of the significant characteristic as well as it is determines the reality of texture pattern in an image. Clumsiness calculates the size of the primitives that compose in the image of texture patterns.A common texture is composed of large primitives and is characterized by a high degree of local uniformity of grey-levels.



A fine texture is constituted by small primitives and is characterized by a high degree of limited local variations of grey-levels.

Dimensionality:

Dimensionality is an inclusive property inside an image. It measures the scale of perceptible dominant direction in an image. An image can have one or several dominant direction(s) or no dominant direction at all. In the latter case, it is said isotropic. The direction is influenced by the shape of primitives as well as by their placement rules.

Dissimilarity:

It measures the extent of precision by way of which one can differentiate among different primitives in a texture. A fine Dissimilarity image is an image during which primitives are clearly visible and separable. in the middle of the factors that influence Dissimilarity, we cite: the grey-levels in the image; the ratio of white and black in the image; and the intensity change frequency of grey-levels.

Busyness:

Refers to the intensity changes from a pixel to its neighborhood: a busy texture is a texture in which the intensity changes are quick and rush; a no busy texture is a texture in which the intensity changes are slow and gradual. One can say, therefore, that busyness is related to spatial frequency of the intensity changes in an image. If these intensity changes are very small, they risk will be invisible. Consequently, the amplitude of the intensity changes has also an influence on busyness. We should note also that busyness has a reverse relationship with coarseness.

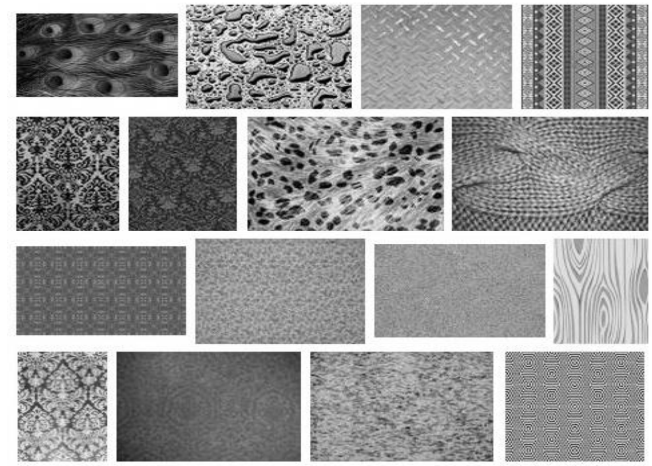


Figure.1 original image

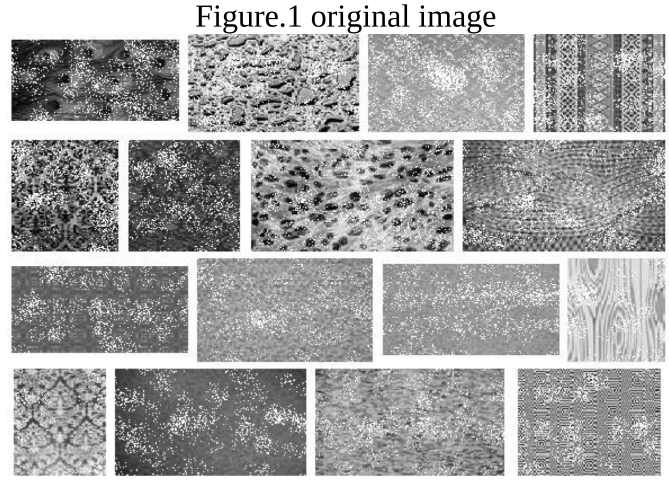


Figure.2

COMPUTATIONAL MEASURES:

AutoCorrelate the image:

The set of computational measures simulating perceptual textural features that we will identify in the next part can be based on two representations (or viewpoints): original images or the autocorrelation function associated with images. Applying computational measures on one or the other of the two representations does not hold the same results. We will show at the end of this paper that, in the framework of content-based image retrieval, adopting multiple representations will allow significant improvement in retrieval effectiveness.

In the framework of content-based image retrieval, multiple representations are used to improve retrieval effectiveness.

The autocorrelation function:

$$f(\delta_i, \delta_j) = \frac{1}{(n-\delta_i)-(m-\delta_j)} \times \sum_{i=0}^{n-\delta_i-1} \sum_{j=0}^{m-\delta_j-1} I(i,j) I(i+\delta_i, j + \delta_j)$$

Where $0 \le \delta_i \le n-1$ and $0 \le \delta_j \le m-1$

δ_i Represent shift on rows

δ_j Represent shift on columns

COMPUTATIONAL FEATURE:

Estimation process of computational measures simulating human visual perception is as follows:

1. The autocorrelation *f(i,j)* is computed on Image *I(i,j)*
2. Then, the convolution of the autocorrelation function and the gradient of the Gaussian function in computed in a separable way. According to rows and columns two functions obtained.
3. Based on these two functions, computational measures for each perceptual feature are computed.

Coarseness Estimation:

Based on the auto correlation function,

1. It is saved in A_c function.
2. For best pattern, the A_c function find out lot of local variations

- First compute derivatives of the A_c function f(i,j) based on the image lines & columns.

Two functions $C_x(i,j), C_y(i,j)$

$$C_x(i,j) = f(i,j) - f(i+1,j)$$
$$C_y(i,j) = f(i,j) - f(i,j+1)$$

- Second we compute derivation of $C_x(i,j), C_y(i,j)$ according to rows & columns

$$C_{xx}(i,j) = C_x(i,j) - C_x(i+1,j)$$
$$C_{yy}(i,j) = C_y(i,j) - C_y(i,j+1)$$

Maximum value detection, we use below equations

$$\begin{cases} C_x(i,j) = 0 \\ C_{xx}(i,j) < 0 \end{cases}$$
$$\begin{cases} C_y(i,j) = 0 \\ C_{yy}(i,j) < 0 \end{cases}$$

A clumsy texture will have small no. of maximum & a fine texture will have large no. of maximum.

Let $Max_x(i,j) = 1$ if pixel (i,j) is a max rows

$Max_x(i,j) = 0$if pixel (i,j) is not a max rows

$Max_y(i,j) = 1$ if pixel (i,j) is a max columns

$Max_y(i,j) = 0$if pixel (i,j) is not a max columns

$$C_s = \frac{1}{\frac{1}{2}\times\left(\frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} max_x(i,j)}{n} + \frac{\sum_{j=0}^{m-1}\sum_{i=0}^{n-1} max_y(i,j)}{m}\right)}$$

To have C_s between 0&1, we normalize coarseness.

Value of C_s close to 1 means, Image contains Maxima, and then it is very coarse texture.

$C_s = 0$ Means, Image contains lot of maxima, it is fine texture.

$C_s = 1$ Or close to 1, image contains object from rather than texture.

C_s Is very close to 0, means the image contain noise data.

Dissimilarity:

The Amplitude M of the Gradient of correlation According to the lines and columns G_x&G_y respectively.

1. We can compute X Auto correlated average amplitude by A_c function by considering the pixels with significant amplitude. Threshold t;
2. No. of pixels (i,j) that have amplitude

$$C_x = f * G_x$$
$$C_y = f * G_y$$
$$M = \sqrt{C_x^2 + C_y^2}$$

G_x and G_y are partial derivatives.

Let $\delta_t(i,j) = 1$ pixel (i,j) amplitude is greater than t,

Let $\delta_t(i,j) = 0$ pixel (i,j) amplitude is inferior t

Let N_t no. of pixel having amplitude superior to t

$$N_t = \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} \delta_t(i,j)$$

The average amplitude M_a

$$M_a = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} M(i,j) \times t(i,j)}{N_t}$$

Then Dissimilarity$C_t = \frac{M_a \times N_t \times C_s^{1/\propto}}{n \times m}$

C_sIs computational measure of clumsiness,$\frac{1}{\propto}$ is a parameter used to C_s significant against the quantity.

Dimensionality Calculation:

Regarding Dimensionality there is two parameters are there

1. Leading Orientation Estimation
2. Dimensionality Estimation

1. Orientation Estimation: It is regarding to the global orientation that contain texture. Based on the autocorrelation function there are two phases are there regarding the orientation.

Existing orientation in the original image is saved in the corresponding autocorrelation function

- By using that, instead of the original image the global orientation instead of local orientation by using original image. It continuous the global orientation can be estimated by following the gradient on the autocorrelation function related to the lines C_X and the columns c_y

The value of Θ refers to

$$\Theta = \arctan C_y / C_x.$$

- We take pixels with significant orientation. Where pixel refers that if its amplitude

M= $\sqrt{C_x^2 + C_y^2}$ is superior to threshold t. this threshold can also be used in Dissimilarity used in orientation.

2. Dimensionality Estimation: It is refers to the visibility of the dominant orientation in an image, and also number of pixels having the dominant orientation Θ_d.

- $\Theta_d(i,j) = 1$ It represents that dominant orientation is present
- $\Theta_d(i,j) = 0$ It represents that dominant orientation is not present. Θ_d is visible when more than t. only
- Nonoriented pixels can be represented by $N_{\Theta_{nd}}$: The degree of Dimentionality can be given by

$$N_{\Theta_d} = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} \Theta_d(i,j)}{(n \times m) - N_{\Theta_{nd}}}.$$

$N_{\Theta_{nd}}$ If it is large it is Dimensionality

$N_{\Theta_{nd}}$ if it is small it is no Dimensionality

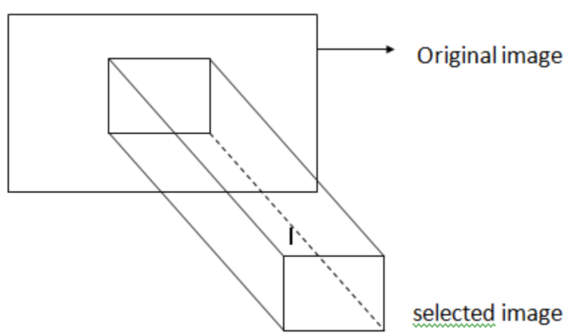
Busyness Estimation: It is related to coarseness in the reverse order. Based on the computational measure of coarseness the equation for busyness is given by

$$B_s = 1 - C_s^{\frac{1}{\alpha}}$$

C_s Represents the computation measure of coarseness

$1/\alpha$ Represents a quantity used to make C_s Busyness is computed based on the coarseness it does not have any effect on texture retrieval

Sub image algorithm:



Thresholds and Normalization:

A threshold was used to get the exact relevant patterns among the images, namely dimensionality and dissimilarity, and was selected as self-motivated (dynamic). Several thresholds were tested, and we found that the threshold which consists in taking the average number of oriented pixels across all orientations present in an image is the best one. This is the threshold used with Dissimilarity and directionality. The different measures proposed were normalized to have their values between 0 and 1. We used what we call range normalization to do so. Range normalization can be done in two simple methods:

1) Compute the range of values for each feature over the whole data set considered. Then, divide each value by this range.
2) Find the highest value for each feature over the whole data set and, then, divide each value of each feature by this maximum.

We used the second method as it guarantees that the resulting values will be necessarily equal or less than 1. Note that we normalized all features (by default, their values between 0 and 1 such as coarseness) in order to keep uniformity over all features.

Conclusion:

A Pattern-based method to compute through content-based image manifestation as well as exploration can be suggested in this article. We all think about perceptual bumpy photos as well as offer to be able to design their particular habits inside content involving host image simply by a couple of features which has a perceptual which means as well as their particular request to be able to pattern-based image exploration. In this article we all use Methods to discover the particular textual habits are Histogram equalization-Redistributes the particular intensities on the image on the entire selection of possible intensities as well as Un pointed masking-Subtracts smoothed image from the unique image to be able to emphasize depth alterations.

The particular number of computational procedures suggested is usually put on content-based photograph access with a significant photograph files established. Right here the actual limit worth sent applications for get the specific style access. As well as normalization should be to slow up the replication involving pixel on the sponsor photograph.

We've each of our one of a kind do the job in this particular document pertaining to bass speaker impression without the distortions although determined aspect put on alternative publishers. Typically alternative publishers or perhaps tools may have deferent representation device involving photos. Below we all suggested a good available agreeable in addition to destroy strategy to include initial pixel vector in the primary in addition to without the distortions bass speaker impression might be put in synchronization with publishers display environment.

REFERENCES:

[1] C.A. Balanis, Antenna Theory Analysis and Design John Wiley & Sons, 2nd ed., 1997. Apeiron, Vol. 12, No. 4, October 2005 407 © 2005 C. Roy Keys Inc. — http://redshift.vif.com

[2] D. Cvetkovic, and H.Muhlenbein, "*The Optimal Population Size for Uniform Crossover and Trucation Selection*", Technical Report GMD-AS- TR-94-11, 1994.

[3] K.A. De Jong and W.M. Spears, "*An Analysis of Interacting Roles of Population Size and Crossover in Genetic Algorithms*", Proceedings of the international Conference on Parallel Problems Solving from Nature (eds. Schwefel, H.P. & Manner, R.), Springer-Verlag, pp. 38-47, 1990.

[4] D.E. Goldberg, Genetic Algorithms, in Search, Optimization & Machine Learning. Addison Wesley, 1997.

[5] J.H. Holland, Adaptive in Natural and Artificial Systems. Ann Arbor, MI: University of Michigan Press, 1975.

[6] J.J. Grefenstette, "*Optimization of Control Parameters for Genetic Algorithms*". IEEE Trans on Systems, Man and Cybernetics.Vol. 16, N°.1, pp 122-128, 1986.

[7] R.A. Fisher, TheGenetical Theory of Natural Selection. Clarendon press, Oxford 1930.

[8] C. Darwin, The Origin of the Species, Cambridge, Ma., Harvard University Press, 1967.

[9] A.D. Channon, and R.I. Damper, "*Towards the Evolutionary Emergence of Increasingly Complex Advantageous Behaviours*".International Journal of Systems Science, 31(7), pp. 843-860, 2000.

[10] T. Bäck, Evolutionary Algorithms in Theory and Practice: Evolution Strategies, Evolutionary Programming, Genetic Algorithms. Oxford University Press, N.Y.,1996.

