# Enhancing Active Vision System Categorization Capability through Uniform Local Binary Pattern

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**Abstract.** Previous research in Neuro-Evolution controlled Active Vision Systems has shown its potential to solve various shape categorization and discrimination problems. However, minimal investigation has been done in using this kind of evolved system in solving more complex vision problems. This partly due to variability in lighting conditions, reflection, shadowing etc, which may be inherent to these kind of problems. It could also be due to the fact that building an evolved system for these kind of problems may be too computationally expensive. We present an Active Vision System controlled Neural Network trained by a Genetic Algorithm that can autonomously scan through an image, pre-processed by Uniform Local Binary Pattern, [8] method. We demonstrate the ability of this system to categorize more complex images taken from the camera of a Humanoid (iCub) robot. Preliminary investigation results show that the proposed Uniform Local Binary Pattern [8] method performed better than the gray-scale averaging method of [1] in the categorization tasks. This approach provides a framework that could be used for further research in using this kind of system for more complex image problems.

**Keywords:** Categorization,Active Vision System, Neuro-Evolution, Neural Network, Genetic Algorithm, Uniform Local Binary Pattern

## 1 Introduction

Active vision is the process of exploring a visual scene in order to obtain relevant features for subsequent meaningful and intelligent processing. This is very important and very useful in that the visual system usually have a form of control, and are intelligently guided to only those areas of the image surface being processed; that have relevant and valuable information to the task at hand. The control of the visual system can be done by various techniques, although, it is natural to use a Neural Network, because of its biological based inspiration and also their suitability for noisy data. However, developing an Active Vision System, particularly using the approach of evolving neural network is still in its elementary stage [5]. In most cases, only simple vision problems have been solved using this approach, which could be attributed to inherent illumination conditions such as reflection and shadowing in natural images, and also the computational cost that generally comes with using evolutionary techniques for more complex image problems. As a result, when the problem domain becomes more complex, the dimension of the feature vector input to the network increases; and therefore the benefits from this kind of system are soon outweighed by the computational cost. Consequently, categorization using active vision has been used for more simple vision problems and discrimination of very few stimuli. For instance in [1], an Active Vision System based Genetic Algorithm evolved Neural Network was used for categorizing five different gray-scale italic letters. In [5], an Active Vision System Genetic Algorithm evolved neural controller was used for basic 2D shape discrimination. In an attempt to overcome these problems , we have used Uniform Local Binary Pattern [8] for feature extraction and enhancement of more complex images taken from a Humanoid (iCub) robot camera. This can filter out to an appreciable degree impacts of image lighting conditions such as reflection and shadowing, and also reduces the feature vector size that is input into the network.

## 2 Related Works

The field of Evolved Active Vision Systems for categorization has been extensively studied. Mirolli and Nolfi [1] used an Active Vision System that is based on a Genetic Algorithm evolved Neural Network to categorize gray-scale italic alphabet letters in different scales (sizes). The movement of the artificial eye was controlled by motor neurons of the output units, which determine the eye location per time step, in-order to capture relevant input features for the neural controller. James and Tucker [5], developed an Active Vision System that is able to discriminate different 2D shapes by moving about in any direction with an ability to zoom and rotate. The system was able to discriminate different 2D shapes irrespective of their scales, location and orientation. An Active Vision System controlled by an evolved Recurrent Neural Network was developed by Morimoto and Ikegami [6] that dynamically discriminates between rectangular and triangular objects. In this system when the agent moves through the environment, it develops neural states which are not just a symbolic representation of rectangles or triangles, but allow it to distinguish these objects. In the same vein Aditya and Nakul [2], used a Neuro-Evolution based Active Vision System to discriminate a target shape. The artificial retina used in their system has the ability to translate in co-ordinate $X$ and $Y$ directions, zoom-in and zoom-out and ability to rotate as it scans over the image features. However in their work they introduced constraints to the environment of the active vision based system. The constraints to the environment are implemented in the form of force field in a certain direction. At each time step during the training and evaluation, a unit force is exerted on the artificial agent by the force field. This implies that at each step, the agent is forced to move a unit direction in the direction of the force field. Consequently, the actual movement of the agent per time step is determined by the vector sum of the change of location in $X$ and $Y$ directions as well as the force movement. The constraints were added in order to make the system closer to the real world and also provides an opportunity to observe if the system is able to develop intelligent strategies for coping with them. In all the experiments, the system was able to perform better in the discriminating tasks, despite the constraints introduced. Floreano et al [3], also implemented an active vision based system that autonomously scans through gray scale images and was able to discriminate triangular shapes from square shapes. The images used in their experiment varied in scale and location. Finally, in relation to other research works listed above , the approach in this paper also uses an Active Vision System based on Genetic Algorithm controlled Neural Network. We have adopted a similar approach used by Mirolli and Nolfi [1], but extended with the enhancement of the images with Uniform Local Binary Pattern [8] to categorize more complex images from a Humanoid (iCub) robot camera.

## 3 Experimental Details

We have used a biologically inspired Active Vision System that combines sensorimotor information in order to determine the task done by an artificial agent. The artificial agent is provided with a moving eye that explores a visual scene (image), in order to extract relevant information and process the sensory stimuli. The vision system is controlled by a Recurrent Neural Network evolved by a Genetic Algorithm, which is similar in approach to [1]. We have adopted the same fitness function used by Mirolli and Nolfi [1], but of a slightly different Recurrent Neural Network architecture, of similar update equations in [7]. We have also adopted the periphery only architecture of [1](Fig. 1), which also gave the best results in all the different architectures used in their experiments. Hereafter, we shall refer to the entire eye region as periphery in the remaining part of this paper. We have done three sets of experiments, which are: (i) the replication of the periphery only architecture of the original active vision system experiment presented in [1] for the categorization of five italic letters that is , $(l, u, n, o, j)$, which uses the gray-scale averaging method of the pixel values of the periphery region; (ii) our proposed method of pre-processing the periphery region with Uniform Local Binary Pattern [8] of the adopted periphery only architecture in [1], for the categorization of the objects on more complex images taken from Humanoid (iCub) robot camera, namely: soft toy, tv remote control set, microphone, board wiper and hammer; (iii) the periphery only architecture , using gray-scale averaging of the pixel values, but in this case is used to categorize the same set of objects of images taken from Humanoid (iCub) robot camera. The neural network, evolutionary process and the fitness function are the same for the three experiments, only that the second experiment have a different input vector size as its visual features are being processed by Uniform Local Binary Pattern [8]. The number of trials and generations in the second and third experiments are 250 and 5000, while that of the first experiment are 50 and 3000. In each experiment we evaluated the performance of the system based on its ability to correctly label the category of the letters or the objects. The three experiments were undertaken so as to do quantitative and qualitative comparisons.

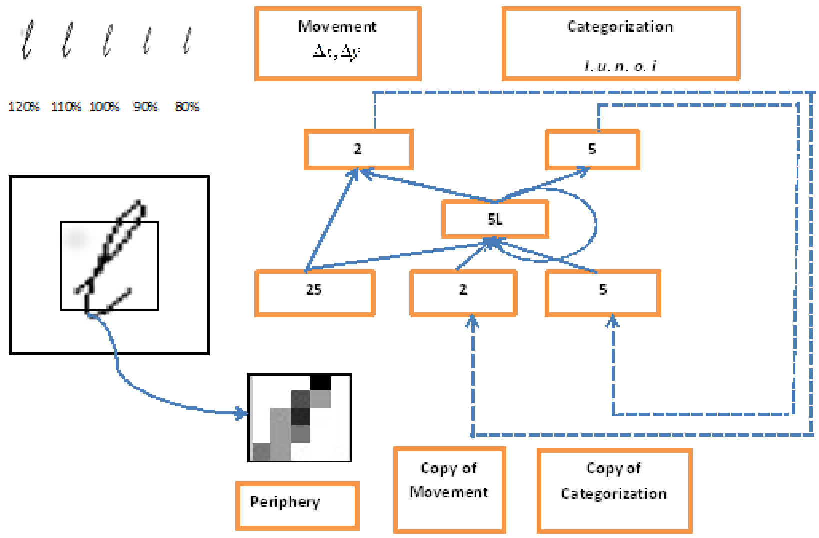


**Fig. 1.** The architecture of our adopted periphery only network used in Experiment One. It has 32 input neurons, 25 of which are for the periphery visual stimuli and 7 for efferent copies of the movement and categorization units. It also has 5 hidden neurons and 7 output neurons (that is, 2 for movement and 5 for categorization units). The left side of the figure, shows the different variations of the letter $l$ and the periphery vision scanning part of the letter, with white image background

**The Neural Network** The Neural Network is a recurrent architecture that consists of one input layer of which vector size is determined by the method of visual features processing: that is 243 in the case of Uniform Local Binary Pattern [8], and 32 for the gray-scale averaging methods. It also has one hidden layer of 5 recurrent neurons, and an output layer 7 neurons. In the output layer, 2 of the neurons determines the movement of the eye per time step (maximal displacement of $[-12, 12]$ pixels in $X$ and $Y$ directions); and the other 5 neurons for labelling of the category of the letters in case of experiment one and the category of the objects in the case of experiments two and three. The input layer consists of units which encode the current state of activations of the neurons for the visual stimuli of the periphery region, the efferent copies of the 2 motor neurons and the 5 categorization units at previous time step $t-1$. The activations of the input neurons are normalized between 0 and 1 and a random value with a uniform distribution within the range of [-0.05;0.05] is added to those of the gray-scale methods at each time step in order to take into account the fact that gray level measured by the photo-receptors of the periphery is subject to noise. The outputs of the neurons in the hidden layer depend on the input received from the input neurons through the weighted connections and the activations of the hidden neurons at previous time step. The input activations scaled by the gained factor are represented by equation (1) below:

$$y_i = gI_i; i = 1, ., k; \tag{1}$$

Where $k$ stands for the size of the input vector, $I$ in the represents the activation values of the input, $y_i$ is the activation values of input scaled by the gain factor $g$. The update equation for the hidden neurons is as shown in the equation (2) below:

$$\tau_i \partial y_i = -y_i + \sum_{j=1}^{n} w_{ji} \sigma(y_j + \beta_j); i = 1, ., 5; \tag{2}$$

The update equation (2) for the hidden neurons is a differential equation. $\tau$ is the decay constant, $y_i$ is the outputs of hidden neurons at previous time step $t-1$, $n$ is the total number of the input and the hidden neurons, $w_{ji}$ is the weight of connections from input neurons to hidden neurons, $\sigma(y_j + \beta_j)$ is the firing rate (where $\beta_j$ stands for the bias terms), $i$ is the number of hidden neurons and $j$ is the number of input neurons. Equation (3) below is used to compute the output activations:

$$y_i = \sum_{j=1}^{5} w_{ji} \sigma(y_j + \beta_j); i = 1, ., 7; \tag{3}$$

where $y_i$ is the activations of the output neurons , $w_{ji}$ is the connection weights from the hidden to output units, while $i$ is the number of output neurons and $j$ is the number of hidden neurons. $\sigma$ is the sigmoid function used as shown equation (4):

$$\sigma(c) = \frac{1}{(1 + e^{-c})} \tag{4}$$

**The Evolutionary Task** In each trial the eye is left to freely explore the image, however, a trial is terminated when the eye can no longer perceive any part of the letter or the object through the periphery vision for three consecutive time steps. The task of the agent is to correctly label the category of the current letter or object during second half of the trial, that is, when the agent has explored the image for enough time. The agent is evaluated by the fitness function $FF$, which comprises of two components: the first one rewards the agent's ability to activate the categorization unit corresponding to the current category more than the other units; the second one rewards the ability to maximize the activation of the correct unit while minimizing the activations of the wrong units, with the activation of the maximization of the correct unit weighting as much as the sum of the minimization of incorrect units:

$$F_1(t,c) = 2^{-rank(t,c)} \tag{5}$$

$$F_2(t,c) = 0.5 * y_r^{t,c} + \sum_{y \in y_w^t} (1-y) * \frac{0.5}{nOL - 1} \tag{6}$$

$$FF = \frac{\sum_{t=1}^{nT} \sum_{c=sFC}^{nC} (0.5 * F_1(t,c) + 0.5 * F_2(t,c))}{nT * (nC - sFC)} \tag{7}$$

where $F_1(t,c)$ and $F_2(t,c)$ are the values of the two fitness components at step $c$ of trial $t$, $rank(t,c)$ is the ranking of the activation of the categorization corresponding to the correct letter or object (that is, from 0, meaning the most activated and 4, meaning the least activated), $y_r^{t,c}$ is the activation of the output corresponding to the right letter or object at step $c$ of trial $t$, $y_w^t$ is the set of activations of the wrong letters or objects at step $c$ of trial $t$, $nOL$ is the number of letters or objects, $nT$ is the number of trials, $nC$ is the number of steps in a trial (that is, 100) and $sFC$ is the time step in which we start to compute fitness (that is, 50). The initial population consists of 100 randomly generated genotypes, each encoding the free parameters of the corresponding neural controller, which include: all the connection weights, gain factors, biases and the decay constants of leaky hidden neurons. The parameters are encoded with 8 bits each. In order to generate the phenotypes: weights and biases are linearly mapped in the range [-5,5], while time constants are mapped in [0,1].

### 3.1 Experiment One

The Experiment has been done in order to show the effectiveness of the gray-scale method in solving a simple image classification problem (i.e letter categorization). The experiment consists of a moving eye located in front of a screen of 100 by 100 pixels and is used to display the letters to be categorized (one at a time). The artificial eye is a periphery only, which consists of a 5 by 5 photo-receptors uniformly distributed over a square area that covers the entire retina of the eye. Each photo-receptor detects the average gray level of an area corresponding to 10 by 10 pixels of the image displayed in front of the screen. The activation of each photo-receptor ranges from 0 to 1, with 0 representing a fully white and 1 representing a fully black visual field. The screen is used to display five italic letters $(l, u, n, o, j)$ of five different sizes each, with a variation of $\pm 10$ and $\pm 20$ percent to the intermediate size (see Fig. 1 for the letter $l$ ). The letters are displayed in black and gray over a white background as shown in Fig. 1 for letter $l$

The agent is evaluated for 50 trials, lasting 100 time steps each. At the beginning of each trial: (i) one of the five letters in one of the 5 different sizes is displayed at the center of the image screen, with each size of each letter presented twice to an individual; (ii) the state of the internal neurons are initialized to 0.0; (iii) the eye is randomly initialized at the centre one third of the screen, so that the agent can always perceive part of the letter with the periphery vision.

### 3.2 Experiments Two and Three

In experiment two, we have used Uniform Local Binary Pattern method [8] for the pre-processing of the periphery region for the task of categorizing objects on images taken from Humanoid (iCub) robot camera; and in experiment three, we adopted the gray-scale method for the same problem. The two systems are used to categorize coloured images (320 by 240 pixels each) of five different objects namely: soft toy, tv remote control set, microphone, board wiper and hammer. Each image of an object has five different sizes with a variation of $\pm 10$ and $\pm 20$ percent to the intermediate size; and each size is varied in five orientations in the range [+4,-4]. The total training set is of 125 images, and the original coloured images are first converted into gray images. The agents are evaluated for 250 trials lasting 100 time steps each. At the beginning of each trial: (i) each object on each image is presented twice to each individual, (ii) the state of the internal neurons are initialized to 0.0, (iii) the eye is initialized in a random position within the central one third of the object. Also, in-order to make the images suited for the systems, in which trials are terminated when the eye (periphery region) loses visual contact with the object for three consecutive time steps; we used Canny Edge Detector to detect the edges on each image loaded per trial, and set rectangular masks on the objects in the images and set every other white pixel outside the boundaries of these to black. Through this we are able to get images that consist of total outside boundaries of black and the objects of white and black. Fig. 2 show the gray images , Fig. 3 shows the images after being processed by the Canny Edge Detector and Fig. 4 shows the final outlook of the images after setting rectangular masks on the Canny Edge Detector processed images. It should be noted that the above processing of the gray images by Canny Edge Detector and rectangular masking, which finally led to the images shown in Fig. 4 are only used to control the movement of the eye, so that every trial is terminated after the periphery vision loses total focus of the object for more than 3 consecutive time steps. It is the gray images that are processed by the Uniform Local Binary Pattern [8] ( experiment two ), and grayscale averaging ( experiment three ); and are used as input vector to the neural network along with efferent copies of the movement and categorization units (that is, activations at previous time step $t-1$ ).

**Experiment Two** The experimental set up consists of a moving eye (artificial agent), covering a total area of 50 by 50 pixels (periphery region) of the presented image per trial. The periphery image region is pre-processed with Uniform Local Binary Pattern [8], in order to enhance its quality and also reduce the feature vector size. In the experiment, we have divided the periphery region into

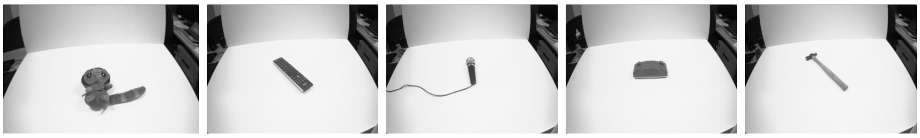

**Fig. 2.** The above figure shows the gray images that are used in the categorization experiment

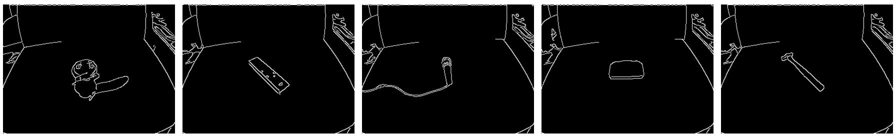

**Fig. 3.** The above figure shows the images after being processed by the Canny Edge Detector

4 blocks of which histogram of uniform patterns are constructed for each block. Histograms of all the blocks are concatenated to form a feature vector, with each block giving a histogram of size 59. The feature vector is normalized between 0 and 1, with 0 representing a fully white visual scene and 1 representing a fully black; which forms the input vector of the neural network along with the efferent copies of the movement and categorization output units

**Experiment Three** We performed a third experiment in-order to do a comparative analysis of the results with the results from our proposed method in Experiment Two. In this experiment, we adopted the gray-scale averaging method in [1] for the processing of the periphery region of the images taken from the Humanoid (iCub) robot camera. The inputs into the neural network are: (i) activations of 5 by 5 photo-receptors, in which each one detects an average gray level of 10 by 10 pixels of the image displayed; and (ii) the efferent copies of the outputs of 2 motor units and 5 categorization units (that is, at previous time step). The activations ranges between 0 and 1, with 0 representing a fully white and 1 representing a fully black visual scene. The results of the experiment are described in section 4

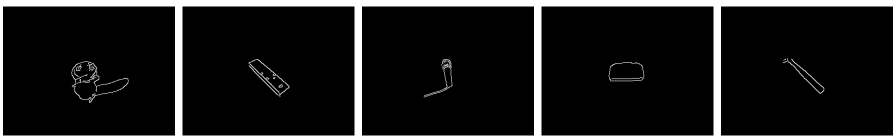

**Fig. 4.** The above figure shows the images after setting a rectangular mask on the Canny Edge Detector processed gray images

## 4 Results

We show here the results of our experiments separately, as we have done three major experiments.

### 4.1 Experiment One

We have done 10 replication of the evolutionary run, (Fig. 5 shows the graph of the best fitness); and also assessed the categorization capability of the system for the five letters $(l, u, n, o, j)$ in the evaluation test (table 1). We have used 25 image datasets in the evaluation stage, with each letter of different size from the one used in the training stage, and of a variation of 0 to 20 percents to the intermediate size. The system was evaluated for about 100000 trials for proper generalization. The replicated gray-scale averaging experiment did very well in the task of categorizing all the letters as demonstrated by higher average activations of the current categories than those of the other categories. The average performance accuracy in all categorization tasks was about 95 percents.

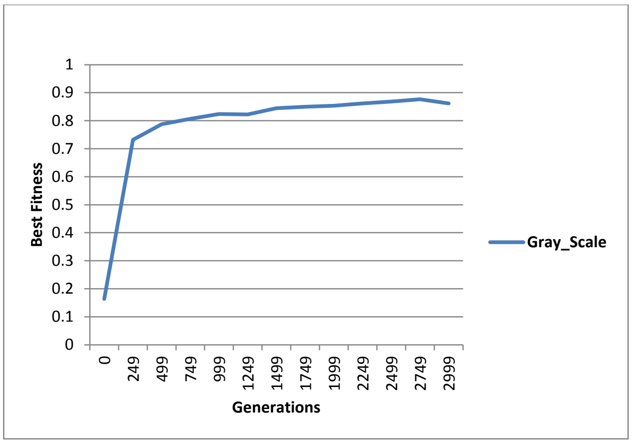


**Fig. 5.** The average of the best fitness in 10 replications of the evolutionary run for the Experiment *One*

### 4.2 Experiment Two

We have also shown here the results of the performance evaluation test of our proposed Uniform Local Binary Patten method [8], for 10 replications of the evolutionary run (Fig. 6). The evaluation test was done for 5 set of objects, namely: soft toy, tv remote control, microphone, board wiper and hammer; on images taken from a humanoid robot camera. Each object is of 2 different sizes,

**Table 1.** Experiment One (Gray-scale): Evaluation Test

| | Average Activation Rates of Letters (Highest Activation Rates in Bold) | | | | |
|---|---|---|---|---|---|
| **Current Letters** | **l** | **u** | **n** | **o** | **j** |
| **l** | **0.950000** | 0.748170 | 0.000017 | 0.006498 | 0.031623 |
| **u** | 0.009783 | **0.793737** | 0.259696 | 0.005544 | 0.033172 |
| **n** | 0.000736 | 0.673059 | **0.875992** | 0.006077 | 0.029533 |
| **o** | 0.018844 | 0.004046 | 0.000151 | **0.930732** | 0.161261 |
| **j** | 0.096664 | 0.002624 | 0.000038 | 0.008332 | **0.885962** |

**Table 2.** Experiment Two (Uniform Local Binary Pattern): Evaluation Test

| | Average Activation Rates of Objects (Highest Activation Rates in Bold) | | | | |
|---|---|---|---|---|---|
| **Current Object** | **Soft Toy** | **TV Remote Control** | **Microphone** | **Board Wiper** | **Hammer** |
| **Soft Toy** | 0.975220 | 0.000331 | 0.000313 | **0.994261** | 0.000011 |
| **TV Remote Control** | 0.000065 | **0.999845** | 0.968086 | 0.000453 | 0.905323 |
| **Microphone** | 0.000057 | **0.999847** | 0.966523 | 0.000464 | 0.901004 |
| **Board Wiper** | 0.696386 | 0.285902 | 0.276539 | **0.710205** | 0.256889 |
| **Hammer** | 0.000061 | **0.999845** | 0.967011 | 0.000444 | 0.907568 |

with a variation of 10 and 20 percents to the intermediate size; and each size of 5 different orientations in the range [+3,-3]. The total evaluation sets are 50 images. The assessment of the performance of the system was done using average of activations of each labelled category for about 100000 trials (table 2). The results from our evaluation test show that the system was able to categorize the tv remote control and board wiper, and did fairly well for others; especially that of the soft-toy, of which its average activation value was slightly lower than that of the highest one. In the case of incorrect categorization of the current categories(soft toy, microphone and hammer), the difference between average activation of the current categories and the higher average activations was very small; especially for that of the soft toy which was about the same with the highest activation. Overall the system has an average performance accuracy of about 50 percents in all categorization tasks (Fig. 7).

**Table 3.** Experiment Three (Gray-Scale): Evaluation Test

| | Average Activation Rates of Objects (Highest Activation Rates in Bold) | | | | |
|---|---|---|---|---|---|
| **Current Objects** | **Soft Toy** | **TV Remote Control** | **Microphone** | **Board Wiper** | **Hammer** |
| **Soft Toy** | **1.000000** | 0.999250 | 0.000139 | 0.994623 | 0.999973 |
| **TV Remote Control** | **1.000000** | 0.999250 | 0.000138 | 0.994623 | 0.999973 |
| **Microphone** | **1.000000** | 0.999250 | 0.000138 | 0.994623 | 0.999973 |
| **Board Wiper** | **1.000000** | 0.999250 | 0.000138 | 0.994623 | 0.999973 |
| **Hammer** | **1.000000** | 0.999250 | 0.000138 | 0.994623 | 0.999973 |

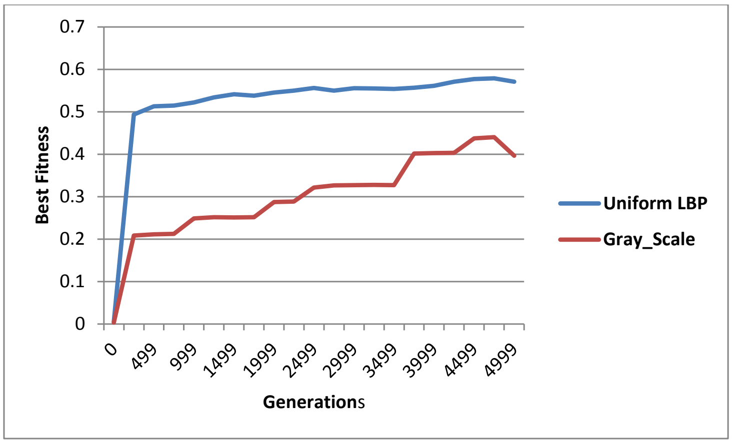


**Fig. 6.** Shows the average of the best fitness of 10 replications of the evolutionary run for the Uniform Local Binary Pattern [8] Experiment Two and gray-scale Experiment Three for categorization of the objects on the images taken from Humanoid (iCub) robot camera

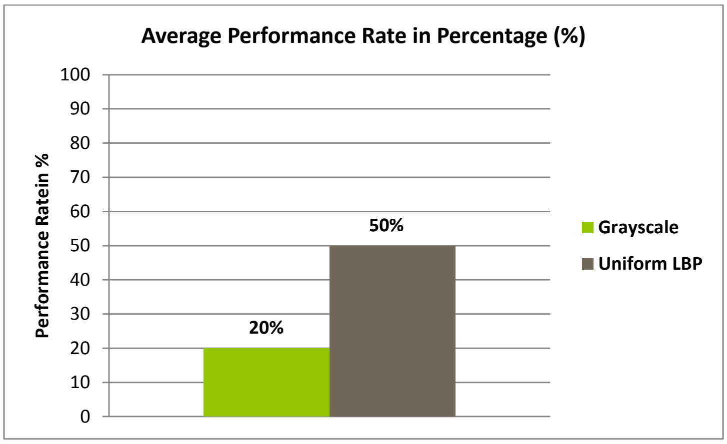


**Fig. 7.** The chart shows the average performance accuracy for the gray-scale and Uniform Local Binary Pattern method [8] in categorizing objects taken from the Humanoid iCub robots camera in 100000 trials

### 4.3 Experiment Three

We have done 10 replications of the evolutionary run (Fig. 6). The performance of the system was evaluated based on average of activations of each labelled category in about 100000 trials (table 3), We used the same set of data of the evaluation stage in Experiment Two, in order to make adequate and unbiased comparison. The results show that the gray-scale method was able to categorize only the soft toy; and even in the case of correct categorization, the current category (soft toy) average activation value was only slightly higher than the second highest average activation value. Overall, the system has an average performance accuracy rate of about 20 percents (Fig. 7)

## 5 Discussion

The first experiment of the gray-scale method was used to assess its capability for ordinary letter categorization. The method did very well in all the letter categorization tasks in the performance evaluation test, with about 95 percents accuracy (table 1). In the second experiment, the proposed pre-processing Uniform Local Binary Pattern Method [8], the system was able to categorize the tv remote control and board wiper; although the activations values are close to those of the categories with second highest activations (table 2). It also did fairly well for the other categories (soft toy, microphone and hammer), in that the difference of average activation values of the current categories and the other categories with higher activations are quite small; especially for the soft toy of which the difference between its average activation and that of the category with higher average activation very insignificant. Overall the system has an average accuracy rates of about 50 percent (Fig. 7). The gray-scale method in the third experiment was only able to categorize the soft toy; and in this case, the average activation value of the current category(soft toy) was only slightly higher than that of the other categories, apart from the microphone (table 3). The system has an average accuracy rate of about 20 percent in all categorization tasks (Fig. 7). Also, observations made from the performance evaluation test for the gray-scale Experiment Three show that the activation values of all the objects in all categorization tasks follows the same pattern; with the soft toy always having the same and highest activations of 1.0, and that of microphone with the lowest activation values, that is very close to zero (table 3). Furthermore, in all categorization tasks all the labelled categories give about the same values, apart from few instances of that of the microphone. The probably reason for this is that the values of the best fitness in all replications of the evolutionary run for the Experiment Three were constantly between 0.4 and 0.45 (Fig. 6); and it may also shows the erratic nature of the gray-scale averaging method in solving complex image categorization problems. Finally, the proposed Uniform Local Binary Pattern [8] method is very promising for the following observed reasons: (i) the differences between the activation rates of the current category and the other labelled categories are very small for incorrect categorization; (ii) the current category always gives high activations, even for the incorrect classifications. We therefore, have an intuition that if the eye could be better controlled to detect the more salient region per time for subsequent processing, we may be able to improve further and achieved better results than gray-scale method, and so get the system also working very well in a variety of categorization tasks. Future work will be in this direction.

## 6 Conclusion

We have investigated using Uniform Local Binary Pattern [8] for pre-processing more complex images taken from Humanoid iCub robot camera for a Neuro-Evolution controlled Active Vision System. Our proposed method had about 50 percent accuracy as compared to gray-scale method of about 20 percent in the same categorization tasks. Future research we be done in bottom up model for filtering features such as colour, intensity and orientation of pixels in generating saliency map, in order to detect salient region in a visual scene; thereby give a more intelligent control of the eye for subsequent processing.

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