

# BETTER PERFORMANCE OF ORTHONORMAL-BACKPROPAGATION NEURAL NETWORK ALGORITHM IN IDENTIFICATION OF OBJECT FEATURES IN STEREOSCOPIC IMAGES

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**Abstract-** Any 3D object can be registered in stereoscopic camera as 2D image pair similar to that of the left eye view and to that of right eye view seen by human eyes. From the stereo pair of images displayed on a screen, the viewer could achieve 3D perceptron by wearing special viewing aids on eyes. On the other hand volumetric display of sectional image of an object display tank concedes 3D view of the object to the viewer without calling for any special viewing aids. This paper reports the computation of the object from stereo pair of images by identifying object features and placing them in respective depth planes. Backpropagation and Orthonormal-backpropagation algorithm of Neural Network are used for extracting the object features in stereoscopic images. Also the efficiency of the Orthonormal-backpropagation algorithm is tested and reported.

Keywords- Artificial Neural Network, Backpropagation, Orthonormal, Stereoscopic images

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## Introduction

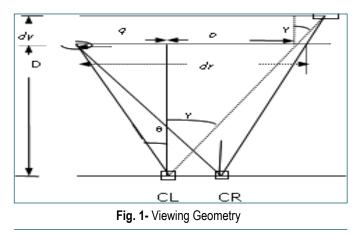
Reconstructing the 3D images of the object from the mono image, stereo image and sequential images is a great concern in stereo imaging. In order to estimate motion correspondences of objects several features were attempted in the past. Some of them were zero crossings of Laplacian of Gaussian operators [1], zero crossing peaks of convolution profiles, edge pixels [2] edge delimited intervals of scan lines [3], L-junctions and rectangles. Depending upon the nature of the distribution of the optical elements of the 3D object scene in 2D planes, each technique would have its advantage for its domination. In another technique of identifying object elements edge detection process was performed first and the regional edges were grouped in windows of subjective sizes.

This project uses artificial neural network architecture with two data set approach. Also backpropagation and Orthonormal - backpropagation algorithm of Neural Network are used for extracting the object features in stereoscopic images.

## **Spatial Relationship of Object Elements**

The stereo pair of images present the view of the 3D object captured in cameras as seen by the left and right eyes. Due to spatial dislocation of the eyes, the components of the 3D object contained in various lateral planes have their appearances distributed to respective pixels in the stereo pair of images. The disparity in the spatial locations of the object elements in the two images would be larger when their lateral positions differ much in distance. After identifying each component of the object in one lateral plane their relationship with related adjacent components could be ascertained by comparing the displacements of the components in the left and right view image planes.

Consider a sphere and a cube as object elements located at lateral spacings separated by 'dy' shown in [Fig-1].



Cameras CL and CR view the elements as seen by left and right eyes of the viewer. The sphere is placed at a distance of D from the cameras. The relationship of spacing between the elements in horizontal direction and that of the lateral displacements depending upon the viewing angles of these two cameras is obtained as follows.

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The spacing *dl* between elements in CL image,

$$dl = p + q$$

The spatial difference dr - dl of elements in CL and CR,

$$dr - dl = tang.dy$$

$$tang = (dl - a)/D$$
(2)
(3)

A complex 3D object is considered to be composed of multiple object elements distributed spatially in various lateral planes of the object. The horizontal spatial distances of the identical object elements in the images of CL and CR compared to the spacing of adjacent object elements produce information about their lateral spacings. Therefore, identifying the object features in the stereo image pair is important in locating their lateral spacings. When once the lateral spacings are determined they will be grouped in ordered way in corresponding lateral image planes constituting the sectional images of the object. Evidently the volumetric display of sectional images in respective lateral display panels concedes 3D vision with parallax effect.

#### Artificial Neural Network (ANN)

An artificial neural network [4,5] is a set of very simple processing elements (neurons) with a high degree of interconnections between them. Such processing architecture is characterized by parallel processing and distributes computing, and is able to learn and adapt to better perform a specific task by modifying the strength of connections between the neurons. Here back propagation [6-8] algorithm used.

#### **Backpropagation Algorithm**

The algorithm towards the training of the network is as follows:

Step 1: The weights and threshold values for network are assigned values that are uniformly distributed over a small range.

Step 2: It is at this point that input values from a training set are presented to the network input layer neurons and the expected output values that are declared with in the set qualified. The network hidden layer neurons then calculate their output. Calculate output vectors using sigmoid function.

Step 3: This is the step in which the weights of NN are updated through the process of propagating backwards the error related to the output neurons results. Calculate the error between network input and the target of the learning set. Adjust the weights of neurons in hidden and output layer.

Step 4: Repeat step 2 and 3 for each vector in the learning set until error rate is acceptably low. This terminating conditional is released, the training is completed and algorithm terminates.

# Mathematical Description - Orthonormal

## Definition:

- An orthogonal set of nonzero vectors {u<sub>1</sub>, u<sub>2</sub>, ..., u<sub>n</sub>} is an orthonormal, if || u<sub>i</sub> || = 1, i = 1, 2, ..., n.
- If u and v belong to an inner product space V and v is not equal to zero, then the vector projection of u along v is

$$\left( (u \cdot v) / \left\| v \right\|^2 \right) * v \tag{4}$$

**Theorem:** (Gram-Schmidt Process) Every finite-dimensional inner product space has an orthogonal basis [9-11].

**Proof:** Let  $\{u_1, u_2, ..., u_n\}$  be a basis of the inner product space V. We shall construct an orthogonal set  $\{v_1, v_2, ..., v_n\}$  of vectors in V, which

is a basis for V. Write  $v_1 = u_1$ . To construct  $v_2$ , subtract from  $u_2$  its vector projection along  $v_1$ . So

$$v_{2} = u_{2} - \left( (u_{2} \cdot v_{1}) / \|v_{1}\|^{2} \right) * v_{1}$$
(5)

This gives  $v_2 \cdot v_1 = 0$  and so  $\{v_1, v_2\}$  is an orthogonal set. Now to construct  $v_3$ , subtract from  $u_3$  its vector projections along  $v_1$  and  $v_2$ . Thus

$$v_{3} = u_{3} - ((u_{3} \cdot v_{1})/||v_{1}||^{2}) * v_{1} - ((u_{3} \cdot v_{2})/||v_{2}||^{2}) * v_{2}$$
(6)

This gives  $v_3 \,.\, v_1 = 0 = v_3 \,.\, v_2$ . Hence, { $v_1, v_2, v_3$ } is an orthogonal set. Proceeding thus and using all the vectors  $u_1, u_2, ..., u_n$ , we construct the orthogonal set B = { $v_1, v_2, ..., v_n$ }

Where

$$v_n = u_n - \left( (u_n \cdot v_1) / \|v_1\|^2 \right) * v_1 - \left( (u_n \cdot v_2) / \|v_2\|^2 \right) * v_2 - \dots - \left( (u_n \cdot v_{n-1}) / \|v_{n-1}\|^2 \right) * v_{n-1}$$
(7)

The sequence  $\{v_1,\,v_2,\,\ldots\,,\,v_n\}$  is the required system of orthogonal vectors.

$$e_{1} = v_{1} / ||v_{1}||, \qquad e_{2} = v_{2} / ||v_{2}||$$
  
Where  $e_{n} = v_{n} / ||v_{n}||$  (8)

The normalized vectors  $e_1, e_2, e_3, \ldots, \ldots e_n$  form an orthonormal set. In this paper, this Gram-Schmidt algorithm is used to convert the random weight matrix into the corresponding orthonormal weight matrix in backpropagation algorithm of artificial neural network.

#### Proposed Orthonormal-Backpropagation Algorithm

Step 1: The initial weights for network in input and hidden layers are assigned as random values that are uniformly distributed over a small range.

Step 2: Convert the random weight matrix into orthonormal weight matrix using Gram-Schmidt orthonormalisation process

$$\mathbf{e}_{n} = \mathbf{v}_{n} / \left\| \mathbf{v}_{n} \right\| \tag{9}$$

Where

$$v_{n} = u_{n} - \left( (u_{n} \cdot v_{1}) / \|v_{1}\|^{2} \right) * v_{1} - \left( (u_{n} \cdot v_{2}) / \|v_{2}\|^{2} \right) * v_{2} - \dots - \left( (u_{n} \cdot v_{n-1}) / \|v_{n-1}\|^{2} \right) * v_{n-1}$$
(10)

Step 3: Input values from a training set are presented to the network input layer neurons and the expected output values that are declared with in the set qualified. The network hidden layer neurons then calculate their output. Calculate output vectors using sigmoid function given by

$$s(z) = 1/(1 + e - z)$$
 (11)

Step 4: This is the step in which the weights of backpropagation neural network are updated through the process of propagating backwards the error related to the output neurons results. Calculate the error between network input and the target of the learning set. Adjust the weights of neurons in hidden and output layer by the value of 'DELTA'

$$DELTA = ALPHA \times DIFF \times OUT$$
(12)

$$DIFF = OUT \times (1 - OUT) \times (TARGET - OUT)$$
 (13)

Where OUT - Network output value, TARGET - Desired output value, ALPHA - Training rate coefficient

Step 5: Repeat step 3 and 4 for each vector in the learning set until 'DELTA' is acceptably low. This terminating conditional is reached, the training is completed and algorithm terminates.

In orthonormal-backpropagation algorithm initial weights for input

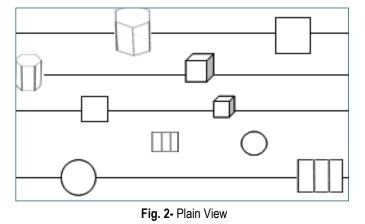
and hidden layer are taken as random (step 1) and converted into orthonormal weight using Gram-Schmidt process (step2). These converted values are taken as initial weights in input layer and hidden layer. Here orthonormalisation is performed only once in step 2 only. After that input and hidden layers weights are calculated using feed forward technique of backpropagation algorithm (step 3 and 4).

## Methodology of Identifying the Network Architecture

This projects initial activity was towards the separation of the consolidated data set in to a training set and a testing set [12]. The first of these sets is training set, which is used for the actual training of network and for determination of the networks recalls ability. The second data set is the testing data set, which is not used in the training process and is used to test the network level of generalization. The different types of data transfer were allocated to bit string representation. The bit strings represent the expected activation of the output neurons in regards to a pattern and are used in the training and testing of the networks constructed during the several stages of network architecture development using input and output necessitated by the problem domain and networks with hidden layer neurons. The initial value for the cycle was set. According to the results, increase the number of cycles.

Object Feature Extraction Using Backpropagation and Orthonormal-Backpropagation Algorithm

Object feature extraction is an important task in determining the sectional images of the object from the given stereo image pair. Standard object elements like cubes, pyramids, prisms, spheres and other conventional shapes are selected for experimentation and backpropagation, orthonormal-backpropagation algorithm of NN is developed and trained, to extract the identification. The tilted version of the object elements are also considered as attributes of the object. The size of the elements and the number of edges contributed by each element also reveal the nature of the geometry which would provide slight differences in their shape in left image and in the right image. The inputs to the ANN are the object size, object position, number of edges, geometrical identity and like. In order to develop the model of ANN an object model with 10 elements distributed in various lateral planes and its plan view shown in [Fig-2] is considered now.



The left eye view and the right eye view images of the object model are given in [Fig-3] and [Fig-4] respectively.

The factors concerning the geometry of various object elements considered in this object model are small, big, position first, position second, round, 11 edges (hexagonal prism with one tilt), 14 edges (hexagonal prism with another tilt), 13 edges(prism tilt first, prism tilt second), 6 edges (small prism, big prism), 10 edges(small prism big prism), 4 edges (cube one tilt), 9 edges(cube with another tilt) and 1 arc (small sphere). Therefore, there are 13 inputs applied to backpropagation and orthonormal-backpropagation algorithms of ANN, which has 11 hidden layers and produces 10 outputs. The output classification are SSP (sphere small), BSP (sphere big), CS (cube small), CB (cube big), PTF (prism tilt first), PTS (prism tilt second), SP (small prism), BP (big prism), CST (cube small tilt) and CBT (cube big tilt).

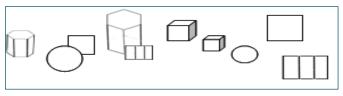


Fig. 3- Left Eye View

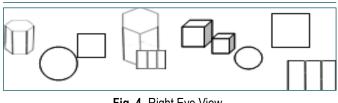


Fig. 4- Right Eye View

### **Discussion and Results of Experimental Setup**

Object element identification process is completed with the backpropagation algorithm of ANN model with 13 inputs. The training of ANN was terminated after 843 cycles when an error goal of 0.01 was achieved. During testing, the backpropagation algorithm of ANN's performance comes closer to 99% accuracy on every trial reported in [Table-1].

Object element identification process is completed with the Orthonormal-backpropagation algorithm of ANN model with 13 inputs. The training of Orthonormal- backpropagation algorithm of ANN was terminated after 460 cycles when an error goal of 0.01 was achieved. During testing, the Orthonormal-backpropagation algorithm of ANN's performance comes closer to 99% accuracy on every trial reported in [Table-1].

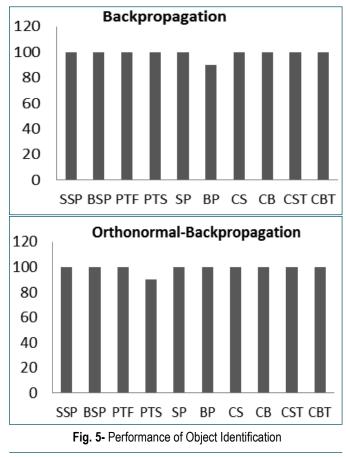
Table 1 -	Object	Identification	Performance	Report
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Sr. No.	Category	Backpropagation Algorithm	Orthonormal- Backpropagation Algorithm
1	SSP	100	100
2	BSP	100	100
3	PTF	100	100
4	PTS	100	90
5	SP	100	100
6	BP	90	100
7	CS	100	100
8	CB	100	100
9	CST	100	100
10	CBT	100	100
Over all percentage		843	460
Cycles		843	460

Noise patterns were also introduced in the training and testing. The backpropagation and Orthonormal-backpropagation algorithms of ANN model performs well in handling noise patterns. Object ele-

Information Science and Technology ISSN: 0976-917X & ISSN: 0976-9188, Volume 3, Issue 1, 2014 ments present in both the images are applied to backpropagation and Orthonormal-backpropagation algorithms and identified. Subsequently, after identification, keeping one element as the reference, the horizontal displacement between it and the adjacent element is noted in both images and recorded. Keeping the same reference element as one of the pair the horizontal disparity is estimated for all image-element-pairs. Subsequently, estimation about the lateral spatial displacements of object elements are made using the geometrical relationship and the concerned object elements are grouped in the respective lateral image planes in the calculated coordinate positions. The computed lateral 2D images would represent the sectional images of the 3D object.

The performance of object identification and the algorithm comparison are plotted in the graph, [Fig-5].



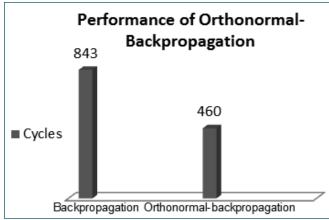


Fig. 6- Algorithm Performance

The training of Orthonormal-backpropagation algorithm of artificial neural network is very fast compared to conventional backpropagation algorithm of artificial neural network, reported in [Fig-6].

### Conclusion

For standard object features contained in a model 3D object, it has been shown that the extracted information matches with that of the original. In practice the objects like natural scenes would contain infinite number of object elements distributed statistically at various spatial locations and a realistic model has to be formulated for such objects. For such objects the stereo pair of images are first put into edge detection process and the identical group of edges in both the images are considered as object elements and ascertained by backpropagation and Orthonormal-backpropagation algorithms of ANN. Obviously the number of inputs to Neural Network algorithms for such objects is very large resulting in increased training time and testing time. However, while generating the real time sectional images of the object from the stereo pair of video images the testing time is important than the training time. With the use of high speed processor the testing time and the time of formulating the sectional images are much lower compared to any other method of image processing tools and hence Orthonormal-backpropagation algorithm of ANN technique proves its supremacy over backpropagation algorithm of ANN and other techniques employed for such processing requirements and environments.

#### Conflicts of Interest: None declared.

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