A NEURAL NETWORK BASED CORNER DETECTION METHOD

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Abstract

Existing corner detection methods either extract boundaries and search for points having maximum curvature or apply a local operator in parallel to neighborhoods of a gray level picture. The key problem in these methods is the conversion of the gray levels of a pixel into a value reflecting a property of *cornerness* at that point. A neural network's ability to learn and to adapt together with its inherent parallelism and robustness has made it a natural choice for machine vision applications. This paper presents the application of neural networks to the problem of detecting corners in 2-D images. The performance of the system suggests its robustness and great potential.
Key words : Corner detection, Artificial Neural Network applications, Neural Network classifier.

1. Introduction

Corner detection is an indispensable procedure in computer vision and image analysis. Objects can appear in various dimensions in the 3-D world. It has become common practice to locate these objects by first detecting the salient features of images. 'Corners' are an important class of such features. Corners are commonly used in computing optical flow and determining structure from motion. In stereoscopic systems, corners are used to identify points of correspondence in 'left' and 'right' images.

Corner detection techniques can be broadly divided into two groups [1]. The first group of corner detection techniques extracts boundaries and searches for points having maximum curvature [2]. These techniques relied heavily on a prior segmentation step and were error prone. This led to the development of the second group of corner detection techniques that were independent of a prior segmentation step. This second group works directly on gray levels. These gray level corner detectors apply a local operator in parallel to neighborhoods of a gray level picture. Existing gray level corner detectors are based on factors such as heuristics [3], second order derivatives [4], differential geometry techniques [5], generalized Hough transforms [6] and median based techniques [7]. Corners have been widely detected by second order differential operators. Most of these methods have been developed as a simple variation of the first order differential operators used in edge detection schemes. Corners in gray level images occur in regions where the intensity level changes rapidly. This has influenced the use of edge detection schemes for corner detection. Gray level corner detectors usually compute a measure of cornerness defined locally. This is generally taken as the product of the magnitude of the gradient and the rate of change of gradient direction [9]. Once the cornerness of the pixels in the image are found, corners can be isolated by a simple thresholding process. The key problem in these methods involves the conversion of the gray levels of a pixel into a value reflecting a property of cornerness at that point.

Although research in computer recognition of objects started several decades ago, the achievements are still quite limited. This prompted the use of biological systems in search for better vision systems. This trend made Artificial Neural Networks (ANNs) a popular and powerful tool. ANNs are able to match or better the performance of many established methods for image processing and pattern recognition [10], by offering simple powerful solutions to problems, mainly in low level vision, such as feature extraction. ANN based pattern recognition involves image segmentation and subsequent classification of the objects within the image. One major problem with such an approach in object identification is the error resulting from segmentation in a poor signal to noise environment. Another problem is the perspective variation [11]. An obvious strength of these ANN based techniques are their ability to match shapes that are not exact. Most models of ANNs usually require several iterations in the learning phase but they recall the stored pattern in one single step. This paper presents an ANN based approach to detect corners of 2-D digital images.

2. Neural Network based Corner Classifier

The ANN based corner detector presented in this paper identifies corner points in 2-D binary and gray level images. Input images were first edge detected and skeletonized. 8x8 pixel sized *sub-images* generated from the edge detected and thinned input images were directly applied to the ***Neural Network based Sub-Image Classifier (NNSIC)***[8]. The NNSIC is a three-layer neural network consisting of an input layer, one hidden layer and an output layer. The NNSIC classifies the sub-images into those "with corners" and those "without corners".

The NNSIC was trained using supervised training techniques. Two distinct classes of data were presented for training. They are the class of sub-images with corners and the class of sub-images without corners. Each training set consists of an 8x8 sub-image and its classification; i.e., the presence or absence of corners. The corners were multiples of 45^0 angles. The corner points were located in the central 4x4 portion of the 8x8 sub-image as shown by the shaded area in Figure 1.

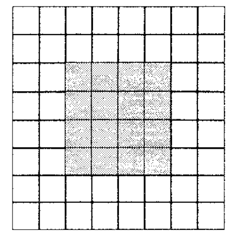


Figure 1 : The central portion of the 8x8 sub-image

This enables an 8x8 sub window to be moved throughout the test image in steps of two pixels. A two pixel wide overlapped, top to bottom and left to right scan of the input image generated the 8x8 sub-images to be input to the classifier.

The bases of the corner angles were made to rotate between 0^0 and 360^0 thereby covering the whole possible range of corner angles. Some generated corners are illustrated in Figure 2.

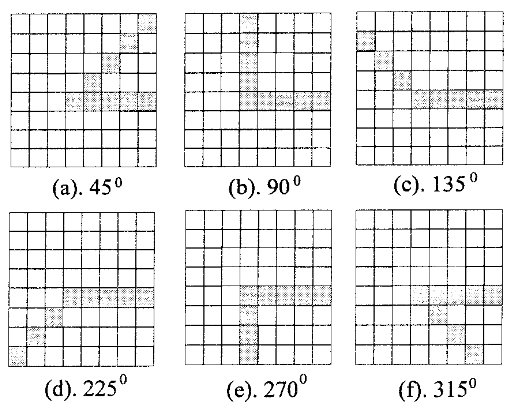


Figure 2 : A few examples of corner angles

The training patterns of the second category were those sub-images without corners. They were randomly generated sub-images containing lines and shaded regions and were not unique. An exhaustive set of input output patterns with an equal representation of each class was used to train the neural network classifier. The final implementation of the NNSIC is the fully trained back-propagation algorithm based multi-layer ANN architecture which is depicted in Figure 3. The NNSIC is fed with 8x8 sub-images obtained from the input image. The neural classifier provides a binary output indicating the presence or absence of a corner.

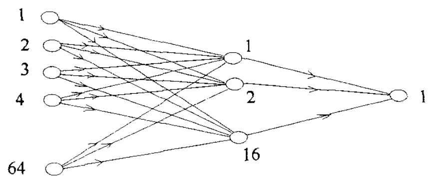
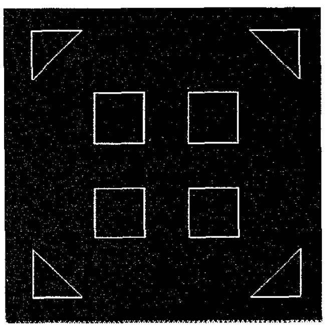


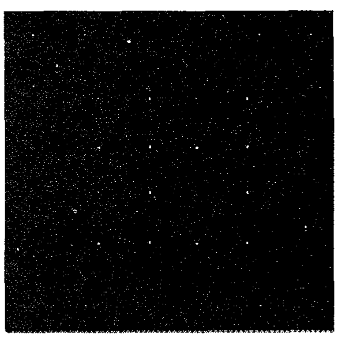
Figure 3 : Architecture of the NNSIC

3. Corner Detection

The generalization capabilities of the NNSIC were tested with a set of images with varying levels of imperfections and noise. Some of the corners tested were either in multiples of 45^0 or close to multiples of 45^0. The NNSIC outputs a label for each input sub-image indicating the presence or absence of a corner point. Figures 4(a), 5(a), 6(a) and 7(a) are some test images and the corners detected are shown in Figures 4(b), 5(b), 6(b) and 7(b) respectively.

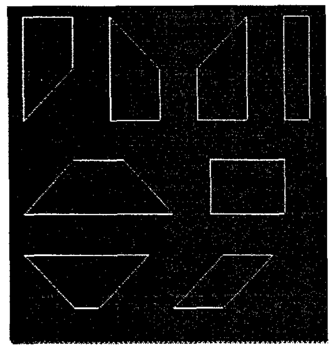


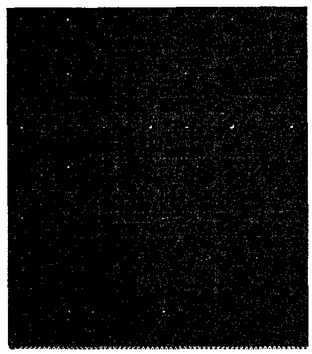
(a)



(b)

Figure 4 : (a) input image (b) corner detected image

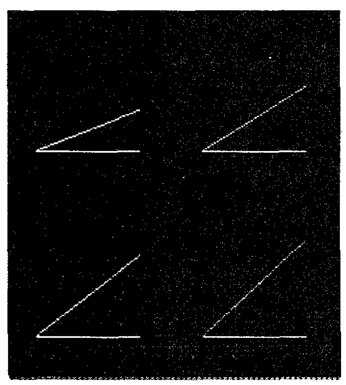




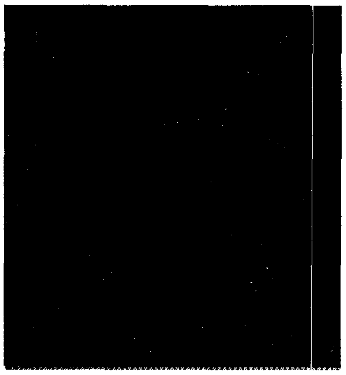
(a)

Figure 5 : (a) input image (b) corner detected image

Figure 4(a) and 5(a) are images consisting of corners of multiples of 45^0. Figure 4(b) and 5(b) indicate that all the corner points have been successfully detected. Figure 6(a) is an image consisting of four corner angles of 20^0, 30^0, 35^0 and 40^0. Figure 6(b) shows that all four corner points have been detected.

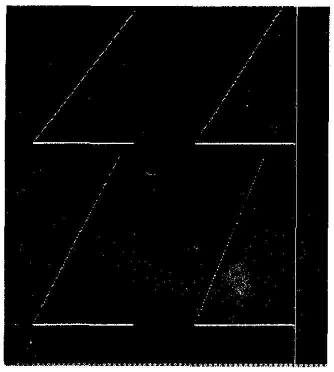


(a)

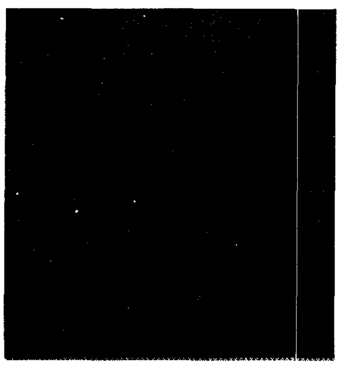


(b)

Figure 6 : (a) input image (b) corner detected image



(a)



(b)

Figure 7 : (a) input image (b) corner detected image

Figure 7(a) is an image with four corner angles, 50^0, 55^0, 60^0 and 65^0. Figure 7(b) shows that only the 50^0 corner angle was detected. A simple analysis provides the reasons for the misclassification by the NNSIC.

The NNSIC was trained with images with corner points occurring in the central 4x4 region. Some of these images are illustrated in Figure 8. The base and edge lengths of the corners in the training images vary from three to six pixels. NNSIC generalizes its output based on the training images. In Figure 8, angles θ_1 and θ_2 (with respect to the base) vary from 33.7^0 and 56.3^0 respectively for Figure 8(a) to 18.4^0 and 71.6^0 respectively for Figure 8(d). Thus it is not surprising that the NNSIC generalizes all the corners to a common range between 33.7^0 and 56.3^0 [8]. Figure 9 shows a 90^0 corner and a simple analysis shows that all angles within $+9.5^0$ and -9.5^0 of a 90^0 corner angle would be detected by the classifier as a 90^0 corner.

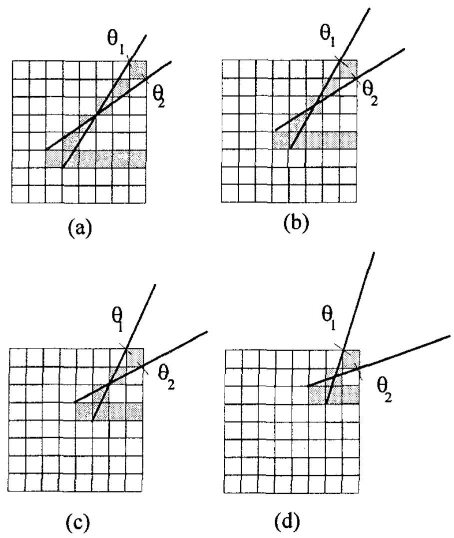


Figure 8 : 45^0 corner angles

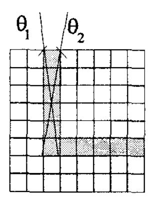


Figure 9 : 90^0 corner angle

4. Conclusions

A functional ANN classifier model was developed and trained with an exhaustive training set for detecting corners. The trained classifier was tested for various images. The performance of the classifier is summarized in table 1.

Table 1 : NNSIC performance results

TYPE OF IMAGES USED	PERCENTAGE DETECTION
Noise-free images with and mostly perfect corners in multiples of 45^0.	**97.55%**
Images with corners which are not necessarily in multiples of 45^0. Some images are noisy and some contain imperfect edges and corners.	**71.0%**

A *perfect* corner in this work is defined as a corner with straight edges and angle in multiples of 45^0. An *imperfect* corner is one with one or more missing pixels. Table 1 summarizes the performance of the NNSIC. It is evident from Table 1 that the NNSIC has excellent generalization properties in detecting corners. The ANN based corner detector is robust and has great potential. The results indicate that ANNs provide a useful tool for analyzing and detecting corners in computer vision. Further work can be made to improve the performance of this neural network classifier. One suggestion is to use a wider range of angles during the classifier training. The NNSIC is trained to orient the corner angles in steps of 45^0. Using a larger sub-image would allow the corner angles to rotate in steps of smaller than 45^0.

5. References

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