

# EDGE DETECTION USING STEERABLE FILTERS AND CNN

Atilla Ozmen <sup>†</sup> and Emir Tufan Akman <sup>‡</sup>

<sup>†</sup> *Department of Electronics Engineering, Kadir Has University  
Cibali, 34230 Istanbul, Turkey  
aozmen@khu.edu.tr*

<sup>‡</sup> *Department of Electrical and Electronics Engineering, University of Istanbul  
Avcilar, 34850 Istanbul, Turkey  
tufane@istanbul.edu.tr*

## ABSTRACT

This paper proposes a new approach for edge detection using steerable filters and cellular neural networks (CNNs) where the former yields the local direction of dominant orientation and the latter, provides iterative filtering. For this purpose steerable filter coefficients are used in CNN as a  $B$  template. The results are compared to the results where only CNN or steerable filters are used. As a result of this study, the performance of the system can be improved since iterative filtering property of CNN and the ability of steerable filters for edge detection are used.

## 1. INTRODUCTION

In the image processing literature all of the methods dealing with the detection of discontinuities in an image, are normally classified under the general edge detection where the traditional techniques are based on the computation of local derivative [1]-[3]. The traditional filters used for edge detection have to be optimized for different kinds of edges. For instance, when the Canny edge filter [4] is applied to a line rather than an edge, it produces two extremum in its output rather than one, each appearing at each side of line. If the filter is optimized for detecting lines it will give spurious responses to edges.

However, another approach for edge detection is the use of orientation techniques. The structures where these techniques are used are known as steerable filters and have been used for image processing tasks, such as texture analysis, edge detection, image data compression, motion analysis, image enhancement and hand-written character recognition [5]-[7]. But these techniques suffer from some drawbacks. For instance, undesired edges may occur in an image. Another disadvantage is that the locations of detected edges are changed by the process.

Also several authors used CNN for the same purpose [8]. In the case of determination of edges rotated at specific orientation, it is necessary to train the CNN. If steerable filter coefficients are used in

CNN, this training process can be avoided. Thus the computation time can be decreased.

In this paper, our proposed approach exploits the use of steerable filters as a  $B$  template in CNN. The motivation of this approach is that the filtering property of CNN and the ability of steerable filters can be used to improve the system performance. However, the CNN outputs can be computed in less time than required by serial digital computer implementations.

The organization of this paper is as follows: Section 2. presents brief definition of steerable filters. In Section 3. our proposed approach is described. Simulation results of this approach are presented in Section 4. Finally, conclusions and discussions are given in Section 5.

## 2. BRIEF DEFINITION OF STEERABLE FILTERS

Steerable filters basically provide directional edge detection since they behave as band-pass filters in a particular orientation [5], [9]. The edge located at different orientations in an image can be detected by splitting the image into orientation sub-bands obtained by basis filters having these orientations. These basis filters represented by  $h^{\theta_i}(t_x, t_y)$ ,  $1 \leq i \leq M$  are the rotated versions of impulse response  $h(t_x, t_y)$  at  $\theta_i$ , the filter orientation and  $k_i(\theta_a)$ ,  $1 \leq i \leq M$ , are called interpolation functions which control the filter orientations.

**Definition:**  $h(t_x, t_y)$  is said to be steerable if it can be expressed at an arbitrary rotation  $\theta_a$ , as a linear sum of fixed rotated versions of itself,  $h^{\theta_i}(t_x, t_y)$ , i.e.

$$h^{\theta_a}(t_x, t_y) = \sum_{i=1}^M k_i(\theta_a) h^{\theta_i}(t_x, t_y) \quad (1)$$

where  $h^{\theta_a}(t_x, t_y)$  is the rotated version of  $h(t_x, t_y)$  at  $\theta_a$  direction and  $k_i(\theta_a)$ ,  $1 \leq i \leq M$ , are interpolation functions.

The following theorem ensures the steering condition [5]:

**Theorem:** The steering condition (1) holds for functions that can be expanded into Fourier series (i.e., periodic or compactly supported) in the following way:

$$h(\rho, \theta) = \sum_{n=-N}^N a_n^h(\rho) e^{jn\theta} \quad (2)$$

where  $\rho = \sqrt{x^2 + y^2}$  and  $\theta = \arg(x, y)$ , if and only if there exists a set of interpolation functions  $k_i(\theta_a)$  satisfying the matrix equation:

$$\begin{bmatrix} 1 \\ e^{j\theta_a} \\ \vdots \\ e^{jN\theta_a} \end{bmatrix} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ e^{j\theta_1} & e^{j\theta_2} & \cdots & e^{j\theta_M} \\ \vdots & \vdots & \ddots & \vdots \\ e^{jN\theta_1} & e^{jN\theta_2} & \cdots & e^{jN\theta_M} \end{bmatrix} \begin{bmatrix} k_1(\theta_a) \\ k_2(\theta_a) \\ \vdots \\ k_M(\theta_a) \end{bmatrix} \quad (3)$$

The number of nonzero coefficients  $a_n^h(\rho)$  gives the minimum number of basis functions required for steering condition.

It is well known that the directional derivative operator is steerable [10], [11]. We consider the first derivative of the Gaussian function in this study. After obtaining first derivative of the Gaussian function rotated at the required orientation, the steerable filter coefficients are evaluated by sampling it.

### 3. THE PROPOSED APPROACH

In this study, we introduce a new approach which is based on the use of steerable filters and CNN for edge detection. As introduced in Section 2., steerable filters can be used for edge detection. But some undesired edges may appear in an output image. This drawback can be avoided by using dynamic and iterative filtering property of CNN.

The simplest CNN is an analog circuit which consists of units called cells. The dynamics of CNN are described by

$$\begin{aligned} \frac{d}{dt} x_{i,j}(t) &= -x_{i,j}(t) + \sum_{p,q \in (N \times N)} A_{p+i,q+j} y_{p,q}(t) \\ &+ \sum_{p,q \in (N \times N)} B_{p+i,q+j} u_{p,q} + I, \quad -N_1 \leq i, j \leq N_1 \\ y(x) &= 0.5(|x + 1| - |x - 1|) \end{aligned} \quad (4)$$

where  $u_{i,j}$ ,  $x_{i,j}(t)$  and  $y_{i,j}(t)$  represent input, state and output, respectively [12], [13].  $N_1$  is radius and  $N_1 = (N - 1)/2$ . Also  $A_{N \times N}$  is called as feedback template while  $B_{N \times N}$  is called as feedforward template.  $N$  represents dimension of CNN and  $I$  is bias term.

In the linear region i.e.  $|x_{i,j}| < 1$ ,  $y_{i,j}(t) = x_{i,j}(t)$ , whole system behaves as a linear system. Therefore the linearized template masks can be defined as:

$$a(n_1, n_2) == \begin{cases} A_{0,0} & (n_1, n_2) = (0, 0) \\ A_{-n_1, -n_2} & (-n_1, -n_2) \in N \times N \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

$$b(n_1, n_2) == \begin{cases} B_{-n_1, -n_2} & (-n_1, -n_2) \in N \times N \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

for simplicity while obtaining the dynamics in the convolution form. In this case, since 4 is independent of initial values as time goes infinity and also bias term  $I$ , is dropped from 4. The transfer function of the central linear system can be written as

$$H(w_1, w_2) = -\frac{B(w_1, w_2)}{A(w_1, w_2)} \quad (7)$$

where  $B(w_1, w_2)$  and  $A(w_1, w_2)$  are discrete space Fourier transform of  $B$  and  $A$  templates, while  $w_1$  and  $w_2$  are spatial frequencies. This transfer function have two important properties; zero-phase and infinite impulse response (IIR). If the  $A$  template has radius zero with  $A_{0,0} = \alpha$ , 7 becomes

$$H(w_1, w_2) = -\frac{1}{\alpha - 1} B(w_1, w_2) \quad (8)$$

This transfer function is equivalent to the FIR filtering of  $B$  template with a weight  $-1/(\alpha - 1)$ .

In this study, steerable filter coefficients which are obtained from the first derivative of Gaussian function are used as a  $B_{N \times N}$  template in CNN.

### 4. SIMULATIONS

In this section, the simulation results for edge detection by using proposed approach are given. Here we consider edge rotated at  $45^\circ$ .

The steerable filter coefficients are evaluated by sampling  $h^{45^\circ}(t_x, t_y)$  from -3 to +3 with 0.67 sampling rate. As a result of this sampling process, 9 coefficients are obtained and these coefficients are used to construct 2D separable filter coefficients. This 2D filter is used as a  $B_{9 \times 9}$  template in CNN. The choose of the coefficient at the center point of  $A_{9 \times 9}$  as 1.3 guarantees that the range of output image is between -1 and 1 [13]. Also  $I$  is chosen as -3.05.

Fig.2 illustrates the edge detection results of this approach. Fig. 1 shows a test image whose size is  $256 \times 256$ . As shown in this figure, only the edge rotated at  $\theta = 45^\circ$  is detected, other edges are filtered. The same input image is filtered by only steerable filters. As illustrated in Fig. 3, while desired edge is detecting, some unwanted edges has occurred at the output image. Fig. 4 shows the difference between test image and the output of steerable filter. It can be seen in this figure, the locations of detected edges

are changed by the process. It is observed in Fig. 5 that this drawback can be avoided by using steerable filter+CNN.

In the case of filtering by CNN, the results are the same as those obtained by using steerable filters+CNN as illustrated in Figs. 6 and 7. But it is necessary to train CNN to detect the edges rotated at  $45^\circ$ . This time consuming problem can be avoided by using our proposed approach, since steerable filter coefficients which are obtained to detect edges rotated at  $45^\circ$  are used as a B template in CNN.

Fig. 8 and 9 show rotation-energy histograms for an image which contains only a line rotated at  $45^\circ$  by using steerable filter and steerable filter+CNN. In Fig. 8, total energy of the image in terms of rotation if only steerable filter is used. In this case total energy smears which is not required. But if our proposed approach is used, the energy reaches its maximum value around  $45^\circ$  as shown in Fig. 9.

## 5. CONCLUSIONS

In this paper, we have proposed a new approach for edge detection application by combining steerable filters and CNNs. As a result of this study, the use of steerable filters as a B template in CNN provides to improve the system performance. Here we use the iterative filtering property of CNN and the ability of steerable filters for edge detection.

Another important point to be considered, the choose of threshold value for  $I$ . If it is chosen as very small, all edges might disappear in the output image. Also the value of  $A_{0,0}$  effects the threshold level and convergence time.

**Acknowledgement:** We would like to thank to Assoc. Prof. O. Nuri Ucan and Research Ass. Koray Kayabol for their valuable comments.

## 6. REFERENCES

- [1] Davis, L. S., "A survey of edge detection techniques," *Computer Graphics and Image Processing*, vol. 46, pp. 248–270, 1975.
- [2] Shaw, G. B., "Local and regional edge detectors: some comparisons," *Computer Graphics and Image Processing*, vol. 9, pp. 135–149, 1978.
- [3] Peli, T., and Mallah, D., "A study of edge detection algorithms," *Computer Graphics and Image Processing*, vol. 20, pp. 1–20, 1982.
- [4] Canny, J. F., "A computational approach to edge detection" *IEEE Patt. Anal. Machine Intell.*, vol. 8, no. 6 pp. 679–698, 1986.
- [5] Freeman, W. T. and Adelson, E. H., "The design and use of steerable filters," *IEEE Trans.*

*on Patt. Anal. and Machine Intell.*, vol. 13, pp. 891–906, Sept. 1991.

- [6] Laine, A. F. and Chang, C. M., "De-noising via wavelet transforms using steerable filters" *Proc. IEEE Int. Sym. on Circuits and Systems (ISCAS'95)*, vol. 3, pp. 1956–1959, May 1995.
- [7] Tufan, E., and Tavsanoğlu, V., "The use of steerable filters for hand-written character recognition," *IX. European Signal Processing Conference (EUSIPCO'98)*, vol. 2, pp. 609–613, Island of Rhodes, Greece, Sept. 1998.
- [8] Guzelis, C., "Image processing applications using CNN", Tubitak Project No: EEEAG - 103, Istanbul, Jan. 1993.
- [9] Tufan, E., *Multisubband structures and their application to image processing*, PhD thesis, South Bank University, Sept. 1996.
- [10] Danielsson, P. and Seger, O., "Rotation invariance in gradient and higher order derivative detectors" *Comp. Vision Graphics Image Processing*, vol. 49, pp. 198–221, 1990.
- [11] Freeman, W. T. and Adelson, E. H., "Steerable filters" *Topical Mtg. Image Understanding Machine Vision Opt. Soc. Amer. Tech. Digest Series*, vol. 14, June 1989.
- [12] Crounse, K. R., Chua, L. O., "Methods for image processing and pattern formation in cellular neural networks: A tutorial," *IEEE Trans. on CAS-I*, vol. 45, no. 10, pp. 583–601, Oct. 1995.
- [13] Chua, L. O., Yang, L., "Cellular Neural Network: Theory," *IEEE Trans. on CAS*, vol.35, no.10, pp. 1257–1290, Oct. 1988.

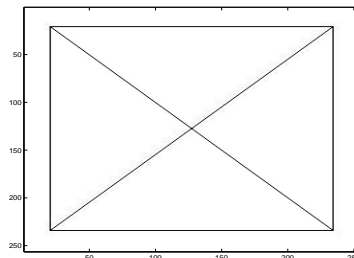


Figure 1: A test image.

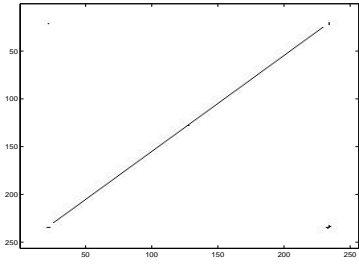


Figure 2: The output of steerable filter+CNN.

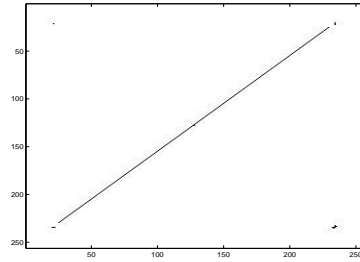


Figure 6: The output of CNN.

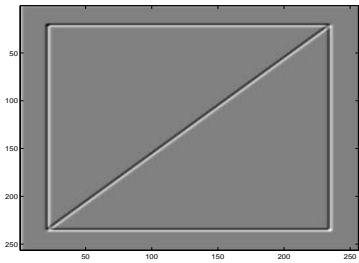


Figure 3: The output of steerable filter.

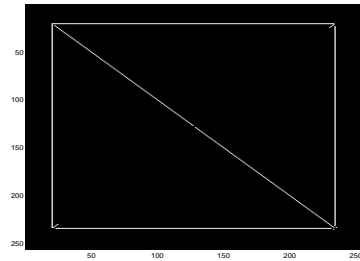


Figure 7: The difference between test image and CNN output.

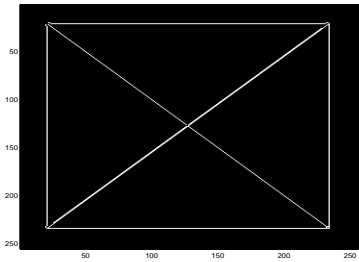


Figure 4: The difference between test image and steerable filter output.

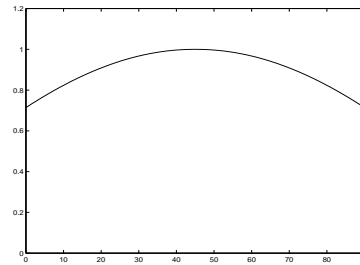


Figure 8: Rotation-energy histogram obtained by using steerable filter.

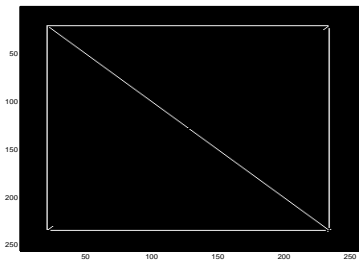


Figure 5: The difference between test image and steerable filter+CNN output.

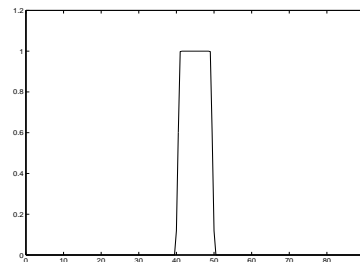


Figure 9: Rotation-energy histogram obtained by using steerable filter+CNN.