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SYNERGISTIC FIBROBLAST OPTIMIZATION BASED BOUNDARY DETECTION IN TAMIL SIGN LANGUAGE IMAGES

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Abstract

Sign Language (SL) is a three dimensional language used for communication by deaf people. The recognition system for SL is always an apprehensive task which is handled by vision collaboration and technology. Basically, detection of edges is deliberated to be the precursor for detection of objects, as the edges are the outline of the objects. Detecting continuous edges in real time images is a hard problem, especially in Tamil Sign Language (TSL) recognition system. This paper proposes an algorithm which finds optimal threshold values (L and H) based on

Synergistic Fibroblast Optimization (SFO) for detection of continuous, smooth and thin edges of TSL hand pose images. A novel SFO algorithm is proposed with sphere objective function and two constraints for reducing the ruined edges. The efficiency of the algorithm is compared experimentally with conventional Canny, Classical PSO and variant based PSO on TSL Consonants images. Experimental results suggested that the novel SFO based canny operator detects edges more accurately, and the edges detected are smoother and thinner when compared to other analyzed algorithms.

Keywords

Tamil Sign Language, Synergistic Fibroblast Optimization, Canny Edge Technique, Edge Detection, Thresholding, Similarity Index

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1. Introduction

Sign language recognition is determined to be a more structured and controlled research area when compared to gesture recognition. There exist different recognition systems for different sign language according to the needs and demands. This leads the researchers to a profound interest to work on different forms of sign language that vary from state to state. Tamil Sign Language (TSL) is a region based sign language, viewed to be a more beneficial mode of confined improvement in their own boundary (Krishnaveni, Subashini & Dhivyaprabha, 2016)(Ghate, 1990). This sign language is a forerunner for regional communication of the Tamil Nadu deaf community. Varied challenges have been encountered while constructing an automated system for SL particularly, identifying the boundaries of the hand shapes. This identifies that the detection of edges is the essential parameter for extracting meaningful features which can be either low level or high level. Tracing the continuous contours accurately is a firm task and it is even harder in noisy images (Jansi & Subashini, 2012). There are several methods to divide the window size into two sub-regions with significant differences in intensities to classify as edge or non-edge. These algorithms cannot produce thin edges which are highly difficult to retrieve in low resolution images. It is also evident that transformation technique such as Hough transform also loses its scope in accurate detection, as it leads its potentiality only in operating simple shapes (Hart, 2009). Synergistic Fibroblast Optimization (SFO) algorithm that follows the theory of swarm intelligence, that imitates the intellect behavior of fibroblast organism, is introduced to find optimum (minima or maxima) solution that resolves real time and uncertainty problems. The core impartial of this paper is to propose a metaheuristic algorithm based canny edge detection operator using novel SFO, to detect fine edges by extracting continuous edges, thus reducing broken and uneven edges. The proposed algorithm is experimented with 18 Tamil consonants static images, each representing the palm side of the right hand and the performance is evaluated with the classical version of Canny and PSO based canny algorithm. Figure 1 portrays the manually generated consonants of Tamil signs that belong to TSL dataset.

The structure of the paper is organized as follows: Section 2 explains the related works based on canny operator based on double thresholding concepts. Section 3 describes the new SFO-based edge detection algorithm. The results and analysis based on evaluation assessments of the experimental results are illustrated in Section 4. Section 5 draws the conclusion and further research directions.

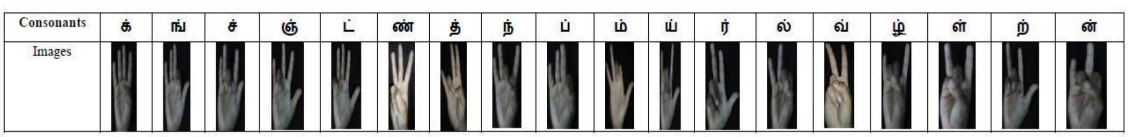

Figure 1: *Manually Generated Tamil Sign Language Dataset (only consonants)*

2. Literature Review

Edge detection is a process of identifying the sharp contrast based on the intensities of an image, by conserving significant structural features of that image (Canny, 1986). In the Canny method, the Gaussian filter algorithm functions as an optimization technique to find the maxima, and the edges are detected based on image gradients. This operator is very much efficient due to its localization process, and it is understood that threshold value is the one which decides the edges in both the directions. The challenge is the choosing of thresholds more likely to detect true weak edges. Henceforth, to enhance the detection of continuous edges, this paper proposes to find the optimal threshold values, by implementing nature-inspired computing algorithms, in integration with biological phenomena of fibroblast cellular organism.

(Xumin Liu, Zilong Duan, Xiaojun Wang and Weixiang Xu, 2016) introduced an improved edge detection algorithm fusion with wavelet transform for efficient detection of edges in digital images and analysis on the visual assessment of results demonstrated its effectiveness. (Shokhan, 2014) applied canny operator for edge detection in low resolution angiography images and the examined results show that the canny method has attained better results. (Shrivakshan and Chandrasekar, 2012) conducted a case study on the edge detection techniques, such as, Roberts, Sobel, Prewitt and Canny and investigated the performance with classification of shark fish digital images. The examined results portray that canny operator gives better results than other conventional methods. (Mamta Juneja and Parvinder Singh Sandhu, 2009) implemented robust edge detection techniques on digital image dataset and the obtained results show that canny operator outperforms than other techniques. (Masoud Nosrati, Ronak Karimi, Mehdi Hariri and Kamran Malekian, 2013) conducted a survey on the edge detection methods, especially, canny method and Gabor filter and the literature study signifies the efficiency of canny operator. (Chinni Jayachandra and Venkateswara Reddy, 2013) applied a canny method to detect edges in digital images stored in CASIA database and K-means algorithm for iris recognition based on pupils. (Nisha, Rajesh Mehra and Lalita Sharma, 2015) implemented canny operator and prewitt operator for detection of edges in benchmark dataset and the experimental results illustrated that canny technique gives better results than prewitt edge detection technique. (Saket Bhardwaj and Ajay Mittal, 2012) conducted a survey on edge detection techniques and the investigational study delivers that modified operators can give better results than other edge detectors.

From the literature works, it is evident that canny operator is able to detect continuous and weak edges present in digital images efficiently rather than other conventional edge detection techniques. But, canny method is still gives slightly poor results in certain cases. In this study, the performance of canny technique is greatly improved by optimizing the hysteresis threshold values using the newly developed Synergistic Fibroblast Optimization (SFO) algorithm. The scope of this study can be further extended to evaluate the performance of SFO optimized Canny to find edges in medical image analysis, benchmark data instances and satellite aerial images.

3. Methodology - SFO Based Edge Detection Algorithm

The objective of this research is to introduce and validate SFO optimized canny method for detection of boundaries in real time Tamil Sign Language digital images. The proposed method detects the continuous edges by reducing the gap between the broken edges in noisy images. The goal is efficiently achieved by developing a new SFO-based approach to produce optimal solution.

In this paper, a new optimization algorithm is introduced in classical canny technique that defines the objective of the paper, to find optimal threshold values for the operation of double thresholding hysteresis method, which is considered to be a non-linear complex problem.

3.1 Synergistic Fibroblast Optimization (SFO) Algorithm

A novel Synergistic Fibroblast Optimization (SFO) algorithm is developed from the intellectual behavior of fibroblast organism role in the dermal wound healing process (Subashini, Dhivyaprabha & Krishnaveni, 2016). The diverse features of fibroblast cellular organism such as differentiation, proliferation, inflammation, migration, reorientation, alignment, ECM synthesis, collaborative, goal- oriented, interaction, regeneration, self-adaptation and evolution is significantly correlated with computational intelligence technique to find the fittest solution in the evolutionary region (John Dallon & Jonathan Sherratt, 1998). In SFO**,** initialization of the population of fibroblast cells f_i, i = 1,2,…,n; with randomly generated position (x_i), velocity (v_i) and collagen deposition (ecm) is done in the n-dimensional problem space. The parameter such as cell speed (s) and diffusion coefficient (ρ) values are defined. Evaluation of the individual cell is done using fitness function F (f_i) for the predefined number of iterations. The reorientation of cell is performed to find optimal (maxima or minima) solution in the evolutionary space. Also, remodeling of collagen deposition (c_i) is upgraded in the extracellular matrix (ecm). The velocity (v_i) and position (x_i) of a cell are changed using the following equations (1)(2).

$$v_i^{(t+1)} = v_i^{(t)} + (1-\rho)c\left(f_i^{(t)}, t\right) + \rho * \frac{f_i(t-\tau)}{\|f_i(t-\tau)\|} \quad (1)$$

where

t = current time;

τ = time lag;

v_i= velocity of i^{th} cell

ρ = 0.5

$$x_i^{(t+1)} = x_i^{(t)} + s * \frac{v_i^{(t+1)}}{\left\|v_i^{(t+1)}\right\|} \quad (2)$$

$s = \frac{s}{k_{ro}L}$, $k_{ro=10^3}$ μ/min, L = cell length;

3.2 Proposed method for edge detection using SFO

Two PSO-based algorithms with different encoding schemes and fitness functions were previously applied to noisy binary images containing simple shapes, such as rectangles, squares, circles, crosses and triangles (Setayesh, Johnston & Zhang, 2011)(Setayesh, Zhang & Johnston, 2009). It is clear that the performance is better in the binary images where the operator did not suite well for non-binary images. A new variant PSO-based algorithm is used to detect continuous edges in noisy images, but the efficiency is poor only in noisy images (Hui Pan, Liang Wang & Bo Liu, 2006). This section describes a new SFO algorithm with sphere fitness function, to detect continuous edges in grey- level noisy images (Dhivyaprabha, Subashini, & Krishnaveni, 2016)(Krishnaveni, Subashini & Dhivyaprabha, 2016).

Encoding Scheme

Step 1: Input a real time noisy Tamil sign language image I(u,v) for detection of boundaries. Tamil Sign Language (TSL) Data set is manually generated with limitation of single handed signs and black background images. The sign image taken for this experimental study falls within the size of 24 bit and JPEG type.

Step 2: Smoothing - Blurring of the image to remove noise by applying a Gaussian filter. The convolution of an image with a core of Gaussian filter using standard deviation of σ = 1.4 is shown in equation (3) given below.

$$B = \frac{1}{159}[24542; 491294; 51215125; 491294; 24542;] \quad (3)$$

Step 3: Determination of gradients - Identify edges by determining gradients of the input image to identify the varying intensity of the image. Gradients at each pixel are found by applying Sobel operator. It can be implemented to approximate the gradient in the x- direction and y-direction respectively in the smoothed image by applying the kernels given in equations (4) and (5) (Canny, 1986).

$$G_x = [-1\ 0\ 1; -2\ 0\ 2; -1\ 0 - 1]; \quad (4)$$

$$G_y = [1\ 2\ 1; 0\ 0\ 0; -1 - 2 - 1;]; \quad (5)$$

The gradient magnitudes can be determined by applying a Euclidean distance measure using the Pythagoras law as shown in equation (6).

$$|G| = \sqrt{G_x^2 + G_y^2} \quad (6)$$

Step 4: Non-maxima suppression –A gradient image has blurred edges transformed into sharp edges by preserving all local maxima and eliminating other pixels in the image. This process consists of the following three steps:

- Round the gradient direction θ to nearest 45°, corresponding to the use of an 8 connected neighborhood pixel values,
- Compare the gradient magnitude of the current pixel with the gradient magnitude of the pixel in the positive and the negative gradient direction.
- If the gradient magnitude of the current pixel is largest, then preserve the value of the edge strength. Otherwise, suppress pixel value in the gradient image.

Step 5: Double thresholding - The resultant edge pixels may still contain noise or irrelevant values. The canny algorithm uses hysteresis double thresholding (high H and low L) method to further suppress the noise content as well as preserve the true image (Canny, 1986) where ***SFO is introduced to identify the optimal threshold values are given in (Procedure 1). Truncation is done to identify the threshold range.***

The probability of a pixel value is represented in the equation (7):

P (z) = p (z/background) P (background) + p (z/object) P (object) or

$$p(z) = P_b \frac{1}{\sqrt{2\pi\sigma_b}} e^{-\frac{(z-\mu_b)^2}{2\sigma_b^2}} + P_o \frac{1}{\sqrt{2\pi\sigma_o}} e^{-\frac{(z-\mu_o)^2}{2\sigma_0^2}}$$

$$p(z) = P_b p_b(z) + P_o p_o(z) \quad (7)$$

$$E_0(T) = \int_{-\infty}^{T} p_0(z)dz \quad (8)$$

The mathematical equation for the probability of incorrectly classifying a background pixel as object is given in (9):

$$E_b(T) = \int_{T}^{\infty} p_b(z)dz \quad (9)$$

The mathematical formula for threshold selection is obtained by minimizing the above expression as denoted in equation (10) (Jansi & Subashini, 2012):

$$T = \frac{\mu_b + \mu_o}{2} \quad (10)$$

The threshold values for set of images in Tamil sign language dataset are found.

Step 6: Edge tracking of image by using SFO algorithm.

Figure 2 depicts the resultant images of a sample image while applying the canny operation.

Procedure 1: To find optimal threshold values (Low L and High H) using SFO.

Step 1: Initialization - A population of fibroblast cells f_i, i = {1,2,3,4,5,6,7,8,9,10} with randomly generated position (x_i) = {1.0, 3.0, 8.0, 6.0, 2.0, 5.0, 7.0, 0.0, 9.0, 4.0} and velocity (v_i) = {0.7770004, 0.5985996, 0.61042523, 0.43213195,0.30436742, 0.868674, 0.5339259, 0.44541568, 0.9589586, 3.2305717E-5}.The number of collagen particles, say c, of size m are (0.0<=m<=1.0) are generated in the extracellular matrix (ecm) and the initialization of two parameters namely cell speed (s) = 15 μmh^{-1}, Length (L) = 10, and diffusion coefficient (ρ) = 0.5.

Step 2: Fitness evaluation - Evaluate the fitness of individual cell which randomly chosen collagen particles found in ecm using benchmark function of Sphere [11]. The mathematical representation of test function is denoted in equation (11).

Sphere function (Continuous, Differentiable, Separable, Scalable, Multimodal)

$$f(x) = \sum_{i=1}^{D} x_i^2 \quad (11)$$

Step 3: Reorientation -The reorientation of cell can be performed based on collagen deposition in the evolutionary region to find optimum (minima and maxima) solution. Compare the previous value ($c_{besti-1}$) of the particle with the current particle (c_{best}) value.

To find minimum optima for a low threshold:

if (c_{best-1}<c_{best})

Set $C_{best} = c_{best}$;

else

Set $C_{best}=c_{best-1}$;

To find maximum optima for a high threshold:

if ($c_{best-1} > c_{best}$)

Set $C_{best} = c_{best}$;

else

Set $C_{best} = c_{best-1}$;

Step 4: Updating velocity and position –The velocity and position of a cell are updated using the following equations (12) and (13).

$$v_i^{(t+1)} = v_i^{(t)} + (1-\rho)c\left(f_i^{(t)}, t\right) + \rho * \frac{f_i(t-\tau)}{\|f_i(t-\tau)\|} \quad (12)$$

$$x_i^{(t+1)} = x_i^{(t)} + s * \frac{v_i^{(t+1)}}{\left\|v_i^{(t+1)}\right\|} \quad (13)$$

where

$s = \frac{s}{k_{ro}L}$, $k_{ro=10^3}$ μ/min, L = cell length;

Step 5: Remodeling –Synthesis of collagen (c_i) can be performed in the extracellular matrix (ecm).

Step 6: Repeat the steps from 2 to 5 until the maximum iterations have attained 10000 and predetermined conditions is to be met.

Step 7: Continuous evolution of swarm in the problem space – Synergistic Fibroblast Optimization (SFO) algorithm return best solution (C_{best}) after the fitness evaluation of 10000 runs.

Step 8: The resultant fittest solutions (C_{best}) low and high threshold values are applied in Tamil Sign Language image dataset shown in Figure 3 and Figure 4.

Step 9: Edge pixels higher than the high threshold value (H) considered as strong. Edge pixels lower than the low threshold value (L) are suppressed and the edge pixels between two thresholds are denoted as weak.

Step 10: The final segmented images are obtained as output.

The yellow marker in Figure 5 portrays that the probability of occurrence of broken edges are ultimately reduced in SFO optimized canny technique when compared to canny method and PSO and m-CPSO based canny techniques.

4. Experimental Results And Analysis

The proposed work is simulated in MATLAB (R2013a) and Java and it is validated in real time Tamil Sign Language (TSL) data instances, especially in consonant datasets with drawbacks of single handed signs with black background images. Acquisition of each sign is done with ten different signers. It is proved both in quantitative and qualitative measures that SFO algorithm has found a better solution than traditional canny, original PSO and a new variant m-CPSO (Krishnaveni, Subashini, & Dhivyaprabha, 2016). The histogram representations of the corresponding segmented images are depicted in Figure 6 reveals the strong detection of continuous edges through the best thresholds chosen by SFO than canny technique, classical PSO and a novel m-CPSO algorithm. The optimal detection of continuous edges is indicated by red arrow in Figure 6. Qualitative measures are done using Similarity Index (SSIM) and correlation coefficient (r) metrics for which the equations (14) and (15) (Avneetkaur, Lakhwinderkaur, & Savitha Gupta, 2012) are given below and the comparison of the results is shown in Table 4.1.

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{14}$$

where

μx = mean of x,

μy = mean of y

$c_1 = (k_1 * L)^2$

$c_2 = (k_2 * L)^2$

$k_1 = 0.01$ and $k_2 = 0.03$ (default values)

L = the dynamic range of the pixel values; By default L = 255, σ_x^2= variance of x , σ_y^2= variance of y, σ_{xy}= covariance of x and y.

$$r = \frac{\Sigma_i (xvalue_i - xvalue_m)(yvalue_i - yvalue_m)}{\sqrt{\Sigma_i (xvalue_i - xvalue_m)}^2 \sqrt{\Sigma_i (yvalue_i - yvalue_m)}^2}$$

(15)

where

$xvalue_i$ = intensity values of i^{th} pixel in image x
$yvalue_i$ = intensity values of i^{th} pixel in image y
$xvalue_m$ = mean intensity values of image x
$yvalue_m$= mean intensity values of image y

When there is a value of *r* =1, if the two digital images are absolutely identical, *r*= 0 if the two images are fully uncorrelated and *r* = -1 if two digital images are fully anti-correlated (Avneetkaur et al., 2012) (Zhou Wang, Alan Bovik, Hamid Sheikh & Eero Simoncelli, 2004). From the objective evaluation, it is understood that the SI values for the applied images using SFO method is relatively higher than the other existing approaches. It is also strongly indicated by Pearson coefficient metrics that the values are higher than the existing methods.

Figure 2: (a) *Input Tamil Sign Image (b) Histogram of the image (c) Smoothed image (d) & (e) Gradient image G_x and G_y (f) Non-maximum suppression of the image*

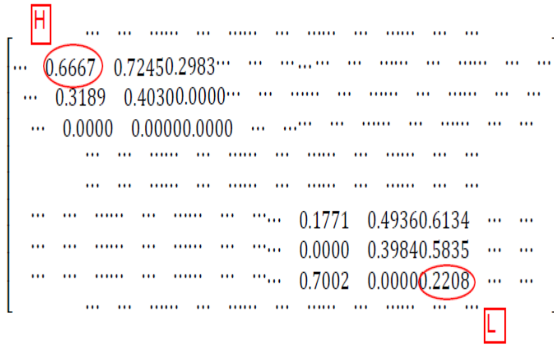

Figure 3: *Best solutions (L and H) for a sample image*

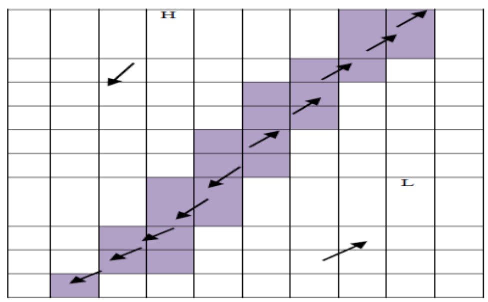

Figure 4: *Example of curve with two regions for a sample image*

Original Image (க்)	Canny	PSO optimized canny	m-CPSO optimized canny	SFO optimized canny

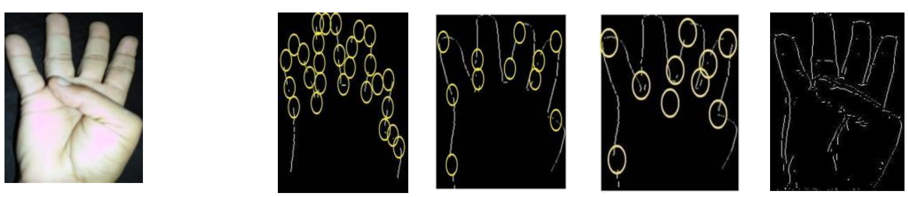

Figure 5: *Visual assessment of proposed method with existing methods*

5. Conclusion And Future Works

In this paper, the novel SFO based canny operator is proposed and applied some other swarm intelligence techniques for comparative analysis. It is tested with real time Tamil Sign Language datasets and the obtained qualitative and quantitative results showed that the novel approach produces promising results than classical Canny and PSO based Canny edge detection methods. In particular, the proposed algorithm does not use any extra preprocessing and post processing techniques. In the future, this study can be extended to optimize the gradient magnitudes in canny operator and other sign language datasets to generalize more on the results of the proposed method. It is also expected to bring new variants in novel SFO for more accuracy in detection edges.

Table 4.1: *Objective Evaluation of Edge Detection Methods Based on Optimization Techniques*

Tamil consonants	Similarity index				Pearson correlation coefficient			
	Canny	*PSO optimized canny*	*m-CPSO optimized canny*	*SFO optimized canny*	*Canny*	*PSO optimized canny*	*m-CPSO optimized canny*	*SFO optimized canny*
க்	**0.03327**	**0.03328**	**0.03329**	**0.10170**	**-0.0197**	**-0.0166**	**-0.0055**	**0.0050**
ங்	0.03900	0.06900	**0.06900**	**0.17413**	0.0199	0.0235	**0.0254**	**0.0704**
ச்	0.24193	0.24195	**0.24196**	**0.24202**	0.0225	0.0236	**0.0254**	**0.0695**
ஞ்	0.13148	0.13153	**0.13154**	**0.13158**	-0.0092	-0.0080	0.0012	**0.0110**
ட்	0.27940	0.27947	**0.27952**	**0.27961**	0.0100	0.0144	**0.0203**	**0.0893**
ண்	0.19201	0.19202	**0.19204**	**0.19207**	0.0657	0.0677	**0.0719**	**0.1233**
த்	0.11461	0.11463	**0.11463**	**0.11469**	0.0185	0.0197	**0.0223**	**0.0974**
ந்	0.12896	0.12899	**0.12900**	**0.12905**	0.0088	0.0071	**0.0075**	**0.0616**
ப்	0.11726	0.11729	**0.11730**	**0.11734**	0.0094	0.0096	**0.0110**	**0.0547**
ம்	0.29844	0.29847	**0.29848**	**0.29852**	0.0229	0.0276	**0.0357**	**0.1110**
ய்	0.28808	0.11625	**0.11626**	**0.11629**	0.0240	0.0254	**0.0457**	**0.1058**
[illegible]	0.10950	0.10953	**0.10955**	**0.10957**	0.0235	0.0204	**0.0388**	**0.0888**
ல்	0.03471	0.03471	**0.03472**	**0.03474**	0.0133	0.0144	**0.0276**	**0.0799**
வ்	0.16243	0.16247	**0.16249**	**0.16253**	0.0267	0.0285	**0.0657**	**0.1223**
ழ்	0.20895	0.20897	**0.20902**	**0.20908**	0.0510	0.0430	**0.0858**	**0.1519**
ள்	0.13169	0.13171	**0.13174**	**0.13177**	0.0264	0.0416	**0.0596**	**0.1224**
ற்	0.10714	0.10717	**0.10720**	**0.10726**	0.0158	0.0142	0.0236	**0.0652**
ன்	0.04100	0.04210	**0.04041**	**0.04044**	0.2340	0.0047	**0.0173**	**0.0530**

Original Sample image (க்)	Canny	PSO optimized canny	m-CPSO optimized canny	SFO optimized canny

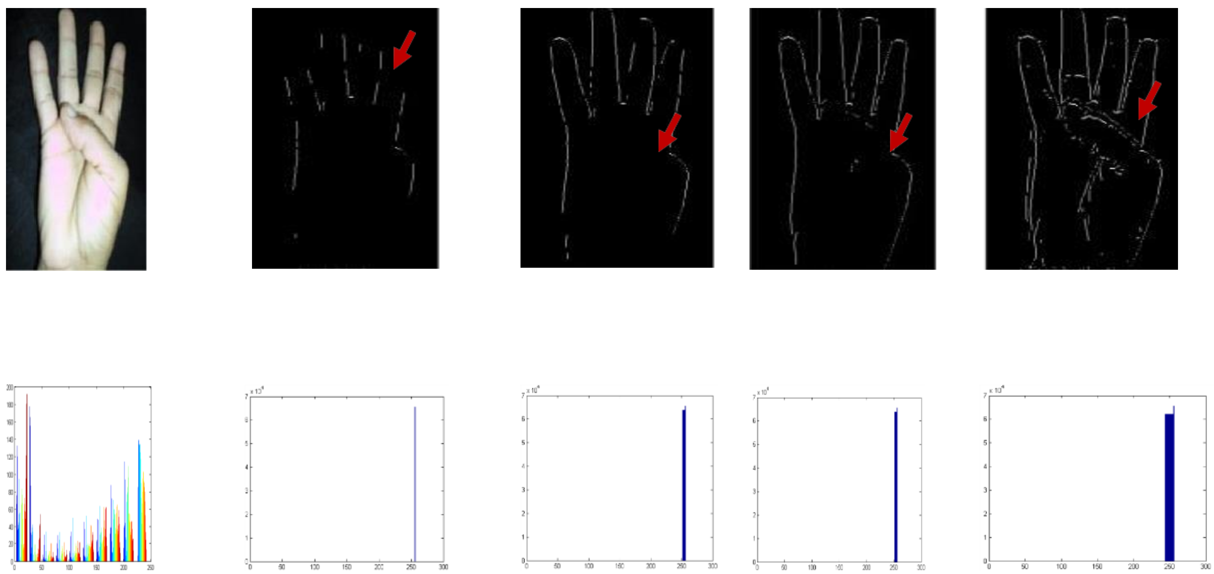

Figure 6: *Histogram representation of the edges detected in a sample image* **(“க்”**, *TSL consonants)*

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