

An Automatic Changeable Edge Detection Model for Digital Images

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Abstract

Edge detection and feature extraction play an important role in digital image processing field. It reduces the amount of data and filters out useless information while preserving the important structural properties in an image. It was observed that using the same edge detection operator for different images make some images suffer from the details (high) and missing (low) edges. This limitation may affect the features for image understanding. Hence, the aim is enhancement of the edge pixels which suffer from the details and missing edge's pixel by adjustment edge pixel in an automatic way for different images. This paper simulates the mechanism of how our body normally controls high and low blood pressure level to regulate the features of high and low edge images. The efficiency of proposed model is demonstrated experimentally on the hand posture dataset. The recognition accuracy obtained is 98.66%. The model provides better performance than conventional methods.

Keywords: Edge detection; Feature extraction; Sign language recognition; Blood pressure regularization; Blood flow

Introduction

The edge detection and feature extraction are main steps in digital image recognition. The features extraction phase starts from the edge detection step. Then the features vectors are created. So, the accuracy of features vectors depends on the quality of output edge. Although, the performances of most features extraction techniques are acceptable for simple noise images. But, some images suffer from the more features due to details edges as shown in Figure 1a, and sometimes low features due to weak edges as shown in Figure 1b. Since there is a need to develop a changeable feature extraction approach to outlining the boundaries of hand [1].

This paper proposes an artificial blood pressure (ABP) model for extracting the features of edge's images. The model is inspired from blood pressure control. The blood pressure tells the doctor how stable or critical patients are. If the blood pressure is too high, this can cause damage to the kidneys or the heart can fail, and low blood pressure can also be serious and any severe fluctuations need to be addressed and treated as soon as possible [2]. In both cases, the blood pressure must be regulated to save a patient life.

As in images, high and low edges effect on image's features. The ABP model has the ability to change depending on the form of edge image (high, normal or low edge). In the normal edge case, the features are extracted without any change in the edge image. In the highest edge case, the edge's pixel will be decreased according to neighbour edge's pixels. In the missing edge case, the edge's pixel will be increased according to neighbour edge's pixels.

The rest of the paper is organized as follows. Section 4 describes the brief information regarding the blood pressure regularization in the human body. Section 5 presents the basic model structure. Section 6 gives the experimental results and their analysis. Finally, concluding remarks are summarized in Section 7.

Biologically Strategy for Normal Control Blood Pressure

Blood pressure (P) is the force of blood pushing against the walls of arteries [3]. Typically, P is recorded as two numbers, written as a ratio, are systolic (P_s) and diastolic (P_d). P_s is the top number, measures the pressure in the arteries when the heart beats (when the heart muscle

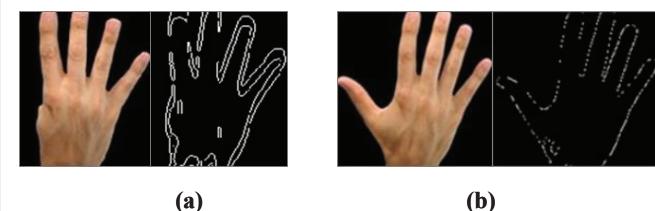


Figure 1: The limitation of using the same edge detection operator for different images. (a) Details edges (high features). (b) Weak edges (low features).

contracts) and P_d are the bottom number, measures the pressure in the arteries between heartbeats (when the heart muscle is resting between beats and refilling with blood). The normal resting blood pressure in an adult is approximately $P_s/P_d = 120/80$ mm Hg (millimeters of mercury) [4,5]. Normally, P is controlled by changing cardiac output (CO) and total peripheral resistance (R) [6], as presented by the formula.

$$P=CO \times R \quad 1$$

The cardiac output (CO) is controlled by blood flow (V) and heart rate (h) [6], as represented by the formula.

$$CO=V \times h \quad 2$$

Thus,

$$P=V \times h \times R \quad 3$$

Under the assumption of that heart rate is equal to one beat and the resistance equal one in normal blood vessel, then,

$$P=V \quad 4$$

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The blood flow (V) is the continuous circulation of blood in the cardiovascular system. Blood flow representing the change in the arterial volume is given by the difference between the rate of flow entering the aorta and the rate of flow from the aorta [7,8]. The mathematical model for blood flow is given by:

$$\frac{dV(t)}{dt} = V_d - V_s \quad 5$$

Where V_d is the end diastolic volume and V_s is the end systolic volume. Thus, the relationship between blood flow and blood pressure depends on the vascular system and obeys an adaptation of Ohm's law [9], known as Darcy's law [10]. That is:

$$\frac{dp(t)}{dt} = \frac{dv(t)}{dt} \quad 6$$

Thus, the change in blood pressure is the difference between the diastolic and the systolic blood volume numbers. If the blood pressure is, 120/80 then the change is 40. If the pressure change is "wide", meaning there is a very large difference between the top and bottom numbers, it indicates that something is going on in the body such as hyperthyroidism, shock or trauma, or any condition that relaxes the blood vessels too much. If the pressure change is a few numbers, this indicates things like blood loss, rapid heart rate, or congestive heart failure, as represented by formula 7. This number is extremely important in the critical care setting, especially when monitoring fluid or blood loss in trauma patients [11] as shown in Figure 2.

$$\frac{dp(t)}{dt} = \begin{cases} < 40 & \text{increase CO} \\ = 40 & \text{normal} \\ > 40 & \text{decrease CO} \end{cases} \quad 7$$

Mapping Blood Pressure to Feature Extraction

The proposed artificial blood pressure (ABP) model is introduced in the context of automatic adaptive feature extraction problem. The probability of false edges considered as high value and the probability of missing edges considered as low value. Specifically, the model simulates the normal regularization of high and low blood pressure by extracting forced features from high and low edge image. In comparison, pixel flow in edge image is the same way the blood flow and the force of features are in a similar manner to blood pressure. A further explanation of similarity between the blood pressure regularization process and adaptive feature extraction process of an image is shown in Figure 3.

Algorithm 1 depicts the process of adaptive feature extraction from an image. The algorithm begins by extracting the edges of an object using the Canny operator [12]. The output of edge detection phase produces one of the following cases:

- High edges, in which some of the edge pixels in the image are details. This case simulates the fact that systolic pressure is the highest arterial blood pressure of a cardiac cycle.
- Low edges, in which some of the edge pixels in the image are weak. In a blood pressure reading, the diastolic pressure is specifically the lowest arterial pressure during relaxation and dilatation of the ventricles of the heart when the ventricles fill with blood.
- Normal edges, in which image does not suffer from detail or weak edge. This case simulates normal blood pressure.

Then, find the neighbour pixels for each edge pixel that has the

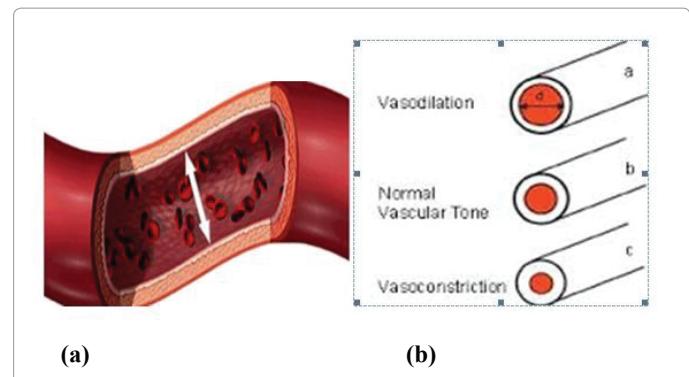


Figure 2: Blood pressure and blood flow. (a) Blood pressure is the measurement force applied to artery walls. (b) Wide, normal and tight blood vessel.

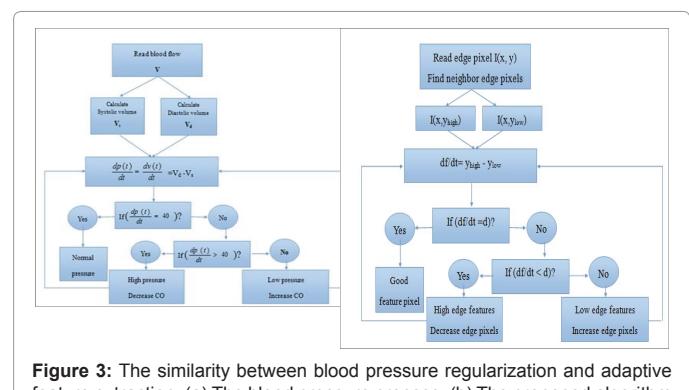


Figure 3: The similarity between blood pressure regularization and adaptive feature extraction. (a) The blood pressure process. (b) The proposed algorithm processes.

same x-value position and have convergent y-value in the result from edge detection phase. Computationally, the process usually begins with the pixel in the first row and first column of the input image and proceeds in raster-scan order. However, any convenient scan sequence can be used.

Next, decompose the neighbour edge pixels to high feature F_{high} (the next edge pixel) and low features F_{low} (the previous edge pixel) as shown in Figure 4. For example, if the edge pixel is $E(10,5)$ and the neighbour edge pixels are $E_1=(10,3)$, $E_2=(10,9)$. Then, the pixel with the maximum x-position of the edge pixel is $F_{high}=E_2=(10,9)$. The pixel with the minimum x-position is $F_{low}=E_1=(10,3)$. This step is motivated by the fact that the blood pressure rises and falls throughout the day.

After that, subtracting the two features vectors $\frac{df}{dt} = F_{high} - F_{low}$. This step is motivated by the fact that the blood flow (V) is the difference between the rate of flow entering the aorta and the rate of flow from the aorta. The output $\frac{df}{dt}$ reflects the force of a feature pixel. A "force" feature, in our terms, is determined by calculating the distance between higher and lower edge pixel. Let d is the distance of good localization of edge pixel, and it is determined as follows.

$\frac{df}{dt}$ equals d , this means that the edge pixel is a good feature representing the object.

$\frac{df}{dt}$ less than d , which means that this pixel is a details feature. So, decrease the edge pixels by ignoring F_{low} and F_{high} . This step is inspired by the fact that if the pressure is high, the blood pressure is reduced by decreasing cardiac output (CO) via a decrease in heart rate (HR).

$\frac{df}{dt}$ greater than d , this means that the pixel is a weak edge. Then

increase the edge pixels by adding new pixels. This step is inspired by the fact that if the pressure is low, the blood pressure is increased by increasing cardiac output and increased total peripheral resistance. Depending on the edge of the input image, (some of the input image pixel positions might be skipped, thereby saving computation time).

```

/*Algorithm 1*/
/* The ABP framework for automatic adaptive feature extraction */
1. Input : Edge image pixel I(x,y)
2. Find : y=yhigh /* yhigh is the max neighbor edge point */
           y=ylow /* ylow is the min neighbor edge point*/
3. Calculate:  $\frac{df}{dt} \leftarrow (y_{high}-y_{low})$ 
/* determine forced features pixel */
4. if(  $\frac{df}{dt} == d$  ) then /* d is a suitable distance between two edges point*/
5.     I(x,y)=1; I(x,yhigh)=1; I(x,ylow)=1; /* Good Feature Pixel */
6. Elseif(  $\frac{df}{dt} > d$  )then /*weak pixels, increase edge pixels*/
7.     m=(yhigh+ylow)/2
8.     I(x,y)=1; I(x,m)=1;I(x,ylow)=1;I(x,yhigh)=1;
9. Else /*Details pixels, decrease edge pixels*/
10.    I(x,yhigh)=0; I(x,ylow)=0; I(x,y)=1;
11. Endif
12. Get: Next Edge image pixel

```

Experiment and Results

The Sign Language Recognition (SLR) system is used in order to illustrate the ABP model. The System consists of mainly three phases are image pre-processing, feature extraction and classification. In the system, the sign is taken from browser window as shown in Figure 5 and the output is its meaning of the sign. The system is implemented in MATLAB 7.0 and runs on 2 GHZ and 2.0 GB RAM.

Dataset description

The signs used in the experiments are the numbers from 1 to 5 in

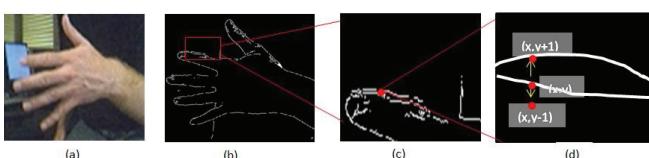


Figure 4: The high and low neighbour pixel (a) Original image. (b) Edge detection phase. (c) Edge pixel. (d) The neighbours of the edge pixel.

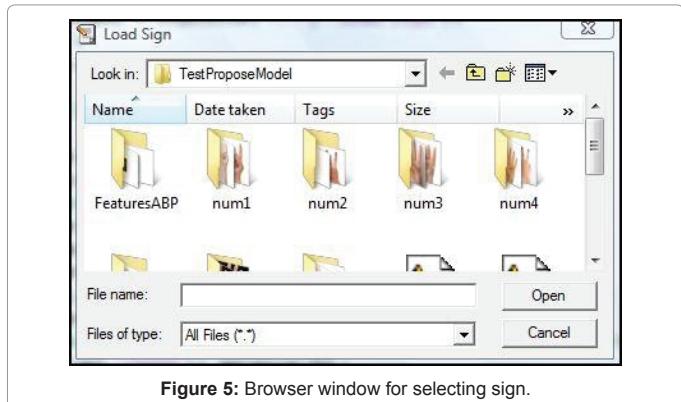


Figure 5: Browser window for selecting sign.

ASL as shown in Figure 6. The signs are collected from [13-15]. The ASL signs for numbers should be signed with the dominant hand. The palm may face toward or away from the signer depending on the preference of the signer. The numbers from 1 to 5 in ASL can be described as [14]:

- Number (1): Form the hand into a fist with the index finger pointed straight up.
- Number (2): Form the hand into a fist with the index and middle fingers pointed straight up.
- Number (3): Form the hand with the thumb, index finger, and middle pointed straight. The index and middle fingers point straight up. Fold the ring and pinky fingers onto the palm of the hand.
- Number (4): Form the hand with the four fingers pointed straight up. Fold the thumb onto the palm of the hand.
- Number (5): Form the hand with all five digits pointed straight and held apart from each other.

Image pre-processing

The images are needed to pre-processing before tested [15]. The pre-processing of the input image is summarized as follows. First, a skin color detection approach is applied [16]. Then convert the image to grey level and remove noise using a median filter [17]. After that, detect hand edges using canny algorithm [18] as shown in Figure 7. Finally, resize the image to 100 × 100 which reduced the image's data without change its details.

Feature extraction phase

The ABP proposed model is applied to the image of hand edge. Visual results of ABP model are shown in Figures 8 and 9; the two sets of images can lead us to the subjective evaluation of the performances of the proposed algorithm.

Figure 8 is a picture of a number "4" in ASL. The Canny edge

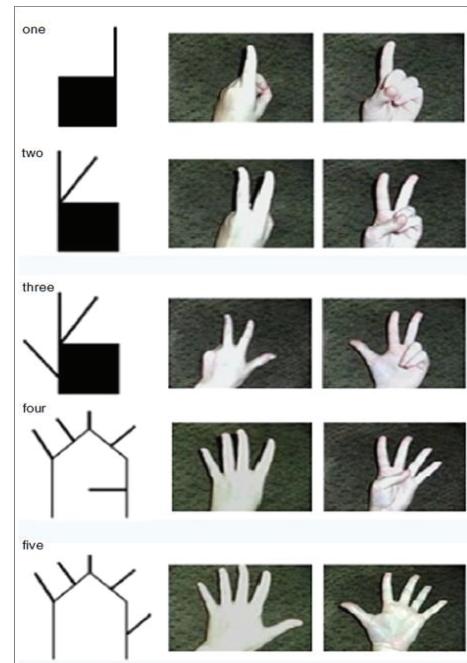


Figure 6: The number from 1 to 5 in ASL.

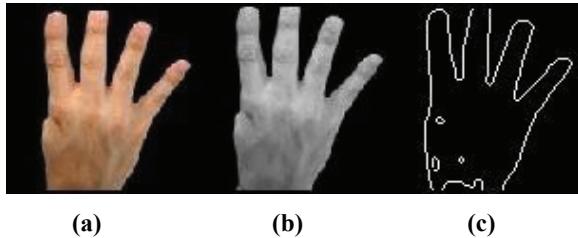


Figure 7: The result of image pre-processing steps. (a) Original Image. (b) Gray level image (c) Image edge extraction.



Figure 8: Number "4" in ASL. (a) Original image. (b) The edge image confused with duplicated contour. (c) The result of the ABP algorithm.

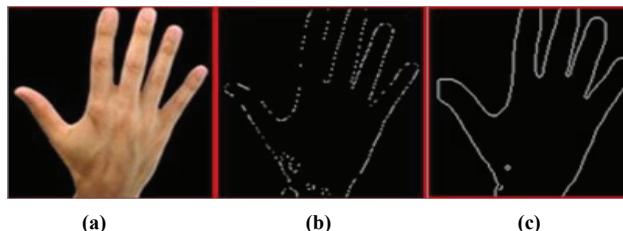


Figure 9: Number "5" in ASL. (a) Original image. (b) The edge image suffers from misshaping some of the lines. (c) The result of the ABP model.

detector has very sharp edges and duplicated contour. Applying dynamical feature extraction technique to a noisy edge image shows the ability to handle details edge in the image.

Figure 9 is a picture of a number "5" in ASL. The edge detectors had problems detecting the different ridges of the cliff. There are a lot of discrepancies in hand fingers, but no clear edges. It does better for some features (i.e., the fingers), it still suffers from misshaping some of the lines. A proposed algorithm constructed using individually selected points would still work better.

Recognition phase

The output of features extraction phase is sent to recognize sign meaning. A standard feed forward back-propagation neural network is used to classify signs. The network consists of three layers. The network based on supervised learning with sigmoid transfer functions. The training chart for NN is shown in Figure 10.

Results

Table 1 displays a confusion matrix showing the efficiency of recognition by ANN. Each sign has 21 samples as shown in Table 1. The system performs that, number '2' has 19% confusion to number '3'. Number '3' has 23% confusion to '5'. Numbers '1', '4' and '5' has not been confused by any numbers.

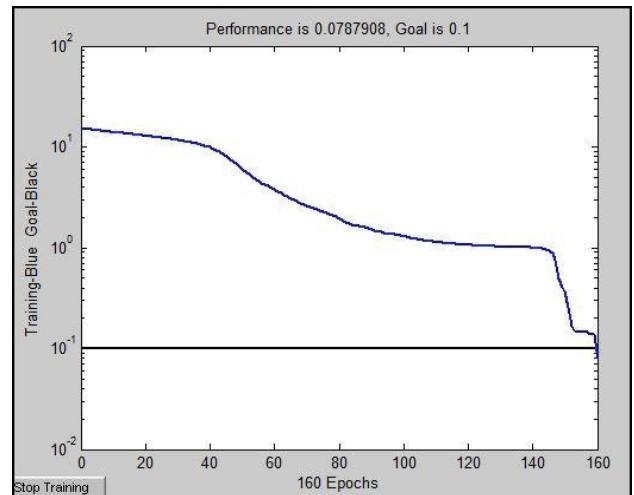


Figure 10: Training chart for 5 signs and 75 samples.

	1	2	3	4	5
1	21	0	0	0	0
2	1	16	4	0	0
3	2	0	14	0	5
4	0	0	0	21	0
5	0	0	0	0	21

Table 1: Confusion matrix for various numbers of ASL.

The performance of the system is evaluated based on its ability to correctly classify samples to their corresponding classes. The metric that we use to accomplish this job is called the recognition rate. The recognition rate is defined as the ratio of the number of correctly classified samples to the total number of samples. The dataset contains 142 signs are divided into training and testing set, 75 samples will be used for training purpose while remaining 67 were used for testing.

$$\text{Recognition Rate} = \frac{\text{num of correct classified sign}}{\text{total num of signs}} \times 100\% \quad (8)$$

The results have been observed in two different ways as shown in Table 2. In the First result, the recognition phase has achieved using the canny method and artificial neural network (without using proposed models). Second, the recognition phase has used the ABP proposed model and ANN. From the Table 2, the different methods give different result in terms of recognition rate. The first experiment the result suffers from low recognition rate because using ANN without any processing of input features. The second method achieved to high recognition rate.

The practical significance of these results is emphasized by comparing them with other methods, which are closed to our system as shown in Table 3. The experiment of our model still, had significantly higher recognition accuracy.

Conclusion

The study was set out to solve the problem of sharp discontinuities edges of objects, which provides low-level features for image understanding. The ABP model is introduced for controlling high and low features in an image. The model is inspired from how our body normally controls high and low blood pressure level. Experiments showed that the proposed model provides better localization features results by decreasing false positives. Indeed, the model has the ability

Model used	Canny+ANN		ABP+ANN	
	Train	Test	Train	Test
Correctly recognized	33	32	74	57
Recognized rate (%)	44.0	47.76	98.66	85.07

Table 2: Cross-validation of ABP model for ASL dataset.

Name of the technique used	Success rate	Difficulties faced
Back propagation Neural Network [1]	80.28%	Neural network requires input feature vectors to have integer values for learning
Contour based [1]	91%	Use of hand gloves
ANN based [1]	94%	Use of hand gloves with 13 sensors
Kinematic Chain Theory based [1]	100%	3 simple gestures
B-Spline Curvature Approximation [1]	96%	Not considered as complete sign language recognizer Information about other body parts is not sufficient
EOH + SVM based [1]	93.75%	A little change in orientation of input gestures makes a significant change in the feature vectors and offers reduced rates of recognition.
Krawtchout+minimum distance Classifier [2]	95.42%	there are prevalently misclassified in sign '2', '3' and '4'.
Leap Motion and Intel RealSense+SVM	72.1%	Some sign representations must include additional data, i.e., orientation of the palm.
k-NN+SVM [4]	90.1%	The system gives 80.8% recognition rate for ambiguous gestures.

Table 3: A comparative study with the result of other approaches.

to change depending on the form of edge image (highest, normal and lowest edge). The extracted features from the proposed model provide valuable features for outline the boundaries of ASL. The future work mainly concentrates on developing the model for more accurate and fast feature extraction.

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