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Feature Edge Extraction for Human Body Cut Injured Detection using Deep Learning

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Abstract: In recent endeavours, the management style of medical patient treatment has been growing continuously. In the meantime, trends demand more accuracy and work performance beyond the level of advancement for waiting in line in hospitals, ending with emergency cases as well. To overcome the delay in response from the hospital end with medical high demand, the doctor-patient ratio is also around 1:700. And the need for blood in a human case is a little crucial based on the blood group. Also, to avoid this scenario and save human lives, we have to implement blood detection on the spot using the image processing technique with deep learning, which can close the gap between the arrangement of the blood bank system and human blood safety support with the patient as well. The current study can only be done after reaching the hospital; using various research attempts to fill this gap. But delay is still needed to reach proper support with advanced technology. To extract the image of blood colour detection using an optical clamp-on Sensor(OCS) deep learning blood detection and amount of blood flow based on healthy body range of blood status with a range of 5 litters for the adult body with advanced BMI technology.

Keywords: *Human Body, Deep Learning, Cut Edge Detection, Image Processing, Convolution Neural Network, Contour Image.*

1. Introduction

The image processing is the first step to identify the colour of the image with various ratio, based on different colour size of the image, then processing the all data of the image give the accuracy of the image and clarity ratio of the image also there is ratio of the image error. To make the high resolution of the image of the injured body parts and the second case in that body parts can have injury that what type body cut is there, there may be with line cut, and cross cut, or blood flow is there or dry blood wound occurrences may be. To recognise it properly real time colour image technique is applied to detect the colour in RGB format. [1] After that we have to look for patient needy diagnosis and treatment preview. Deep learning (DL) is one of the emerging techniques to support with high accuracy of the images of human body. Ratio of the RGB colour will be taken as 256*256 resolutions. In which can help doctors to understand the cut edge clear image. In the previous research, a 2D image process was used for the image beam, the dimensional number system, and the images [2]. Recent time the image process with various methods revolutionised by researcher in 3D as well with human body parts and getting exact part to be contour it with black and white images or colour images also[3]. For digital way data collection is measure role for indentifying the data size and making it with image process technology advanced and fasted process, previously data collection was with measuring the area manually of the body parts based in body name [4]. In manual process we can get error in measuring the adjacent body parts, in computer edge we researcher are trying to resolve this error in image process with various technique like edge detection of image, feature extraction of the image, contour image detection of the images with non contact 3D measurements, so compare with 2D image process 3D images process is far better approved in recent research [5]. Image-based systems can provide morphometric measurements utilizing advanced digital techniques demonstrate a level of fidelity and consistency that closely parallels that of traditional measurement methods [7]. The key component of the fundamental elements of image-based remote body assessment for the apparel sector revolves around the automated identification and isolation of key anatomical landmarks from both primary and secondary images [8]. Precise identification of human body feature points is crucial in developing Digital human representations. Lin and Wang (references [9, 10]) proposed a systematic methodology that utilizes Oblique and lateral views of individuals to construct 3D human simulations, relying on feature points extracted from spotted line contour segment . In the domain of human action recognition, Ali and Aggarwal (reference [14]) employed a method based on outline arc calculation to identify key points like the Patella and pelvis.

And automatic human body image feature extraction identified silhouettes front and back point of view [15]. This research manuscript presents a streamlined, straightforward, and resilient algorithm for locating edge points corresponding to key features of the physical structure using

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frontal and lateral images [10-13]. Contours are obtained by subtracting the background. Contours are obtained by subtracting the background. To depict the contour curves, we employ canny edge detection functions [9] along with Freeman's 8-associated path codes [7]. Subsequently, the curves are partitioned into a sequence of portions, with the orientation of each segment indicated by the values of its second linking codes. The obtaining of feature points employs defined criteria for evaluating variations in segment directions. Subsequently, the proposed approach underwent testing with ten human subjects, accurately obtaining all 101 predefined features. Among these feature points, 28 points possess topological attributes that precisely delineate the concave and convex regions of the curve, established by landmarks pertinent to attire measurements. In [12-, 13] from the front images, 56 landmarks were retrieved from the front images, whereas 62 critical points were removed from the side images. In contrast with [12, 13], our work has more detected feature points. Furthermore, our approach employs various contour detection methods as well as feature point extraction rules. For starters, The background exclusion method utilized is better suited for intricate backgrounds compared to the procedure employed in references [12,13].Once land mark of the body is detected then we have to detect the bleeding parts detection based on medical team can understand the how depth blood flow and how the treatment should continue.

2. Edge Feature Points Detection

2.1. Automated Photo Capturing

Initially, the imaging device is positioned at a distance of 6 meters from the subjects and 1.5 meters above ground level, capturing two for two images: two of the contextual image and two of the participant subject. These investigations are conducted with images of dimensions 4000×3000 pixels and an activated flash to minimize shadows. To expedite data manipulation, the anterior and lateral views are adjusted to 1900 pixels and 600×800 pixels, respectively, while maintaining the integrity of the human subject. Subsequently, these images are further reduced to dimensions of 201×311 pixels, respectively. Simultaneously, associated sections of the contexts undergo identical treatment. Simultaneously, identical treatments are applied to equivalent elements within the setting body parts.

Figure 1. Shows the pre-processing and photographic results of a male model. [1] (a to b) The head-on shot and its context, (c to d) the lateral shots and their context.

To minimize the influence of hair on the outcomes of the tests, participants are instructed to don light attire and head cover. Participants are instructed to maintain an upright standing position in front of a gray wall for measuring shoulder width; individuals should stand with their arms extended out to each side Figure 1 displays the results of photographing and pre-processing a male model. All images in this paper are from reference [1] experiment. After any accident happened based on that study experiments chart is plotted in this research article chart 1, chart2, and chart3.

2.2. Outline identification and shape rendering

The algorithm for extracting the body shape employs conventional background reduction techniques to segregate the subject within the images.

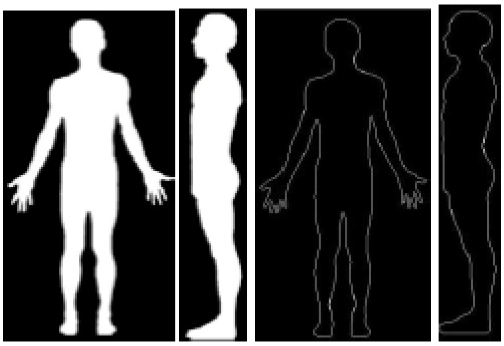
1) calculate the removal data between the current picture to the contextual image as outlined::

$$\begin{vmatrix} C\text{ij(Red)} \\ C\text{ij(Green)} \\ C\text{ij(Blue)} \end{vmatrix} = \begin{vmatrix} Yij(Red) \\ Yij(Green) \\ Yij(Blue) \end{vmatrix} - \begin{vmatrix} Zij(Red) \\ Zij(Green) \\ Zij(Blue) \end{vmatrix} \quad (1)$$

Where i,j is the function of Omega denotes the domains of pictures, and Yij and Zij represent the reg, green, and blue colour values of the immediate picture(i,j) and contextual data set(i,j). The distinction between pixels in the forepart and rear is evaluated using the following method.

2) E(_ij)=data1×Cij(red)+data2×Cij(Green)+data3×Cij(Blue**) (2)**

Where data1, 2, 3 represent the scaled value with colors RGB channels, with clear light mode image has been captured. The scaled value has been binary coded with high response 1. If the value of E(i,j) surpasses a predefined cut-off, denoted as E_∇T, the Picture element (i,j) is categorized as a candidate attraction point, and the other way around for the scene image. Following that binary picture set with high and low resolution (1, 0) depending upon the shape of the human body can be made. Our research work examined delta T with value ranges 36 practically.



(a) (b) (c) (d)

Figure 2. Darkness Body and contour body line: (a) Outline Maker retrieval output of the front facing picture; (b) the Outline separation output of the lateral picture; (c) Human picture contoured f^C from the subject's front picture; (d) Human picture contour S^C from the subject's side visual. [1]

Figures 2(a)-(b) show how outline of the subject's Fore and flank angles are extracted. Following the extraction of human line counter images outline from two dimensional pictures, the canny edge detector [8] is utilized to identify the contours of the human body from the pair of computerise images. Figures 2(c to d) shows the extracted unique-pixel and complete contour curves. The Shadows points on Fc and Sc Care are represented as:

$$Fc=\{f0,f1,f2,..fn\},Sc=\{s0,s1,s2,..sn\} \quad (3)$$

Where contour and shallow image from starting point outline with zero level to n numbers outline arch, fi, and si are clockwise starting from the initial point, arrange the subsequent points in a clockwise direction and f^c and s^c have (n) and (m) points, correspondingly. To instantly recognize these points, 6 by 6-connected chain codes [6, 7] are applied to the pixels outlining the body's edges. outlines. The network connecting chain code uses the numbers "0" through "6" and A to F to represent 30° increments in an anticlockwise path starting from an starting level flat path segment "0". The depiction of body contours utilizes a sequence of pixel chain codes.

Fc=00 00 00 00 00 00 070...

Sc=00 00 00 00 00 070 00

2.3. Facet Edge Elicitation

The outline body line map of the body is viewed as connections between Chains of line sections. Figure 3 depicts some line segments are positioned along the frontal curve's head. the starting unit, labelled as object 1 links with the starting point function (f0) with consecutive points sharing the code value of zero in sequential order, thereby spanning from function 1 to 12 points. The subsequent segments represent the connections between adjacent points in a consistent direction, followed by a reversal of direction from the previous point. For instance, segment "a2" extends from point f12 to point f13. After getting the skin area we need to apply again region segmentation for achieve the target location of cut body parts. Parts can be like nose, chick, throat, hand finger or leg etc.

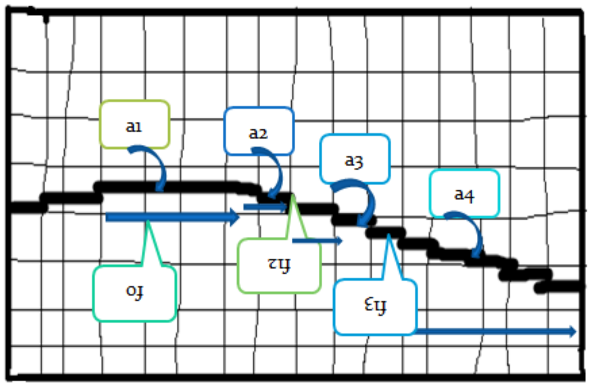
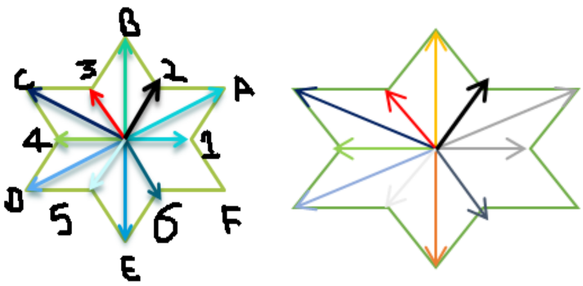


Fig 3. depicts a section of Segments of lines positioned at the forefront.

The line segment connecting code of the 2nd point is additionally, considering the initial point, is used to determine the line segment's leaning or direction.

If the starting line connecting and corner to corner two joining meet one of the conditions revealed in Figure 4, the southpaw of the face view person picture contour Crescent of the newly join the line points is deemed the resulting the map image of the curve picture.

The Ongoing line meeting points path is represented by an arrow with colour marked red, while the directions of the two adjacent portions are denoted by blue lines with arrows. Blue lines with arrows are used to represent the two adjacent segments. If one of the two adjacent segments is 45° clockwise, the other must be 45° anticlockwise to the current segment line. So, there are 15 to 16 conditions to be used to evaluate a distinctive point.



(a) (b)

Fig 4. (a) Twelve cases of the line joining path. (b) Architecture for line segment. d2-d1=-1, d2-d3=1 (4)

Another perception principle is applied if the present line path forms a right angle with the preceding one; the initial point of the current segment is deemed a pivotal aspect of the mankind depiction. Total perception principles can be articulated as clockwise direction to get the magnitude value; it can be positive and negative value. The value is d1,d2,d3,d4,d5,d6 and anti clockwise A,B,C,D,E,F six faces condition to find the magnitude values. Where data point (1 to 3) represent the pitches of three neighbouring pathways. Mathematical process from path points (4-a) and (4-b) coincide to the illustrated situations in Figures 4(b-f); formulas (4-c) and (4-d) illustrated in picture 4(a); and methods (4-e), and (4-f). Another judgement principle is that the clear range of data2 minus d1 equals 2(d1-d2=2) in formula (4-f), which corresponds to the condition that two states are at right angles. Figure 5 depicts the validation procedures for some dot marked; with the counting from the first left top body dot point on the head designated as the first edge dot picture H1. The path for a10-11 is 0, 5, 6, and 7 in sequence. Because the ternary meeting points correspond to the condition depicted in Figure 4(f), from starting dot place of a10 serves as the secondary edge map dot point F1. Similarly, mathematical rules can be used to detect point-to-point locations.

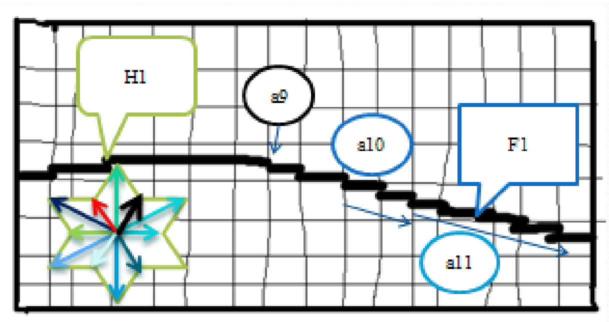


Fig 5. Shows pivot dot level H1 and F2 obtained from the head.

The algorithm's detailed steps are described below (using the front outline as an example):

1) Determine the Orientations of the meeting points. The surface path of the curves are presented as point0, point1,…, point(n-1), with p^k representing the Digital representation of the point's value fk. When first level function 0 is added to the line series V. If L_k-L_{k-1} $\mathit{not\ equal\ to}$ 0 ;(0<k>n) F^k gets put into Value v.

2) The identification of edge KNN feature image with various point sequence for each points the value range start with value range 0,1,2,3, Up to U-1. Indicated the pixels points' representation.

3) In which the range the pixel size will vary from starting constant K to positive and negative range like k-1, k+1 ranges. Which satisfy the mathematical dot point concept for 4 equations as shown.

3. Evaluation

The algorithm is demonstrated in Deep learning CNN using Google Collab and Mat lab 2009a with all 102 feature points preceptor from 20 human dotted points. It demonstrates this method demonstrates efficacy and resilience. Figure 6 depicts the edge feature picture points in both views. That the colour images mark the similar edge-to-edge points as the identified and shown. Visual inspection demonstrates the edge feature picture location points are generally Precise and dependable..

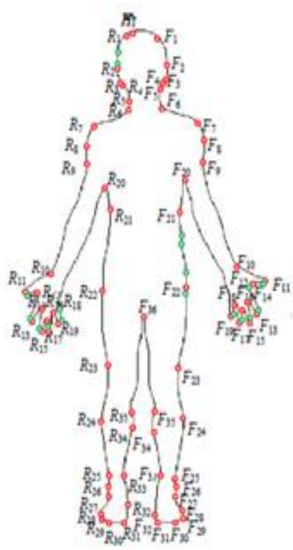


Fig 6. Colour Marked with Edge Feature picture point Red containing [1] 71 Forward-facing ones and 30 sideways ones.

The examination outcomes of 20 subjects, ten for male and ten for female have been displayed in

Table1. The outcomes of the twenty pictures

Number	Sex	Age	Height (cm)	Weight of Object	The detected Points	Grouped Detected Point
10	Male	26	150-160	60-65kg	Font-118 Side-32	Front-71 Side-30
10	Female	25	140-150	50-55kg	Front-113 Side-32	

From the male model's frontal outline curves, a total of 118 points were detected. However, only 72 of these points are utilized as feature points. For starters, hand concavity and convexity vary greatly between individuals. There are 18 to 20 points presented for digital tips and their root location from the 61 picture points where hard is used for identification fingertips also. In the second case, figure 6 shows six additional picture points indicated with green colour for head picture points and waist of the front shape outline curves. Also, six additional picture points were in hidden parts which are not located and ignored due to the counterpart of the image same side. In [15], 35 landmarks were assessed. It described body dimension landmarks using such as "Rock bottoms," culmination", Apex", Extreme point," and others. Leong [16] embarked on the mathematical descriptions for picture edge location identification. So the reference to the [14-17] they have grouped the concept for the betterment of image point identifications. With [18] expresses their concept by explaining the combined assessment is better in effectiveness for cut point features. Simulate the mankind picture as a collection of elements. Elements are identified through primitive detection or image segmentation. A hierarchical algorithm draws conclusions about these parts and determines the optimal Compilation [21-26]. Investigated outcomes demonstrate that the proposed method extracts edge-picture points consistently and competently taken with 500 real time image recognition with digital camera photos, And Most of the picture has been traced with face and hand gesture as traveling time and walking time openly body, remaining are closed with cloths.

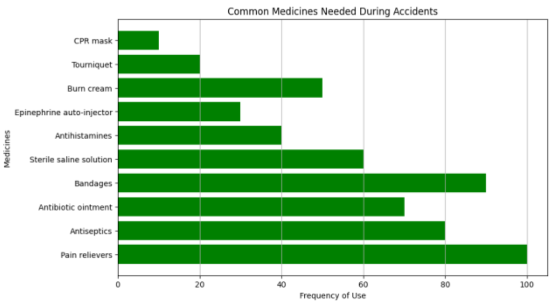


Chart 1. Common Medicine needed as per requirement of injury time plotted graph.

So it can be easy for without overlapped body image process in traveling time but in clinical test can be done easily to detect the injured complete parts and recognize by doctors. The 28 key calibration monuments, which adhere to defined standards, can be effectively utilized within the framework of an apparel-based company [28-30].

Furthermore, all of the location with pin points has clear with representation in centric parts properties that making them suitable for the establishment of a synthetic human avatar and to able to identify the human picture. For gesture recognition, the points of Tips and bases of fingers are particularly useful. After that identified body again can have region extraction for exact pointed to gain the accuracy of the images.

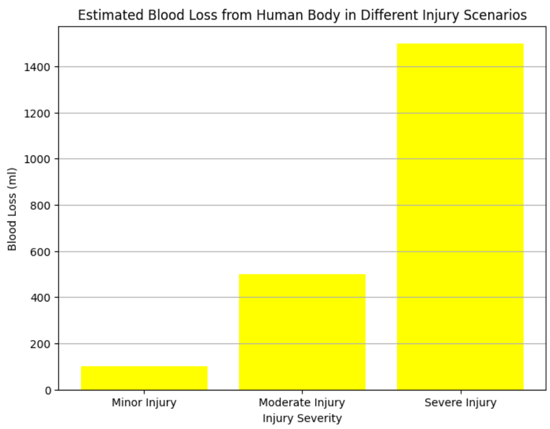


Chart 2. Blood loss based Injury types

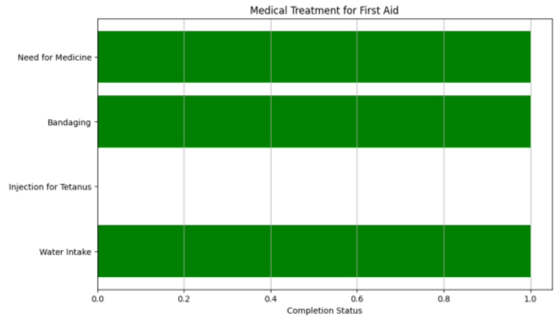


Chart 3. Medical Treatment once injury happened

4. Conclusion

In this research article work is a find the exact point of human body parts from each side of the body from in face view and side view of pictures. The proposed approach can extract 102 feature points by identifying the variations between side points by front viewpoints for each aspect. There are twenty people, ten males and ten females, who were examined in research work experiments and 102 locations of body points were correctly identified. So this demonstrates that the process is a relatively robust and deep learning concept we can take exact point identification as well. Once the clear image is captured and CNN-based helps us to get an injured picture the point of the body short also identified due to changes in pixels-to-pixel variation. Point-based mechanism is a very reliable and efficient way of approach. Based on the geometric algorithm method every point has been identified for various shapes of the human body, which vary in each person's health status. Furthermore, when compared to previous research, the applied approach shows better results and performance for feature edge extraction based on the image of the point location. in the future edge detection using deep learning, we plan to collect human picture dimensions and create some more concepts of dimensional layers with 2D to 3D models based on the feature edge extraction for new model points for better accuracy and performance. In any case injury happened and we need urgent medical treatment behalves the plot chart plotted in above chart 1, 2, and 3 with their graph. Each graph has the tested code with python library in Google colab open source software. When we apply for deep learning medical support in advance technology this AI based deep learning will be more supporting for real time doctor and patient support in advance medical support.

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