Image Segmentation Using SUSAN Edge Detector

Devidas D. Dighe[1], J.J.Chopade[3] and N.L.Bhale[3]

***Abstract*-The details of the SUSAN edge finding algorithm are given, followed by an analysis of the algorithm's validity. Finally, examples of the output of the edge detector are presented and discussed. Firstly, however, a brief review of existing approaches is given. This section has described application of the SUSAN principle to the detection of image edges and lines accurately and quickly. The localization of the features is independent of the mask size used, and noise suppression is good. Connectivity of edges and lines at junctions is good. The SUSAN principle can be viewed as an efficient way of finding features using local information from a pseudo-global viewpoint. ; it is the image regions which define the features at their edges and boundaries, and the features themselves are not the *primary* objects of investigation. At the end the SUSAN detector is used for edge based segmentation and dominantly it is found suitable for character or the number identification purpose. It can be clearly seen that SUSAN provides much better edge localisation and connectivity. Also edges with SUSAN are one pixel thick The with Canny edge detection is found to be ten times slower than SUSAN approach so faster edge detection and can be used for live edge detection.**

***Keywords*:-USAN- Univalue Segment Assimilating Nucleus SUSAN - Smallest Univalue Segment Assimilating Nucleus LoG - Laplacian of a Gaussian g- geometric threshold for deciding USAN area *intra*-pixel – edge lies inside the pixel inter-pixel – edge lies in between two pixels**

I. INTRODUCTION

THERE has been an abundance of work on different approaches to the detection of one dimensional features in images. Some of the earliest methods of enhancing edges in images used small convolution masks to approximate the first derivative of the image brightness function, thus enhancing edges. These filters give very little control over smoothing and edge localization. Marr and Hildreth proposed the use of zero crossings of the LoG. Contours produced using the LoG filter have the property, convenient for some purposes, of being closed. However, connectivity at junctions is poor, and corners are rounded. the LoG filter gives no indication of edge direction, which may be needed by higher level processes. An edge detector must satisfy--- 1.Good detection 2.Good localization. 3.Only one response to a single edge. 1These criteria are equally detectors was that they should be appropriate to being used as part of a real time system using real image sequences. Therefore it has become apparent that for the purpose of this work, one final criterion is important; Speed. The algorithm should be fast enough to be usable in the final image processing system. Canny has formulated his criteria mathematically. He uses the criteria functionals to derive ``optimized'' edge filters for each image type. The SUSAN brightness comparison function has been optimized to give the lowest number of false negatives and false positives. In the case of localization, the SUSAN feature detectors are extremely computationally efficient. quantitative criteria are defined, those being proportional to the number of false negatives, false positives, multiple detections and incorrectly localized pixels..

Canny investigated the use of ``directional operators'',This improves both the localization and the reliability of detection of straight edges; the idea does not work well on edges of high curvature. Haralick proposes the use of zero crossings of the second directional derivative of the image brightness function. There is a problem with ``phantom edges'' created by the second directional derivative at ``staircase structures''. Connectivity at junctions is poor. Fleck describes the use of the second directional derivative for edge finding, with various extensions to the basic use of zero crossings. The problem of phantom edges is reduced with a test using the first and third derivatives,overall algorithm is computationally expensive. Noble uses mathematical morphology to find image structure. these are used to enhance edges and find two dimensional features. Connectivity at junctions is good, The algorithm, including edge tracking, is fairly computationally expensive. Venkatesh,. describe the approach of using ``local energy'' (in the frequency domain) to find features. The local energy is found from quadrature pairs of image functions, such as the image function and its Hilbert transform this is at the expense of optimizing the signal to noise ratio . The edge detector described here uses a completely new definition of edges, and in doing so, solves many of the problems which existing algorithms have failed to overcome.

II. PRINCIPLE – OF SUSAN

The SUSAN principle is implemented using digital approximation of circular masks, (windows or kernels). If the brightness of each pixel within a mask is compared with the

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brightness of that mask's nucleus, then an area of the mask can be defined which has the same (or similar) brightness as the nucleus. The concept of each image point having associated with it a local area of similar brightness is the basis for the SUSAN principle. This area is known as USAN (Univalue Segment Assimilating Nucleus) and contains much information about the structure of the image. From the size, centroid and second moment of the USAN, two dimensional features and edges can be detected. This approach has many differences to other well-known methods, the most obvious being that no image derivatives are used and no noise reduction is needed. As seen in the fig 1, the USAN area is at a maximum when the nucleus lies in a flat region of the image surface. It falls to half of this maximum very near a straight edge and falls even further when inside a corner. This property of USAN's area is used as the main determinant of the presence of the edges and two-dimensional features.

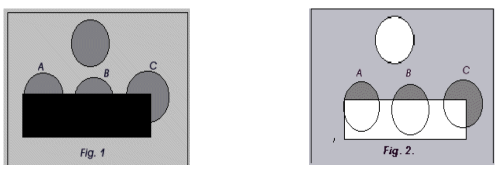


Figure 1 - Fig 1. Four circular masks at different places on a simple image. Fig 2. Four circular masks with similarity coloring; inverted SUSANs are shown as grey parts of the masks.

Inverted SUSAN area has edges and two-dimensional features strongly enhanced with the two-dimensional features more strongly enhanced than edges. This gives rise to the acronym SUSAN (Smallest Univalue Segment Assimilating Nucleus). The strength of the SUSAN principle is that the use of controlling parameters is much simpler and less arbitrary and therefore easier to automate than Other edge detection algorithms.

III. THE SUSAN EDGE DETECTOR

The edge detection algorithm described here follows the usual method of taking an image and, using a predetermined window centered on each pixel in the image, applying a locally acting set of rules to give an edge response. This response is then processed to give as the output a set of edges.

The SUSAN edge finder has been implemented using circular masks (sometimes known as windows or kernels) to give isotropic responses. Digital approximations to circles have been used, either with constant weighting within them or with Gaussian weighting -- this is discussed further later. The usual radius is 3.4 pixels (giving a mask of 37 pixels), and the smallest mask considered is the traditional three by three mask. The 37 pixel circular mask is used in all feature detection experiments unless otherwise stated. The mask is placed at each point in the image and, for each point, the brightness of each pixel within the mask is compared with that of the nucleus. Originally a simple equation determined this comparison -- see Figure 2;

$$c(\vec{r}_2\vec{r}_0)=\begin{cases}1 & if\ /I(\vec{r})-I(\vec{r}_0)/\le t\\ 0 & if\ /I(\vec{r})-I(\vec{r}_0)/> t_1\end{cases} \quad \ldots\ldots(1)$$

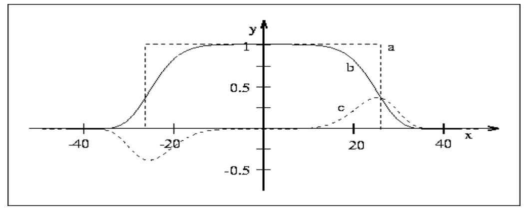


Figure 2 a) The original similarity function (y axis, no units) versus pixel brightness difference (x axis, in greylevels). For this example the pixel brightness difference ``threshold" is set at ± 27 greylevels. b) The more stable function now used. c) The boundary detector B (see later text).

Where $\vec{r}_0$ is the position of the nucleus in the two dimensional image, $\vec{r}$ is the position of any other point within the mask, I ($\vec{r}$) is the brightness of any pixel, **t** is the brightness difference threshold and **c** is the output of the comparison. This comparison is done for each pixel within the mask, and a running total, **n**, of the outputs (**c**) is made;

$$n(\vec{r}_0)=\sum_{\vec{r}} c(\vec{r},\vec{r}_0). \quad \ldots\ldots \quad (2)$$

This total **n** is just the number of pixels in the USAN, i.e. it gives the USAN's area. As described earlier this total is eventually minimized. The parameter **t** determines the minimum contrast of features which will be detected and also the maximum amount of noise which will be ignored. Further discussion later will show why performance is not dependent on any ``fine-tuning" of the value of **t**.

Next, **n** is compared with a fixed threshold **g** (the ``geometric threshold"), which is set to $3n_{max}/4$, where n_{max} is the maximum value which **n** can take. The initial edge response is then created by using the following rule:

$$R(\vec{r}_0)=\begin{cases} g-n(\vec{r}_0) if n(\vec{r}_0)<g \\ 0 otherwise\end{cases} \quad \ldots\ldots(3)$$

where $R(\vec{r}_0)$ is the initial edge response. This is clearly a simple formulation of the SUSAN principle, the smaller the USAN area, the larger the edge response. When non-maximum suppression has been performed the edge enhancement is complete. When finding edges in the absence of noise, there would be no need for the geometric threshold at all. However, in order to give optimal noise rejection **g** is set to $3n_{max}/4$. This value is calculated from analysis of the expectation value of the response in the presence of noise only -- see later. The use of **g** should not result in incorrect dismissal of correct edges for the following reasons. If a step edge (of general curvature) is considered, it can be seen that **n** will always be less than (or equal to) $n_{max}/2$ on at least one side of the edge. In the case of a curved edge, this will correspond to the boundary of the region which is convex at the step edge. Thus valid edges should not be rejected. If the edge is not an ideal step edge but has a smoother profile then **n** will have even lower minima so that there is even less danger of edges being wrongly rejected.

The algorithm as described gives quite good results, but a much more stable and sensible equation to use for **c** in place of Equation 1 is

$$c(\vec{r},\vec{r}_0) = e^{-\left(\frac{I(\vec{r})-I(\vec{r}_0)}{t}\right)^6} \qquad \ldots\ldots(4)$$

This equation is plotted in Figure (b). The form of Equation 4 was chosen to give a ``smoother'' version of Equation 1. This allows a pixel's brightness to vary slightly without having too large an effect on **c**, even if it is near the threshold position. The exact form for Equation 4, i.e., the use of the sixth power, can be shown to be the theoretical optimum; see later for analytic comparison of shapes varying from one extreme (Gaussian) to the other (square function, as originally used). This form gives a balance between good stability about the threshold and the function originally required (namely to count pixels that have similar brightness to the nucleus as ``in'' the univalue surface and to count pixels with dissimilar brightness as ``out'' of the surface). The equation is implemented as a look up table for speed. (The threshold **t** determines, of course, the minimum contrast of edges)

Computation of the edge direction is necessary for a variety of reasons. Firstly, if non-maximum suppression is to be performed the edge direction must be found. It is also necessary if the edge is to be localized to sub-pixel accuracy. Finally, applications using the final edges often use the edge direction for each edge point as well as its position and strength. In the case of most existing edge detectors, edge direction is found as part of the edge enhancement.

As the SUSAN principle does not require edge direction to be found for enhancement to take place, a reliable method of finding it from the USAN has been developed. This method is now described. The direction of an edge associated with an image point which has a non zero edge strength is found by analyzing the USAN in one of two ways, depending on the type of edge point which is being examined. For examples of the two types of edge points, see Figure 3.

It can be seen that points (a) and (b) have USAN shapes which would be expected for an ideal step edge. In this case (which shall be known as the `` *inter*-pixel edge case'') the vector between the centre of gravity $\bar{\vec{r}}$ of the USAN and the nucleus of the mask is perpendicular to the local edge direction. The centre of gravity is found thus;

$$\bar{\vec{r}}(\vec{r}_0) = \frac{\sum_{\vec{r}} \vec{r}\, c(\vec{r},\vec{r}_0)}{\sum_{\vec{r}} c(\vec{r},\vec{r}_0)}. \qquad \ldots\ldots(5)$$

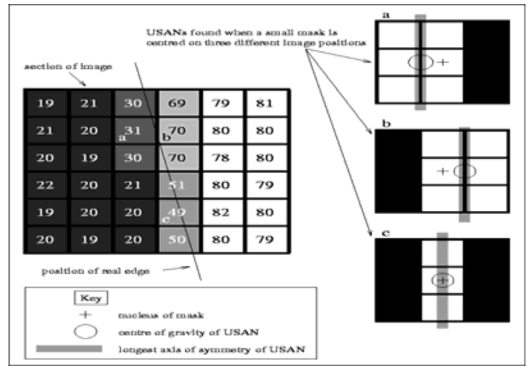


Figure 3: The two main edge types; a typical straight edge in a section of a real image, with brightness indicated by the numerical text as well as the shading of the pixels. The USANs for three points of interest are shown as the white regions of a small (3 by 3) mask. Points (a) and (b) are standard edge points, lying definitely on one side of the edge or the other. Point (c) lies on a band of brightness half way between the brightnesses of the two regions generating the edge. It therefore has a differently shaped USAN, and a centre of gravity coinciding with the nucleus.

This simple rule allows the edge direction to be found for this type of edge point.The point shown in case (c) lies on a thin band which has a brightness roughly half way between the brightness of the two regions which generate the edge. This occurs when the real edge projects very close to the centre of a pixel rather than in between pixels (or when the edge is not a sharp step edge in the first place) and when the edge contrast is high. In this case, (which shall be known as the `` *intra*-pixel edge case'') the USAN formed is a thin line in the direction of the edge, as can be seen in Figure 3. The edge direction is thus calculated by finding the longest axis of symmetry. This is estimated by taking the sums

$$\overline{(x-x_0)^2}(\vec{r}_0) = \sum_{\vec{r}} (x-x_0)^2 c(\vec{r},\vec{r}_0), \qquad \ldots\ldots(6)$$

$$\overline{(y-y_0)^2}(\vec{r}_0) = \sum_{\vec{r}} (x-x_0)^2 c(\vec{r},\vec{r}_0) \qquad \ldots\ldots(7)$$

$$\overline{(x-x_0)(y-y_0)}(\vec{r}_0) = \sum_{\vec{r}} (x-x_0)(y-y_0) c(\vec{r},\vec{r}_0) \ldots(8)$$

(No normalization of the sums is necessary with the second moment calculations.) The ratio of $\overline{(y-y_0)^2}$ to $\overline{(x-x_0)^2}$ is used to determine the orientation of the edge; the sign of $\overline{(x-x_0)(y-y_0)}$ is used to determine whether a diagonal edge has positive or negative gradient. Thus in the case of edge points like (c) the edge direction is again found in a simple manner.

The remaining question is how to automatically determine which case fits any image point. Firstly, if the USAN area (in pixels) is smaller than the mask diameter (in pixels) then the intra-pixel edge case is assumed. Figure 3 shows clearly the logic behind this. If the USAN area is larger than this threshold, then the centre of gravity of the USAN is found, and used to calculate the edge direction according to the inter-pixel edge case. If however, the centre of gravity is found to lie less than one pixel away from the nucleus then it is likely that the intra-pixel edge case more accurately describes the situation. (This can arise for example if the intermediate brightness band is more than one pixel wide, when larger mask sizes are used.) The edge direction can be found to varying accuracy using this method, depending on the intended application. If the final output desired is simply a binarized edge image it may be enough to simply categorize an edge element as being ``vertical'' or ``horizontal''.

An interesting point about the SUSAN edge detector is shown by the USAN areas in Figure 3. It can be simply seen that as an edge becomes blurred, the area of the USAN at the centre of the edge will decrease. Thus we have the interesting phenomenon that the response to an edge will increase as the edge is smoothed or blurred. This is most unusual for an edge detector, and is not an undesirable effect. Finally, therefore, the edge response image is suppressed so that non-maxima (in the direction perpendicular to the edge) are prevented from being reported as edge points. Following this, the ``strength thinned'' image can be ``binary thinned''. This means that standard thinning processes can be used to ensure that the edges obey required rules about number-of-neighbour connectivity, so that remaining noise points can be removed, and so that edge points incorrectly removed by the non-maximum suppression can be replaced. A set of rules for binary thinning has been implemented (still making use of the strengths in the non-suppressed edge response image) which work well to give a good final binarized edge image. If the position of an edge is required to accuracy greater than that given by using whole, it may be calculated in the following way. For each edge point, the edge direction is found and the edge is thinned in a direction perpendicular to this. The remaining edge points then have a 3 point quadratic curve fit (perpendicular to the edge) to the initial edge response, and the turning point of this fit (which should be less than half a pixel's distance from the centre of the thinned edge point) is taken as the exact position of the edge.

With respect to the scale-space behavior of the SUSAN edge detector, scale-space graphs showing edge localization against mask size (e.g., plotting a single horizontal line from the edge image against mask size, in the manner of Witkin give vertical lines. This is obviously a desirable feature, as it means that accuracy does not depend on mask size. This is to be expected; the minimum USAN area when approaching an edge occurs on top of the edge regardless of the mask size.

In summary then, the algorithm performs the following steps at each image pixel: 1.Place a circular mask around the pixel in question (the nucleus). 2.Using Equation 4 calculate the number of pixels within the circular mask which have similar brightness to the nucleus. (These pixels define the USAN.) 3.Using Equation 3 subtract the USAN size from the geometric threshold to produce an edge strength image.4.Use moment calculations applied to the USAN to find the edge direction. 5.Apply non-maximum suppression, thinning and sub-pixel estimation, if required.

Computation of Edge direction :We find the sum of second moments of USAN about the nucleus to find the orientation of the edge. This can be found to varying accuracy depending on the mask used. The edge response obtained from above is suppressed so that non-maxima (in the direction perpendicular to the edge) are prevented from being reported as edge points). Following this, the "strength thinned" image can be binary thinned using standard thinning processes.

II. ANALYSIS OF THE SUSAN EDGE DETECTOR

A. A simple derivation is now given which shows the theoretical coincidence of the exact SUSAN edge position and the zero crossing of the second derivative of the image function.

A minimum in the USAN area (in this case USAN length) will be equivalent to the edge definition which places the edge at the position of inflection of the curve, that is, where

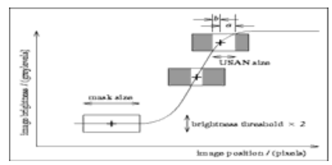


Figure 4: A monotonically increasing one dimensional input signal and three mask positions showing USAN size varying with signal gradient. The USAN is shown as the white portion of the mask. The mask centred on the signal inflection has the smallest USAN.

the second derivative of the image function is zero. See Figure 4 for an example image function and three one dimensional mask positions. This mathematical equivalence in no way means that the SUSAN edge finding method is performing the same function as a derivative based edge detector. No derivatives are taken; indeed, no direction of maximum gradient is However, the preceding argument shows why the SUSAN edge detector gives edges to good sub-pixel accuracy even with edges that are not perfect step edges.

It can be seen from the preceding discussion that the initial response of the SUSAN edge detector to a step edge will be increased as the edge is smoothed. The response is also

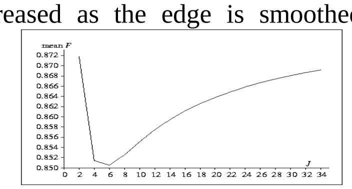


Figure 5: A plot of an objective formulation of expected false negatives and positives against the J factor in the brightness comparison function.

broadened. It is clear that the optimal value for **J** is 6. This gives the form of the function used in the SUSAN filters. The optimal value for **g**, the geometric threshold, is found by calculating the mean expectation value for **N** over the same realistic range of image noise as before. With no noise present, $< N >$ is 1; its mean value in the presence of noise is calculated (using the integral shown in Equation 24) to be close to 0.75. Therefore the value of **g** which is likely to provide the correct amount of noise rejection is $3/4$ of the maximum possible USAN size.

B. Testing of the SUSAN Edge Detector

Suffice it to say that the initial response given by SUSAN was better than the best results of the four detectors used in these tests, using all six suggested ``failure measures''. A one dimensional test of the SUSAN response to various edge types has been carried out using the input signal shown in Figure 6.

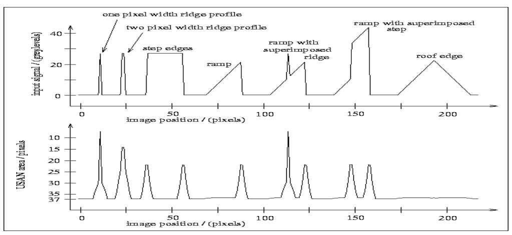


Figure 6: The initial response of the SUSAN edge finder to various edge types.

The results are good. All the edge types are correctly reported apart from the roof edge. (Note that even the roof edge produces a very small local maximum in the response.) The ridge edges are picked up correctly, and produce only one response, as desired. Thus the SUSAN edge detector is shown to report lines correctly and not just edges. With the two pixel width ridge it is of course a matter of definition whether one ridge or two edges should be reported. The response is symmetrical about each edge type, which results in sub-pixel accuracy giving excellent results. Only second order derivative detectors (Noble's detector) will give a response to the roof edge. To test both edge detectors and two dimensional feature detectors a test image which includes two dimensional structures of many different types has been designed. This is shown in

Figure 7: An image designed to test corner and edge detectors
Figure 8 : Output of the SUSAN edge finder (t=10) given the test image.

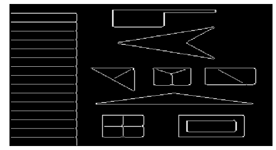


Figure 9 : Output of the Canny edge finder (σ=0.5) given the test image

the SUSAN edge detector possesses the following attributes: 1.Edge connectivity at junctions is complete. 2.The reported edges lie exactly on the image edges 3.The edges around and inside the brightness ramp are correctly found and no false edges are reported. Thus it is shown that the edge detector copes with finding edges of regions with low or smooth variation of brightness. Following points of interest compare to Canny edge detector:

Very few junctions involving more than two edges are correctly connected. Some sharper corners have broken edges. Incorrect edges within the brightness ramp were nearly as strong as the weakest correct edges and eliminated by selecting exactly the right final threshold for binarization.For normal real images a larger value of σ is needed, usually at least $\sigma = 1.0$. This results in even greater breaks at junctions, and incorrectly rounded corners. The Canny edge detection is approximately 10 times slower than SUSAN edge detection. The results of the tests described show the SUSAN edge detector to be accurate, stable and very fast on both test and real images. It has given very good results in all the tests.

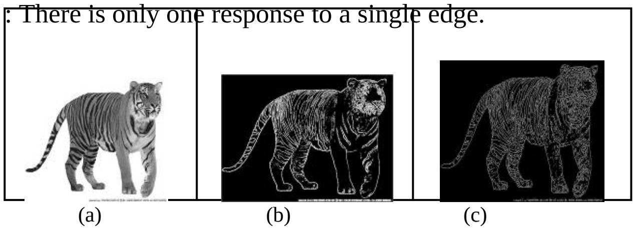
Finally, the idempotence of the SUSAN principle is investigated. It has been suggested that feature enhancement should be idempotent. This means that after one application of the enhancement process, further applications should make no change to the processed image. Testing has been carried out which shows SUSAN edge detection to be idempotent. when tested on a chequer board pattern it was found that none of the other tested operators was idempotent. Investigation of idempotence can be applied at two very different levels for feature detectors. Repeating the initial enhancement on itself is one level, that is, only using the first stage of a feature detector (example, Sobel enhancement). Taking the final output of the complete algorithm (including non-maximum suppression and thinning if appropriate) and feeding this back into the complete algorithm is the other level (example, the Canny edge detector). In the testing performed the test image was fed into an edge enhancement algorithm, this output was fed back into the algorithm, and the output of this was fed back in once more. Thus each algorithm was run a total of three times. For each algorithm the outputs after one pass and after three passes were examined. The results show that the initial response of the SUSAN enhancement gives maximal ridges (one pixel thick) which are still evident, and no double edges have been produced. In contrast, a 3 by 3 Sobel operator produces multiple responses at nearly all of the edges & Canny algorithm produces multiple responses at nearly all of the edges.

III. RESULT OF SUSAN EDGE DETECTOR

Figure 10 : SUSAN edge detector algorithm results

IV. COMPARISON OF SUSAN WITH OTHER EDGE DETECTORS

Features of an image have been extracted using SUSAN Principle and Sobel Operator for comparison. It can be clearly seen that SUSAN provides Much better edge localisation and connectivity. Also edges with SUSAN are one pixel thick .The SUSAN principle took much lesser time than any other algorithm. SUSAN have a degree of uniformity, and reduces false positives. The center of gravity of USAN and its distance of this from the nucleus is found. A proper corner will have center of gravity that is not near the nucleus and thus false corners can be rejected. Good Detection : There are a minimum number of false negatives and false positives. Good Localization : The edge location is reported as close as possible to the correct position. Response : There is only one response to a single edge.



(a) (b) (c)

Figure 11: (a)Original Image (b)Edges extracted using Sobel (c)Edges Extracted using SUSAN

V. STEPS IN EDGE BASED SEGMENTATION

1. Take an input image which is a color image. 2. Median filtering the image to remove noise if present. 3. find edges by using SUSAN edge detector. 4. Smoothing image to reduce the number of connected components obtained by using edge detection. 5. Calculating connected components after smoothing so after smoothing region size will not be too small. 6. There will be mx connected components. Here we can give a value between 1 and mx for L or in a loop you can extract all connected components. By giving 17,18,20,23,27,29 to L, we can segment the image completely. 7. Store the extracted image in an array

VI. RESULT AND CONCLUSION OF EDGE BASED SEGMENTATION ALGORITHM

Below segmentation of images have been extracted using the SUSAN principle. As can be seen edges have good localization and are one pixel thick . The images can also edge extracted using Canny edge detector and using Sobel operator , but The SUSAN principle took much lesser time than any other algorithm. Here, features of an image have been extracted using SUSAN Principle and Sobel Operator are already compared .It can be clearly seen that SUSAN provides much better edge localisation and connectivity. Also edges with SUSAN are one pixel thick .The with Canny edge detection is found to be ten times slower than SUSAN approach. The results are stable for Canny but the edge connectivity at junction is poor and corners are rounded. It is worth noting here that in the absence of multiple features the SUSAN principle bypasses the "Uncertainty Principle of edge detection " which applies to most feature detectors (and most obviously the Gaussian based ones) with respect to Canny's first and second criteria.

Other methods include second order derivatives. The fact that SUSAN edge and corner enhancement uses no image derivative, explains why the performance in the presence of noise is good. The integrating effect of the principal together with its non-linear response gives strong noise rejection.

Figure 12: edge segmentation result

VII. REFERENCES

[1] N. Pal and S. Pal, “A Review of Image Segmentation Techniques,” Pattern Recognition, vol. 26, pp. 1277– 1294, 1993.

[2] Lecture on Segmentation (Edge Based) by Bryan S. Morse, Brigham Young University, 1998–2000 .

[3]. http://iria.math.pku.edu.cn/~jiangm/courses/dip/html/node120 to 125.html

[4] .http://www.fmrib.ox.ac.uk/~steve/susan/susan/node3 to 15 .html

[5] G.R. Arce and S.A. Fontana. On the midrange estimator. *IEEE Trans. on Acoustics, Speech and Signal Processing*, ASSP-36:920--922, 1988.

[6] A. Blake and A. Zisserman. *Visual Reconstruction*. MIT Press, Cambridge, USA, August 1987.

[70] R. Deriche. Using Canny's criteria to derive a recursively implemented optimal edge detector. *Int. Journal of Computer Vision*, 1(2):167--187, 1987.

[8] R.M. Haralick. Digital step edges from zero crossing of second directional derivatives. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 6(1):58--68, January 1984.

[9] D. Marr and E.C. Hildreth. Theory of edge detection. *Proc. Roy. Soc. London.*, B-207:187--217, 1980.

[10] V.S. Nalwa and T.O. Binford. On detecting edges. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 8(6):699--714, November 1986.

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