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Texture Classification of 3D MR Images using 2.5D Rank Filters

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Abstract— ***The 3-D items utilized in 3D computer games and augmented reality are empty polygon networks with surfaces concerned them. Then again, volume information portrayal stores the external surface highlights, yet in addition the highlights inside the volume. For instance, representation of 3-D MRI/CT information is tied in with appearing inside parts as well. Envisioning volumetric information requires more video memory. A large portion of the genuine 3D volume information created particularly by MRI scanners is dim dimension pictures. This paper tends to a novel system of texturizing the MRI information slides and its handling for extraction of shallow and volumetric highlights.***

Keywords—***Superficial & Volumetric Features, 3-D Images, Texture Classification, Monotone-coloring.***

I. INTRODUCTION

The term 'texture' refers to patterns arranged in a line or a curve. Textures in a digital image make one derive a meaningful interpretation of some kind of geometric regularity of spatially repeated patterns. Moreover, texture also exhibits relevant data about the spatial course of action of shading or dark powers in a picture or in a chose district of it. Meaningful interpretation of latent textures of various tissues in a physiological body is an important requirement for a medical professional as a preoperative measure.

This paper describes a computationally efficient technique to detect various texture characteristics terns in a given digital image. The computational tool used for this purpose is 'Rank Filters;, which are essentially directional filters. These filters would cause radical changes in the original content of a given image but precisely extract various textures..

II. LITEERATURE SURVEY

Apart from detecting latent textures in a given image, one can also artificially create texture images. Fig. 1 shows a texture image, which is artificially generated using a cellular automaton rule.

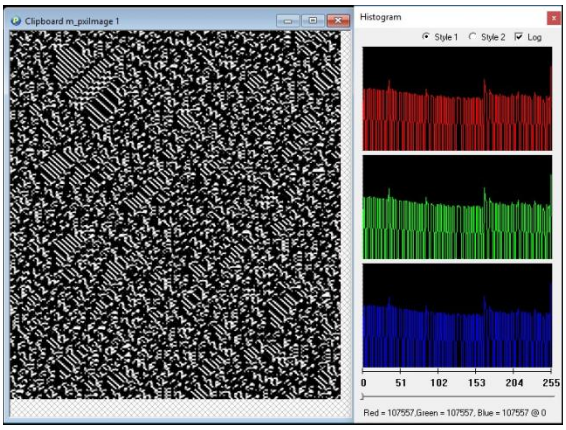

Fig. 1: Texture image generated by a cellular automaton rule Image textures are powerful features used in image segmentation and classification. Two features are generally used for image segmentation, viz, 'spatial frequency' and 'average gray level'. One could make use of 'structural approach' or 'statistical approach' in developing algorithms for texture detection. Usually statistical approach is considered for texture classification purposes because of ease in parametrization and quantification of texture features.

A factual way to deal with picture texturization would permit quantitative proportions of different courses of action of forces in a district of intrigue. What's more, this methodology would be much increasingly simple to register and henceforth is broadly utilized. It is to be noticed that idle surfaces in a picture are comprised of examples of sporadic sub designs. Edge recognition is one such strategy by which one could recognize edge pixels and edge subtleties help decide attributes of surface complexities. For example, headings of edges could be treated as attributes of surfaces in deciding examples in the surfaces.

Consider a district with N pixels in a given picture. Any slope based edge locator calculation could be connected to this area, which would yield two yields for each pixel p, viz, 'angle greatness Mag(p)' and 'inclination course' Dir(p). Presently, the edges per unit zone of a given picture is defined by the expression $\frac{|\{p|Mag(p) > T\}|}{N}$ for some predefined threshold T. Let $H_{mag}(R)$ be the normalized histogram of the gradient magnitudes of the region of interest R, and let $H_{dir}(R)$ be the normalized histogram of the gradient orientations of the region of interest R. Both are normalized according to the size N_R Then, one can define a quantitative measure $F_{mag,dir} = (H_{mag}(R), H_{dir}(R))$ for describing texture of the region of interest R.

Another system to evaluate surface is 'co-event lattice', which characterizes highlights of a surface utilizing certain spatial relations of comparative dark qualities.

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Such numerical highlights could be utilized for surface characterization. A portion of the standard highlights from a standardized co-event framework are given underneath.

$$\text{Angular } 2^{nd} \text{ moment} = \sum_i \sum_j p[i,j]^2$$

$$\text{Contrast} = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} n^2 p[i,j], \text{ where } |i-j| = n$$

$$\text{Correlation} = \frac{\sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (ij)p[i,j] - \mu_x \mu_y}{\sigma_x \sigma_y}$$

$$\text{Entropy} = -\sum_i \sum_j p[i,j] ln(p[i,j])$$

where *p[i, j]*_is the *[i, j]*th entry in a gray-level spatial dependence matrix, and Ng is the number of gray-values in the quantized image. It is to be noted that the co-occurrence matrix based feature extraction will not yield comfortable visual perception.

III. PROPOSED METHOD

As laid out before, the term 'surfaces' alludes to 'rehashed examples' in a given picture.

Algorithm for texture detection

In this the 2-D image is scanned by a 3X3 window;

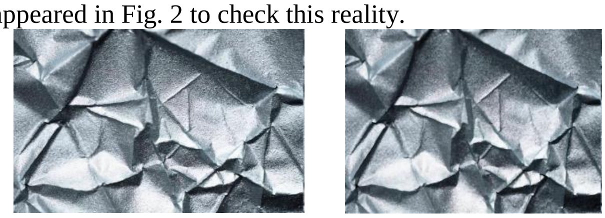
0	1	2
7	X	3
6	5	4

every one of the picture esteems "{x(0), x(1), x(2), x(3), x(4), x(5), x(6), x(7)}" is contrasted and the focal picture pixel worth comparing to cell X.

In the event that x(i) : $0 \leq I \leq 7$ is not exactly or equivalent to the focal pixel esteem, at that point x(i) is alloted the esteem 0, generally esteem 1. This yields a parallel string of length 8. The decimal estimation of this string is put away as the focal picture pixel value.

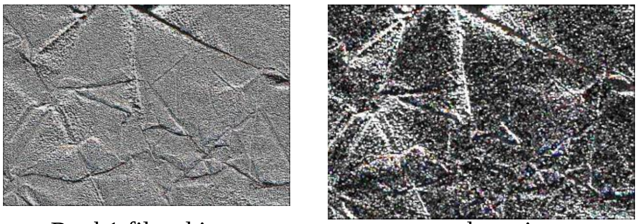
The whole picture is filtered and the subsequent picture is the surface removed adaptation of the given picture. For comfort, this calculation is alluded to as Rank1 channel. One can build four increasingly rank channels. The calculation for texturizing a picture stays same in each of the four cases with the special case that Rank 1 channel uses the succession "{x(0), x(1), x(2), x(3), x(4), x(5), x(6), x(7)}". Rank 2 channel uses the arrangement "{x(1), x(2), x(3), x(4),x(5), x(6), x(7), x(0)}". Rank 3 channel uses the succession "{x(2), x(3), x(4), x(5), x(6), x(7), x(0), x(1)}" and Rank 4 channel uses the arrangement "{x(3), x(4), x(5), x(6), x(7), x(0), x(1), x(2)}".

Fig. 2 demonstrates an example picture, its four finished forms got utilizing Rank1, Rank2, Rank3 and Rank4 channels and their morphologically opened adaptations. Surfaces in a specific bearing in a given picture need not be equivalent to those in different ways. Allude to the pictures appeared in Fig. 2 to check this reality.



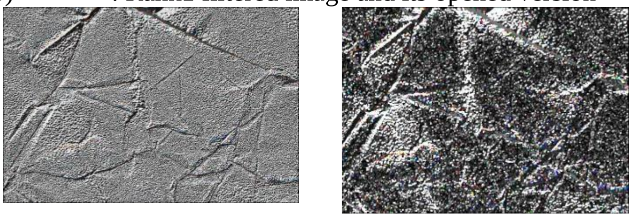
Sample image   Opened version of sample image

(a): Sample image and morphologically opened version



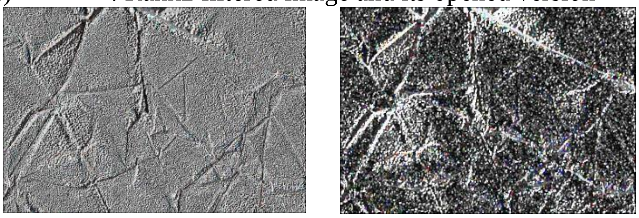
Rank1 filterd image   opened version

(b) : Rank1 filtered image and its opened version



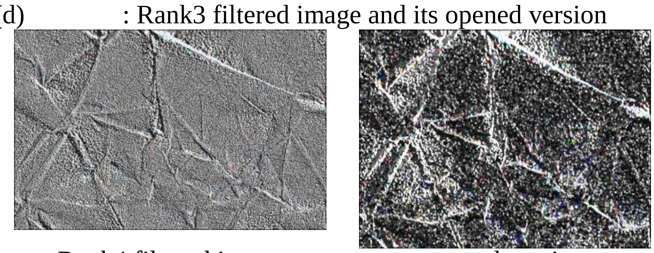
Rank2 filtered image   opened version

(c) : Rank2 filtered image and its opened version



Rank3 filtered image   opened version

(d) : Rank3 filtered image and its opened version



Rank4 filtered image   opened version

(e) Rank4 filtered image and its opened version

Fig. 2: Sample image and its four texture versions

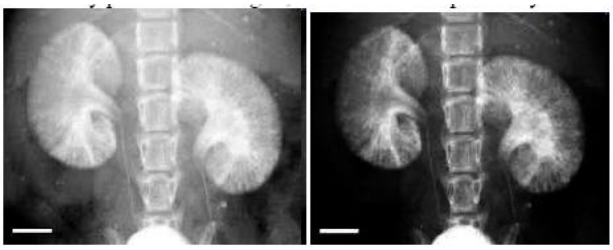
Algorithm for morphological opening

The given 2D image is scanned by a 3X3 window.

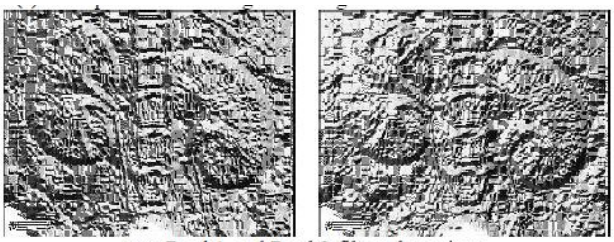
Image is eroded with 3x3 structuring element using the formula $A\theta B = INF_{(x,y)\in D_B}[A_{x,y} + B(x,y)]$ as $E(A,B) = INF_{(x,y)\in D_B}[A_{-x,-y} - B(x,y)]$ where D_B is the domain of the image B, and INF is an operation of infimum over the intersection of the domains; now eroded image is again dilated using 3x3 structuring element using the formula $D(A,B) = A \oplus B =$ $EXTSUP_{(x,y)\in D_B}[A_{x,y} + B(x,y)]$, where DB is the area of the picture B, and EXTSUP is a task of supremum over the association of the spaces.

IV. TEXTURE CLASSIFICATION OF 2D MEDICAL IMAGES

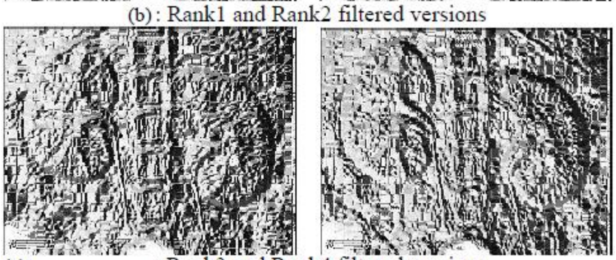
Textures of a medical image play an important role in support of a surgeon to decide the angle at which the surgical blade should be used to make incision so that the loss of blood due to surgery is kept minimum. A case study was carried out to verify the validity of the above statement and the result of the study presented in Fig. 3, which is self-explanatory.



(a) : Sample medical image and its gamma corrected version



(b) : Rank1 and Rank2 filtered versions



(c) : Rank3 and Rank4 filtered versions

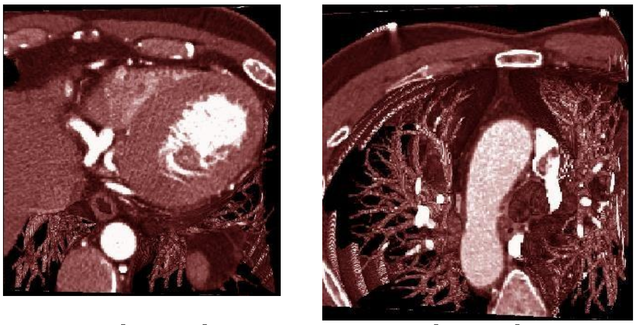
Fig. 3: Ultrasound scanned image of a human kidney and its textures obtained using rank filters
Courtesy: Pentagram Research Centre Pvt Ltd.,

All four texture versions of the image obtained using rank filters could be seen to provide a visual proof of the fact textures in an image are direction sensitive and so they could be used for image segmentation purposes.

V. TEXTURE CLASSIFICATION OF 3D MR IMAGES

The concept discussed in the above sections could be extended to texture classification of 3D images also. One such approach to classify textures of a 3D image is slice wise texturization of a 3D image. A 3D image is essentially a stack of 2D images called slices. Fig. 4 shows a sub set of 2D image slices, which constitute 3D image. Ray casting method is used to visualize the 3D image on a 2D computer monitor using 2D image slices. The volume rendering strategies straightforwardly render each voxel in volumetric network on to the 2D screen, so each voxel in the volumetric information is possibly obvious. Volume beam throwing processes a 2-D picture from the volumetric 3-D picture. Fig. 5 demonstrates the volumetric MR picture showed in a 2D PC screen. Some of the 3D image slices shown in Fig. 4.

Fig. 4: 96 slices of the MR image shown in Fig 5



Front side visualization　　Rear side visualization

Fig. 5: 3D MR image visualization on a 2D monitor

Fig. 5 shows the monotone colored version of the 3D MR image of a human heart dissected in two parts. Fig. 6 shows the MR image dissected from slice 40 to 120 and its 3D edge detected version.

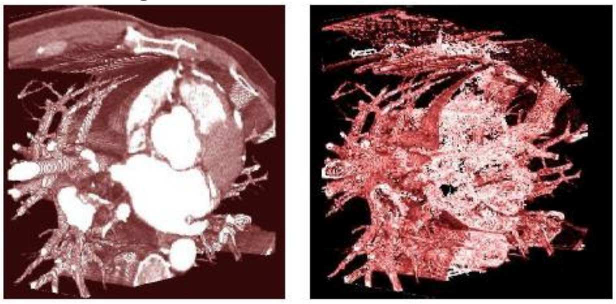


Fig. 6: Slices from 40 to 120 and its edge detected version Fig. 7 shows the monotone colored version of the slice wise rank1 filtered image and its edge detected version.

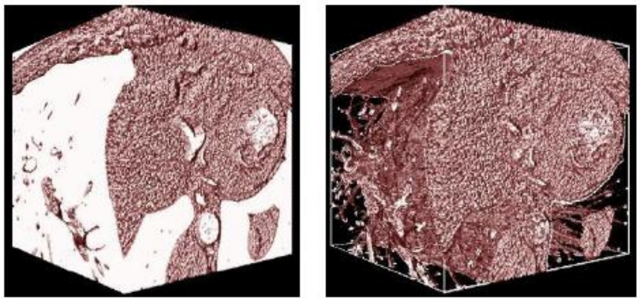


Fig. 7: Rank1 filtered image and its edge detected version

Fig. 8 shows the monotone colored version of the slice wise rank1 filtered image dissected from slice 40 to 120 and its 3D edge detected version.

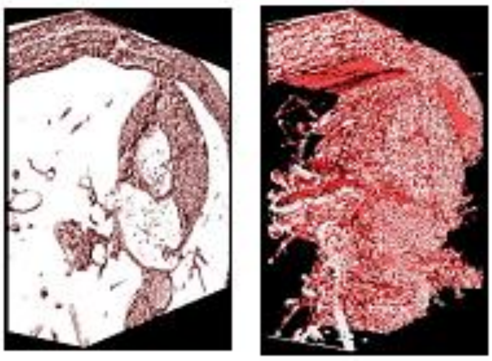


Fig. 8: Slices 40-120 of Fig. 7 and its edge detected version

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Fig. 9 shows the monotone colored version of the slice wise rank4 filtered image and its edge detected version..

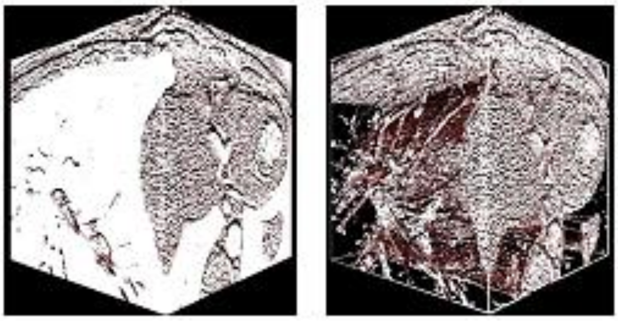

Fig. 9: Rank4 filtered image and its edge detected version

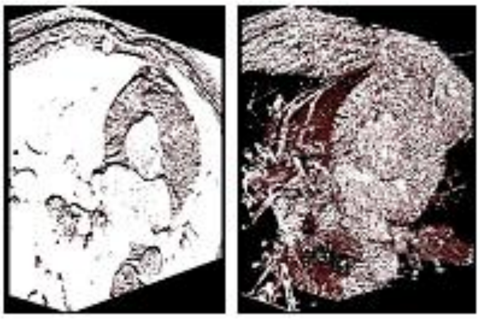

Fig. 10: Slices 40-120 of Fig. 9 and its edge detected version

Fig. 10 shows the monotone colored version of the slice wise rank4 filtered image dissected from slice 40 to 120 and its 3D edge detected version

3D cellular automaton updating rule for 3D edge detection

peruse monotone hued 3D picture voxel shrewd; for each voxel read voxel values in its seven neighborhood; discover Rmax, Gmax, Bmax, Rmin, Gmin and Bmin values in the seven neighborhood;

figure Rd=Rmax-Rmin, Gd=Gmax-Gmin and Bd=Bmax-Bmin; if Rd, Gd and Bd are for the most part positive and they are not exactly a edge esteem at that point make the focal voxel values '0'

else keep the focal voxel all things considered and move the 3x3x3 filtering window (seven neighborhood) to the following voxel. The general impact is the edge identified form of the monotone hued 3D picture.

VI. CONCLUSION

This paper presents a novel strategy for surface order of 3D MR pictures and their handling utilizing cell rationale exhibit preparing based edge identification calculation.

REFERENCES

1. Rajan E.G., 2003, “Symbolic computing: signal and image processing”, Anshan Publications, Kent, United Kingdom.
2. Rajan E. G., Springer, “Cellular logic array processing for high through put image processing systems”, Sadhana, 18(2), 279-300.
3. Rajan E. G., 1994, “Fast algorithm for detecting volumetric and superficial features in 3-D images”, International Conference on Biomedical Engineering, Osmania University, Hyderabad, Telangana.
4. Rajan E. G., 1996, “Medical imaging in the framework of cellular logic array processing”, in Proc. 15th Annu. Conf. Biomedical Society of India, Coimbatore Institute of Technology.
5. G. Ramesh Chandra, Towheed Sultana, G. Sathya, 2011, “Algorithms for Generating Convex Polyhedrons In A Three Dimensional Rectangular Array Of Cells”, International Journal of Systemics, Cybernetics and Informatics, 24-34.
6. G. Ramesh Chandra, and E. G. Rajan, 2012, “Generation of Three Dimensional Structuring elements over 3x3x3 Rectangular Grid”, CIIT International Journal of Digital Image Proc. 4(2), 80-89.
7. G. Ramesh Chandra and E. G. Rajan, 2012,“Algorithms for generating convex polyhedrons over three dimensional rectangular grid”; Signal & Image Processing : An International Journal (SIPIJ), 3(2), 197-206.
8. G. Ramesh Chandra and E. G. Rajan, CCSIT, Springer, “Algorithm for Constructing Complete Distributive Lattice of Polyhedrons Defined over Three Dimensional Rectangular Grid- Part II”; CCSIT Conference, Bangalore, proceedings are published by LNICST, 202-208.