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A Novel Method for Compression of Pressure Ulcer Image using Region of Interest Method

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***Abstract* - Other than lossy and lossless compression methods, the third option in pressure ulcer image compression could be the hybrid approach. Hybrid approach combines both lossy and lossless compression scheme. Here diagnostically important regions (Region of Interests) are lossless coded and the non regions of interests are lossy coded. Such hybrid approaches are referred as regionally lossless coding. Many researchers have proposed various hybrid medical image compression techniques. In these techniques, region of interests are first segmented and a suitable coding is done for ROI and non ROI. By doing so, high compression ratios can be obtained and quality of diagnostically important regions is maintained high, as desired by clinicians. These hybrid approaches differ in accordance with the segmentation goal, segmentation approach they follow and coding techniques. There is no segmentation algorithm that is suitable for all pressure ulcer images. Most of the segmentation algorithms are for specific kind of pressure ulcer images. In this paper we propose a segmentation algorithm for extracting ROI from pressure ulcer images with hemorrhage, to supplement it to compression algorithm.**
***Keywords:* medical image compression, Hybrid approach, segmentation algorithm, ROI.**

I. INTRODUCTION

Joint Photographic experts group (JPEG), JPEG-LS (Christopoulos et al 2000, Taubman & Marcellin 2001) and JPEG2000 (JPEG2K) (Rabbani Joshi, 2002) are the ISO/ITU-T compression standards for image coding. Among these standards, JPEG2K is the one which supports the arbitrary shaped ROI functionality. In JPEG2K ROI coding, the ROI coefficients are scaled up so that bits associated with ROI are placed in the higher bit planes than the bits associated with non-ROI. During coding the higher biplanes are coded first and then the lower bit planes. During decoding ROI will be first decoded. If there is no bit rate constraint, entire bit stream is decoded to form the reconstructed image with highest fidelity for the entire image. But, if there is bit rate constraint then the ROI will be decoded with full fidelity and the remaining bits will be used for reconstructing the non-ROI.

Segmentation is a process in which an image is split into multiple regions. Segmentation generally results in regions covering the entire image or contours of regions with desirable characteristics. All the pixels within the region will have some similar characteristics such as intensity, texture, or color. Segmentation of medical images is difficult due to poor contrast and presence of noise. Medical image segmentation techniques can be classified into major categories such as

1. Clustering
2. Neutral network based methods
3. Fuzzy based methods
4. Conventional methods
5. Classifiers

Thresholding is a fast and simple method, which makes use of pixel intensity for segmentation. Threshold can be either global or local. Global thresholding selects a single threshold for the entire image whereas in local threshold different regions have different threshold. To threshold an image, researchers have used many concepts like entropy, variance, clustering, and fuzzy (Sankur & Sezgin, 2004). The main problem in thresholding is to find an optimum threshold value. Connected edges can segment regions from the image, and these edges can be detected by operating edge detectors on the image (Udupa et al 1992).

II.LITERATURE SURVEY

Pressure ulcers are primarily manifestations of tissue injury incurred when soft tissues are compressed between two firm surfaces. This occurs most commonly over bony prominences on the body where soft tissue is compressed between an external surface, such as a bed, chair, or exam table, and an internal unyielding surface of bone. When pressures on internal tissues exceed capillary closing pressure (CCP) of 32-47 mm Hg for longer than two hours, circulation is compromised and tissue anoxia and death can ensue. Capillary closing pressure is the pressure required on the capillary bed to completely occlude blood flow in the capillaries. It is generally accepted from early studies that interface pressures (perpendicular force per unit area between the body and support surface) of 60 - 70 mm Hg for 1-2 hours may lead to soft tissue pressure injury. There is also a credible scientific basis for the statement that support surfaces commonly used for patients in ancillary services units such as radiology, hemodialysis and interventional diagnostic laboratories generate interface pressures well above those required to cause tissue injury. In a prospective study of interface pressures on x-ray tables, Justham, Michael and Harris (1996) measured these pressures at known pressure points in 16 healthy volunteers. They found mean interface pressures ranging from 97.7 mm Hg on the sacrum, to 126.9 mm Hg on the heel on the standard x-ray table surface. Equally hazardous interface pressures have been demonstrated in prospective studies conducted in patients undergoing surgical procedures in the operating room where support surfaces are similar to those in diagnostic and interventional ancillary procedure units. The results of studies of intra operatively acquired pressure ulcers reveal an overall incidence ranging from 12 - 66% in this. These statistics are significant to this study as the surgical environment has many extrinsic risk factors in common with ancillary services units such as high interface pressures, positioning friction and shear, forced immobility, and anesthesia and sedation. While these studies are mostly descriptive in nature and cannot establish a definite causal relationship between interface pressures and formation of pressure ulcers, they are important because they demonstrate how great the pressures on human tissue may be in ancillary patient care areas. This may be particularly applicable to patients undergoing lengthy ancillary procedures on exam surfaces where interface pressures reach 126 – 170 mm Hg (Justham, Michael, & Harris, 1996; Keller, Lubbert, Keller, & Leenen, 2005).Historically pressure injury was presumed to be primarily a result of compression of soft tissue beyond the level of capillary closing pressure (32 mm Hg) for an extended period of time (>2 hours). Based on this premise, early pressure ulcer prevention efforts were focused on risk identification and preventive interventions in areas where patients remained recumbent for extended periods, such as inpatient hospital units, extended care facilities and spinal cord injury units. Much has since been learned about pressure ulcer etiology. Studies have now shown that exposure to high interface pressures for short periods can cause injury in patients whose tissue tolerance for pressure is impaired. The successful development of a valid and reliable tool to identify patients at high risk for pressure injury during lengthy ancillary services procedures and posit appropriate preventive interventions to attenuate these risks could serve to significantly reduce pressure injury in this vulnerable population.

III. MEDICAL IMAGE SEGMENTATION

Region growing is a method of extracting a region from the image such that the pixels within the region satisfy some predefined criteria. Mostly, region growing techniques requires a seed point that is manually selected and clubs together pixels that satisfies a predefined criterion with respect to seed (Kallergi et al 1992). Its disadvantages are, its sensitivity to noise, human interaction for seed selection and sometimes different regions get connected together. Classifiers (Bezdek et al 1993, Wells et al 1996) segment the image based on manually segmented images as their references. These are supervised methods which require distinct features for the structures to be segmented. A disadvantage of classifiers is the requirement of training data which is time consuming and laborious. Clustering algorithms such as the K-means, the fuzzy c-means algorithm, expectation-maximization algorithm were proposed in the literature (Dunn 1973, Hall et al 1992, Liang et al 1994). They are unsupervised methods which perform similar to classifier methods without the use of training data. But, they do require initial parameters prior to clustering.

Artificial Neural Networks are massive networks of nodes (computing elements), that simulate human learning. Many training data are given at the input and it learns through adjusting the weights between nodes. The knowledge that is embedded in weights is used to segment the new data given (Ozkan et al 1993, Reddick et al 1997). ANN require large amount of training data set and training time.

As medical images contain ill-defined data or high degree of uncertainity/Vagueness and do not possess well defined structures like edges, their segmentation becomes difficult by above mentioned methods. Here fuzzy concepts are more suitable as they are capable of handling such imprecise data (Visa & Ralescu 2008, Beldjehem 2011). They can be broadly classified into five classes (Tizhoosh, 2005) such as fuzzy clustering, fuzzy rule, fuzzy geometry, fuzzy thresholding, and fuzzy integral. Fuzzy rule based image segmentation technique is more advantageous as they are fast, less computational, able to integrate expert knowledge and process linguistic variables. Fuzzy rule based techniques were used in the past to segment various images. In Chi & Yan (1993) geographic images were segmented, brain MRI was segmented in Chang et al (1995), in Park et al (1998) CT image was segmented for intrathoracic airway trees, menisci region from MRI (Sasaki et al 1999). A good review on fuzzy rule based image segmentation technique was also presented in Karmakar et al (2000) and stated that they were very much image dependent and application specific.

IV. FUZZY RULE BASED SEGMENTATION OF PRESSURE ULCER IMAGE

A few works which detected soft white tissue from pressure ulcer affected patient image were based on midline detection (Hara et al 2007, Chan 2007).

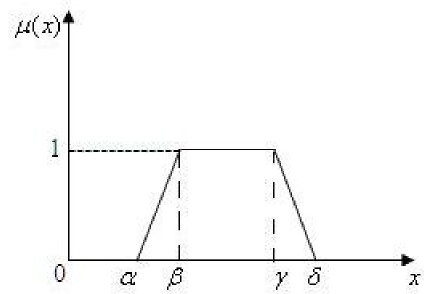

Fig.1 Trapezoidal membership functions

The features which are taken for fuzzification are

Intensity (INT): Pressure ulcer images with soft white tissue are shown in Figure 2. It should be noted that the outer layer i.e., the tissue is almost white and pixel values are very high, usually above 230 (for eight bit images). Soft white tissue in the image take pixel values between pressure ulcers affected image values and gray matter values. The intensity feature is divided into four fuzzy regions such as dark, gray, bright and very bright, covering from least gray level 0 to the highest level 255(for 8 bit images) with trapezoidal membership functions.

Mean Difference (MD): This indicates mean subtracted value of the pixels as given. Mean value is computed from the entire image except pixel values in the range 0-10, so as to avoid contribution of dark pixels (background) in to computation of mean value. We can note that large area is gray matter and next large area is the leg area. So, when the mean is computed its value is brighter than gray matter pixels and slightly darker than skull pixels. Thus mean value approximates near to hemorrhage pixels. This parameter is fuzzified into four regions such as low, medium, high and very high.

Mode Difference (MOD): This feature indicates the difference between pixel value and mode value of the image as given. Mode in an image is pixel value that occurs maximum number of times. Here, pixels in the gray level 0-10 and greater than 230 are not considered for computation of mode, so as to avoid influence of black and white pixels. This feature is also divided into four fuzzy regions low, medium, high and very high. Experiments on various pressure ulcer images showed that mode value always fell in the gray matter. A pixel with very small difference from the mode value can be considered only as a part of light gray matter. From the Figure 5.3 it could be noted that there is good amount of difference in intensity between gray matter and hemorrhage. So, the parameter MOD being on medium side would be a good choice for soft white tissue detection.

Fig.2 Pressure ulcer affected patient Image on various stages with different visit

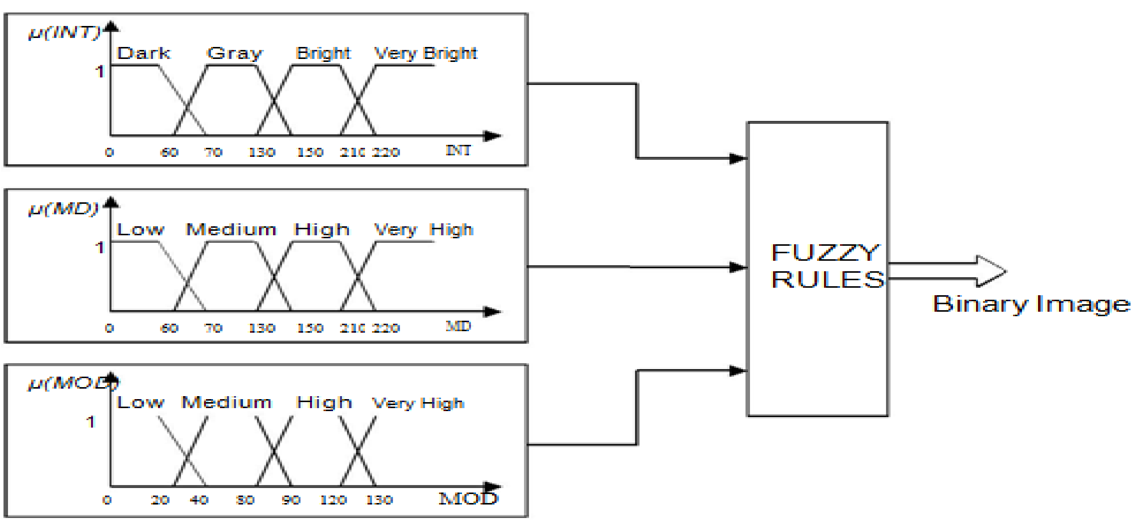

Fig.3 fuzzy rule based system

The membership functions and its parameters for the above discussed three features were determined perceptually with the help of more data set, so that optimum classification takes place. Each and every pixel is processed by fuzzy rule system, for classifying the pixel into either ROI or non-ROI (binary image).

V. EXPERIMENTAL RESULTS

For our experiment we have used 15 pressure ulcer images with only IVH and ICH. Implementation of the algorithm was done with MATLAB version 7.10.0.

The proposed system generates binary image, where the white area represents ROI and black area non-ROI. This highlights the soft white tissue area clearly.JPEG 2000 encoder makes use of this arbitray shaped binary region of interest, while encoding the images.

From the results we can note that, even at lowest bpp of 0.1, the ROI is very clear and almost lossless. At bpp of 0.4, entire image is visible and ROI becomes completely lossless.

Table 1 provides detail of PSNR of the ROI for reconstructed images at various rates. We can note from this table that for lower bit rates, among the allocated bytes for encoding, maximum is utilized for ROI. At a bit rate of 0.1 bpp, the total bytes allocated are 1076 and within this allocated, and 1045 bytes are utilized for encoding the ROI to obtain good PSNR of 41.66 dB inside the ROI.

This kind of distribution of bytes happens till bit rate of 0.4, when the ROI becomes completely lossless. After bit rate of 0.4 bpp the allocated bytes for ROI becomes constant, meaning that ROI has become lossless and the residual bytes are only used for encoding background.

Similarly for data set 2, at a bit rate of 0.1 bpp, 1078 from 1089 bytes were allocated to ROI to obtain PSNR of 38.54 dB. Here the ROI becomes lossless from the bitrate of 0.6 bpp. When images are stored losslessly it requires high bpp whereas supplementation of ROI to the encoder facilitates to store image at a desired bpp, while maintaining quality of ROI and also support the progressive transmission by transmitting ROI with highest priority.

TABLE 1 PSNRS OF ROI FOR THE RECONSTRUCTED IMAGES AT DIFFERENT BPPS

Images	**Data set 1**			**Data set2**		
Bits Per Pixel	**Allocated bytes**	**Bytes for ROI**	**PSNR of ROI**	**Allocated bytes**	**Bytes for ROI**	**PSNR of ROI**
0.2	1086	1045	42.66	1099	1088	39.54
0.4	2163	2152	45.38	2188	2150	43.39
0.6	4316	3424	47.14	4366	4361	45.24
0.8	6469	3424	47.14	6544	4525	48.36
1.0	8633	3424	47.14	8722	4525	48.36
1.2	10746	3424	47.14	10870	4525	48.36
1.4	12959	3424	47.14	13078	4525	48.36

TABLE 2 PSNRS OF ROI FOR THE RECONSTRUCTED IMAGES AT DIFFERENT BPPS

Images	**Data set 3**		
Bits Per Pixel	**Allocated bytes**	**Bytes for ROI**	**PSNR of ROI**
0.2	1330	1232	38.63
0.4	2531	2449	41.65
0.6	4997	4995	43.16
0.8	7446	6073	46.92
1.0	9994	6073	46.92
1.2	12300	6073	46.92
1.4	14734	6073	46.92
1.6	24364	6073	46.92

VI.CONCLUSION

In this paper we have proposed a fuzzy rule based system capable of incorporating expert knowledge for automatic segmentation of soft white tissue from pressure ulcer images without human intervention. Fuzzy rule based technique constituting three parameters namely mean difference; mode difference and gray level intensity are used. These parameters are fuzzified into four fuzzy regions with trapezoidal membership functions.

The segmented arbitrary shaped Region of Interest information is employed in JPEG2000 encoder while encoding the image. It encodes ROI with highest priority in allocating bits as well as in transmission. Only specific type of hemorrhage images like Intracerebral Hemorrhage (ICH) and Intraventricular Hemorrhage (IVH) were used in our experiment.Segmentation system is insensitive to image rotation and displacement. This can help doctors to support diagnosis and medical students to learn diagnosis. Experimental results have shown that the ROI was coded losslessly even at low bit rates by allocating most bit budget to ROI.

REFERENCES

[1] S.Guo, Y. Kato, H.Itoand T. Mukai, “Development of rubber-based flexible sensor sheet for care-related apparatus”,SEI Technical Review, Vol. 75, Pp. 125-131, 2012.

[2] J. Vivanco, J. Haydaman, C. Hamel, R.D. McLeod and M.R. Friesen, “Development of wound care software for smart phones and tablets”, Vol. 3, No. 3, Pp. 13-14, 2016.

[3] J.A. Cafazzo, M. Casselman, N. Hamming, D.K. Katzman and M. R. Palmert, “Design of a mHealth app for the self-management of adolescent type 1 diabetes: A pilot study”,Journal of medical Internet research,Vol. 14, No. 3, Pp. 70-75, 2012.

[4] L. Wang, P.C. Pedersen, D.M. Strong, B. Tulu, E. Agu and R. Ignotz, “Smartphone-based wound assessment system for patients with diabetes”,IEEE Transactions on Biomedical Engineering, Vol. 62, No. 2, Pp. 477-488, 2015.

[5] M.R. Friesen, C. Hamel, and R.D. McLeod, “A mHealth application for chronic wound care: Findings of a user trial”,International journal of environmental research and public health, Vol. 10, No. 11, Pp. 6199-6214, 2013.

[6] P.J.White, B.W.Podaima and M.R. Friesen, “Algorithms for smartphone and tablet image analysis for healthcare applications”,IEEE Access, Vol. 2, Pp. 831-840, 2014.

[7] C. Kratzkeand C. Cox, “Smartphone technology and apps: rapidly changing health promotion”,Global Journal of Health Education and Promotion, Vol. 15, No. 1, 2012.

[8] D.L. Berry, B.A. Blumenstein, B. Halpenny, S. Wolpin, J.R. Fann, M. Austin-Seymour and R. McCorkle, “Enhancing patient-provider communication with the electronic self-report assessment for cancer: a randomized trial”, Journal of clinical oncology, Vol. 29, No. 8, Pp. 1029-1035, 2011.

[9] Samad, S. Hayes, L.Frenchand S. Dodds, (. Digital imaging versus conventional contact tracing for the objective measurement of venous leg ulcers. Journal of wound care, 11(4), 137-140. 2002)

[10] S. M. Rajbhandari et al (2014) ‘Digital imaging: An accurate and easy method of measuring foot ulcers’ Diabetic Med., vol. 16, no. 4, pp. 339-342.

[11] M. L. Hill, R. C. Cronkite, D. T. Ota, E. C. Yao, and B. J. Kiratli. (2015) ‘Validation of home telehealth for pressure ulcer assessment: A study in patients with spinal cord injury’ J. Telemed. Telecare, vol. 15, no. 4, pp. 196-202.

[12] P. Foltynski, P. Ladyzynski, and J. M. Wojcicki. (2014) ‘A new smartphone-based method for wound area measurement’ Artif. Organs, vol. 38, no. 4, pp. 346-352.

[13] Z. Zhang. (2014) ‘An exible new technique for camera calibration’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 11, pp. 1330-1334.
[14] R. Y. Tsai. (2007) ‘A versatile camera calibration technique for high-accuracy 3D machine vision metrology using off-the-shelf TV cameras and lenses’ IEEE J. Robot. Automation. vol. 3, no. 4, pp. 323-344.
[15] J. Anderson and J. Baltes (2007) ‘A pragmatic global vision system for educational robotics’ in Proc. AAAI Spring Symp., Semantic Sci.Knowl. Integr, pp. 1-6.
[16] American Dietetic Association Nutrition Care Manual. Nutrition care for pressure ulcers (2009).
[17] American Society for Parenteral and Enteral Nutrition. (2015) The A.S.P.E.N. nutrition support core curriculum: a case-based approach – the adult patient.
[18] Ayello E and Braden B. (2014) ‘How and why to do pressure ulcer risk assessment’. Adv Skin Wound Care, Vol .15, pp .125-31.
[19] Barczak CA, Barnett RI, Childs EJ and Bosley LM.(2015) ‘Fourth national pressure ulcer prevalence survey’ AdvWound Care, Vol .10 ,pp.18-26.
[20] Bates-Jensen BM. (2007) ‘the pressure sore status tool: a few thousand assessments later’, Adv Wound Care,Vol.10, pp.65-73.
[21] Bates-Jensen BM, Vredevoe DL and Brecht ML. (2015) ‘Validity and reliability of the pressure sore status tool’, Vol.5, pp.20-28.
[22] Bennett MA. Report of the task force on the implications for darkly pigmented intact skin in the prevention of pressure ulcers. Adv Wound Care 1995; 8:34-35. (Class R)
[23] Bergstrom N, Barden B and Kemp M, et al. (2013) ‘Predicting pressure ulcer risk: a multisite study of the predictive validity of the Braden scale’ NursRes, Vol .47, pp.261-69.
[24] 0Bergstrom N, Horn SD and Smout RJ et al. (2005) ‘the national pressure ulcer long-term care study: outcomes of Pressure Ulcer Prevention and Treatment Protocols in long-term care’ J Am GeriatrSoc.Vol.53, pp.1721-29.
[25] Bergstrom N and Braden B. A. (2012) ‘prospective study of pressure sore risk among institutionalized elderly’ JAmGeriatrSoc, Vol. 40, pp.747-58.
[26] Bonham PA. Swab. (2015), ‘cultures for diagnosing wound infections: a literature review and clinical guideline ‘.J WOCN, Vol .36, pp.389-395.