Abstract—Applications of ultrasound images have expanded from fetal imaging to abdominal and cardiac diagnosis. Liver—being the largest gland in the body and responsible for metabolic activities require to be to be diagnosed and therefore subject to utmost injury. Although, ultrasound imaging has developed into three and four dimensions providing higher amount of information; it requires highly trained medical staff due to the image complexity and dimensions it contain. Since 2D ultrasound images are still considered to be the basis of clinical treatments, computer aided automated liver diagnosis is very essential. Due to the limitations of ultrasound images, such as loss of resolution leading to speckle noise, it is difficult to detect shape of organs. In this project, we propose a shape detection method for liver in 2D Ultrasound images. Then we compare the accuracies of the method for both noise and after noise removal.

I. INTRODUCTION

Ultrasound is an imaging technique which is mostly used in medical images, which is also known as ultrasonography where high frequency sound waves are used to visualize internal organs. Ultrasound has been an interdisciplinary research field for specialists from various disciplines such as biology, physics, computer science, medical sciences. Researches include the image enhancement, segmentation, noise reduction, compression, storage and data transmission of medical images[1]. In recent years, medical image processing has become a significant field of study for computer science. Medical Imaging modalities include angiography, magnetic resonance imaging (MRI), medical radiation and computed tomography (CT) scanners [2]. Each of these modalities have their own features and characteristics that are better or weak from each other. These imaging modalities are not only used by clinicians and surgeons for diagnosis and prognosis, but they also use these imaging modalities in computer aided diagnosis of organs within the human body. The diagnosis includes spatial heterogeneity and related changes to the anatomical structure.

II. LITERATURE REVIEW

Researchers and specialists have been working on different aspects of medical image analysis of different organs within the human body, such as brain, heart, kidney, lungs, hip joints. They have worked on segmentation, image transformation, edge detection of the organs and showed improvements. The most common difficulties to work on ultrasound images have been found from the Previous works are collect images in good quality(though contains speckles), remove speckle noises, estimate missing boundaries and occlusion([43]). All of these happens because of different tissues and blood vessels around the organs of our interest. Most of the works till now are noise cleaning, enhance the edge contrast to detect the organs of our interest and segmentation. By keeping all of these in mind we can divide our work in separate parts like first clean the the image to make it workable second find the contour and estimate the error third go for the shape detection though we will apply shape detection in the raw images to compare the result.

A. Noise Cleaning

There is a huge influence of quality of the data in any kind of shape or object detection problem from ultrasound images. Attenuation, speckle, shadow and signal drop out are the main reasons behind the complications of ultrasound image related works. The orientation dependence of acquisition resulted in missing boundaries and occlusion ([43]).

Chung and Henry applied snake model earlier which was first proposed by Kass et al (is 1987) to remove noises from the ultrasound images. The discrete snake model promises better noise immunity and accurate convergence. There are different variations of snake model and in most of the cases they minimize the energy function value which controls the smoothness of the contour ([41]).

In 2018, another work on speckle noise reduction was done where authors used Speckle Reducing Anisotropic Diffusion method which surpassed all the previous works like linear and non linear filtering methods such as Gaussian filter, Mean filter, non local means and anisotropic diffusion filter which were not taking into account the noise characteristics of ultrasound images([38]).

B. Boundary Detection

It is a common problem in computer vision applications that objects in images could not be recognized ([3], [4]) and so the need for recognition of irregular shapes is necessary. Shape is commonly defined in terms of the set of contours...
that describe the boundary of an object. In contrast to gradient- and texture-based representations, shape is more descriptive at a larger scale, ideally capturing the object of interest. Gestalt school of perception has recognized this and established the principle of holism in visual perception (Palmer, 1999; Ko-ka, 1935) ([5]).

Earlier in 2000 Sayan and Devid proposed a edge guided boundary detection method. In that method they did the work in three steps first enhance contrast and reduce speckle second fit weak membrane and finally they use a knowledge based approach to remove false edge and then apply delineation to enhance boundary which performed well but there were some limitations like it depends on the quality of edge detection of the object([31], [39]).

There was another work which used vector graphic approach to detect the boundary of kidney([31]). After the vector graphic formation, the boundary points of the kidney were identified. The error points were removed and the interpolation was then performed for contouring the kidney from its background. Experiments had been carried out step by step for validation purposes. Test result based on 30 kidney ultrasound image slices showed that the developed algorithms were able to detect 86.67 percent true ROIs. When compared to manual contouring, the sensitivity of this boundary detection technique was in between 94.95 percent to 97.75 percent and the specificity was in between 99.26 percent to 99.92 percent. Based on the results, this new semi-automatic technique is reliable to be used for contouring the kidney from three-dimensional ultrasound images.

C. Shape Detection

Shape detection of regular geometric features such as squares, triangles, rectangles and polygons in digital images is an important practice in image analysis and computer vision applications such as automatic inspection and assembly. Various methods for regular geometric shape detection have been researched till date [6]. These methods can be divided into two categories. One is the whole object as the area of interest and the second is contour of the object. Shape detection techniques that use contour to include Moment Invariant-based technique and it has been used to identify objects since 1962[7].

Iavarinen et al. used morphological operators with Freeman Chain Code to obtain contour of an object. They calculated the chain code histogram (CCH) of the object to find the approximation of its shape[3]. They proposed a shape descriptor model. A binary image was taken from the original grey-level image by segmentation. The defect areas are marked with black color and the non-defect areas with white color. The contour image is then obtained by basic morphological operations. Finally, the contour is smoothed with the Gaussian filter because the chain code (and thus the proposed shape descriptor) is sensitive to noise. The model was implemented on machine printed text and irregular shaped objects. In the case of irregular objects basic morphological operations-dilation and erosion were used to process the image. A 3x3 structuring element is used. To fill up small holes and guls present in the binary image a morphological closing operation (dilation followed by erosion) is applied to the image. The contour image is obtained by subtracting the closed image from the dilated image. Finally, the contour is smoothed with the Gaussian filter. The results of experiments with machine-printed text and with true irregular objects are good. It showed that similar shaped objects were grouped together. However, the sensitivity to small rotations limits the generality of the proposed shape descriptor.

A feature detection method to estimate nose shape is presented in the paper by Lijun Yin and Anup Basu Where individual templates are designed for the nostril and nose-side [47]. First, the feature regions are limited to certain areas by using two-stage region growing methods. Second, the predefined templates are applied to extract the shape of the nostril and nose-side.[45]

The important nose features lie in the shapes of nostril and nose side. In order to compose a facial expression, it is necessary that the shape of nostril and nose-side is accurate. The shape of nostril and nose side changes when a person is smiling or laughing. To detect the nostril shape correctly, a geometric template is applied on the nostril region, which is a twisted pair curve with a leaf-like shape. To estimate the nose-side, parabolic function is used since the nose-side shape is like that of a vertical parabola. Since the nose shape is a symmetric, therefore the cost function of the left side is equal to the right side. The overall performance (measured over all tested frames) of the model gives an indication of the capability of the system to detect most nose features correctly (only 18 frames out of 270 frames showed that the position error in nose area was beyond 3 pixels).

The Hough Transform (HT) is the most popular technique that has been used expansively to extract analytic features, such as straight lines, circles, and ellipse because of its robustness against noise, clutter, object defect, shape distortion etc. ([8], [9], [10], [11]).

B. Solaiman, B. Burdsall and Ch. Roux proposed HT in order to have a precise detection and localization of the aorta. The use of a priori anatomic knowledge of the approximate radius of the aorta has already been discussed in the previous section. Priori information concerning the approximate aorta position in the image plane is simply integrated through the use of a weight function, in the Hough space, assuming the value zero in areas where the aorta is not allowed to be detected (central part of the image), and unity in the rest of the image. Finally, the Canny-Deriche edge detector is used because it allows the accurate estimation of the normal vectors, and thus, increasing the efficiency of the accumulation.[50]

Hough Transform (HT) is still used for detecting organs or joints within the human body. Wang et al. used Gabor-based Hough Transform to estimate candidate femoral head circles and determined a fine circle from the candidates by analyzing the anatomical features of the femoral head and its spatial relation to the acetabulum[12]. Liu et al. [13,14] proposed a novel shape-detecting response function to evaluate the fitting degree of the ring of concentric circles based.
on the shape information. In another study on hip X-ray images, Ruppertshofer et al. proposed a multi-level based Discriminative Generalized Hough Transform [15] approach to detect the femoral heads in whole-body MR images. Aghayan et al. [16] utilized Hough Transform to detect femoral heads in calculation and visualization of range of motion of hip joint from MRI. Chen et al. [17] performed Circular Hough Transform (CHT) to detect femoral head ball in automatic extraction of femur contours. ([36])

Memis et. al [49] presented a new two-level scheme based on the Circular Hough Transform (CHT) and Integro-Differential Operator (IDO) to detect the spheric and aspheric femoral heads in MR images in 2D. Primarily, MR slices are divided vertically into two equal halves to automatically separate the hip joints. Then Canny edge detection method is performed on each of the halves to obtain edge images. Thereafter, healthy and pathological femoral heads are detected by performing the CHT over edge images in the first stage of proposed method. In the second stage, femoral head circle detected with CHT is fine-tuned by performing Daugmans IDO. Performance evaluations of the proposed femoral head detection scheme were carried out on healthy and pathological hip joints in 24 coronal MR image sections belong to 13 patients with Legg-Calve-Perthes Disease (LCPD). For performance evaluations on 24 healthy and 24 pathological hip joints the Root Mean Square Error (RMSE) and Dice Similarity Coefficient (DSC) values were measured for automatically detected femoral heads. They observed 1.96 mm. (std. 1.21 mm.) mean RMSE for center coordinates, 1.45 mm. (std. 1.39 mm) mean RMSE for radii, 0.8978 (std. 0.0733) mean DSC on healthy femoral heads and 3.56 mm. (std. 3.19 mm.) mean RMSE for center coordinates, 1.56 mm. (std. 1.33 mm.) mean RMSE for radii, 0.8529 (std. 0.0927) mean DSC on pathological femoral heads. Proposed femoral head detection scheme has promising results for the detection and the segmentation of the spheric and aspheric femoral heads and also has a potential to be used in detection of the other anatomical structures having a circular shape.

In addition to that, shape detection of kidney in ultrasound images have also proved to be a extensive research field. Cardenes et al. [18] created a software called UsimagTool that uses three filters (anisotropic Wiener, Speckle Reduction Anisotropic Diffusion, and Tensor guided Anisotropic Diffusion) and one segmentation algorithm based on a Markov random field model to process ultrasound images. The visualization of the processed Ultrasound image is performed in three main viewers. Each viewer shows two dimensional slices from different 3D data, and support the following functions: zoom, display any of the three orthogonal views, flip the x,y, or z axis, transpose the axis of the slice being viewed, display points selected, show image details, view a color overlay image, show pixel value and location of cursor, change intensity window and level, and switch between different visualization random field model to process ultrasound images.

Although many state-of-the-art segmentation methods, e.g., generalized Hough transform (GHT) and marginal space learning (MSL) have been proposed for medical imaging, they are often anatomy-specific and customized for the unique features in the image data [45,46]. The reason why lung field segmentation in CXR (Chest X-Ray) images continues to be challenging, compared to other anatomy, is because of complex contours, low contrast, more inhomogeneous regions, and superimposed anatomical structures. GHT has several drawbacks such as computational expense given its vast global search, vulnerability to noise in edge orientation and location, and being fragile under rotation and scaling [47].

Roger and Alian presents a method that uses shape information to accurately determine the intensity ranges of objects present in a grey-scale image. The technique introduced is based on the computation of the shape gradient, a numerical value for the difference in shape. In this case, the difference in shape is caused by the change in threshold value applied to the image. The use of this gradient allows us to determine significant shape change events in the evolution of object forms as the threshold varies. The gradient is computed using generating boundary points, generating union of circles from the boundary points and Union of Circles matching [51].

Xu T et. al proposed an efficient automatic segmentation technique for lung boundary detection in chest radiographs. They proposed a method where they used global edge and region force (ERF) field, to make the automatic initialization and segmentation stages of the CAD framework more robust. In the proposed method, a Shape Learning Model [48] was used that learns the shape of the lung using PCA analysis. In this stage, the shape and grey level of the objects are learnt by statistically analyzing the training image dataset. These learning tasks are executed by grey level appearance model (GLAM) generation shape model generation. Different shapes were aligned by using generalized Procrustes analysis and principal component analysis (PCA) is performed to approximate any shape in the training set.

A year later Jacinto and Jorge come up with a mixed approach to track robust shape in sequence of ultrasound images. They proposed an algorithm based on bank of non linear filters organized in a tree structure where they used multiple model to cope with robust shape tracking. It decides which model to be applied in an instance of time([40]).

In 2015 Li, Guodong and Cheng proposed a set of methods for segmenting liver from CT images. The proposed framework consists of three steps: 1) preprocessing; 2) initialization; and 3) segmentation. In the first step, a statistical shape model is constructed based on the principal component analysis and the input image is smoothed using curvature anisotropic diffusion filtering[38]. In the second step, the mean shape model is moved using thresholding and Euclidean distance transformation to obtain a coarse position in a test image, and then the initial mesh is locally and iteratively deformed to the coarse boundary, which is constrained to stay close to a subspace of shapes describing the anatomical variability. Finally, in order to accurately detect the liver surface, deformable graph cut was proposed, which effectively integrates the properties and inter-relationship of the input images and
initialized surface.\[52\]

Although, specialists have worked on improving ultrasound images for different organs of human body but not much has been done to detect liver.

Due to the complications of ultrasound images such as speckle noise and in-homogeneous intensity profile, shape detection of liver in 2D ultrasound images has not been sufficiently investigated by researchers.

REFERENCES

[1] I. Bankman, Handbook of Medical Image Processing and Analysis, academic press, 2008

[2] A.G. Webb, Introduction to Biomedical Imaging, Wiley 2003

[3] Jukka Iivarinen and Ari Visa, Shape recognition of irregular objects, Helsinki University of Technology, Laboratory of Computer and Information Science Rakentajanaukio 2 C, Finland.

[4] M. Sonka, V. Hlavac, and R. Boyle. Image Processing, Analysis and Machine Vision. Chapman and Hall Computing, 1993.

[5] Alexander Toshev, Ben Taskar and Kostas Daniilidis, Shape-based Object Detection via Supervised Stria Boundary Segmentation, February 2011.

[6] Ayan Acharya, Kaushik Chattopadhyay, Deepyamani Maiti and Amit Konar, An Artificial Ant Based Novel and Efficient Approach of Regular Geometric Shape Detection from Digital Image, Proceedings of 11th International Conference on Computer and Information Technology (ICICT 2008), 25-27 December, 2008.

[7] N. Pathak, Visual Pattern Recognition by Moment Invariants. IRE Transactions on Information Theory, IT-8:179-187, 1962.

[8] P.V.C. Hough. Methods and means for recognizing complex patterns. US patent 3006954, 1962

[9] R.O. Duda and P.E. Hart, Use of Hough transformation to detect lines and curves in pictures. Comm. Assoc. Comput. 15(1), pp. 11-15, 1972.

[10] R.K.K. Yip, P.K.S. Tam and D.N.K. Leung, Modification of the Hough transform for circles and ellipse detection using a 2-dimensional Array, Pattern Recognition, 25, pp. 1007-1022, 1992.

[11] A.S. Agudo, M.E. Montiel and M.S. Nixon, Ellipse Detection via gradient direction in the Hough transform, Proceedings of IEEE International Conference on Image Processings and its Applications, pp 375-378, July, 1995

[12] L. Wang, M. Kohnen, O. Friman, H. K. Hahn, Fast automated segmentation of femoral heads in fluoroscopic x-ray images, in: Biomedical Imaging: From Nano to Macro, 2011 IEEE International Symposium on, pp. 984988

[13] S.-J. Liu, Z. Zou, S.-D. Luo, S.-H. Liao, A novel harmonic field based method for femoral head segmentation from challenging CT data, in: Computing Measurement Control and Sensor Network (CMCSN), 2016 Third International Conference on, IEEE, 2016, pp. 9295.

[14] Z. Zou, S.-H. Liao, S.-D. Luo, Q. Liu, S.-J. Liu, Semi-automatic segmentation of femur based on harmonic barrier, Computer methods and programs in biomedicine 143 (2017) 171184

[15] H. Ruppertshofen, D. Kunze, C. Lorenz, Multi-level approach for the discriminative generalized hough transform*, in: CURAC 2011: 10. Jahrestagung der Deutschen Gesellschaft für Computer und Robotenassistierte Chirurgie, Magdeburg, Germany, 15-16 September 2011, CURAC, 2011

[16] S. Aghayan, W. Lee, Calculation and visualization of range of motion of hip joint from mri, in: Computer-Based Medical Systems (CBMS), 2014 IEEE 27th International Symposium on, IEEE, 2014, pp. 143148

[17] Y. Chen, X. Xie, W. K. Leow, T. S. Howe, Region-based extraction of femur contours from hip x-ray images, in: International Workshop on Computer Vision for Biomedical Image Applications, Springer, 2005, pp 200-209

[18] R. Crdenes, A. Vega, A. Grande, C. Grande, Lucilio and M. Moreno, E. Moreno and M. Fernandez, UsimagTool: an Interactive Research Tool for Ultrasound Image Processing*, in: Biometrics and BioEngineering (BIBE), IEEE Seventh International Symposium, IEEE, 2007

[19] Avner, S. Via Bonitaker, R. Image Denoising with Unsupervised, Information-Theoretic, Adaptive Filtering, University of Utah TR, UUCS-04-013, 2004

[20] Borenstein, E., Ullman, S.Class-specific, top-down segmentation ECCV, 2002

[21] Breau R. H., Clark E., Bruner B., Cervini P., Atwell, T., Knoll, G., Leibovich, B. C A simple method to estimate renal volume from computed tomography, Can Urol Assoc J.; 7(5-6): pp.189192,2013

[22] Cheong, B., Muthupillai, R., Rubin, M. F., Flamm, S. E. Normal Values for Renal Length and Volume as Measured by Magnetic Resonance Imaging, Clin J Am Soc Nephrol, 2, 38 45, 2007

[23] Drioi, L. Cohen-Or D., Yeshurun, H.Fraction- based image completion. SIGGRAPH, in: BioInformatics and BioEngineering (BIBE), IEEE Seventh International Symposium, IEEE, 2007

[24] R. Crdenes, A. Vega, A. Grande, C. Grande, Lucilio and M. Moreno, E. Moreno and M. Fernandez, UsimagTool: an Interactive Research Tool for Ultrasound Image Processing*, 2003

[25] Efros, A., Freeman, W. T., Image quilting for texture synthesis and transfer. SIGGRAPH, in: BioInformatics and BioEngineering (BIBE), IEEE Seventh International Symposium, IEEE, 2007

[26] R. Crdenes, A. Vega, A. Grande, C. Grande, Lucilio and M. Moreno, E. Moreno and M. Fernandez, UsimagTool: an Interactive Research Tool for Ultrasound Image Processing*, 2001

[27] Freeman, W. T., Jones, T. R., Pasztor, E., Example-based super-resolution, in: Computer Graphics and Applications. IEEE, 2002

[28] Freiman, M., Kronman, A., Esses, S. J., Joskowicz, L., Sosna, J. Non-parametric Iterative Model Constraint Graph min-cut for Automatic Kidney Segmentation, in: MICCAI, pp.73-80, 2010

[29] Hafizah, W. M., Supriyanto, E.Comparative Evaluation of Ultrasound Kidney Image Enhancement Techniques, in: International Journal of Computer Applications, 2011

[30] Leibovich, B. C. Kidney Segmentation from Ultrasound Images Using Gradient Vector Force, in: IJCA Special Issue on Recent Trends in Image Processing and Pattern Recognition, pp.104-109, 2010

[31] Leventon, M., Grimson, E., Faugeras, O., Statistical shape influence in geodesic active contours in: Proc. IEEE Comput. Vis. Pattern Recogn., Hilton Head, S.C., pp. 316-322, 2000

[32] Liang, L., Liu, C., Xu, Y., Guo, B., Shum, H. Y. Real-time texture synthesis by vector-based sampling. Microsoft Research, 2001

[33] Mahmud, W. M. H. W., Supriyanto, E., Assessment of Kidney Volume Measurement Techniques for Ultrasound Images, in: International Journal for Integrated Engineering, 6(3) pp. 33-38, 2014

[34] Sayan D. Pathak, Vikram Chalana, David R. Haynor, and Yongmin Kim. Edge-Guided Boundary Delination in Prostate Ultrasound Images in: IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 19, NO. 12, DECEMBER 2000

[35] B. Solaian, B. Burdsall and Ch. Roux, Hough transform and uncertainty handling. Application to circular object detection in ultrasound medical images in: 0-8186-8821-1/98 1998 IEEE

[36] Jun Xie, Yifeng Jiang, and Hung-tat Tsui, Segmentation of Kidney From Ultrasound Images Based on Texture and Shape Priors in: IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 24, NO. 1, JANUARY 2005

[37] Karthik Kalyan, BinaL Jakhaia, Ramachandra Dattatreya Lele, Mukund Joshi and Abhay Chowdhary, Artificial Neural Network Application in the Diagnosis of Disease Conditions with Liver Ultrasound Images in: Hindawi Publishing Corporation: Advances in Bioinformatics, Volume 2014, Article ID 708279, 14 pages, http://dx.doi.org/10.1155/2014/708279

[38] Hyunho Choi, Jeang Jeong. Speckle Noise Reduction in Ultrasound Images using SRAD and Guided Filter in: 978-1-5386-2615-3/18 IEEE
[44] Alison Noble, Djamal Boukerroui, Three generations of medical image segmentation: methods and available software. Int J Bioelectromag 2007;9:678

[45] Elnakib A, Gimelfarb G, Suri JS, El-Baz A, Medical image segmentation: a brief survey. In: Multi modality state-of-the-art medical image segmentation and registration methodologies in: New York: Springer; 2011

[46] Assheton P, Hunter A, A shape-based voting algorithm for pedestrian detection and tracking in: Pattern Recogn 2011;44(5):110620

[47] Xu, T., Mandal, M., Long, R., Cheng, I. and Basu, A, An edge-region force guided active shape approach for automatic lung field detection in chest radiographs 2012

[48] Lijun Yin and Basu, A, Nose shape estimation and tracking for model-based coding in: IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings (Cat. No.01CH37221)

[49] Memi, A., Albayrak, S., Bilgili, F, A new scheme for automatic 2D detection of spheric and aspheric femoral heads: A case study on coronal MR images of bilateral hip joints of patients with Legg-Calve-Perthes disease. in: Computer Methods and Programs in Biomedicine, 175, 8393. doi:10.1016/j.cmpb.2019.04.001

[50] B. Solaiman, B. Burdsall and Ch. Roux, Hough transform and uncertainty handling. Application to circular object detection in ultrasound medical images. in: 0-8186-8821-1/98 10.00 0 1998 IEEE

[51] Roger Tam and Alain Fournier, Determination of Intensity Thresholds via Shape Gradients. in: UBCTechnicalReport TR-00-08, August, 2000

[52] Guodong Li, Xinjian Chen, Fei Shi, Weifang Zhu, Jie Tian, Automatic Liver Segmentation Based on Shape Constraints and Deformable Graph Cut in CT Images. in: IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 24, NO. 12, DECEMBER 2015
This figure "timeline.png" is available in "png" format from:

http://arxiv.org/ps/1911.10352v1