

A Technique for the Detection of Cystic Focal Liver Lesions from Abdominal Images

Sreeja P, Hariharan S

Abstract- Computer aided detection of cystic focal liver lesions (FLL) from Computed Tomography (CT), Magnetic Resonance (MR) or ultra sound (US) abdominal images is a challenging task in pattern recognition and image processing. Region of interest (ROI) is taken from unenhanced/enhanced images from different imaging modalities. A simple and novel algorithm is applied in MATLAB platform and the lesions are clearly identified and highlighted. The proposed algorithm is based on template matching, but it overcomes certain difficulties incurred while applying to biomedical images. The new algorithm progresses in a semiautomatic fashion and can be modified to a fully automatic system for the detection of liver lesions. The algorithm was evaluated on different CT, MR and US abdominal images. The results demonstrate the efficiency of the proposed technique for reliable detection of liver lesions from different imaging modalities.

Index Terms- Imaging modalities, template matching, cystic focal liver lesions and correlation

I. INTRODUCTION

Template matching is one of the important and classical techniques in digital image processing for item detection and pattern matching. This technique basically includes the comparison of a template image with the reference image and finds a similarity matrix. Different methods of finding the similarity are explained in the literature. A number of algorithms have been devised for long years which explain the significance. Template matching is widely used in the biomedical engineering for the processing of images of internal organs from different imaging modalities. In [1] Yongbum Lee *et al* described an improved method of template matching for the automatic detection of pulmonary nodules in helical CT. L. Ding *et al* explained selection of template and template matching for volume image registration in the case of brain images in [2]. Medical image registration using template matching based on Normalized Cross-Correlation (NCC) using Cauchy-Schwartz inequality was described by Sarvaiya J N *et al* [3]. Lena Costaridou explained various difficulties with the template matching in medical image analysis in his book [4]. It explains optimization based template matching and image registration algorithm while maintaining its simplicity. A tracking method of tissues in long ultrasound sequences of liver is proposed in [5] in which search ranges of template matching changes adaptively.

Kinda Anna Saddi *et al* described the challenges in the extraction of liver tissue due to the similarity of densities with adjacent organs and partial volume effect. To solve these problems shape model and template matching algorithm were suggested [6][7]. Liver is the body's largest compound gland. It is a major metabolic organ, and is important for degrading alcohol and drugs. It stores glycogen, secretes glucose, plasma proteins and lipoproteins into the blood, and secretes bilirubin, secretory IgA, and bile salts as components of bile. It has a dual blood supply and a thin capsule of dense connective tissue. Its high blood flow, microscopic anatomy and rich biochemical environment favour the rapid growth of metastatic deposits in the liver. The non-invasive nature of medical imaging makes it popular though it is expensive. Hence it is very important to extract the maximum possible information from any image obtained. Visual interpretation of liver images by specialized physicians decides whether liver tissue is normal or abnormal. The decision depends on the ability of the radiologist to distinguish certain characteristics of the image and compare them with those from different pathologies. However, several studies had shown that the characterization accuracy of liver diseases using only simple visual interpretation was estimated to be around 72% [7]. Here comes the significance in designing and developing computer assisted image processing techniques which help the doctors to improve their diagnosis. This has gained significant attention in past few decades. Liver diseases can be classified into two main categories such as Focal diseases and Diffused diseases. The Focal diseases are abnormalities that are concentrated within a small area of liver parenchyma, whereas the diffused diseases are where the abnormalities are distributed over the whole extent of liver tissue [8]. The focal liver lesions are generally classified as benign and malignant. These can be cysts and tumors which are the abnormal growths or structures. A cyst is a fluid filled balloon or bubble like structure (sac) that can grow in any part of the body. Liver cysts are mostly congenital (have from birth itself) or caused from contact with some form of parasites and usually may not have malignant potential. A tumor is an abnormal lump or swelling of tissue because of the uncontrolled build-up of cells. Malignant tumors are cancerous and may invade other parts of the body. Also liver is the most common site of metastasis. To identify the malignant potential of the FLLs invasive methods are usually employed. Hence it is extremely important to distinguish cystic focal liver lesions [8] noninvasively with the help of analysis of abdominal images. Hepatic cysts are common benign liver lesions that occur in 2%–7% of the population.

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These lesions may be isolated or multiple and vary from a few millimetres to several centimeters in diameter. Hepatic cysts are typically discovered incidentally and have no malignant potential. Certain diseases such as polycystic liver disease and polycystic kidney disease are associated with multiple hepatic cysts. The walls are usually imperceptible, and the cyst does not enhance after intravenous administration of contrast material. Similarly, at MR imaging a hepatic cyst is iso-intense relative to water and does not enhance after administration of contrast agent[9].

II. CHARACTERISTICS OF BIOMEDICAL IMAGES

USG and CT are directed for diagnosis of biliary obstruction or gallbladder diseases and for differentiation of cysts from solid liver lesions. The gold standard for detection and location of focal lesions is MRI or triple phase dynamic spiral CT. MR imaging is an important diagnostic tool in the detection and characterization of focal liver lesions. Advantages of MR imaging include multi-planar imaging capability, superior contrast resolution, and no ionizing radiation. Faster imagers and new imaging sequences allow dynamic imaging for lesion characterization. The radiographic density of liver parenchyma is same or normally greater than the density of other solid organs of the upper abdomen (spleen, kidneys and pancreas). The normal range of attenuation values among normal liver is 20 to 40HU (Hounsfield Unit) while that of a hepatic cyst varies from 0 to 10 HU.

III. NECESSITY OF A NEW TECHNIQUE

Template matching is a conventional image processing technique which is commonly used in item detection and image comparison. It is used for finding small part of an image which matches a template image and for pattern recognition by establishing a correspondence between the reference image and sensed image. The main criterion of the correlation based template matching algorithm is that it searches for the location of exact match between the search image and the template. As this method merges the feature detection step with the matching part, it fails to detect the salient objects. In the case of biomedical image processing which is often associated with characteristic features, it is difficult to apply specially designed image processing methods for visualization and analysis of medical images [10]. Also it exists as a fact that the tissues may vary from person to person and also it may vary in the same person from time to time [11][12]. Hence the correlation based template matching can find only the exact matching location while it neglects the other similar locations. This may cause difficulty in detection of all locations in the presence of multiple lesions. The size and shape of the template also become deciding factors which also makes difficulty in the detection of lesions. The method is less sensitive to intensity differences between the search and template image.

IV. TEMPLATE MATCHING

One of the basic methods of template matching uses a convolution mask (template), tailored to a specific feature of the search image, which is to be detected. It gives the measure of the degree of similarity between an image and template. This technique can be easily performed on grey images or edge images [13].

V. DIFFERENT METHODS OF TEMPLATE MATCHING

The literature contains different methods with mathematical description of template matching. Some of these methods are briefly explained here. Let the search image be $S(x, y)$ where (x, y) represent the coordinates of each pixel in the search image. Select a part of the search image to use as a template, $T(x_t, y_t)$; (x_t, y_t) represent the coordinates of each pixel in the template. Move the center (or the origin) of the template $T(x_t, y_t)$ over each (x, y) point in the search image and calculate the sum of products between the coefficients in $S(x, y)$ and $T(x_t, y_t)$ over the whole area of the template. The position with highest sum of product value is identified as the best match. This method is referred to as 'Linear Spatial Filtering' and the template is called a filter mask. [14]

A. Sum of Absolute Differences (SAD)

The template matching can also be implemented by comparing the intensities of the pixels, using the **SAD** measure. In digital image processing, the sum of absolute differences is a measure of the similarity between image blocks. It is calculated by taking the absolute difference between each pixel in the original block and the corresponding pixel in the block being used for comparison. These differences are summed to create a simple metric of block similarity, the L^1 norm of the difference image or *Taxicab* or Manhattan distance between two image blocks. Let $I_s(x_s, y_s)$ be the intensity of a pixel in the search image with coordinates (x_s, y_s) and $I_t(x_t, y_t)$ be the intensity of a pixel in the template with coordinates (x_t, y_t) . The absolute difference in the pixel intensities is defined as

$$Diff(x_s, y_s, x_t, y_t) = |I_s(x_s, y_s) - I_t(x_t, y_t)| \quad (1)$$

$$SAD = \sum_{i=0}^{Trows} \sum_{j=0}^{Tcols} Diff(x+i, y+j, i, j) \quad (2)$$

The mathematical representation of the idea about looping through the pixels in the search image as we translate the origin of the template at every pixel and take the SAD measure is the following:

$$SAD = \sum_{x=0}^{Srows} \sum_{y=0}^{Scols} SAD(x, y) \quad (3)$$

$Srows$ and $Scols$ denote the rows and the columns of the search image and $Trows$ and $Tcols$ denote the rows and the columns of the template image, respectively. In this method the lowest SAD score gives the estimate for the best position of template within the search image. The sum of absolute differences may be used for a variety of purposes, such as object recognition, the generation of disparity maps for stereo images, and motion estimation for video compression. This method provides a simple way to automate the searching for objects inside an image, but may be unreliable due to the effects of contextual factors such as changes in lighting, color, viewing direction, size, or shape. The method is simple to implement and understand, but it is one of the slowest methods. The SAD may be used in conjunction with other object recognition methods, such as edge detection, to improve the reliability of results [15][16][17].

B. Sum of Squared Differences (SSD)

This metric is also known as the Euclidean Distance metric. It sums the square of the absolute differences between pixels in the original image and the corresponding pixels in the template image. This metric is the square of the l^2 norm of the difference image. The cross correlation template matching also uses sum of squared differences (SSD).

$$d(u, v) = \sum_{x,y} (I_s(x_s, y_s) - T(x_{s-u}, y_{s-v}))^2 \quad (4)$$

Cross correlation,

$$c(u, v) = y I_s(x_s, y_s) T(x_{s-u}, y_{s-v}) \quad (5)$$

I_s is the image, T is the template and summation is over positions x, y under the template positioned at (u, v) . SSD can be viewed as the squared Euclidean distance. Expanding equation (4),

$$d(u, v) = \sum_{x,y} (I_s(x_s, y_s)^2) - 2I_s(x_s, y_s)T(x_{s-u}, y_{s-v}) + T(x_{s-u}, y_{s-v})^2 \quad (6)$$

$T(x_{s-u}, y_{s-v})^2$ is constant.

Assuming that the term $(I_s(x_s, y_s)^2)$ is approximately constant which is called the local image energy the remaining term the cross correlation.

$c(u, v) = I_s(x_s, y_s) - T(x_{s-u}, y_{s-v})$ is a measure of the similarity between the image and the template; the larger the value of c , the more similar the image and template are [18]

C. Normalized Cross Correlation (NCC)

Another method of finding the similarity metric is by computing the normalized cross correlation (also called as correlation coefficient). The maximum values or peaks of the computed correlation values indicate the matches between a template and the image. The normalized cross correlation (NCC) between an image and a template image can be calculated as follows. [19] [20]

$$NCC = \frac{\sum_{(i,j) \in \omega} I_1(i, j) \cdot I_2(x+i, y+j)}{\sqrt{\sum_{(i,j) \in \omega} I_1^2(i, j) \cdot \sum_{(i,j) \in \omega} I_2^2(x+i, y+j)}} \quad (7)$$

Even though NCC is insensitive to scaling of image intensity, the computational complexity is not acceptable in most of the applications.

D. Maximum Absolute Difference (MAXAD)

This metric is also known as the uniform distance metric. It sums the maximum of absolute values of the differences between pixels in the original image and the corresponding pixels in the template image. This distance metric provides the l^∞ norm of the difference image. The general MaxAD distance metric is given below [21]

$$d_\alpha(I, T) = \lim_{\alpha \rightarrow \infty} \sum_{i=1}^N (|I(i, j) - T_i|)^{\alpha} \quad (8)$$

this can be simplified as

$$d_\alpha(I, T) = \max_i \sum_{i=1}^N (|I(i, j) - T_i|)^{\alpha} \quad (9)$$

The algorithm is based on the pixel level grey value of the search image and the template image. Each pixel gives a quantitative measure of a parameter that is directly related to a spatial domain grey level value. Grey level differences in tissues are small compared to the accuracy with which the measurements carried out for a safe dose of x-rays to the patients. These limitations necessitate development of new analysis techniques that will improve detection and diagnostic ability. In certain medical images, visual texture conveys useful diagnostic information. The perception of texture has been the subject of extensive psychological study. A limited level of complexity can be appreciated by the human eye-brain complex. Obviously, the improvements in grey level based techniques increase the level of information extracted from images. It also enhances the appearance and thereby providing visibility to the radiologist. The proposed method is based on the grey value of both search image and template image. The algorithm is based on simple mathematical operation on the two images which avoids the complexity of computation which is the main drawback of the conventional correlation based template matching. The computation time is also reduced. The simple mathematical operation based on grey level enables the new algorithm to detect the lesions of different size and shape. It never searches for exact match between the two images, but it differentiates the liver parenchyma from the lesions. This algorithm provides good result to the images of three different modalities. The block diagram of the proposed algorithm is shown in fig1. The abdominal image is read initially. The image pre-processing is to be carried out as per the requirement. Here the ROI is taken manually which is cropped to select the template image. To carry out the proposed image processing application some mathematical restructuring operations were done on the images. The lesions which are detected and clearly differentiated from normal liver parenchyma are obtained as the output of the proposed algorithm. The time taken for the computation is not even noticeable.



A Technique for the Detection of Cystic Focal Liver Lesions from Abdominal Images

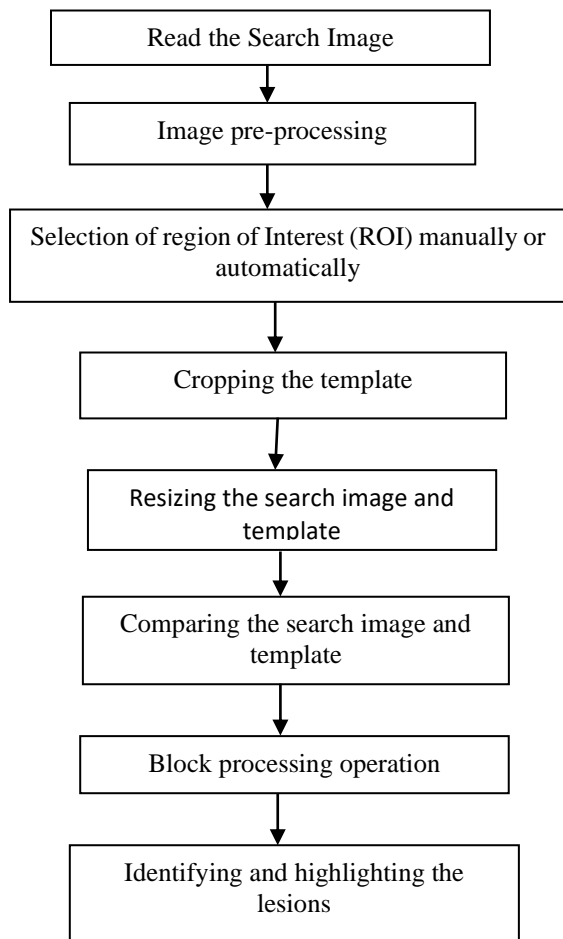


Fig. 1 Block diagram of the proposed algorithm

VI. RESULTS AND DISCUSSIONS

The algorithm is applied to images from the three common imaging modalities viz, US, CT and MRI. The images include various classes of cystic focal liver lesions such as simple cyst, polycystic liver disease and hydatid cyst. It is found that in the processed images with the lesions highlighted clearly. From these results it can be proved that the clear detection of different types of focal liver lesions can be done with the help of the new algorithm. This is helpful to the radiologist to detect the lesions without any manual error because of the enhancement of the lesions of even very small size. Different images and the processed output images in the two cases are consolidated in the figure below for clear observation. Fig 2a to Fig 6a shows original images of various types of cystic focal liver lesions from CT, MRI, and USG. Fig 2b shows the output image of the proposed algorithm. From the figure it can be seen that lesions of different sizes are detected clearly. Figure 2c shows the result of the correlation based template matching algorithm. For both cases the same template is chosen. The rectangle shown in Fig2c is taken as the template. With the conventional system the same location of the cropped template is marked with a white bordered rectangle. But the proposed algorithm highlights all the lesions irrespective of their size and shape. Because of the enhancement the lesions can be easily differentiated from normal liver parenchyma. A simple cyst of Fig 3a is enhanced in Fig 3b with the new algorithm and the result of correlation based template matching is shown in Fig 3c. The lesion of very low grey level difference in the CT

image of Fig 4a is enhanced very clearly after application of the new algorithm as shown in Fig 4b. Fig 5a is an MR image of large hydatid cyst and Fig 5b is the output image after processing. Fig 6a and Fig 6b demonstrate the application of the algorithm in ultra sound image. From these results it can be proved that the clear detection of different types of focal liver lesions can be done with the help of the new algorithm. This is helpful to the radiologist to detect the lesions without any manual error because of the enhancement of the lesions of even very small size. Fig 7 shows a graph showing the variation of execution time with the size of the template. The size of the template for each case is taken as the same. The size of the template varies in each case as the selection of the template is done manually. To plot the graph the search image and the templates are resized in each case as indicated in the table1. The execution time is found to be more or less same for the template of the same size for the images from different imaging modalities. It can also be seen that as the template size decreases the execution time increases. As the size of the template increases the execution time reduces, reaches nominal values and remains in the same range. The path of variation is found to be the same for all the five cases. This shows the reliability and efficiency of the algorithm.

Original Image

Proposed algorithm

Conventional algorithm

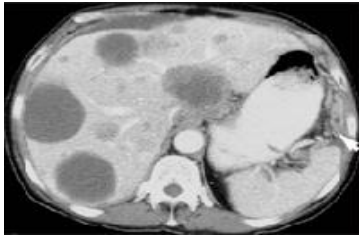


Fig 2a

Fig2b

Fig 2c

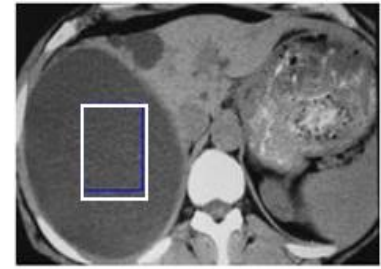
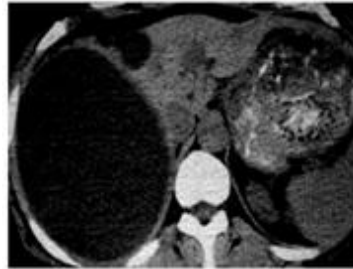
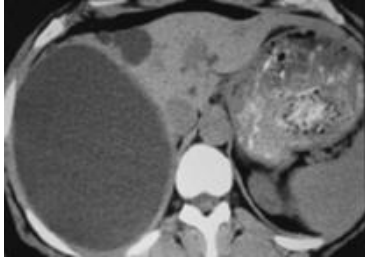


Fig 3a

Fig3b

Fig 3c

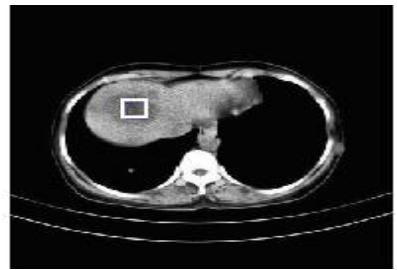
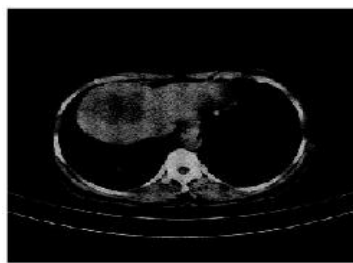
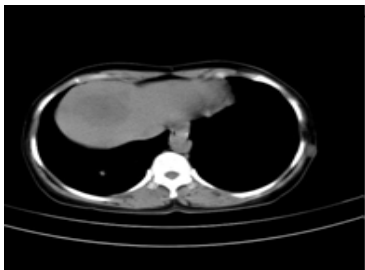


Fig 4a

Fig4b

Fig 4c

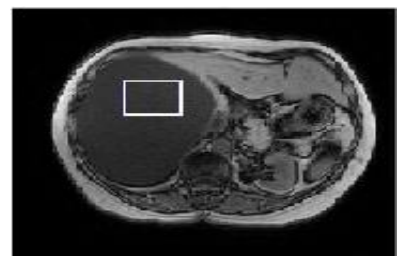
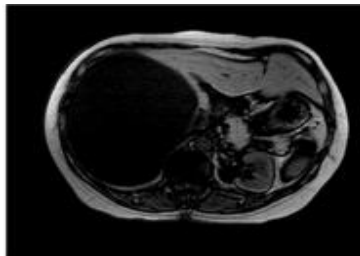
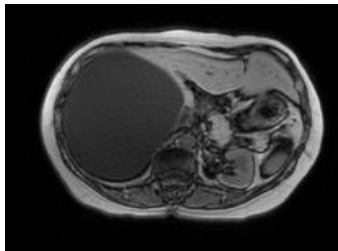


Fig 5a

Fig 5b

Fig 5c

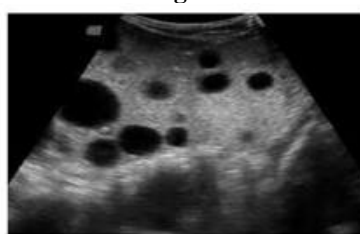
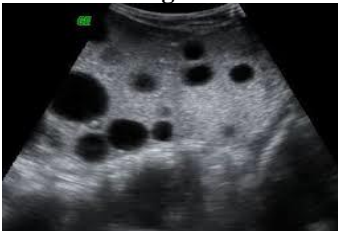


Fig 6a

Fig 6b

Fig 6c

Table 1 Execution time for different template size of different images

Size of Template	Execution Time(sec)				
	Image 1	Image 2	Image 3	Image 4	Image 5
[2 2]	42.14	44.05	41.72	42.28	42.88
[4 4]	16.30	13.60	13.72	13.90	13.51
[5 5]	11.81	12.62	10.63	10.81	11.07
[8 8]	7.47	9.01	6.20	6.79	7.07
[10 10]	7.49	6.57	5.72	6.16	5.61
[20 20]	6.29	4.55	4.53	5.27	5.59
[25 25]	5.47	5.22	5.52	4.34	4.03
[40 40]	5.15	5.09	4.36	3.86	4.18
[50 50]	5.99	4.39	4.29	4.19	3.73
[80 80]	4.91	4.19	4.06	3.99	4.14

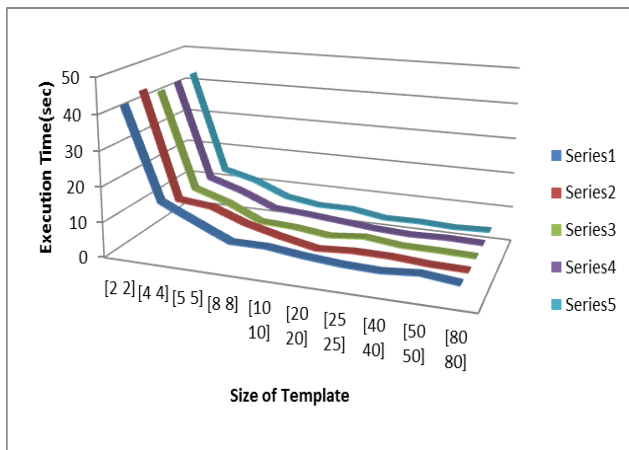


Fig. 7 Size of Template Vs Execution Time

VIII. CONCLUSION

The proposed algorithm gives encouraging results after processing images from three common imaging modalities viz. USG, CT, and MRI. The algorithm is based on grey level difference and simple mathematical operation. The lesions of different size and shapes can be easily detected. The computational complexity is reduced considerably which will reduce the computation time. The size of the template image also plays a vital role in the execution time which can be observed from the graph. The execution time for the normal size remains approximately same and it follows the same path for different images. Thus the algorithm helps to detect different FLLs effectively and efficiently.

REFERENCES

- [1] Yongbum Lee, Takeshi Hara, Hiroshi Fujita, Shigeki Itoh and Takeo Ishigaki, "Automated detection of pulmonary Nodules in Helical CT images based on an improved template matching Technique" IEEE Transaction on medical Imaging, Vol 20, No.7, July 2001
- [2] L. Ding, A Goshtasby, & M. Satter, "Volume Image Registration by template matching", Elsevier, Image and vision computing, 821-832, 2001
- [3] Sarvaiya J N, Patnaik S and Bombaywala S, "Image Registration by Template Matching Using Normalized Cross-Correlation", IEEE international conference on Advances in Computing, Control and Telecommunication Engineering, 2009
- [4] Lena Costaridou, "Medical Image Analysis Methods" CRC, Taylor and Francis, Taylor and Francis group, 2005
- [5] Satoshi Kondo, Konica Minolta "Liver Ultrasound Tracking Using Long-term and Short-term Template Matching", Proc. MICCAI workshop: Challenge on Liver Ultrasound Tracking, 2014
- [6] Kinda Anna Saddi, Mika'el Rousson, Christophe Chefid' hotel, and Farida Cheriet, "Global-to-Local Shape Matching for Liver Segmentation in CT Imaging",

<http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.126.6650>

- [7] B.B. Gosnik, S.K. Lemon, W.Scheible, and G.R. Leupold "Accuracy of ultrasonography in diagnosis of hepatocellular disease", AJR, vol.133, pp. 19-23, 1979.
- [8] R.Suganya, S.Rajaram "Classification of Liver Diseases from Ultra sound Images Using a Hybrid Kohonen SOM and LPND Speckle Reduction Method", IEEE international conf.on signal proc. Comp. and cont., Wagnaghat Solan India, pp 1-6, , 2012
- [9] Karen M Harton MD, David A Bluemke MD, Ralphe H Hruben MD, Philippe Soyar MD, PhD Elliote K Fishman MD, "CT and MR Imaging of benign hepatic and biliary tumors", vol. 19 Issue 2, March, 1999
- [10] Atom P Dhawan, "Medical Image Analysis" IEEE Press series in Biomedical Engineering, second edition, 2011
- [11] R. M. Pickett: "The perception of visual texture. J. of Experimental Psychology." 68: 13, 1964.
- [12] A.H. Mir, M. Hanmandlu, S.N. Tandon, "Texture Analysis of CT Images" IEEE Engineering In Medicine And Biology, IEEE 14 (6), 781-786, , Nov Dcec 1995
- [13] Roger M. Dufour, Eric L. Miller, Member, IEEE, and Nikolas P. Galatsanos, Senior Member, IEEE, "Template Matching Based Object Recognition With Unknown Geometric Parameters", IEEE Transactions on Image Processing, vol. 11, no. 12, December 2002
- [14] Chin-Sheng Chen, Jian-Jhe Huang, Chien-Liang Huang, "Template Matching using Statistical Model and Parametric Template for Multi-Template " Journal of Signal and Information Processing, 4, 52-57, 2013
- [15] https://en.wikipedia.org/wiki/Template_matching
- [16] Mikhail J. Atallah "Faster Image Template Matching in the Sum of the Absolute Value of Differences Measure" IEEE Transactions on Image Processing, vol. 10, no. 4, April 2001
- [17] T.Mahalakshmi, R.Muthaiah and P.Swaminathan School of Computing, SASTRA University, "Review Article, An Overview of Template Matching Technique in Image Processing", Research Journal of Applied Sciences, Engineering and Technology 4(24): 5469-5473, 2012
- [18] Konstantinos G. Derpanis, "Relationship Between the Sum of Squared Difference (SSD) and Cross Correlation for Template Matching", December 23, 2005
- [19] Sarvaiya, J.N.Patnaik, S.; Bombaywala, S. "Image Registration by Template Matching Using Normalized Cross-Correlation", Advances in Computing, Control, & Telecommunication Technologies, ACT '09. International Conference IEEE, 2009.
- [20] D. M. Tsai ,C.T. Lin, "Fast normalized cross correlation for defect detection", Pattern Recognition Letters 24, 2625-2631, 2003
- [21] www.mathworks.com
- [22] R C Gonzalez, R E Woods, "Digital Image processing", Prentice Hall 2002
- [23] R C Gonzalez, R E Woods, "Digital Image processing using MATLAB", Prentice Hall 2002

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