TEST Engineering & Management

May-June 2020
ISSN: 0193-4120 Page No. 3772-3778

Auto Multi-ROI Detection on Medical Images for Data Hiding using Improved ORB Features and Optimised Clustering Algorithms

[1]R. Sreejith, [2]S. Senthil

[1]Research Scholar, School of C&IT, REVA University, Bangalore, India, r_sreejith@hotmail.com
[2]Director, School of Computer Applications, REVA University, Bangalore, India
senthil.s@reva.edu.in

Article Info
Volume 83
Page Number: 3772-3778
Publication Issue:
May-June 2020

Article History
Article Received:*19 November 2019*
Revised: *27 January 2020*
Accepted: *24 February 2020*
Publication: *12 May 2020*

Abstract

Telemedicine plays a vivacious role in collaborative clinical decision making, however secure and scalable data sharing mechanism is a challenge. The Office of the National Coordinator for Health Information Technology's (ONC) has given a roadmap for data protection and regulation that telemedicine architecture should abide. To address the confidentiality problem, various encryption schemes are used along with several steganography methods to hide the clinical data in respective medical images. By doing so, Integrity and confidentiality of these data can be maintained concerning telemedicine applications. Several pieces of research were done to embedded Electronic Patient Record(EPR) into the Non-Region-of-Interest (NROI) segment of that medical image, of which ROI is selected by a practitioner. The Paper proposes two distinct mechanisms for auto multi Region-of-Interest detection which can be used for any EPR embedding purposes. Auto ROI detection is done by extracting feature points from the medical image using improved Oriented FAST and Rotated BRIEF (ORB) and ROI framing using controlled K-Means and HDBSCAN clustering algorithms. The experimental result shows that the proposed methods are efficient to the all type of medical image for Auto RONI detection.

Keywords: *Telemedicine, Data Hiding, Steganography, Region-of-Intrest, Feature Extraction, Clustering, ORB, KMeans, HDBSCAN.*

1. Introduction

The rapid growth in digitization also hit the world of medical sciences in different aspects of technology and purpose. The development in hospital digital systems allows consultants and patients to share information between then for telediagnosis and telesurgery. To serve the purpose, medical images and Electronic Patient Record (EPR) of the corresponding patient have to be shared, which is often closely coupled to the patients' privacy. The public network chain called Internet brings several security threats such as Confidentiality and Integrity along with the comfort and convenience [1]. There are a couple of studies conducted along the globe to prove the necessity, challenge and need for the security of such tightly coupled telemedicine applications[2].

The above said concerns related to the integrity and privacy of medical data can adversely affect the growth of telemedicine application and its benefits to society [3]. Trust by the consumer is so important in such a system to improve healthcare availability, quality and effectiveness worldwide. The need and demand for remote healthcare units are rapidly increasing to make the diagnosis and follow-up of treatment more accurate and ease. To make this vision

TEST Engineering & Management
May-June 2020
ISSN: 0193-4120 Page No. 3772-3778

happened, there are numerous researches happened to explore the possibilities of technology in the healthcare environment. Most of the patient records consist of Medical image and related information including personal information, diagnosis report and even payment credentials. Cryptography and Steganography are the most common techniques used even today to make these data secure over the network in telemedicine applications.

Most of the studies focus on steganography and data hiding methods which hide patient records in the medical images. Later, the studies focus on reversible data hiding methods by which the medical image quality can be maintained. Such feed-forward researches in the area result in the technique called Region-of-Intrest (ROI) based data hiding or tamper localisation which focuses on embedding data in Region-of-Non-Intrest (RONI) [4]. ROI detection is manually done by a practitioner for each of the image, which is a time-consuming process throughout. For data integrity purpose, ROI detection can be done based on the depth of the image as this ROI will never be used for diagnosis. The proposed work focuses on contributing an auto multi-ROI detection framework in medical images for data embedding purpose using feature extraction algorithms[5] and clustering algorithms.

2. Existing and Related Techniques

Due to the rapid increase in demand and technology in telemedicine sector, there are enormous study happened in this platform to exploit the benefits of telehealthcare. To know more about the scope, let us discuss a few studies happened to improve telemedicine opportunities for the social benefit. Also, we will look deep into the technological area which may help to support the scope of the proposed study.

Medical Patient Records are one of the most secrecy preserved information as per different Information Acts by various government bodies. When the use of technology to store and transfer those data are rapidly increasing to serve the purpose of healthcare remoting concept, there are a lot of information handling roadmaps given by different organisations such as Office of the National Coordinator for Health Information Technology's (ONC) to heal the privacy issues [3]. The common way to handle is the use of steganography and data hiding techniques where the Electronic Patient Record (EPR) will be embedded in a cover medical image. This will wrap the presence of such information inside the image. Later, the basic technique alone is not meeting the purpose as the concept of confidentiality is not confined. Then the concept of encrypting patient records to confirm the confidentiality of data came to practice. For this purpose, different encryption techniques have been developed with a higher security scale. There are several comparison research[6] happened to define which is the best object detection method for the specified purpose.

Zailiang Chen, Huajie Huang, Hailan Shen and Beiji Zou proposed two algorithms that use the saliency map[7]. These two algorithms are designed for different application scenarios. The algorithm is applicable to extract ROI of simple images that needs less runtime. The algorithm based on salient regions is adaptable to compute ROI of complex images with a linear increase in runtime. For such images, they have combined these two algorithms in accordance with the need of extraction that gets completed with an accurate ROI in considerably minimal runtime.

M. Kasiselvanathan, V. Sangeetha and A. Kalaiselvi have proposed an algorithm[8] for palm pattern images using SIFT feature extractor method. They have implemented matching, recognition, authentication and their matching performance using OpenCV. The results show that basic SIFT feature extractor method gives considerably fast and improved performance than the conventional ORB method.

Ali Nozari Pour, Ehsan Eslami, Javad Haddadnia proposed a new dimension[9] for the vein pattern extraction called 'square thresholding' which drastically improves the feature extraction of vein-patterns. To achieve this they have computed the average grey level of the pixels in a 5×5 neighbourhood which is then compared with 9×9 neighbourhoods. They have verified the algorithm that they proposed with 1,200 images. They were able to gain accuracy of 96.41% through their test over the specified images.

A novel approach is introduced by Mythili Thirugnanam and

S. Margret Anouncia in their work for the auto-ROI extraction from radiographic images with context to industry[10].The result outlines the inevitability of segregating foreground & background images in industrial radiographs by an intensity-based filtering approach. The results produced shows that clustering techniques are better for extracting circular defects and forelongated defects the edge-based methods perform the best.

Samuele Salti, Alioscia Petrelli et.al has proposed a method for traffic sign detection via interest region extraction[11]. They made a combined approach of 'solid image analysis and pattern recognition techniques' that can be able to handle the problem of traffic sign detection from data in mobile mapping. They claim the difference of their system from the majority of other systems is that pipeline runs based on interest regions extraction whereas other methods use sliding window detection.

From the extensive literature study, the research focus is turned towards designing a framework for extracting ROIs from medical image data hiding and data sharing applications using feature extraction algorithms and clustering algorithms which runs in a minimal system requirement.

May-June 2020
ISSN: 0193-4120 Page No. 3772-3778

3. Proposed work

The focus of the work falls on helping a data hiding or steganography algorithm to support finding ROI on the medical area by which the electronic patient record details can be embedded in RONI regions of that medical image. In a medical image of any clinical report say Xray, CT scan, MRI or any such images, mostly 50 per cent of the region has useful clinical data of the patient. But finding the same by a medical practitioner and defining such non-ROI manually may not be a practical scenario for any data hiding system[12][13]. To support this research gap we define a feature description based multi Region-of-Intrest detection on medical images which supports telemedicine data-hiding algorithms[14].

Most of the ROI algorithms use saliency analysis and detection which focus on edge differencing method and frequency differencing methods. For data hiding purpose such methods are more complex and computational resources are overused. As the ROI we are about to define is only for steganography purposes and not used for any diagnosis purposes, we shall go with feature-points based ROI algorithm which shows optimisation of computation resources and time. The proposed work uses different feature point extraction algorithms and unsupervised clustering algorithms to define multiple ROI over the medical images.

Feature Extraction using Improved Oriented FAST and Rotated BRIEF (ORB)

Ethan Rublee, Vincent Rabaud, Kurt Konolige and Gary R. Bradski introduced an algorithm[15] ORB which is a worthy substitute to SIFT and SURF feature extraction algorithms in terms of computation cost and matching performance.

The algorithm is essentially a blend of FAST keypoint detector and BRIEF descriptor with numerous enhancements for the performance. Initially, ORB uses FAST to define keypoints, then to find the closer M points among the extracted feature points using the Harris corner measure. It also usesa triad to produce multiscale-features. FAST feature extractor does not consider the orientation of the feature points extracted. To handle the rotation invariance problem, calculated the intensity weighted centroid of the patch with the located corner at the centre. The vector direction from this point to centroid defines the orientation of the features. The computed movements with x and y that are in a circular position of radius r, where r is the size of the patch improve the rotation invariance of the matching algorithm.BRIEF descriptors are used in ORB which poorly perfume with rotation. To gain control over this, a greedy search is done among all possible binary tests to find the one that has both high means and variance near to 0.5 and the result is called rBRIEF.

Multi-probe LSH is used for descriptor matching which is an improved traditional LSH. The paper proves ORB is much faster than SURF and SIFT. Also, ORB descriptor works better than SURF. ORB feature extractor and the matching algorithm will be a good choice if the computation system is low-power devices or computational time is a constraint.

Dongyue Sun, Sunjie Zhang & Yongxiong Wang in their work[16], introduced an algorithm for feature extraction called 'Accelerated Segment Test and Oriented FAST and Rotated BRIEF (AGAST-ORB)' for optimising the extraction of feature points using the improved AGAST algorithm.

Feature points clustering using K-means and HDBSCAN

To address the problem of data learning and clustering, there are several machine learning algorithms set corresponding places throughout the research. Unsupervised machine learning algorithms are such a machine learning algorithms which train itself without any labelled fields in data.K-means clustering algorithm is one among such unsupervised learning method which has high control over clustering methods and has a good proved computational efficiency.

The K-means algorithm specifies or identifies a k number of centroids over which every data point are allocated to the nearest cluster by observance the centroids as minimal as possible. The term 'means' in the K-means refers to averaging of the data used for finding centroid. A randomly selected centroids group is selected as an initial group which will be used as the starting points for every cluster. Then the learning part is done by optimizing the position of the centroid by continuous iteration. The process iteration ends with creating optimized clusters when the centroids become stable or the defined iterations achieved. We will be defining a control function to determine the number of optimized clusters needed for each image feature points which may be single ROI or multi-ROI based on the cluster derivation.

Ricardo J. G. B. Campello, Davoud Moulavi, Joerg Sander in their study[17], proposed an " improved density-based hierarchical clustering method", which constructs a simplified tree of significant clusters with a clustering hierarchy. The work results in a complete density-based clustering hierarchy which extracts all possible groups of infinite range density thresholds and from which simplified clusters can be defined.

In the proposed work, improved ORB feature extraction algorithm is used to extract the feature points and feature descriptors from the medical images.

May-June 2020
ISSN: 0193-4120 Page No. 3772-3778

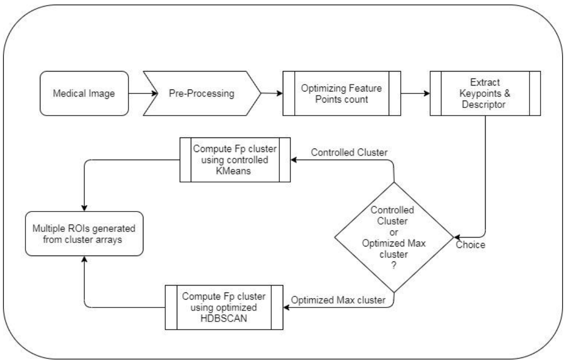

Figure 1: ROI detection

The above figure (Figure 1) shows the system flow of the proposed work. The flow starts with the input medical image followed by pre-processing. Next step will compute the optimal feature points extracted by the Feature extractor module. The preprocessed image is fed to the Feature extraction module to define feature points and descriptors. Based on the user specification either of the clustering methods is invoked (1) Controlled clustering (2) Optimized max clustering. Algorithm 1 & 2 clearly explains the process of the proposed work. If the system demands the minimal ROIs then method one is advisable. If the base system demands the maximum ROIs from the Image[18], for example: to be shared as visual shares second method will be advisable. Once the clustering process is completed, the procedure will return the ROIs coordinate to the base system.

Algorithm 1: Main Algorithm - ROI Detection

procedure MAIN(img[])
Get the Medical image and convert it to grayscale vector.
Compute the feature threshold ‘Fn’by summing up the image dimensions.
Initiate performance measure scale.
Set the ORB feature point required ‘nfeatures’ as ‘Fn’.
Extract the keypoints ‘kp’ and descriptors from the medical image.
rois[] = ROI(kp,img.Xshape,img.Yshape)
for each roi **in** rois **do**
  return Xmin, Ymin, Xmax, Ymax for each which defines each ROI.
Return ROI coordinated to the calling application function to proceed with the ROI regions.

Algorithm 2: ROI Finder

Procedure ROI (kp,Xshape,Yshape)
Kpx <- Sort the kp coordinates with respect to increasing X coordinates.
Kpy <- Sort the kp coordinates with respect to increasing Y coordinates.
for each k **in** kpx **do**
  find the current and previous x the coordinate difference, add to Dx.
for each k **in** kpy **do**
  find the current and previous y the coordinate difference, add to Dy.
Find the Threshold Distance by
  Tx <- $\log_2$(Xshape)
  Ty <- $\log_2$(Yshape)
Computing X represent & Y represent by
  for each coordinate c **in** Dx **do**
    if c[x] ≥ Tx **then**
      increment Xr
  for each coordinate c **in** Dy **do**
    if c[y] ≥ Ty **then**
      increment Yr
if Controlled clustering **then**
  Compute the Optimal Cluster count as
  C_count = floor(Xr + Yr)
  if C_count == 0 **then**
    C_count=1
  Define and fit the Kmeans cluster with the cluster count as C_count and data as Kp.
else if optimized Max cluster **then**
  Compute the hdbscan cluster with metric as ‘manhattan’, minimum cluster size as ceil of √√ len (fp).
for 0 **to** cluster_label_max+1 **do**
  Set cluster x coordinate, y coordinate and the label to the cluster_array.
for each set **in** cluster_array **do**
  Compute Ceil of Min (x), Ceil of Min(y), Floor of Max(x), Floor of Max(y) to ROI array.
Return the ROI array to the main function.

4. Performance Analysis and Results

The proposed method is designed with a purpose to constrain limited with data hiding and not for any diagnostic purpose. By auto defining the ROIs, the data embedding system can embed the medical data over the RONI regions as per the desired data hiding methods[19]. There are few embedding techniques which uses virtual cryptography technique for secured handling of medical images by transferring medical images as ROI shares[13][20]. The results shown below are processed with the threshold distance calculated by computing logarithmic coordinate shapes base two. The threshold distance can be optimized based on the system requirement or demand. Figure 2.(a) & (b) shows the ROI framed on an input image of Bone Xray and Brain CT scan respectively. From the result, it is clear that the features are defines based on the descriptors and density of the section by which the centroid focus on the differential edge features. Figure 3 & 5 shows a multi ROI selected on a grouped report of PET scan and MRI scan of the brain. The result proves the ROI detection works in-depth with the single and grouped medical image of any type of medical image with optimal feature extraction. To check the efficiency of the algorithm on an almost flat image test is done an

May-June 2020
ISSN: 0193-4120 Page No. 3772-3778

ultrasound image as shown in Figure 3. The result shows a satisfying result in finding ROI even on a considerably flat image. Many medical images have visible visual information on the image, the algorithm frames such information as ROI if the region has a depth field as shown in Figure 6 which is a CT scan of the thorax.

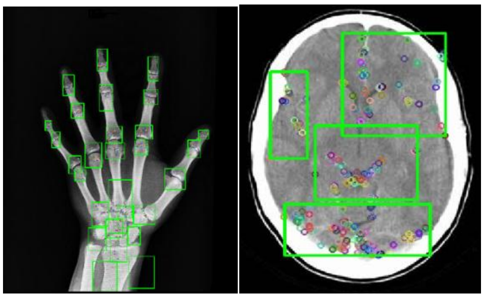

Figure 2: (a): ROI of Bone XRay (b) Multi ROI of CT scan Brain

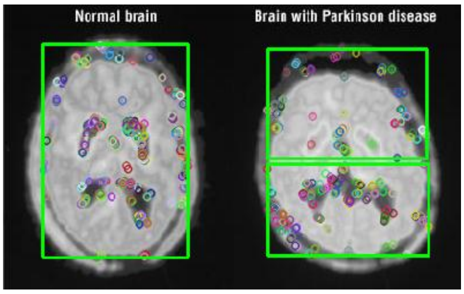

Figure 3: ROI detection in a combined PET scan Brain

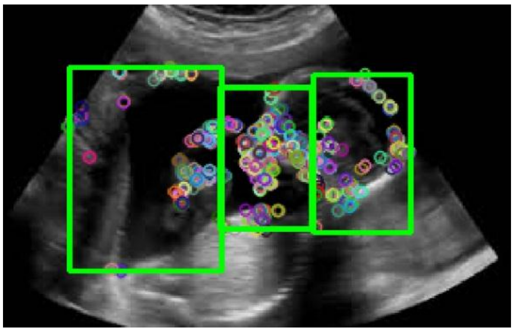

Figure 4: Multi ROI in an Ultrasound image

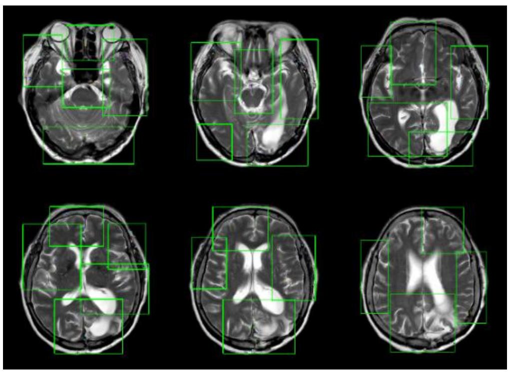

Figure 5: Multi ROI in a group Brain MRI Scan

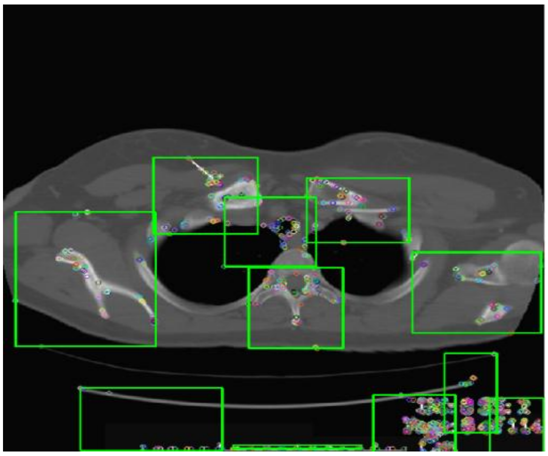

Figure 6: ROI on CT Scan of Thorax

The performance of the proposed framework is analysed based on the computation time against the type of medical images and numbers of ROI generated. For the computational consistency and to evaluate the performance of the proposed algorithm, the tests are done on a minimal requirement environment with 2.7Ghz clock speed processor with no GPU boosts and 4 GB of DDR3 RAM running a 32 bit OS. The algorithm is implemented using Python Language. The test results are bounded purely to these environmental constraints. The algorithm is tested on different medical image data set of fixed image dimensions after converting it to the grayscale point. Table 1 shows the average computational time required by the proposed algorithm on the above-specified system environment. The result produced is satisfying even in the range of low computation system environment. As there is no similar work addressing this gap is found in the literature, no comparative analysis is made for the same.

Table 1: Average Computational Time on the different image set

Image	**Single (s)**	**Group (s)**	**ROI recreation accuracy**
Xray	0.105	-	100%
MRI	0.131	0.152	100%
CT scan	0.094	0.112	100%
Ultrasound	0.116	-	100%
PET	0.127	0.163	100%

5. Conclusion

Telemedicine applications are gaining advantages over the last decades due to the interoperable communication facilities of health centres over the world. This hard growth of application invites several threats and vulnerability to the Electronic Patient Record (EPR) transfer over the public network. Also, the increase in such medical record resource demands several global alternative ways to handle such situations. One of the common ways is to separate the medical image to ROI and RONI regions by which several embedding, cryptographic and visual encryption (transfer of shares) algorithms can be applied to gain control over security and integrity of medical records. The proposed work focus on supporting such above mentioned algorithms by providing auto-detected ROIs to provide their functionalities as required. To achieve this, we defined a framework which provides two way of ROIs definition, a) Controlled Clustering and b) Optimized Max clustering as per the requirement of the base using algorithms. For Controlled Clustering method algorithm uses improved ORB feature extraction algorithm and controlled KMeans clustering. And for the second method algorithm uses Max optimized HDBSCAN clustering. The above experimental results clearly show the efficiency of the algorithm to adopt any low-level specification system environment and have a recreation accuracy of 100% in ROI definition. Further study can be extended to neural network-based ROI detection based on the training for better data hiding as well as diagnostic purposes.

References

[1] H. M. B. S. Y. R. R. C. G. Coatrieux, "Relevance of watermarking in medical imaging," Proc. of IEEE EMBS Int. Conf. on Information Technology Applications in Biomedicine,, p. 250–255, 2000.

[2] R. Ashley, "Telemedicine: Legal, Ethical and Liability considerations," Journal of the American Dietetic Association, 2002.

[3] J. C. K. T. M. Hale, "Privacy and Security Concerns in Telehealth," American Medical Association Journal of Ethics , vol. Volume 16, no. 12, pp. 981-985, December 2014.

[4] X. Q. ,. G. X. Yuling Liu a, "A ROI-based reversible data hiding scheme in encrypted medical," J. Vis. Commun. Image R., vol. 39, pp. 51-57, 2016.

[5] A. Olaode, G. Naghdy and C. Todd, "Unsupervised Region of Intrest Detection Using Fast and Surf," Computer Science & Information Technology,, vol. 5, no. 4, pp. 63-72, 2015.

[6] K. U. Sharma and N. V. Thakur, "A review and an approach for object detection in images," Int. J. Computational Vision and Robotics, vol. Vol. 7, no. Nos. 1/2, pp. 196-237, 2017.

[7] Z. Chen, H. Huang, H. Shen and B. Zou, "ROI extraction based on visual salience and visual evaluation," Int. J. Autonomous and Adaptive Communications Systems,, vol. Vol. 9, no. Nos. 1/2, pp. 57-70, 2016.

[8] M. Kasiselvanathan, V. Sangeetha and A. Kalaiselvi, "Palm pattern recognition using scale invariant feature transform," Int. J. Intelligence and Sustainable Computing, , vol. 1, no. No. 1, p. 44 , 2020.

[9] A. N. Pour, E. Eslami and J. Haddadnia, "A new method for automatic extraction of region of interest from infrared images of dorsal hand vein pattern based on floating selection model," Int. J. Applied Pattern Recognition,, vol. Vol. 2, no. No. 2, pp. 111-127, 2015

[10] M. Thirugnanam and S. M. Anouncia, "A novel approach for automatic region of interest extraction in industrial radiographic images," Int. J. Computational Vision and Robotics, vol. Vol. 4, no. No. 3, pp. 235 -246, 2014 .

[11] S. Salti, A. Petrelli, F. Tombari, NicolaFioraio and L. D. Stefano, "Traffic sign detection via interest region extraction," Pattern Recognition, vol. 48, no. 4, pp. 1039-1049, 2015.

[12] F. A. J. A. S. G. B. Shabir A. Parah, "Hiding clinical information in medical images: A new high capacity and reversible data hiding technique," Journal of Biomedical Informatics, vol. 66, p. 214–230, 2017.

[13] A. Bakshi and A. K. Patel, "Secure telemedicine using RONI halftoned visual cryptography without pixel expansion," Journal of Information Security and Applications, vol. 46 , p. 281–295, 2019.

[14] Z. Brahimi, M.-K. Kholladi, A. T. Hamid Bessalah and F. Mostefai, "An efficient technique for secure transmission of the region of interest in medical images," Int. J. Signal and Imaging Systems Engineering, , vol. Vol. 7, no. No. 2, pp. 116-125, 2014.

[15] E. Rublee, V. Rabaud, K. Konolige and G. Bradski, "ORB: An efficient alternative to SIFT or SURF," in 2011 International Conference on Computer Vision, Barcelona, 2011.

[16] [16] [16] S. Z. &. Y. W. Dongyue Sun, "Improved feature point extraction and mismatch eliminating algorithm," Systems Science & Control Engineering, vol. 8:1, pp. 11-21, 2020.

[17] R. J. G. B. Campello, D. Moulavi and J. Sander, "Density-Based Clustering Based on Hierarchical Density Estimates," Advances in Knowledge Discovery and Data Mining,Springer Berlin Heidelberg, vol. 7819, pp. 160-172, 2013.

[18] R. Keshavarzian and A. Aghagolzadeh, "ROI based robust and secure image watermarking using DWT and Arnold map," AEU - International Journal of Electronics and

May-June 2020
ISSN: 0193-4120 Page No. 3772-3778

Communications, vol. 70, no. 3, pp. 278-288, 2016 .

[19] K.-H. Chiang, K.-C. Chang-Chien, R.-F. Chang and a. H.-Y. Yen, "Tamper detection and restoring system for medical images using wavelet-based reversible data embedding," J. Digit. Imaging, pp. 77-90, 2008.

[20] S. Nithya and K. Amudha, "Watermarking and encryption in medical image through ROI-lossless compression," in International Conference on Communication and Signal Processing (ICCSP) , 2016.