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Investigation and Detection of Upper Airway by Using Region Growing Segmentation during Sleep

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ABSTRACT-This paper exhibits another procedure to detect and analysis of obstructive sleep apnea (OSA) in people. We identified class of the individual, such as normal class, abnormal-medium and abnormal high. The merits of the proposed approach is that it requires less mathematical calculation and does not require any manual adjustments and does not depend on the patient posture. The proposed of region growing segmentation technique is acquire great exactness. It is a quick technique to help for good outcome. Our contribution is to extract the different features of detected by people. Exploratory outcomes on genuine rest apnea information demonstrate the precision of the proposed display. We acquire stepwise outcome.

KEYWORDS-Region of interest (ROI), image processing, obstructive sleep apnea (OSA), 3D region growing.

I. INTRODUCTION

Sleep apnea is a serious chronic disorder in which there is absence of wind current at the nose and mouth forat least 10 seconds. There are two types of sleep apnea: central sleep apnea (CSA) and obstructive sleep apnea (OSA). In CSA (Central sleep apnea) is substantially less basic sleep apnea. Heart failure is the most widely recognized reason for focal rest apnea. In OSA Obstructive sleep apnea is atypical sleep disorder. Obstructive sleep apnea happens when tissues in the upper aviation routes come excessively near each other during sleep, temporarily blocking the inflow of air. Upper aviation route implies the air goes through the nose, mouth and throat [3].Morning headaches, snoring, excessive daytime sleepiness, dry mouth, loss memory, irritation and dispressions these are the symtoms of sleep apnea.Many hazard variables are their like male, overweight, smokers, alcoholic and so forth.

Magnetic resonance imaging (MRI) is extensively associated as a protected and dependable procedure inconcentrate the hidden mechanisms of human speech production [1]. As per the reports from world wellbeing association, the OSA influences around 4% of men and 2% of ladies, which implies that there are around 200 million OSA patients everywhere all over the world [4]. The essential strategy for diagnosing rest apnea is by undergoing the polysomnography (PSG) test. PSG is uncomfortable, costly, and constrained accessibility [5].

The objective of segmentation is to simplify bespeak of an image into something that is more significant and simpler to investigate. Image segmentation is normally utilized to find items and limits in pictures. Regions are utilized to translate pictures. A region may correspond to a special object, or different parts of an object.

II. OBJECTIVES

The objectives of this paper are as follows

- (a) To identify the issue in pharyngeal aviation route
- (b) To explore of obstructive occasions
- (c) To extract feature of images



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III. LITERATURE SURVEY

Z.Raeesy et al. [1] automatic segmentation of huge database of phonic tract pictures for thepurposes of speech generation studies. This appeal to utilize PCA-based recursive limitboundary segmentation (RBS) historic point labelling appeal to andoriented active shape models (OASM). The downside of this paper is that the manual examination and segmentation of phonic tract shapes can bean extremely duty concentrated and tedious assignment.

H.Ammar et al. [2] exhibited another appeal fordetecting apneaevent isdisplayed in this paper. The procedure of this paper, initially to identify breathing development than re-establish this growth. Toallow the distinguish betwixt normal breathing event and OSA event. The behoof of the proposed approach are that it doesn't require any manual changes and does not rely on upon the patient stance. By utilizing measurable investigation a superior of the identification and preferable outcomes. At last apnea occasions and typical breathing are identified.

S.Guttaet al. [3] oxygen saturation and breath signals are the mostnormally utilized physiological signals for sleep apneadiscovery. Exhibit a numerical model relating theperipheral oxygen saturation (SpO2) to the breath signal. The model parameters evaluated by solving a nonlinear least square optimization issue. Results on real sleep apneainformation demonstrate the precision of the proposed display. The significant favorable circumstances of this paper are to joining sensor information with the cardiorespiratory model data of sleep apneainformation framework.

Fan Liu et al. [4] proposes another structure to enhance the execution of recognizing OSA (obstructivesleep apnea) occasions. The key idea of this structure is to partition every potential occasionsegment intovariousphases, from which theyadditionally separate fine-grained components to describe respiratorypattern comprehensively. But the one drawback is that theoptimize the proposedstrategy to be visible signs of improvement grouping execution when contrasted with this paper.

G.Memis et al. [5] in this paper, they appear a multimodal approach for the obstructivesleep apnea (OSA) classification task.Particularly theyextract features from electrocardiograph (ECG) and saturation of peripheral oxygen (SpO2) signals and combine the features with a proper fusionstrategy. Here they utilize multimodal appeal to that performsfeature level fusion of two physiological signals, namely the electrocardiography (ECG) and saturation of peripheral oxygen (SpO2) for efficient OSA classification.The proposed multimodel appeal to the feature-levelcombination gives the best precision with the SVM strategy. When utilizing the single modular approach, the exactness diminishes. The drawbacks of this paper are that the duty lies on the examination of morevigorous combination forms by utilizing appropriate element determination strategies.

Z. Moussavi et al. [6] this paper reports on a pilotenquiry of auditoryproperties of respiratory vox in connection to obstructive sleep apnea (OSA). Utilizes the breathing high-pitched data asinput. Thesounds power spectral energy and phase responses were calculated for each respiratory phase, in this duty theydemonstrated the distinctions in auditoral properties of the upper aviation route in connection to OSA amid alertness. Thesignificant points of interest of this paper is that breathing sound recording is moderately simple to do however one trouble is give low quality breathing sounds.

Cheng Shi et al. [7] they built up a real time sleep apnea monitoringframework called apnea Med Assist II. This has three sensors specifically, ECG, SpO2 and breath sensor.these sensor are associated with a smarthphone through Bluetooth. The apneaMedAssist II framework is a totally mechanized remote diagnosing framework. Real points of interest issmart phone implementation also makes it available for a larger population. The patients no longerneed to go a rest lab and can have the test done in the solace of his home.

L. Almazaydeh et al. [8] this paper concentrates on anautomated classification algorithm which processes short duration epochs of the electrocardiogram (ECG) information. Newsleepapneaclassificationprocedures are nowdays being created by bioengineers for most agreeable and auspicious identification. The presented classificationprocedure depends on support vectore machines (SVM) and has been prepared and tried onsleep apnea recordings from subjects with and without OSA.Built up a model utilizing the ECGsignal features and evaluated its effectivesness. Results demonstrates the SVM with direct bit demonstrates the best exactness.

B. Xie et al. [9] Sleep apnea and hypopnea syndrome (SAHS) is atypicalsleep disorder which is described by irregular breathabnormal breath pause or reduction during sleep. This paperexaminesreal time sleep apnea and hyponea



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syndrome (SAHS) detection based on electrocardiograph (ECG) and saturation of peripheral oxygen (SpO2) signals individually and in combination. This paper studies the real time SAHS detection based on ECG and SpO2 signals, bothalone and in mix. Proposed SpO2 features showed a superiordiagnostic capacity than ECG highlights. The real points of interest can give an attractive discovery execution.

A.Yadollahi et al. [10] recorded tracheal sound, flow rate and head position from 11 individuals with OSA during sleep and wakefulness.They explored two methodologies forcalibrating the parameter of acoustical flow estimation model based on the knowninformationrecorded during wakefulness and sleep. The results to be visible that the acoustical flow estimation parameterschange from wakefulness to sleep. The major advantages are that to provide the preferable exactness.



A. Block diagram



Figure 1: Block diagram of system

- (a) ROI: To take an image as an input and to select the region of interest. An ROI is manually selected (red), two seeds are placed within the ROI and a threshold is determined based on the first image.
- (b) Pre-processing: The next block is the pre-processing block. Pre-processing is the strategy of improving information images preceding computational handling. The aim of image enhancement is to enhance the interpretability or impression of data in images human watchers, or to give `better' contribution for other computerized picture handling strategies.
- (c) Region growing: 3D region growing strategy is an image segmentation technique. The principle objective of image segmentation is to partition an image into regions. Region based segmentation is a system for deciding the locale specifically. The first image is segmented utilizing multiseeded 3-D region growing. There are numerous varieties of region growing, but the basic steps that are basic to all region growing techniques are as per the following. Initial, at least one seeds should be put in the image that will be segmented (at least one seed for each segment). The motivation behind these seeds is to serve as starting points for the segmentation procedure. These seeds can be set physically by the client, or automatically by an algorithm. Automatic seed placement is generally favoured, but automatic placement is not always reliable (or even possible). Each seed is produced using one or few associated pixels. Once the seeds are put, the growing process can start. To develop each seed into an area, the region growing procedure begins by analyzing each of the pixels or voxels that constitute the neighbours of an offered seed, to figure out whether these neighbors should be added to the region.
- (d) Feature extraction: The purpose of feature extraction to extract the various features such as, SUM, VAR, MINAX, ENRG, ENTRP, MAXPRB, MEAN, CONTR, DISSM, and HOMOGNT.
- (e) Classification: The goal of normalized minimum distance classifier to classify in three conditions namely, normal, abnormal-medium and abnormal-high.



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B. Flow chart



Figure2: Flowchart of system

To take input image than read this image. After that to demonstrate this image. RGB image is converted into gray scale image. Region of interest (ROI) is selected. Toput the two seeds from the hardpalate to the epiglottis in the midsagittal slice of the reference frame. Two seeds are set inside the mid-sagittal slice, one in the nasopharyngeal airway and one in the oropharyngealairway.ROI resize (200*200 pixels). Contrast adjustment of this pixel. 3D region growing methodology is animage segmentation system. Morphology is a branch of science dealing with the examination of theframe and structure of organisms and their particular basic components. This includes aspects of the outward



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appearance (shape, structure, color, and pattern, size), i.e. outside morphology, and also the frame and structure of the interior parts like bones and organs, i.e. inward morphology. The Gray Level Coocurrence Matrix (GLCM) technique is away of extracting second order statistical texture features. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The minimum distance classifieris utilized toclassify unknown imageinformation to classes which minimize the distance between the image data and the class in multi-feature space.

V. RESULTS

Demonstrate the three different outputs from three different images. Fig. 4 shows the normal condition of patient. Fig. 5 and 6 shows the abnormal medium and high condition of patient. Before these condition we completed different levels such as read image, image is converted into gray image, select region of interest, different feature extractions, and finally to classify image into three conditions like normal, abnormal-medium and abnormal-high. The extracted features are show in the table no. I.

	Normal	Abnormal
Normal	19	1
Abnormal	0	10

Figure 3: confusion matrix

The figure 3 shows the confusion matrix of result and to calculate the accuracy, sensitivity and specificity are as below, Where, Total image = 100, Train image = 70, Test image = 30, Positive (P) = 20, Negative (N) = 10 Formula of accuracy is given below, to calculate the accuracy of result.

la of accuracy is given below, to calculate the accuracy of result.
$$T_{p+T_p} = 10^{+10}$$

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Accuracy =
$$\frac{1p+1n}{p+n} = \frac{19+10}{20+10} * 100 = 96.6\%$$

The sensitivity or true positive rate (TPR) is as follows,

Sensitivity (TPR)
$$= \frac{Tp}{p} = \frac{19}{20} * 100 = 95\%$$

The specificity or true negative rate (TNR) is as follows,

pecificity (TNR) =
$$\frac{\text{Tn}}{\text{n}} = \frac{10}{10} * 100 = 100\%$$

Where, Tp is true positive and Tn is true negative.



Figure 4: Normal



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•	MAIN_3_5_17 - 🗆 🗙
	STEPS STEPS STEPS
	CLASS:- ABNORMAL-MED

Figure 5: Abnormal medium

ANALYSIS AND DETECTION	MAIN_3_5_17		
BROWSE IMAGE ROI PREPROCESS REGION GROWING EXTRACT FEATURE CLASSIFICATION		RLAY	
	MINAX	85.4008	

Figure 6: Abnormal high

Table I: comparison of three different inputs and extract feature	ıre
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Feature extracted	Normal	Abnormal medium	Abnormal high
SUM	790256	409085	746345
MEAN	2.5e-0.5	2.5e-0.5	2.5e-0.5
VAR	1.52298e-09	4.87114e-09	2.5785e-09
CONTR	1878.79	1638.23	1187.54
DISSM	36.4424	36.099	28.5622
ENRG	8.59176e-05	0.000219841	0.000128137
ENTRP	9.4632	8.44419	8.99447
HOMOGNT	0.0609548	0.0532428	0.0787587
MAXPRB	0.000145522	0.000278671	0.000166143
MAJAX	275.284	236.457	188.849
MINAX	83.651	43.695	85.4008



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VI. CONCLUSION

In this paper, we have proposed a region growing segmentation technique for identification and investigation of obstructive rest apnea (OSA). We extricate different components features such as SUM, VAR, MINAX, ENRG, ENTRP, MAXPRB, MEAN, CONTR, DISSM, and HOMOGNT. We assessed our model on three different conditions such as normal, abnormal-medium and abnormal-high. Result demonstrates the identified sleep apnea is present or not in persons with different features.

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