International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-5, June 2019

An Effective Methodology for Identification of Bone Related Diseases using Bivariate Gaussian Mixture Model

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***Abstract:** Medical imaging deals with the analysis of medical data and helps to have more complete study regarding the diseases. Among the various diseases attributed to human anatomy, bone fracture is one such complication which needs to be diagnosed appropriately. This article formulates a methodology for the identification of bone fracture more appropriately such that effective treatment can be imparted. The works are carried out on benchmark dataset and the results showcase accuracy of around 95%.*

***Keywords:** Bone Fracture, Accuracy, Medical Image, Bivariate Gaussian Mixture Model, Recognition Rate.*

I. INTRODUCTION

Medical imaging is a specialized area of image processing which deals with the analysis of the diseases and helps to have a precise interpretation about disease such that effective treatment can be imparted. Many models have been proposed in the literature for the treatment and analysis of medical related data. The diseases pertaining to human anatomy are mostly considered for the analysis of medical diseases and various methods are considered for extracting the diseased structure. Mechanisms like X-Rays, CT Scans, and MRI images are duly available for extracting the images of the human anatomy. However, among these methodologies, based on the severity of the disease several scanning mechanisms are preferred. Among the various diseases available for medical related diseases, most of the articles were presented in the literature based on the deformities of the brain. The main reason behind this consideration is that the deformities of brain may lead towards severe abnormalities and in particular cases leads towards mortality. Therefore, much emphasis was given to brain related diseases [1], [2], [3], [4]. However, apart from the brain, there are other concerns which trigger recurrently and which may requires immediate medical interventions, these diseases include bone fractures, rib fractures, heart and kidney diseases. There are some predominant symptoms that may be helpful for identification of the diseases related to kidneys, liver, rib etc. and basing on these symptoms an appropriate landmark can be identified and thereby further treatments can be justified.

Manuscript published on 30 June 2019.
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However, in case of bone fractures it is very difficult to understand the hairline fractures and a small delay in the identification of these fractures lead towards the removal of the organs. Therefore, it is necessary to develop insights into these diseases so that the vital organs can be restored. Many articles are therefore proposed in the literature and among these most of the works are based on neural network approaches [5], [6], Edge based methods [7], [8], contour based [9], [10], morphological operations [11], [12] and statistical modeling approaches [13], [14]. Among these models, the diagnosis of a fracture is not accurate because of the reasons; these models are mostly based on the symptoms, the shape of the bone, size, color during the fracture etc. However, the anatomy of the humans differ from patient to patient and they do not have the uniform structure, and therefore considering this as a factor and analyzing is not adequate, also the symptoms are not current , therefore it is needed to develop methods that can overcome this disadvantages' Hence, in this article of the thesis, a Bivariate Gaussian Mixture is considered. The main reason behind the choice of the model is that, bivariate models considers two features and therefore one can associate the symptom along with the structure of the bone, and therefore, one can expect good recognizing accuracy of the symptom. The rest of the paper is structured as follows, the section 2 of the paper highlights a brief introduction about fracture together with symptoms, and section 3 presents the bivariate Gaussian mixture model. In section 4, the dataset considered is presented. The Methodology is highlighted in section 5, the experimentation along with the derived results are presented in the section 6 of the article. The performance evaluation metrics and the evaluation results are presented in section 7, the concluding section 78 summarizes the article.

II. BONE FRACTURE AND SYMPTOMS

Any partial or complete break in the continuity of bone is generally referred as a fracture. This discontinuity may be very narrow, termed as the hair line fracture, and sometimes due to the severity of the fracture, the bone may be broken into several pieces or may result into a wild break, which needs surgery. The treatment depends on the type of fracture and the intensity. Other factors which weakens the bone strength and leads to breakage include; bone cancer, ontogenesis and the result of these fractures are sometimes called as pathological fractures.

A. Symptoms

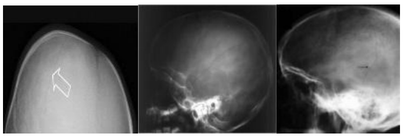
In spite that the bone tissue does not contain any nociceptors, whenever a fracture is witnessed, it leads into severe pain, for the reasons that

a. Breaking in the periosteum, which is a continuous
b. Edema caused due to bleeding at broken vessel evokes pain
c. Muscle spasms
d. Hematoma, near the fracture place

B. Types of bone fractures

The bone fractures are mostly classified into 7 types namely

a. Linear Fracture: Any fracture that is parallel to the bones long axis is termed as the linear fracture



b. Traverse Fracture: A fracture that is located exactly 90 degrees to the bone long axis is called traverse fracture

c. Oblique Fracture: A fracture that is located diagonally with an angle above 30 degrees is generally considered as oblique fracture

d. Spiral Fracture: A twisted bone, if witnessed is called a spiral fracture

e. Impacted fracture : when a fracture is witnessed, in which if one bone gets pushed into the other is called impacted fracture

f. Wedge Fracture : Fractures occurred near the vertebrae are considered to be wedge fractures

g. Avulsion Fracture ; is a deviation in bone fragment is identified ,it is termed as avulsion fracture

III. BIVARIATE GAUSSIAN MIXTURE MODEL

Every image is a group of image regions. Every region in the image is quantized by a pixel having sway of the random factors like vision, brightness, contrast etc. In order to model the pixel intensities within each of the image regions, we assume that every region follow a bivariate Gaussian mixture model. The probability density function of the pixel intensities is given by

$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2(\sqrt{1-\rho^2})} e^{-\left[\frac{1}{2(1-\rho^2)}\left[\left(\frac{x_2-\mu_1}{\sigma_1}\right)^2 - 2\rho\left(\frac{x_1-\mu_1}{\sigma_1}\right)\left(\frac{x_2-\mu_2}{\sigma_2}\right) + \left(\frac{x_2-\mu_2}{\sigma_2}\right)^2\right]\right]} \quad (1)$$

$\mu 1$, $\mu 2$ are any real numbers

$$\sigma 1 > 0,\ \sigma 2 > 0;\ -1 <= \rho <= 1 \quad (1.1)$$

Where $\mu 1$, $\sigma 1$ are the mean and variance of the image, ρ is called the shape parameter.

IV. DATASET CONSIDERED

Published By:
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International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-5, June 2019

V. METHODOLOGY

In order to propose the present method, we have considered a dataset, presented in section 4 of the article. Each of the images are considered and preprocessed such that they are free from noise. The features inside the image regions are identified and each image is given as input to the bivariate Gaussian mixture model. The Probability density functions against each of the images are calculated and this phase is called the training phase. During the testing phase, the processes is repeated and the most relevant images with similar PDF are compared to ratify the type of the fracture.

VI. EXPERIMENTATION AND RESULTS DERIVED

In order to evaluate the proposed model we have conducted the experimentation of our algorithm Finite Bivariate Gaussian Mixture Model on different images namely B0 and B1 where the images B0 and B1 contain 4 sub regions namely bone fracture image with linear fracture (named as B0S1 and B1S1), bone fracture image with traverse fracture (named as B0S2 and B1S2), bone fracture image with oblique fracture (named as B0S3 and B1S3) and bone fracture image with spiral (named as B0S4 and B1S4).
It is assumed that the pixel intensities in each of the segment of the medical image follow a Bivariate Gaussian distribution. The evaluation of the segmentation model carried out by using the objective evaluation technique namely Jaccord Coefficient (J.C), Volumetric Similarity (V.S), Variation of Information (V.O.I), Global Consistency Error (G.C.E) and Probabilistic Rand Index (P.R.I), and the formulas for calculating these metrics are given as follows:

$$Jaccord\ Coefficient\ (JC) = \frac{|X\cap Y|}{|X\cup Y|} = \frac{a}{a+b+c} \quad (2)$$

$$Volume\ Similarity\ (VS) = 1 - \frac{||X|-|Y||}{|X|+|Y|} = 1 - \frac{|b-c|}{2a+b+c} \quad (3)$$

Where, $a = |X \cap Y|, b = \left|\frac{X}{Y}\right|, c = \left|\frac{Y}{X}\right|, d = |\underline{X \cup Y}|$

$$GCE\ (S,S') = \frac{1}{N} min\ \{\sum LRE(S,S',x_i), \sum LRE(S',S,x_i)\} \quad (4)$$

Where, $LRE = \frac{|C(S,x_i)\backslash C(S',x_i)|}{|C(S,x_i)|}$

S and S' are segment classes and x_i is the pixel.

VOI (X,Y)= H(X) = H (Y) – 2I(X;Y) (5)

Where, X and Y are two clusters

$$PRI(S_t,\{S\}) = \frac{1}{\binom{N}{2}} \sum_{i,j,i<j}[I(l_i^{S_t} = l_j^{S_t})p_j + I(l_i^{S_t} \neq l_j^{S_t})(1-p_j)] \quad (6)$$

Where, $p_j = P(l_i = l_j) = \frac{1}{K}\sum_{k=1}^{K} I(l_i^k = l_j^k)$ and the values range from 0 to 1. 1 denotes the segments are identical.

Table 1 Segmentation Metrics used for detection of Fractures

Image	Quality Metric	GMM	Bivariate GMM
B0S1	J.C	0.089	0.795
	V.S	0.432	0.891
	V.O.I	0.4665	5.232
	G.C.E	0.2802	0.4223
	P.R.I	0.504	0.7958
B0S2	J.C	0.0677	0.819
	V.S	0.4212	0.8914
	V.O.I	1.9724	6.2894
	G.C.E	0.2443	0.4664
	P.R.I	0.416	0.6847
B0S3	J.C	0.0434	0.784
	V.S	0.123	0.926
	V.O.I	0.7684	5.5318
	G.C.E	0.089	0.4001
	P.R.I	0.576	0.706
B0S4	J.C	0.0456	0.911
	V.S	0.2233	0.643
	V.O.I	1.268	4.1619
	G.C.E	0.056	0.2949
	P.R.I	0.189	0.5628
B1S1	J.C	0.141	0.826
	V.S	0.413	0.7910
	V.O.I	1.6499	4.4115
	G.C.E	0.1874	0.2752
	P.R.I	0.9256	0.686
B1S2	J.C	0.098	0.896
	V.S	0.0433	0.918
	V.O.I	2.4215	6.6411
	G.C.E	0.2838	0.4661
	P.R.I	0.4807	0.6322
B1S3	J.C	0.0222	0.946
	V.S	0.4223	0.4869
	V.O.I	1.2411	6.7129
	G.C.E	0.1466	0.4559
	P.R.I	0.9576	0.7202
B1S4	J.C	0.455	0.854
	V.S	0.429	0.786
	V.O.I	-8.8e-16	5.0898
	G.C.E	0.119	0.4062
	P.R.I	0.065	0.5573

VII. PERFORMANCE EVALUATION

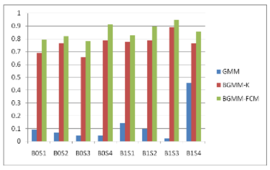

Fig. 1. Graph showing the performance of GMM and BGMM- using Jaccard coefficient

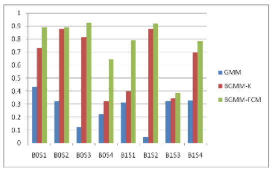

Fig. 2. Graph showing the performance of GMM and BGMM-using Volumetric Symmetry

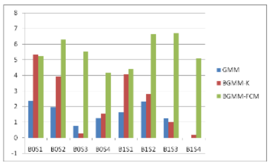

Fig. 3 Graph showing the performance of GMM and BGMM- using Variation of Information

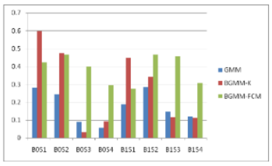

Fig.4. Graph showing the performance of GMM and BGMM- using Global Consistency Error

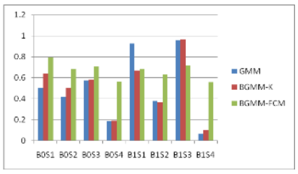

Fig. 5 Graph showing the performance of GMM and BGMM- using Probability Random Index

The performance of the retrieved medical image is done by using subjective and the objective quality testing. The objective quality testing methodologies are most frequently used and compared to segmentation evaluation technique. Since, the objective methodologies are performed with respect to numerical formulas and thereby allowing to compare different algorithms.

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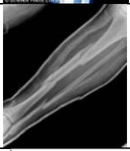
The segmentation outputs obtained are evaluated using segmentation quality metrics such as Jaccord coefficient (JC), Volume Similarity (VS), Variation of Information (VOI), Global Consistency Error (GCE) and Probabilistic Rand Index (PRI) and the outputs obtained after reconstruction is evaluated using image quality metrics namely Average Difference (AD), Maximum Distance (MD), Image Fidelity (IF), Mean Squared Error (MSE) and Signal to Noise Ratio (SNR). The results obtained are presented in Table 3 and graphs are presented from Figure 1 to Figure 5 respectively.

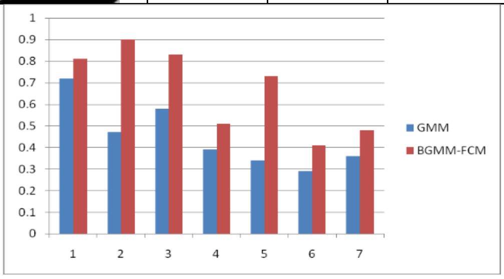
Table 2 Formulas for Quality Metrics used in General

Quality Metrics	Formula to Evaluate
Average Difference	$\frac{\sum_{j=1}^{M}\sum_{k=1}^{N}[F(j,k)-\hat{F}(j,k)]}{MN}$ Where M, N are image matrix Rows and Columns
Maximum Distance	$Max\{\lvert F(j,k)-\hat{F}(j,k)\rvert\}$
Image Fidelity	$1-\left[\frac{\sum_{j=1}^{M}\sum_{k=1}^{N}[F(j,k)-\hat{F}(j,k)]^2}{\sum_{j=1}^{M}\sum_{k=1}^{N}[F(j,k)]^2}\right]$ Where M, N are image matrix Rows and Columns
Mean Squared Error	$\frac{1}{MN}\frac{\sum_{j=1}^{M}\sum_{k=1}^{N}[O\{F(j,k)\}-O\{\hat{F}(j,k)\}]^2}{\sum_{j=1}^{M}\sum_{k=1}^{N}[O\{F(j,k)\}]^2}$ Where M, N are image matrix Rows and Columns
Signal to Noise Ratio	$20.\left(\frac{MAX_I}{\sqrt{MSE}}\right)$ Where MAX_I is the maximum possible pixel value of an image, MSE is the Mean Squared Error

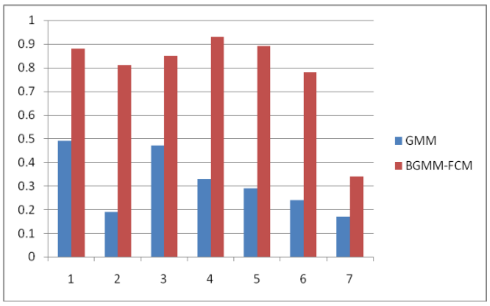
After developing the segmentation algorithm, the algorithm is applied to Linear Bone fracture images obtained from the UCI database of dimensions 150x174 and 163x199 respectively. The initial parameters obtained are used for the reconstruction by assigning each pixel in the PDF. A methodology for Seizures identification is conducted basing on BGMM. The bone fracture is classified into seven types Linear, Transverse, Oblique, Spiral, Wedge, Impacted, Avulsion and the likelihood estimates of each of these regions are estimated. Each pixel is compared against the region and if it does not satisfy the likelihood estimates, they are classified as Bone Fracture. This process is repeated for all the images. The performance of the reconstructed image are evaluated using image quality metrics is presented below.

Table 3. The performance of GMM, BGMM using Quality Metrics

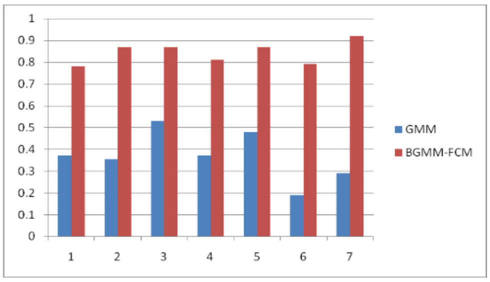
Image	Quality Metric	GMM	Bivariate GMM
	AD MD IF	0.719 0.489 0.47	0.81 0.88 0.78
	AD MD IF	0.47 19 0.4534	0.90 0.81 0.87
	AD MD IF	0.58 0.47 0.53	0.83 0.85 0.87
	AD MD IF	0.49 33 0.47	0.51 0.93 0.81
	AD MD IF	0.44 0.29 0.48	0.73 0.89 0.87
	AD MD IF	0.29 0.24 0.19	0.41 0.78 0.79
	AD MD IF	0.46 0.17 0.29	0.48 0.44 0.92



Graph 6(A) Comparison of GMM VS BGMM – based on Average Difference



Graph 6 (B) Comparison of GMM VS BGMM – based on Maximum Distance



Graph 6 (C) Comparison of GMM VS BGMM – based on Image Fidelity

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From the above Table, it can be clearly seen that the model developed shows better results with respect to the quality metrics. The model is compared with the existing models based on Gaussian Mixture Model.

VIII. CONCLUSION

In this article, a novel methodology is proposed for the identification of the bone fractures more effectively using bivariate Gaussian Mixture model. The results derived are computed against the bench mark metrics and segmentation metrics. The results showcase that the developed method produces better recognition rate when compared to the earlier methods and the model can be utilized in remote areas where there is a primary health center without specialized hospital or doctor facility to carry the first aid and to identify the type of fracture more effectively.

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