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UNSUPERVISED LUMBAR SPINE IMAGE SEGMENTATION USING ENHANCED ROR WITH IMPROVED PRINCIPAL COMPONENT ANALYSIS

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Abstract: This chapter proposes an enhanced ROR using improved principal component analysis (IPCA) with wavelet feature extraction for lumbar spine image segmentation. Initially the preprocessing is carried out with improved principal component analysis followed up with wavelet feature extraction. Then segmentation is carried out using enhanced ROR technique.

Keywords: IPCA (Improved Principal Component Analysis), ROR (Robust Oulyingness Ratio, PCA (Principal Component Analysis), DWT (Discrete Wavelet Transform), Supervised, Unsupervised,

摘要：**本章提出了一种增强的** ROR，**使用改**进的主成分分析（IPCA）**和小波特征提取**进行腰椎图像分割。 **最初**，**使用改**进的主成分分析进行预处理，然后进行小波特征提取。 **然后使用增强的** ROR **技**术进行分割。

关键词：IPCA（**改**进的主成分分析），ROR（稳健的欧林比，PCA（**主成分分析**），DWT（**离散小波**变换），监督，无监督，

1.INTRODUCTION

Image segmentation is an important step in image processing which helps in interpretation and understanding of the image. The goal of image segmentation is to partition an image into a set of disjoint regions with uniform and homogeneous attributes such as intensity, color, tone or texture, etc. In image segmentation the desired objects are separated from the background so that the image could be interpreted in a better way. In general, the color and texture features in a natural image are very complex so that the fully automatic segmentation of the object from the background is very hard.

Unsupervised (automatic) methods (e.g., threshold, watershed, edge detection, morphological operation, neural network, region growing, and shape analysis provide segmentation results without prior-knowledge about the images and do not require user interaction. These methods are usually applicable for the segmentation of well-circumscribed objects. When applied to a stack of medical images, they are able to generate rough segmentation results. These results can be further refined by the intervention of human experts

2.AREA OF RESEACH

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Segmentation is very vital as a first step in Medical Image Analysis (MIA) due to the error resulting from the segmentation is transferred to later steps in MIA. It causes incorrect analysis of image finally. Therefore a correct segmentation method is important. The algorithm is called image segmentation algorithms, play a vital role in numerous biomedical imaging applications and also necessary to be a universal algorithm for better understanding the type, location and detection of the various diseases (Rastgarpouret al; 2013).

In the recent years, various schemes for processing medical images appeared in literature. Researchers have developed many schemes and techniques such as such as Clustering, Threshold, Classifier, and Region Growing for segmenting and characterizing the medical images. The following section provides some common and important approaches that are already appeared so far in the literature on medical image segmentation.

There various image segmentation techniques based on clustering. For examples of clustering algorithm are K-means (KM) clustering, Moving K-means (MKM) clustering and Fuzzy C-means (FCM) clustering. Clustering is the process of separating data into group of similarity. It also known as procedure of organizing objects into groups whose members are similar in certain way, whose goal is to identify structures or clusters existing in a group of unlabelled data. Clustering algorithm is normally being used in computer, engineering and mathematics field (Sulaiman et al; 2010). In the past few decades, the uses of clustering algorithm have been broadening to medical fields, due to the development and advancement of medical imaging fields. Examples of medical images are image of brain, bone, and also chest. Clustering algorithm is suitable in biomedical because it will make the analysis easier.

Segmentation via clustering can also be used to detect the three regions at the brain image. Magnetic Resonance Image (MRI) of brain is one of medical imaging tools used to detect abnormality in brain. From the MRI brain images, the radiologist normally interested to look for three significant regions. The three regions are White Matter (WM), Grey Matter (GM) and Cerebro Spinal Fluid spaces (CSF). Figure 2.14shown three regions of normal MRI brain image. The precise measurement of these three regions is important for quantitative pathological analyses and so becomes a goal of lots of method for segmenting MRI brain image data.

In this work segmentation via clustering method named Adaptive Fuzzy K-means (AFKM) clustering is used to segment the MRI brain image into three different regions. The AFKM method is proposed to prove that it can classify and segment the (Zijdenbos et al; 1994) MRI brain image better than conventional method. AFKM clustering algorithm is combination of KM, MKM and FCM clustering. The features of AFKM are to provide a better and more adaptive clustering process.

3. METHODOLOGY

3.1 Preprocessing using Improved Principal Component Analysis for Lumbar Spine Image Segmentation

Acquisition of the centroids of the lumbar spine image

For a 2-D discrete function $f(x,y)$, the moment of order $(p+q)$ can be defined by

$$M_{p,q} = \sum_{x=1}^{M} \sum_{y=1}^{N} x^p y^q f(x,y) \qquad p,q = 0,1,2,\cdots$$

…….. (1.1)

Where $(p+q)$ is the order of the moment and, M and N represent the numbers of sampling points in space. And well we can define the 0th moment as follows

$$M_{0,0} = \sum_{x=1}^{M} \sum_{y=1}^{N} f(x,y)$$

……. (1.2)

Further, when $p=1$ and $q=0$, and, $p=0$ and $q=1$,

$$\bar{x} = \frac{M_{1,0}}{M_{0,0}}, \quad \bar{y} = \frac{M_{0,1}}{M_{0,0}}$$

……. (1.3)

here $(\bar{x},\bar{y})$ is defined as the centroid coordinates of the object.

When aligning images, we compute the 0th and first-order moments of static image $\boldsymbol{S}$ and moving image $\boldsymbol{M}$ respectively by using equations (1)-(3), and then procure the centroids $(\bar{x}_s,\bar{y}_s)$ and $(\bar{x}_m,\bar{y}_m)$.

Principal Component Analysis (PCA), also called Karhunen-Loeve Transform (KLT), is an orthogonal transform based on the statistical feature and has been used extensively in the field of image processing. In this paper, suppose that $\boldsymbol{Y} \in R^{2\times J}$ and $\boldsymbol{y}_i = [y_{i1} \quad y_{i2}]^T$ ($i = 1,2,\cdots,J$) is an element of the vector set $\boldsymbol{Y}$, and then the eigenvectors of the covariance matrix of $\boldsymbol{Y}$ is invariant to rotation transformation.

Proof. Let matrix $\boldsymbol{Y}$ be rotated by the angle θ, the rotation matrix is expressed:

$$\boldsymbol{R} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix},$$

Then

$$\boldsymbol{RR}^T = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix}\begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},$$

and $\boldsymbol{Y}_R = \boldsymbol{YR}$. $\boldsymbol{M}_{\boldsymbol{Y}_R}$ is the mean vector of $\boldsymbol{Y}_R$ and is expressed as follows:

$$\boldsymbol{M}_{\boldsymbol{Y}_R} = \boldsymbol{E}\{\boldsymbol{Y}_R\}$$

……. (1.4)

where $\boldsymbol{E}\{\cdot\}$ is the expected value of the argument. $\boldsymbol{Cov}_{\boldsymbol{Y}_R}$ is the covariance matrix of set $\boldsymbol{Y}_R$ and is given by the expression

$$\begin{aligned} \boldsymbol{Cov}_{\boldsymbol{Y}_R} &= \boldsymbol{E}\{\boldsymbol{Y}_R\boldsymbol{Y}_R^T\} = \boldsymbol{E}\{(\boldsymbol{YR})(\boldsymbol{YR})^T\} \\ &= \boldsymbol{E}\{\boldsymbol{YRR}^T\boldsymbol{Y}^T\} = \boldsymbol{E}\{\boldsymbol{Y}(\boldsymbol{RR}^T)\boldsymbol{Y}^T\} \\ &= \boldsymbol{E}\{\boldsymbol{Y}^T\boldsymbol{Y}\} = \boldsymbol{Cov}_{\boldsymbol{Y}} \end{aligned}$$

…… (1.5)

From equation 5.5 we know, the covariance matrix of $\boldsymbol{Y}_R$ is the same as that of $\boldsymbol{Y}$, which means that they have the same eigen values and eigenvectors. Therefore, the eigenvectors of the covariance matrix of $\boldsymbol{Y}$ are invariant to rotation transformation, which is to be proved.

According to the process of PCA, the eigenvectors of the covariance matrix are obtained and then are formed into the kernel matrix $\boldsymbol{A} = \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix}$, in which the value e_{11} is used to compute the arcsine value and the rotation angle is obtained. As mentioned before, the method for acquiring the rotation angle from the moving image $\boldsymbol{S}$ by PCA is listed as bellow.

Step1. The image matrix $\boldsymbol{P}_S$ is built, namely, the origin of coordinates is moved to the centroids of the image $\boldsymbol{S}$, which means that the coordinates of the image $\boldsymbol{S}$ are centralized. The $\boldsymbol{P}_S$ denotes the two-row matrix of the coordinates (x,y) in the

image $\boldsymbol{s}$, where the number of elements (i.e. the number of columns) is $M \times N$, that is, $\boldsymbol{P_S} \in R^{2\times(M\times N)}$.

$$\begin{cases} p_S(1,(i-1)\times N+j) = (i-\overline{x_S})\times s(i,j) \\ p_S(2,(i-1)\times N+j) = (j-\overline{y_S})\times s(i,j) \end{cases}$$

…… (1.6)

here $i = 1,2,\cdots,M; j = 1,2,\cdots,N$.

Step2. The matrix $\boldsymbol{P_S}$ is performed by the following operation

$$\begin{cases} \overline{x_P} = \dfrac{1}{M\times N}\sum_{i=1}^{M\times N} p_S(1,i) \\ \overline{y_P} = \dfrac{1}{M\times N}\sum_{i=1}^{M\times N} p_S(2,i) \end{cases} \quad \ldots\ldots \quad (1.7)$$

$$\begin{cases} \overline{p_S}(1,i) = p_S(1,i) - \overline{x_P} \quad (i = 1,2,\cdots,M\times N) \\ \overline{p_S}(2,i) = p_S(2,i) - \overline{y_P} \quad (i = 1,2,\cdots,M\times N) \end{cases}$$

Step3. By using PCA, the covariance matrix of $\overline{\boldsymbol{P_S}}$ is solved and the transformation kernel matrix $\boldsymbol{A_S}$ is got.

Step4. According to $\boldsymbol{A_S}$, the rotation angle θ_S is obtained:

$$\theta_S = \arcsin(e_{11}) \times \frac{180}{\pi}$$

…… (1.8)

3.2 The Lumbar Spine Image Registration using PCA

Image registration or image alignment algorithms can be classified into intensity-based and feature-based. One of the images is referred to as the reference or source and the others are respectively referred to as the target, sensed or subject images. Image registration involves spatially registering the target image(s) to align with the reference image. Intensity-based methods compare intensity patterns in images via correlation metrics, while feature-based methods find correspondence between image features such as points, lines, and contours. Intensity-based methods register entire images or sub-images. If sub-images are registered, centers of corresponding sub images are treated as corresponding feature points. Feature-based methods establish a correspondence between numbers of especially distinct points in images. Knowing the correspondence between numbers of points in images, a geometrical transformation is then determined to map the target image to the reference images, thereby establishing point-by-point correspondence between the reference and target images.

3.3 Algorithm for Spine Image Registration

Step 1: By computing the centroids of the static image $\boldsymbol{s}$ and the moving image $\boldsymbol{M}$, the translation parameters for registration are derived, namely

$$\Delta x = \overline{x_m} - \overline{x_s}, \quad \Delta y = \overline{y_m} - \overline{y_s}$$

…… (1.9)

Step 2: By using KLT, the rotation parameters for registration are acquired, namely

$$\Delta\theta = \theta_m - \theta_s$$

…… (1.10)

Step 3: The moving image $\boldsymbol{s}$ is translated by $(-\Delta x, -\Delta y)$ and rotated by $-\Delta\theta$, which means that the alignment of tow images are performed.

Although PCA can complete the image alignment, its accuracy needs to further be boosted. Therefore, we incorporate EPCA in order to tackle the image alignment.

Improved PCA

Step1: Compute the centroids $(\overline{x_s}, \overline{y_s})$ and $(\overline{x_m}, \overline{y_m})$, and, the rotation angles α_s and α_m of static image $\boldsymbol{s}$ and the moving image $\boldsymbol{M}$

respectively according to the image moments and IPCA.

Step2: Derive the initial values Δx, Δy and $\Delta\theta$ for registration according to equations 5.9 and 5.10.

Step3:Use Δx , Δy and $\Delta\theta$ as the initial translation and rotation parameters for ICP, namely

$$\boldsymbol{T}_0^0 = [\Delta x \quad \Delta y]^T,\ \boldsymbol{R}_0^0 = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix}$$

Step4: Generate the binarized images $\boldsymbol{B_S}$ and $\boldsymbol{B_M}$ with gray value being 0 or 1.

Step5: Extract two point sets of coordinates representing all the pixels with gray value being 1 in the images $\boldsymbol{B_S}$ and $\boldsymbol{B_M}$ respectively.

Step6: Perform and derive the final rotation and translation matrices $\boldsymbol{R}_0^{k+1}$ and $\boldsymbol{T}_0^{k+1}$.

3.4 Wavelet Feature Extraction for Lumbar Spine Image Segmentation

Recently Discrete Wavelet Transform (DWT) has been widely adopted for image analysis. DWT provides both the spatial and frequency domain information of the image. In this paper, DWT analyses the image by decomposing it into various sub bands by passing the image via low and high pass filtering, to extract the features such as energy, mean, variance, and standard deviation.

At first, the input image is passed through a half band digital low pass filter and high pass filter with impulse response g[n] and h[n] respectively. The convolution operation in discrete domain and the signal at the output of down sampler is defined as follows.

$$x[n] \otimes g[n] = \sum_{k=-\infty}^{\infty} x[k]\, g[n-k] \quad \text{..... (1.11)}$$

$$y[n] = \sum_{k=-\infty}^{\infty} g[k]\, x[2n-k] \quad \text{..... (1.12)}$$

$$y[n] = \sum_{k=-\infty}^{\infty} h[k]\, x[2n-k] \quad \text{..... (1.13)}$$

The 2-D image $I(x,y)$ is represented as a pxq matrix $I(i,j)$ where each element represents the gray scale intensity of one pixel in the image. In the decomposition structure g[n] and h[n] represents low pass and high pass filters response in computation of coefficients. The set of wavelet coefficients are given by $W_{j,CA}, W_{j,CH}, W_{j,CV}, W_{j,CD}$ from which the features such as the energy, mean, variance and standard deviation corresponding to the 2Dimage is obtained.

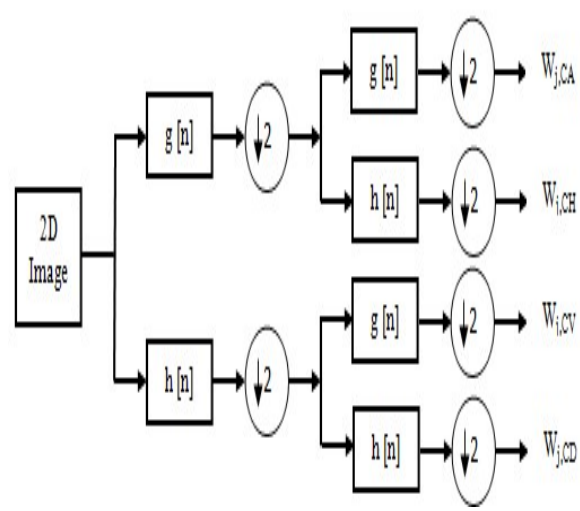

Figure .1.1 Decomposition Structure of DWT.

3.5 Enhanced ROR for Unsupervised Lumbar Spine Image Segmentation

Algorithm for Enhanced ROR Segmentation

Step1: The image component values drawn during a matrix square measure reborn to integers, since the image is in uint8 (Unsigned whole number eight bit) customary that isn't convenient for any process.

A=image pixels in uint8 customary.

A1=double (A)

Now A1 contain whole number values of pixels.

Step2: The median for the square measure 1st calculated.

MED1=Median (A1)

MED1 contains median values of A1.

As an example,

A1=1,32,14,15,47,82,24,53,87,69,20;

To search out median in ascending order,

Sorted_A1=1,14,15,20,24,32,47,53,69,82,87; If the full range of components N, N=odd, then median=middle price of sorted information.

N=even, then median=average of middle 2 values.

MED1= Median (A1) =32. Since N=11.

Step3: This {median price| median | average | norm} obtained is once more subtracted from the whole number value of image and once more median is taken for the output.

Sub_A1=absolute price (A1-MED1);

For the higher than example, Sub_A1= 31,0,18,17,15,50,8,21,55,37,12;

For the obtained new information Sub_A1 once more a median is calculated. MED2=Median (Sub_A1) For the higher than example MED2=18

Step4: The obtained output is then divided by a worth of 0.6457 that is that the median of ordinary} normal random variables.

W= MED2 /0.6457

For the higher than example, W=27.87

Finally a matrix of ROR values is obtained by,

ROR = (A1-MED)/W.

Step5: The entire operation is performed for the image values in matrix type. The new output matrix obtained is named ROR price matrix and therefore the prices square measure referred to as the median absolute deviation or the ROR value.

Determining Cluster Size

With the assistance of obtained ROR values for every element a cluster size is being determined mechanically. The cluster size id determined as follows,

Step1: The distinctive ROR worth's by eliminating the continuation values within the ROR value matrix are sorted in ascending order.

U= distinctive values (ROR)

Step2: Once getting the distinctive values the full range of distinctive components is set. SZ= Size (U)

Step3: The obtained size worth is split by a variety worth that is to be mounted. In our technique we've got mounted it to twenty five. The resultant worth is that the cluster size. Cluster Size = SZ / vary

Based on the obtained cluster size colors square measure to be appointed so as to mention for every cluster size. Since the cluster size varies for each image, the color assignment method takes place within the following method. Pictures square measure pictured in colors starting from 0 to 255.

T= 255/ cluster size.

Unsupervised ROR Segmentation

After decisive the colors to assign and also the cluster size consequent step is to cluster the image pixels supported it. The agglomeration method here is finished with the assistance of ROR values, cluster size and also the colors assigned. The distinctive ROR values obtained is currently split into cluster size teams with every cluster containing a group of vary ROR values. As an example if there are two hundred distinctive ROR values suggests that it'll be splitted into eight (200/25) clusters with every cluster containing twenty five completely different ROR values in its cluster. That ROR values happiness to initial cluster are assigned the primary color and also the second being assigned with second color. This method continues for all clusters, that particular cluster will be split into two and the two new clusters are again checked for tolerance. After complete checking of tolerance the segments are visualized.

S.No	Image	TP	TN	FP	FN	Accuracy	Sensitivity	Specificity
1	Im1	218889	2132	401	2135	94.372	0.97	0.82
2	Im2	219438	4332	321	4237	94.839	0.96	0.83
3	Im3	229123	5621	442	5569	94.103	0.96	0.87
4	Im4	276489	5673	309	5641	92.178	0.96	0.88
5	Im5	272630	5998	329	5903	92.874	0.95	0.81
6	Im6	271763	7030	367	6986	94.026	0.97	0.84
7	Im7	210385	8092	451	7908	95.014	0.95	0.89
8	Im8	220543	8194	355	8096	93.563	0.96	0.88
9	Im9	243999	8991	318	8996	93.902	0.97	0.87
10	Im10	273409	9301	409	9219	95.003	0.95	0.84
11	Im11	206872	9891	361	9813	94.184	0.95	0.83
12	Im12	226490	9621	332	9987	95.037	0.96	0.81

Vertebri Extraction

To extract the vertebripart in three dimensional cross sectional view of human body the ROR segmented image is converted into binary image. This binary image contains a bunch of objects that are separated from each other. The pixels that belong to an object are denoted with 1 which represents true while those pixels that are the background 0 represents false. For example, binary image that looks like this:

0 0 0 0 0 1 1 1 0 0
0 1 0 1 0 0 1 1 0 0
0 1 1 1 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 1
0 0 0 0 0 0 0 0 1 1

Between them and therefore the initial worth of every cluster is taken into account to be the color for the cluster.

Meeting Tolerance

In order to check the correctness of segmentation process, a tolerance checking is being done. The obtained clusters pixel values are determined and the minimum and maximum value of each cluster is obtained. The middle value of each cluster is also obtained. V= mid value (cluster) the tolerance of 60 % is checked for each cluster with a condition as follows,

V1= (60 * V)/100;

V2= V1 + V;

Condition (Min Value (cluster) < V1) or (Max value (Cluster) >V2.

4.Results and Discussions

This section discusses on the performance of the proposed mechanism. The proposed HMRF-ROR-PSO method is implemented using MATLAB software tool. Table 1.1 and Table 1.2 shows the performance analysis of proposed method and existing method respectively in terms of true positive, true negative, false positive, false negative, sensitivity, specificity and accuracy. Table 1.3 projects the performance analysis of the proposed HMRF-ROR-PSO method against the existing method. It is to be noted from the performance analysis the clustering accuracy is improved along with the reduction in time taken for segmentation.

Table 1.1 Performance analysis of the existing method

Table 1.2 Performance analysis of the EROR method

S.No	Image	TP	TN	FP	FN	Accuracy	Sensitivity	Specificity
1	Im1	220191	2378	398	2291	98.377	0.98	0.81
2	Im2	220873	4491	311	4359	97.848	0.96	0.79
3	Im3	231382	5643	410	5632	98.497	0.97	0.84
4	Im4	281679	5761	294	5763	98.483	0.96	0.81
5	Im5	273285	6094	311	6085	97.028	0.98	0.78
6	Im6	272376	7123	343	7013	98.169	0.97	0.81
7	Im7	211067	8054	429	8054	98.285	0.97	0.85
8	Im8	221845	8123	350	8127	97.849	0.98	0.81
9	Im9	244653	9129	299	9018	98.296	0.98	0.82

10	Im10	274590	9358	395	9371	98.742	0.97	0.79
11	Im11	207676	9912	331	9917	98.676	0.98	0.79
12	Im12	236123	9734	304	9995	98.673	0.97	0.79

Table 1.3 Performance analysis of Time taken for Segmentation

S.No	Image	Existing	EROR-IPCA-WFE
1	Im1	29.336	20.983
2	Im2	28.989	21.873
3	Im3	29.025	21.845
4	Im4	29.566	23.759
5	Im5	29.387	20.001
6	Im6	29.702	21.632
7	Im7	29.342	19.064
8	Im8	29.478	19.056
9	Im9	28.894	19.638
10	Im10	29.433	19.856
11	Im11	29.336	19.758
12	Im12	28.989	20.001

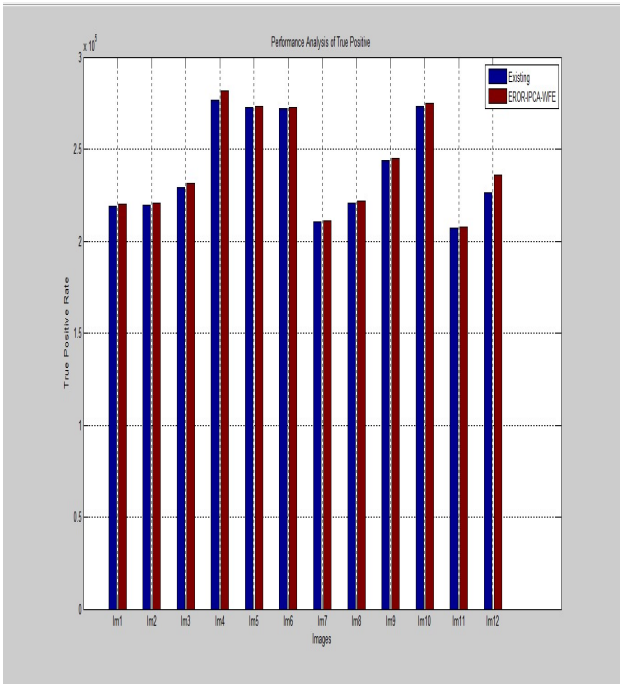

FIGURE 1.2 PERFORMANCE ANALYSIS OF TRUE POSITIVE

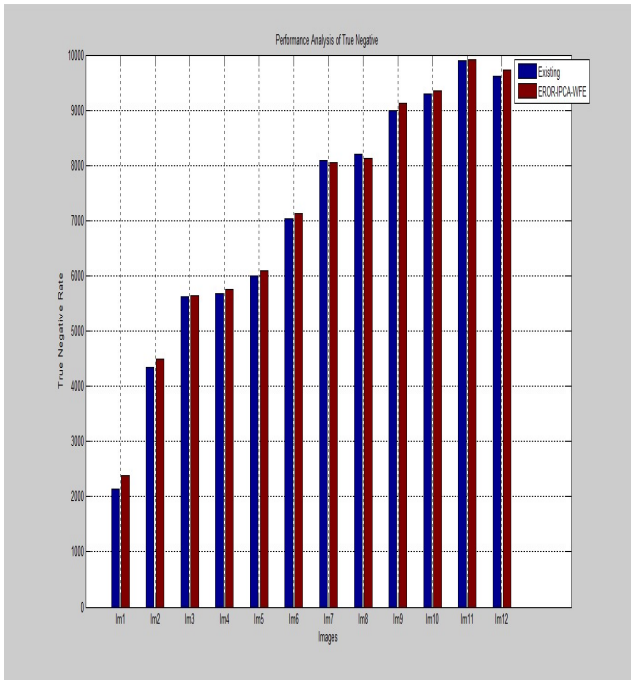

FIGURE 1.3 PERFORMANCE ANALYSIS OF TRUE NEGATIVE

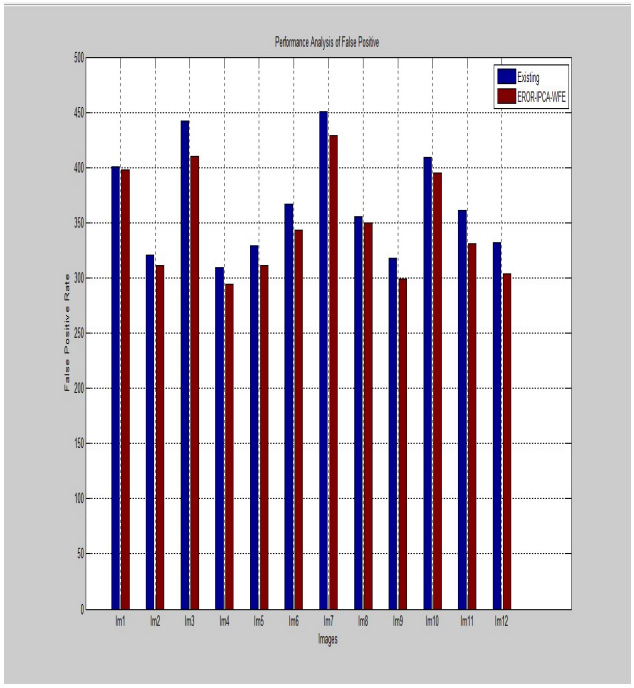

FIGURE 1.4 PERFORMANCE ANALYSIS OF FALSE POSITIVE

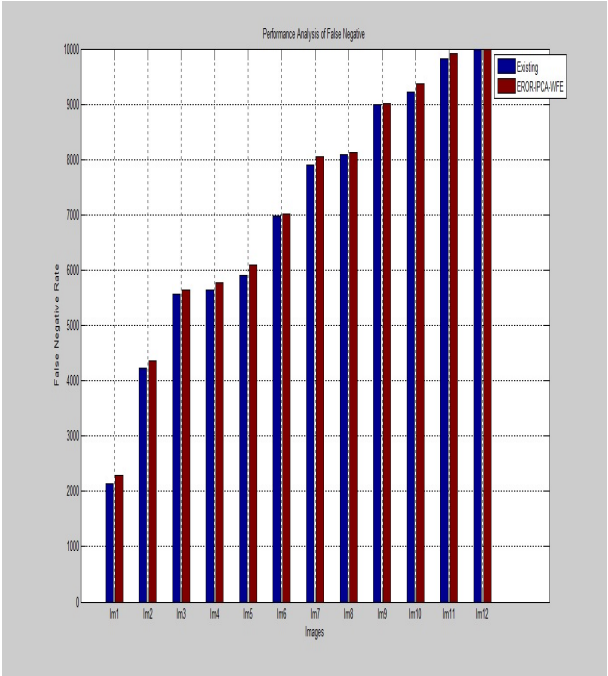

FIGURE 1.5 PERFORMANCE ANALYSIS OF FALSE NEGATIVE

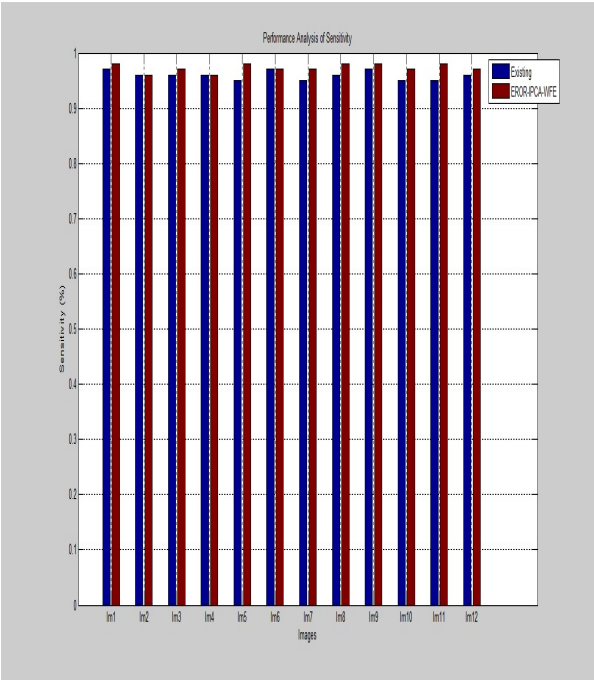

FIGURE 1.6 PERFORMANCE ANALYSIS OF SENSITIVITY

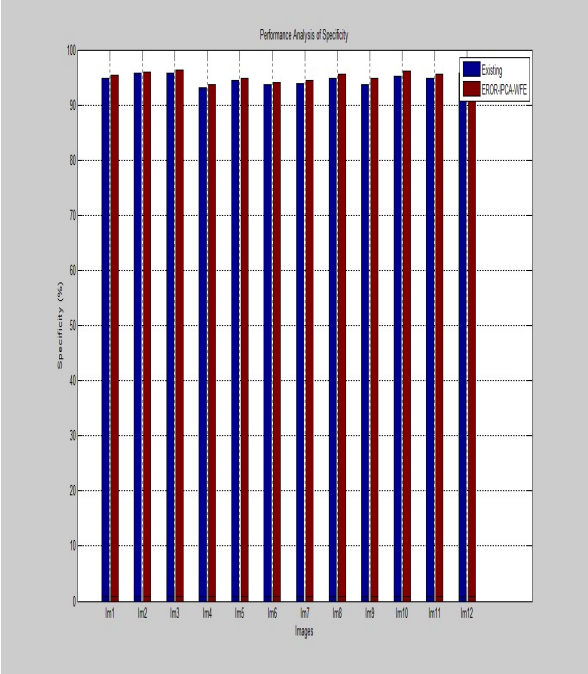

FIGURE 1.7 PERFORMANCE ANALYSIS OF SPECIFICITY

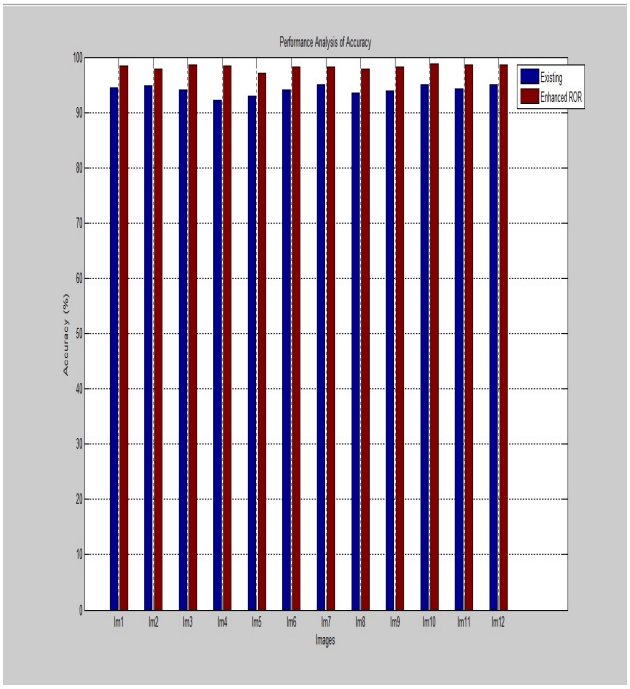

FIGURE 1.8 PERFORMANCE ANALYSIS OF ACCURACY

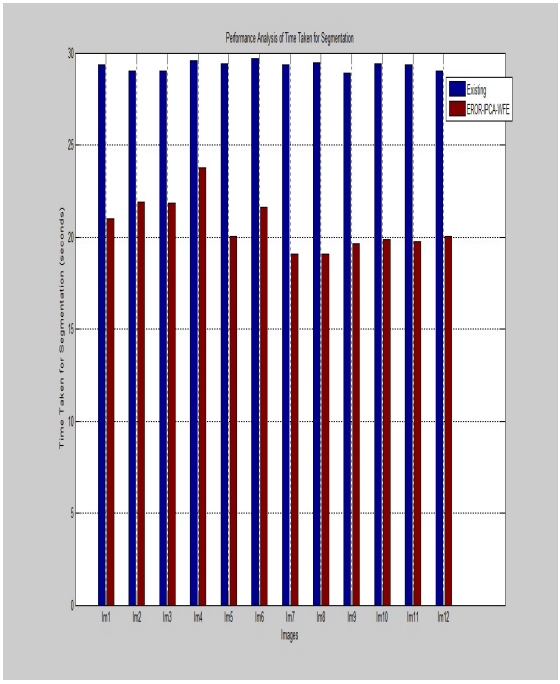

FIGURE 1.9 PERFORMANCE ANALYSIS OF TIME TAKEN FOR SEGMENTATION

5.CONCLUSION

This work proposes an unsupervised lumbar spine image segmentation using enhanced ROR with improved principal component analysis. Initially the preprocessing is carried out with improved principal component analysis followed up with wavelet feature extraction. Then segmentation is carried out using enhanced ROR technique. 12 images are

taken for segmentation and the results are promising than that of the existing method.

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