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Differentiation of Mild Cognitive Impairment Conditions in MR Images using Fractional order Jacobi Fourier Moment Features

Abstract: Mild Cognitive Impairment (MCI) is the asymptomatic, preclinical transitional stage among aging and Alzheimer's Disease (AD). Detection of MCI can ensure the timely intervention required to manage the disease's severity. Morphological alterations of Lateral Ventricle (LV) is considered as a significant biomarker for disease diagnosis. This research aims to analyze the shape alterations of the LV region using Fractional Order Jacobi Fourier Moment (FOJFM) features, which are categorized by their generic nature and capabilities to perform time-frequency analysis. T1-weighted transaxial view brain MR images (HC = 92 and MCI = 63) are obtained from publicly available Open Access Series of Imaging Studies (OASIS) database. The LV region is delineated using Weighted Level Set (WLS) segmentation method and results are compared to Ground Truth (GT) images. FOJFM features are employed to characterize the morphometry of LV region. From this segmented region, 200 features are computed by varying the value of order and fractional parameters. Random Forest (RF) and Support Vector Machine (SVM) classifiers are used to differentiate Healthy Control (HC) and MCI subjects. Results show that WLSE is able to delineate the LV structure. The segmented region shows good correlation with the GT area. FOJFM features are observed to be statistically significant in discriminating HC and MCI subjects with $p < 0.05$. For MCI subjects, the feature values show higher variation as compared with HC brain, which might be due to the surface expansion of ventricular area during disease progression. SVM and RF classifiers show high performance F-measure values of 93.14% and 86.24%, respectively, for differentiating MCI

conditions. The proposed moment based FOJFM features are able to capture the morphological changes of LV region related to MCI condition. Hence the proposed pipeline of work can be useful for the automated and early diagnosis of diseased conditions

Keywords: Mild Cognitive Impairment, Lateral Ventricle, Segmentation, Feature Extraction, Classification

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1 Introduction

Alzheimer's Disease (AD) is an incurable, progressive neurological condition that causes memory and cognitive skills to deteriorate over time [1]. Mild cognitive impairment (MCI) is a stage between normal aging and early dementia that has been identified as a risk factor for AD. MCI is often diagnosed with clinical examinations, cognitive tests, and brain imaging. Early and precise diagnosis of MCI can help prolong the deterioration of subject's cognitive abilities for months or years and aid in the early initiation of treatment [2-3].

Non-invasive Magnetic Resonance (MR) brain imaging is widely used for the diagnosis of MCI conditions for its spatial resolution and soft tissue contrast [4]. In T1-weighted brain MR images, CSF appears as a dark region (black), providing better contrast among white matter (lighter gray) and gray matter (dark gray) tissues. CSF behaves irregularly and exhibits turbulent flow in CSF spaces leading to the enlargement of Lateral Ventricle (LV) structure [5]. This causes structural changes in the brain ventricular region and is considered as an essential imaging biomarker for the differentiation of MCI conditions. These brain ventricles are highly concave and irregular in shape, posing a significant challenge for segmentation, feature extraction, and machine learning algorithms while assessing disease detection [5, 6].

The geometry of objects provides structural information about the image, which can be quantified using image descriptors. Shape-based features such as moments are extensively used to characterize image patterns in a variety of

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image processing applications [7]. Moment features are useful in satisfying the core semantic description criteria because of their geometric invariance and independence. However, there is a conflict between robustness and discriminability in these features, restricting the ability to further improve description quality. To overcome this limitation, Yang suggested Fractional Order Jacobi Fourier Moment (FOJFM), a class of orthogonal moments defined by their time-frequency analysis and generic nature capacity [7]. The FOJFM's time-frequency analysis capability enables it to fine tune the zero distributions of radial kernels by changing the value of a fractional variable. This unique aspect is useful for addressing issues with information suppression and extracting local image features [7].

In this work, an attempt has been made to analyse the shape alteration of LV region in Healthy Control (HC) and MCI subjects. The delineation of LV from whole brain image is performed using the Weighted Level Set Evolution (WLSE) segmentation method. FOJFM features are used to detect changes in LV shape morphology in HC and MCI subjects. Further, Random Forest (RF) and Support Vector Machine (SVM) classifiers are employed to statistically examine and classify the performance of extracted features.

2 Methodology

2.1.1 MR Image Database

In this work, T1-weighted skull stripped MR images in the transverse plane are obtained from Open Access Series of Imaging Studies (OASIS) neuroimaging public dataset. Based on the Clinical Dementia Rating (CDR) index, a total of 155 (HC = 92 and MCI = 63) right handed subjects are selected for the study. These brain MR images are skull stripped, atlas registered and corrected for bias field [8]. In this work single slice criterion is used such that the ventricular area replaces ventricular volume. The MR images are 256×256 pixels in resolution and the 90th image slice is considered for further analysis [6].

2.1.2 Weighted Level Set Segmentation

Weighted level set technique is employed to delineate LV from whole brain MR images. In this method, a weighting approach is used for the evaluation of energy terms used in the edge-based active contour method employed with the level set framework [9]. During segmentation, the edge information is

considered to be the critical image feature that moves the emerging contour to the desired object boundaries. To acquire information about edge intensities, the following edge indicator function is described as follows

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2} \quad (1)$$

where $g \in [0,1]$, G_σ represents Gaussian kernel function, variable σ represents standard deviation, convolution process is denoted by $*$ and I represent an image on a region Ω . The parameter g normally takes smaller values at the boundary of the object than at the smooth areas. From the value of parameter g , the level set basic function is written as

$$\varepsilon(\theta) = R(\theta) + Length(\theta) + Area(\theta) \quad (2)$$

where the distance regularization term is denoted as $R(\theta)$, the area and length energy terms are represented as $Area(\theta)$ and $Length(\theta)$ respectively. By substituting length and Area terms in the above equation, the proposed energy function is written as follows

$$\begin{aligned} \varepsilon(\theta) = & \mu \int_{\Omega} p(|\nabla \theta|) dx + (1 - \omega(\theta, r)) \\ & \int_{\Omega} g \delta(\theta) |\nabla \theta| dx + \omega(\theta, r) \int_{\Omega} g H(\theta) dx \end{aligned} \quad (3)$$

In eq 2, the energy function can be optimized by solving the gradient flow equation and is defined as

$$\begin{aligned} \frac{\partial \theta}{\partial t} = & \mu \text{div}(d_p(|\nabla \theta|) \nabla \theta) + (1 - \omega(\theta, r)) \\ & \delta(\theta) \text{div}\left(g \frac{\nabla \theta}{|\nabla \theta|}\right) + \omega(\theta, r) g \delta(\theta) \end{aligned} \quad (4)$$

where the function d_p is specified as $d_p(s) = p'(s)/s$ by the first derivative of $p(s)$. This is appropriate to note that in above equation, $\omega(\theta, r)$ the weighting term resulted in a constant value within the span of $[0, 1]$ when expressed as a function of θ and r .

2.1.3 Fractional Order Jacobi Fourier Moment Features

The segmented binary LV images are used for the extraction of features using FOJFM. These features include global and local image descriptors, as well as two intriguing property: time-frequency analysis and generic nature capabilities. They are also orthogonal and rotationally invariant in nature [7]. Let fractional variable β be a positive rational number $\beta \in \mathbb{R}^+$. The fractional order Jacobi polynomial is written as

$$G_n(\beta, c, d, t) = \frac{n! \overline{(d)}}{\overline{(c+n)}} \sum_{k=0}^n (-1)^k \frac{\overline{(c+n+k)}}{(n-k)! k! \overline{(d+k)}} t^{ak} \quad (5)$$

The fractional order Jacobi polynomial's orthogonality equation $G_n(\beta, c, d, t)$ on the unit radius is expressed as

$$\begin{aligned}
 & \int_0^1 G_n(c, d, r) G_n(c, d, r) w(c, d, r) dr \\
 &= \int_0^1 G_n(c, d, t^\beta) G_n(c, d, t^\beta) w(c, d, t^\beta) dt^\beta \\
 &= \int_0^1 G_n(\alpha, c, d, t) G_n(\alpha, c, d, t) w(c, d, t^\beta) dt^{\alpha\beta} \\
 &= \int_0^1 G_n(\beta, c, d, t) G_n(\beta, c, d, t) w(c, d, t^\beta) \beta t^{\beta-1} dt \\
 &= \int_0^1 G_n(\beta, c, d, t) G_n(\beta, c, d, t) w(\beta, c, d, t) dt = b_n(c, d) \delta_{nn}
 \end{aligned} \quad (6)$$

where $w(\beta, c, d, t)$ is the weighting function, written as

$$w(\beta, c, d, t) = w(c, d, t^\beta) \beta t^{\beta-1} = \beta (1-t^\beta)^{c-d} t^{\beta d-1} \quad (7)$$

Referring to Eq. (5), (6) and (7), the normalized fractional order Jacobi polynomial $J_n(\beta, c, d, r)$ can be defined as

$$\begin{aligned}
 J_n(\beta, c, d, r) &= \left[\frac{w(\beta, c, d, r)}{r b_n(c, d)} \right]^{\frac{1}{2}} G_n(\beta, c, d, r) \\
 \int_0^1 J_n(\beta, c, d, r) J_n(\beta, c, d, r) r dr &= \delta_{nn}
 \end{aligned} \quad (8)$$

The normalized fractional order Jacobi polynomial $J_n(\beta, c, d, r)$ can be utilized to define new orthogonal moments of fractional order, which we name FOJFM.

$$\begin{aligned}
 F_{nm} &= \frac{1}{2\pi} \int_0^{2\pi} \int_0^1 V_{nm}^*(\beta, c, d, r, \theta) f(r, \theta) r dr d\theta \\
 &= \frac{1}{2\pi} \int_0^{2\pi} \int_0^1 J_n(\beta, c, d, r) \exp(-jm\theta) f(r, \theta) r dr d\theta
 \end{aligned} \quad (9)$$

where $\beta \in R^+$, $c, d \in R$ and $c-d > -1$, $d > 0$; $f(r, \theta)$ represents the image function in polar coordinates. $V_{nm}^*(\beta, c, d, r, \theta) = J_n(\beta, c, d, r) \exp(-jm\theta)$ are the complex conjugate of the FOJFM basis functions. Since basis of these functions are pairwise orthogonal, every image can be described in terms of the moments and the basis functions.

$$\begin{aligned}
 f(r, \theta) &= \sum_{n=0}^{+\infty} \sum_{m=-\infty}^{+\infty} F_{nm} V_{nm}(\beta, c, d, r, \theta) \\
 &\approx \sum_{n=0}^K \sum_{m=-K}^K F_{nm} V_{nm}(\beta, c, d, r, \theta)
 \end{aligned} \quad (10)$$

Thus, a combination of 200 moment features are computed by considering different values of c , d and β . The extracted FOJFM features from segmented binary images of LV region are statistically examined using Statistical Package for Social Sciences (SPSS). Further, for the categorization of HC and MCI subjects, the statistically significant moments are given as an input to the RF and SVM classifiers.

3 Results and Discussion

Figure 1 (a-b) shows a representative set of T1-weighted MR images transaxial view (mid slice) for HC and MCI subjects. From the figure, it can be observed that the horns of the LV are prominently visible and it appears as a single connected region for HC and MCI subjects. In addition, the size of the LV in MCI subjects is larger than in HC subjects. The enlargement of the frontal and occipital horns, as well as an increase in ventricular size, are more prominent in MCI subjects as the disease progresses.

Figure 1: Representative set of HC and MCI T1-weighted MR images (a-b) overlay segmented images (c-d) and its corresponding segmented LV mask (e-f)

The overlay of segmented output on the original image is shown in Figure 1 (c-d). The specific region of interest is labelled around the LV boundary and extracted from the whole brain region. Since these segmented images are retrieved from the low-intensity region, the parameters must be fine-tuned to avoid contour leakage around the LV boundary.

Figure 2: Variation in representative (a-b) FOJFM features of LV for HC and MCI subjects

Figure 1 (e-f) shows the segmentation result of LV region using WLSE method. The segmentation of the LV region is precise, as can be seen in the image. Additionally, a dice score metric is used to compare the segmented image to the Ground Truth (GT) image for segmentation validation. For HC and MCI subjects, dice score metric of 0.83 and 0.85 are obtained,

respectively. The acquired dice score values demonstrate that the WLSE technique is capable of accurately segmenting the LV region.

200 FOJFM features are derived from the segmented LV of HC and MCI subjects to analyse the structural variations of the LV region. Out of these extracted features, 188 features are statistically significant with $p < 0.05$. Figure 2 (a) demonstrates the scatter plot representation of the first FOJFM feature (first moment). High discrimination is observed among the HC and MCI subjects.

Figure 2 (b) shows the box-plot representation for the statistically significant mean values of FOJFM measures for HC and MCI subjects. It can be seen that for all the statistically significant moments, the values of MCI subjects are higher as compared to HC subjects. This indicates that the structural variations of LV region in MCI subjects are higher than in HC subjects.

Table 1: Classification performance (%) of LV features for differentiating HC and MCI subjects.

Classifier	Accuracy	Sensitivity	Specificity	F-Measure
SVM	93.90	93.90	93.26	93.14
RF	86.50	86.14	86.14	86.24

Further, this FOJFM features are given as input to the RF and SVM classifiers. The performance is assessed for the differentiation of HC and MCI subjects as presented in Table 1. From the table it can be noted that SVM performed well in terms of specificity, accuracy, sensitivity and F-measure. The statistically significant moment values acquired a high classification F-measure value of 93.14% for HC versus MCI subjects, respectively.

4 Conclusion

Early detection of MCI is critical for clinical trial preparation, which can assist in reducing disease progression. Recent advancements in MR image analysis have enabled the evaluation of structural alterations in brain sub-anatomical regions. The morphological changes of the LV are considered a significant imaging diagnostic biomarker for diagnosing MCI conditions.

In this study, the morphological alterations of LV region is analysed using FOJFM features, which are characterized by their generic nature and ability to perform time-frequency analysis. Prior to this, the delineation of LV region is performed using the WLSE approach and validated with GT images for HC versus MCI subjects. RF and SVM classifiers

are used to evaluate the performance metric of statistically significant moment features. The WLSE segmentation approach can precisely delineate the LV region in both HC and MCI subjects. Extracted FOJFM features from segmented binary images are found to be statistically significant in distinguishing between HC and MCI subjects. This illustrates that FOJFM features and the WLSE segmentation method can capture structural differences in the LV region between the two classes. In combination with the features, the SVM classifier can classify HC and MCI subjects with high detection accuracy. The proposed workflow could be effective for automated and early disease diagnosis.

Author Statement

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