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# MRI Observations of Japanese Encephalitis in Newborn

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*Abstract* — ***Japanese encephalitis (JE) is one of severe viral encephalitis that affects individuals in Asia, western Pacific countries, and northern Australia. Although 67,900 JE cases have been estimated among 24 JE epidemic countries annually. Japanese encephalitis epidemics have been reported in many parts of the India. The incidence has been reported to be high among pediatric group with high mortality. The incidence of JE in recent times is showing an increasing trend, it claims 1495 lives in 2014 in India. The MRI is an important tool for establishing the diagnosis of Japanese encephalitis and it helps to differentiate from other viral encephalitis. In this paper Particle filtering approach is used to segment the brain MR image of JE victim and its volumetric analysis is performed. This analysis play important role for neurologist for early detection of JE.***

***Keywords- Japanese encephalitis; newborn; particle filter, MRI, segmentation.***

## I. INTRODUCTION

Japanese encephalitis (JE) is the most important cause of viral encephalitis in Asia. It is a mosquito-borne flavivirus, meaning it is related to dengue, yellow fever and West Nile viruses. The first case of JE was documented in 1871 in Japan. A recent literature review estimates nearly 68 000 clinical cases of JE globally each year, with up to 20 400 deaths due to JE. The case-fatality rate among those with encephalitis can be as high as 30%.

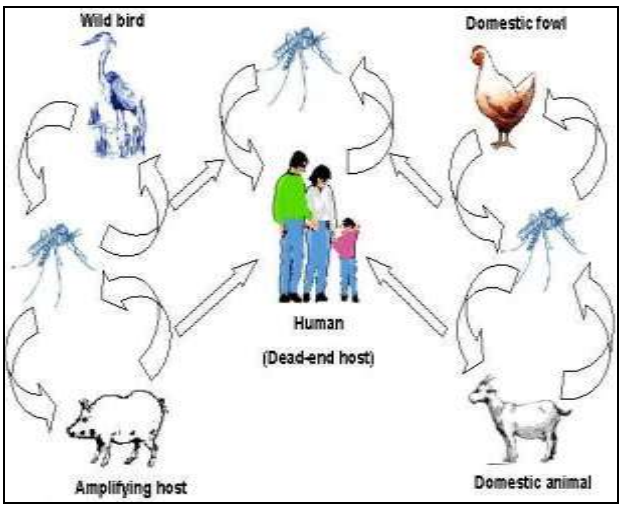



***Figure 1 Life Cycle of Japanese encephalitis (JE)***

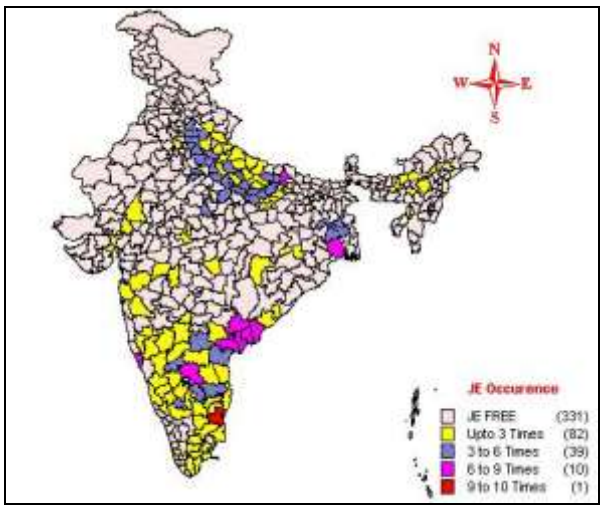



***Figure 2 Distribution of Japanese encephalitis (JE) in India***

Permanent neurologic or psychiatric sequelae can occur in 30%–50% of those with encephalitis [1-2].Japanese encephalitis (JE)-epidemics have been reported in many parts of the India and it was first reported in 1955 in Tamil Nadu. The virus has spread to over 171 districts in 19 states. The incidence has been reported to be high among pediatric group with high mortality. The incidence of JE in recent times is showing an increasing trend. JE claims 1495 lives in 2014. It appears that JE may become one of the major public health problems in India [3]

This scenario shows severity of disease and appeals early detection of JE. Fig 4 shows the state wise JE reported cases The disease is endemic in 179 districts of 21 states of which Assam, Bihar, Tamil Nadu, Uttar Pradesh and West Bengal have been reporting more than 80% of disease burden. The details regarding the state wise cases & deaths are mention in Table 1.

The segmentation of newborn brain structures from magnetic resonance images (MRI) is crucial for the study of normal development and comparison to neuro-developmental disorders at early stages. The development of new segmentation methods for this age group is driven by the increasing use of MRI to study newborns. The MRI is an important tool for establishing the diagnosis of Japanese encephalitis [24]. In this paper volumetric analysis of JE victims is done using particle filtering approach..

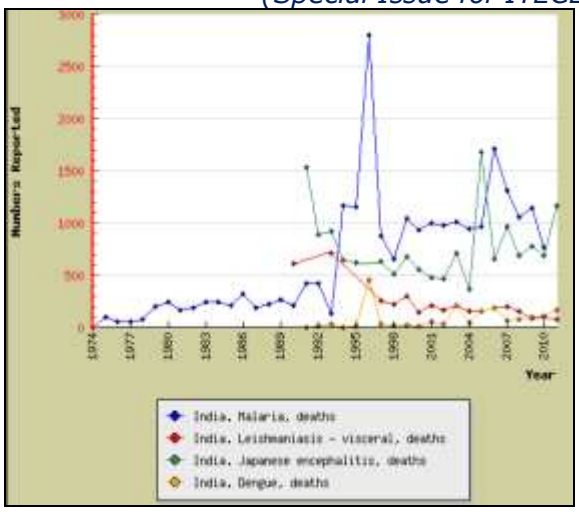



*Figure3 Disease wise comparison*

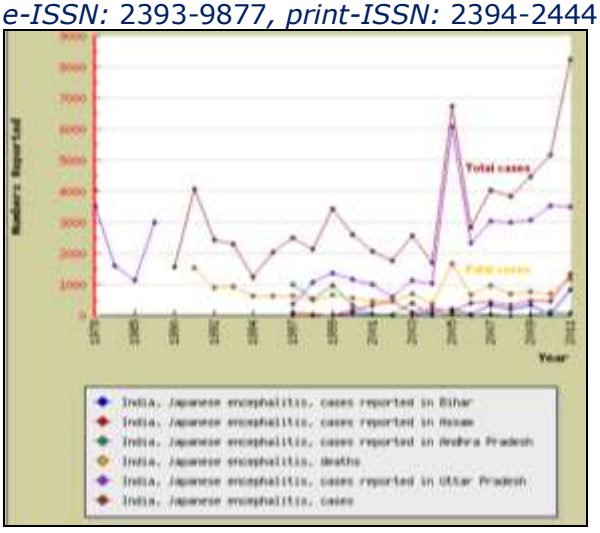



*Figure 4 State wise cases reported in India*

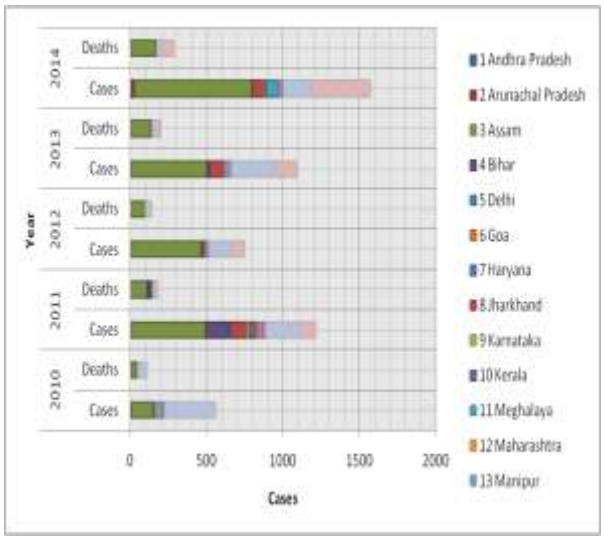



***Table 1 The detailed statewise cases reported of JE victims in India***

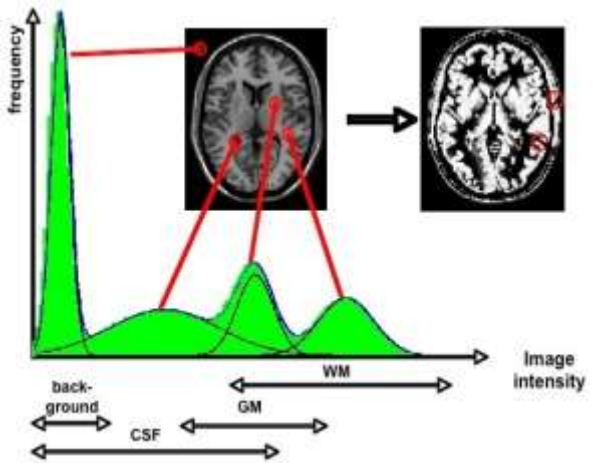



***Figure 5: Distribution of different tissues of brain.***

This paper is organized as follows. Section 2 gives an overview of newborn brain MRI & its potential challenges .Section 3 gives an overview of the PSO method. In Section 4 the experimental results are presented, and, finally, the conclusions are stated in Section 5.

## II. MATERIALS AND METHOD

Segmentation of newborn brain MRI is different from segmentation of adult brain MRI. In adults, tissue is usually classified as either gray matter, white matter, or cerebrospinal fluid based solely on image intensity [4]. In newborn MRI, it is necessary to identify additional tissue classes in order to best characterize brain development. In the newborn infant, the process of white matter myelination progresses rapidly throughout the first year of life and is an important biomarker for brain maturation [5- 7].

The Segmentation of newborn brain MRI is considerably more difficult than segmentation of adult MRI due to reduced contrast and increased noise in images from neonates as well as inverted contrast between gray matter and white matter [8]. Intensity-based classification relies on the contrast between tissue types adjacent in feature space and adequate signal compared to image noise [9]. Statistical classification identifies [10] an optimal boundary, in feature space, between tissue types, and the separability of two tissue types or classes is related to the overlap between classes in feature space.

The goal of newborn brain MRI segmentation [11] is to delineate the two hemispheres and the cerebellum at a large scale, and tissues such as cortical and central gray matter, myelinated and unmyelinated white matter and cerebro-spinal fluid (CSF), at a finer scale [12,13]. Additional challenges compared to the segmentation of adult brain MRI are

the lower signal-to-noise ratios and stronger partial volume effects, the reduced and inverted image contrast and the lack of suitable atlases for the developing brain [14-18]. These factors make it impossible to apply existing adult brain segmentation methods to the newborn brain.

Prastawa et al. [19] introduced a method for tissue segmentation based on nonparametric kernel density estimates. A drawback is that the atlas was created by averaging semi-automatic segmentations. However, Xue et al. [20] only segmented the CSF, CGM, and WM tissues. Weisenfeld et al. [21] used an iterative sample editing process, estimating the segmentation with the use of STAPLE. Makropoulos et al. [22] propose a novel multi-structure Expectation-Maximization (EM) based segmentation technique for the subdivision of the whole brain.

The mentioned tissue segmentation algorithms have their own merits and de-merits. Therefore, there is a need for an accurate automatic technique to parcellate the brain into multiple structures .In this paper we proposed the particle filtering approach for brain tissue segmentation and diagnosis of Japanese encephalitis victims.

## III. PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is a population-based optimization algorithm modeled after the simulation of social behavior of birds in a flock [23,24]. The algorithm of PSO is initialized with a group of random particles and then searches for optima by updating generations. Each particle is flown through the search space having its position adjusted based on its distance from its own personal best position and the distance from the best particle of the swarm. The performance of each particle, i.e. how close the particle is from the global optimum, is measured using a fitness function which depends on the optimization problem.

Each particle, i, flies through an n–dimensional search space, Rn, and maintains the following information:

- xi, the current position of ith particle ( x - vector ),
- pi, the personal best position of ith particle ( p - vector ), and
- vi, the current velocity of ith particle i (v - vector ).

The personal best position associated with a particle, i, is the best position that the particle has visited so far. If *f* denotes the fitness function, then the personal best of i at a time step t is updated as:

$$Pi(t+1) = \begin{cases} Pi(t) & \text{if } f(Xi(t+1)) > f(Pi(t \\ Xi(t+1) & \text{if } f(Xi(t+1)) < f(Pi(t \end{cases} \quad (1)$$

If the position of the global best particle is denoted by gbest , then :

$$gbest \in \{P1(t), P2(t), \ldots\ldots\ldots, Pm(t)\} = \min\{f(P1(t)), f(P2(t), \ldots., f(Pm(t) \quad (2)$$

The velocity updates are calculated as a linear combination of position and velocity vectors. Thus, the velocity of particle i is updated using equation (3) and the position of particle i is updated using equation (4).

$$Vi(t+1) = wVi(t) + c1 * r1 * (Pi(t) - Xi(t) + c2 * r2 * (gbest - Xi( \quad (3)$$

$$Xi(t+1) = Xi(t) + Vi(t+ \quad (4)$$

$$w = \frac{i}{iter\ N}$$

In the formula, w is the inertia weight [25], c1 and c2 are the acceleration constants, r1 and r2 are random numbers in the range [0,1] and Vi must be in the range [-Vmax, Vmax], where Vmax is the maximum velocity.

## IV. RESULTS

We examined patients with JE by MRI after the onset of their illness. The proposed algorithm was tested on following images. Fig 6 shows the T-2 weighted Brain MR image of JE victims as input; and the best segmentation image after final iteration of PSO. Different anatomical structures of brain are parcellated and displayed with different colors.

### 4.1 Volumetric Analysis

The volumetric analysis of different anatomical structures of brain MR images of JE victims plays significant role in early detection of JE. This volumetric analysis provides more accurate information to neurologist for diagnosis and better treatment planning of the disease. The detailed volumetric analysis of brain MR images of JE victims are summarized in table 2

### 4.2 Tissue Segmentation

I.

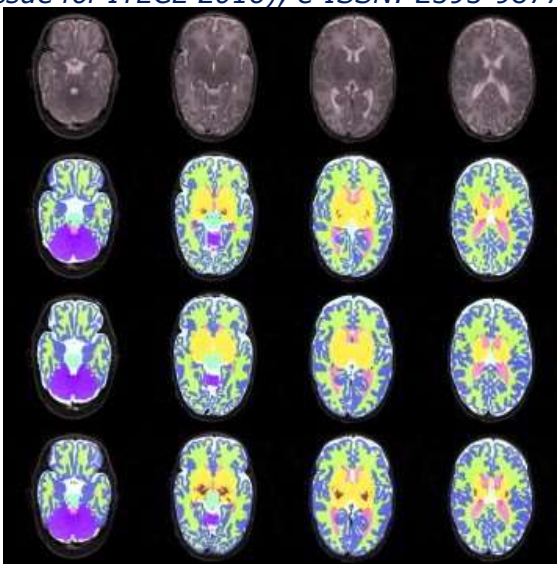
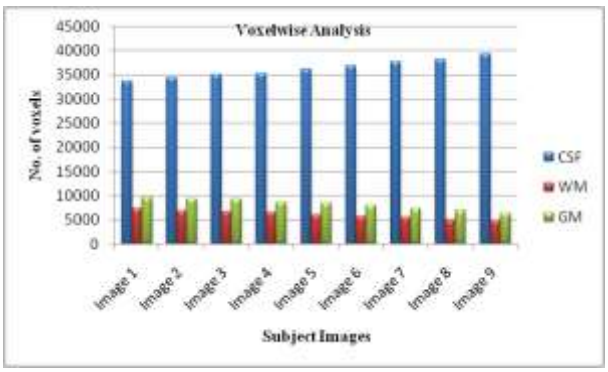
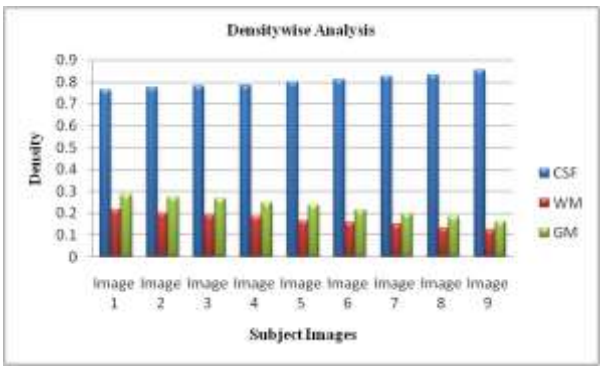
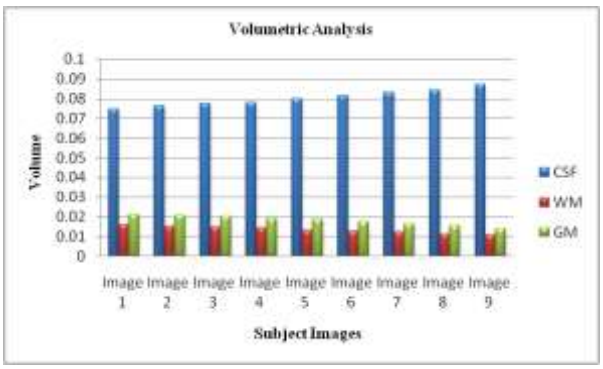


***Figure 6: The segmented result for MRI brain images***



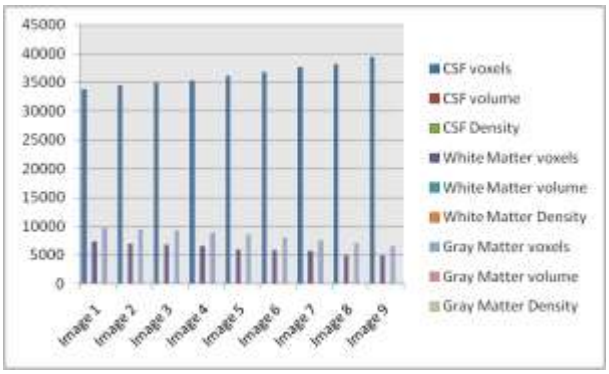




***Table 2. The detailed volumetric analysis of brain MR Images of images of JE victims***

## V. CONCLUSION

Japanese encephalitis still remains significant public health problem in South East Asian countries including India. The MRI is an important tool for establishing the diagnosis of Japanese encephalitis. MRI findings of Japanese encephalitis help to differentiate from other viral encephalitis, encephalopathy and acute disseminated encephalomyelitis. PSO is used to segment the brain MR image of JE victim and its volumetric analysis is performed. This plays important role for neurologist for early detection of JE.

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