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MULTIMODAL DATA FUSION FOR ALZHEIMER'S PATIENTS USING DEMPSTER-SHAFER THEORY OF EVIDENCE

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Abstract
The paper is part of an investigation by the authors on development of a knowledge based framework for multimodal medical image in collaboration with the All India Institute of Medical Science, New Delhi. After presenting the key aspects of the Dempster-Shafer Evidence theory we have presented implementation of registration and fusion of T_1 and T_2 weighted MR images and CT images of the brain of an Alzheimer's patient for minimising the uncertainty and increasing the reliability for diagnostics and therapeutic planning.
Keywords: Multimodality, Image Fusion, Dempster-Shafer Theory, Alzheimer's Disease.

1. Introduction

The combination and fusion of multimodality medical images is generating increasing clinical interest, but the absence of robust automatic registration algorithms standing in the way of entering these techniques in the routine clinical use. First part of the paper concerns registration of multi modal medical images and the second part concerns the medical image fusion. Presently we have concentrated in registration of CT,T_1 and T_2 weighted MR images of brain (axial section) of a patient suffering from Alzheimer's Disease (AD) where the ventricular region is considered as the region of interest (ROI). After registration the T_1 and T_2 weighted MR images are fused using Dempster - Shafer theory of combination of evidences [17],[8],[18].

In computerised therapy planning the registration of multisensor medical images is an important step prior to fuse the information of anatomical and functional details in a single knowledge based framework. The present paper is part of an investigation being carried out by the authors [7],[8],[9],[16] to develop a knowledge based framework for combining different modalities of medical imaging such as CT, MR, PET, SPECT, USG which ever is relevant for a particular pathological investigation. When the region of interest (ROI) of any diseased part of human body is captured by different imaging sensors (like CT, MR, PET, SPECT, USG) it is desirable to establish the point to point correspondences and finally to match the relevant multimodal images of the ROI. Dutta Majumder et.al.[1],[2],[4],[5],[9],[16] have suggested a semi automatic registration method using theory of shape and also geometric invariance properties of bio-medical images. In shape theory based registration[2],[4],[5],[6],[9] we deal with the problem of recognition and localisation of partially occluded two dimensional medical images obtained from CT and MR modality. For this purpose a set of local features of the shape using the concept of differential geometry is generated. The mathematical model developed is based on 2D shape analysis and non-rigid shape matching of objects in affine and projective frameworks. The model concerns (a) selection of invariant features as the control points on the 2D planar contour of the ROI under investigation (b) to find the closest match among the multisensor images where one set of invariants are mapped onto the other. The control points on the chosen concavity are computed to specify the identification and comparison among interspecies and intraspecies biological homology.

In present experiment we have used image data of patient suffering from Alzheimer's disease which is a most common degenerative

disease of the brain[12],[13],[14]. The ventricular region of brain is affected due to AD. The deformation of the ventricle of AD patient indicate the overall prognosis of the disease [12],[13],[14] and is considered as the ROI in present problem. For the Alzheimer's disease patient the medical features are detected at the ventricular region which is deformed due to pathology and also due to the overall change in shape of the intracranial cavity of brain volume. Applications of PET and SPECT imaging are expected to shed new light on Alzheimer's diagnosis [15]. But PET and SPECT data are not available for such clinical or research studies to us as yet. So our attempt is to improve the diagnosis and treatment planning with CT and MR images.

The primary task prior to the registration and fusion of the images is to do the segmentation which consists of division of original images into ROI. Among the various approaches to feature segmentation we have adopted Canny-edge-detector[11] to extract the boundary pixel chains of the edges and vertices. Canny's segmentation technique is implemented to extract the continious contour of the deformed ventricle of the brain images from the modalities used. Canny's segmentation algorithm is chosen as it optimises the following criteria : (a)low error rate which is achieved by maximum signal to noise ratio, and (b)better localisation of the edge points. Here the input image is convolved by the Gaussian smoothing filter having some smoothing factor s. By chosing the double thresholding values the required images are obtained and finally this algorithm performs the edge linking as a by product of thresholding[11]. From the new shape based theory and its application as developed by Dutta Majumder et.al.[1],[2],[3],[4],[6],[7],[8],[9],[10] the complete matching is accomplished by mapping one image contour onto the other under the transformation of co-ordinate and by comparison between the images or an image and its model. In this paper we have developed the information combination operators for data fusion and some aspects of Dempster-Shafer Evidence accumulation theory for classification of multimodal medical images[8],[17],[18].

2.Medical Image Fusion using Dempster-Shafer Evidence Accumulation Theory

The four major classes of data fusion operators used or recommended [8] for multisensor images are (1) Probabilistic and Bayesian Theory (2) Fuzzy Sets and Possibility Theory (3) MYCIN like Pseudo Probabilistic Systems (4) Dempster-Shafer (D-S) Evidence Accumulation Theory.

Let x_i denote the information from sensor i, then we have to chose an information combination operator F, in order to perform $F(x_1, x_2....x_n)$ under some restrictions. One is closure constraint to remain in the same mathematical framework - such as a probability is to be combined with probability only, which may not be required in the case of fuzzy sets. Fusion operators are classified to three groups namely (i) severe (ii) indulgent and (iii) cautions.

Let x_1, x_2 denote two real variables in the interval $I = [0, 1]$ representing the degrees of belief to be combined then under closure property $F(x_1, x_2)$ also has values in I. For Fuzzy Operators :

(a) F is conjunctive if $F(x_1, x_2) \leq min(x_1, x_2)$; it is considered to be a "severe" group behaviour.

(b) F is disjunctive if $F(x_1, x_2) \geq max(x_1, x_2)$; it is considered an "indulgent" behaviour.

(c) F behaves like a compromise, if $x_1 \leq F(x_1, x_2) \leq x_2$ if $x_1 \leq x_2$ and $x_2 \leq F(x_1, x_2) \leq x_1$ if $x_2 \leq x_1$ is considered as a cautious behaviour.

The next group of operators are context independent but the behaviours depends on values of x_1 and x_2. So the operator may be severe if both x_1 and x_2 are high enough or it may be indulgent if both are low. These operators can be found in fuzzy sets and possibility theory and in MYCIN like systems.

The third group is context dependent operators behave in a conjunctive way if x_1, x_2..... are consonant; in a disjunctive way if they are dissonant, and behave like a compromise if they are partly conflicting. The CD operators are particularly important for classification problems, because of their adaptive features. The context dependent operators may have to take into account situations when the sources may be giving conflicting information about one class (event) and consonant about another class or the sources may have different global reliability, or the sources may be reliable when giving an opinion about one class and not reliable for another class. A detailed comparative analytical study of these groups were presented elsewhere [8]. In this work we have applied Dempster-Shafer evidence theory[17],[18] .

To establish a relationship of D-S evidence theory and probality theory we take a probability space (S,χ,μ) where S is sample space, χ is some subsets of S , $\Phi\epsilon\chi$ is a σ - algebra, and μ is a probality measure.
It has been shown that (a) if (S,χ,μ) is a probality space and $\chi = 2^S$, then μ is a probality measure and (b) if (S,χ,μ) is a probality space, then μ_* is a belief function and μ^* is a plausibility function on 2^S.
It may be noted that 2^S is a set of all subsets of S and μ_* is a dual of μ^*. But μ is defined on χ and not on 2^S. We can extend μ to 2^S as follows :
(a) $\mu_*(A) = Sup(\mu(X) \mid X \subseteq A \text{ and } X\epsilon\chi)$, for any $A \subseteq S$
(b) $\mu^*(A) = Inf(\mu(X) \mid A \subseteq X \text{ and } X\epsilon\chi)$, for any $A \subseteq S$
$bel(\Phi) = 0, bel(S) = 1$
$bel(A_1 \cup A_2.. \cup A_k) \geq \sum(-1)^{|I|+1}_{(I\subseteq(1....k))_{(I\neq\Phi)}} bel(\cap_{i\epsilon I} A_i)$
when $i\epsilon I$.

2.1 Dempster-Shafer Theory of Combination of Evidences
Let Θ be the frame of discernment (finite). Relevant properties are subsets of Θ. Based on observing evidence E, the function $m(*)$ provides the following basic probality assignments (BPA) on Θ:
$m : 2^\Theta - - > [0,1]$
$m(\Theta) = 0$

$\sum_{A\subseteq\Theta} m(A) = 1$
The subset A of frame Θ is called the focal element of evidence E, if $m(A) > 0$
For a proposition B, $bel(B) = \sum_{A\subseteq B} m(A)$
$Pls(B) = \sum_{A\cap B\neq\Phi} m(A)$
The two above equations specify the lower and the upper bound of belief measure B. Let m_1 and m_2 are two BPAs induced from two independent evidences (sources) E_1 and E_2.
And $\sum_{A_i\cap B_j = \Phi} m_1(A_i)m_2(B_j) < 1$ is met, then the combined BPA, by D.S. combination rule,

$$m(C) = m_1(C) + m_2(C) \quad (1)$$

$$m(C) = \frac{\sum_{A_i\cap B_j=C} m_1(A_i)m_2(B_j)}{1 - \sum_{A_i\cap B_j=\Phi} m_1(A_i)m_2(B_j)} \quad (2)$$

for $C \neq \Phi$ and $m(C) = 0$, for $C = \Phi$
2.2 Assignment of Mass Function for Image Fusion using D-S Model
If Θ be the set of all elementary propositions $m(\Theta)$ which is the probality mass function indicate at what extent a sensor is able to distinguish any elementary proposition. From the concept of probability mass m bel and pls measure functions are defined in terms of proposition.
Belief for a proposition S_i is defined by, $bel(S_i) = \sum_{S_i\epsilon\Theta,2^\Theta} m(\Theta, 2^\Theta)$
where $S_i = A_1 \cup A_2 \cup A_3$ where A_1, A_2 and A_3 are the three classes defined in the problem.
So S_i is the sum of all possible combination of probality masses as,

$$bel(A_1\cup A_2\cup A_3) = m(A_1)+m(A_2)+m(A_3) + m(A_1 \cup A_2) + m(A_1 \cup A_3) + m(A_2 \cup A_3) + m(A_1 \cup A_2 \cup A_3) \quad (3)$$

and the plausibility measure $pls(S_i)$ is simply

$$pls(S_i) = 1 - bel(\bar{S}_i) \quad (4)$$

Thus from the D-S theory a number in the interval [0,1] is used which indicates the degree of evidence to support a proposition.
Thus $m : 2^\Theta - > [0,1]$
and $\sum m(A) = 1$ for all a contained in Θ.
and similarly the null hypothesis is assigned as $m(\beta) = 0$ such that the subset A of the frame of discernment Θ is the focal element having all non-zero probability mass value.
$bel(S) = \sum_m(A)$
For all A contained in S and $pls(S) = \sum_{A\cap B\neq\beta} m(A)$ In present problem of fusion we have considered the T_1 and T_2 weighted MR images of brain of an Alzheimer's patient. The two images Im1 and Im2 are complementary to each other. By D-S method of fusion the probability masses are assigned in a area where the union of classes defined are mixed. To estimate the probability masses the different classes defined in a region must be differentiated by the each sensor. So classification of different tissue regions is an essential step prior to data fusion. Before implementation of data fusion the images acquired by different sensors are brought to the same reference frame and are registered by using shape based theory discussed in first part of our work. In image1(Fig.7) and in image2(Fig.8) the classes are discriminated in grey matter, white matter, cerebrospinal fluid (CSF), ventricle and in bones. The grey matter and the white matter together is the brain region and according to our notation it is class C_1, the ventricle and CSF together are denoted by C_2. The overlapping regions of C_1 and C_2 are denoted by $C_1 \cup C_2$ as C_3 and the outer bony layer of each slice is denoted by C_4. So the four classes of brain are defined as C_1, C_2, C_3 and C_4. To assign the proba-

bility masses for each class a central or focal element is chosen . These central element is related to each class of the Im1 and Im2. The null mass m(0) is defined for each class which is not assigned.

To determine the probability masses the frame of discernment is proposed as $\Theta = (C_1, C_2)$. The power set 2^{Θ} is then given by $(\Theta, (C_1), (C_2), (C_1 \cup C_2))$. The mass functions are assigned for two images as m_1 and m_2 respectively and mass functions assigned for each class as $m_1(C_1)$, $m_1(C_2)$, $m_1(C_1 \cup C_2)$ for Im1 and $m_2(C_1)$, $m_2(C_2)$, $m_2(C_1 \cup C_2)$ in Im2.

The D-S theory of evidence combines the two mass functions to yield an overall mass functin m defined earlier. According to this definition we have,

$$m(C_1) = \frac{m_1(C_1)m_2(C_1)+m_1(C_1)m_2(C_1\cup C_2)}{1-(m_1(C_1)m_2(C_2)+m_1C_2)m_2(C_2))} \quad (5)$$

$$m(C_2) = \frac{m_1(C_2)m_2(C_2)m_1(C_2)m_2(C_1\cup C_2)}{1-(m_1(C_1)m_2(C_2)+m_1(C_2)m_2(C_1))} \quad (6)$$

$$m(C_1 \cup C_2) = \frac{m_1(C_1\cup C_2)m_2(C_1\cup C_2)}{1-(m_1(C_1)m_2(C_2)+m_1(C_2)m_2(C_1)} \quad (7)$$

$$m(C_1) + m(C_2) + m(C_1 \cup C_2) = 1 \quad (8)$$

$$bel(C_1) = m(C_1);\ bel(C_2) = m(C_2);\ bel(C_1 \cup C_2) = m(C_1)+m(C_2)+m(C_1\cup C_2) = 1 \quad (9)$$

For a pixel the decision is taken in favour of either C_1 or C_2 as to whether $bel(C_1) > bel(C_2)$ or vice varsa.

3.Experiments, Results & Discussion

The experiment is performed using Silicon Graphics Work Station. All images are converted from RGBA mode to grey mode in Tiff format. Canny's segmentation process is applied on the raw images. The features are localised to one pixel precision. The three modality images T_1 weighted MR, T_2 weighted MR and CT images are shown in (Fig.1),(Fig2) and in (Fig.3). Registered images of T_1, T_2 weighted MR in affine and in projective plane are shown in (Fig.4), (Fig.5). The registered images of CT, T_1 and T_2 weighted MR in affine and in projective plane are shown in (Fig.6) and (Fig.7). After registration the T_1 weighted MR (Fig.8) and T_2 weighted MR (Fig.9) are fused together at different pixel ranges where some artificially lesions are generated in (Fig.8), and in (Fig.9) to demonstrate the fusion process. The fused image is shown in (Fig.10) where all the image information from the two images are present.

The three classes are considered as C_1 Brain matter both grey and white, C_2 ventricle and cerebrospinal fluid or CSF and $C_3 = C_1 \cup C_2$. From the grey level histogram (Fig.11) and (Fig.12) for image Im1 (Fig.8) and Im2 (Fig.9) the mass function for each class are assigned by classification of pixels in different grey value ranges.

In pixel based classification the distribution of different pixels over a specified grey level is considered (fig(11) for Im1 and grey level distribution is shown in(fig.(12) for Im2. In Im1 the pixels are spread over the range 20 to 190. Primarily we have considered the distribution of pixels over the ranges below 130, in between 130 - 190 and above 190.

When M is the no. of pixels lying in the region over a specified grey level and if N is the dimension of the region ($N = N_1 \times N_2$) taken a small image of brain.

(a) for pixels having grey values less than 130, $m_1(C_2) = 1$, $m_1(C_1) = 0$ and $m_1(C_1 \cup C_2) = 0$

(b) for pixels grey level greater than 190, $m_1(C_1) = 1$, $m_2(C_2) = 0$, $m_1(C_1 \cup C_2) = 0$

(c) for pixels grey level values between 130 and 190, $m_1(C_1) = 0.49$; $m_1(C_2) = 0.3$ and $m_1(C_1 \cup C_2) = 0.193$.

Similarly for image2 Im2, the range of grey levels distributed over the pixels, (a) for pixels having grey values less than 90 $m_2(C_1) = 1$, $m_2(C_2) = 0$, $m_2(C_1 \cup C_2) = 0$

M' No. of pixels over a specified grey level for class C_1 and M_1' No. of pixels over a specified grey level for class C_2, N' is the image dimension considered. (b)for pixels having grey values 90 to 135 $m_2(C_2) = 0$, $m_2(C_1) = 0.552$ and $m_2(C_1 \cup C_2) = 0.498$. (c) for pixel having grey values 135 & 140, $m_2(C_1) = \frac{M'}{N'}$ and $m_2(C_2) = \frac{M_1'}{N'}$

$m2(C_1 \cup C_2) = 1 - (\frac{M'}{N'} + \frac{M_1'}{N'})$

Thus $m_2(C_1) = 0.01$, $m_2(C_2) = 0$ and $m_2(C_1 \cup C_2) = 0.99$

(d)for 140 to 197 range $m_2(C_1) = 0.03$, $m_2(C_2) = 0.07$ and $m_2(C_1 \cup C_2)0.9$

(e)between 197 and 255, $m2(C_1) = 0$, $m_2(C_2) = 0.9$ and $m_2(C_1 \cup C_2) = 0.1$.

According to these mass function values assigned in different grey level ranges the belief measure and pls measure indicate in which class a pixel belongs in the fused image.

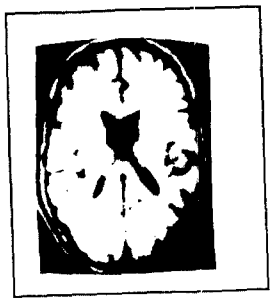

Fig.1 T1 weighted MR image of brain of an AD patient (axial section)

Fig.2 T2 weighted MR image of brain of an AD patient (axial section)

Fig 3.CT image of brain of an AD patient (axial section)

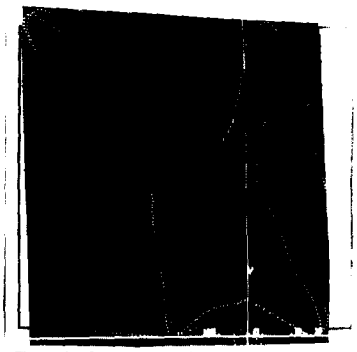

Fig.4 Registration of T1 and T2 weighted MR Images of brain of the AD patient in ventricular region by affine transformation

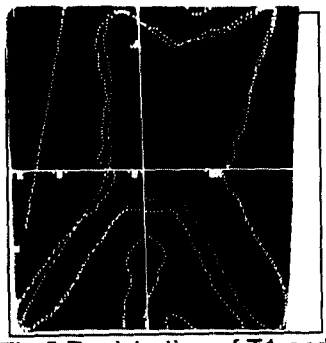

Fig.5 Registration of T1 and T2 MR of brain of the AD patient in ventricular region by projective transformation

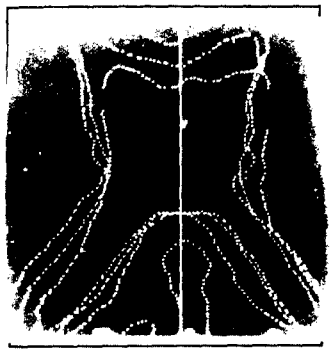

Fig 6 Registration of T1 MR, T2 MR and CT images of brain of the AD patient in affine plane,

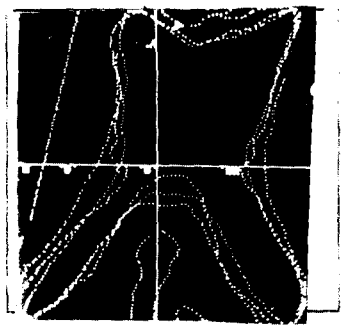

Fig 7 Registration of T1 MR, T2 MR and CT images of brain of the AD patient in projective plane,

Fig 8 T1 weighted MR image of brain of the AD patient where an artificially lesion is generated (Im1) image captured by sensor 1 for data fusion

Fig 9 T2 weighted MR image of brain (Im2) of the AD patient image captured by sensor2 for data fusion

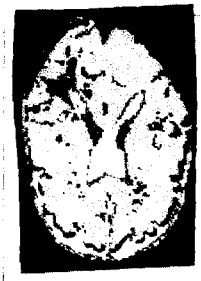

Fig 10 The fused image of brain of the AD patient, data fusion of Im1 and Im2 . The fusion between T1 and T2 weighted MR image of brain is shown

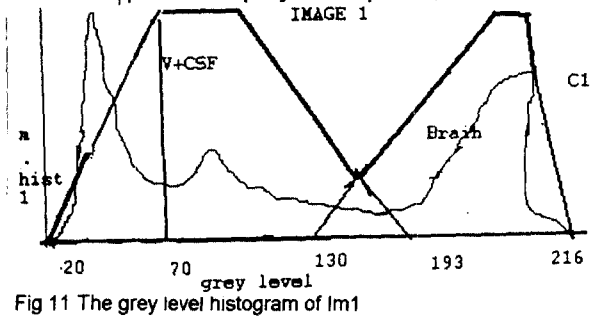

Fig 11 The grey level histogram of Im1

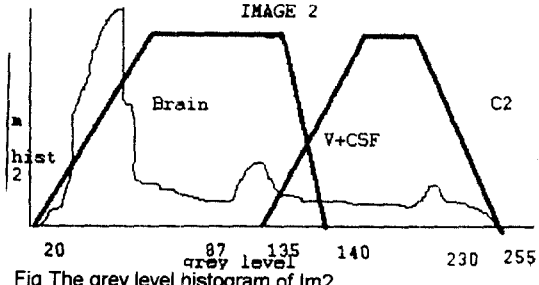

Fig The grey level histogram of Im2

4.Conclusion

The registration process performs the intregration of information from the multimodality medical imaging to a single reference frame. This process for both the anatomical and functional images incorporate more accuracy in diagnosis procedures and provide improved therapeutic planning to the clinicians.

All detected anatomical and functional features of the pathological growth related to ROI can be analysed simultaneously when the images are fused in a single reference frame after registration. The fusion process enables the combination of pathological and structural information from multisensors images As a result the pathological and also the struc-

tural details from the of the region of interest can be obtained from the resultant fused images . According to expert in Alzheimer's disease the degeneration of an organic compound called 'myelin' occurs in brain. From the fusuion CT and MR images the degeneration of myelin and also the ventricular dilation can be predicted because the degeneration of myelin is an indication of the prognosis of the disease.

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References

1. D.Dutta Majumder, A Unified Approach to Artificial Intelligence, Pattern Recognition, Image Processing, Computer Vision In Fifth Generation Computer Systems, International Journal Of Information Sciences 45,391-431,1988.

2. D.Dutta Majumder, A Study On A Mathematical Theory Of Shapes In Relation To Pattern Recognition And Computer Vision, Indian Journal Of Theoritical Physics, Vol.43, No.4, pp.19-30, 1995.

3. D.K Banerjee, S.K. Parui , and D.Dutta Majumder ,A Shape Metric For 3-D Objects, Indian Journal Of Applied Math., 25, pp. 95-111, 1994.

4. S.K. Parui and D.Dutta Majumder, A New Definition Of Shape Similarity, Pattern Recognition Letter, Vol. 1, pp. 87-120, 1982.

5. S.K. Parui and D.Dutta Majumder, Shape Similarity Measure For Open Curves, Pattern Recognition Letter, Vol.1, pp.129-134, 1983.

6. S.K. Parui and D.Dutta Majumder Symmetry Analysis By Computer, Pattern Recognition. Vol.16, pp.63-67, 1983.

7. D.Dutta Majumder and M.Bhattacharya, A Shape Based Approach To Automated Screening Of Malignancy In Tumors In Tomographic And Other Related Images IETE Conf, NASELSOM-97.

8. D.Dutta Majumder and M.Bhattacharya, Some Experiments on Uncertainty Management in Multimodal Image Fusion System for Diagnosis and Therapy Planning,International Conf. on Recent Advances in Statistics ans Probality, Calcutta, December 29, 1997 - Jan 1 1998.

9. D.Dutta Majumder and M.Bhattacharya, A Study on Multimodal Medical Image Processing System for Diagnosis and therapy Planning, International Conf. CODEC, Calcutta, 14 - 17 January 1998.

10. B.B Chaudhuri and D. Dutta Majumder, Two Tone Image Processing and Recognition, Wiley Eastern Limited, pp:1-63, 88-100.

11. John Canny, A Computational Approach To Edge Detection, IEEE Trans. On Pattern Analysis And Machine Intelligence Unit. Vol Pami-8, No-6, Nov 1986.

12. H.Arai,K.kobasaki et.al. A computed tomography study of Alzheimer's disease, J.Neurol 1983, Vol 229, pp:69-77.

13. H.Creasay, M.Schwartz et.al. Qualitative computed tomography in dementia Of Alzheimer's type, Neurology 1986, Vol.36,pp:1563-1568.

14. de Leon MJ, AE George et.al. Alzheimer's disease: Longitudinal CT studies of ventricular change, AJNR 1989 Vol.10 pp:371-378.

15. Medical Imaging International Journal, Vol VI, No 5, pp:9-19,1996

16. S.Banerjee, D.P.Mukherjee, D.Dutta Majumder , Point landmarks for registration of CT and MR images ,Pattern Recognition Letters 16, 1995 ,pp:1033-1042.

17. G.Shafer, A Mathematical Theory of Evidence, Princeton University Press, Princeton, NJ.

18. David L.Hall, Mathematical Techniques in Multisensor Data Fusion, Artech House, Boston.