

**CALCULATION OF TRUE T_1 , T_2 AND PROTON DENSITY
IMAGES FOR THE ELIMINATION OF SIGNAL
INTENSITY ARTIFACTS IN SEGMENTATION OF BRAIN
TISSUE IN MAGNETIC RESONANCE IMAGING**

by

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ABSTRACT

CALCULATION OF TRUE T_1 , T_2 AND PROTON DENSITY IMAGES FOR THE ELIMINATION OF SIGNAL INTENSITY ARTIFACTS IN SEGMENTATION OF BRAIN TISSUE IN MAGNETIC RESONANCE IMAGING

Segmentation of tissues in medical imaging is an essential subject because it helps the radiologists to be able to identify diseases, tumors and follow the degenerative diseases. In Magnetic Resonance Imaging (MRI) one factor that causes a problem during segmentation is the inhomogeneity in the magnetic field. Mainly the RF coil inhomogeneity effect causes intensity inhomogeneity through the image. This intensity inhomogeneity may cause segmentation algorithms to fail for a specific imager system. In case an algorithm that can be used in many imagers is needed the difference in the tissue intensities and the RF coil inhomogeneity change may cause greater failures. To overcome this problem a method which uses calculated T_1 , T_2 and proton density parameters is proposed. These parameters are calculated from MRI images using four sampling points (four sets of images of the same region with different parameters) and using Levenberg-Marquardt Method. Then maximum likelihood classification is applied to distinguish the tissues and the segmented images were constructed. Gray Matter, White Matter and Cerebrospinal Fluid were segmented in MR brain images of seven volunteers. The subject heads were scanned with three different MR imagers. Tissue segmentation was performed with the weighted T_1 , T_2 and Proton Density images along with the computed true T_1 , T_2 and PD. Comparisons across image slices; across imagers and across subjects indicated that significant improvement can be achieved if the computed T_1 , T_2 and PD images are used for the segmentation of brain tissue.

Keywords: T_1 , T_2 , PD, Levenberg-Marquardt, maximum likelihood classification, RF coil inhomogeneity .

ÖZET

BEYİN DOKUSU SEGMENTASYONUNDA SİNYAL YOĞUNLUĞUNA BAĞLI HATALARIN ELENMESİ İÇİN GERÇEK T_1 , T_2 AND PROTON YOGUNLUĞU GÖRÜNTÜLERİNİN HESAPLANMASI

Tıbbi görüntülerde dokuların segmentasyonu radyologlara sağladığı yararlar bakımından önemli bir konudur. Radyologlar bu yöntemi hastalıkları teşhis etmede tümörleri belirlemede ve dejeneratif hastalıkların takibinde kullanabilir. Manyetik Rezonans Görüntüleme de segmentasyon sırasında karşılaşılan sorunlardan bir tanesi manyetik alandaki bozukluklardır. RF coil deki alan bozukluğu nedeniyle alınan sinyal yoğunluğundaki değişim görüntünün parlaklık değerlerini etkiler. Bu etki belli bir görüntüleme sistemi için segmentasyonda problem yaratabilir. Birden çok görüntüleme sisteminde kullanılacak bir algoritma düşünülecek olursa doku parlaklıklarında ve RF coil alanı bozukluklarındaki değişim nedeniyle hata oranı artabilir. Bu alismada ilgili problemlerin özülmesi için hesaplanmış T_1 , T_2 ve proton yoğunluğu değerlerini kullanan bir algoritma önerilmektedir. Bu parametreler aynı bölgenin farklı dört parametre ile görüntülenmesi ve Levenberg-Marquardt Methodu nun uygulanması ile hesaplanmıştır. Daha sonra yapılan sınıflandırma sonucunda segmentasyon sonucu elde edilen görüntüler oluşturulmuştur. Üç farklı MR cihazında görüntülenmiş yedi farklı bölgenin beyin görüntüleri Gri madde, Beyaz Madde ve Serebrospinal sıvı olarak ayrıştırılmıştır. Doku ayrıştırma için T_1 , T_2 ve PD görüntüleri kullanılarak ve hesaplanmış gerçek T_1 , T_2 PD görüntüleri kullanılarak yapılmıştır. Karşılaştırmalar kesitler arasında, görüntüleme cihazları arasında ve algoritmalar arasında yapılmış ve sonuç olarak hesaplanmış T_1 , T_2 ve PD görüntüleri kullanıldığında beyin dokularının ayrıştırılmasında oldukça iyi sonuçlar elde edilmiştir.

Anahtar Sözcükler: T_1 , T_2 , PD, Levenberg-Marquardt, maksimum benzerlik sınıflandırması, RF coil düzensizlikleri.

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LIST OF SYMBOLS

T_1	Longitudinal Relaxation Time
T_2	Transversal Relaxation Time
T_2^*	Variant of the Transversal Relaxation Time
T_R	Repetition Time
T_E	Echo Time
B_0	Main Magnet Magnetic Field
B_1	Coil Magnetic Field
M_z^0	Proton Intensity
A_E	Acquired Signal Intensity
C_{xx}	Covergance Matrix
ρ	Spin Density
α	Flip angle
μ	vectors

LIST OF ABBREVIATIONS

MR	Magnetic Resonance
MRI	Magnetic Resonance Imaging
NMRI	Nuclear Magnetic Resonance Imaging
NMR	Nuclear Magnetic Resonance
PET	Positron Emission Tomography
SPECT	Single Photon Emission Computed Tomography
RF	Radio Frequency
CT	Computed Tomography
T	Tesla
SNR	Signal to Noise Ratio
WM	White Matter
GM	Gray Matter
CSF	Cerebrospinal Fluid
PD	Proton Density
ML	Maximum Likelihood
3D	Three Dimensional

1. INTRODUCTION

Magnetic resonance imaging (MRI) is an imaging technique used primarily in medical settings to produce high quality images of the inside of the human body. MRI is based on the principles of nuclear magnetic resonance (NMR), a spectroscopic technique used by scientists to obtain microscopic chemical and physical information about molecules. The technique was called magnetic resonance imaging rather than nuclear magnetic resonance imaging (NMRI) because of the negative connotations associated with the word nuclear in the late 1970's. MRI started out as a tomographic imaging technique, that is it produced an image of the NMR signal in a thin slice through the human body. MRI has advanced beyond a tomographic imaging technique to a volume imaging technique.

MRI outputs multidimensional data array (images) which represent the spatial distribution of some measured physical quantity. MRI can generate two dimensional or three dimensional images from the acquired data. MR signals acquired to produce the required data comes directly from the imaged object. In this aspect MR is a form of emission tomography like PET and SPECT but unlike these imaging methods there is no need for radioactive injection to the patient in MR imaging.

The two main advantages of using MRI are;

- 1)it does not have a negative effect on patient health
- 2)it is extremely rich in information content

MR scanners operate in the radio frequency (RF) range. So the imaging process does not involve the use of ionizing radiation and therefore does not have the associated harmful effects.

The MR pixel values are dependent on a series of parameters. These parameters include nuclear spin density (ρ), spin lattice relaxation (T_1), the spin spin relaxation (T_2), susceptibility effects and chemical shift differences. These parameters' effect on MR image can be controlled by changing repetition time(T_R), echo time (T_E), and flip angle(α). Therefore, the same anatomical structure can be visualized in different images. MR images can be made to be the map of stationary spins, moving spins, relaxation times, water diffusion coefficients which are the areas of spectroscopic imaging, diffusion imaging, angiographic imaging and functional imaging.

MR imaging is an information intense method. It contains detailed information about tissue contrast and is extremely qualitative. On the other hand the quantitative functions of MR imaging is limited. In order to make MR imaging a quantitative method accurate measurement of tissue volume is needed. This introduces the problem of automatic volume segmentation.

Tissue segmentation is a difficult process due to the time and machine dependencies. Also intensity inhomogeneities in images make segmentation a hard process to be handled [1,2]. In this study we attack inhomogeneity problem caused by B1 inhomogeneity and we propose a method that gives machine and time independent segmentation results. We test our proposal on several subjects across various brand and model MRI devices.

2. BACKGROUND

2.1 MR Coils

Although the MR imager looks as same as the X-ray Computed Tomography (CT) scanner these two scanners do not have very much in common. A MR scanner consists of three main components: a main magnet, a magnetic field gradient system and an RF system.

2.1.1 The Main Magnet

The main magnet is either a resistive, a permanent or a superconducting magnet. The main function of this magnet is to produce a strong and uniform magnetic field referred as the B_0 magnetic field, for polarization of nuclear spins in an object. The type of magnet used depend on the strength of the magnetic field required. The resistive magnets are used for fields below 0.15T, the permanent magnets are used for fields between 0.15T and 0.3T and the superconducting magnets are used for the higher magnetic fields. The field strength is operation dependent. Generally for clinical studies the magnetic field strength is between 0.5T to 2T. The homogeneity of the main magnet is important to acquire good image quality. This is even more important in spectroscopic imaging. Homogeneity of a magnetic field is defined as the maximum deviation of the field over a given volume within a region of interest.

$$Homogeneity = \frac{B_{0,max} - B_{0,min}}{B_{0,mean}} [1] \quad (2.1)$$

However the main magnet itself is not capable of producing very homogenous magnetic fields so the general approach to overcome homogeneity problem is to use a

secondary compensating magnetic field which is generated by the shim coils to bring the magnetic field to a desired homogeneity.

2.1.2 The Gradient System

The gradient system consisting of three orthogonal gradient coils is a crucial component of an MRI scanner because gradient fields are essential for signal localization.

One of the important specifications to a gradient system is the gradient strength. Gradient strength is measured in milliteslas per meter (mT/m) and the higher the strength the better the gradient system is. The gradient strength required for a scanner cannot be lower than the magnetic field inhomogeneity. Most of the clinical systems have a gradient strength of approximately 10 mT/m.

Another important specification to a gradient system is the time interval for the system to reach up to its full strength and is called the rise time. A system with a shorter rise time is better than a system with a longer rise time. For conventional imaging systems a rise time of 1.0ms for a rise of 0 to 10mT/m is considered to be good. Some imaging methods need shorter rise times.

2.1.3 RF System

The RF system is composed of two coils. A transmitter coil for generating a rotating magnetic field, which is referred as B_1 , for the excitation of a spin system. The receiver coil converts a precessing magnetization into an electrical signal. In some cases these two coils can be combined in one which acts like a transmitter and receiver coil and named as transceiver coil. All of these coils are called RF coils because they resonate at radio frequency.

The desirable feature of a RF coil is to provide an uniform B_1 field and high detection capability. To be able to maintain this feature different coil types are used for different applications.

2.2 Signal Intensity Artifacts

Signal intensity artifacts are often encountered during MR imaging. These artifacts lower the image quality and interfere with interpretation. Signal intensity artifacts can generally be minimized by optimal coil design and tuning.

Intensity artifacts may occur due to several reasons. Improper coil tuning can lead to shading artifact. Where as improper patient or coil positioning can lead to minor or in some cases major intensity artifacts on the image. Another cause of artifacts may be protocols. Even perfectly functioning coils may lead to image artifacts if the protocols are not optimized. On the other hand ferromagnetic foreign materials in the imager can lead to signal degrading artifacts. Also performing ultrafast imaging with coil that were not designed for that type of imaging may lead to signal intensity artifacts.

For optimum image quality all the effects must be taken into consideration and some of these must be a part of MR imaging quality assurance program.

2.2.1 Signal Intensity Artifacts Inherent in Local Coil Imaging

Local coils are typically designed to help evaluate a specific anatomic area. It is known that the coils sensitivity decreases as the distance between the coil and the tissue increases. This causes the local coil's region of sensitivity is superimposed on the MR image as a intensity gradient.

The shape of the coil is an important issue in MR imaging. There are two

main types of local coils. These are surface coils and volume coils. Surface coils are generally planar or curvilinear coils where as volume coils surround the anatomy to be imaged. The intensity gradient is more apparent in surface coils then the volumetric coils. Figure 1 shows a phantom study which was made using a surface coil (body coil) and Figure 2 shows a study with a volumetric coil (ex. head coil).

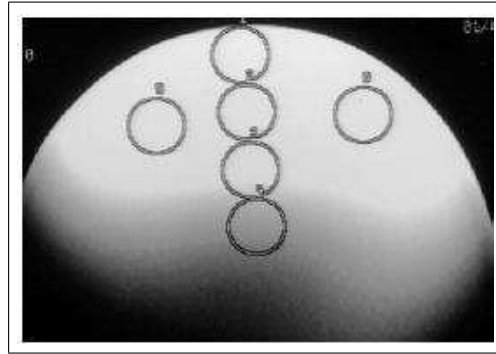


Figure 2.1 A phantom study image acquired by using a surface (body) coil. [2]

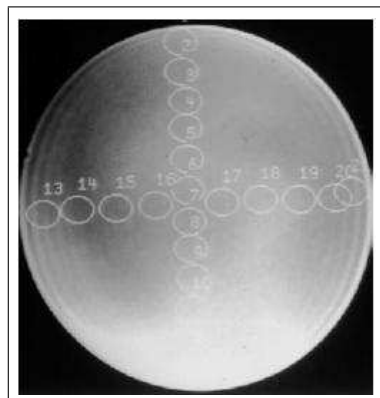


Figure 2.2 A phantom study image acquired by using a volumetric (head) coil. [2]

Another coil related intensity artifact is local intensity artifact. This artifact results because of the varying positions of the voxels in the image and follows a diagonal pattern on the axial plane. This artifact is caused by the eddy currents that are created by the radio frequency. These currents may have additive and subtractive effect on the image intensity profile depending on the relative vector relationships. This artifact is only seen in the axial plane because there is no signal generating longitudinal component to sum vectorially with the coil's vector sensitivity profile. For example in

an MR imager with clock wise rotation additive effect is seen on the upper left hand corner and subtractive effect is seen on the lower right hand corner as seen in Figure 3.

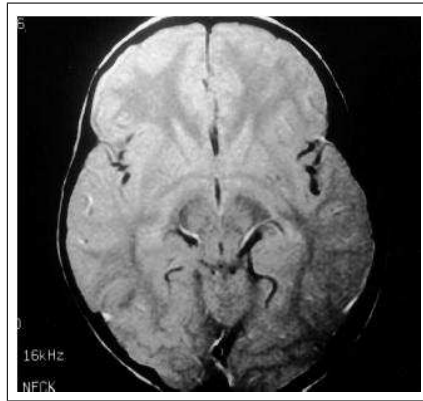


Figure 2.3 Additive and Subtractive effects of imager. [2]

Local intensity shift artifact is seen more obviously with the surface coils than with the volume coils and can be minimized with optimal coil design and tuning.

Uneven coil loading can also cause intensity artifacts. The causes of this may be non equidistant coil elements, poor phase tuning and poor positioning of the coil relative to the anatomic area of interest. Uneven coil loading degrades the image quality by affecting the output impedance of the coil and reducing the achievable signal to noise ratio (SNR).

These signal intensity artifacts are often encountered in clinical imaging and usually ignored. However in patients with white matter disease signal intensity artifacts can reduce the ability to determine disease extent because the radiologists use the symmetry for diagnosis.

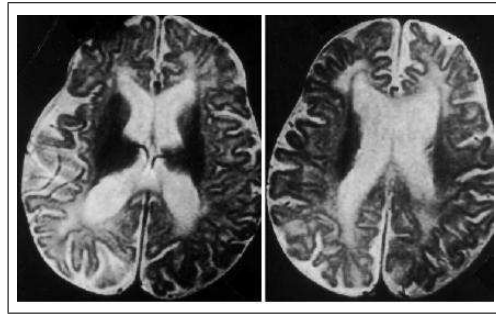


Figure 2.4 Image of a patient with white matter disease. The intensity inhomogeneity on the image reduces the radiologists ability to make a decision. [2]

2.2.2 Signal Intensity Artifacts due to Positioning or Protocol Errors

Signal intensity artifacts can also be caused by improper positioning of the coils or patients. Improper positioning artifacts can be severe or subtle. A quadrature coil that is inverted relative to B_0 will result in signal cancellation in regions where signal addition is expected under normal circumstances. This is caused by the phase inversion of one quadrature signal relative to other at the quadrature combiner input. Figure 5 shows an example of severe signal intensity artifact due to improper positioning of breast coil. The band of cancellation caused by orienting the coil 180° opposite to B_0 is clearly seen on the image. Another example of these artifacts can be seen on Figure 6. The artifact here is subtle, caused by the improper positioning of the body coil. On Figure 6b the coil is positioned properly and the artifacts are not seen.

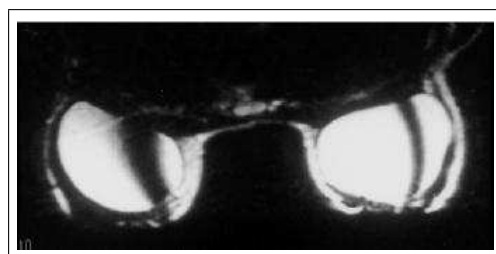


Figure 2.5 Severe intensity artifact caused by improper coil positioning. [8]

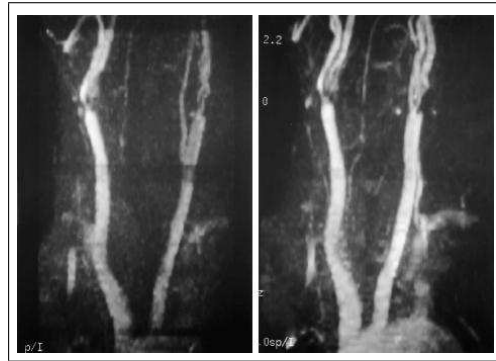


Figure 2.6 Subtle intensity artifact by poor coil positioning.[3]

Signal intensity artifacts and image degradation can occur in a perfectly functioning coil if the protocols are not optimized. In MR angiography the image is directly proportional to the contrast to noise ratio. This represents the ratio of blood brightness to background tissue brightness and is a direct function of the acquisition sequence used, voxel size, coil sensitivity, and effectiveness of the saturation pulse.

The received signal is proportional to the voxel size and is normally constant in similar types of tissues. Stationary signal is suppressed by a transmit pulse whose amplitude depends on the average value of the signal received from the given section. The suppression signal is then set to a value large enough to dephase signal in the average stationary voxel, resulting a signal compression in these voxels. Stationary signal will manifest as a residual signal if not dephased which will then appear brighter in conjunction with the coil sensitivity profile. The result will be an inhomogeneous intensity profile over a homogenous media as seen in Figure 7.

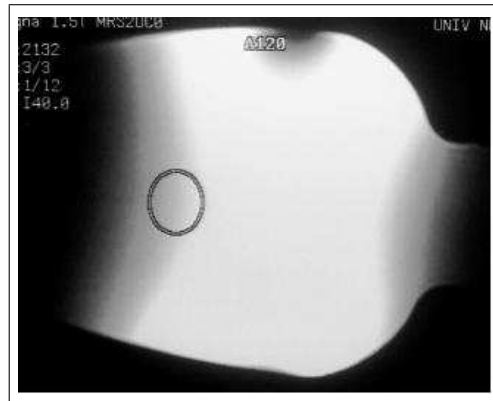


Figure 2.7 Intensity inhomogeneity [12]

2.2.3 Signal Intensity Artifacts due to Local Coil or System Malfunction

Decoupling failure is one of the most common problems of local receive only coils. Decoupling mechanism failure can either be complete or partial and may cause both internal and surface heating in the patient. Decoupling mechanisms are mechanisms that prevent radio frequency to currents flowing into the receive only coils which would result in local distortion if the field and signal intensity variations in the image. Severe decoupling failure may cause in bright and dark bands to appear on the image and minor detuning of the decoupling may cause minor shading effect on the image. However artifacts caused by coil decoupling errors does not respond to protocol optimization and will worsen with gradient imaging.

Above all improper coil tuning causes a shading artifact which can mimic many of the other artifacts. Quadrature coils require exact phase adjustment and of the individual coils elements, which contribute to the image reproduction. Shading can result if any of the constituent elements in the coil is not adjusted properly. These artifacts does not respond to protocol optimization either however, they do not worsen with gradient imaging. Unlike local intensity shift artifact they are seen on all planes.

Signal degrading artifacts may be caused by ferromagnetic foreign bodies within the images. This is can be understood because the artifact will occur with any coil.

Also signal intensity artifacts may occur if ultrafast imaging sequences are used with the coils that are not designed for this type of imaging. Rapid sequences are used for ultrafast imaging so the eddy currents may occur and banding artifact may be seen on the images.

There are some other artifact that are not caused by the local coils. These may be caused by many factors. These artifacts are seen on many images with different coils.

Finally, it is important to know the causes of the signal intensity artifact to be able to get the optimal images for evaluation. Since most of the radiologists use the symmetry between the tissues for diagnostic purposes, it is very important to get optimal images form the imager.

2.3 Image Artifacts Caused by Coil Inhomogeneities

An image artifact is any feature which appears in an image which is not present in the original imaged object. An image artifact is sometime the result of improper operation of the imager, and other times a consequence of natural processes or properties of the human body.

Artifacts reduce the image quality and therefore the diagnostic capability. False positives and false negatives can occur.

One of the main causes of the artifacts is the inhomogeneity problem. It is very essential to have a homogeneous magnetic field to achieve images of good quality. Any condition that disturbs the homogeneity of the magnetic field causes various problems according to the field they disturb.

2.3.1 Main Magnetic Field (B_0) Artifacts

All magnetic resonance imaging assumes a homogeneous B_0 magnetic field. An inhomogeneous B_0 magnetic field causes distorted images. The distortions can be either spatial, intensity, or both.

Intensity distortions result from the field homogeneity in a location being greater or less than that in the rest of the imaged object. The T_2^* in this region is different, and therefore the signal will tend to be different. For example, if the homogeneity is less, the T_2^* will be smaller and the signal will be less.

Spatial distortion results from long-range field gradients in B_0 which are constant in time. They cause spins to resonate at Larmor frequencies other than that prescribed by an imaging sequence. Ideally, spins at a single position should experience a single magnetic field and resonate at a single frequency. With a distorted gradient, there is no linear relationship between position and frequency. Because linearity is assumed in the imaging process, the resultant image is distorted.

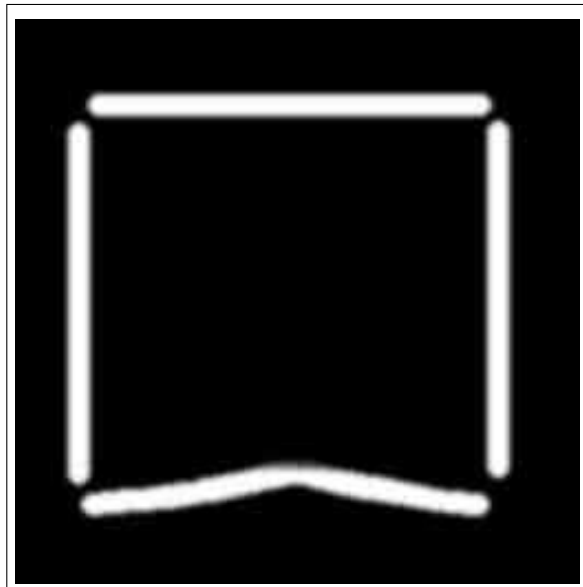


Figure 2.8 Distortion of the image due to B_0 inhomogeneity

Figure 1.1 demonstrates the main magnet inhomogeneity. Four cylindrical tubes

are arranged to form a square. The bottom tube seems bent due to the inhomogeneity in the B_0 .

2.3.2 Gradient Field Artifacts

Artifacts arising from problems with the gradient system are sometimes very similar to those described as B_0 inhomogeneities. An gradient which is not constant with respect to the gradient direction will distort an image. This is typically only possible if a gradient coil has been damaged. Other gradient related artifacts are due to abnormal currents passing through the gradient coils. In Figure 1.2 the frequency encoding (left/right encoding) gradient is operating at half of its expected value.

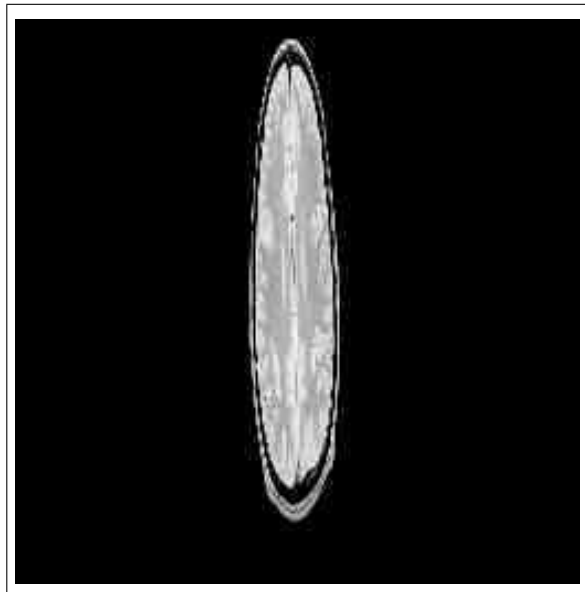


Figure 2.9 Distortion of the image due to malfunctioning gradient coil

2.3.3 RF Field (B_1) Artifacts

An RF inhomogeneity artifact is the presence of an undesired variation in signal intensity across an image. The cause is either a nonuniform B_1 field or a nonuniform sensitivity in a receive only coil. Some RF coils, such as surface coils, naturally have variations in sensitivity and will always display this artifact. The presence of this

artifact in other coils represents the failure of an element in the RF coil or the presence of metal in the imaged object. For example a metal object which prevents the RF field from passing into a tissue will cause a signal void in an image.

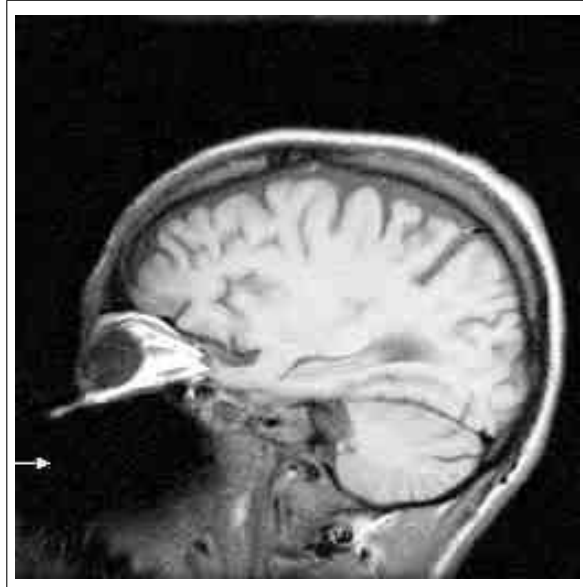


Figure 2.10 Distortion of the image due to B_1 inhomogeneity

The patient in Figure 1.3 has a large amount of non ferromagnetic metal dental work in the mouth which is pointed by the arrow. The metal shielded the regions near the mouth from the RF pulses thus producing a signal void. The Dental work did not significantly distort the static magnetic field B_0 . The metal does not significantly distort the static magnetic field B_0 at greater distances; therefore, the image of the brain is not significantly distorted.

3. A REVIEW OF STUDIES ON ELIMINATION OF IMAGE ARTIFACTS

Magnetic Resonance Imaging is the gold Standard modality for exploring the brain on its anatomical and pathological sides. For the study of brain pathologies (Multiple sclerosis, Alzheimer disease, Creuzfeldt Jacob), some quantitative measurements like volume measurement or tissue atrophy are needed. Generally these studies rely on T1 images since this type of image reveals brain tissues with more contrast other kinds of brain imaging. For these analysis, computer vision tasks are involved like segmentation and tissue classification.

It is necessary to correct for intensity differences between MR acquisitions in order to optimally use large datasets. It must be noted that the variation of the MR acquisition parameters (echo time, repetition time, as well as the type of MR scanner) do not affect linearly the image intensities. The intensity correction between two MR of two different subjects cannot just be linear. Some papers have focused on the MR histograms and intensity correction, mostly for inhomogeneity correction in MR images (due to magnet field inhomogeneities) [7,8]. Other authors have focused on intensity correction in longitudinal time-series MR [4], but the images have to be accurately spatially aligned which makes this method difficult to apply to inter-subject correction. Other papers have proposed methods to correct for inter-subject MR intensity, either based on histogram matching [5], or on a statistical observation model [6]. Some authors used an anatomically-consistent correction scheme (in the sense that the intensity correction is derived from the anatomical information)[9].

A number of studies have explored the potential of various supervised and unsupervised pattern recognition techniques for the segmentation of MRI data. Consistently, these studies have reported results that are in visual agreement with the expert's judgement, but a number of factors reducing the robustness and the reliability of the classifiers are reported, the leading of which are 1) intraslice intensity

variations introduced by inhomogeneity in the radio frequency field, 2) inter-slice intensity variations, and 3) inter-patient intensity variations. Because of the existence of these acquisition artifacts, the development of fully automatic segmentation methods for MRI data needs to be processed before the algorithm is applied to the images. In some cases semi-automatic techniques are developed in which user intervention is used for correction of the artifacts.

They can be classified into two main categories: nonretrospective (empirical) and retrospective (post-processing). Nonretrospective methods require prior information to perform the correction. They include phantom-based method, simulation method, extra body coil scan, and special acquisition scheme. These methods provide an independent measurement of the scanner's bias field and do not require assumptions about the bias pattern or the patients' anatomy in other words they cannot take the complex electromagnetic properties of the human body into account, the correction based on these prior information is not accurate. Some nonretrospective methods usually need modification of imaging procedures and cannot be applied to previously acquired MR images. They are time consuming and costly, and they are unable to remedy inhomogeneities due to patient-specific magnetic susceptibility and RF [10].

The post-processing techniques are the most commonly used approaches in the quantitative analysis of MR images. Guillemand and Wells used an expectation-maximization algorithm to iteratively classify and correct the images based upon some initial probability estimates [11]. Decarli et al. compared local and composite medians of specific tissue classes [12]. Lee and Vannier applied the fuzzy c-means-clustering algorithm to estimate bias in MR images [13]. Koivula et al. employed the compensating function to small variations within homogenous areas by extensive averaging. Wang et al. used histogram matching to correct variations in scanner sensitivity [14]. Sled et al. developed an iterative deconvolution approach combined with a polynomial filtering to estimate the distribution of the true tissue intensities. Other approaches have modeled the gain field by polynomial methods, interpolation between user-selected points, sophisticated iterative segmentation and B-spline fitting. Homomorphic Unsharp Masking (HUM) has often been used in practice [15,16]. HUM is a post-processing technique

that behaves as a sort of band notches filters, where certain spatial frequency ranges in the image are selected and removed. It is used to remove lowfrequency components from an image, and typically does not alter tissue boundaries. Such approaches were described by Lim, Harris and Narayana. In this kind of approaches, cerebrospinal fluid (CSF) and other high-intensity structures were first replaced by the averaged pixel intensity of the parenchyma. The resulting image was then filtered with median filters. The thus smoothed image rejects the in-plan RF profile. To remove the inhomogeneity, this smoothed image was subtracted from the original image. After that, the image was normalized using the averaged CSF pixel intensity. HUM is conceptually straightforward. It is very fast and can be easily implemented. Drawbacks, however, exist with this approach. Firstly, the smoothed image contains only low frequency components. Secondly, the approach does not take into account the influence of CSF.

3.0.4 T_2 Relaxometry

Another method used in quantitative analysis is T_2 relaxometry. It consists of maps based on T_2 relaxation times. Spin echo or gradient echo imaging can be used to perform T_2 relaxometry. Generally spin echo sequences are used with 2 or more different T_E values. While differentiating T_E values it is important that values close to the desired tissues T_2 value must be chosen to get better results. Also as the T_1 value increases the signal to noise ratio increases giving better results however this time the acquisition time increases. This is the case using single spin echo sequences, there is the possibility to perform relaxometry by using multi spin echo sequences.

T_2 relaxometry is used for determining iron overload in liver and spleen, lesion detection in breasts and quantitative analysis of brain tissue. T_2 relaxometry in human brain has also been successfully used to differentiate normal from abnormal tissues. Increased signal on T2-weighted MRI is a feature to identify cerebral abnormalities. The measurement of T2 has been shown to be useful in the assessment of hippocampal sclerosis, particularly if there are only subtle changes that may not be evident visually, in the evaluation of some tissue regions as contralateral hippocampus, amygdale, white matter, and thalamus. Due to the large number of subdivisions of brain anatomy,

sometimes it is difficult to select a small region to perform relaxometry. Nevertheless, with a whole brain map, small segmented regions are selected and the mean T2 value, or histogram, for each segment can be generated.

4. METHOD

For the elimination of RF coil inhomogeneity artifacts we propose a method that depends on true T_1 , T_2 and PD images instead of the weighted MR images. So the method requires data acquisition at different T_E and T_R values. If there is motion between the image acquisitions a registration algorithm is applied to the images. Then we use the proposed method which is calculating the true T_1 and T_2 values of the tissues from the acquired images. Then from the calculated T_1 and T_2 images we use Gaussian probability functions for the image segmentation.

4.1 Data Acquisition

To be able to calculate the true T_1 and T_2 values for brain tissue we need to acquire images at different imaging parameters.

Signal Intensity in MRI can be reduced to:

$$A_E = M_z^0(1 - e^{-T_R/T_1})e^{-T_E/T_2} \quad (4.1)$$

where A_E is the signal intensity acquired, M_z^0 is the , T_R is the repetition time and T_E is the echo time.

For the calculation of T_1 values first of all a short T_E must be selected to eliminate the T_2 effect on the image as seen in Equation 3.1. For this purpose we used the $T_E=15\text{ms}$. With short T_E duration the signal intensity is reduced to equation 3.2. The exponentially increasing curve in Figure 4.1 can be sampled by changing T_R values.

$$A_E = M_z^0(1 - e^{-T_R/T_1}) \tag{4.2}$$

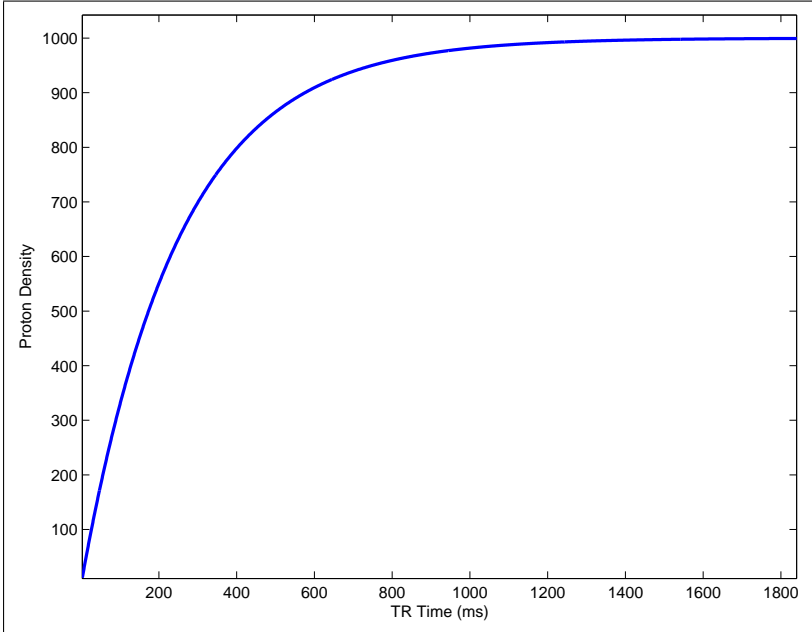


Figure 4.1 T_1 relaxation characteristic curve.

For the calculation of T_2 values T_R was used as 3000ms to eliminate the T_1 effect on the images and T_E was varied to be able to sample the decreasing exponential function in Figure 4.2 to obtain true T_2 images.

$$A_E = M_z^0 e^{-T_E/T_2} \tag{4.3}$$

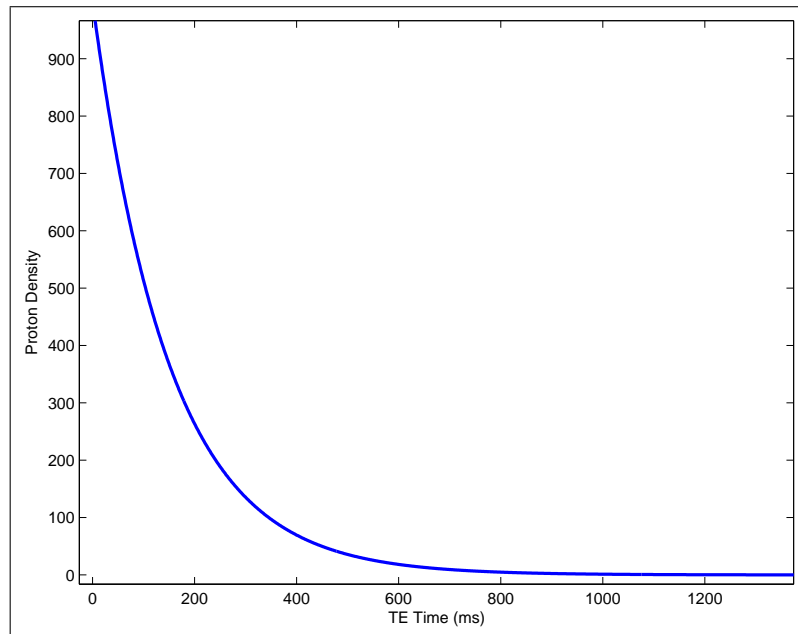


Figure 4.2 T_2 relaxation characteristic curve.

For accurate calculation of the true relaxation parameters the sampling on the related curve is an important issue. However sampling many points on the curve is not very efficient regarding MRI studies because the images are acquired in terms of minutes. This reduces the patient comfort and acquisition costs. To overcome acquisition problem we have made a phantom study with a homogenous phantom.

In the phantom study we have made 12 acquisitions for T_1 weighted images and 11 acquisitions for T_2 weighted images. Then we calculated the true relaxations parameters from these acquisitions. Then considering the time and cost of the study we reduced the number of samples to four. Then considering that the calculation using all parameters reveal the real relaxation parameter value, we started to calculate parameters using four different sample points each time. By looking at the standard deviations and the error introduced compared to the calculation with all samples we ended up with optimal sampling points.

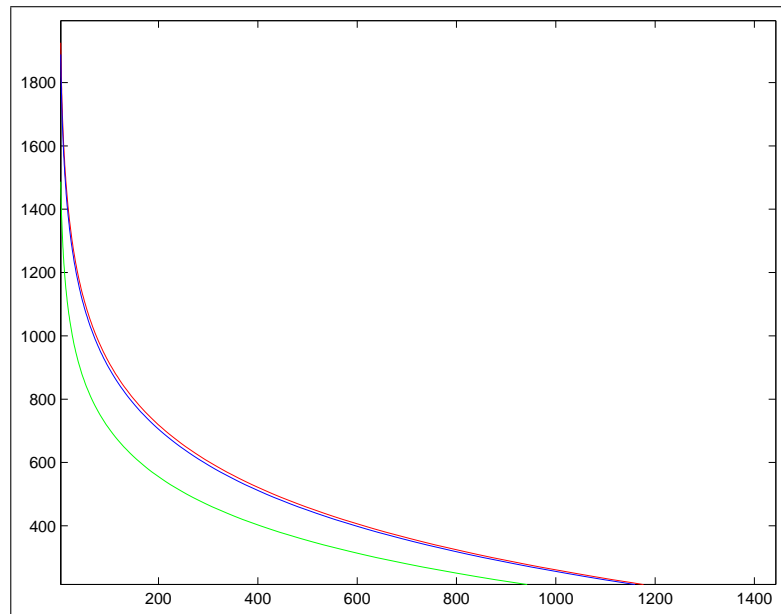


Figure 4.3 An example of Phantom study. Red line represents the characteristic T_2 curve that is calculated using all points. The blue line represents the characteristic curve calculated by selecting the optimized points and the green line represents the characteristic curve calculated by other four points.

In T_2 weighted images we used T_R as 3000ms and varied T_E as 10, 103, 175 and 278ms and in T_1 weighted images we used T_E as 15ms and varied T_R as 250, 500, 1000 and 2000ms.

4.2 Registration

MR provided four intensity values for a single pixel in our study. Multi-modal MR nature of MRI makes the tissue classification an easier task provided that the subject does not move between the acquisitions.

Motion was one of the problems that had to be eliminated before processing the data. For a pixel to represent the same region of the tissue in the brain the head motion had to be eliminated. To be able to achieve that in data acquisition we used the stabilizers of the MR imager.

In case of head motion between images we had to use an image registration algorithm. We used the image registration algorithm developed by Periaswamy and Farid[17]. This algorithm was designed for affine registration but it is also capable of doing rigid image registration. The parameters that the algorithm use for registration are also an important issue. Without adjusting the parameters it was observed that the algorithm caused some changes on the anatomy of the tissue. To eliminate this problem we made a study to find the optimum registration parameters. We first made a study on the synthetic images to find out the effects of the parameters on the registered images. Then used the original data set to find out the parameters that were required for a registration without deformation. The resulting parameters were used for the registration of the required images. The parameters used were 6 outer and 600 inner loops for the registration of images with very high intensity variations and 6 outer and 400 inner loops for the registration of the other images.

4.3 Calculation of T_1 and T_2 Images

To be able to construct true T_1 and true T_2 images we first calculate the T_1 and T_2 values for each pixel.

Using Equation 4.2 which represents the T_1 effect by eliminating the T_2 . Using the four points that we acquired from the images we use the Levenberg-Marquadt algorithm for fitting a curve to the points we have and obtain the real T_1 curve. The parameters that are obtained gives us the PD and true T_1 value.

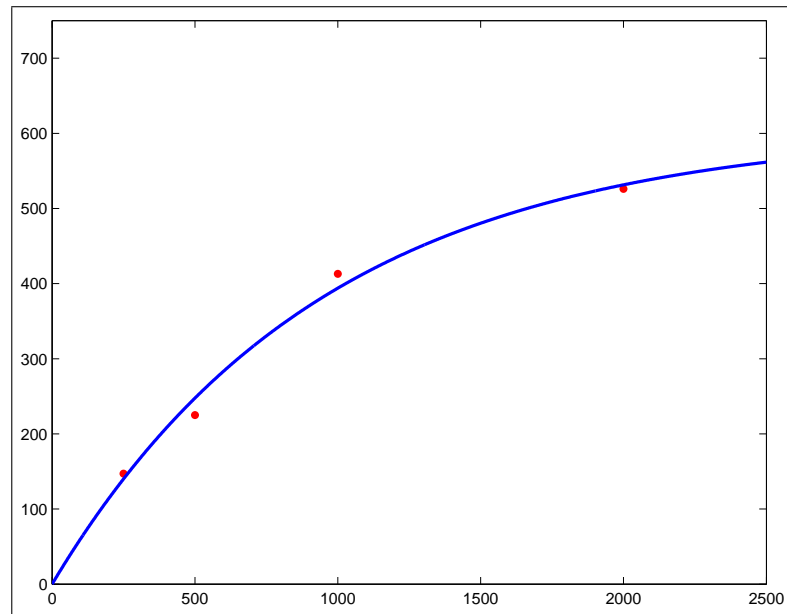


Figure 4.4 An example for T_1 curve fit. The red points indicate the data acquired and the blue line is the fitted curve. x-axis represents the T_R in milliseconds and y-axis represents the pixel value.

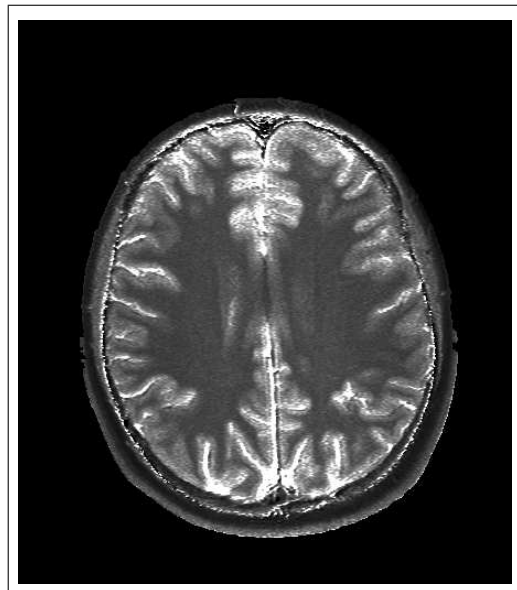


Figure 4.5 An example of a true T_1 image.

Likely for calculation of the true T_2 image we use the same principle. However this time Equation 4.3 is used as the reference equation.

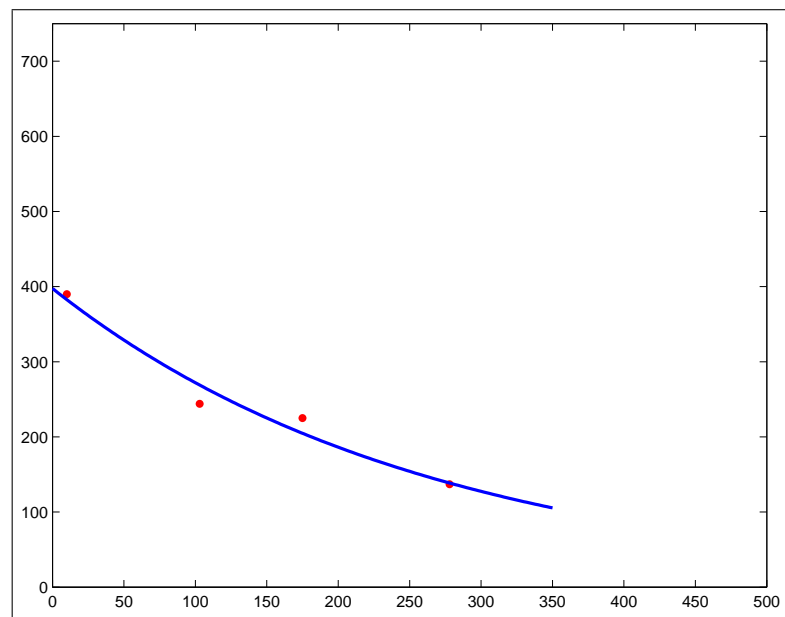


Figure 4.6 An example for T_2 curve fit. The red points indicate the data acquired and the blue line is the fitted curve. x-axis represents the T_E in milliseconds and y-axis represents the pixel value.

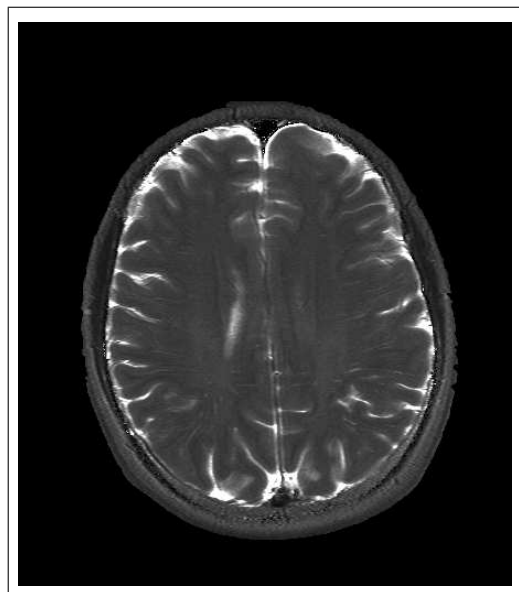


Figure 4.7 An example of a true T_2 image.

By placing the calculated values on the image the true T_1 , T_2 and PD images are reconstructed.

4.4 Segmentation

Maximum likelihood algorithm was used for the classification of the tissues. The data we acquire for the classification of the tissues consists of thirty points for each tissue for the training data set and sixty points for each tissue for the evaluation data set. While selecting the data sets, to be able to consider the RF field inhomogeneities, twenty points were selected from each slice. Three slices for each patient were used. The two datasets do not have points in common.

Both the training and evaluating datasets contain information about weighted images and calculated images in T_1 , T_2 and PD categories. This enables us to be able to classify the tissues according to various conditions.

The data that is to be used for segmentation are classified by

$$f_{x_1, x_2}(x_1, x_2) = \frac{1}{\sqrt{(2\pi)^n \det(C_{xx})}} e^{-(1/2)(x-\mu_x)'C_{xx}^{-1}(x-\mu_x)} \quad (4.4)$$

In Equation 4.4 x and $-\mu_x$ are each two by one vectors with components x_k and $E x_k$ respectively. For $1k2$ C_{xx} is the associated two by two covariance matrix.

After the multivariate gaussian density curves are calculated then the images can be segmented. Using the same segmentation algorithm the evaluation dataset is also evaluated and confusion matrix is produced. The scatter diagrams can be seen in Figure 3.7, the gaussian density curves can be seen in Figure 3.8 and the results of the segmentation and confusion matrices can be seen in results section.

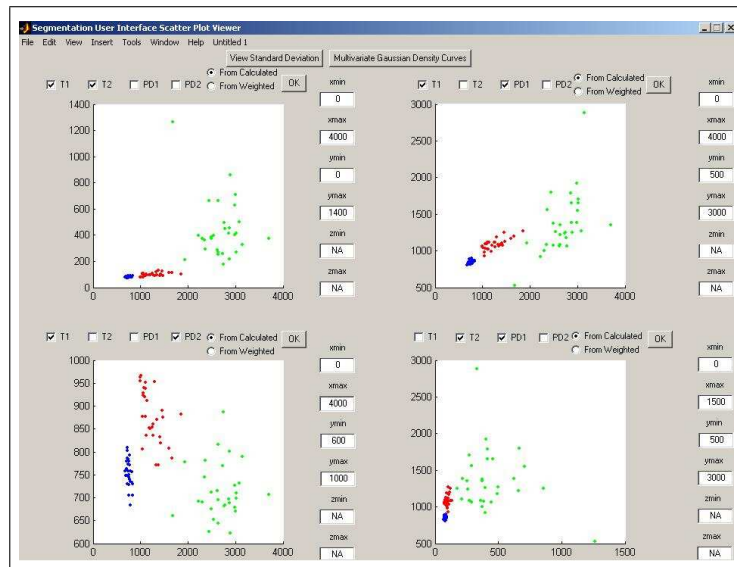


Figure 4.8 The scatter diagrams produce by the training sets

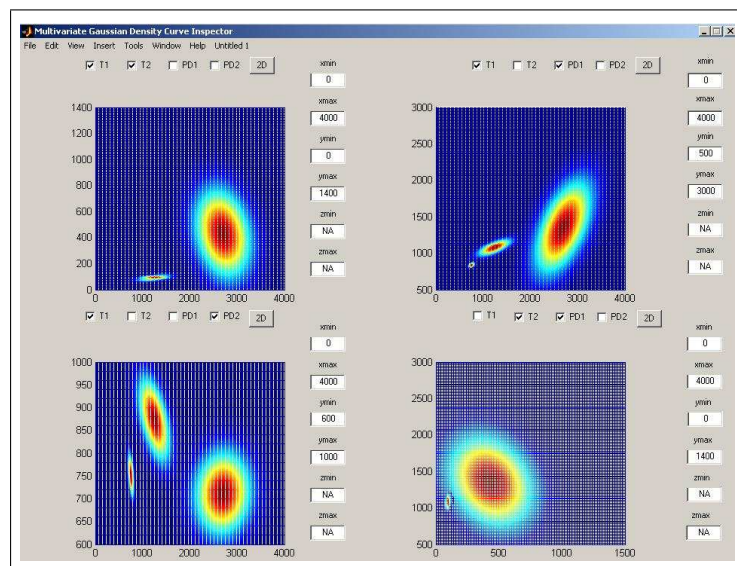


Figure 4.9 The multivariate gaussian functions associated with the scatter diagrams in Figure 4.8.

5. RESULTS

For the evaluation of the results seven patients and three different MR machines were used. To not to introduce T_2 change problem into the algorithm all MR machines were chosen as 1,5 T. The subjects used in the experiment consisted of five males and two females with the age avarage of 27. Each subject was imaged once in each MR machine with eight different T_E and T_R values. Four of these eight sequences were used to calculate true T_1 and the rest was used to calculate T_2 values.

After all the calculations were performed each subject had a true T_1 , true T_2 and a true PD image and after performing the segmentation process a segmented image for all of the slices. This data was used to build the comparison tables.

Four main procedures were applied to test the algorithm.

The first test applied is the Machine Dependency Test. In this test the algorithm was tested in between the machines. The same subject is used and the machine the subject was imaged was differentiated. The algorithm was trained for a subject imaged in a machine and the testing data was taken from the same subject but imaged in a different machine. This test was aimed to simulate the different inhomogeneity characteristics of the different machines.

Patient dependency test was used to test the algorithm for the differentiation of the RF inhomogeneity when a different subject was introduced to the system. The algorithm was trained by a subject imaged in a machine and tested on a different subject imaged in the same machine.

The third test which is named as Across Imager Test I was performed to evaluate data for the main goal of the study which is to segment different patients by forming only one evaluation set. In this test the training data consists a subject imaged on

an imager and the evaluation data was selected from a different patient on a different imager. Introducing both the inhomogeneity effect of the machinery and the patient.

Patient Dependency Test II was performed using all training data acquired and all evaluation data gathered. This test was used to test the algorithm for verification of the positive results gathered from the other tests and see if all data gave a meaningful result.

One of the goals of this study was to develop a segmentation algorithm free of RF inhomogeneity effect and image intensity profiles by calculation the true T_1 , T_2 and PD of the tissues.

For all the true T_1 , T_2 and PD images the normal tissue intensity distributions yield less confusion with less overlapping regions on the intensity histogram.

In Table 5.1 and 5.2 difference between weighted and computed (true) tissue distributions are illustrated. In these tables WM has a mean of 147 and 805 for the weighted and true T_1 images, with a standard deviation 67 and 225 respectively. These values for GM are 120 and 1531 for mean and 63, and 551 for the standard deviation.

Table 5.1
Mean Values of the Calculated And Weighted Images

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
T1	147	120	68	805	1531	4500
T2	46	106	635	89	114	4670

Table 5.2
Standard deviations of Calculated and Weighted Images

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
T1	67	62	36	225	551	1620
T2	13	36	114	18	25	654

If we assume gaussian distribution for the the tissue classification then the probability of a pixel will belong to WM tissue given its T_1 weighted intensity is:

$$P_{WM}(I) = \frac{1}{\sqrt{(2\pi)\rho_{WM}}} e^{-(1/2)(I-\mu_{WM})^2/\rho_{WM}} \quad (5.1)$$

similarly the same probability for GM is;

$$P_{GM}(I) = \frac{1}{\sqrt{(2\pi)\rho_{GM}}} e^{-(1/2)(I-\mu_{GM})^2/\rho_{GM}} \quad (5.2)$$

Then the intersection of these two probabilities gives us the points of confusion. This intersection is 0.83 . Knowing this intersection the possibility of confusing GM as WM is 0.43 , while the probability of confusing WM as GM is 0.40. If we carry the same computation for the computed WM and GM these probabilities are 0.29 and 0.31 respectively. Therefore it is less likely to confuse WM as GM or vice versa in the true T_1 images.

The same argument can be carried for other tissues in T_2 and PD images from Tables 5.1 and 5.2.

It is more difficult to illustrate the confusion in two or three dimensional spaces. Therefore we tested the ability to distinguish tissues with multi-modal image sets experimentally.

Three evaluations were performed for each 7 subjects for each of the classification methods. A total of 42 experiments were carried out for each of the cases of Machine Dependency Test, Patient Dependency Test. A total of number of experiments were performed for Across Imager Test I and one test was applied for Across Imager Test II. For the cases having more then one result the best result among the total number of results is presented in the text.

The tables presented are confusion matrix tables. The rows represent the tissue groups selected by the radiologists and are accepted as the gold standard in comparison. The column side is divided into two main groups as weighted and calculated. These groups represent the results taken from the algorithm. The weighted group represents the results taken using the weighted images that were directly taken from the MR machines. Where as the calculated column represent the results taken from the calculated images. The result of the algorithm were considered while forming the tables. The amount of points that match the tissue group as the result of the algorithm was divided by the gold standard and put into the table in percent form producing a confusion matrix table with the diagonal normalization axis.

For the Machine Dependency Test the algorithm managed to give slightly better results when the trained data and the evaluated data were taken from the same imager. Moreover when the trained data and the evaluated data were from different imagers, ML classifier's ability to differentiate the tissues on true images is significantly superior compared to the case with weighted MR images as seen in Table 5.3.

Table 5.3

An example of Machine Dependency Test results for different imagers classified by true T_1 and true T_2

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	16.66	83.33	0	98.33	1.67	0
GM	48.33	38.33	13.33	0	100	0
CSF	0	1.67	98.33	0	0	100

Table 5.3 was generated using true T_1 and true T_2 images. The same classification can be carried out by using different classification combinations such as T_2 and PD. In this case the algorithms ability to distinguish WM increases compared to the true T_1 and true T_2 classification. The results for this classification can be seen in Table 5.4.

Table 5.4

An example of Machine Dependency Test results for different imagers classified by true T_2 and true PD

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	98.33	1.67	0	100.00	0	0
GM	23.33	76.67	0	16.67	83.33	0
CSF	0	6.67	93.33	0	5.00	96.00

In order to combine the encompassing capabilities of the two different classification methods a tree dimensional classification method was also tested. In this case which is illustrated in Table 5.5 we used true T_1 , true T_2 and true PD images to test the algorithm. In this case it was observed that the best result in two classification algorithms combined to give the final result which gave better result than the other two classification methods used.

Table 5.5

An example of Machine Dependency Test results for different imagers classified by true T_1 , true T_2 and true PD

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	16.67	83.33	0	100.00	0	0
GM	16.67	83.33	0	5.00	95	0
CSF	0	8.33	91.67	0	3.33	96.67

When the same imager was tested for different subjects in Patient Dependency Test, which is intended to test the algorithm for its ability to standardize the training dataset for a single imager, ML classifier produced considerable improvement in the results especially in distinguishing WM when the true MR images are used as can be seen in Table 5.6.

Table 5.6

The Patient Dependency Test results classified by true T_1 and true T_2

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	33.33	66.67	0	86.67	13.33	0
GM	11.67	88.33	0	0	93.33	6.67
CSF	0	13.33	86.67	0	0	100

The results for the other two classification types yield results similar to the results produced in the Machine Dependency Test. True T_2 and true PD classification increased the algorithms ability to distinguish GM. Using this improvement when we used three dimensional classification the results were superior compared to the two dimensional classifications in most of the cases. The results for true T_2 and true PD classification and three dimensional classification can be observed in Tables 5.7 and 5.8 consecutively.

Table 5.7The Patient Dependency Test results classified by true T_2 and true PD

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	40.00	66.00	0	93.33	6.67	0
GM	8.33	88.33	3.33	0	96.67	3.33
CSF	0	1.33	96.67	0	0	100

Table 5.8The Patient Dependency Test results classified by true T_1 , true T_2 and PD

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	31.67	68.33	0	100.00	0	0
GM	8.33	91.67	0	0	98.33	1.67
CSF	0	0	100.00	0	0	100

To test the main goal of the study Across-Imager Test I was implemented. In this test the training data is acquired from an imager and the evaluation of the data in a different imager is carried out. The same object (patient) was used in this classification algorithm. The result indicate that the proposed method has the ability to improve segmentation between imagers. The results of the true T_1 and true T_2 classification can be seen in Table 5.9.

Table 5.9The Across-Imager Test I results classified by true T_1 and true T_2

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	3.10	96.90	0	99.76	0.24	0
GM	0	48.81	51.19	16.19	83.81	0
CSF	0	2.62	97.38	0	0.24	99.76

The expectation from the algorithm when it was run by using true T_2 and PD classification algorithm was to improve the results for the GM differentiation. However this time this expectation was not positive for all the cases. Even in some cases the performance of segmenting GM was lower than true T_1 and true T_2 classification an example of this can be seen in Table 5.10.

Table 5.10The Across-Imager Test I results classified by true T_2 and PD

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	7.62	77.86	5.71	100.00	0	0
GM	0	43.57	56.43	24.53	75.48	0
CSF	0	10.24	89.76	0	7.86	92.14

When the combination effect is taken into consideration it could be expected that the algorithm does not produce better results in three dimensional classification however the results indicate that the combination effect still exists and improves segmentation. Table 5.11.

Table 5.11

The Across-Imager Test I results classified by true T_1 , true T_2 and PD

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	11.19	87.62	1.19	99.76	0.24	0
GM	0	43.81	56.19	14.05	85.95	0
CSF	0	4.76	95.24	0	4.76	95.24

Considering the all data gathered from all the subjects and imagers, the results of Across Imager Test II showed that the calculated data sets helped the algorithm in correct identification of the tissues as seen in Table 5.12.

Table 5.12

The Across Imager Test II results classified by true T_1 and true T_2

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	52.38	47.62	0	99.29	0.71	0
GM	19.05	80.95	0	5.24	92.14	2.62
CSF	0	10.00	90.00	0	2.86	97.14

The aim of Across Imager Test II was to test the results of the algorithm for evaluation of patients by training the algorithm with the data from all imagers. It was aimed to see whether all training data combined was to give improved results.

In all of the cases the algorithm improved the results of the segmentation. However the improvement was not as good as the single machine trained data specially for GM. But the level of improvement can easily be recognized compared to the weighted classification. WM

Table 5.13The Across Imager Test II results classified by true T_2 and PD

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	42.38	57.19	0	100	0	0
GM	48.81	51.19	0	15.24	82.86	1.90
CSF	0	10.00	90.00	0	1.43	98.57

Once again introducing a third dimension to the classifier improves its ability to distinguish between tissues. The results show slight improvement compared to two dimensional classification methods. This can be due to the high number of evaluation points and their weights.

Table 5.14The Across Imager Test II results classified by true T_1 , true T_2 and PD

	Weighted			Calculated		
	WM	GM	CSF	WM	GM	CSF
WM	52.38	47.62	0	96.90	3.10	0
GM	19.29	80.71	0	5.24	92.38	2.38
CSF	0	11.90	88.10	0	2.86	97.14

After observing the numerical analysis of the classifier the segmented images are produced. The examples illustrated are obtained by applying three dimensional classification. Just as shown by the numerical examples the images illustrate the algorithms ability to improve segmentation.



Figure 5.1 Image of segmented WM by Weighted Data

The significant improvement that is demonstrated by the tables can be easily visualized by examining the output images of the algorithm. The images presented are the result of Across Imager Test I and are both produced by using weighted and calculated datasets. The presented images are grouped by tissue groups and displayed consecutively for easy visualization of the differences.

Figure 5.1 is produced by using weighted dataset and is the image of WM. As can be seen from the figure the amount of WM classified by the algorithm using weighted data set is very small in amount and it does not represent the anatomical position of the tissue. In Figure 5.2 again WM matter is displayed but this time the image is produced by using calculated datasets. The amount of WM classified increases in a positive way by representing the anatomical model.

Similar results can be seen when Figures 5.3 and 5.4 are observed. The weighted calculation, even though better results are taken compared to the WM, yields to a very small portion of the GM where as the calculated training set enables us to identify GM by producing significantly improved image. The resulting image is very close properties compared to the real anatomical model.

When the resulting images of the algorithm for CSF is observed another important result can be achieved. It was sometimes observed that the weighted dataset had the tendency to distinguish CSF better in some cases. From the images formed we can see that the algorithm classified all of the image as CSF. This result is observed in most of the cases and by this way we can conclude that the better results given in the tables for CSF are the result of this effect. On the other hand the improvement of the calculated training dataset is again clearly seen and the images formed can be compared by looking at Figures 5.5 and 5.6.

To be able to demonstrate the future work 3D rendered images are also presented. In Figure 5.7 the model created looks almost identical to a real brain where as in Figure 5.8 the main problem with the rendering process which is the axial resolution of the image is presented. This is caused by the thick slices that were acquired during imaging. This was due to our desire to gather high SNR for better calculations. To improve the 3D rendered images in the future we have to gather images using thinner slices to get better axial resolution. Rendered images can be used for quantification of the brain tissues in future studies.

Looking at Figures 5.1 and 5.2 we can easily see the significant improvement in the results just as illustrated by the numerical examples. In Figure 5.1 there is almost no WM classified besides the points classified as WM does not appear to be at the right location. In Figure 5.2 a significant improvement can be observed by the implementation of three dimensional classification.

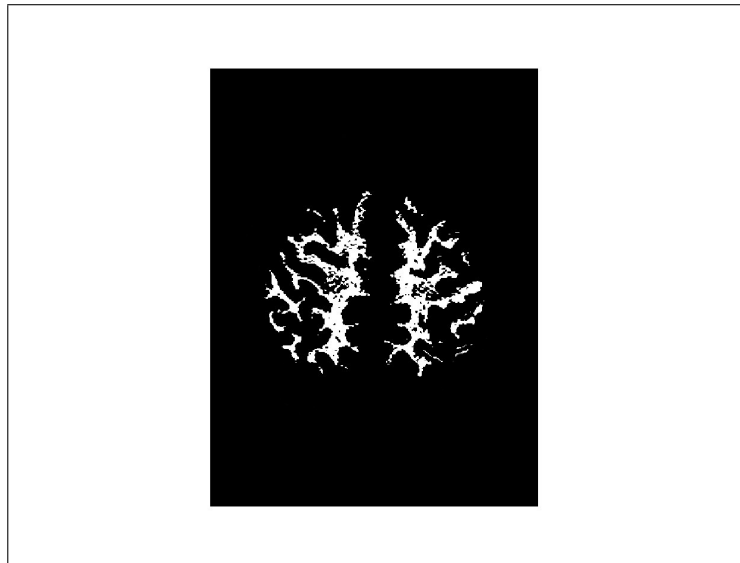


Figure 5.2 Image of segmented WM by Calculated Data

Likely in Figures 5.3 and 5.4 close results are demonstrated for GM. The weighted data gives considerably better results as just seen in numerical analysis for GM. The algorithms improvement by introducing the calculated parameters can easily be seen in Figure 5.4.

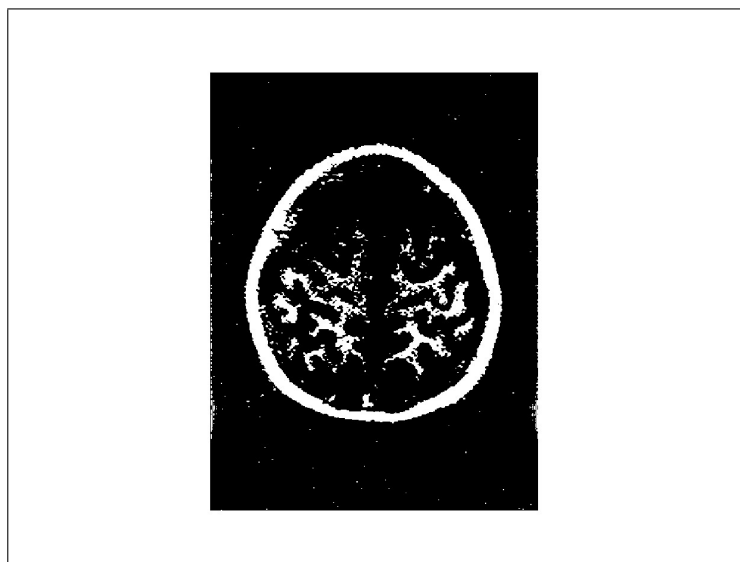


Figure 5.3 Image of segmented GM by Weighted Data

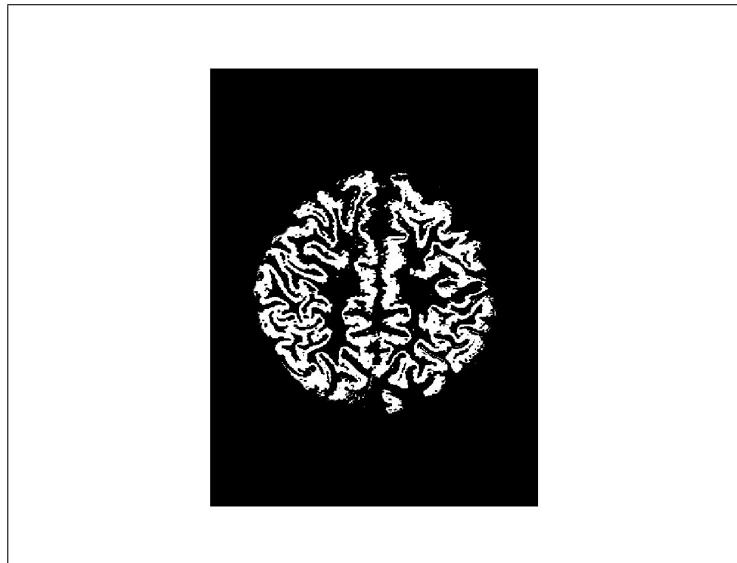


Figure 5.4 Image of segmented GM by Calculated Data

In Figure 5.5 the weighted classification considers the rest of the image as CSF. This can demonstrate the high percentage of the weighted algorithm to classify the CSF correctly is caused by this effect. The improvement achieved can be seen in Figure 5.6.

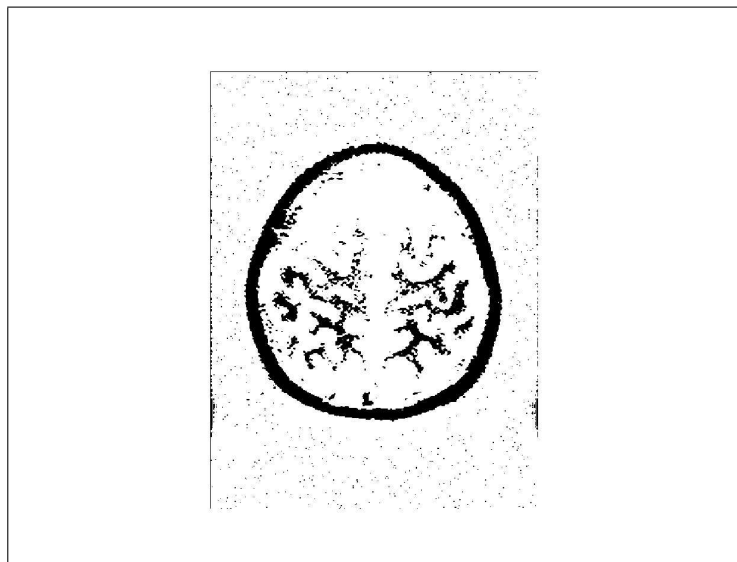


Figure 5.5 Image of segmented CSF by Weighted Data

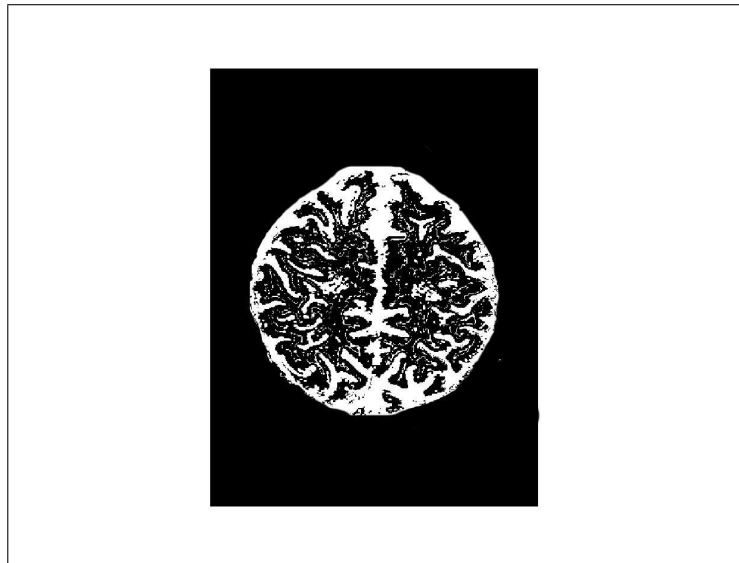


Figure 5.6 Image of segmented CSF by Calculated Data

When we observe the 3D rendering of the results given by calculated images it is seen that a realistic brain image can be produced. When we look at the rendered image from the sideview as seen in Figure 5.8 it is seen that the resolution is relatively low. This is due to the low number of slices. By using a data with higher saggital resolution we can obtain a realistic brain model. Also Figure 5.9 shows the segmented WM only.

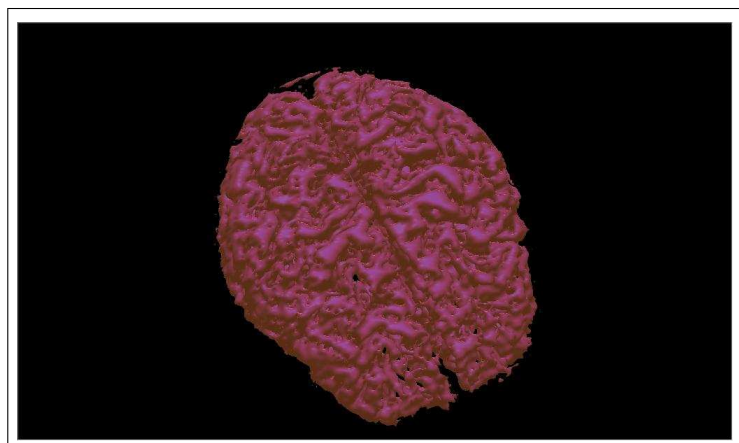


Figure 5.7 The result of 3D rendering of the segmented images

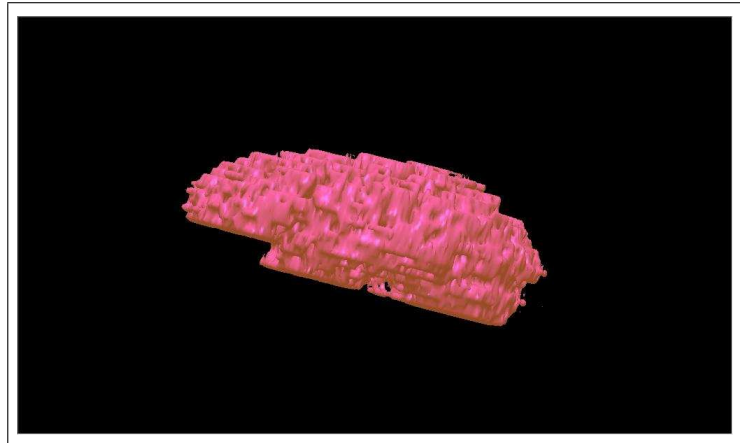


Figure 5.8 The result of 3D rendering of the segmented images from the sagittal position

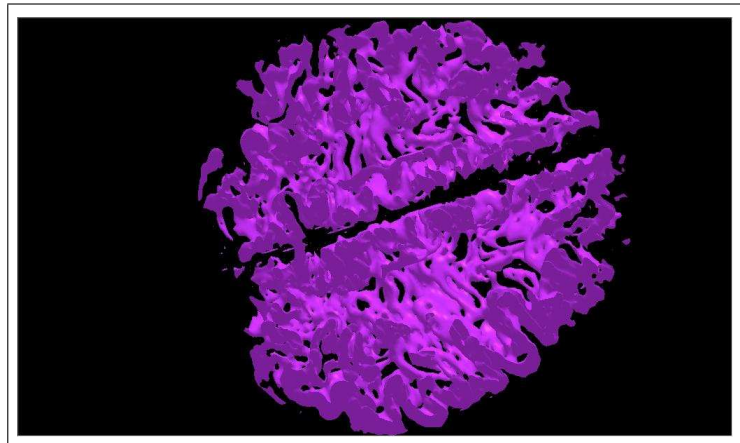


Figure 5.9 The result of 3D rendering of WM from the segmented images

6. CONCLUSIONS AND FUTURE WORK

Multi-modal MR image segmentation has been studied extensively in the literature. In all of the studies various classification algorithms such as ML classifier, neural networks, k-means have been tested and compared. While some classifiers performed better than the others, all these techniques suffer from the intensity inhomogeneities inherent in the weighted MR images. We have shown the severity of the confusion when ML classifier is used without correcting the intensity artifacts due to RF field inhomogeneities. Although the other techniques might not be effected as seriously these classification algorithms will also benefit from the lesser variation in computed MR images.

Even though the information presented in the Results section is composed of the best result given by the algorithm approach taken in this study may pave the way for a standardization of image segmentation in MR images making it possible to follow patient condition quantitatively in time independent of imaging device.

Future work can be proposed by improving the sagittal resolution of the image sets and producing higher quality 3D rendered images for the analysis various diseases. By this way a more precise volume can be calculated and this can be used in follow up of degenerative diseases and calculation of the tumor volumes.

Also by studying the true T1, T2 and PD values gathered from patients we can produce a database for the classification of the tumors or other pathologies and help physicians for the diagnosis of these disease without performing biopsies or any other invasive methods. To be able to perform this task patient with confirmed pathologies must be used in the study. Also a group of wide pathologies will be needed.

Finally to be able to improve the segmentation to a next step a neural network system can be integrated with the associated algorithm. By this way we may manage

to obtain better results in tissue segmentation and eliminate the intersecting areas.

APPENDIX A. TABLES OF RESULTS

A.1 Machine Dependency Test

Table A.1
Patient 1 Trained in Machine 1 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	96.97	3.33	0.00
	GM	20.00	80.00	0.00	1.67	98.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	0.00	100.00	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	98.33	1.67	0.00	98.67	1.33	0.00
	GM	6.67	93.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.2
Patient 1 Trained in Machine 1 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	73.33	26.67	0.00	83.33	16.67	0.00
	GM	11.67	83.33	0.00	3.33	96.67	0.00
	CSF	0.00	6.67	93.33	0.00	3.33	96.67
$T_2 - PD$	WM	98.88	1.67	0.00	100.00	0.00	0.00
	GM	23.33	76.67	0.00	16.67	83.33	0.00
	CSF	0.00	6.67	93.33	0.00	5.00	95.00
$T_1 - T_2 - PD$	WM	1.67	98.33	0.00	75.00	8.33	16.67
	GM	6.67	83.33	10.00	1.67	98.33	0.00
	CSF	0.00	8.33	91.67	0.00	5.00	95.00

Table A.3
Patient 1 Trained in Machine 1 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	30.00	66.67	3.33	5.00	91.67	3.33
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_2 - PD$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	28.33	68.33	3.33	11.67	85.00	3.33
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	3.33	86.67	10.00	5.00	91.67	3.33
	CSF	0.00	1.67	98.33	0.00	0.00	100.00

Table A.4
Patient 1 Trained in Machine 2 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	6.67	93.33	0.00	98.33	1.67	0.00
	GM	18.33	76.67	0.00	0.00	93.33	6.67
	CSF	0.00	8.33	91.67	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	91.67	8.33	0.00
	GM	0.00	56.67	43.33	0.00	73.33	26.67
	CSF	0.00	8.33	91.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	18.33	76.67	0.00	16.67	98.33	0.00
	CSF	0.00	21.67	78.33	0.00	0.00	100.00

Table A.5
Patient 1 Trained in Machine 2 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	90.00	10.00	0.00	95.00	5.00	0.00
	GM	6.67	93.33	0.00	0.00	93.33	6.67
	CSF	0.00	3.33	96.67	0.00	21.67	78.33
$T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	16.67	81.67	1.67	0.00	95.00	5.00
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	90.00	10.00	0.00	93.33	6.67	0.00
	GM	0.00	83.33	11.67	1.67	96.67	1.67
	CSF	0.00	1.67	98.33	0.00	1.67	98.33

Table A.6
Patient 1 Trained in Machine 2 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	80.00	10.00	0.00	98.33	1.67	0.00
	GM	45.00	51.67	3.33	0.00	83.33	16.67
	CSF	0.00	5.00	95.00	0.00	3.33	96.67
$T_2 - PD$	WM	11.67	88.33	0.00	98.33	1.67	0.00
	GM	0.00	31.67	68.33	0.00	96.67	3.33
	CSF	0.00	1.67	98.33	0.00	3.33	96.67
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	96.67	13.33	0.00
	GM	0.00	75.00	25.00	0.00	86.67	13.33
	CSF	0.00	33.33	66.67	0.00	1.67	98.33

Table A.7
Patient 1 Trained in Machine 3 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	20.00	80.00	0.00	98.33	1.67	0.00
	GM	0.00	91.67	8.33	0.00	98.33	1.67
	CSF	0.00	5.00	95.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	85.00	15.00	0.00
	GM	0.00	90.00	10.00	0.00	91.67	8.33
	CSF	0.00	5.00	95.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	10.00	90.00	0.00	95.00	5.00	0.00
	GM	0.00	83.33	16.67	0.00	95.00	5.00
	CSF	0.00	3.33	96.67	0.00	1.67	98.33

Table A.8
Patient 1 Trained in Machine 3 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	1.67	95.00	3.33	0.00	96.67	3.33
	CSF	0.00	0.00	100.00	0.00	3.33	96.67
$T_2 - PD$	WM	1.67	98.33	0.00	100.00	0.00	0.00
	GM	0.00	98.33	1.67	0.00	96.67	3.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	23.33	20.00	56.67	83.33	16.67	0.00
	GM	0.00	95.00	5.00	0.00	98.33	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.9
Patient 1 Trained in Machine 3 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	1.67	95.00	3.33	0.00	96.67	3.33
	CSF	0.00	0.0	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	00.00	95.00	5.00	0.00	96.67	3.33
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	0.00	96.67	3.33	0.00	96.67	3.33
	CSF	0.00	3.33	96.67	0.00	0.00	100.00

Table A.10
Patient 2 Trained in Machine 1 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	13.33	86.67	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	8.33	91.67	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	6.67	93.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.11
Patient 2 Trained in Machine 1 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	81.67	18.33	0.00	100.00	0.00	0.00
	GM	40.00	60.00	0.00	6.67	91.67	1.67
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	100.00	0.00	0.00
	GM	11.67	61.67	26.67	13.33	86.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	81.67	18.33	0.00	98.33	1.67	98.33
	GM	35.00	63.33	1.67	3.33	95.00	1.67
	CSF	0.00	1.67	98.33	0.00	0.00	100.00

Table A.12
Patient 2 Trained in Machine 2 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	13.33	86.67	0.00	98.33	1.67	0.00
	GM	23.33	76.67	0.00	0.00	90.00	10.00
	CSF	0.00	20.00	80.00	0.00	16.67	83.33
$T_2 - PD$	WM	5.00	95.00	0.00	83.33	16.67	0.00
	GM	0.00	70.00	30.00	0.00	86.67	13.33
	CSF	0.00	20.00	80.00	0.00	15.00	85.00
$T_1 - T_2 - PD$	WM	13.33	86.67	0.00	93.33	6.67	0.00
	GM	13.33	76.67	10.00	0.00	91.67	8.33
	CSF	0.00	23.33	76.67	0.00	1.67	98.33

Table A.13
Patient 2 Trained in Machine 2 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	21.67	78.33	0.00	5.00	95.00	0.00
	CSF	0.00	3.33	96.67	0.00	1.67	98.33
$T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	3.33	95.00	1.67	1.67	98.33	0.00
	CSF	0.00	3.33	96.67	0.00	1.67	98.33
$T_1 - T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	5.00	95.00	0.00	0.00	100.00	0.00
	CSF	0.00	3.33	96.67	0.00	1.67	98.33

Table A.14
Patient 3 Trained in Machine 1 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	91.67	8.33	0.00	98.33	1.67	0.00
	GM	16.67	83.33	0.00	8.33	88.33	3.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	90.00	10.00	0.00	98.33	1.67	0.00
	GM	3.33	96.67	0.00	0.00	96.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	93.33	6.67	0.00	98.33	1.67	0.00
	GM	3.33	96.67	0.00	0.00	98.33	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.15
Patient 3 Trained in Machine 1 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	70.00	30.00	0.00	85.00	11.67	3.33
	GM	51.67	48.33	0.00	1.67	98.33	0.00
	CSF	0.00	11.67	88.33	0.00	1.67	98.33
$T_2 - PD$	WM	38.33	61.67	0.00	96.67	3.33	0.00
	GM	50.00	50.00	0.00	6.67	93.33	0.00
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	41.67	58.33	0.00	93.33	6.67	0.00
	GM	50.00	50.00	0.00	0.00	100.00	0.00
	CSF	0.00	11.67	88.33	0.00	0.00	100.00

Table A.16
Patient 3 Trained in Machine 1 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	83.33	16.67	98.33	1.67	0.00
	GM	48.33	38.33	13.33	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	15.00	85.00	0.00	100.00	0.00
	CSF	0.00	58.33	41.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	95.00	5.00	0.00
	GM	100.00	0.00	0.00	0.00	95.00	5.00
	CSF	0.00	58.33	41.67	0.00	0.00	100.00

Table A.17
Patient 3 Trained in Machine 1 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	83.33	16.67	98.33	1.67	0.00
	GM	48.33	38.33	13.33	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	15.00	85.00	0.00	100.00	0.00
	CSF	0.00	58.33	41.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	95.00	5.00	0.00
	GM	100.00	0.00	0.00	0.00	95.00	5.00
	CSF	0.00	58.33	41.67	0.00	0.00	100.00

Table A.18
Patient 3 Trained in Machine 2 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	3.33	96.67	0.00	91.67	8.33	0.00
	GM	25.00	66.67	8.33	0.00	75.00	25.00
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	91.67	8.33	0.00
	GM	0.00	31.67	68.33	3.33	91.67	5.00
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	91.67	8.33	0.00
	GM	0.00	0.00	100.00	6.67	81.67	11.67
	CSF	0.00	40.00	60.00	0.00	5.00	95.00

Table A.19
Patient 3 Trained in Machine 2 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	83.33	16.67	0.00	91.67	8.33	0.00
	GM	6.67	93.33	0.00	0.00	96.67	3.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	96.67	3.33	0.00
	GM	16.67	81.67	1.67	3.33	95.00	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	95.00	5.00	0.00	96.67	3.33	0.00
	GM	5.00	93.33	1.67	1.67	91.67	6.67
	CSF	0.00	5.00	95.00	0.00	0.00	100.00

Table A.20
Patient 3 Trained in Machine 2 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	0.00	100.00	88.33	11.67	0.00
	GM	0.00	0.00	100.00	0.00	85.00	15.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	0.00	100.00	88.33	11.67	0.00
	GM	0.00	0.00	100.00	0.00	85.00	15.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	0.00	100.00	86.67	13.33	0.00
	GM	0.00	0.00	100.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.21
Patient 3 Trained in Machine 3 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	16.67	63.37	20.00	0.00	81.67	18.33
	CSF	0.00	100.00	0.00	0.00	35.00	65.00
$T_2 - PD$	WM	0.00	100.00	0.00	91.67	6.67	1.67
	GM	0.00	100.00	0.00	0.00	100.00	0.00
	CSF	0.00	100.00	0.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	95.00	5.00	0.00
	GM	15.00	83.33	1.67	0.00	91.67	8.33
	CSF	0.00	100.00	0.00	0.00	25.00	75.00

Table A.22
Patient 3 Trained in Machine 3 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	75.00	25.00	0.00
	GM	0.00	100.00	0.00	0.00	66.67	33.33
	CSF	0.00	100.00	0.00	0.00	16.67	83.33
$T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	100.00	0.00	0.00	75.00	25.00
	CSF	0.00	100.00	0.00	0.00	21.67	78.33
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	78.33	21.67	0.00
	GM	0.00	100.00	0.00	0.00	80.00	20.00
	CSF	0.00	100.00	0.00	0.00	18.33	81.67

Table A.23
Patient 3 Trained in Machine 3 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	93.33	6.67	0.00	98.33	1.67	0.00
	GM	15.00	83.00	1.67	8.33	91.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	95.00	5.00	0.00	98.33	1.67	0.00
	GM	10.00	88.33	1.67	8.33	91.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	93.33	6.67	0.00	0.00	0.00	100.00
	GM	15.00	83.33	1.67	8.33	91.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.24
Patient 4 Trained in Machine 1 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	83.33	16.67	0.00	95.00	5.00	0.00
	GM	11.67	88.33	0.00	0.00	98.33	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	88.33	11.67	0.00	98.33	1.67	0.00
	GM	5.00	95.00	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	93.33	6.67	0.00	93.33	6.33	0.00
	GM	6.67	93.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.25
Patient 4 Trained in Machine 1 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	96.67	3.33	0.00
	GM	0.00	58.33	41.67	3.33	96.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	91.67	6.67	0.00
	GM	0.00	71.67	28.33	11.67	88.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	85.00	6.67	8.33
	GM	0.00	63.33	36.67	1.67	81.67	16.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.26
Patient 4 Trained in Machine 1 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	98.33	0.00	1.67
	GM	23.33	76.67	0.00	11.67	88.33	0.00
	CSF	0.00	5.00	95.00	0.00	0.00	100.00
$T_2 - PD$	WM	98.33	0.00	1.67	98.33	0.00	1.67
	GM	75.00	25.00	0.00	11.67	88.33	0.00
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	96.67	1.67	1.67	98.33	0.00	1.67
	GM	31.67	68.87	0.00	11.67	88.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.27
Patient 4 Trained in Machine 2 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	38.33	61.67	0.00	83.33	10.00	6.67
	GM	40.00	60.00	0.00	0.00	83.37	16.67
	CSF	0.00	65.00	35.00	0.00	10.00	90.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	3.33	96.67	0.00	0.00	85.00	15.00
	CSF	0.00	68.33	31.67	0.00	13.33	86.67
$T_1 - T_2 - PD$	WM	1.67	98.33	0.00	96.67	0.00	3.33
	GM	8.33	91.67	0.00	0.00	90.00	10.00
	CSF	0.00	65.00	35.00	0.00	11.67	88.33

Table A.28
Patient 4 Trained in Machine 2 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	3.33	96.67	0.00	0.00	100.00	0.00
	CSF	0.00	8.33	91.67	0.00	1.67	98.33
$T_2 - PD$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	5.00	95.00	0.00	3.33	96.67	0.00
	CSF	0.00	6.67	93.33	0.00	1.67	98.33
$T_1 - T_2 - PD$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	0.00	100.00	0.00	1.67	98.33	0.00
	CSF	0.00	6.67	93.33	0.00	1.67	98.33

Table A.29
Patient 4 Trained in Machine 2 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	45.00	55.00	0.00	98.33	1.67
	CSF	0.00	26.67	73.33	0.00	15.00	85.00
$T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	80.00	20.00	1.67	98.33	0.00
	CSF	0.00	25.00	75.00	0.00	11.67	88.33
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	98.33	0.00	1.67
	GM	0.00	100.00	0.00	0.00	95.00	5.00
	CSF	0.00	30.00	70.00	0.00	13.33	86.67

Table A.30
Patient 4 Trained in Machine 3 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	71.67	28.33	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.31
Patient 4 Trained in Machine 3 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	71.67	28.33	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.32
Patient 4 Trained in Machine 3 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	71.67	28.33	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.33
Patient 5 Trained in Machine 1 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	96.97	3.33	0.00
	GM	20.00	80.00	0.00	1.67	98.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	0.00	100.00	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	98.33	1.67	0.00	98.67	1.33	0.00
	GM	6.67	93.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.34
Patient 5 Trained in Machine 1 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	73.33	26.67	0.00	83.33	16.67	0.00
	GM	11.67	83.33	0.00	3.33	96.67	0.00
	CSF	0.00	6.67	93.33	0.00	3.33	96.67
$T_2 - PD$	WM	98.88	1.67	0.00	100.00	0.00	0.00
	GM	23.33	76.67	0.00	16.67	83.33	0.00
	CSF	0.00	6.67	93.33	0.00	5.00	95.00
$T_1 - T_2 - PD$	WM	1.67	98.33	0.00	75.00	8.33	16.67
	GM	6.67	83.33	10.00	1.67	98.33	0.00
	CSF	0.00	8.33	91.67	0.00	5.00	95.00

Table A.35
Patient 5 Trained in Machine 1 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	30.00	66.67	3.33	5.00	91.67	3.33
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_2 - PD$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	28.33	68.33	3.33	11.67	85.00	3.33
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	3.33	86.67	10.00	5.00	91.67	3.33
	CSF	0.00	1.67	98.33	0.00	0.00	100.00

Table A.36
Patient 5 Trained in Machine 2 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	6.67	93.33	0.00	98.33	1.67	0.00
	GM	18.33	76.67	0.00	0.00	93.33	6.67
	CSF	0.00	8.33	91.67	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	91.67	8.33	0.00
	GM	0.00	56.67	43.33	0.00	73.33	26.67
	CSF	0.00	8.33	91.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	18.33	76.67	0.00	16.67	98.33	0.00
	CSF	0.00	21.67	78.33	0.00	0.00	100.00

Table A.37
Patient 5 Trained in Machine 2 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	90.00	10.00	0.00	95.00	5.00	0.00
	GM	6.67	93.33	0.00	0.00	93.33	6.67
	CSF	0.00	3.33	96.67	0.00	21.67	78.33
$T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	16.67	81.67	1.67	0.00	95.00	5.00
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	90.00	10.00	0.00	93.33	6.67	0.00
	GM	0.00	83.33	11.67	1.67	96.67	1.67
	CSF	0.00	1.67	98.33	0.00	1.67	98.33

Table A.38
Patient 5 Trained in Machine 2 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	80.00	10.00	0.00	98.33	1.67	0.00
	GM	45.00	51.67	3.33	0.00	83.33	16.67
	CSF	0.00	5.00	95.00	0.00	3.33	96.67
$T_2 - PD$	WM	11.67	88.33	0.00	98.33	1.67	0.00
	GM	0.00	31.67	68.33	0.00	96.67	3.33
	CSF	0.00	1.67	98.33	0.00	3.33	96.67
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	96.67	13.33	0.00
	GM	0.00	75.00	25.00	0.00	86.67	13.33
	CSF	0.00	33.33	66.67	0.00	1.67	98.33

Table A.39
Patient 5 Trained in Machine 3 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	20.00	80.00	0.00	98.33	1.67	0.00
	GM	0.00	91.67	8.33	0.00	98.33	1.67
	CSF	0.00	5.00	95.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	85.00	15.00	0.00
	GM	0.00	90.00	10.00	0.00	91.67	8.33
	CSF	0.00	5.00	95.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	10.00	90.00	0.00	95.00	5.00	0.00
	GM	0.00	83.33	16.67	0.00	95.00	5.00
	CSF	0.00	3.33	96.67	0.00	1.67	98.33

Table A.40
Patient 5 Trained in Machine 3 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	1.67	95.00	3.33	0.00	96.67	3.33
	CSF	0.00	0.00	100.00	0.00	3.33	96.67
$T_2 - PD$	WM	1.67	98.33	0.00	100.00	0.00	0.00
	GM	0.00	98.33	1.67	0.00	96.67	3.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	23.33	20.00	56.67	83.33	16.67	0.00
	GM	0.00	95.00	5.00	0.00	98.33	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.41
Patient 5 Trained in Machine 3 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	1.67	95.00	3.33	0.00	96.67	3.33
	CSF	0.00	0.0	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	00.00	95.00	5.00	0.00	96.67	3.33
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	0.00	96.67	3.33	0.00	96.67	3.33
	CSF	0.00	3.33	96.67	0.00	0.00	100.00

Table A.42
Patient 6 Trained in Machine 1 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	90.00	10.00	0.00	96.67	3.33	0.00
	GM	1.67	98.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	88.33	11.67	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	1.67	98.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	93.33	6.67	0.00	96.67	3.33	0.00
	GM	1.67	98.33	0.00	1.67	98.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.43
Patient 6 Trained in Machine 1 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	95.00	5.00	0.00
	GM	0.00	61.67	38.33	6.67	93.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	0.00	56.67	43.33	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	0.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	90.00	10.00	0.00
	GM	0.00	61.67	38.33	1.67	98.33	0.00
	CSF	0.00	8.33	91.67	0.00	6.67	93.33

Table A.44
Patient 6 Trained in Machine 1 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	93.33	6.67	0.00
	GM	45.00	55.00	0.00	6.67	93.33	0.00
	CSF	0.00	11.67	88.33	1.67	5.00	93.33
$T_2 - PD$	WM	93.33	6.67	0.00	100.00	0.00	0.00
	GM	11.67	88.33	0.00	1.67	98.33	0.00
	CSF	0.00	15.00	85.00	0.00	8.33	91.67
$T_1 - T_2 - PD$	WM	95.00	5.00	0.00	96.67	3.33	0.00
	GM	15.00	85.00	0.00	1.67	98.33	0.00
	CSF	0.00	15.00	85.00	0.00	6.67	93.33

Table A.45
Patient 6 Trained in Machine 2 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	36.67	63.33	0.00	1.67	98.33	0.00
	GM	53.33	46.67	0.00	0.00	88.33	11.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	40.00	60.00	0.00	95.00	5.00	0.00
	GM	0.00	93.33	6.67	0.00	95.00	5.00
	CSF	0.00	8.33	91.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	36.67	63.33	0.00	96.67	3.33	0.00
	GM	0.00	88.33	11.67	0.00	93.33	6.67
	CSF	0.00	3.33	96.67	0.00	0.00	100.00

Table A.46
Patient 6 Trained in Machine 2 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	66.67	33.33	0.00
	GM	35.00	65.00	0.00	0.00	93.33	6.67
	CSF	0.00	23.33	76.67	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	78.33	21.67	0.00
	GM	21.67	78.33	0.00	0.00	93.33	6.67
	CSF	0.00	16.67	83.33	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	80.00	20.00	0.00
	GM	23.33	76.67	0.00	0.00	93.33	0.00
	CSF	0.00	16.67	83.33	0.00	0.00	100.00

Table A.47
Patient 6 Trained in Machine 2 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	93.33	6.67	0.00
	GM	45.00	55.00	0.00	6.67	93.33	0.00
	CSF	0.00	11.67	88.33	1.67	5.00	93.33
$T_2 - PD$	WM	93.33	6.67	0.00	100.00	0.00	0.00
	GM	11.67	88.33	0.00	1.67	98.33	0.00
	CSF	0.00	15.00	85.00	0.00	8.33	91.67
$T_1 - T_2 - PD$	WM	95.00	5.00	0.00	96.67	3.33	0.00
	GM	15.00	85.00	0.00	1.67	98.33	0.00
	CSF	0.00	15.00	85.00	0.00	6.67	93.33

Table A.48
Patient 6 Trained in Machine 3 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	18.33	81.67	0.00	95.00	5.00	0.00
	GM	0.00	100.00	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	1.67	98.33
$T_2 - PD$	WM	45.00	55.00	0.00	96.67	3.33	0.00
	GM	0.00	98.33	1.67	0.00	90.00	10.00
	CSF	0.00	0.00	100.00	0.00	50.00	50.00
$T_1 - T_2 - PD$	WM	45.00	55.00	0.00	86.67	13.33	0.00
	GM	0.00	98.33	1.67	0.00	93.33	6.67
	CSF	0.00	0.00	100.00	0.00	33.33	66.67

Table A.49
Patient 6 Trained in Machine 3 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	96.67	3.33	88.33	11.67	0.00
	GM	0.00	1.67	98.33	5.00	93.33	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	13.33	86.67	83.33	10.00	6.67
	GM	0.00	0.00	100.00	0.00	88.33	11.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	81.67	11.67	6.67
	GM	0.00	1.67	98.33	0.00	96.67	3.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.50
Patient 6 Trained in Machine 3 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	6.67	91.67	1.67	0.00	96.67	3.33
	CSF	0.00	1.67	98.33	0.00	5.00	95.00
$T_2 - PD$	WM	93.33	6.67	0.00	98.33	1.67	0.00
	GM	0.00	98.33	1.67	0.00	96.67	3.33
	CSF	0.00	3.33	96.67	0.00	1.67	98.33
$T_1 - T_2 - PD$	WM	96.67	3.33	0.00	100.00	0.00	0.00
	GM	0.00	100.00	0.00	0.00	98.33	1.67
	CSF	0.00	3.33	96.67	0.00	1.67	98.33

Table A.51
Patient 7 Trained in Machine 1 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	83.33	16.67	0.00	95.00	5.00	0.00
	GM	11.67	88.33	0.00	0.00	98.33	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	88.33	11.67	0.00	98.33	1.67	0.00
	GM	5.00	95.00	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	93.33	6.67	0.00	93.33	6.33	0.00
	GM	6.67	93.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.52
Patient 7 Trained in Machine 1 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	96.67	3.33	0.00
	GM	0.00	58.33	41.67	3.33	96.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	91.67	6.67	0.00
	GM	0.00	71.67	28.33	11.67	88.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	85.00	6.67	8.33
	GM	0.00	63.33	36.67	1.67	81.67	16.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.53
Patient 7 Trained in Machine 1 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	98.33	0.00	1.67
	GM	23.33	76.67	0.00	11.67	88.33	0.00
	CSF	0.00	5.00	95.00	0.00	0.00	100.00
$T_2 - PD$	WM	98.33	0.00	1.67	98.33	0.00	1.67
	GM	75.00	25.00	0.00	11.67	88.33	0.00
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	96.67	1.67	1.67	98.33	0.00	1.67
	GM	31.67	68.87	0.00	11.67	88.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.54
Patient 7 Trained in Machine 2 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	38.33	61.67	0.00	83.33	10.00	6.67
	GM	40.00	60.00	0.00	0.00	83.37	16.67
	CSF	0.00	65.00	35.00	0.00	10.00	90.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	3.33	96.67	0.00	0.00	85.00	15.00
	CSF	0.00	68.33	31.67	0.00	13.33	86.67
$T_1 - T_2 - PD$	WM	1.67	98.33	0.00	96.67	0.00	3.33
	GM	8.33	91.67	0.00	0.00	90.00	10.00
	CSF	0.00	65.00	35.00	0.00	11.67	88.33

Table A.55
Patient 7 Trained in Machine 2 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	3.33	96.67	0.00	0.00	100.00	0.00
	CSF	0.00	8.33	91.67	0.00	1.67	98.33
$T_2 - PD$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	5.00	95.00	0.00	3.33	96.67	0.00
	CSF	0.00	6.67	93.33	0.00	1.67	98.33
$T_1 - T_2 - PD$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	0.00	100.00	0.00	1.67	98.33	0.00
	CSF	0.00	6.67	93.33	0.00	1.67	98.33

Table A.56
Patient 7 Trained in Machine 2 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	45.00	55.00	0.00	98.33	1.67
	CSF	0.00	26.67	73.33	0.00	15.00	85.00
$T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	80.00	20.00	1.67	98.33	0.00
	CSF	0.00	25.00	75.00	0.00	11.67	88.33
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	98.33	0.00	1.67
	GM	0.00	100.00	0.00	0.00	95.00	5.00
	CSF	0.00	30.00	70.00	0.00	13.33	86.67

Table A.57
Patient 7 Trained in Machine 3 - Evaluated in Machine 1

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	71.67	28.33	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.58
Patient 7 Trained in Machine 3 - Evaluated in Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	71.67	28.33	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.59
Patient 7 Trained in Machine 3 - Evaluated in Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	71.67	28.33	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

A.2 Patient Dependency Test

Table A.60
Machine 1 Trained in Patient 1 - Evaluated in Patient 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	73.33	26.67	0.00	83.33	16.67	0.00
	GM	11.67	88.33	0.00	3.33	96.67	0.00
	CSF	0.00	6.67	93.33	0.00	3.33	96.67
$T_2 - PD$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	33.33	66.67	0.00	23.33	76.67	0.00
	CSF	0.00	8.33	91.67	0.00	5.00	95.00
$T_1 - T_2 - PD$	WM	88.33	11.67	0.00	91.67	6.67	1.67
	GM	6.67	70.00	23.33	11.67	88.33	0.00
	CSF	0.00	8.33	91.67	0.00	5.00	95.00

Table A.61
Machine 1 Trained in Patient 1 - Evaluated in Patient 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	25.00	75.00	0.00	0.00	96.67	3.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	100.00	0.00	0.00
	GM	5.00	95.00	0.00	0.00	98.33	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	15.00	85.00	0.00	0.00	96.67	3.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.62
Machine 1 Trained in Patient 1 - Evaluated in Patient 4

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	95.00	5.00	0.00	98.33	1.67	0.00
	GM	26.67	73.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	10.00	90.00	0.00	3.33	96.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	96.67	3.33	0.00	100.00	0.00	0.00
	GM	23.33	76.67	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.63
Machine 1 Trained in Patient 1 - Evaluated in Patient 5

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	90.00	10.00	0.00
	GM	33.33	66.67	0.00	15.00	85.00	0.00
	CSF	0.00	11.67	88.33	0.00	5.00	95.00
$T_2 - PD$	WM	100.00	0.00	0.00	98.33	1.67	0.00
	GM	10.00	90.00	0.00	3.33	96.67	0.00
	CSF	0.00	11.67	88.33	0.00	10.00	90.00
$T_1 - T_2 - PD$	WM	100.00	0.00	0.00	96.67	3.33	0.00
	GM	25.00	75.00	0.00	3.33	95.00	1.67
	CSF	0.00	11.67	88.33	0.00	8.33	91.67

Table A.64
Machine 1 Trained in Patient 1 - Evaluated in Patient 6

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	91.67	8.33	0.00	98.33	1.67	0.00
	GM	25.00	75.00	0.00	1.67	98.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	75.00	25.00	0.00	90.00	10.00	0.00
	GM	3.33	96.67	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	88.33	11.67	0.00	96.67	3.33	0.00
	GM	6.67	93.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.65
Machine 1 Trained in Patient 1 - Evaluated in Patient 7

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	98.33	1.67	0.00
	GM	35.00	65.00	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	13.33	86.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	13.33	86.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.66
Machine 2 Trained in Patient 1 - Evaluated in Patient 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	88.33	11.67	0.00	98.33	1.67	0.00
	GM	11.67	88.33	0.00	3.33	96.67	0.00
	CSF	0.00	3.33	96.67	0.00	3.33	96.67
$T_2 - PD$	WM	0.00	100.00	0.00	95.00	5.00	0.00
	GM	0.00	100.00	0.00	0.00	96.67	3.33
	CSF	0.00	10.00	90.00	0.00	1.67	98.33
$T_1 - T_2 - PD$	WM	45.00	55.00	0.00	96.67	3.33	0.00
	GM	0.00	100.00	0.00	1.67	96.67	1.67
	CSF	0.00	11.67	88.33	0.00	3.33	96.67

Table A.67
Machine 2 Trained in Patient 1 - Evaluated in Patient 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	1.67	95.00	3.33	0.00	96.67	3.33
	CSF	0.00	0.0	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	00.00	95.00	5.00	0.00	96.67	3.33
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	0.00	96.67	3.33	0.00	96.67	3.33
	CSF	0.00	3.33	96.67	0.00	0.00	100.00

Table A.68
Machine 2 Trained in Patient 1 - Evaluated in Patient 4

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	13.33	86.67	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	8.33	91.67	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	100.00	0.00	0.00	100.00	0.00	0.00
	GM	6.67	93.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.69
Machine 2 Trained in Patient 1 - Evaluated in Patient 5

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	81.67	18.33	0.00	100.00	0.00	0.00
	GM	40.00	60.00	0.00	6.67	91.67	1.67
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	100.00	0.00	0.00
	GM	11.67	61.67	26.67	13.33	86.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	81.67	18.33	0.00	98.33	1.67	98.33
	GM	35.00	63.33	1.67	3.33	95.00	1.67
	CSF	0.00	1.67	98.33	0.00	0.00	100.00

Table A.70
Machine 2 Trained in Patient 1 - Evaluated in Patient 6

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	13.33	86.67	0.00	98.33	1.67	0.00
	GM	23.33	76.67	0.00	0.00	90.00	10.00
	CSF	0.00	20.00	80.00	0.00	16.67	83.33
$T_2 - PD$	WM	5.00	95.00	0.00	83.33	16.67	0.00
	GM	0.00	70.00	30.00	0.00	86.67	13.33
	CSF	0.00	20.00	80.00	0.00	15.00	85.00
$T_1 - T_2 - PD$	WM	13.33	86.67	0.00	93.33	6.67	0.00
	GM	13.33	76.67	10.00	0.00	91.67	8.33
	CSF	0.00	23.33	76.67	0.00	1.67	98.33

Table A.71
Machine 2 Trained in Patient 1 - Evaluated in Patient 7

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	21.67	78.33	0.00	5.00	95.00	0.00
	CSF	0.00	3.33	96.67	0.00	1.67	98.33
$T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	3.33	95.00	1.67	1.67	98.33	0.00
	CSF	0.00	3.33	96.67	0.00	1.67	98.33
$T_1 - T_2 - PD$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	5.00	95.00	0.00	0.00	100.00	0.00
	CSF	0.00	3.33	96.67	0.00	1.67	98.33

Table A.72
Machine 3 Trained in Patient 1 - Evaluated in Patient 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	91.67	8.33	0.00	98.33	1.67	0.00
	GM	16.67	83.33	0.00	8.33	88.33	3.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	90.00	10.00	0.00	98.33	1.67	0.00
	GM	3.33	96.67	0.00	0.00	96.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	93.33	6.67	0.00	98.33	1.67	0.00
	GM	3.33	96.67	0.00	0.00	98.33	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.73
Machine 3 Trained in Patient 1 - Evaluated in Patient 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	70.00	30.00	0.00	85.00	11.67	3.33
	GM	51.67	48.33	0.00	1.67	98.33	0.00
	CSF	0.00	11.67	88.33	0.00	1.67	98.33
$T_2 - PD$	WM	38.33	61.67	0.00	96.67	3.33	0.00
	GM	50.00	50.00	0.00	6.67	93.33	0.00
	CSF	0.00	1.67	98.33	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	41.67	58.33	0.00	93.33	6.67	0.00
	GM	50.00	50.00	0.00	0.00	100.00	0.00
	CSF	0.00	11.67	88.33	0.00	0.00	100.00

Table A.74
Machine 3 Trained in Patient 1 - Evaluated in Patient 4

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	83.33	16.67	98.33	1.67	0.00
	GM	48.33	38.33	13.33	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	15.00	85.00	0.00	100.00	0.00
	CSF	0.00	58.33	41.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	95.00	5.00	0.00
	GM	100.00	0.00	0.00	0.00	95.00	5.00
	CSF	0.00	58.33	41.67	0.00	0.00	100.00

Table A.75
Machine 3 Trained in Patient 1 - Evaluated in Patient 4

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	83.33	16.67	98.33	1.67	0.00
	GM	48.33	38.33	13.33	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	15.00	85.00	0.00	100.00	0.00
	CSF	0.00	58.33	41.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	95.00	5.00	0.00
	GM	100.00	0.00	0.00	0.00	95.00	5.00
	CSF	0.00	58.33	41.67	0.00	0.00	100.00

Table A.76
Machine 3 Trained in Patient 1 - Evaluated in Patient 5

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	3.33	96.67	0.00	91.67	8.33	0.00
	GM	25.00	66.67	8.33	0.00	75.00	25.00
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	91.67	8.33	0.00
	GM	0.00	31.67	68.33	3.33	91.67	5.00
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	91.67	8.33	0.00
	GM	0.00	0.00	100.00	6.67	81.67	11.67
	CSF	0.00	40.00	60.00	0.00	5.00	95.00

Table A.77
Machine 3 Trained in Patient 1 - Evaluated in Patient 6

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	83.33	16.67	0.00	91.67	8.33	0.00
	GM	6.67	93.33	0.00	0.00	96.67	3.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	96.67	3.33	0.00	96.67	3.33	0.00
	GM	16.67	81.67	1.67	3.33	95.00	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	95.00	5.00	0.00	96.67	3.33	0.00
	GM	5.00	93.33	1.67	1.67	91.67	6.67
	CSF	0.00	5.00	95.00	0.00	0.00	100.00

Table A.78
Machine 3 Trained in Patient 1 - Evaluated in Patient 7

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	0.00	100.00	88.33	11.67	0.00
	GM	0.00	0.00	100.00	0.00	85.00	15.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	0.00	100.00	88.33	11.67	0.00
	GM	0.00	0.00	100.00	0.00	85.00	15.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	0.00	100.00	86.67	13.33	0.00
	GM	0.00	0.00	100.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

A.3 Across Machine Test I

Table A.79
Trained in Patient 1 Machine 1 - Evaluated in Patient 2 Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	16.67	63.37	20.00	0.00	81.67	18.33
	CSF	0.00	100.00	0.00	0.00	35.00	65.00
$T_2 - PD$	WM	0.00	100.00	0.00	91.67	6.67	1.67
	GM	0.00	100.00	0.00	0.00	100.00	0.00
	CSF	0.00	100.00	0.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	95.00	5.00	0.00
	GM	15.00	83.33	1.67	0.00	91.67	8.33
	CSF	0.00	100.00	0.00	0.00	25.00	75.00

Table A.80
Trained in Patient 1 Machine 2 - Evaluated in Patient 2 Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	75.00	25.00	0.00
	GM	0.00	100.00	0.00	0.00	66.67	33.33
	CSF	0.00	100.00	0.00	0.00	16.67	83.33
$T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	100.00	0.00	0.00	75.00	25.00
	CSF	0.00	100.00	0.00	0.00	21.67	78.33
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	78.33	21.67	0.00
	GM	0.00	100.00	0.00	0.00	80.00	20.00
	CSF	0.00	100.00	0.00	0.00	18.33	81.67

Table A.81
Trained in Patient 2 Machine 1 - Evaluated in Patient 3 Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	93.33	6.67	0.00	98.33	1.67	0.00
	GM	15.00	83.00	1.67	8.33	91.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	95.00	5.00	0.00	98.33	1.67	0.00
	GM	10.00	88.33	1.67	8.33	91.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	93.33	6.67	0.00	0.00	0.00	100.00
	GM	15.00	83.33	1.67	8.33	91.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.82
Trained in Patient 2 Machine 2 - Evaluated in Patient 3 Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	83.33	16.67	0.00	95.00	5.00	0.00
	GM	11.67	88.33	0.00	0.00	98.33	1.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	88.33	11.67	0.00	98.33	1.67	0.00
	GM	5.00	95.00	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	93.33	6.67	0.00	93.33	6.33	0.00
	GM	6.67	93.33	0.00	0.00	100.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.83
Trained in Patient 3 Machine 1 - Evaluated in Patient 4 Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	96.67	3.33	0.00
	GM	0.00	58.33	41.67	3.33	96.67	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	91.67	6.67	0.00
	GM	0.00	71.67	28.33	11.67	88.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	85.00	6.67	8.33
	GM	0.00	63.33	36.67	1.67	81.67	16.67
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.84
Trained in Patient 3 Machine 2 - Evaluated in Patient 4 Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	98.33	0.00	1.67
	GM	23.33	76.67	0.00	11.67	88.33	0.00
	CSF	0.00	5.00	95.00	0.00	0.00	100.00
$T_2 - PD$	WM	98.33	0.00	1.67	98.33	0.00	1.67
	GM	75.00	25.00	0.00	11.67	88.33	0.00
	CSF	0.00	3.33	96.67	0.00	0.00	100.00
$T_1 - T_2 - PD$	WM	96.67	1.67	1.67	98.33	0.00	1.67
	GM	31.67	68.87	0.00	11.67	88.33	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.85
Trained in Patient 4 Machine 1 - Evaluated in Patient 5 Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	38.33	61.67	0.00	83.33	10.00	6.67
	GM	40.00	60.00	0.00	0.00	83.37	16.67
	CSF	0.00	65.00	35.00	0.00	10.00	90.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	3.33	96.67	0.00	0.00	85.00	15.00
	CSF	0.00	68.33	31.67	0.00	13.33	86.67
$T_1 - T_2 - PD$	WM	1.67	98.33	0.00	96.67	0.00	3.33
	GM	8.33	91.67	0.00	0.00	90.00	10.00
	CSF	0.00	65.00	35.00	0.00	11.67	88.33

Table A.86
Trained in Patient 4 Machine 2 - Evaluated in Patient 5 Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	3.33	96.67	0.00	0.00	100.00	0.00
	CSF	0.00	8.33	91.67	0.00	1.67	98.33
$T_2 - PD$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	5.00	95.00	0.00	3.33	96.67	0.00
	CSF	0.00	6.67	93.33	0.00	1.67	98.33
$T_1 - T_2 - PD$	WM	98.33	1.67	0.00	100.00	0.00	0.00
	GM	0.00	100.00	0.00	1.67	98.33	0.00
	CSF	0.00	6.67	93.33	0.00	1.67	98.33

Table A.87
Trained in Patient 5 Machine 1 - Evaluated in Patient 6 Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	45.00	55.00	0.00	98.33	1.67
	CSF	0.00	26.67	73.33	0.00	15.00	85.00
$T_2 - PD$	WM	0.00	100.00	0.00	83.33	16.67	0.00
	GM	0.00	80.00	20.00	1.67	98.33	0.00
	CSF	0.00	25.00	75.00	0.00	11.67	88.33
$T_1 - T_2 - PD$	WM	0.00	100.00	0.00	98.33	0.00	1.67
	GM	0.00	100.00	0.00	0.00	95.00	5.00
	CSF	0.00	30.00	70.00	0.00	13.33	86.67

Table A.88
Trained in Patient 5 Machine 2 - Evaluated in Patient 6 Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	71.67	28.33	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.89
Trained in Patient 6 Machine 1 - Evaluated in Patient 7 Machine 2

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	71.67	28.33	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

Table A.90
Trained in Patient 6 Machine 2 - Evaluated in Patient 7 Machine 3

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_2 - PD$	WM	0.00	100.00	0.00	100.00	0.00	0.00
	GM	71.67	28.33	0.00	0.00	76.67	23.33
	CSF	0.00	0.00	100.00	0.00	0.00	100.00
$T_1 - T_2$	WM	96.67	3.33	0.00	98.33	1.67	0.00
	GM	8.33	91.67	0.00	5.00	95.00	0.00
	CSF	0.00	0.00	100.00	0.00	0.00	100.00

A.4 Across Machine Test II

Table A.91
Trained in All Patients and Machines - Evaluated in all Patients and Machines

		Weighted			Calculated		
		WM	GM	CSF	WM	GM	CSF
$T_1 - T_2$	WM	52.38	47.62	0	99.29	0.71	0
	GM	19.05	80.95	0	5.24	92.14	2.62
	CSF	0	10.00	90.00	0	2.86	97.14
$T_2 - PD$	WM	42.38	57.19	0	100	0	0
	GM	48.81	51.19	0	15.24	82.86	1.90
	CSF	0	10.00	90.00	0	1.43	98.57
$T_1 - T_2$	WM	52.38	47.62	0	96.90	3.10	0
	GM	19.29	80.71	0	5.24	92.38	2.38
	CSF	0	11.90	88.10	0	2.86	97.14

REFERENCES

1. Ozkan M., Dawant B.M. and Maciunas R.J. , "Neural Network Based Segmentation of Multi-Modal Medical Images: A Comparative and Prospective Study", *IEEE Trans. Med. Imag.*, vol. 12, 1993, pp 534-544.
2. Deichmann R., Good C.D. and Turner R., "RF Inhomogeneity Compensation in Structural Brain Imaging", *Magnetic Resonance in Medicine*, vol. 47, 2002, pp 398-402.
3. Guenneugues M., Berthault P. and Desvaux H., "A Method for Determining $B - 1$ Field Inhomogeneity. Are the Biases Assumed in Heteronuclear Relaxation Experiments Usually Underestimated?", *Journal of Magnetic Resonance*, vol. 136, 1999, pp 118-126.
4. Chen J., Feng Z. Jin and J.M., "Numerical Simulation of SAR and $B - 1$ Field Inhomogeneity of Shielded RF Coils Loaded with Human Head", *IEEE Trans. Biomedical Imaging*, vol. 45, 1998, pp 650-658.
5. Liang Z. and Lauterbur P.C., *Principles of Magnetic Resonance Imaging*, IEEE Press, New York; 1999.
6. Chen J., Feng Z. and Jin J.M., "Numerical Simulation of SAR and B_1 Field Inhomogeneity of Shielded RF Coils Loaded with Human Head", *IEEE Trans. Biomedical Imaging*, vol. 45, 1998, pp 650-658.
7. Andersen A.H., Zhang Z., Avison M.J. and Gash D.M., "Automated Segmentation of Multispectral Brain Images", *Journal of Neuroscience Methods*, vol. 122, 2002, pp 13-23.
8. Collewet G., Davenel A., Toussaint C. and Akoka S., "Correction of Intensity Nonuniformity in Spin-echo T_1 -Weighted Images", *Magnetic Resonance Imaging*, vol. 20, 2002, pp 365-373.

9. Suckling J., Sigmundson T., Greenwood K., and Bullmore E.T., "A Modified Fuzzy Clustering Algorithm for Operator Independent Brain Tissue Classification of Dual Echo Images", *Magnetic Resonance Imaging*, vol. 17, 1999, pp 1065-1076.
10. Valdes-Cristerna R., Medina-Banuelos V. and Yanez-Suarez O., "Coupling of Radial Basis Network and Active Contour Model for Multispectral Brain MRI Segmentation", *IEE Trans. on Biomedical Imaging*, vol. 51, 2004, pp 459-470.
11. Velthuizen R.P., Heine J.J., Cantor A.B., Lin H., Fletcher L.M. and Clarke L.P., "Review and Evaluation of MRI Nonuniformity Corrections for Brain Tumor Response Measurement.", *Medical Physics*, vol. 25, 1998, pp 1655-1665.
12. Narayana P.A. and Borthakur A., "Effect of Radio Frequency Inhomogeneity Correction on the Reproducibility of Intracranial Volumes using MR Image Data", *Magnetic Resonance in Medicine*, vol. 33, 1995, pp 396-400.
13. Sled J.G., Zijdenbos A.P. and Evans A.C., "A Nonparametric Method for Automatic Correction of Intensity Non-Uniformity in MRI Data", *IEEE Trans. Med. Imaging*, vol. 17, 1998, pp 87-87.
14. Zhou L.Q., Zhu Y.M., Bergot C. and Laval-Jenatet A.M., "A Method of Radio-frequency Inhomogeneity Correction for Brain Tissue Segmentation in MRI", *Computed Medical Imaging*, vol. 25, 2001, pp 379-389.
15. Koivula A., Alakuijala J., and Tervonen O., "Image Feature Based Automatic Correction of Low-Frequency Spatial Intensity Variations in MR Images", *Magnetic Resonance Imaging*, vol. 15, 1997, pp 1167-1175.
16. Vaidyanathan M., Clarke M.P., Heidtman C., Velthuizen R.P. and Hall L.O., "Normal Brain Volume Measurements Using Multispectral MRI Segmentation", *Magnetic Resonance Imaging*, vol. 15, 1997, pp 87-97.
17. Jonston B, Atkins M.S., Mackiewich B and Anderson M., "Segmentation of Multiple Sclerosis Lesions in Intensity Corrected Multispectral MRI", *IEEE Trans. Med. Imaging*, vol. 15, 1996, pp 154-169.

18. Vaidyanathan M., Clarke M.P., Heidtman C., Velthuisen R.P. and Hall L.O., "Normal Brain Volume Measurements Using Multispectral MRI Segmentation", *Magnetic Resonance Imaging*, vol. 15, 1997, pp 87-97.
19. Saeed N., "Magnetic Resonance Image Segmentation Using Pattern Recognition and Applied to Image Registration and Quantification", *NMR Biomedicine*, vol. 11, 1988, pp 157-169.
20. Nyul L.G. and Udupa J.K., "On Standardizing the MR Intensity Scale", *Magnetic Resonance in Medicine*, vol. 42, 1999, pp 1072-1082.
21. Shattuck D.W., Sandor-Leahy S.R., Schaper K.A., Rottenberg D.A. and Leahy R.M., "Magnetic Resonance Tissue Classification Using a Partial Volume Model", *Neuroimage*, vol. 13, 2001, pp 856-875.
22. Dash M. and Lui H., "Feature selection for classification", *Intelligent Data Analysis*, vol. 1, 1997, pp 131-156.