A Study of Techniques for Segmenting the Spinal Cord

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Abstract: *The spinal cord is one of the most important organs that controls communication between the brain and various parts of the body. It is highly susceptible to harmful infections and many diseases. An important criterion of clinical management is the appropriate localization and division of the spinal cord. Segmentation poses risks associated with variation in human anatomy and contrast variation in Magnetic Resonance Imaging. Therefore, an effective segmentation technique should be developed for effective division of the spinal cord and disc localization. In comparison, the survey contained here in provides an overview of different segmentation schemes for spinal cord segmentation. Now, there is an urgent need to develop an effective segmentation approach that is better than the current one segmentation methods. In this research article, a detailed survey of the various research activities presented by specific segmentation schemes based on the semi-automated, active contour model, Introduced partitioning, deformable model, probabilistic model and graph based partitioning. In addition, in-depth analysis and discussion are provided in accordance with the year of publication, evaluation dimensions, segmentation scheme, and magnetic Resonance Image Datasets, Dice Equivalence Coefficient (DSC), Accuracy.*

Keywords: Segmentation, IVD, MRI, Spinal Cord, Dice Equivalence Coefficient (DSC)

I. INTRODUCTION

Later, advances in telecommunications and information technology (IT) played a vital role in the development of the healthcare sector. This development has had a significant impact on the field of medical imaging, where digital imaging techniques are gradually replacing the film radiographic method. This development facilitates the transfer, storage, retrieval, analysis, and interpretation of distributed multimedia patient data . The spinal cord between each pair of adjacent vertebrae is the interVertebral disc (IVD). These discs have the ability to deform and act as a buffer to allow vertebral movement. IVD degeneration can lead to a variety of problems, including paralysis, neck pain, muscle wasting, numbness, and back pain. Detecting spinal cord abnormalities is a challenging task (Law et al., 2013). Computed tomography (CT) and magnetic resonance imaging (MRI) are different instrument approaches used to capture images of the human body. Among these approaches, MRI has gained significant prominence in the field of medical research (Sahane and Shinde, 2016). In addition, spinal MRI (An et al., 2004; Michopoulou et al., 2009) is the most preferred technique for diagnosing IVD degeneration. The main advantages of taking MR image are the absence of radioactive contamination and high resolution (HR), which are not affected by any kind of harmful radiation. Raw MRI images cannot be used directly without pre-processing; So as a first step, pre-processing should be done to prepare the image for further processing by removing the sound and increasing the image contrast

The pre-processing mechanism involves several different steps, including intensification normalization, skull-stripping, and image de-noising (Sahane and Shinde, 2016). Following this, relevant features such as texture, shape, and color are extracted with the intention of increasing MRI segmentation accuracy. The next step, that is, after feature extraction, is image segmentation; The division and analysis of medical images is one of the most extensive areas of research in the medical field, as this stage plays a critical role in the detection and treatment of abnormalities (Priya, Umaibanu, 2017). The development of an effective segmentation scheme for the partitioning and localization of MR image disks is difficult (Law et al., 2013). In general, spinal cord segmentation is mainly used for the measurement of spinal cord atrophy (Coulon et al., 2002) and for the extraction of MRI metrics on parts of the spinal cord (Cohen-Adad et al., 2011). Several types of studies are being conducted for disc feature quantification and identification of spinal cord abnormalities. Most studies rely on spontaneously extracted data (Niemelainen et al., 2008). Since manual evaluation of disc data involves inherent time complexity and fatigue, an effective computer-assisted diagnostic system should be developed (Law et al., 2013). Therefore, an enhanced automated image segmentation scheme (Priya and Umaibanu, 2017) should be explained in order to effectively detect spinal cord damage from the given MRI images.

The main impetus for spinal cord segmentation is the measurement of a cross-sectional area for quantitative assessment and treatment monitoring of disease progression in multiple sclerosis. In principle, the automatic or semi-automatic spinal cord and white matter (WM) / gray matter (GM) segmentation offer greater potential for longitudinal and group studies, as manual deletion is time consuming and prone to inter- or intra-operator variables (D2016).

The main purpose of this article is to provide a comprehensive survey of different spinal cord segmentation approaches to spinal cord segmentation and disc localization. The survey describes current segmentation approaches and embraces in various research initiatives. We examine and validate the efficiency and segmentation performance of various specific approaches. The survey is completed based on the year of publication, the segmentation method practiced, the datasets used, the implementation tool, and the evaluation measures. Besides, the accuracy range and Dice Equivalence coefficients are taken into account for performance evaluation of recommended spinal cord segmentation methods. Current segmentation approaches are classified into thirteen categories, and then research gaps and problems are explored through further surveys.

II. A Descriptive Study of the Related Work

This section presents and considers a review of various segmentation schemes for effective spinal cord segmentation. In line with this introductory illustration, spinal cord segmentation technologies are broadly classified into Optimization based segmentation, fuzzy c-means (FCM) based segmentation, Active contour model based segmentation, Semi-automated segmentation, Propagation Segment (PropSeg) based segmentation ,Deformable model based segmentation, Learning-based segmentation, Expectation Maximization (EM) based segmentation, Gradient Vector Flow (GVF)-based segmentation, Probabilistic model based segmentation, Graph-based segmentation, Level set based segmentation, and other segmentation schemes. Examination of different spinal cord segmentation approaches provides a broader perspective on occupational approaches and their advantages and disadvantages.

2.1 Optimization Based Segmentation Techniques

Chris McIntosh et al. (2011) based on an artificial life architecture" Spinal Crawlers" method for abnormal diagnosis of spinal cord. The live-wire scheme was used to increase the local optimality of the spinal crawlers using the best paths around the world. Segmentation results showed that the envisioned model was fast and capable of providing an excellent clinical diagnosis in a short period of time. Jeremy Kawahara et al. (2013) suggested an isometric log-ratio-based principal component analysis (ILR-based PCA) procedure for determining the optimal segregation of the spinal cord globally using minimally invasive short-path search. The PCA was embraced in this study to capture partial volume effects and axial cross-sectional similarities of the spinal cord and to represent cross-sectional forms of the spinal cord. The proposed scheme calculations were possible and reduced the operating time and memory requirement. Ferran Prados et al. (2016) presented a collaborative effort based on the fully automated gray matter (GM) and spinal cord segmentation scheme for abnormal diagnosis. The cross-sectional area (CSA) and GM segmentation is based on similarities and differences between the optimized patch match label fusion (OPAL) algorithm and the propagated segmentation (steps) algorithm. In performance evaluation, multiple sclerosis (MS) subjects and healthy subjects were used. The segmentation results obtained showed better accuracy than the traditional approaches. And Xinjiang Su. (2016) proposed a Gabor Filter Bank based scheme for the division and localization of IVDs. Initially, the Gabor filter bank was used to isolate the structural features of the IVD; After this, the Gabor features of the spine were calculated and the spinal curves were identified

Following this, the Gabor feature images (GFI) of the IVD were calculated and modified according to the spinal curves. Through clustering analysis, localization of IVDs was performed. Later, the division of the IVDs was carried out by implementing the algorithm in the Optimal GraceSkey, with the data formed by combining the Gabor features of the spine with the localization results. The program surpassed traditional plans by achieving effective localization and differentiation of IVDs in diagnosis and spinal surgery.

2.2 FCM Based Segmentation Techniques

This subsection discusses research papers that suggest and describe FCM-based segmentation for effective spinal cord segmentation. FCM is a well-known algorithm used for clustering. FCM membership allows each data point to be associated with a specific cluster center based on the distance between cluster centers and data points. Data points near a given cluster center gain high membership in this cluster. Min Chen et al. (2013) developed the FCM-based topology-preserving anatomy-driven segmentation (TOADS) algorithm for effective spinal cord segmentation. This method performed the final division through the use of foresight, with regard to target anatomy and its neighboring structures. This method has proven to be resistant to art forms and sound, which usually leads to deterioration of performance. Sophia K. Michopoulou et al.(2009) Atlas-Robust-FCM (R-FCM) was developed for quantitative assessment of IVD during spinal surgery and during disc degeneration diagnosis. It was a partitioning plan based on the probabilistic atlas, which used previous anatomical insights, combining smooth controls and an indistinct clustering system. The scheme achieved strong and excellent segmentation performance.

2.3 Active Contour Model Based Segmentation

The Studies reporting the use of spinal cord segmentation based on the active contour model are discussed below.

Mark A. Horsefield et al. (2010) developed a semi-automatic scheme based on an active surface model for CSA evaluation of spinal cord with small deviations in circular and longitudinal axes. Compact parameterization of the string surface allowed rapid separation by marking the centerline of the string into specific string slices with limited manual support. The expanded active model based approach outperformed the compared segmentation methods in terms of sensitivity and reproducibility.

Deepti Prasad Mukherjee et al. (2010) design an automatic Segmentation Scheme to assist the Rehabilitation surgery planning process. This segmentation scheme suggested an active tracing application for border demarcation.

Oktay, Albayrak, and Akgul (2014) developed a window-based automated initialization scheme for detected disc localization in the spinal cord. Here, a successful division of unilaterally shaped IVDs was achieved by adopting Active Appearance Models (AAM). The imaging artifact problem was solved by incorporating the intensity insight of the given MR images. The associated IVD was compared with the adjacent lumbar IVD using contextual features. The proposed segmentation scheme surpasses other modern approaches considered in terms of accuracy.

2.4 Semi-Automated Segmentation

This subsection discusses queries that refer to semi-automated spinal cord segmentation approaches.

So, Mohamed-Maunir el Mendili et al. (2015a) Introduced a spinal cord segmentation technology based on semi-automation for the diagnosis of trauma and neurodegenerative diseases. This approach was developed with the aim of estimating CSA of the spinal cord and cervical region of the chest in a large group of patients with different spinal cord disorders. This planned approach ensures better partitioning performance than other artistic approaches.

Adam Cadotte et al. (2015) developed a semi-automated segmentation approach for spinal cord segmentation from HR T2-weighted MRI. Images were split using a 1-D template matching algorithm. The centerline of the split image was corrected using an extended split approach. This semi-automated segmentation scheme performed better than manual segmentation schemes at low cerebral spinal fluid (CSF) volume, high spinal cord curvature, accuracy and processing time.

2.5 Propagation Segment (PropSeg) Based Segmentation

The Studies reporting the use of spinal cord segmentation based on the propagation segment based segmentation are discussed below.

D Leener, Kadoury, and Cohen-Adad (2014) presented a spinal cord segmentation approach based on an autoimmune prophylaxis for abnormal diagnosis of spinal cord. This algorithm is based on the propagation of a modifying model, which consisted of three steps, namely: (i)Initialization, orientation and position of the spinal cord were identified using circular hough transitions; (ii) Propagation of the low-resolution (LR) deformed model compared to the spinal cord, (iii) Global deformation and purification process, implemented for precise spinal cord segmentation.

Subsequently, D Leener, Cohen-Adad, and Kadoury (2015) developed a segmentation scheme for direct intra-subject and inter-subject spinal cord comparison of the vertebral level identification approach and the projection. This approach depends on the multi-resolution propagation of the tubular deformable model. The proposed scheme was very robust and capable of providing an impartial assessment of spinal cord injury.

2.6 Deformable Model Based Segmentation

Research papers using distorted models for effective spinal cord segmentation and research report are considered in this brief subsection.

Min Chen et al. (2011) introduced an automated segmentation scheme developed by combining topology-protective classification and registration-based deformity atlas to solve problems in spinal cord MR images. This partitioning approach involves two steps; That is, (1) the alignment of the intensity atlas relative to the MRI to be divided by the distorted registration, and (2) the resulting mapping intensity applied to the statistical atlas and topology template relative to the atlas. This scheme, unlike other segmentation approaches, maintained an excellent spinal cord topology and consistent segmentation.

De Leener, Cohen-Adad, and Kadouri (2014) developed a model that could be mechanically modified based on the repetitive propagation of effective spinal cord division. The main purpose of this approach was the efficient management of spinal cord curves and the image contrast-to-noise ratio. This scheme is capable of managing datasets with maximum throughput without the intervention of user bias.

2.7 Learning-Based Segmentation

This subsection discusses queries that refer to learning based segmentation approaches.

Koh, Chaudhary and Dhillon (2012) designed Computer-Aided Diagnosis (CAD) for lumbar spine segmentation based on a two-tier classification scheme. This classification was developed for the diagnosis of disc herniation using a variety of classifiers, including the K-Means Classifier, the Perceptron Classifier, the Support Vector Machine (SVM) Classifier, and at least the Square Classifier. These classifiers are diagnosed according to a feature created by ROI, which includes the spinal cord, IVD, and vertebrae. Finally, the fair classifier was adopted to make the final decision on the use of the score values of the classifier. This project was able to effectively detect herniated discs.

Chengwen Chu et al. (2015) introduced a fully automated scheme for localization and division of vertebral bodies (VBs) from a given MRI. First, random forest regression was used for the localization of 3D VBs. Then, votes from randomly sampled image patches were compiled to determine the probability map of the targeted VB. The available Probability Map was further configured with the Hidden Markov Model (HMM), with the intention of eliminating ambiguity due to nearby VBs. Voxel's posterior probability is calculated by combining certain probabilities with insights into the prior probabilities learned from the training dataset.

Perone, Calabrese and Cohen-Adad (2017) have developed a pipeline based on the end-to-end learning scheme for fully automated GM segmentation. The project used an in-depth learning architecture that relied on address spatial pyramid pooling (ASPP) to manage previous Vivo and Vivo MRI acquisitions.

This project provided excellent generalization and accuracy in dividing the XVO Vivo HR Acquisition data set. This approach does not limit the use of 3D dilated convolutions.

2.8 Expectation Maximization (EM) Based Segmentation

The current subdivision considers the research papers, reports on research studies, and adopts spinal cord segmentation based on expected maximization (EM)

Andrew J. Asman et al. (2014) developed a registration model based on the group-wise slice to create a representation of the cervical spinal cord morphology model. The main functions of the developed approach were: (i) modeling of existing abnormalities in the cervical spinal cord, (ii) rapid registration of the target splenic cord slice to be modeled, and (iii) selection of geodesically suitable atlases for target image segmentation. Simulation results indicate that the planned approach is better than the traditional plans compared to the robustness and accuracy.

R. Priya and M. Umaibanu (2017) also introduced the EM Dependent Spinal Cord Segmentation based on the Automatic and Complete Pipeline. The employment plans were a robust fitness firefly (SFF) algorithm and an improved weighted EM (WEM). The scheme detected spinal cord defects on the basis of MRI and divided the spinal cord with improved segmentation accuracy at lower frequencies than comparable techniques.

2.9 Gradient Vector Flow (GVF)-Based Segmentation

We now comment on different research activities using GVF (GradientVector flow) based spinal cord segmentation.

Jaehan Koh et al. (2010) introduced an automated segmentation scheme for the separation of the dural sac and spinal cord from T2-weighted sagittal MRI without human support. For the determination of candidate blobs, the GVF field was used. The methodology was used to evaluate the connected component during the final partitioning. Through quantitative analysis, the developed GVF-based segmentation approach performed better than any other scheme with respect to the overlapping matrix.

Ruiz-Espana, Arana and Moratal (2015) proposed a GVF algorithm for distinguishing IVD shape features. Here, spinal stenosis was differentiated and detected using the signal intensity approach. Intra-Class Correlation (ICC) and Kappa statistics were evaluated in the context of variability assessment. This scheme provided better reproduction along with the actual result measuring the severity of the pathology.

2.10 Probabilistic Model Based Segmentation

This subsection discusses studies using spinal cord segmentation based on the probabilistic model.

Alomari Raja'S et al. (2010) developed a probabilistic model for the integration of the context, shape, and position of the IVD for the purpose of detecting abnormalities in the discs. Based on the combined features and disk level modeling obtained, the abnormal status of the IVD was determined. This approach includes some other domain features such as age, height, and some other insights related to patients. Due to the use of combined features the scheme was very flexible and gave accurate results.

Corso, Raja'S and Chaudhary (2008)introduced a two-level probabilistic framework for labeling and localization of IVD. This scheme hybridized pixel level insight as well as high level insight like spatial relationship between IVDs. This scheme was able to insulate high level assumptions from pixel level variations. This approach has outperformed other existing segmentation schemes in terms of accuracy.

2.11 Graph-Based Segmentation

This subsection discusses studies using spinal cord segmentation based on the graph based segmentation model Zhenyu Tang and Josef Pauli (2011)proposed a fully automatic scheme for extracting the spinal curve required for gait modeling. The scheme consists of two phases; The first step was IVD position extraction and the second step was the extraction of disk positions using the vertebra registration scheme.

Subsequently, the cubic spine approach was adopted to determine the curvature of the spine through interpolation of the center of the split vertebrae. The developed graph based segmentation scheme ensured better comparison performance based on maximum accuracy.

Fatemeh Nasiri and Hamid Soltanian Zade (2013) developed a fully automatic segmentation scheme based on the graph cut (GC) algorithm for IVD segmentation. Initially, a graph was constructed from the given image pixels and two additional nodes, i.e. zinc (t) and source (s) supported by seed points. ROI was extracted from the segmented image by applying GC with the support of post-processing mechanisms such as content-based and transformational modification. The main merit of this scheme was the achievement of 95% high accuracy.

2.12 Level Set Based Segmentation

This subsection discusses research reports on studies that accept spinal cord segmentation based on the level set.

George Hille et al. (2018) introduced a level set based segmentation scheme for 3D vertebral body splitting. Intensity correction was the first step in dealing with bias field artifacts as well as low user support. Subsequently, vertebral body probability maps based on the hybrid level-set segmentation pattern were guided. This scheme achieved relatively good accuracy and rigidity as it was evident through the segmentation results.

2.13. Other Segmentation Methodologies

This subsection considers other segmentation schemes adopted in various investigations aimed at effective spinal cord segmentation.

Cheng Chen et al. (2015) developed a fully automated data-drive approach to segmentation and localization of 3D IVD from MR spine images. Joint optimization of test and training positioning was performed to calculate displacement based on test image geometric control and training data. Subsequently, IVD segmentation was performed by classifying the background or front pixels around the disk centers. The scheme includes additional flexible neighborhood controls to achieve improved segmentation accuracy.

The scheme includes additional flexible neighborhood controls to achieve improved segmentation accuracy.

Julio Urrutia et al. (2016) developed a grading system based on a PIFIRMAN classification scheme for conducting an independent study of the Intra-Inter Observer Agreement. The grading of IVD Degeneration (IDD) is important in the assessment of degenerative status in patients with low back pain. The performance of adequate agreement between individual observers and the same observer on individual occasions was carried out using the Pfirman classification method. The developed project provided high quality segmentation accuracy and excellent communication between radiologists and physicians.

Sara M. Dupont et al. (2017) Introduced multi-atlas based technology for spinal cord white and gray matter separation. It should be noted that in the study of spinal cord morphology, atlas-based approaches are increasingly used. The authors have developed a template registration framework that combines the separation of white and gray matter to describe the exact gray matter shape of each individual subject. T2* - This approach was validated using 24 healthy subjects, 8 healthy subjects, diffusion weighted images through weighted images, and 5 patients with spinal cord injury.

Charley Gros et al. (2018) developed a fully automated framework for spinal cord segmentation and intramodular MS lesion segmentation from typical MRI data of MS and non-MS cases. This method relies on a series of two convulsive neural networks (CNNs). CNNs were specially trained in dice loss. This framework is open source and is available in the Spinal Code Toolbox.

III. The Summary of Analysis

We now present simple summaries of studies dealing with spinal nerve segmentation based on the adopted segmentation approach, year of publication, used datasets, evaluation parameters, implementation tool, MR images used, accuracy obtained, and dice coefficient. The latter is considered here in view of the fact that most of the studies surveyed use this coefficient for evaluation.

3.1 The Image Based on Segmentation Techniques

Figure 1 shows the breakdown of spinal cord segmentation methods suggested in the surveyed studies. Among the research papers considered, the most commonly used segmentation schemes are active contour model based segmentation, learning based segmentation, optimization based segmentation and EM based segmentation.

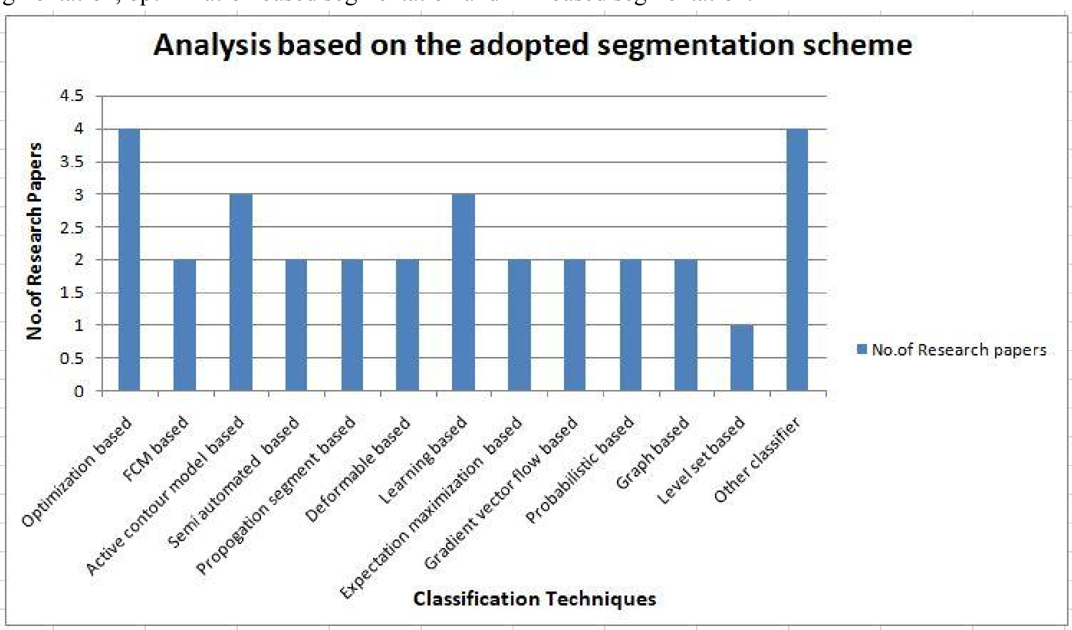

Figure 1: The adopted segmentation approaches in the survey.

3.2 Image Based on the Implementation Tool

Table 1 shows the various implementation tools used in investigations aimed at the effective segmentation of the spinal cord. Commonly implemented implementation tools are JAVA, C ++, Osirix Software, JIM (Xinapse System), Impax Web 200 Program, JMP Statistical Software, PASW Software, NVIDIAGeforce GTX, and MATLAB. From Table 1, it can be concluded that MATLAB is the most practiced implementation tool for effective spinal cord segmentation in the studies reported here.

Application Tools	Research papers
JAVA	Chen et al. (2013)
C++	De Leener, Kadoury and Cohen-Adad (2014);Cadotte et al. (2015)
Osirix Software	De Leener, Cohen-Adad and Kadoury (2015)
JIM (Xinapse System)	Prados et al. (2016); De Leener, Cohen-Adad and Kadoury (2014); Datta et al. (2017)
PASW Software	Yu et al. (2012)
JMP Statistical Software	Riesenburger et al. (2015)
Impax Web 200 Program	Urrutia et al. (2016)
MATLAB	El-Mendili et al. (2015a,b); Asman et al.(2014); Datta et al. (2017); Chen et al. (2015);Zhu et al. (2016); Michopoulou et al. (2009);Raja'S et al. (2010); Chu et al.

Table 1: Implementation tool used

3.3 Image Based on the Evaluation Metrics

Table 2 shows the statistics according to the side of the evaluation measures used in specific studies. The evaluation measures used in the surveyed studies are: Accuracy, Sensitivity, Specificity, Accuracy, DSCs, Speed, Equivalence Index (SI), and Housedorf Distance (HSD). It can be seen from the chart that most of the studies participated in the survey address the criteria of accuracy. Sensitivity, specificity, HDS, and DSC are other commonly used evaluation metrics.

Accuracy	30%
Dice Similarity Coefficients (DSC	13%
Hausdorff Distance (HSD)	10%
Sensitivity	8%
Specificity	7%
Jaccard Similarity Coefficients JS	3%
False Positive Rate	3%
Precision	3%
Mean Surface Distance error (M	3%
Similarity Index	3%
Mean Absolute Distance	2%
Speedup	2%
Recall	2%
Others	7%

Table 2: Analysis based on the evaluation matrics

3.4 The MR Imaging Types

Figure 2 shows simple statistics based on the MR images used. Commonly used MR image types are T2-weighted MR images, T1-weighted MR images, and T2-weighted sagittal images. Other datasets include T1-weighted sagittal images, T2-weighted mid-sagittal images, T2-weighted MR images, and T2-weighted turbo spin echo images.

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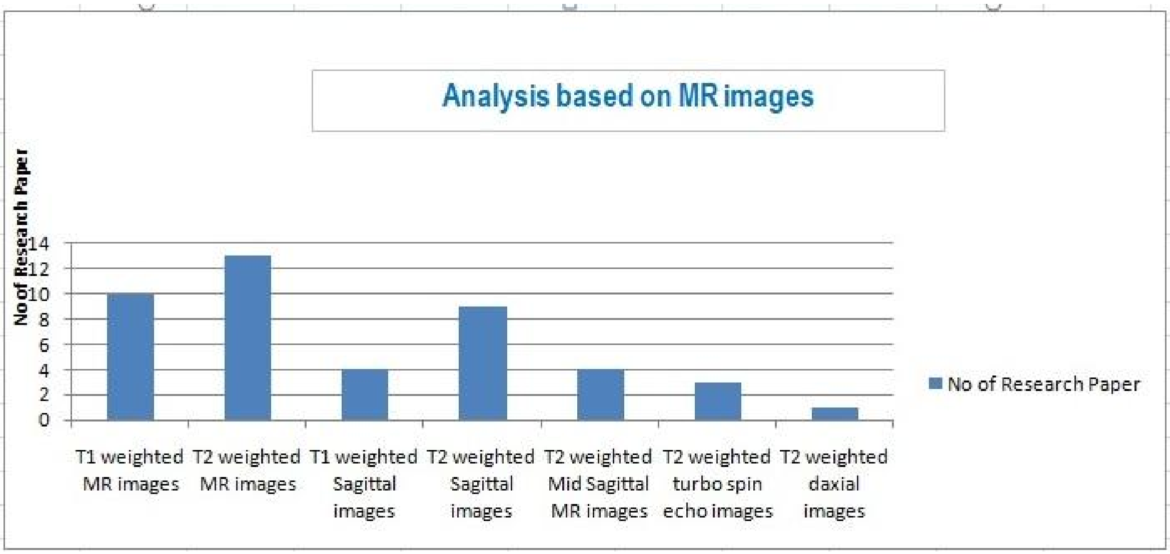

Figure 2: Analysis based on MR images

3.5 Statistics Based on Accuracy

Table 3 displays the breakdown of the surveyed publications based on the values of the accuracy measure. The table shows that the accuracy level within the range of 80% -85% was achieved through the techniques suggested in the two research papers; A level of 85% -90% was reported in one research activity, followed by eight research papers suggesting techniques, the accuracy of which ranges from 90% to 95% and the accuracy value to 95% -99.9%. Achieved by techniques reported in nine research papers.

Accuracy range	Research papers
80%-85%	Prados et al. (2016); Griffith et al. (2007)
85%-90%	Chen et al. (2015)
90%-95%	McIntosh et al. (2011); Kawahara et al. (2013); Koh et al. (2011); Raja'S et al. (2010); Oktay, Albayrak and Akgul (2014); Chu et al. (2015); Nasiri and Zade (2013); Hille et al.
95%-99.9%	De Leener, Cohen-Adad and Kadoury (2015); El-Mendili et al. (2015); Zhu et al. (2016); Ghosh and Chaudhary (2014); Ghosh et al. (2011); Ruiz-Espagna, Arana and Moratal (2015); Priya and Umaibanu (2017); Koh, Chaudhary and Dhillon (2012); Corso, Raja'S and Chaudhary (2008

Table 3: Accuracy measurement values reported in surveyed publications

IV. Conclusion

The primary purpose of this article is to analyze the various research papers available from different platforms and to survey, classify, and evaluate the various segmentation schemes adopted for effective spinal cord segmentation. Completes simple statistical analysis and discussion based on the year of publication, the evaluation measures used, the implementation tools, the nature of the practical segmentation scheme, and the accuracy range. Furthermore, this survey recommends an important future potential for effective spinal cord segmentation through an overview of the research challenges faced. The most commonly used segmentation method is active contour model based partitioning.

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