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A study on spinal cord segmentation techniques

by

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Abstract: One of the vital organs, which manage the communication between the brain and different body parts, is the spinal cord. It is highly prone to the traumatic injuries and to several diseases. The vital criteria for the clinical management are the appropriate localization and segmentation of the spinal cord. The segmentation experiences the risks, associated with the diversity in the human anatomy and contrast variation in Magnetic Resonance Imaging (MRI). Hence, an efficacious segmentation method must be devised for the effective segmentation and disc localization of the spinal cord. Correspondingly, the here contained survey provides the review of the distinct segmentation schemes for the spinal cord segmentation. At present, there is an urgent requirement for the development of an effective segmentation approach so as to outperform the existing segmentation methods. In this research article, a detailed survey on several research works presenting the recommended segmentation schemes, based on the active contour model, semi-automated segmentation, deformable model, probabilistic model, graph-based segmentation, and so on, is presented. Additionally, an in-depth analysis and discussion are provided, in accordance with the publication year, evaluation metrics, segmentation scheme, Magnetic Resonance (MR) image datasets, Dice Similarity Coefficient (DSC) and accuracy. Subsequently, the research gaps and risks, related to distinct segmentation schemes are considered for directing the researchers towards a better future investigation field.

Keywords: segmentation, intervertebral discs (IVD), MR image, spinal cord, Dice coefficient

1. Introduction

In the recent period, the advancement in the telecommunications and Information Technology (IT) has played the essential catalysing role for the healthcare sector development. This advancement has exerted a highly significant influence on the medical imaging field, where the digital imaging techniques are progressively replacing the film radiographic method. This development aids in the transmission, storage, retrieval, analysis, and interpretation of the distributed multimedia patient data (Orphanoudakis, Kaldoudi and Tsiknakis, 1996; Zikos, Kaldoudi and Orphanoudakis, 1997). The spine components interceding between every pair of adjoining vertebrae are the InterVertebral Discs (IVD). These discs have the capability of deforming and play the role of a buffer for permitting vertebral movement. The degeneration of the IVD leads to a variety of issues, like paralysis, neck pain, muscle strength loss, numbness, back pain, and tingling. The diagnosis of the disorders in the spinal cord is a challenging task (Law et al., 2013). The different kinds of instrumental approaches, employed for capturing the human body images, are Ultrasonography (US), Computer Tomography (CT) and Magnetic Resonance Imaging (MRI). Among these approaches, the MRI has gained a major significance in the area of medical research (Sahane and Shinde, 2016). Moreover, the mostly preferred technique for the IVD degeneration diagnosis is the spinal MRI (An et al., 2004; Michopoulou et al., 2009). The main advantages of the MR image taking are lack of radioactive contamination, and High Resolution (HR), not influenced by any type of harmful radiation.

The raw MRI images cannot be utilized directly without pre-processing; so as a first step, the pre-processing must be done for making the image ready for further processing through the noise removal and enhancement of image contrast. The pre-processing mechanism comprises a number of distinct steps, such as intensity normalization, skull-stripping, image de-noising and so on (Sahane and Shinde, 2016). Followed by this, the relevant features, like texture, shape, and color, are extracted with the intention of enhancing the MRI segmentation accuracy. The next step, namely, after the feature extraction, is the image segmentation; the segmentation and analysis of medical images are one of the prevalent research areas in the medical field, as this step plays a crucial role in the diagnosis and treatment of abnormalities (Priya and Umaibanu, 2017). The development of an effective segmentation scheme for the segmentation and localization of the MR image discs is a difficult task (Law et al., 2013). Generally, the segmentation of the spinal cord is done mainly for the quantification of the spinal cord atrophy (Coulon et al., 2002) and for the extraction of the MRI metrics in the spinal cord segments (Cohen-Adad et al., 2011). Many kinds of studies are carried out for handling the disc feature quantification and identification of abnormalities in the spinal cord. Most of the studies are dependent on the manually segmented data (Niemelainen et al., 2008). As the manual assessment of disc data involves inherently time complexity and tediousness, an effective computer-assisted diagnosis system must be devised (Law et al., 2013). Thus, an enhanced automatic image segmentation scheme must be elaborated for purposes of an effective detection of the spinal cord disorders from the given MRI images (Priya and Umaibanu, 2017).

The key motivation for spinal cord segmentation is to obtain a cross-sectional area (CSA) measurement for quantitative assessment of disease progression and therapeutic monitoring in MS (multiple sclerosis). The spinal cord segmentation is utilized for co-registration and spatial normalization to a common coordinate space, which quantifies morphometric changes or performs atlas-based quantitative multiparametric analyses for examining the structural and functional integrity of the spinal cord. In principle, automatic or semi-automatic spinal cord and White Matter (WM) / Gray Matter (GM) segmentation offer a huge potential for longitudinal and group studies, since manual delineation is time-consuming and prone to inter- or intra-operator variability (De Leener et al., 2016).

The major goal of this article is the provision of an extensive survey on the distinct spinal cord segmentation approaches for the segmentation and disc localization in the spinal cord. The existing segmentation approaches, adopted in the different research undertakings are explained in this survey. We analyse and validate the efficiency and segmentation performance of the different proposed approaches. This survey is carried out by considering the publication year, practiced segmentation methodology, utilized datasets, implementation tool, and evaluation metrics. In addition, the accuracy range and the DSCs are taken into account for the performance evaluation of the recommended spinal cord segmentation methods. The existing segmentation approaches are categorized into thirteen categories, and then, the research gaps and issues are investigated through the further survey.

This paper is organized as follows: this Section 1 gave a brief introduction about the article, Section 2 provides the literature survey on the existing research work, related to the spinal cord segmentation, while the detailed analysis and discussion of the survey results is contained in Section 3. The research challenges, experienced by the existing approaches, are discussed in Section 4, and the paper is concluded in Section 5.

2. A descriptive study of the related work

An extensive review of the different segmentation schemes for the effective spinal cord segmentation is presented and considered in this section. Figure 1 portrays the categorization of the different spinal cord segmentation schemes. Conform to this introductory illustration, the spinal cord segmentation techniques are widely categorized as Fuzzy C-Means (FCM) based segmentation, Propagation Segment (PropSeg) based segmentation, Optimization based segmentation, Active contour model based segmentation, Semi-automated segmentation, Deformable model based segmentation, Expectation Maximization (EM) based segmentation, Gradient Vector Flow (GVF)-based segmentation, Learning-based segmentation, Probabilistic model based segmentation, Graph-based segmentation, Level set based segmentation, and the other segmentation schemes. The inspection of the various spinal cord segmentation approaches gives a broad perspective on the employed approaches together with their merits and demerits.

2.1. FCM based segmentation techniques

The research papers, in which the FCM based segmentation for the effective spinal cord segmentation is proposed and described, are discussed in this subsection. FCM is a well known algorithm, utilized for clustering. FCM allocates membership for every data point with respect to each particular cluster center based on the distances between the cluster centers and the data points. The data points, which are near to a given cluster center obtain higher memberships in this cluster.

Min Chen et al. (2013) developed the FCM based Topology-Preserving Anatomy-Driven Segmentation (TOADS) algorithm for the effective spinal cord segmentation. This method performed the final segmentation through the utilization of the prior insight, concerning the target anatomy along with its neighboring structures. The method proved to be resistant to the artefacts and noise, usually leading to performance degradation.

Sofia K. Michopoulou et al. (2009) developed the Atlas-Robust-FCM (R-FCM) for the quantitative evaluation of the IVD during the spine surgery and disc degeneration diagnosis. This was a segmentation scheme based on the probabilistic atlas, which utilized the prior anatomical insight, integrated with the smoothness constraints and fuzzy clustering mechanism. The so developed scheme was robust and achieved superior segmentation performance.

2.2. PropSeg based segmentation techniques

We now present a distinct current of research, which employs the PropSeg based spinal cord segmentation approach.

De Leener, Kadoury and Cohen-Adad (2014) presented an automatic PropSeg based spinal cord segmentation approach for the abnormality diagnosis in the spinal cord. This algorithm was based on the propagation of a deformable model, and was composed of three steps, namely: (i) Initialization: the spinal cord's orientation and the position were identified by utilizing the circular Hough transforms; (ii) Propagation of the Low-Resolution (LR) deformable model relative to the spinal cord, and (iii) Global deformation and refinement process, which were implemented for the accurate spinal cord segmentation.

Then, De Leener, Cohen-Adad and Kadoury (2015) developed a segmentation scheme by concatenating the vertebral level identification approach and the PropSeg for carrying out the direct intra-subject and inter-subject spinal cord comparison. This approach was dependent on the tubular deformable model's multi-resolution propagation. The devised scheme was highly robust and was capable of providing the bias-free estimation of spinal cord atrophy.

2.3. Optimization based segmentation techniques

We summarise in this subsection the research papers, reporting on the use the optimization based spinal cord segmentation.

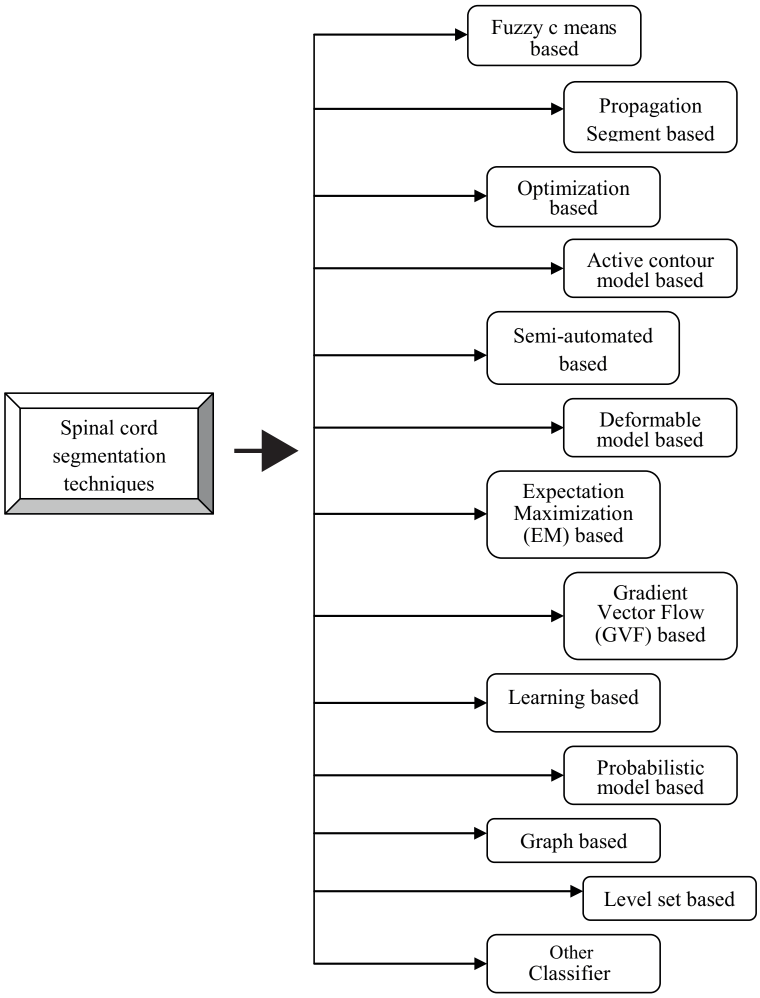

Figure 1. Categorization of distinct segmentation schemes

Chris McIntosh et al.(2011) introduced an artificial life archetype based "Spinal Crawlers" methodology for the abnormality diagnosis in the spinal cord. The live-wire scheme was employed for the augmentation of the local optimality of Spinal Crawlers with the globally best paths. The segmentation results demonstrated that the devised model was fast and capable of providing a superior clinical diagnosis within minimum time.

Jeremy Kawahara et al. (2013) suggested Isometric Log-Ratio based principal component analysis (ILR-based PCA) procedure for the determination of the spinal cord's globally optimal segmentation through the utilization of the minimal path search in high dimensional space. The PCA was adopted in this study for representing the cross-sectional shapes of the spinal cord by capturing the partial volume effects and axial cross sectional dissimilarities in the spinal cord. The devised scheme was computationally feasible and minimized the runtime and memory requirement.

Ferran Prados et al. (2016) introduced a collaborative effort based completely automated Grey Matter (GM) and spinal cord segmentation scheme for the abnormality diagnosis. The segmentation of the Cross-Sectional Area (CSA) and GM was done by executing the Optimized Patch Match Label fusion (OPAL) algorithm and the Similarity and Truth Estimation for Propagated Segmentations (STEPS) algorithm. In the assessment of performance, both the Multiple Sclerosis (MS) subjects and the healthy subjects were utilized. The obtained segmentation results showed better accuracy than that of the traditional approaches.

Xinjian Zhu et al. (2016) suggested a Gabor filter bank based scheme for the segmentation and localization of the IVDs. Initially, the Gabor filter bank was employed for extracting the IVD's structural features; after this, the spine's Gabor features were estimated and the spinal curves were identified. Following this, the IVD's Gabor Feature Images (GFI) were computed and modified in accordance with the spinal curves. Through the clustering analysis, the localization of the IVDs was done. Subsequently, the segmentation of the IVDs was carried out by executing the optimum grayscale algorithm, working with the data formed by concatenating the spine's Gabor features with the localization results. This scheme outperformed the conventional schemes by achieving effective localization and segmentation of IVDs during the diagnosis and spine surgeries.

2.4. Active contour model based segmentation techniques

The studies, in which the use of the active contour model based spinal cord segmentation has been reported, are discussed below,

Mark A. Horsfield et al. (2010) developed an active surface model based semi-automatic scheme for the CSA assessment of spinal cord with slight variations in radius along the circular as well as the longitudinal axis. The cord surface's compact parameterization permitted the rapid segmentation by marking the center-line of cord on specific cord slices with limited manual support. The developed active model based approach outperformed the compared segmentation approaches in terms of sensitivity and reproducibility.

Dipti Prasad Mukherjee et al. (2010) designed an automatic segmentation scheme for aiding the process of rehabilitation surgery planning. This segmentation scheme suggested an active tracing application for the boundary segmentation. The scheme was executed on the energy minimization surface of unique contour. The major distinction of the developed scheme from the other segmentation schemes was that it was capable of providing superior visual guidance of the Intra Spinal Micro Stimulation (ISMS) implant through the segmentation of the neighboring Regions of Interest (ROI).

Esha Datta et al. (2017) introduced a Morphological Geodesic Active Contour (MGAC) model based automated GM segmentation for the spinal cord. This research had a multi-fold objective, namely (i) to devise a registration based GM segmentation approach, (ii) to assess the reproducibility and accuracy of the two dimensional Phase Sensitive Inversion Recovery (PSIR) imaging, (iii) to analyze the algorithmic performance at distinct contrasts and resolutions, (iv) to elaborate the extension of the algorithm to the 3D scans, and (v) to illustrate the medical potential for the MS patients. This scheme minimized the image pre-processing requirements and increased the capacity of recognizing the objects with non-sharp edges, as well as recognition along with stable and quick contour evolution.

Jaehan Koh et al. (2011) presented a saliency-driven attention model based unsupervised segmentation approach for the automatic extraction of the spinal canal from the MR image's sagittal plane. The bottom-up Gabor filter attention framework was adopted for the extraction of the contextual information. Next, to this, the attention model's thresholded saliency map was concatenated with the level set active segmentation model for the extraction of the spinal canal. The obtained segmentation results demonstrated the maximum compatibility degree between the human-intervention schemes and the automated segmentation approach.

Oktay, Albayrak and Akgul (2014) developed a detected window based automated initialization scheme for the disc localization in the spinal cord. Here, the successful segmentation of the IVDs of arbitrary shape was achieved by adopting the Active Appearance Models (AAM). The imaging artefact issue was resolved through the inclusion of the intensity insight of the given MR images. The comparison of the concerned IVD with the adjacent lumbar IVD was done through the utilization of the context features. The devised segmentation scheme outperformed the other considered modern approaches in terms of accuracy.

2.5. Semi-automated based segmentation techniques

The investigations, referring to the semi-automated spinal cord segmentation approaches are discussed in this subsection.

Thus, Mohamed-Mounir El Mendili et al. (2015a) presented a spinal cord segmentation technique, based on semi-automation, for the diagnosis of the trauma and neurodegenerative diseases. This approach was developed with the intention of estimating the CSA of the spinal cord in the thoracic as well as the cervical regions in a huge set of patients with distinct spinal cord abnormalities. This devised approach reportedly assured superior segmentation performance over the other state of the art approaches.

Mohamed-Mounir El Mendili et al. (2015b) suggested also a semi-automated Double Threshold-based Method (DTbM) for allowing the cervical spinal cord template construction. The segmentation accuracy of the thoracic cord and cervical cord regions was visually quantified and scored by the radiologist. A standardization pipeline was developed for constructing the cervical template. This DTbM approach assured superior performance over the other schemes in terms of execution speed and accuracy.

Adam Cadotte et al. (2015) developed a semi automated segmentation approach for the spinal cord segmentation from the HR T2-weighted MRI. The images were segmented by applying the 1-D template matching algorithm. The segmented image's center-line was corrected by employing the elaborated segmentation approach. This semi automated segmentation scheme provided excellent performance over the manual segmentation schemes in terms of accuracy and processing time even in conditions of low Cerebral Spinal Fluid (CSF) volume and high spinal cord curvature.

2.6. Deformable model based segmentation techniques

The research papers, reporting on the research, which employed the deformable model for the effective spinal cord segmentation, are considered in this short subsection.

Min Chen et al. (2011) presented an automatic segmentation scheme constructed by integrating the topology preserving classification and the registration based deformable atlas for resolving the issues in the spinal cord MR images. This segmentation approach comprises two steps; namely (1) alignment of the intensity atlas with respect to the MRI to be segmented by utilizing the deformable registration, and (2) the obtained mapping was applied to the intensity atlas associated statistical atlas and topology template. This scheme maintained a perfect spinal cord topology and consistent segmentation in contrast to the other segmentation approaches.

De Leener, Cohen-Adad and Kadoury (2014) designed automatic deformable model based on the iterative propagation for the effective spinal cord segmentation. The main intention of this approach was the efficient management of the spinal cord curvatures and the image contrast-to-noise ratio. The scheme designed was capable of dealing with the datasets with maximum throughput without the intervention of the user bias.

2.7. EM based segmentation techniques

The present subsection considers the research papers, reporting on the research studies, adopting the expectation maximization (EM) based spinal cord segmentation.

Andrew J. Asman et al. (2014) developed a registration model based on the group wise slice for creating the representation of the cervical spinal cord appearance model. The main functions of the devised approach were: (i) modeling of existing variations in the cervical spinal cord population, (ii) rapid registration of the target spinal cord slice to be modeled, and (iii) selection of geodesically suitable atlases for the target image segmentation. The simulation results implied that the devised approach outperformed the conventional schemes compared in terms of robustness and accuracy.

Liao, Ting and Xiao (2017) presented an automatic atlas-free scheme for the cervical spinal cord segmentation on the midsagittal T2-weighted MRI. The constraints to be utilized at the distinct stages were obtained through the transformation of the pertinent anatomical insight. After this, the EM and Dynamic Programming (DP) were adopted for identifying the posterior and anterior edges of the spinal canal and the vertebral column. Following this, the region growing was employed for segmenting the IVDs. Then, the median filtering was employed for segmenting the spinal cord edges. This scheme assured superior performance with respect to the detection accuracy and robustness and required only minimum manual support.

R. Priya and M. Umaibanu (2017) presented an EM dependent spinal cord segmentation based on the automatic and complete pipeline. The employed schemes were the Strong Fitness Firefly (SFF) algorithm and the improved Weighted EM (WEM). This scheme detected the spinal cord abnormalities on the basis of the MRI and segmented the spinal cord with enhanced segmentation accuracy within the lesser number of iterations than the compared techniques.

2.8. GVF based segmentation techniques

We now comment upon the different research works, utilizing the GVF (Gradient Vector Flow) based spinal cord segmentation.

Jaehan Koh et al. (2010) introduced an automatic segmentation scheme for the extraction of the dural sac and spinal cord from the T2-weighted sagittal MRI without human support. For the determination of the candidate blobs, the GVF field was used. The methodology was used to carry out the connected component evaluation during the final segmentation. Through the quantitative analysis, the fact that the devised GVF based segmentation approach provided superior performance over the other scheme with respect to the mutual overlap metric.

Ruiz-Espana, Arana and Moratal (2015) suggested a GVF algorithm for the extraction of the IVD shape features along with the detection of the disorders in the contour. Here, the spinal stenosis was segmented and detected by utilizing the signal intensity approach. The Intra-Class Correlation (ICC) and the Kappa statistics were evaluated in the context of assessing the variability. This scheme provided improved reproducibility along with the realistic outcome quantifying the pathology severity.

2.9. Learning based segmentation techniques

The reports on the research utilizing the learning based spinal cord segmentation are considered in this subsection.

Perone, Calabrese and Cohen-Adad (2017) devised an end-to-end learning scheme based pipeline for the fully automated GM segmentation. This scheme utilized a Deep Learning architecture dependent on the Atrous Spatial Pyramid

Pooling (ASPP) for dealing with the ex vivo as well as in vivo MRI acquisitions. This scheme provided superior generalization and accuracy in segmenting the ex vivo HR acquisition data set. This approach did not limit the utilization of the 3D dilated convolutions.

Subarna Ghosh and Vipin Chaudhary (2014) presented a heuristics and machine learning based localization and labeling scheme for the IVD in sagittal lumbar MRI. The spinal cord abnormalities were detected through the extraction of features from the rectangular shaped disc bounding boxes. After this, the machine learning-based fully automatic scheme was employed for performing the simultaneous segmentation of vertebra, dural sac and the IVDs from the MRI. The segmentation was performed with the support of the adjacent pixel insight in an auto-context framework. The devised scheme was robust and achieved better outcome during the disc detection as well as the MRI segmentation in the comparison performed.

Chengwen Chu et al. (2015) presented a fully automatic scheme for the localization and the segmentation of the Vertebral Bodies (VBs) from the given MRI. At first, the random forest regression was employed for the localization of 3D VBs. Then, the votes from the randomly sampled image patches were aggregated for determining the probability map of the target VB. The obtained probability map was regularized further by employing the Hidden Markov Model (HMM), with the intention of eliminating the ambiguity due to the adjacent VBs. The voxel's posterior probability was estimated by integrating the determined likelihood with the insight on the prior probability learned from the training dataset.

Koh, Chaudhary and Dhillon (2012) designed a two-level classification scheme based Computer-aided diagnosis (CAD) framework for the segmentation of the lumbar spine. This classifier, for the diagnosis of the disc herniation, was developed by the utilization of the heterogeneous classifiers, like k-means classifier, perceptron classifier, Support Vector Machine (SVM) classifier, and least mean square classifier. These classifiers performed the diagnosis in accordance to the generated feature set from the ROI's, which comprises the spinal cord, IVD, and the vertebrae. Finally, the ensemble classifier was adopted for taking the final decision through the utilization of the classifier's score values. The devised scheme was capable of diagnosing the herniated discs effectively.

2.10. Probabilistic model based segmentation techniques

The studies, which employed the probabilistic model based spinal cord segmentation are discussed in this subsection.

Alomari Raja'S et al. (2010) designed a probabilistic model for the concatenation of the IVD's context, appearance, and location, for purposes of detection of the disorders in the discs. On the basis of the obtained joint features and the disc level modelling, the IVD's abnormality status was decided. This approach included some other domain features, like age, height and some other insight, related to the patients. This scheme was highly flexible and provided accurate results because of the utilization of the joint features.

Corso, Raja'S and Chaudhary (2008) introduced a two-level probabilistic framework for the labelling and localization of the IVD. This scheme hybridized the pixel-level insight, like appearance, and the high-level insight, like spatial relationship among IVDs. The scheme was capable of insulating the high-level inferences from the variations at the pixel level. This approach outperformed the other existing segmentation schemes in the aspects of accuracy.

2.11. Graph-based segmentation techniques

This subsection discusses the research reports on studies adopting the graph based spinal cord segmentation.

Zhenyu Tang and Josef Pauli (2011) suggested a fully automatic scheme for the spine curve extraction needed for the modelling of gait. This scheme comprised of two phases; the first phase was the IVD position extraction and the second phase was the extraction of the disk positions by utilizing the vertebra registration scheme. Subsequently, the cubic spline approach was adopted for determining the spine curve through the interpolation of the segmented vertebrae's center. The devised graph-based segmentation scheme assured better comparative performance in terms of maximum accuracy.

Fatemeh Nasiri and Hamid Soltanian Zade (2013) developed a Graph Cut (GC) algorithm based fully automatic segmentation scheme for the IVD segmentation. Initially, a graph was built from the provided image pixels and the two extra nodes, namely the sink (t) and the source (s) with the support of the seed points. The ROI was extracted from the segmented image by applying GC with the support of the post-processing mechanisms, such as content-based and morphological refinement. The main merit of this scheme was the achievement of the high accuracy of 95%.

2.12. Level set based segmentation techniques

The publications, presenting the research work, in which the spinal cord segmentation was performed by utilizing the level set based segmentation are discussed here below.

Max W. K. Law et al. (2013) introduced a level set based unsupervised IVD segmentation technique for the segmentation of the middle sagittal spine MRI. The anisotropic oriented flux detection approach was employed for differentiating the IVDs from the adjacent structures with analogous intensity for support in the ambiguous disc boundary recognition. The target IVD's positional and orientation insight was inferred through the vertebral body tracking; these were integrated for the construction of the energy function. The IVD segmentation was performed through the minimization of the energy function with the support of the level set based active contour framework.

Georg Hille et al. (2018) presented a level set based segmentation scheme for segmenting the 3D vertebral body. The first step was the correction of intensity for handling the bias field artefacts as well as the possibly low user support. After this, the hybrid level-set segmentation was guided by the vertebral body probability maps based on appearance. This scheme achieved superior precision and robustness in the comparison, as this was demonstrated through the segmentation results.

2.13. Other segmentation methodologies

The other segmentation schemes, adopted in the different investigations, aiming at the effective spinal cord segmentation, are considered in this subsection,

Jeremy Kawahara et al. (2013) developed an auto-context segmentation scheme with global geometric features for capturing the high-level insight and relationships among the candidate shapes. The auto-context scheme was able to provide joint detection and regularization of the spinal cord's subtle irregularities. The main qualities of the developed segmentation scheme was the low run time and high segmentation accuracy.

Cheng Chen et al. (2015) developed a fully-automatic data-driven approach for the segmentation and localization of the 3D IVD from the MR spine images. The joint optimization of the test and training displacement was done for the estimation of displacement by considering the test image geometric constraint and training data. Then, the IVD segmentation was done through the classification of the pixels in the background or foreground around the disc centers. The additional smooth neighborhood constraint was incorporated in this scheme for achieving enhanced segmentation accuracy.

Subarna Ghosh et al. (2011) presented a fully automated CAD system for the herniated disc detection from the sagittal lumbar MRI. Initially, the ROI was extracted from the input image, and then, a classifier with maximum accuracy was produced through the integration of the extracted features. This research work demonstrated the fact that the hybridization of the extracted features leads to the achievement of excellent accuracy and sensitivity.

Julio Urrutia et al. (2016) developed a Pfirrmann classification scheme based grading system for performing an independent study on the intra- and inter-observer agreement. Grading of IVD Degeneration (IDD) was important in the degenerative status evaluation for the patients suffering from low back pain. The demonstration of the adequate agreement between the distinct observers and the same observer on the individual occasions was carried out with the use of the Pfirrmann classification method. The developed scheme provided high quality segmentation accuracy and excellent communication between the radiologists and physicians.

Ron I. Riesenburger et al. (2015) designed a Pfirrmann and modified Pfirrmann grading systems for the classification of the lumbar disc degeneration. The devised system incorporated the variables, like high-intensity zone, Modic Changes and disc height reduction, for handling the lumbar disc degeneration. This scheme outperformed the other segmentation approaches by relating the grading mechanism to the symptoms of the patients, which was not permitted by most of the other schemes.

Li-Peng Yu et al. (2012) presented the Pfirrmann grading system, for providing the semi-quantitative and morphologic evaluation during the degeneration of IVDs. This was a subjective rating model, for the estimation of the severe disc degeneration. Here, the modified Pfirrmann and Pfirrmann grading systems were employed for inspecting the relationship among the disc degeneration and Modic Changes.

James F. Griffith et al. (2007) developed a modified Pfirrmann grading system for the lumbar disc degeneration analysis. The main intention of this research was to support in the assignment and investigation of severity in the lumbar disc degeneration for learning the effect of particular variables on the disc degeneration. This scheme was capable of providing the disc structure perception along with the exploration of the good tissue discrimination. The modified Pfirrmann grading system turned out to be discriminatory, user-friendly, interpretable, and reliable.

Sara M. Dupont et al. (2017) introduced a multi-atlas based technique for the spinal cord white and grey matter segmentation. It should be noted that in the study of the spinal cord morphology, atlas-based approaches are increasingly used. The authors developed a template registration framework, which integrated the white and grey matter segmentation to describe the precise grey matter shape of every individual subject. This approach was validated using 24 healthy subjects by means of T2*-weighted images, 8 healthy subjects, with utilization of diffusion weighted images, and also 5 patients with spinal cord injury.

Charley Gros et al. (2018) developed a fully-automatic framework for spinal cord segmentation and intramedullary MS lesions segmentation from usual MRI data of MS and non-MS cases. This method depends on a sequence of two Convolutional Neural Networks (CNNs). CNNs were trained separately with the Dice loss. This framework is open-source and is available in the Spinal Cord Toolbox.

3. Research gaps

The research gaps and risks, which arise in connection with the research work, related to the segmentation of the spinal cord are elucidated in this section.

And so, the research issues faced by the PropSeg based segmentation were, first, that the devised PropSeg method experienced high time complexity (De Leener, Kadoury and Cohen-Adad, 2014). The developed multi-resolution based PropSeg could not achieve a reliable inter-subject and intra-subject comparison of the spinal cord (De Leener, Cohen-Adad and Kadoury, 2015). Then, the elaborated Atlas-RFCM was influenced by the spatial priors and the increase in the analogous bias inherent to the schemes based on atlas (Michopoulou et al., 2009).

The challenges experienced by the optimization based segmentation were as follows: the developed Spinal Crawlers were not applicable for the massive datasets (McIntosh et al., 2011); the anticipated optimization of the run-time and space was not attained by the ILR-based PCA (Kawahara et al., 2013); the segmentation performance of the developed OPAL technique can be enhanced only through the elimination of the MS lesions (Prados et al., 2016). The designed Gabor filter based segmentation scheme was not able to categorize the IVD degeneration degree and to achieve accurate determination of the spine curvature (Zhu et al., 2016).

The research issues, faced by the active contour model based segmentation were the following ones: the developed automatic spinal cord image segmentation scheme was not capable of aiding the intraoperative surgery and the ISMS operation (Mukherjee et al., 2010); the accurate assessment of the GM area in the lesions of the spinal cord was not done by the developed MGAC framework based segmentation (Datta et al., 2017); and the developed saliency-driven attention model based segmentation was not applicable to the definite test scenarios and could not achieve the expected speedup (Koh et al., 2011).

The research gaps, which arose in the case of the semi-automated spinal cord segmentation were: the deficiency of evaluation of scan-rescan reproducibility characterised the devised semi-automation based segmentation because of the restraints of the imaging protocol (El-Mendili et al., 2015a) and the DTbM technique could not attain the expected scan-rescan reproducibility, either (El-Mendili et al., 2015b). The manual initialization and the requirement of template database creation before the segmentation operation were the drawbacks of the devised semi-automated based segmentation of Cadotte et al. (2015). The proposed deformable atlas-based registration was not capable of segmenting the spinal cord finer structures like GM and specific white matter columns (Chen et al., 2011). The devised algorithm, based on the deformable model's iterative propagation was unable to accommodate the contrast of the CSF and the lower spinal cord (De Leener, Cohen-Adad and Kadoury, 2014).

The major issues, faced by the EM based segmentation techniques, were as follows: first, the devised group wise slice dependent registration model could not assure compact representation and minimal computational complexity (Asman et al., 2014). The algorithm developed in Liao, Ting and Xiao (2017) cannot be applied to the lower lumbar spinal levels; the poor performance was visualized for the application over the long spinal segments with large cord lesions. The GVF algorithm, recommended in Ruiz-Espagna, Arana and Moratal (2015) could not detect the minimal disc contour abnormalities.

The issues, encountered by the probabilistic model based segmentation were the following ones: the developed probabilistic model was unable to perform the subsequent diagnostic chores as the necessary features dependent on the abnormality type were unavailable (Raja'S et al., 2010). The two-level probabilistic model from Corso, Raja'S and Chaudhary (2008) could not achieve the anticipated performance during the spinal cord segmentation.

The challenges faced by the learning based segmentation techniques can be summarised as follows: the devised ASPP based learning model of Perone, Calabrese and Cohen-Adad (2017) was unable to provide improved results for segmenting the ex vivo HR spinal cord MR image. The machine learning and heuristics based segmentation approach from Ghosh and Chaudhary (2014) could not provide accurate diagnosis, quantification, and localization during the stenosis and herniation. The learning based CAD model proposed by Koh, Chaudhary and Dhillon (2012) was unable to handle the massive datasets, and the anticipated performance was not achieved by this segmentation approach.

The graph-based segmentation method of Tang and Pauli (2011) faced the hindrance of minimal variations between the vertebra intensity and the disk intensity. The unsupervised IVD based segmentation, presented by Law et al. (2013) was unable to perform the precise discrimination of the cartilaginous disc-annuli and the longitudinal ligaments attached at the anterior and posterior sides of the spinal discs. The 3D vertebral body segmentation scheme, proposed by Hille et al. (2018) could not execute the co-registration of the provided multimodal spinal cord images.

The research gaps, which can be identified for the segmentation schemes other than the previously categorized approaches were, regarding the literature reviewed: the auto-context based segmentation method of Kawahara et al. (2013) was unable to handle a huge cord dataset with distinctly differentiated parameters. The classification scheme of Urrutia et al. (2016) could not achieve the accurate decision-making during the procedure of clinical diagnosis. The advantages of the grading system, presented in Riesenburger et al. (2015) were left unexplored as there were symptoms that were not considered. The modified Pfirrmann grading system, proposed by Yu et al. (2012) was unable to detect the degenerative vertebral disc diseases at the earlier stages.

4. The summary of analysis

We now present the simple summaries of the survey presented of the studies dealing with spinal cord segmentation in terms of the adopted segmentation approach, year of publication, utilized datasets, evaluation parameters, implementation tool, utilized MR images, obtained accuracy and Dice coefficient. The latter is considered here in view of the fact that most of the studies surveyed use this coefficient for evaluation.

4.1. The image based on segmentation techniques

Figure 2 shows the breakdown of spinal cord segmentation methodologies proposed in the studies surveyed. Among the considered research papers, the more frequently employed segmentation schemes are the active contour model based segmentation, learning based segmentation, semi-automation based segmentation and the EM based segmentation.

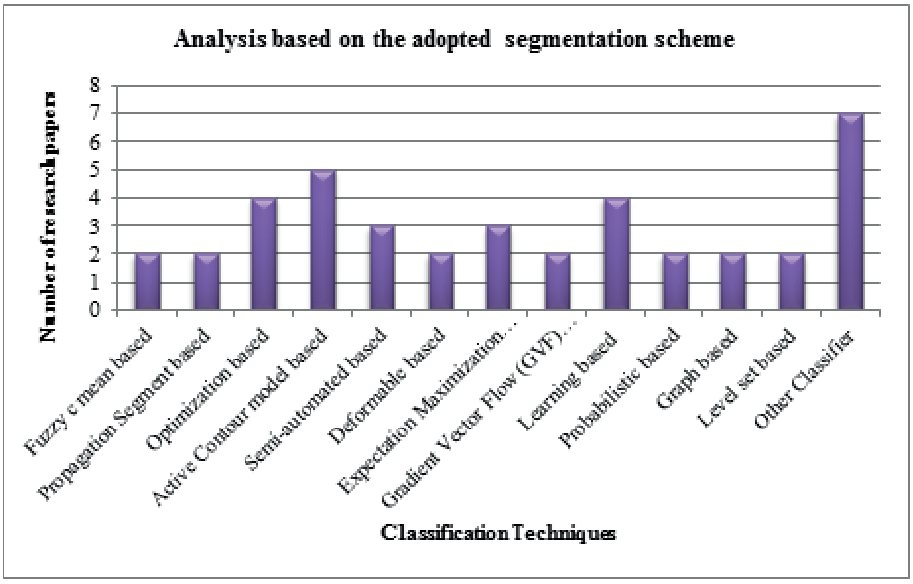

Figure 2. The adopted segmentation approaches in the survey

4.2. The image based on publication year

Table 1 catalogs the studies regarding the publication year. From the table, it is clear that most of the analysed reports were published in 2015, 2011 and 2010.

4.3. Image based on the implementation tool

Table 2 shows the different implementation tools employed in the investigations, aiming at the effective segmentation of the spinal cord. The commonly utilized implementation tools are JAVA, C++, Osirix software, JIM (Xinapse System), Impax Web 200 Program, JMP Statistical Software, PASW Software, NVIDIA Geforce GTX, and MATLAB. From Table 2, it might be concluded that MATLAB was the most frequently practiced implementation tool for effective spinal cord segmentation in the studies here reported.

Table 1. The years of publication of the studies surveyed

Published Year	**Number of research papers**
2017	4
2016	4
2015	8
2014	4
2013	4
2012	3
2011	5
2010	5
2009	1
2008	1
2007	1

Table 2. Implementation tools used in the studies surveyed

Implementation 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)
Impax Web 200 Program	Urrutia et al. (2016)
JMP Statistical Software	Riesenburger et al. (2015)
PASW Software	Yu et al. (2012)
NVIDIA Geforce GTX	Hille et al. (2018)
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. (2015); Priya and Umaibanu (2017)

4.4. Image based on the evaluation metrics

Table 3 shows the statistics according to the aspect of the evaluation metrics employed in the particular studies. The evaluation metrics, applied in the studies surveyed are: accuracy, sensitivity, specificity, precision, DSCs, speedup, Similarity Index (SI), Hausdorff Distance (HSD), and so on. From the chart, it can be seen that the vast majority of the studies surveyed addresses the metric of accuracy. The other often applied evaluation metrics are sensitivity, specificity, HDS, and DSCs.

Table 3. Analysis based on the evaluation metrics

Accuracy	30%
Dice Similarity Coefficients (DSCs)	13%
Hausdorff Distance (HSD)	10%
Sensitivity	8%
Specificity	7%
Jaccard Similarity Coefficients JSCs)	3%
False Positive Rate	3%
False Negative Rate	3%
Precision	3%
Mean Surface Distance error (MSDE)	3%
Similarity Index	3%
Weighted Kappa	3%
Mean Absolute Distance	2%
Speedup	2%
Recall	2%
Others	7%

4.5. The MR imageing types

The simple statistics, based on the utilized MR images is depicted in Fig. 3. The usually utilized MR image types are the T2-weighted MR images, T1-weighted MR images, and the T2-weighted sagittal images. The other datasets include the T1-weighted sagittal images, T2-weighted mid-Sagittal images, T2-weighted MR images, and T2-weighted turbo spin echo images.

4.6. The kinds of utilized datasets

Here, Table 4 presents the shares of the different datasets used in the surveyed investigations, aiming at the effective spinal cord classification. The commonly utilized datasets in these studies are the IBSR dataset, ex vivo dataset, Spine Web database, and the Clinical routine spine MRI database. Among these datasets, the most often utilized dataset is the Clinical routine spine MRI database.

Table 4. Analysis based on the utilized dataset

IBSR dataset	20%
ex vivo data set	20%
SpineWeb database	20%
clinical routine spine MRI dataset	40%

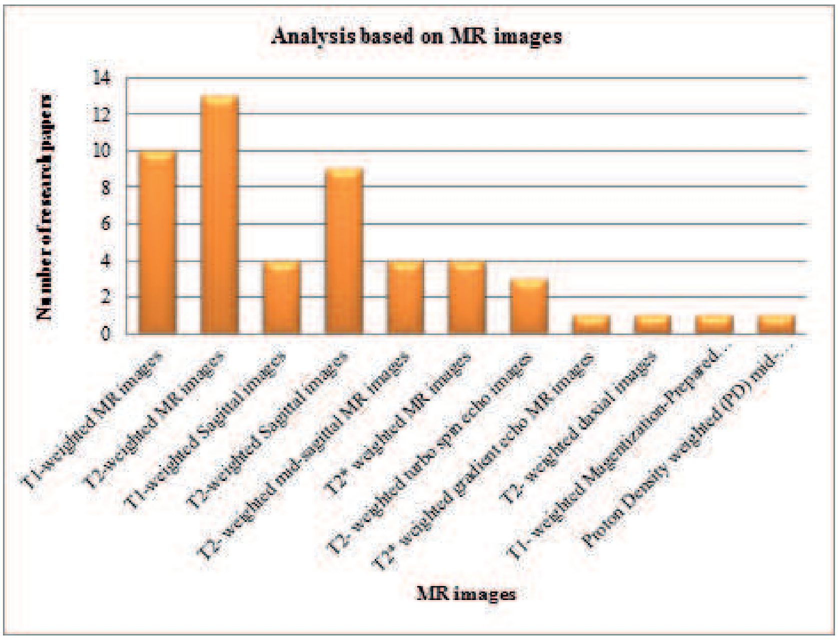

Figure 3. Analysis based on the MR images

4.7. Statistics based on the Dice similarity coefficient

This subsection shows, in Table 5, the statistics of the studies here surveyed, according to the DSC values obtained. It can be easily seen that one research paper reported on a study with DSC in the range of 70%-80%, two achieved the DSCs in the range of 80%-85%, while DSCs in the range of 85%-90% were achieved by four works. Further, the DSCs in the range of 90%-95% were attained in six studies, and the DSCs in the range of 95%-99.9% were reached in three of the reported research works.

Table 5. Analysis based on the obtained DSC values

Dice coefficient value range	**Research papers**
70%-80%	Koh et al. (2011)
80%-85%	Chen et al. (2015); Ghosh and Chaudhary (2014)
85%-90%	De Leener, Kadoury and Cohen-Adad (2014); Datta et al. (2017); Michopoulou et al. (2009); Hille et al. (2018)
90%-95%	Chen et al. (2013); De Leener, Cohen-Adad and Kadoury (2014, 2015); Cadotte et al. (2015); Zhu et al. (2016); Law et al. (2013)
95%-99.9%	Horsfield et al. (2010); El-Mendili et al. (2015b); Prados et al. (2016)

4.8. Statistics based on accuracy

Table 6 displays the breakdown of the surveyed publications, based on the values of the accuracy measure. The table shows that the accuracy measure within the range of 80%-85% was achieved by the techniques, proposed in two research papers; the measure of 85%-90% was reported in one research work, then, eight research papers proposed the techniques, for which the accuracy measure belonged to the range of 90%-95%, and the accuracy value of 95%-99.9% was achieved by the techniques, reported in nine research papers.

5. Conclusion

This survey article presents an extensive review of the different segmentation schemes, adopted for purposes of the effective spinal cord segmentation. The primary intention of this article is to survey, categorize and assess the various segmentation schemes adopted for the effective spinal cord segmentation by analysing a number of research papers available from various platforms. The analysis and discussion is complemented by the simple statistics, considering the year of publication, the utilized datasets, the evaluation metrics used, the implementation tools, the nature of the applied segmentation scheme, the accuracy range, and the Dice coefficient values. Moreover, the major future scope for the effective spinal cord segmentation is recommended in this survey through the review of the encountered research challenges. From the detailed analysis of the material surveyed, it can be proposed that the widely used evaluation metrics for the performance evaluation are the accuracy and DSCs. The most frequently employed segmentation methodology appears to be the active contour model based segmentation.

Table 6. The accuracy measure values reported in the surveyed publications

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. (2018)
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

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