# Regmentation: A New View of Image Segmentation and Registration

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**ABSTRACT**

Image segmentation and registration have been the two major areas of research in the medical imaging community for decades and still are. In the context of radiation oncology, segmentation and registration methods are widely used for target structure definition such as prostate or head and neck lymph node areas. In the past two years, 45% of all articles published in the most important medical imaging journals and conferences have presented either segmentation or registration methods. In the literature, both categories are treated rather separately even though they have much in common. Registration techniques are used to solve segmentation tasks (e.g. atlas based methods) and vice versa (e.g. segmentation of structures used in a landmark based registration).

This article reviews the literature on image segmentation methods by introducing a novel taxonomy based on the amount of shape knowledge being incorporated in the segmentation process.

Based on that, we argue that all global shape prior segmentation methods are identical to image registration methods and that such methods thus cannot be characterized as either image segmentation or registration methods. Therefore we propose a new class of methods that are able solve both segmentation and registration tasks. We call it *regmentation*.

Quantified on a survey of the current state of the art medical imaging literature, it turns out that 25% of the methods are pure registration methods, 46% are pure segmentation methods and 29% are regmentation methods. The new view on image segmentation and registration provides a consistent taxonomy in this context and emphasizes the importance of regmentation in current medical image processing research and radiation oncology image-guided applications.

**Keywords: Image segmentation, image registration, survey paper, image regmentation**
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## 1. INTRODUCTION

Medical Image segmentation and registration have been important research topics over the last two to three decades and several state of the art surveys exist for segmentation [1,2,3,4,5,6] as well as for registration techniques [7,8,9]. However, in the scope of this work, three open question statements exist that have not been addressed so far. The first question addresses possible similarities between segmentation and registration methods. Some registration approaches can be used to solve segmentation problems and vice versa. The first question therefore is: what methods form the intersection set?

The second question is a direct consequence of the first question. If an intersection set of segmentation and registration methods exists, there is obviously an ambiguity in the current nomenclature of segmentation and registration approaches. This ambiguity makes it difficult both to properly classify an approach and to perform literature research. The second question therefore is: what is a proper taxonomy for segmentation and registration methods that does not have ambiguity?

The third question regards the need for a classification scheme that can be used to determine the usability of a method for a given structure to segment or to register. In the current literature, methods are often classified based on the technical class of the technique used, but not based on the type of segmentation or registration problem that it can be applied for. While many segmentation methods are very generic and can be applied to a variety of different segmentation problems other approaches are very specialized and can only be used in a small application domain. The third question is: what is an adequate classification scheme for determining the usability of a method for a given anatomical structure to segment or register?

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The taxonomy presented in this work tries to address the open questions described above. In particular, a new classification scheme is proposed that comprises a new class of techniques that can be used to solve segmentation and registration problems. It is called regmentation.

## 2. CLASSIFICATION OF SEGMENTATION TECHNIQUES

There are three main characteristics which influence the segmentation of an object in an image: object boundaries, object homogeneity and object shape. Object boundaries and object homogeneity are image or signal based characteristics. Therefore, they are affected by image specific disturbances like noise or reconstruction artifacts. Furthermore, they are modality dependent. For example, an object may have very dominant boundaries in a computed tomography (CT) image and only poor boundary representation in an ultrasound image. An object's shape is image independent and in most imaging modalities — apart from small deviations like perspectival mapping distortions — also independent from the acquisition technique. The concepts of object boundary, object homogeneity and object shape have a strong influence on the development of segmentation methods. Segmentation techniques try to detect boundaries and homogeneous regions in the images and incorporate shape information to restrict the shape of the resulting segmentation.

Some methods like thresholding or region growing rely more on the image or signal information while other methods like model based approaches have a stronger focus on modeling the object's shape in the segmentation process. In the literature, segmentation approaches are therefore often classified according to the amount of boundary, homogeneity or shape knowledge they incorporate. Over the last three decades, several surveys about medical image segmentation have been published. Nikhil et al. [1] distinguish threshold methods from iterative pixel classification, surface based segmentation techniques, edge detection methods and fuzzy set theory methods. Hu et al. [5] categorize segmentation techniques into four groups whereas each group is defined by the image features used by the segmentation technique: region-based, boundary-based, hybrid and atlas-based. Zuva et al. [6] distinguish between threshold, edge and region-based methods. Pham et al. [3] use eight categories: thresholding approaches, region growing methods, classifiers, clustering methods, Markov random field models, artificial neural networks, deformable models and atlas guided methods. Thresholding, classifier, clustering and Markov random field methods are considered as pixel classification methods.

Although the nomenclature used in the described literature is not fully consistent and some single approaches have been assigned to different groups, two main classes of algorithms can be identified: image-based algorithms and shape-based algorithms. The number of subcategories used in the literature varies and hybrid categories are used in some articles to classify algorithms which show characteristics of multiple categories.

In this work, a more generic view on the classification of segmentation approaches is proposed. The proposed taxonomy is based on a continuum between two extremes: purely image based algorithms and strong shape based methods. All segmentation algorithms are classified inside this continuum according to the amount of shape information used by the method. An aspect that derives from this view is the shape generalizability and shape specializability of an algorithm. The more shape information an algorithm incorporates, the more specialized it gets. For example, a geometric active contour or snake with a low elasticity can only be used to segment objects which smooth boundaries. In contrast, a threshold can be used to segment arbitrary shapes with the same parameter setting. Figure 1 shows a schematic view of this taxonomy.

The proposed taxonomy contains four categories: voxel based methods, region based methods, methods with local shape priors and methods with global shape priors. The single categories will be explained in detail in the upcoming Sections. The categories have been chosen, because they form clearly identifiable groups in the continuum between image and shape based methods. Of course other ways to separate the continuum exist. There will also be segmentation algorithms which can be argued to fall into one or another category. However, in comparison to other classification schemes, all algorithms are embedded into the same continuum and can therefore be clearly distinguished from each other and set into context to other algorithms.

In many publications [3,5,6] machine learning techniques like clustering/classification methods represent either separate classification categories [3] or form subcategories, for example sometimes they are considered as subcategories of region based methods [5,6]. In this work, machine learning methods are not considered part of the segmentation classification scheme as described above, because they are not per se segmentation methods. Rather, they can be used to support segmentation mainly by finding appropriate parameters for a segmentation method. In Figure 1, it is indicated that the number of parameters of a segmentation method increases with the amount of shape domain knowledge used. For

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example, purely image based methods like thresholding or histogram based methods only need very few parameters — in a simple thresholding case only one parameter exists that represents the threshold. For such methods, it may be enough to examine some representative cases or to consult a domain expert. Model based approaches like mass spring models are characterized by many parameters, since they model complex shape knowledge. Machine learning methods

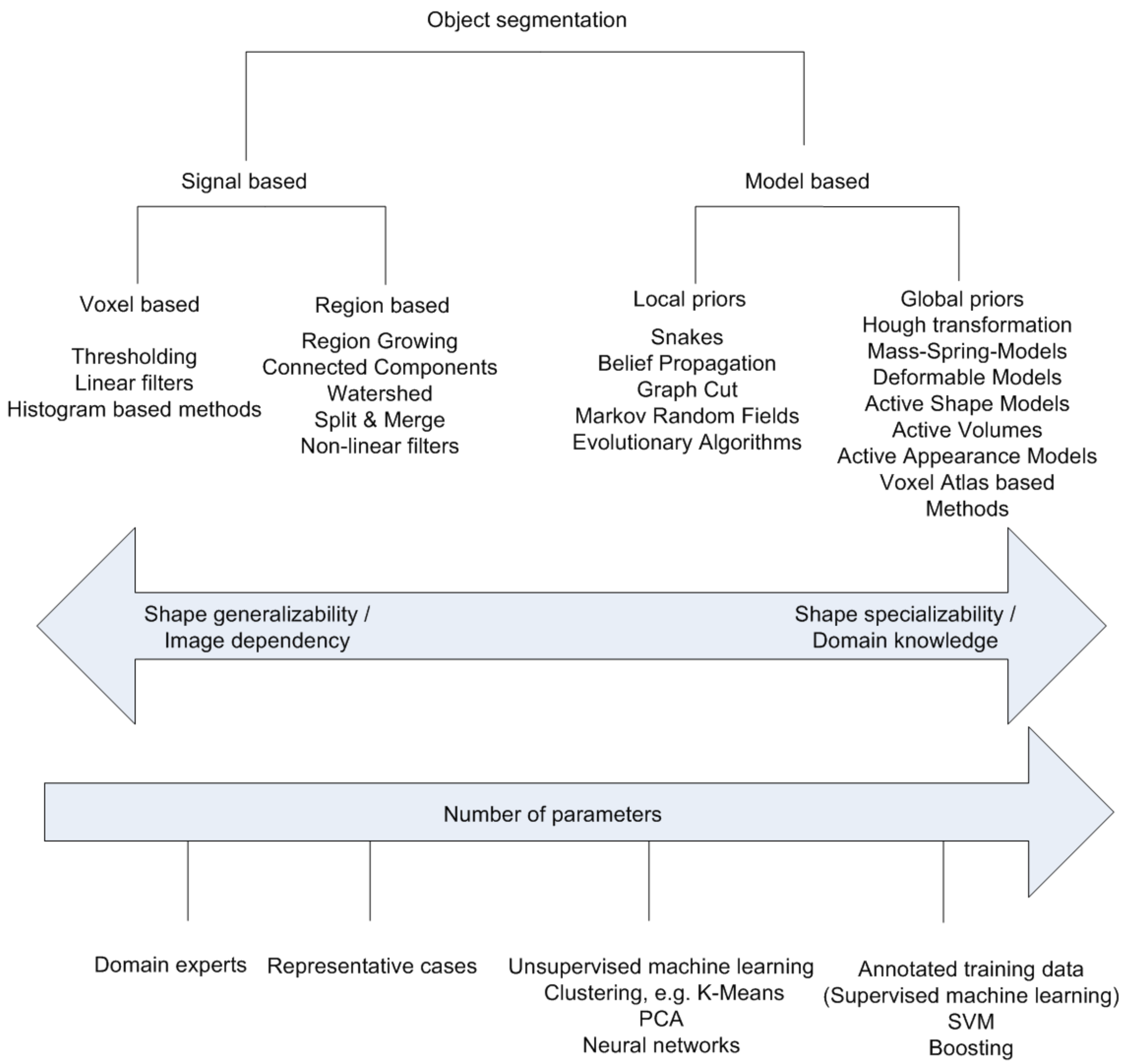


Figure 1: Proposed classification scheme of methods for segmenting objects in medical images. The methods having the broadest application area concerning shape variability, i.e. showing the best shape generalizability are shown on the left. Those methods usually have only few parameters, because they do not incorporate much domain specific knowledge. The approaches shown on the right are highly specialized, i.e. they are often only suitable for one particular structure to segment and incorporate a high amount of domain specific parameters. Nowadays, typically supervised machine learning algorithms are used to cope with the high parameter count by incorporating a training base of known cases that serves as a model for the given problem statement..

can be used to automatically find appropriate parameters for such methods in order to increase their robustness on a diverse test database. They can therefore help to automate complex segmentation algorithms. Furthermore, for structures with a strong shape variation like chromosomes [10], white matter [11] or prostatic glands [12] often multiple low

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parameter segmentation methods are combined to extract a set of simple image features. Machine learning algorithms are then used to cluster the image features such that a meaningful segmentation of the target structure can be achieved.

In the classification view presented in this work, machine learning algorithms are supportive tools to help to automate segmentation methods or to support segmentation methods by performing statistical analysis on a set of data that is originally generated by the segmentation algorithms. Machine learning methods can therefore be coupled with any existing segmentation algorithm. However, such a coupling does not add a new level of complexity to the data and it does not add any further image or shape domain knowledge to the existing segmentation algorithm. That means, it does not change the classification of an algorithm according to the taxonomy presented in this work. Therefore, machine learning methods are not part of the presented classification scheme.

In the following Sections, the four classification groups as shown in Figure 1 are discussed in detail. A large number of medical image segmentation approaches have been proposed in the literature working either on two-dimensional or three-dimensional data. In each classification group, the most important methods for medical image segmentation are described. Often complex segmentation methods consist of a whole pipeline using algorithms from different classification groups. In such a case, a method is classified by the algorithm that uses the most shape knowledge. For example, an approach that uses a thresholding followed by model based segmentation is considered a model based method.

### 2.1 Voxel based methods

The first classification group for image segmentation according to the taxonomy presented in the previous Section as well as in Figure 1 consists of voxel based methods. The voxel based methods group consists of methods that purely rely on image information and do not incorporate any prior shape knowledge about the structure to segment. That makes them suitable to segment structures that strongly vary in shape and at the same time show good image contrast. However, since they are purely based on image signal information, voxel based methods are not very well able to deal with image noise, reconstruction artifacts or low object contrast. The following gives an overview of well-known voxel based methods that are used for medical image segmentation.

The simplest approach to address the segmentation problem is to classify a voxel solely based on its intensity. Such methods do not incorporate any local relationships between the voxels. From that perspective, segmentation can be made by determining a value range that assumingly uniquely contains the gray values of the structure to be segmented. This approach is called thresholding and is often used by more sophisticated methods as a preprocessing step. Here, thresholding is used to create a segmentation that is not very accurate, but can be used as an adequate starting point for other algorithms.

The only required parameters are the intensity thresholds separating the classes. As in some image acquisition techniques – such as CT – the absolute intensity values directly correlate with physical properties of the tissue. Thus thresholds can be directly determined by domain experts.

However in other cases the absolute image intensities of the classes are not known but it can be assumed that they are different from all other objects' intensities. Here, methods based on the intensity histogram can be used to automatically determine the thresholds. The probably most popular method for finding a single threshold separating two classes is Otsu's method [13] which has been extended to multiple classes [14]. It finds the global maximum of the between-class variance:

$$\sigma^2_{betweenModfied} = \sum_{j=1}^{k} \omega_j \mu_j^2 \quad ,$$

where k is the number of object classes, $\mu_j$ is the mean intensity of the class and $\omega_j$ is the probability of each class given by the histogram.

Furthermore machine learning techniques can be used to obtain thresholds. For example the k-means clustering algorithm finds a local maximum of the same objective function as multilevel Otsu [87], but in contrast to that, it can be easily extended to multi-spectral image data.

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In Figure 2, the segmentation result of a cardiac CT data set using the Otsu-method is shown. In complex segmentation scenarios, thresholds and histogram-based methods tend to produce either small islands that are not part of the object to be segmented (but share the same gray value) or result in segmentation holes.

Voxel based methods are very simple and are usually not suited for complex segmentation problems. They rely purely on image content and do not include any shape specific knowledge about the structure to segment. However, they are useful for segmenting structures with a strong shape variation which at the same time show good image contrast. For example, Aarle et al. [15] propose a threshold selection strategy to segment dense objects in tomographic images like

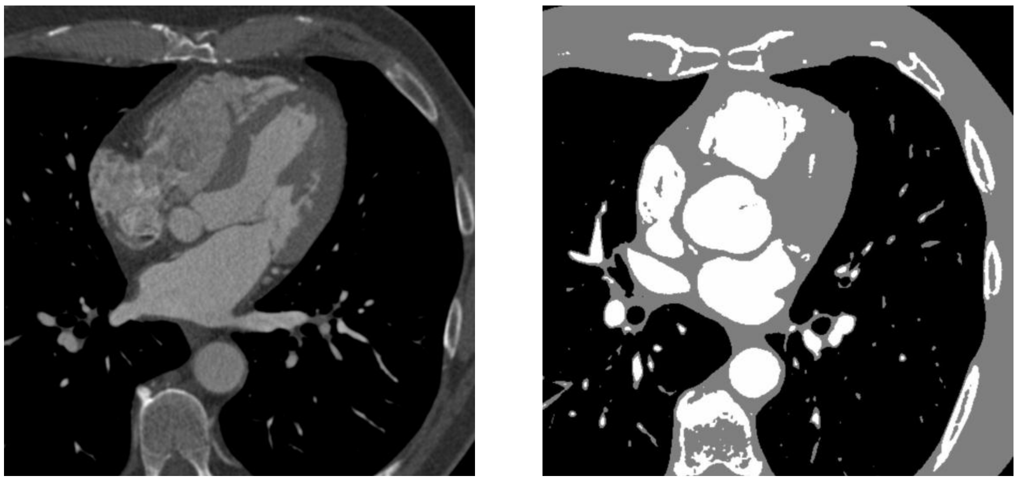

Figure 2: A CT image of the heart (left) and a segmentation using the Otsu method (right).

phantom scans. Voxel based methods are used in cell image segmentation [16, 17] where tens to hundreds of single cells with varying shape can be segmented simultaneously. Machine learning methods are often coupled with voxel based methods to increase their flexibility and robustness on diverse test bases. For example, Zhang et al. use voxel based methods together with several machine learning techniques to segment cervigram images [18]. Yin et al. [16] apply classification methods together with voxel based methods for cell image segmentation.

Voxel based techniques are often used as a pre-processing step in more complex segmentation pipelines. Sometimes, certain intensity areas in the image can be neglected, because the structure of interest does not contain any gray values from that intensity area. Voxel based methods are a simple and fast way to achieve that goal, helping to reduce the complexity of the segmentation problem for further processing steps. Furthermore, because voxel based methods usually have no prior shape knowledge and only few parameters to set, they can be easily automated.

### 2.2 Region based methods

The second classification group for image segmentation according to the taxonomy presented in Figure 1 consists of region based methods. Region based methods are mainly based on image signal information, but they incorporate local relationships between voxels, for example for building contiguous regions.

One of the most prominent region based methods in 2d and 3d is the region growing algorithm. Here, segmentation grows from initially placed points – called seeds – by aggregating neighboring pixels or regions according to some similarity criterion. Region growing is often used to segment homogeneous regions like vessels trees which vary in shape but share a similar intensity (see Figure 3). The main limitation of region growing clearly is its tendency to leak into neighboring objects sharing similar intensities with the structure to be segmented. Nevertheless region growing is a widely used segmentation method due to its computational simplicity and the fact that the connectivity of all voxels grown from a seed point is ensured.

Other widely known region based segmentation methods include the watershed algorithm [88] and the split and merge algorithm [89]. A further category of region based methods are filtering methods. In medical imaging, image filters are mainly used for point, edge or tube detection. In many literature overview publications [1, 5, 6], such kind of methods forms a separate category of segmentation algorithms. However, like the region based methods described above filters

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are image based methods that incorporate local relationships between voxels in order to classify a voxel in the image. In the context of the shape knowledge driven taxonomy presented in Figure 1, they are therefore classified as region based methods.

Edge detection is commonly used in medical image segmentation, because the boundaries of anatomical structures are often characterized by an intensity difference between the tissues. Such intensity discontinuities or edges can be found by computing the derivatives of the local image intensity function. Usually those derivatives are approximated by convolving the volume with filter masks. Several edge detection filters have been proposed, for example, the Canny

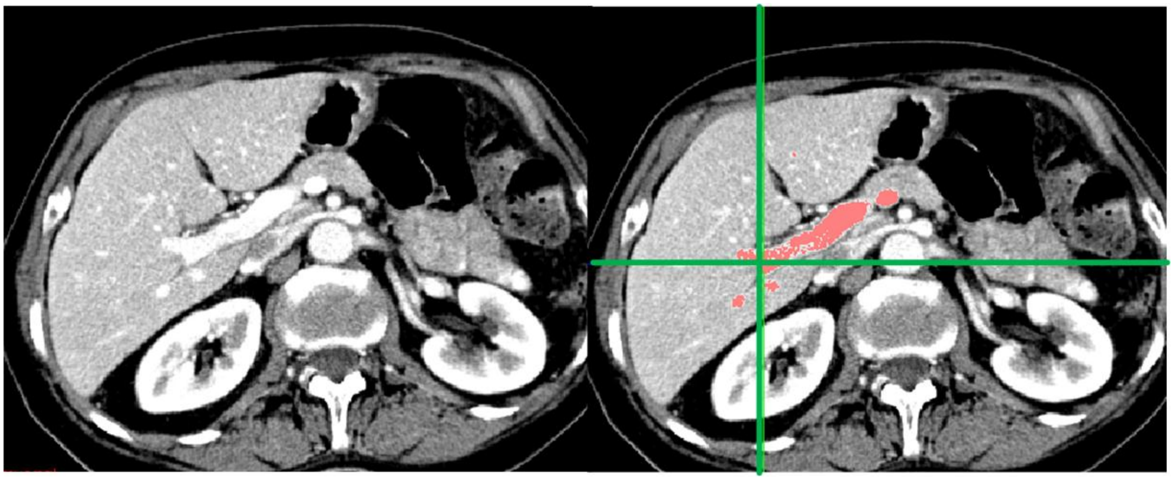

Figure 3: The region growing algorithm applied to segment the portal vein of the liver. The original image is shown on the left. The right image shows the resulting segmentation that grew from a seed point at the position of the shown cross.

edge detection filter [21]. However, filter results frequently need to be post processed, because object contours are often not closed. While image filtering alone is in most cases not sufficient for image segmentation, the concept of edge detection plays a central role in algorithms that incorporate additional shape information. In particular, a large amount of local and global model based segmentation approaches as described in the upcoming Sections incorporate edge detection methods for searching object boundaries.

Another well-known type of filtering methods is the class of filters proposed by Sato et al. [22] and Frangi et al. [23]. Those filters are based on second order derivatives of the image and scale space theory [24]. The approximated second order derivatives are combined to form the local Hessian matrix around a voxel. Using eigenanalysis, the Hessian matrix can be evaluated to detect tube like structures in an image. This property makes such filters ideally suited to detect all kinds of vessels in an image, for example pulmonary vessels [25], coronary and retinal arteries [26] or liver vessels [27]. They are therefore sometimes called vesselness filters. A subsequent segmentation can be achieved by thresholding the filter output or by applying region growing methods [27].

Region based methods have a lot of advantages. They are almost as flexible as voxel based methods and can be applied to a large variety of different segmentation problems. However, they incorporate neighborhood relations which is a very natural way of describing medical image content since neighboring voxels are in most cases related. This makes region based methods generally more robust than voxel based methods. They also do not incorporate complex shape knowledge which limits the amount of parameters to set for a region based method.

Apart from their application to vessel detection and segmentation, they are widely coupled with machine learning techniques to detect tumors or lesions of all kind. Usually filter based methods are used to describe the local texture around a voxel. Using a set of positive and negative examples, machine learning methods are then applied to automatically find the most characteristic features for that neighborhood. Such strategies have been applied to retinal lesion detection [28], pulmonary nodule detection [29], the detection of hepatocellular carcinoma [30] or the detection of white matter changes [31].

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Generally, region based methods are very well suited for segmentation of objects that strongly vary in shape. Apart from pathological structures, for example, they have been applied to hippocampus segmentation [32] and neuron membrane segmentation [33]. However, since they only incorporate direct neighborhood relations, they are mainly based on image appearance. This limits their applicability to objects that are homogeneous in terms of intensity or texture pattern. They are therefore usually applied to small objects instead of complex structures like organs.

### 2.3 Shape methods with local priors

The third classification group for image segmentation according to the taxonomy presented in Figure 1 consists of segmentation methods that incorporate prior shape knowledge about the structure to segment.

However, this prior shape knowledge is modeled locally, for example by enforcing that the surface of the object has a certain degree of smoothness. Furthermore, since local prior shape methods do not have a global idea of the shape to be segmented, they are not restricted to segment a specific shape but can be applied to various types of shapes.

A well-known method for two dimensional image segmentation based on local shape priors is the active contour or snake approach [34]. A snake is a contour or curve parametrically defined in an image B(x, y) on the image plane $(x, y) \in \Re^2$ as $s(p) = (x(p), y(p))^T$, with $x(p)$ and $y(p)$ being the coordinate functions. $p \in [0,1]$ is the parametric domain. The shape of the snake is given by minimizing the energy functional

$$\Sigma(s) = I(s) + E(s),$$

where *I(s)* and *E(s)* are representations of two energies: the internal snake energy *I* and the external snake energy *E*, respectively. The internal energy defines the rigidity and the tension of the contour, i.e. it defines how smooth and flexible the snake is. The internal energy therefore is a local shape prior, which determines how the object to be segmented should locally look like. The image driven part of the method is given by the external energy. It determines what kinds of image features attract the contour.

An example for an internal energy is

$$I(s) = \int_0^1 w_1(p) \left|\frac{\partial s}{\partial p}\right|^2 + w_2(p) \left|\frac{\partial^2 s}{\partial p^2}\right|^2 dp,$$

where $w_1$ and $w_2$ define tension and rigidity of the snake, respectively. As an attracting image feature, often the image gradient is taken, i.e. the contour will evolve towards intensity differences in the image. The external energy then is

$$E(s) = \int_0^1 -|\nabla(G_\sigma B(x,y))| dp.$$

Here, $\nabla(G_\sigma B(x, y))$ denotes the gradient of the image *B* smoothed by a Gaussian *G*. The standard deviation $\sigma$ controls the extent of edges that attract the contour. A local minimum of Σ is usually found using numerical algorithms as described in [35].

Snakes have been widely used for two dimensional image segmentation problems. The three dimensional generalization of snakes is called deformable model or deformable surface [35]. The advantage of the snake formalism is that the shape prior is very intuitive and easy to control. For example, if the structure to segment is a bone that does not contain any sharp edges, rigidity and tension of the snake can be set high. That way the snake is less dependent on the image signal and therefore also less affected by noise or discontinuous and weak edges. On the contrary, if the structure to segment does not comprise a smooth surface, the internal energy of the snake can be set more versatile in order to adapt to the structure.

The image driven part of the snake is generally very flexible, since many different external energies are possible. For example, snakes are used in ultrasound as well as in MR and CT which are imaging modalities that have very different image characteristics. In consequence of this flexibility, snakes are used to segment various kinds of anatomical structures including spicules in Mammography [36], tree structures [37], the aorta in MRI [38] and solid organs [35].

A disadvantage of snakes is their dependency on initialization and lack of topological adaptation. A snake will most likely get stuck in local minima if initialized far away from the structure to segment. This complicates automation of the

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method in comparison to most voxel based methods which are often easy to automate. Another drawback is that the flexibility of the snake is set globally for the whole contour, i.e. the stiffness of the snake is the same at all of its parts. This often means that the snake is not able to fully adapt to the structure in some parts while in other parts it may be already too flexible and leak into neighboring structures.

Apart from snakes, there are many other ways to incorporate local shape knowledge in the image segmentation process. The basic principle, however, remains the same. Figure 4 shows a schematic view of this process. Generally, an image driven term and a shape preserving term are defined. The image driven term is defined based on some image features. Image features can be, for example, intensity, edges, and points of interest or regional homogeneity. The shape preserving

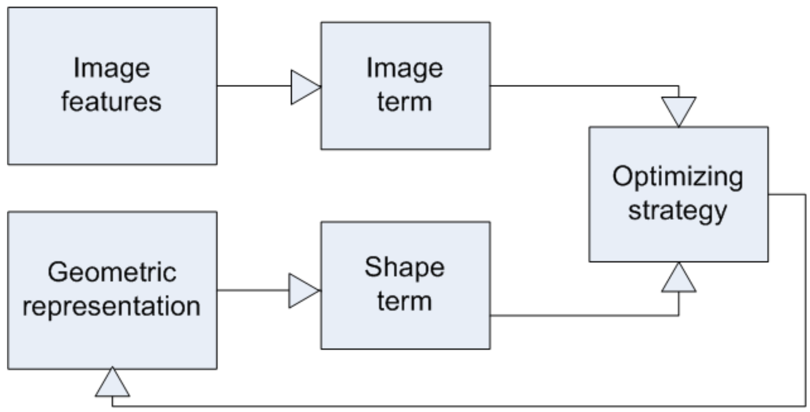


Figure 4: Incorporation of local shape knowledge into the segmentation process. An image driven term and a shape preserving term are combined by an optimizer such that the shape representation is adapted to the image.

term is defined based on the geometric shape representation used for adaptation. For example, the shape could be represented by an interconnected point cloud. The shape preserving term could, for example, enforce that the distance between points should not change much.

Both image and shape preserving terms are combined and balanced using some kind of optimization strategy. There are many ways how such an optimization can be performed. Often the optimization problem is embedded into the well-known frameworks of Graph Cuts [39, 40, 41, 42, 43], Markov Random Fields [44, 45, 46, 47] or Graph based optimization [48, 49, 50, 51, 52]. After optimization, the geometric shape representation is updated. This process repeats until the structure of interest is segmented.

Local prior shape methods are widely used in image segmentation. Due to the incorporation of local shape knowledge and in comparison to the mainly image based voxel and region based methods, they can be used to segment objects with low contrast boundaries such as lymph nodes [46] in CT or the mitral annulus in 3d ultrasound [42]. As mentioned before in the example of snake segmentation, local shape prior methods are sensitive to initialization. However, since the shape priors are only defined locally — for example by enforcing certain smoothness — they are usually flexible enough to adapt to a nearby structure if initialized closely. This makes these methods ideal for interactive segmentation [53, 41]. Other applications of local shape prior methods include bone segmentation [43], cell segmentation [54] and detection of vessel-like structures [55, 51].

Local prior shape methods are also used for interactive and automatic segmentation of whole organs such as the kidneys [40], the prostate [47] or the bladder [50]. However, these organs have rather simple shapes and do not have strong shape variations between individuals. That is the reason why more complex organs like the liver or the heart are usually not segmented using local shape priors.

### 2.4 Shape methods with global priors

The fourth and last classification group for image segmentation according to the taxonomy presented in Figure 1 consists of segmentation methods that incorporate global shape knowledge about the structure to segment. These methods enforce the segmentation to be similar to one or a group of reference shapes. This way, complex objects can be robustly

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segmented even on low contrast images. Figure 5 outlines the principle of global prior shape methods which is similar to the scheme of local prior shape methods presented in Figure 4. An image driven term and a shape preserving term are combined by an optimizer such that the shape representation is adapted to the image. However, the shape preserving term is additionally based on a representation of reference shapes as mentioned above.

There are mainly two kinds of global prior shape methods: geometric model based segmentation approaches and voxel atlas based segmentation methods. They mainly differ in terms of the shape representation and adaptation process used.

**Geometric model based segmentation.** In geometric model based segmentation, shape is represented by geometric objects like point clouds and polygonal surfaces [56, 57, 58, 59, 60, 61], simplex meshes [62], B-spline representations [63], level set representations [64, 65, 66, 67, 68, 69], geometric grids [70] or finite element triangulations [71].

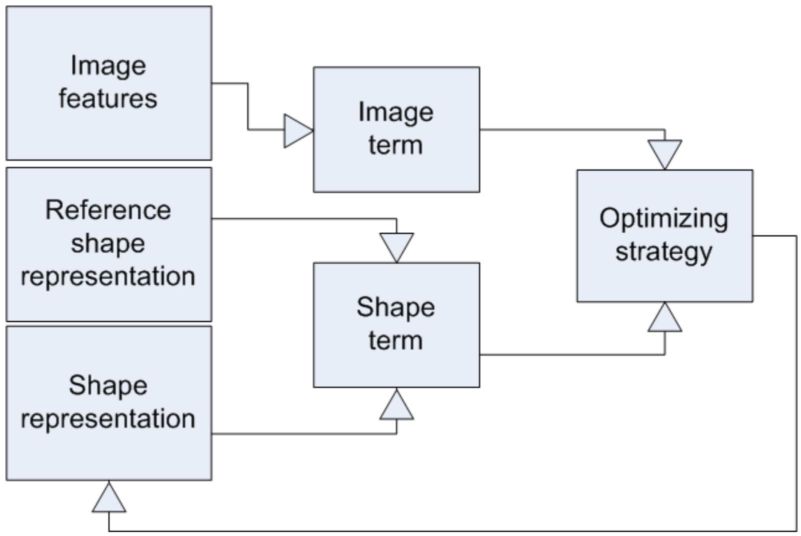


Figure 5: Schematic view of the incorporation of global shape knowledge into the segmentation process. In comparison to local prior shape methods, the shape preserving term is additionally based on a reference shape representation that enforces the shape representation to be similar to a group of reference shapes.

Figure 6 shows the principle of geometric model based segmentation. Based on the chosen shape representation, an instance of the object to be segmented—hereafter called model—is created that is used as an initial shape. For example, the initial shape can be the mean shape of some representative shapes of the structures to be segmented — hereafter called templates — or simply the shape of one particular case.

The model is then placed in the image directly on the structure to be segmented or with significant overlap. This is necessary, because geometric model based segmentation is very sensitive to initialization. Unlike local prior shape methods, the model must also be roughly aligned with the structure to segment in terms of orientation. This is due to the fact that the adaptation of the model is in most cases performed based on a local boundary search which makes the handling of strong orientation mismatches difficult. Since geometric model based segmentation is usually used to segment complex shapes, often automatic model initialization methods are used which estimate the pose of the model in the image.

The initial model that has been placed in the data set adapts to the structure to be segmented according to the scheme presented in Figure 5. Like for local prior shape methods, image features like edges are searched in the image and integrated into an image term. Usually image features are used that describe the boundary of the structure to segment.

As described above, the shape preserving term of geometric model based segmentation is based on the geometric shape representation and on the template shape representation. There are many ways to model a group of template shapes. The simplest way is to define a single object to be the template. Frequently, three dimensional deformable model based approaches [35] are initialized with a single template shape if the shape variance of the structure to segment is not high. For example, lymph nodes [72] are always spherical objects so in most cases it is sufficient to use a sphere as initialization. The external energy is then set such that the segmentation stays similar to the template shape.

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However, for anatomical structures that strongly vary between individuals a single template shape is not sufficient. For such structures, a representative set of template shapes is necessary. Usually, several dozens of templates are used depending on the complexity of the structure to be segmented. However, using many templates also increases the complexity of the decision process of whether the current model is similar to the template shape set. Therefore, usually dimension reduction techniques like principle component analysis are applied to the template shape set in order to extract a limited amount of significant modes of variation that sufficiently describe the template set. This technique is called statistical shape modeling and has been proposed by Cootes et al. [73, 74]. It is the most frequently used method for geometric model based segmentation of complex anatomical structures with a high amount of shape variation. Statistical shape modeling has been applied to segment the liver in CT [56, 57, 58, 63], the heart and heart chambers in CT [59, 60], the prostate in MR [75] or bone structures in X-ray fluoroscopy [76]. Because geometric model based

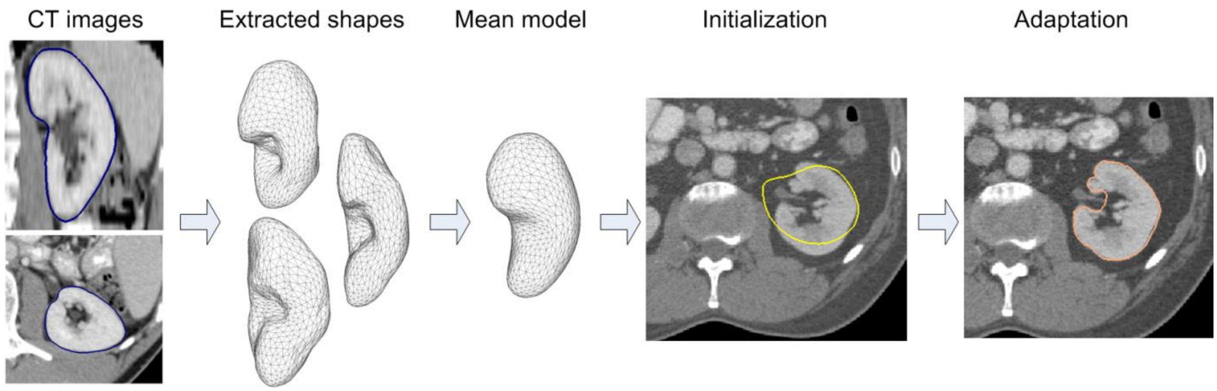


Figure 6: Principle of geometric model based segmentation. An organ is manually delineated in a set of images. For each image a geometric representation of the organ is built. The built shapes are averaged to build a mean model. This model is then placed in an unseen data set and adapted to the image.

segmentation depends on knowing the expected shape of the structure to segment a-priori, it is less suited for segmenting objects that can have arbitrary shapes like tumors. Here, local prior model based segmentation methods are more appropriate, since they only require the surface of the object to meet some local smoothness criteria. Instead, geometric model based segmentation is used to segment complex shapes that vary in shape, but are not completely arbitrary. Here, the incorporation of global shape knowledge prevents the segmentation to leak into neighboring structures and to generate non plausible shapes. They are therefore especially suited for organ segmentation, since organs typically have complex shapes that vary in certain limits between individuals.

**Voxel atlas based segmentation.** The second main type of global prior shape methods is voxel atlas based segmentation. Figure 7 outlines its basic principle. In voxel atlas based segmentation, two images — a reference image called atlas and the input image to segment — are registered based on the voxel representation of both images. In the atlas image, the structures to segment are already contoured. After registration, both images are in alignment such that the segmented structures in the atlas image can be directly transferred to the input image. That way, all structures in the input image that are labeled in the atlas are segmented.

The quality of voxel atlas based segmentation mainly depends on two aspects: the atlas building strategy and the registration method that is applied to register an input image with the atlas [77]. There are many ways to build an atlas. In some applications, it is sufficient to use a single image as the atlas, for example in intra-patient atlas segmentation. Here, all images to be segmented stem from the same patient. The atlas is then created from the first image that is taken during treatment. All following images are directly registered with this first image. However, this means, that for each new patient, a new atlas has to be created. Therefore, usually the atlas is constructed more generically such that it fits not only to one patient but a group of individuals. A simple way to create a generic atlas is to average several representative non-pathologic images from different patients. However, it has been shown that patient variability is too high for most anatomical structures for an average atlas to work well [78]. Possible solutions are population specific atlases where an

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average atlas is built for several population groups, for example based on gender or age [79]. Another approach tries to select the most similar image from a labeled data base of known cases as the atlas [80, 81]. Aljabar et al. [82] extend this method by selecting a set of the most similar images and registering each image individually with the input image. The segmentation results from every individual registration are afterwards combined to improve the overall segmentation for the input image.

After building an appropriate atlas, the registration with the input image is performed. Since this step is independent from the atlas building or labeling, generally any registration method can be used. In fact, this step solves a pure registration problem. Therefore, rigid, locally rigid or deformable registration methods can be applied depending on the structure to segment.

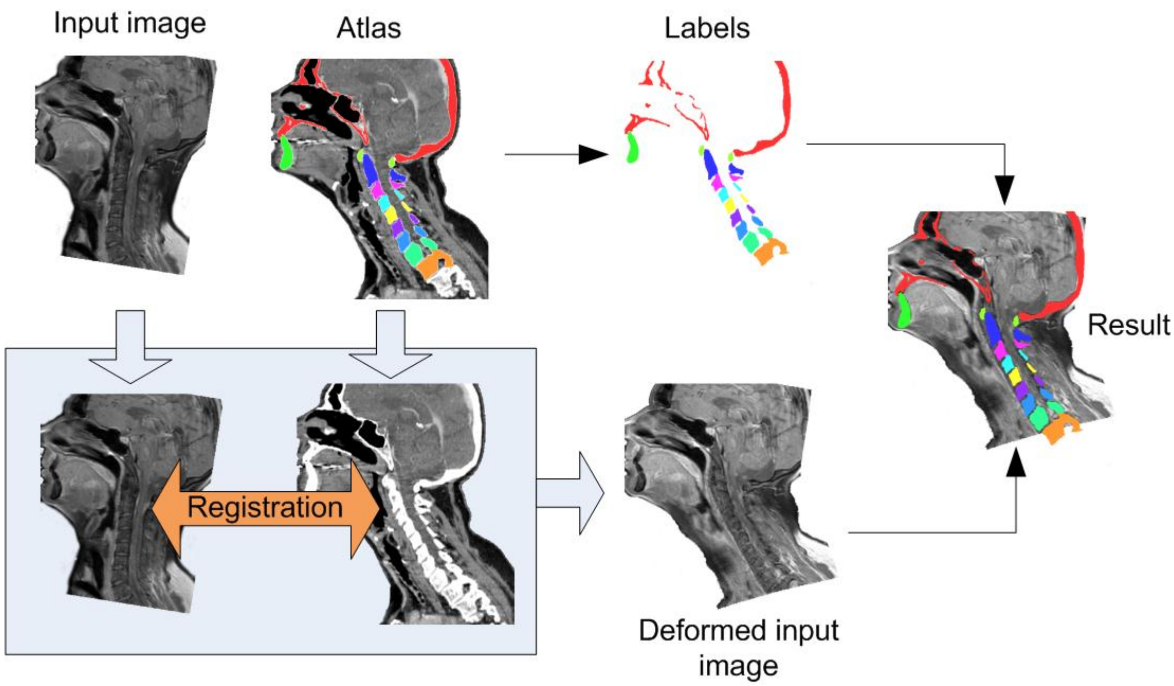


Figure 7: Principle of voxel atlas based segmentation. A labeled image (the atlas) is registered with an input image. The labels from the atlas are then overlaid with the deformed input image so the segmented structures of the atlas are also available in the input image.

Voxel atlas based segmentation is the method with the highest amount of prior global shape knowledge according to the taxonomy presented in Figure 1. This is, because not only information about the shape of a single organ is considered, but implicitly there is information about every visible structure and its relation to all other visible structures available in the atlas. By registering the atlas with an input image, the relation between the structures — for example the heart is above the liver and is neighboring the lungs — is implicitly considered. That means, the segmentation of a single structure like the heart cannot leak too much into neighboring structures, because the neighboring structures themselves claim space in the input image during registration. Another interesting property of voxel atlas based segmentation is the ability to map arbitrary regions from the atlas to the input image. For example, in head and neck radio therapy, it is necessary to delineate the lymph node regions in order to avoid radiation exposure. These lymph node regions do not correspond to any anatomical structures but are conglomerates of lymph nodes, fat, glandular tissue and vessels. However, the regions can be delineated in the label image of the atlas. Since the atlas is registered with the input image, arbitrary regions can then be mapped from the atlas label image to the input image.

This strategy is used many atlas based approaches for lymph node segmentation [78, 83]. Voxel atlas based segmentation has many advantages, because of the high amount of prior global shape knowledge they incorporate. However, this ability also makes them less flexible in practice. While a single structure can be modeled globally in an efficient way, for example using geometric model based segmentation as described above, a group of different structures

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and their relations are very difficult to model globally. Each image that is used for atlas building stems from only one specific patient. That means, it is just a snapshot of all possible variations in terms of organ shape, organ positions, organ orientations, respiration state or heart cycle. A complete global view of the whole body therefore would require an immense amount of images to build the atlas. However, even if enough images would be available, appropriate selection strategies are missing that can handle such amounts of data. Therefore, voxel atlas based segmentation is in practice limited to certain anatomical regions like the head and neck region [84, 78, 83, 85] where the amount of variation is relatively low and a small amount of images is sufficient to build a complete atlas. Another way to utilize voxel atlas based segmentation is to use it as a coarse initialization method for other segmentation approaches. This way the missing accuracy of the atlas in areas of high variation is compensated, for example by a local prior shape method [86].

## 3. REGMENTATION: A NEW VIEW OF SEGMENTATION AND REGISTRATION

As mentioned in the beginning of this work, similarities between segmentation and registration methods exist. Some registration approaches can be used to solve segmentation problems and vice versa. In the literature, those hybrid approaches are usually either assigned to be registration or segmentation methods depending on the scope within the methods are used. Additionally, sometimes the terms segmentation for registration and registration for segmentation are used to classify them in further categories. However, this point of view leads to an ambiguity, because some methods fall into multiple categories. For example, voxel atlas based segmentation would fall into the category segmentation, because it is used to solve a segmentation task. Furthermore, it would be classified as a registration method, because the technique used to solve the segmentation problem is a registration method. Lastly, it would also be classified as a registration for segmentation method for the same reason.

The reason why this ambiguity exists is that a method is classified based on two characteristics that are not related. The first characteristic is the problem statement that a methods tries to solve, for example a segmentation problem. The second characteristic is the technique that a method uses to solve the problem. Both characteristics are individual and unrelated but are often used at a single criterion for classification. The shape driven taxonomy for segmentation methods presented in the previous section allows for a new view on segmentation and registration methods. This new view resolves the ambiguity of current segmentation and registration classification schemes by proposing a new class of algorithms which will be called *regmentation* in the following.

The introduction of global shape knowledge in segmentation as described in the previous sections plays a key role in regmentation. Since information about the shape of one or multiple structures is available in a global context, global prior segmentation methods can also be used to solve the problem statement of registration for these structures. Figure 8 illustrates this process. For example, model based segmentation uses geometric shape models that are adapted to objects which are visible in the image. The models are constructed based on template shapes that all have been aligned in a certain coordinate system. The set of template shapes defined in this coordinate system could therefore be regarded as an atlas. Furthermore, the geometry of the model is globally defined, that means, for example, the lower peak of the left cardiac ventricle stays the lower peak after adaptation and is not adapted to the top border of the ventricle. This means, if a model from the atlas is adapted to two different data sets, a correspondence between both data sets is given in the

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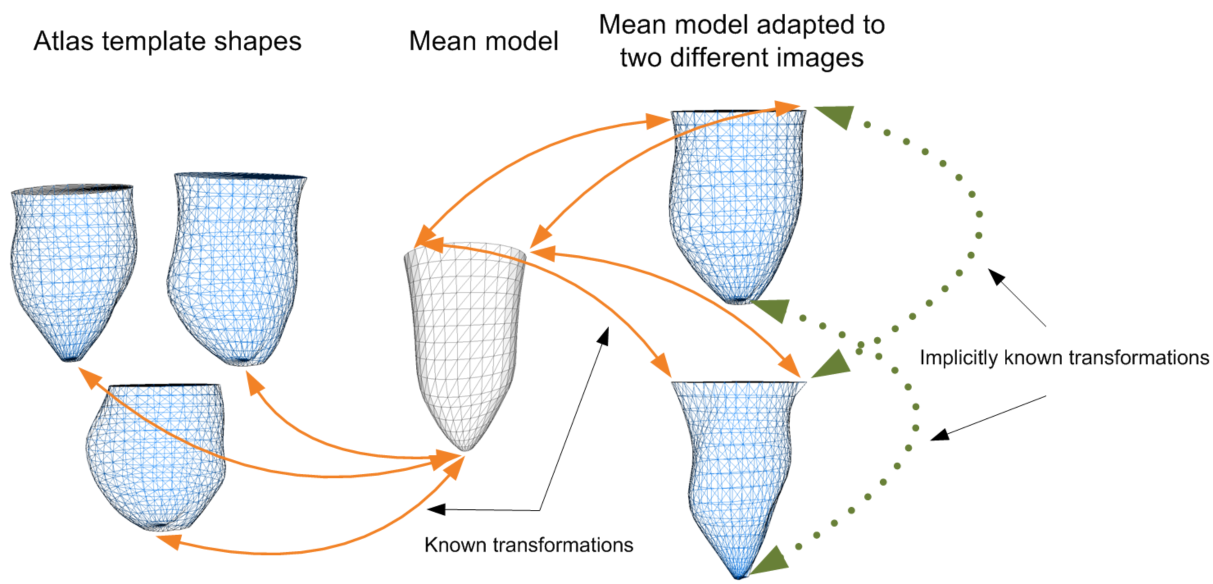


Figure 8: Principle of solving a registration problem with geometric model based segmentation methods. The set of template shapes is regarded as an atlas. A mean model is constructed from the atlas and is adapted to two different data sets. Transformations from the atlas to the mean model are known as well as the transformations from the mean model to the adapted model (continuous arrows). Therefore, implicitly, the transformation between both adapted models is also known (dotted arrows), thus solving the registration problem between both images.

adapted state. Naturally, a correspondence between the model in the atlas and the adapted model is also given. Therefore, a mapping between both data sets can be established by using the correspondence chain from the adapted model in the first data set to the atlas and back to the adapted model in the second data set. Such a mapping is in fact a registration. Global prior segmentation methods are therefore both segmentation and registration methods. In other words, they are regmentation methods, because they cannot be differentiated from the problem statement solving point of view.

The presented view of regmentation leads to a new classification scheme for segmentation and registration methods that consists of three categories. The first category is represented by pure segmentation methods. According to the scheme presented in in Figure 5, these are voxel and region based segmentation methods as well as local shape prior methods. These approaches can solely be used to solve a segmentation problem, since they lack of global knowledge. No correspondence establishment and therefore no registration is possible. The second category consists of pure registration methods. These methods are classical registration approaches that are able to establish a mapping between two data sets, but lack an atlas in which structures are segmented. If such an atlas is added, they become regmentation methods which form the third category. This category consists of all global prior segmentation approaches.

The benefit of the described scheme is that the built categories are disjunctive. All segmentation and registration algorithms can be classified as being exclusively part of one category. Furthermore, the proposed classification is a problem solving driven scheme, which means, it does not matter which kind of technique is used to solve the problem. Appropriate techniques for solving a segmentation and registration problem can be directly taken from the regmentation category. The applicability of the proposed scheme is demonstrated in the following Section by a comprehensive classification of articles from international medical imaging journals and conferences of the last two years.

## 4. CLASSIFICATION OF EXISTING METHODS

This Section demonstrates the practical applicability of the taxonomy presented in this work in comparison to the classical view of segmentation and registration methods. It also aims at demonstrating the current direction of research in the field of medical image segmentation and registration. 855 articles from 6 renowned international medical imaging journals and conferences of the last two years (2010-2011) have been investigated and classified. The conferences and journals were mainly chosen by their impact factor and relevance to the medical imaging community.

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The conferences investigated have been:

• Medical Image Computing and Computer-Assisted Intervention (MICCAI), in the year 2010 (96 articles). The MICCAI conference is one of the most renowned conferences in the field of medical imaging.

• IEEE Conference on Computer Vision and Pattern Recognition (CVPR), in the years 2010 (13 articles) and 2011 (6 articles). CVPR is one of the top ranked conferences in the field of Computer Vision and Pattern Recognition. Usually a significant amount of articles in the field of medical imaging are published every year.

• IEEE International Symposium on Biomedical Imaging (ISBI), in the years 2010 (126 articles) and 2011 (220 articles). The ISBI conference is one of the biggest biomedical imaging conferences and contains comprehensive tracks on segmentation and registration regarding all imaging modalities.

• SPIE Medical Imaging, in the years 2010 (132 articles) and 2011 (116 articles). SPIE Medical Imaging is one of the biggest conferences which focus solely on advances in medical imaging.

The journals chosen for the study were:

• IEEE Transactions on Medical Imaging, volume 29, issues 1-12 in 2010 (56 articles) and volume 30, issues 1-8 in 2011 (33 articles). Transactions on Medical Imaging has an impact factor of 3.5 (2010) and is one of the most renown medical imaging journals.

• Medical Image Analysis, volume 14, issues 1-8 in 2010 and volume 15, issues 1-4 in 2011. Total articles: 57. Medical Image Analysis has an impact factor of 4.2 (2011) and is one of the most renown medical imaging journals.

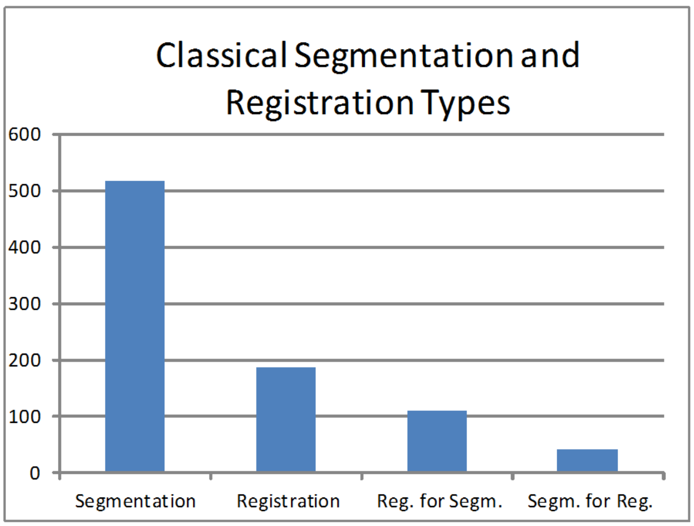


Figure 9: Amounts of articles from recent selected conferences and journals classified as either *segmentation*, *registration*, *segmentation for registration* or *registration for segmentation*. The term *segmentation for registration* denotes work that target at solving a registration problem and make use of segmentation methods for guiding the registration, for example by segmenting corresponding areas in the images. The term *registration for segmentation* denotes the inverted problem: solving a segmentation problem guided by a registration as it is used for example in voxel based atlas registration.

Figure 9 shows the classical four categories of segmentation and registration from the literature. The category *segmentation* denotes all segmentation approaches including voxel and region based methods as well as local and global prior segmentation approaches. The category *registration* consists of pure registration methods. The category *segmentation for registration* is formed by segmentation methods that are used to solve a registration task. The category *registration for segmentation* is formed by methods that address the inverted task. In order to ease the comparison of the classical with the proposed classification scheme, the described four classical categories have been made disjunctive. Here, the last two categories had priority, that means, a method that would have been assigned to be a *segmentation for registration* method and a *segmentation* method is considered as a *segmentation for registration* method. The category *registration for segmentation* is treated analogous. As it can be seen in Figure 9, in the classical scheme, the majority of

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investigated methods are segmentation methods followed by pure registration approaches. The hybrid categories consist of comparable few articles. This view suggests that the intersection set of segmentation and registration methods is relatively small. However, as it will be shown in the following, the opposite is true. In the four described classical categories, the segmentation approaches are now further investigated by applying the proposed sub-classification of Figure 1. That means, in each classical category, the segmentation methods are classified as being either voxel based methods, region based methods, local prior or and global prior shape methods. Moreover, the sub-category global prior shape methods lists voxel atlas based segmentation approaches separately, since their incorporation of global shape knowledge significantly differs from the other global prior shape methods. The subdivision of the classical categories will answer the question of how much shape knowledge is used in current state of the art approaches. Finally, it will reveal that the classical classification scheme can be easily transformed into the proposed classification.

Figure 10 shows the distribution of methods in the classical category segmentation. It can be seen that most of the current segmentation approaches make use of prior shape knowledge. Purely voxel based methods are only used in very few methods whereas the amount of region based approaches is comparable to local or global prior shape methods.

Figure 11 shows the distribution of segmentation approaches in the classical category *segmentation for registration*. Again, the majority of methods use prior shape knowledge while the largest single category is formed by region based methods. This is due to the fact that many registration methods rely on a detection of feature points in the image which in turn are often segmented using region based approaches. Voxel based methods only play a minor role in this category.

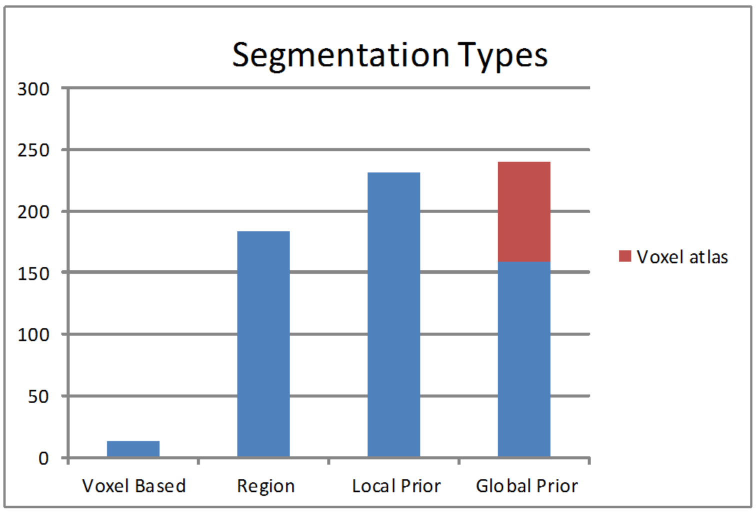


Figure 10: Classification of articles from recent selected conferences and journals into the four segmentation types voxel based, region based, shape based with local priors and shape based with global priors as defined in Figure 1. Within the global prior methods, voxel based atlas approaches are denoted separately, since they operate at voxel level in comparison to most other global shape prior methods. It can be seen that most of the current segmentation approaches make use of prior shape knowledge.

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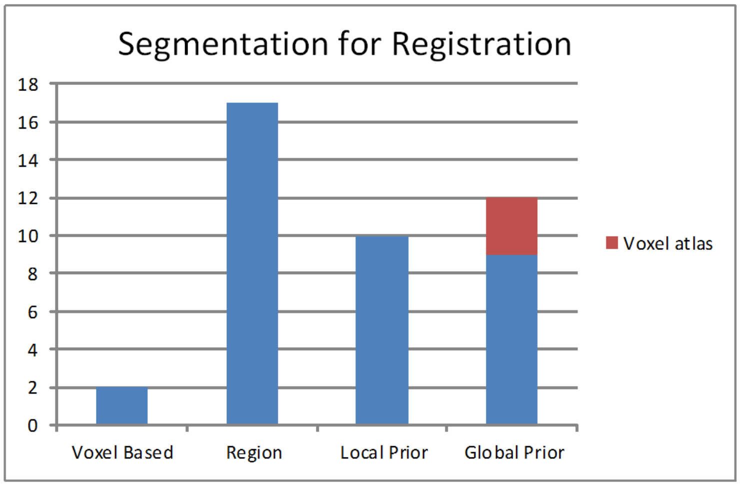


Figure 11: Conference and journal articles of the category *segmentation for registration* (cf. Figure 9) have been classified regarding the applied segmentation technique (cf. Figure 1). Most approaches of this category incorporate local or global shape knowledge.

In Figure 12, the segmentation methods used in the classical category *registration for segmentation* are sub-classified. Global prior shape methods form by far the largest class. All other classes are only represented by a small amount of methods. Among the global prior methods, voxel atlas based approaches are the most dominant technique.

By building the proposed sub-categories of segmentation methods in each classical category, the classical classification view can be transferred into the scheme proposed in this work. Here, all global prior based methods from each classical category are moved to the new category *regmentation*, because they can be used to address segmentation and registration problems. The classical hybrid categories *segmentation for registration* and *registration for segmentation* are moved to the categories registration and segmentation, respectively, because they address either registration or segmentation problems. Figure 13 shows the resulting classification. In comparison to the classical scheme in Figure 9, it is now

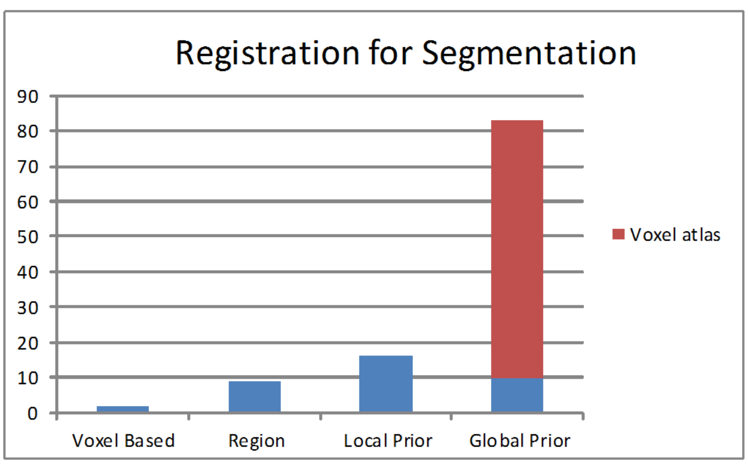


Figure 12: Conference and journal articles of the category *registration for segmentation* (cf. Figure 9) have been classified regarding the applied segmentation technique (cf. Figure 1). Voxel based atlas methods are used in the majority of approaches.


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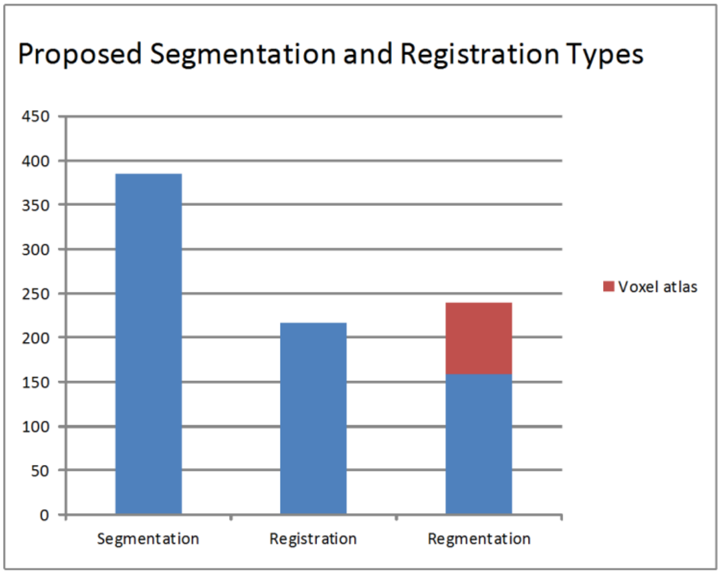


Figure 13: Proposed classes of segmentation and registration approaches according to the taxonomy developed in this work. The segmentation category consists of methods that can be used to solve segmentation problems. The category registration classifies methods for registration tasks. Approaches that can be used to solve both problems fall into the category regmentation.

evident that a large amount of recently published methods can be used to address both segmentation and registration problems. In fact, more articles about regmentation techniques have been published than classical registration approaches which shows that regmentation plays a key role in current medical imaging research.

## 5. APPLICATIONS IN RADIATION ONCOLOGY

Image segmentation and image registration have innumerable applications in medical imaging including diagnosis, disease progression monitoring, therapy planning, simulation, navigation and visualization.
In radiation oncology image segmentation, registration and regmentation have a particularly high significance during radiation treatment planning:

- *Inverse planning* requires a precise outline of target organs (e.g. the tumor and in some cases draining lymph nodes) and risk organs. Manual contouring is very time consuming especially in regions with many different important structures such as the head and neck. Region based or local shape prior based segmentation methods can be used to facilitate the delineation of the tumor, whereas voxel atlas based regmentation methods are used for the joint automatic delineation of the risk organs (e.g. [90]).

- In order to incorporate tissue density into the dose computation, the radiation treatment plan must be available for a native CT scan. However, this imaging modality has a low soft tissue contrast and thus it is not as suitable as for example MRI for organ contouring. M*ulti modal contouring* can exploit the advantages of different modalities, but requires an accurate image fusion. This can be achieved by the means of deformable image registration.

- In case an additional radiation treatment plan has to be created for a patient – possibly due to anatomical changes – the time consuming creation from scratch can be avoided by transforming the original plan based on a deformable image registration of the underlying medical images. This can be regarded as a personalized atlas based regmentation.

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Furthermore, image segmentation and registration methods can be used during the actual radiation treatment. Initially, a registration between the patient and the plan is required which can be verified using *image guided radiotherapy*. Advanced technologies such as *adaptive radiation therapy* can use image segmentation and registration techniques to for example track and consider the patient's anatomical variations due to respiratory motion.

## 6. CONCLUSION

In this article, a new shape knowledge driven taxonomy for segmentation and registration algorithms is proposed. The taxonomy is based on a continuum between two extremes: purely image based methods and strong shape dependent methods. Using this shape driven taxonomy, the following conclusions on segmentation algorithms can be drawn. First, the less shape knowledge is incorporated in the segmentation process the more general a certain segmentation algorithm can be used. However, the objects to be segmented must exhibit a strong image contrast. Contrary to that, the more shape knowledge is incorporated the lesser image contrast is required but also the more specialized a segmentation algorithm becomes.

Following this taxonomy, it also becomes evident that a strong link between segmentation and registration algorithms exists. As soon as global prior shape knowledge for a specific object is incorporated in a segmentation method, the same method can also be used for registration of images showing the object. In the current survey literature, such methods would be either classified as segmentation or registration algorithms depending on the scope of the work. We therefore propose a new category of algorithms for resolving this ambiguity. It is called regmentation. As a result, three disjunctive groups are built: pure segmentation methods, pure registration methods and regmentation algorithms. Based on a comprehensive state of the art literature study, we show that 29% of all scientific papers in the classical scope of image segmentation and registration can be classified as regmentation methods. This emphasizes the relevance of our new view which is intended to be a guideline for better differentiation between methods in this important field when applied to medical imaging or oncology problems.

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