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Robust cranial cavity segmentation in CT and CT perfusion images of trauma and suspected stroke patients

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A robust and accurate method is presented for the segmentation of the cranial cavity in computed tomography (CT) and CT perfusion (CTP) images. The method consists of multi-atlas registration with label fusion followed by a geodesic active contour levelset refinement of the segmentation. Pre-registration atlas selection based on differences in anterior skull anatomy reduces computation time whilst optimising performance. The method was evaluated on a large clinical dataset of 573 acute stroke and trauma patients that received a CT or CTP in our hospital in the period February 2015–December 2015. The database covers a large spectrum of the anatomical and pathological variations that is typically observed in everyday clinical practice. Three orthogonal slices were randomly selected per patient and manually annotated, resulting in 1659 reference annotations. Segmentations were initially visually inspected for the entire study cohort to assess failures. A total of 20 failures were reported. Quantitative evaluation in comparison to the reference dataset showed a mean Dice coefficient of 98.36 ± 2.59%. The results demonstrate that the method closely approaches the high performance of expert manual annotation.

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1. Introduction

Computed Tomography (CT) is the first choice of imaging modality for different acute clinical conditions (Burke et al., 2012; Larson et al., 2011; Talwalkar and Uddin, 2015). CT is widely available and is a cheaper and faster imaging method with fewer contraindications compared to Magnetic Resonance Imaging (MRI). However, the use of a high strength magnetic field in MRI forms a direct risk for a larger spectrum of patients in comparison to the use of ionising radiation in CT, such as patients with metallic implants or suffering from claustrophobia. Modern CT scanners provide both high spatial and temporal resolution at full brain coverage. CT perfusion (CTP) is a 4-dimensional (4D) imaging technique with contrast agent enabling the visualisation of cerebral haemodynamics, such as cerebral blood flow and volume and mean transit time. Based on cerebral haemodynamics, penumbra, infarct core and collateral flow can be assessed, and these may prove beneficial for selecting acute stroke patients for reperfusion therapy beyond the recommended time window (Powers et al., 2015). Despite the wide use of CT in emergency imaging for stroke and trauma, little progress has been made in the field of automated analysis and quantification of brain CT images. The fundamental step in the development of such algorithms is the segmentation of the cranial cavity.

Segmentation of the cranial cavity in CT is complicated by the presence of surrounding structures that share the same range of image intensity values as the brain parenchyma. Particularly the orbital region, the frontal sinus cavities and the infratentorial region prove to be difficult, as illustrated by Fig. 1. Therefore, intensity based thresholding does not suffice in completing the task of segmenting the cranial cavity in CT. 2-dimensional (2D) segmentations can be obtained in this manner with some minor additional image processing. However, obtaining a complete segmentation of the cranial cavity is far more complex. The differences in cranial and cerebral anatomy among the patient population constitute a wide spectrum of natural and pathological variety that can be seen in everyday clinical practice. Pathology, trauma, surgical intervention and foreign objects may deform the skull and brain tissue, deteriorate soft tissue contrast and produce artefacts that reduce image quality. Therefore, a method robust to both anatomical variation and differences in image appearance is required.

Related work has mainly been limited to MR imaging (Heckemann et al., 2006; Klesieck et al., 2016; Lötjönen et al., 2010; van der Lijn et al., 2012). Conversely, sparse literature is available in CT. Recent work by Aguilar et al. (2015) and
Muschelli et al. (2015) demonstrate methods that extract the cranial cavity from CT images. However, Aguilar et al. (2015) failed to include patients with any form of pathology and their method was validated using a small set of eighteen patients. Muschelli et al. (2015) propose a method that utilises software designed for MR brain images (jenkinson et al., 2012). They validated their method on a small dataset of thirty-six patients that meet specific criteria. Both methods fail to demonstrate a robustness to pathology, clinical relevance or possibility of wide clinical application.

Cranial cavity segmentation forms the basis for many clinical and epidemiological applications. First is the development of computer aided detection (CAD) systems for stroke related cerebral pathology including haemorrhages, space occupying pathology, vascular occlusions and early signs of ischemia such as the loss of white matter and grey matter differentiation. CAD could not only improve the radiologist’s diagnostic accuracy in the evaluation of imaging studies, but has the potential to vastly expedite this process. Furthermore, a segmentation of the cranial cavity would reduce the area needed to be evaluated by an automated system. This would not only remove the possibility of false positives outside the diagnostically relevant area, but also reduce the overall computation time of the CAD system. Second is the full automation of clinically used scoring systems such as the Alberta Stroke Program Early CT Score (ASPECTS) (Barber et al., 2000). ASPECTS divides a major vascular territory in the brain into several regions and subtracts points for any evidence of early ischemic change, resulting in a score that reflects the severity of the ischemic stroke of the patient. Finally, the automatic attainment of quantitative data, such as volumetric measurements, could be employed for large-scale epidemiological studies. Intracranial volume is an important morphometric measure used in different research fields, including the domain of neurodegenerative pathology and hydrocephalus (Hedman et al., 2012).

The main objective of this work is to present a robust method for the 3-dimensional (3D) segmentation of the cranial cavity from non-contrast CT and CTP images of trauma and suspected stroke patients. The motivation is twofold: isolation of the cranial cavity from all irrelevant information contained in the image facilitating subsequent analysis and the production of an accurate and reproducible volume measurement of the cranial cavity. We propose a method combining multi atlas-based segmentation of the cranial cavity refined by a levelset approach to accurately include all soft tissue. We demonstrate its robustness by application to a large clinical database of 573 patients with limited exclusion criteria representing everyday clinical practice.

2. Method

Our method consists of multiple stages that increasingly refine the detail in the segmentation of the cranial cavity. The primary stage involves multi-atlas registration with pre-registration atlas selection and label fusion. A semi-offline atlas ranking scheme based on anatomical similarity to the patient reduces overall computation time whilst selecting the most appropriate images for registration. Subsequently the result of atlas registration is used as an initialisation for a multi-phase levelset approach based on the image gradient. The initial phase allows for correction of errors introduced during atlas registration and a fast propagation of the segmentation. The final phase refines the segmentation along the inner boundary of the cranial cavity.

All parameters for the method were set as a result of pilot experiments performed on a separate training dataset described in Section 3.1.

A schematic overview of the proposed method is shown in Fig. 2.

2.1. The cranial cavity

The cranial cavity contains all soft tissues and cerebrospinal fluid (CSF). This includes the meninges, cerebrum and ventricles, cerebellum and brain stem. At the level of the eyes and optical nerves, cranial cavity is included until the location of the optic foramen and superior orbital fissure. Vasculature and other soft tissue of the cerebral region is not included.

2.2. Atlases

A total of 8 atlas non-contrast CT images were selected from the training data, as described in Section 3.1, to encompass four types of anatomical variation observed. Atlas candidate selection was based on the variation in size and shape of the frontal sinus cavity of the skull observed in the patient population. The presence or absence of this cavity in the forehead was noticed to be of influence during image registration. Examples of varying skull anatomy within the atlas cohort are shown in Fig. 3. An atlas label of the cranial cavity is obtained as follows. Soft tissue is segmented by
thresholding the atlas image between a range of 0–300 Hounsfield Units (HU). Subsequently a morphological opening operation with a ball kernel with a radius of 10 voxels is used to separate intracranial soft tissue from surrounding, connected structures such as the eyes. A largest connected component analysis is performed to retrieve a coarse segmentation of the cranial cavity. The initial segmentation is manually refined to include all structures as described in Section 2.1.

A second atlas label, referred to as the anterior region label, is used to mask all connected soft tissues and cavities in the anterior region of the skull. As described in Section 2.3, a CT template image with a mask of the anterior region is registered to the atlas image. The masked region in the atlas image is thresholded at a minimum value of 300 HU to segment all boney anatomy. Subsequently this is manually refined by precise labelling of the non-brain soft tissue and cavities in this region as shown in Fig. 4. All manual adjustments to atlas labels are performed by trained medical students using ITK-SNAP (version 3.2.0) (Yushkevich et al., 2006) with a window width and level setting of 400/100, supervised by an experienced neuroradiologist (FJAM) with over ten years of experience.

2.3. Atlas selection

All 8 atlas images in the database are spatially normalized by offline affine registration to a common space of a CT template image (Rorden et al., 2012). This template consists of high resolution images of healthy adult individuals. Elastix (version 4.800) (Klein et al., 2010) is used with the following parameters: advanced Mattes mutual information, adaptive stochastic gradient descent optimisation, 32 histogram bins, a multi-scale method using Gaussian smoothing at 4 scales of 8, 4, 2 and 1 voxels, and a maximum number of iterations of 250 for each scale. Incoming patient data is processed in the same manner. The averaged and optimised template image, although also obtained from CT, has a different distribution of intensity values in comparison to the atlas and patient images. Therefore, mutual information is used as the metric for registration.

A mask consisting of a right pyramid originating in the centre of the template space, similar to that shown in Fig. 4, is applied to all images. To quantify the differences in frontal sinus cavity, the mean square error between each atlas and the patient image is calculated voxel wise in the masked region. All atlases are ranked according to the calculated metric for each patient image. The two top ranking atlas images are selected for elastic registration to the patient image.

2.4. Image registration and label fusion

The database of atlas images contains the non-contrast CT image as well as a binary mask of the entire head of the atlas subject. Incoming patient images are downsampled with a factor of 2 and thresholded at a minimum value of 100 HU to obtain a rough segmentation of the patient. This downsampling reduces the overall computation time without negatively affecting the final result, as it is an intermediate step. A binary morphological closing operation is performed with a ball kernel with a radius of 5 voxels, followed by slice-by-slice hole filling to obtain a binary mask of the entire head of the patient.

The two top ranking atlas images selected from the database are registered to the resampled patient image using an affine registration followed by non-rigid b-spline registration. Elastix is used with the binary head masks for the atlases and patient image as moving and fixed masks respectively. The following parameters are used for the affine registration: advanced mean squares, adaptive stochastic gradient descent optimisation using 2048 samples, 32
histogram bins, a multi-scale method using Gaussian smoothing at 5 scales of 16, 8, 4, 2 and 1 voxels, and a maximum number of iterations of 500 for each scale. Subsequent non-rigid b-spline registration is applied with the following parameters: advanced mean squares, adaptive stochastic gradient descent optimisation using 2048 samples, 32 histogram bins, a multi-scale method using Gaussian smoothing at 3 scales of 4, 2 and 1 voxels, a grid spacing of 5.0 mm, and a maximum number of iterations of 500, 500 and 1000 for the three scales respectively. As the intensity value distributions within the patient and atlas images are equal, advanced mean squares is used as metric for both stages of image registration.

The resulting transformation fields are applied to the cranial cavity labels of the utilized atlases using Transformix (version 4.800). The transformed labels are fused to a single cranial cavity label by only considering voxels that are in congruence after transformation. This approach ensures that a favourable initial segmentation is created in the event of a failed registration of one of the atlas images. The selection and fusion of two atlas images combines the robustness of a multi-atlas approach while keeping the computation time to a minimum. The fused cranial cavity label is upsampled to the original input image size. The undersegmentation and loss of detail as a result of label fusion and upsampling is inconsequential, as this is used as an initial segmentation for further refinement. The anterior region labels of the top ranking atlases are transformed to the original patient image. The transformed anterior region labels are combined into a single label by considering all non-zero voxels in both labels. The result is combined with segmentations of bone and air in the patient CT image to obtain an enclosing boundary of the cranial cavity as shown in Fig. 5. The segmentations of bone and air are obtained by applying thresholds of a minimum of 350 HU and maximum of 0 HU respectively.

2.5. Levelset refinement

The fused cranial cavity label obtained from atlas registration is further employed as an initialisation for a two-stage Geodesic Active Contour (GAC) driven by a speed function based on the image gradient (Caselles et al., 1997). The two separate stages reduce computation time without compromising the final result. The GAC is described by the following differential equation:

\[ \Phi_t + g(1 + \varepsilon \kappa) | \nabla \Phi | - \alpha \varepsilon \gamma \frac{\nabla g \cdot \nabla \Phi}{ | \nabla g | } = 0 \] (1)

With \( \Phi \) as the levelset function, advection weighting \( \alpha \), curvature weighting \( \varepsilon \), mean curvature \( \kappa \) and the gradient based speed function \( g \) given as:

\[ g(I) = e^{-\left( \frac{I - \gamma \gamma}{\sigma_c^2} \right)} \] (2)

With the image gradient \( \nabla I \) calculated with a gradient weighting factor \( \gamma \) using Gaussian derivative at scale 1.0 voxels.

The gradient based speed function is calculated with \( \gamma = 80 \), using a fusion of the patient image and the aforementioned enclosing boundary mask obtained from transformation of the atlas anterior region labels. The speed is fixed at a value of \(-1.0 \)
3. Patient data

3.1. Patient selection

This study was approved by the institutional ethics committee, and the requirement for informed consent was waived. Anonymised data was obtained by retrospectively searching our clinical-research image database for all adult patients that received a non-contrast CT or CTP of the head at the Radboud University Medical Center, Nijmegen, the Netherlands between January 1st 2015 and December 31st 2015. Training data consisted of all patients that received a scan in the month of January 2015. From this, all atlas images were selected and excluded from the training set. Test data consisted of all remaining scans selected within the inclusion period. One scan was used per patient. If no CTP image existed for a certain patient, a non-contrast CT was used. Therefore, the number of patients included is equal to the number of images processed.

The 4D CTP acquisition had different exposures per time point resulting in different noise levels per time point. The temporal average was calculated optimally weighted according to the exposure of the individual time point to maximize the signal to noise ratio (Manniesing et al., 2016). This resulted in a single high quality 3D volume reconstruction from each 4D CTP image.

All images were visually inspected for quality. Exclusion criteria were limited to: severe motion artefacts or abnormal head position e.g. due to severe rotation. A total of 16 non-contrast CT and 7 CTP images were excluded. In total 573 patients were included for evaluation. A schematic overview of all study data and patients’ age and gender distributions is shown in Fig. 6.

3.2. Acquisition protocol

All images were acquired using a 320-row Toshiba Aquilion ONE CT scanner manufactured by Toshiba Medical Systems Corporation, TMSC, Otawara, Japan. The CTP protocol consisted of 19 volumetric acquisitions which started with a high dose acquisition at 200 mAs, 5 s after contrast injection, followed by 13 scans every 2 s at 100 mAs, followed by 5 scans every 5 s at 75 mAs. Each volumetric acquisition was made at 80 kV at 0.5 s rotation time and had 16 cm coverage. CTP image reconstruction was done with a smooth reconstruction kernel. The CT protocol consisted of one helical head scan at 120 kV. CT image reconstruction was done with a smooth reconstruction kernel. The average image size was 512 x 512 x 320 voxels with voxel sizes of 0.43 x 0.43 x 0.5 mm.

3.3. Reference standard

Manual annotations were obtained to serve as a reference standard to train and validate the method. The CT image was thresholded between 0 and 300 HU to acquire the soft tissue. A binary morphological opening operation was performed with a ball kernel with a radius of 10 voxels to separate the cranial cavity from surrounding, connected structures. This was followed by a largest connected component analysis to obtain an approximation of the bounding box of the intracranial tissue. Within the voxel coordinate ranges determined, one random slice was selected for each anatomical plane. The three randomly selected slices for each patient were manually annotated by two trained observers, as described in Section 2.2, using ITK-SNAP. The anatomy included in the reference standard was defined in the same manner as the atlas cranial cavity label described in Section 2.2. This resulted in an extensive database of 1659 manually refined reference annotations.

4. Experiments

The goal of this work was to produce a robust method capable of segmenting the cranial cavity in non-contrast CT and CTP images of the head. Minimal exclusion criteria were imposed while creating our dataset to evaluate the performance of the method in everyday clinical practice. Therefore, we utilised consecutive scan
Fig. 6. Schematic overview of study data.
5. Results

5.1. Observer variability of reference standard

All data was processed by the proposed method using a 4 core processor at 2.3 GHz and 16GB RAM. The mean ± standard deviation processing time for an individual scan was 357.2 (5 min 57 s) ± 27.9 s.

Table 1 shows the quantitative evaluation of the inter-observer variability, intra-observer variability and the performance of the method in comparison to each observer independently for a subset of ten non-contrast CT images. The DSC for the inter-observer variability was reported as 99.53 ± 0.22%. Whereas the performance of the method was evaluated as slightly but significantly lower. This is also illustrated in the box plots in Fig. 7.

5.2. Qualitative evaluation

Visual inspection revealed a total of twenty failures. Variations of anatomy of the skull not represented in the atlas database lead to the selection of inappropriate atlas images for registration. This results in registration errors and an improper creation of the fused labels used for levelset initialization, leading to erroneous segmentation. An example of failed segmentation is shown in Fig. 8.

Results were evaluated as excellent in general. Segmentation proved to be most difficult at the base of the skull and cervical region. These areas also consist of vasculature and other surrounding soft tissues that are not completely separated from the cranial cavity by the enclosing boundary mask. Minor over-segmentation of the base of the skull was not assessed as a failure, as the inclusion of the vessels in that region are of importance for subsequent image processing. Furthermore, the addition of levelset refinement in some cases resulted in segmentation of the cervical vasculature. Small over- and under-segmentations were seen in anterior areas. This was caused by minor registration imperfections that slightly misaligned the anterior region mask with the patient image. This was also determined not to be a failure, as a near perfect segmentation was still obtained.

The patient cohort contained numerous cases where surgical intervention had deformed the cranial cavity or introduced foreign objects that resulted in image artefacts. Successful segmentations were obtained despite these abnormalities. Examples of the performance of the method in cases following surgical intervention are shown in Figs. 9 and 10.

5.3. Quantitative evaluation

Table 2 shows the comparison of quantitative evaluation between the initial segmentation obtained from atlas registration and label fusion and the final segmentation achieved with the addition of levelset refinement for all 553 images included in the test.
dataset. For CT, CTP and the total dataset the addition of levelset refinement significantly improves the overlap with the reference standard as indicated by the DSC values. In Fig. 11 it can be seen that this results in higher median DSC values and lower standard deviations for all datasets. Visual inspection showed a noteworthy improvement of the initial segmentation after addition of the levelset refinement. The soft tissue along the inner edge of the skull would otherwise not be included in the final result, as illustrated in Fig. 12.

6. Discussion and conclusion

In this work we presented a method of head CT segmentation of the cranial cavity using multi-atlas registration with pre-registration atlas selection followed by a levelset refinement of the final result. The main contribution is that we have developed a method that closely approaches the high accuracy of manually annotating head CT studies. Furthermore, the method has proven to be robust independent of gross pathology or foreign objects observed in everyday clinical practice.

Robustness was demonstrated by evaluating the method on a large database comprised of 573 patients. A total of twenty failures were reported. These failures were a direct result of atlas registration errors caused by anatomical variance not included in the atlas database. In total 553 images and corresponding manually annotated reference standards were used for quantitative analysis. To our knowledge, this is the largest quantitative evaluation of a brain segmentation algorithm both in CT as well as in the MR domain to date.

Multi-atlas registration has shown to produce segmentations with a good degree of overlap with the reference standard. A mean DSC of $97.35 \pm 3.45\%$ was reported after registration and

Table 2
Quantitative evaluation of segmentations after atlas registration and after additional levelset refinement. Reported for non-contrast CT, CTP and total dataset as mean ± standard deviation. DSC is Dice similarity coefficient, HD is Hausdorff distance, MHD is modified HD, 95% HD is 95 percentile HD, CMD is contour mean distance and AVD is absolute volume difference. $p$-values were computed with a paired sample $t$-test between Registration and Registration + Levelset for CT, CTP and the total dataset for each evaluation measure. * indicates a significant result with $p$-value <0.05.

<table>
<thead>
<tr>
<th></th>
<th>CT Registration</th>
<th>CT Levelset</th>
<th>CTP Registration</th>
<th>CTP Levelset</th>
<th>Total Registration</th>
<th>Total Levelset</th>
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<td>DSC (%)</td>
<td>97.52 ± 2.55</td>
<td>98.48 ± 1.46*</td>
<td>97.03 ± 4.71</td>
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<td>98.36 ± 2.59*</td>
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<td>HD (mm)</td>
<td>10.49 ± 10.79</td>
<td>10.72 ± 10.87</td>
<td>9.55 ± 7.07</td>
<td>9.20 ± 7.00</td>
<td>10.16 ± 9.68</td>
<td>10.20 ± 9.73</td>
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<td>MHD (mm)</td>
<td>0.18 ± 0.40</td>
<td>0.13 ± 0.27*</td>
<td>0.19 ± 0.60</td>
<td>0.24 ± 1.07</td>
<td>0.18 ± 0.48</td>
<td>0.17 ± 0.66</td>
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<tr>
<td>95% HD (mm)</td>
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<tr>
<td>CMD (mm)</td>
<td>0.08 ± 0.16</td>
<td>0.06 ± 0.11*</td>
<td>0.08 ± 0.25</td>
<td>0.09 ± 0.36</td>
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<td>AVD (%)</td>
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label fusion for the total dataset. However, the addition of levelset refinement significantly increases this evaluation measure and improves the final segmentation to a high level of detail.

The method has proven to be accurate producing a mean DSC of \(98.36 \pm 2.59\%\) for the total dataset. Whereas the inter-observer variability was reported as \(99.53 \pm 0.22\%\). However, this was evaluated on a small dataset of ten non-contrast CT images. We expect this difference to diminish when evaluated on a larger dataset comprised of both non-contrast CT and CTP images. The calculated DSC for the total dataset is therefore a lower bound. An indiscriminate choice in slices for each orthogonal plane ensured that the method was quantitatively evaluated at an array of locations within the extents of the segmented volumes, thereby demonstrating a lack of bias towards specific regions within the cranial cavity. However, this random selection often resulted in an outer boundary location with little brain tissue to be used for evaluation. Slight over- or under-segmentation in these cases had a large influence on the calculated measures. Average values were taken over all patients for all measures, still this negatively weighed on the final quantitative results. Nevertheless, the results demonstrate that the proposed method closely approaches the high performance of expert manual annotation.

In comparison, recent work by Klesiek et al. (2016) used a state-of-the-art deep learning approach to segment the cranial cavity in MR images from publicly available datasets. Their method produced a mean DSC of \(95.8 \pm 1.0\%\) taken over 135 scans from three datasets. Similar performance was reported on a separate challenging dataset comprised of 53 multimodal MR images of patients with brain tumours. Although our method is based on a different imaging modality, this puts the performance of the method into perspective and demonstrates a similarity to a state-of-the-art method in the field.

Quantitative evaluation shows a slight difference in performance between the CT and CTP datasets. This may be the result of multiple factors. First, the atlas database solely consists of non-contrast CT images and therefore registration performance may be different for CTP images. Second, the addition of contrast agent and a different signal-to-noise ratio in CTP images may have an effect on the speed function calculation for levelset refinement. Finally, the amount of low outlier values was close to equal for both datasets, despite a large difference in size between the two datasets, thereby negatively influencing the mean values for the CTP dataset in comparison to CT. Nevertheless, qualitative assessment did not reveal a noteworthy difference in final segmentation results between non-contrast CT and CTP images.

The average processing time for an individual case was approximately six minutes using standard computer hardware. This does not pose a problem in a research setting; however, for online clinical applications this may not suffice. The processing time can considerably be reduced with dedicated hardware and hardware specific programming to satisfy clinical time constraints.
Fig. 9. Patient with coil surrounded by soft tissue causing high intensity artefacts. CT image and final segmentation result for axial (a, b) sagittal (c, d) and coronal view (e, f).
Fig. 10. Patient that has undergone invasive cranial surgery, leading to substantial deformation of the cranial cavity. CT image and final segmentation result with presence of a large haemorrhage in right cerebral hemisphere for axial (a, b) sagittal (c, d) and coronal view (e, f).
Fig. 11. Box plot of Dice similarity coefficient (DSC) calculated for the initial segmentation obtained after atlas registration and label fusion and the final result achieved with the addition of levelset refinement. Results shown for CT, CTP and total dataset. Corresponding mean ± standard deviation values are listed in Table 2. The central line indicates the median value, the box edges depict the 25th and 75th percentiles and the whiskers show the extremes at 1.5 interquartile range excluding the outliers. Depicted with outliers as * (top) and without outliers for better visualisation (bottom).

Robust and accurate cranial cavity segmentation forms the basis for automated cranial CT analysis. This has a number of relevant applications. Isolation of diagnostically pertinent information in cranial CT images assists in the development of CAD systems for stroke and other cerebral pathologies. CAD systems are not impaired in the same manners as human observers and introduce an element of consistency in the method of patient evaluation. This could improve prediction of outcome, appropriate patient triage and the development of treatment methods. Additional image processing is necessary to detect, segment and quantify cerebral anatomy and pathology. With this method as a consistent initial step, this facilitates automated quantitative and volumetric
measurements. This is useful not only as diagnostically relevant data for CAD, but also for large-scale epidemiological studies and clinical trials.

Future work consists of increasing the robustness of the method by the addition of atlas images to the database and extending the method to be independent of patient age. Also, reduction of computation time would make the method more suitable for online clinical applications. Additional segmentation of large cerebral anatomy, such as white matter, grey matter and CSF is the next necessary step in the development of CAD systems for cerebral pathologies.

In conclusion, we presented a method using multi-atlas registration with pre-registration atlas selection in combination with a levelset method to segment the cranial cavity in CT images. Our method provides robust and accurate segmentations as the fundamental first step towards automated evaluation of cranial CT exams.

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