Employing Weak Annotations for Medical Image Analysis Problems

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Abstract

To efficiently establish training databases for machine learning methods, collaborative and crowdsourcing platforms have been investigated to collectively tackle the annotation effort. However, when this concept is ported to the medical imaging domain, reading expertise will have a direct impact on the annotation accuracy. In this study, we examine the impact of expertise and the amount of available annotations on the accuracy outcome of a liver segmentation problem in an abdominal computed tomography (CT) image database. In controlled experiments, we study this impact for different types of weak annotations. To address the decrease in accuracy associated with lower expertise, we propose a method for outlier correction making use of a \textit{weakly labelled atlas}. Using this approach, we demonstrate that weak annotations subject to high error rates can achieve a similarly high accuracy as state-of-the-art multi-atlas segmentation approaches relying on a large amount of expert manual segmentations. Annotations of this nature can realistically be obtained from a non-expert crowd and can potentially enable crowdsourcing of weak annotation tasks for medical image analysis.

\textbf{Keywords:} Medical Image Segmentation, Weak Annotations, Expertise, Bounding Boxes, Continuous Max-Flow, Crowdsourcing

1. Introduction

In the recent past, collaborative and crowdsourcing platforms \cite{Estelles-Arolas2012} have been investigated for their ability to obtain large amounts of user interactions for the annotation of image databases. Particularly, the capacity to outsource simple human intelligence tasks to a crowd population and simultaneously draw from client computing resources for interfacing, are being increasingly appreciated in the imaging community \cite{McKenna2012, Maier-Hein2014, Mavandadi2012}. First studies employing collaborative \cite{Hachn2014, Rajchl2016b} or crowdsourcing platforms \cite{Maier-Hein2014, Albarqouni2016} via web interfaces have been proposed for biomedical image segmentation. Since such interfaces often have limited capacity to interact with image data, weak forms of annotations (e.g. bounding boxes, user scribbles, image-level tags, etc.) have been investigated to reduce the required annotation effort. Recent studies have shown that placing bounding box annotations is approximately 15 times faster than creating pixel-wise manual segmentations \cite{Lin2014, Papandreou2015}.

However, in contrast to annotating natural images \cite{Lin2014, Russell2008} or recognising instruments in a surgical video sequence \cite{Maier-Hein2014}, the correct interpretation of medical images requires specialised training and experience \cite{Nodine2000, Gurari2015}, and therefore might pose a challenge for non-expert annotators, leading to incorrectly annotated data \cite{Cheplygina2016}. Nonetheless, considering the limited resources of available clinical experts and the rapid increase in information of medical imaging data (e.g. through high-resolution, whole-body imaging, etc.) alternative approaches are sought. Particular challenges arise, when trying to develop machine learning based approaches that can be scaled to very large datasets (i.e. population studies). Many of the currently available approaches re-
require large amounts of labelled training data to deal with the variability of anatomy and potential pathologies.

1.1. Related Work

To reduce the annotation effort, many well-known studies propose segmentation methods employing simple forms of user annotations to obtain voxel-wise segmentations \[ (\text{Boykov and Jolly, } 2000) \] or \[ (\text{Rother et al., } 2004) \]. \[ \text{Rajchl et al., } 2017 \] [\text{Koch et al., } 2017]. \text{While adjusting hyperparameters can be considered an interaction, in this study we concentrate on simplified forms of pictorial input (\text{Olabarriaga and Smeulders, } 2001), called weak annotations (WA).} Such annotations have been extensively used in the literature, particularly in the context of medical object segmentation problems. \[ \text{Boykov and Jolly, } 2000 \] used user-provided scribbles (SC) or brush strokes as input and hard constraints to an interactive graphical segmentation problem. Similarly, \[ \text{Baxter et al., } 2015 \] \[ \text{Baxter et al., } 2017 \] and \[ \text{Rajchl et al., } 2012 \] expressed this problem in a spatially continuous setting by using prior region ordering constraints and exploiting parallelism via GPU computing. The GrabCut algorithm \[ (\text{Rother et al., } 2004) \] employs rectangular regions (RR) as bounding boxes to both compute a colour appearance model and spatially constrain the search for an object. These spatial constraints further allow to reduce the computational effort \[ (\text{Pitiot et al., } 2004) \]. \text{The segmentation platform ITK-SNAP} \[ (\text{Yushkevich et al., } 2006) \] combines RR with SC and employs a pre-segmentation (PS) to initialise an active contour model.

While the above object segmentation methods concentrate on how to accurately compute segmentations based on WA, recent studies have examined how to efficiently acquire the required annotations. Collaborative annotation platforms such as LabelMe\footnote{http://www.labelme.org/} \[ (\text{Russell et al., } 2008) \] or \[ (\text{Lin et al., } 2014) \] were proposed to distribute the effort of placing image annotations to a crowd of users. Such crowdsourcing approaches have been successfully used in proof-reading connectomic maps \[ (\text{Haehn et al., } 2014) \], identification of surgical tools in laparoscopic videos \[ (\text{Maier-Hein et al., } 2014) \], polyps from computed tomography (CT) colonography images \[ (\text{McKenna et al., } 2012) \] or the identification of the fetal brain \[ (\text{Rajchl et al., } 2016b) \]. However, most studies concentrate on tasks that require little expertise of the crowd, as the objects to identify are either known from everyday life \[ (\text{Russell et al., } 2008) \] \[ (\text{Lin et al., } 2014) \] or foreign to background context \[ (\text{Maier-Hein et al., } 2014) \]. \[ \text{Russell et al.} (2008) \] and \[ \text{Lin et al.} (2014) \] concentrated on object recognition tasks in natural images, the latter constrained to objects “easily recognizable by a 4 year old”. \[ \text{Maier-Hein et al., } 2014 \] asked users to identify a foreign surgical object in a video scene and \[ \text{Haehn et al., } 2014 \] provided an automated pre-segmentation to be corrected by users. \[ \text{McKenna et al., } 2012 \] compensated for the lack of expertise in reading the colonography images by improving image rendering, implementing a training module and using a large number of redundant users \[ (i.e. \text{20 knowledge workers per task}) \]. Expertise in the interpretation of medical images is largely acquired through massive amounts of case-reading experience \[ (\text{Nodine and Mello-Thoms, } 2000) \] and it has been shown that novices performed with lower accuracy than an average expert in tasks such as screening mammograms for breast cancer \[ (\text{Nodine et al., } 1999) \] \[ \text{Nodine and Mello-Thoms, } 2000 \]. In contrast to \text{diagnostic interpretation} of medical images, automated segmentation pipelines merely require the \text{identification} of anatomical structures \[ (i.e. \text{it requires less expertise to identify the liver in a CT image than a lesion in the liver}) \].

1.2. Contributions

In this study, we examine types of commonly employed WA and investigate the impact of reducing the annotation frequency \[ (i.e. \text{only annotating every } k\text{-th slice in a volume}) \] and the expertise on the segmentation accuracy. For this purpose, we employ a well-known graphical segmentation method and provide weak image annotations as initialisation and constraint to the segmentation problem at hand. We address the problem of liver segmentation from a database of abdominal CT images and corresponding non-redundant annotations. It is of great importance for both planning for laparoscopic surgery and computed-assisted diagnosis \[ (\text{Wolz et al., } 2012) \] and requires extensive manual annotation effort because of its high spatial resolution and large field of view. \text{Further, we propose and evaluate how a weakly labelled atlas} can be used for the detection and removal of incorrect annotations and achieve similar accuracy using weak annotations as a state-of-the-art fully-supervised automated segmentation method \[ (\text{Wolz et al., } 2012) \].

2. Methods

To study their impact on accuracy, we simulate user annotations from expert manual segmentations \[ M \] subject to different expertise levels and annotation frequency:
Expertise

We assume that the task of placing an annotation itself is defined well enough to be handled by a pool of general users with any experience level. However, the correct identification of anatomical structures might pose a challenge to non-expert users. We define expertise as the rate of correctly identifying an object of interest in a 2D image slice extracted from a 3D volume. If an error occurs, the user annotates the wrong object or rates that the object is not visible in this slice. We define the error rate (ERR ∈ [0, 1]), i.e. the frequency of misidentification, as a measure of expertise. An annotation error is detected when the organ is not visible in this slice. We define the error rate (ERR ∈ [0, 1]), i.e. the frequency of misidentification, as a measure of expertise. An annotation error is detected when the organ is not visible in this slice.

Annotation Rate

We collect an equal amount of annotations from each of the three slice directions \( d \in D \) at an annotation rate (AR ∈ [0, 1]). When computing the AR, we annotate every \( k \)-th slice, where \( k = AR^{-1} \). Note, that each slice was annotated at most once, i.e. annotations are non-redundant.

2.1. Annotation strategies

For all experiments, we simulate following forms of weak annotations from expert manual segmentations \( M \): Rectangular (bounding box) regions (RR)

Similarly to [Rother et al., 2004], the user is asked to draw a tight rectangular region around the object. We compute a bounding box based on the maximum extent of \( M \) within the respective image slice. An example RR (cyan) computed from \( M \) (blue) is shown in Fig. 1.

Merging pre-segmentations (PS)

Inspired by recent work in [Hachin et al., 2014], a user merges regions computed from an automated pre-segmentation method. We use a multi-region max flow intensity segmentation with the Potts energy, according to [Yuan et al., 2010b]

\[
E(u) = \sum_{\Omega L} (D_L(x)u_L(x) + \alpha_{\text{Potts}}|\nabla u_L(x)|)dx, \\
\text{s.t. } u_L(x) \geq 0 \text{ and } \sum_{\Omega L} u_L(x) = 1
\]

To obtain piecewise constant regions. The data fidelity term for each label \( L = 1, \ldots, N_L \) is defined as the intensity L1-distance

\[
D_L(x) = |L(x) - l_L|,
\]

where \( l_L \) denotes the \( L \)-th most frequent intensity according to the histogram of the image volume. For all experiments, we fix \( N_L = 16 \). The GPU-accelerated solver was provided with the ASETS library [Rajchl et al., 2016a]. After convergence, a discrete label map is calculated voxel-wise as arg max \( u_L(x) \).

To obtain connected individual segments, the obtained segmentation is subsequently partitioned via 4-connected component analysis. Given such pre-segmentation (PS), the user is tasked to merge subregions, such that they contain the object of interest (i.e. the liver). We simulate the merging similar to BD, such that \( \forall \text{PS} \cap M \neq \emptyset \). A simulated PS annotation is shown in Fig. 1 in yellow and the corresponding \( M \) in blue.

2.2. Annotations as Segmentation Priors

To be employed as priors in a volume segmentation problem, the annotations from individual slice directions \( d \in D \) need to be consolidated to account for voxels \( x \) located on intersecting slices: The binary SC annotations from all slice directions \( d \in D \) are combined to a volume annotation \( SC_{Vol} \)

\[
SC_{Vol}(x) = \cup_{d=1}^D SC_d(x), \quad \text{and employed as foreground samples } S_{FG} = SC_{Vol}.
\]
Figure 1: Weak annotation types (top left to bottom right): image, expert manual segmentation (blue), scribbles (SC, green), binary decision making (BD, magenta), rectangular bounding box regions (RR, cyan) and merging of pre-segmentations (PS, yellow).

Figure 2: Example pre-segmentation (PS) results on an abdominal CT volume: Top row (from left to right): CT slice images in transverse, coronal and sagittal direction. Bottom row: Corresponding PS segmentation labels after $\arg\max_x \mu_L(x)$, when minimising $f$, using $\beta$, $N_L = 16$ and $\alpha_{Potts} = 0.05$. 
All binary annotations $A_d \in \{BD, RR, PS\}$ and all unannotated slices $U_d$ are similarly combined to volumes to establish $S_{BG}$. Note, that $A_d(x) = 1$ denotes the user rated the location $x$ as "foreground" and $U_d(x) = 1$ denotes, that the user has not seen this location.

$$A_{Vol}(x) = \bigcup_{d=1}^{D} A_d(x); \quad U_{Vol}(x) = \bigcap_{d=1}^{D} U_d(x);$$  \hspace{1cm} (5)

The background samples $S_{BG}$ are computed as all voxels $x$ that are outside $A_{Vol}$ and are annotated:

$$S_{BG}(x) = \neg A_{Vol}(x) \cap \neg U_{Vol}(x).$$  \hspace{1cm} (6)

The resulting samples $S_{FG}$ and $S_{BG}$ can then be used to compute intensity histograms or to enforce spatial constraints. For all experiments, we employ SC annotations as priors for foreground voxels and [BD, RR, PS] annotations as priors for background voxels. For each of these three combinations (e.g. SC and BD, etc.), we calculate $S_{FG}$ and $S_{BG}$ for each volume image to be segmented.

### 2.3. Segmentation Problem

The method employed to obtain a segmentation can be considered as a black box to be replaced by any specialised pipeline that suits a specific problem. For our experiments, we employ a well-known interactive flow maximisation (Boykov and Jolly [2000], Rajchl et al. [2012]) approach to compute image segmentations from the input annotations $A$, subject to a certain AR and ERR. For this purpose, we use the continuous max-flow solver (Yuan et al. 2010a, Rajchl et al. 2016a) supporting GPU acceleration and allowing us to tackle the computational load for our experiments. We find a solution by minimising an energy $E(u)$ defined for the labelling or indicator function $u$ at each voxel location $x$ in the image $I$, s.t. $u(x) \in [0,1]$ as,

$$E(u) = \int_{\Omega} (D_f(x) u(x) + D_t(x) (1 - u(x)) + \alpha |\nabla u(x)|) dx,$$  \hspace{1cm} (7)

Here, the data fidelity terms $D_f(x)$ are defined as the negative log-likelihood of the probabilities $\omega_{1,2}$, computed from normalised intensity histograms of the foreground (FG) and background (BG) region, respectively,

$$D_f(x) = -\log(\omega_1(I(x))) \quad \text{and} \quad D_t(x) = -\log(\omega_2(I(x))),$$  \hspace{1cm} (8)

as described in (Boykov and Jolly 2001). Additionally, we employ a soft spatial constraint by setting the cost for regions annotated as FG and BG, to a minimum:

$$D_t(x) = 0, \quad \forall x \in \text{FG}; \quad D_t(x) = 0, \quad \forall x \in \text{BG}; \hspace{1cm} (9)$$

Consolidated volume annotations (see Section 2.2) are used to compute samples $S_{FG}$ and $S_{BG}$ of FG and BG, respectively. $S_{FG}$ and $S_{BG}$ are subsequently employed to compute $\omega_{1,2}$ in (8) and as spatial constraints in (9). After optimisation of the energy in (7), the resulting continuous labelling function $u$ is thresholded at 0.5 to obtain a discrete segmentation result for the FG, as described in (Yuan et al. 2010a).

### 2.4. Outlier Detection & Removal

We propose a method for quality assessment to mitigate the impact of annotation errors on the accuracy of the segmentation results (e.g. when using databases labelled by crowds with low expertise). Note, that contrary to other studies (McKenna et al. 2012, Lin et al. 2014), we do not require redundant annotations for outlier detection. Instead, we propose to make use of redundant information in the flawed and weakly labelled atlas database and retrieve similar image slices and their annotations in the fashion of multi-atlas segmentation pipelines (Wolz et al. 2012, Aljabar et al. 2009).

If spatial variability is accounted for (e.g. through registration), we can retrieve slices from other atlas volumes and use their annotations to compute an agreement measure to rate a given annotation. For this purpose, we borrow from the concept of the SIMPLE method (Langerak et al. 2010), where an iteratively refined agreement is used to assess the quality of individual atlases in a multi-atlas segmentation approach.

#### Weakly Labelled Atlas as Quality Reference

We assume that $S$ subjects $s_i = \{s_1, \ldots, s_g\}$ have been weakly (and potentially erroneously) annotated and aim to automatically detect the slices of each subject $s_i$ that have an annotation of insufficient quality (e.g. the wrong organ has been annotated or the organ was present, but not detected). In the following, the $j$-th slice of subject $s_i$ in direction $d$ is denoted by $v_{ijd}^*$. For each slice in the database $v_{ijd}^*$, we first find a subset of the most similar spatially corresponding images $v_{ijd}^*$ of the subjects $s_q$ in the weakly labelled atlas using a global similarity measure, such as the sum of squared differences. We then calculate a consensus segmentation $\hat{O}_I$ from the annotations of these anatomically similar image slices using mean label fusion. For each of these selected atlas annotations, the overlap between the annotation and the estimated consensus segmentation is calculated with an accuracy metric.
For this purpose, we use the Dice similarity coefficient (DSC) between the regions A and B as a measure of overlap:

\[
DSC = \frac{2|A \cap B|}{|A| + |B|}
\]

Using the mean regional overlap \(\mu^0\) between the atlas annotations and the consensus segmentation \(\hat{O}_1\), we can discard potentially inaccurately annotated atlas slices if their DSC with \(\hat{O}_1\) is less than this average \(\mu^0\). Following Langerak et al. (2010), we calculate another fusion estimate \(\hat{O}_2\) using the reduced subset of both anatomically similar and reasonably accurate annotations and calculate another mean DSC, \(\mu^2\), and reject the annotations corresponding to \(v^i\) if its DSC with \(\hat{O}_2\) is less than \(\mu^2\).

This procedure is repeated for each annotation in the database. Note that the weakly labelled atlas can be built from the database itself so that no external/additional input is required. An illustration of the approach is provided in Fig. 3.

**Data:** weak annotation for \(v^i\); corresponding WAs in the weakly labelled atlas \(Q\): \(wa^i_q\), \(q \in Q\)

**Result:** \(v^i\) is outlier: yes/no

\(Q^i\) ← \(\{p \in Q : |Q^i| = N_{\text{similar}}\) and \(\sum_{q \in Q^i}||v^i_q - v^i_d|| \rightarrow \min\} ; i = 1; \)

while \(i \leq N_{\text{iterations}}\) do

\(\hat{O}_i\) ← MajorityVote(\(wa^i_q\), \(q \in Q^i\));

\(\mu_i\) ← Average(\(\text{Dice}(\hat{O}_i, wa^i_q)\), \(q \in Q^i\));

\(Q^{i+1}\) ← \(\{p \in Q : \text{Dice}(\hat{O}_i, wa^i_q) \geq \mu_i\}\); \(i \leftarrow i + 1\)

end

if \(\text{Dice}(wa^i_q, Q^{N_{\text{iterations}}}) \geq \mu_{N_{\text{iterations}}}\) then

return yes;

else

return no;

end

**Algorithm 1:** Outlier detection using a weakly labelled, flawed atlas database.

3. Experiments

**Image Database**

The image database used in the experimental setup consists of 150 (114 \(\alpha\), 36 \(\beta\)) abdominal volume CT images with corresponding manual segmentations from expert raters. Available labelled anatomical regions include the liver, spleen, pancreas and the kidneys. All scans were acquired at the Nagoya University Hospital with a TOSHIBA Aquilion 64 scanner and obtained under typical clinical protocols. The volume images were acquired at an in-plane resolution of 512 x 512 voxels (spacing 0.55 to 0.82 mm) and contain between 238 and 1061 slices (spacing 0.4 to 0.8 mm).

**Pre-processing & Generation of Weak Annotations**

Prior to the experiments, all volume image data were affinely registered using the NiftiReg library (Modat et al., 2010) (default parameters) to a random subject to spatially normalize the images and to account for variability in size. Weak annotations are generated for each slice in each direction \(d\) in all volume images of the database, subject to the annotation rate \(AR = \{1, 0.5, 0.33, 0.25, 0.1, 0.05, 0.01\}\) and the error rate \(ERR = \{0, 0.05, 0.1, 0.25, 0.5\}\).

**Liver Segmentation with Weak Annotations**

The weak annotations are fused to compute \(S_{FG}\) and \(S_{BG}\) (see 22) to subsequently compute the data terms \(D_d(x)\) in 19 and the soft constraints in 20. A continuous max-flow segmentation (Yuan et al., 2010a), minimizing 21 is computed to obtain a segmentation result. The regularisation parameter \(\alpha = 4\) in 21 and the parameters \(\alpha_{Potts} = 0.05\) and \(N_k = 16\) in 19 were determined heuristically on a single independent dataset. For the outlier detection, \(N_{\text{iterations}}\) was set to 2. All experiments were performed on an Ubuntu 14.04 desktop machine with a Tesla 40c (NVIDIA Corp., Santa Clara, CA) with 12 GB of memory.

**Experimental Setup**

20 consecutively acquired subject images are used as a subset to examine the impact of \(AR\), \(ERR\) and type
of weak annotation on the mean segmentation accuracy. An average DSC is reported as a measure of accuracy between the obtained segmentations and the expert segmentations $M$ for all the parameter combinations of ERR, AR and all examined annotation types (SC in combination with (BD, RR, PS)), resulting in 2100 single volume segmentations results. Further, the proposed outlier detection (see Section 2.4) is employed using annotations from all 150 subjects. The annotations after outlier removal are used for repeated segmentations, resulting in additional 2100 segmentations. A study on atlas selection [Aljabar et al., 2009] suggests an optimal subset size for brain segmentation to be 20. We increased $N_{similar}$ of the globally similar atlases $Q$ to 30, to account for the variation in abdominal soft tissue organs, such as the liver. A series of paired T-tests is computed to determine significant changes in accuracy at a $p = 0.05$ level between resulting DSC before and after outlier detection.

4. Results

![Figure 4: Example segmentation results](image)

Segmentation Accuracy

Fig. 4 depicts example segmentations of transverse slices on a single subject as comparative visual results with obtained DSC ranges. Visual inspection suggests that a DSC $>0.9$ can be considered an acceptable segmentation result. A DSC of lower than 0.8 can be considered a segmentation failure. Mean accuracy results of all examined methods are shown in Fig. 6. The main contribution to a decrease in accuracy was observed to be high error rates. Without outlier correction, acceptable segmentation results could be obtained with all annotation types, down to an AR of 25%. Using rectangular regions, this accuracy can still be obtained when annotating 1% of available slices, when the ERR is simultaneously less than 5%. In a densely annotated database (i.e. AR = 100%) more than 10% of erroneous annotations lead to segmentation failure. This is particularly interesting for medical image analysis studies considering a crowdsourcing approach with non-redundant annotations of non-experts. This effect still persists to a degree, after outlier correction at the highest tested ERR of 50%.

Performance after Outlier Correction

The mean accuracy improves after the proposed outlier correction, however slight decreases in accuracy are observed at lower error rates. This is mainly due to the decreased number of available annotations after correction. The differences in mean DSC after outlier removal range from $-0.05$ to $+0.94$ (BD), $-0.0006$ to $+0.94$ (RR) and $-0.02$ to $+0.92$ (PS). Statistically significant changes are visualised in Figure 6 (bottom row) and numerical ranges reported in Tab. 4.

| ANN Type | BD | RR | PS |
|----------|----|----|----|
| incr. $N$ (DSC) | 8 (+0.94) | 18 (+0.94) | 10 (+0.92) |
| decr. $N$ (DSC) | 14 (-0.05) | 3 (-0.0006) | 5 (-0.04) |

![Figure 5: Surface rendering of example segmentation results](image)
Figure 6: Top Row: Accuracy results for each annotation type, subject to AR and ERR, without outlier detection. Middle Row: Accuracy results with proposed outlier detection. Bottom Row: Results of paired T-tests between top and middle row (p < 0.05). Increased and decreased mean accuracy are depicted in red and blue, respectively. Black elements show no significant difference.

| Annotation Rate (AR) [%] | Type | 100   | 50    | 33    | 25    | 10    | 5     | 1     |
|--------------------------|------|-------|-------|-------|-------|-------|-------|-------|
| BD                       | 94.3 (0.8) | 94.3 (1.2) | 94.0 (1.4) | 93.3 (2.2) | 88.7 (3.7) | 87.0 (4.0) | 86.9 (3.7) |
| RR                       | 94.6 (0.8) | 94.5 (0.8) | 94.4 (0.8) | 94.3 (0.8) | 94.1 (0.9) | 93.2 (1.2) | 92.1 (1.9) |
| PS                       | 92.1 (1.4) | 92.7 (1.4) | 92.9 (1.4) | 92.8 (1.8) | 89.6 (4.0) | 88.2 (4.8) | 88.8 (4.1) |

5. Discussion

In this study, we tested types of weak annotations to be used for liver segmentation from abdominal CTs. We
examined the effects of different expertise levels and annotation rates of crowd populations for their impact on the segmentation accuracy outcome and proposed a method to remove potential incorrect annotations. In the conducted experiments each of the slices was annotated at most once, reducing the effort associated with the acquisition of redundant annotations.

Segmentation Accuracy
While the max-flow segmentation was employed without any problem-specific adaptions, it yields comparably high accuracy to a state-of-the-art hierarchical multi-atlas approach described in [Wolz et al., 2012], where a mean DSC of 94.4% was reported for the segmentation of the liver. Comparable accuracy was obtained when employing RR annotations at AR = 10% and no errors present or for BD at AR = 50% and ERR = 10%. After the proposed outlier correction, using RR at an AR of 25%, errors of up to 25% yielded similarly high accuracy - a scenario realistic enough to be obtained by a non-expert crowd. Both BD and PS annotation types performed similarly robust to RR at higher annotation rates and yielded acceptable accuracy at AR down to 25% and ERR of up to 25% without outlier correction.

Impact of Expertise and Annotation Rate
An expected decrease in accuracy with both higher ERR and lower AR is observed for all annotation types. We report more robust behaviour of the RR annotations and at a wide range of ERR and at an AR of down to 5%. For BD and PS annotations, AR of less than 25% yielded insufficient accuracy, even at the highest expertise levels (i.e. ERR = 0). For all annotation types, the presence of errors has a larger impact at high AR, suggesting that the total amount of incorrectly annotated image slices is related with segmentation failure, rather than its rate. Without correction, high ERR were tolerated in annotation rates of 1-10%, however lead to segmentation failure (i.e. DSC <0.8) at higher AR. This suggests that an increased number of annotations is not beneficial if performed at an high error rate.

Outlier Correction
The proposed weakly labelled atlas-based outlier detection approach performed well, yielding maximal improvements of >0.9 DSC in accuracy, which is particularly observed in presence of high error rates (see Fig. 6). Its application allows to obtain high quality (DSC >0.9) segmentations at the maximum tested ERR of 50%. At lower ERR, small decreases in accuracy are found. These are associated with a decrease in AR due to outlier removal. This effect can be seen when no annotation errors were present in the atlas prior to outlier correction (i.e. ERR = 0%). Fig. 6 nicely illustrates the existence of an upper accuracy bound (i.e. where ERR = 0%) and the comparable performance at higher ERR after correction.

Conclusions
We tested forms of weak annotations to be used in medical image segmentation problems and examined the effects of expertise and frequency of annotations in their impact on accuracy outcome. Resulting segmentation accuracy was comparable to state-of-the-art performance of a fully-supervised segmentation method and the proposed outlier correction using a weakly labelled atlas was able to largely improve the accuracy outcome for all examined types of weak annotations. The robust performance of this approach suggests that weak annotations from non-expert crowd populations could be used obtain accurate liver segmentations and the general approach can be readily adapted to other organ segmentation problems.

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