Robust Medical Instrument Segmentation Challenge 2019

A Preprint

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ABSTRACT

Intraoperative tracking of laparoscopic instruments is often a prerequisite for computer and robotic-assisted interventions. While numerous methods for detecting, segmenting and tracking of medical instruments based on endoscopic video images have been proposed in the literature, key limitations remain to be addressed: Firstly, robustness, that is, the reliable performance of state-of-the-art methods when run on challenging images (e.g. in the presence of blood, smoke or motion artifacts). Secondly, generalization; algorithms trained for a specific intervention in a specific hospital should generalize to other interventions or institutions.

In an effort to promote solutions for these limitations, we organized the Robust Medical Instrument Segmentation (ROBUST-MIS) challenge as an international benchmarking competition with a specific focus on the robustness and generalization capabilities of algorithms. For the first time in the field of endoscopic image processing, our challenge included a task on binary segmentation and also addressed multi-instance detection and segmentation. The challenge was based on a surgical data set comprising 10,040 annotated images acquired from a total of 30 surgical procedures from three different types of surgery. The validation of the competing methods for the three tasks (binary segmentation, multi-instance detection and multi-instance segmentation) was performed in three different stages with an increasing domain gap between the training and the test data. The results confirm the initial hypothesis, namely that algorithm performance degrades with an increasing domain gap. While the average detection and segmentation quality of the best-performing algorithms is high, future research should concentrate on detection and segmentation of small, crossing, moving and transparent instrument(s) (parts).

Keywords Instrument segmentation · multi-instance segmentation · instrument detection · minimally invasive surgery · robustness · generalization · surgical data science · robot assisted surgery

1 Introduction

Minimally invasive surgery has become increasingly common over the past years [1]. However, issues such as limited view, a lack of depth information, haptic feedback and increased difficulty in handling instruments have increased the complexity for the surgeons carrying out these operations. Surgical data science applications [2] could help the surgeon to overcome those limitations and to increase patient safety. These applications, e.g. surgical skill assessment [3], augmented reality [4] or depth enhancement [5], are often based on tracking medical instruments during surgery. Currently, commercial tracking systems usually rely on optical or electromagnetic markers and therefore also require additional hardware [6, 7], are expensive and need additional space and technical knowledge. Alternatively, with the recent success of deep learning methods in the medical domain [8] and first surgical data science applications [9, 10], video-only based approaches offer new opportunities to handle difficult image scenarios such as bleeding, light over-/underexposure, smoke and reflections [11].

As validation and evaluation of image processing methods is usually performed on the researchers’ individual data sets, finding the best algorithm suited for a specific use case is a difficult task. Consequently, reported publication results are often difficult to compare [12, 13]. In order to overcome this issue, we can implement challenges to find algorithms that work best on specific problems. These international benchmarking competitions aim to assess the performance of several algorithms on the same data set, which enables a fair comparison to be drawn across multiple methods [14, 15].

One international challenge which takes place on a regular basis is the Endoscopic Vision (EndoVis) Challenge [1]. It hosts sub-challenges with a broad variety of tasks in the field of endoscopic image processing and has been held annually at the International Conference on Medical Image Computing and Computer Assisted Interventions (MICCAI) since 2015 (exception: 2016). However, data sets provided for instrument detection/tracking/segmentation in previous EndoVis editions comprised a relatively small number of cases (between ~500 to ~4,000) and generally represented best cases scenarios (e.g. with clean views, limited distortions in videos) which did not comprehensively reflect the challenges in real-world clinical applications. Although these competitions enabled primary insights and comparison of the methods, the information gained on robustness and generalization capabilities of methods were limited.

To remedy these issues, we present the Robust Medical Instrument Segmentation (ROBUST-MIS) challenge 2019, which was part of the 4th edition of EndoVis at MICCAI 2019. We introduced a large data set comprising more than 10,000 image frames for instrument segmentation and detection, extracted from daily routine surgeries. The data set contained images which included all types of difficulties and was annotated by medical experts according to a

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1 https://endovis.grand-challenge.org/
pre-defined labeling protocol and subjected to a quality control process. The challenge addressed methods with a projected application in minimally invasive surgeries, in particular the tracking of medical instruments in the abdomen, with a special focus on the generalizability and robustness. This was achieved by introducing three stages with increase in difficulty in the test phase. To emphasize the robustness of methods, we used a ranking scheme that specifically measures the worst-case performance of algorithms.

Section 2 outlines the challenge design as a whole, including the data set. The results of the challenge are presented in section 3, with a discussion following in section 4. The appendix includes challenge design choices regarding the organization (see appendix A), the labeling and submission instructions (see appendix B and C), the rankings across all stages (see appendix D) and the complete challenge design document (see appendix E).

2 Methods

The ROBUST-MIS 2019 challenge was organized as a sub-challenge of the Endoscopic Vision Challenge 2019 at MICCAI 2019 in Shenzhen, China. Details of the challenge organization can be found in Appendix A and E. The objective of the challenge, the challenge data sets and the assessment method used to evaluate the participating algorithms are presented in the following.

2.1 Mission of the challenge

The goal of the ROBUST-MIS 2019 challenge was to benchmark algorithms designed for instrument detection and segmentation in videos of minimally invasive surgeries. Specifically, we were interested in (1) identifying robust methods for instrument detection and segmentation, (2) assessing the generalization capabilities of the methods proposed and (3) identifying the image properties (e.g. smoke, bleeding, motion artifacts) that make images particularly challenging. The challenges’ metrics and ranking schemes were designed to assess these properties (see section 2.3).

The challenge was divided into three different tasks with separate evaluations and leaderboards (see Figure 1). For the binary segmentation task, participants had to provide precise contours of instruments, using binary masks, with ‘1’ indicating the presence of a surgical instrument in a given pixel and ‘0’ representing the absence thereof. Analogously, for the multi-instance segmentation task, participants had to provide image masks by allotting numbers ‘1’, ‘2’, etc. which represented different instances of medical instruments. In contrast, the multi-instance detection task merely required participants to detect and roughly locate instrument instances in video frames in which the location could be represented by arbitrary forms, such as bounding boxes.

As detailed in section 2.3, the generalizability and performance of all participating algorithms was assessed in three stages with increasing levels of difficulty:

- **Stage 1**: Test data was taken from the procedures (patients) from which the training data were extracted.
- **Stage 2**: Test data was taken from the exact same type of surgery as the training data but from procedures (patients) not included in the training.
- **Stage 3**: Test data was taken from a different but similar type of surgery (and different patients) compared to the training data.

Before the algorithms were submitted to the challenge, participants were only informed of the surgery types for stages 1 and 2 (rectal resection and proctocolectomy, see section 2.2.1). For the third stage, the surgery type (sigmoid resection) was referred to as *unknown surgery* to enable the generalizability to be tested.

2.2 Challenge data set

2.2.1 Data recording

All data was recorded with a Karl Storz Image 1 laparoscopic camera (Karl Storz SE & Co. KG, Tuttlingen, Germany), with a $30^\circ$ optic lens. The Karl Storz Xenon 300 was used as a light source. Data acquisition was executed during daily routine procedures at the Heidelberg University Hospital, Department of Surgery in the integrated operating room (Karl Storz OR1 FUSION®). Whenever parts of the video showed the outside of the abdomen, these frames were manually excluded for the purpose of anonymization. To reduce storage and memory usage, image resolution was reduced from $1920 \times 1080$ pixels (HD) in the primary video to $960 \times 540$. Videos from 30 minimally invasive surgical procedures taken in three different types of surgery, namely 10 rectal resection procedures, 10 proctocolectomy procedures and 10 procedures of sigmoid resection procedures, served as a basis for this challenge. A total of 10,040 images were extracted from these 30 procedures according to the procedure summarized in section 2.2.2.


| Task                      | Easy | Medium | Hard |
|---------------------------|------|--------|------|
| Binary segmentation       | ![Input](#) | ![Contour](#) | ![Contour](#) |
| (a) input                 | ![Input](#) | ![Contour](#) | ![Contour](#) |
| (b) contour               | ![Input](#) | ![Contour](#) | ![Contour](#) |
| Multiple instance         | ![Input](#) | ![Contour](#) | ![Contour](#) |
| detection/segmentation    | ![Input](#) | ![Contour](#) | ![Contour](#) |
| (a) input                 | ![Input](#) | ![Contour](#) | ![Contour](#) |
| (b) contour               | ![Input](#) | ![Contour](#) | ![Contour](#) |

Figure 1: Various levels of difficulty represented in the challenge data for the binary segmentation (two upper rows) and multi-instance detection/segmentation tasks (two lower rows). Input frames (a) are shown along with the reference segmentation masks for all tasks. The latter are shown as contours (b).

2.2.2 Data extraction

The frames were selected according to the following procedures: Initially, whenever the camera was outside the abdomen, the corresponding frames were removed to ensure anonymization. Next, all videos were sampled at a rate of 1 frame/sec, eliciting 4,456 extracted frames. To increase this number, additional frames were extracted during the surgical phase transitions, resulting in a total of 10,040 frames. Labels for the surgical phases were available from the previous challenge *EndoVis Surgical Workflow Analysis in the SensorOR*. All of these frames were annotated as described in 2.2.3.

2.2.3 Label generation

As stated in the introduction, a labeling mask was created for each of the 10,040 extracted endoscopic video frames. The assignment of instances was done per frame, not per video. The instrument labels were generated according to the following procedure: First, the company Understand AI performed initial segmentations on the extracted frames. Following this, the challenge organizers analyzed the annotations, identified inconsistencies and agreed on an annotation protocol (see Appendix B). A team of 14 engineers and four medical students reviewed all of the annotations and, if necessary, refined them according to the annotation protocol. In ambiguous or unclear cases, a team of two engineers and one medical student generated a consensus annotation. For quality control, a medical expert went through all of the refined segmentation masks and reported potential errors. The final decision on the labels was made by a team comprised of a medical expert and an engineer.

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2. https://endovissub2017-workflow.grand-challenge.org/
3. https://understand.ai
2.2.4 Training and test case definition

A training case comprised a 10 second video snippet in the form of 250 endoscopic image frames and a reference annotation for the last frame. For training cases, the entire video was provided as context information along with information on the surgery type. Test cases were identical in format but did not include a reference annotation.

For the division of the data into training and test data, in accordance with the described testing scheme, all sigmoid resection procedures were reserved for stage 3. The two shortest videos per procedure (20%) were selected from the remaining 20 videos for stage 2 in order to have as much training data as possible. Finally, every 10th annotated frame from the remaining 16 videos was used for stage 1 testing. All other frames were released as training data.

No validation cases for hyperparameter tuning were provided by the organizers; hence, it was up to the challenge participants to split the training cases into training and validation data. In summary, this led to a case distribution as shown in Table 1.

Table 1: Case distribution of the data with frames per stage and surgery. Empty frames (ef) were classed as the % of frames in which an instrument did not appear.

| PROCEDURE            | TRAINING | TESTING |
|----------------------|----------|---------|
|                      | Stage 1  | Stage 2 | Stage 3 |
| proctocolectomy      | 2,943 (2% ef.) | 325 (11% ef.) | 225 (11% ef.) | 0 |
| rectal resection      | 3,040 (20% ef.) | 338 (20% ef.) | 289 (15% ef.) | 0 |
| sigmoid resection *   | 0        | 0       | 0       | 2,880 (23% ef.) |
| **TOTAL**            | 5,983 (17% ef.) | 663 (15% ef.) | 514 (13% ef.) | 2,880 (23% ef.) |

*unknown surgery

2.3 Assessment method

2.3.1 Metrics

The following metrics were used to assess performance:

- Binary Segmentation: Dice Similarity Coefficient ($DSC$) [16] and Normalized Surface Dice ($NSD$) [17],
- Multi-instance Detection: Mean Average Precision ($mAP$) [18],
- Multiple Instance Segmentation: Multiple Instance Dice Similarity Coefficient ($MI_DSC$) and Multiple Instance Normalized Surface Dice ($MI_NSD$).

The $DSC$ is a widely used overlap metric in segmentation challenges [19, 20] and is defined as the harmonic mean of precision and recall:

$$DSC(Y, \hat{Y}) := \frac{2|Y \cap \hat{Y}|}{|Y| + |\hat{Y}|},$$

where $Y$ denotes the reference annotation and $\hat{Y}$ the corresponding prediction of an image frame.

The $NSD$ served as a distance-based measurement for assessing performance. In contrast to the $DSC$, which measures the overlap of volumes, the $NSD$ measures the overlap of two surfaces (mask borders) [17]. Furthermore, the metric uses a threshold that is related to the inter-rater variability of the annotators. In our case, the inter-rater variability was computed by a pairwise comparison of a total of 5 annotators over $n = 100$ training images, which resulted in a threshold of $\tau := 13$. Further analysis revealed that thresholds above 10 had no effect on rankings.

According to the challenge design, the indices of instrument instances between the references and predictions did not necessarily match. The only requirement was that each instance was assigned a unique instrument index. Thus, all multi-instance tasks required the prediction and references to be matched, which was computed by applying the Hungarian algorithm [21].

To compute the $MI_DSC$ and $MI_NSD$, matches of instrument instances were computed. Afterwards, the resulting performance scores for each instrument instance per image have been aggregated by the mean. The choice of the

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4The implementation of all metrics can be found here: [https://phabricator.mitk.org/source/rmis2019/](https://phabricator.mitk.org/source/rmis2019/)

5[https://github.com/deepmind/surface-distance](https://github.com/deepmind/surface-distance)
metrics (MI\_DSC and MI\_NSD were based on the Medical Segmentation Decathlon challenge \[19\] for the binary segmentation and the multi-instance tasks.

Finally, the mAP is a metric that is widely used for object detection tasks \[18\]-\[22\]-\[23\]. It computes the precision-recall-curve over all images and averages precision values by computing the area under the curve. The mAP requires that true positives (TP), false negatives (FN) and false positives (FP) are defined. The assignment of matching candidates was done using the Hungarian algorithm. For this purpose, the intersection over union (IoU) was computed for each possible pair of reference and prediction instances, which simply measures the overlap of two areas, divided by their union:

\[
\text{IoU}(Y, \hat{Y}) := \frac{|Y \cap \hat{Y}|}{|Y \cup \hat{Y}|},
\]

where in both cases \(Y\) denotes the reference annotation and \(\hat{Y}\) the corresponding prediction of an image frame. Assigned pairs of references and predictions \((Y, \hat{Y})\) were defined as TP if their \(\text{IoU}(Y, \hat{Y}) > \xi := 0.3\). Reference instances without or with a smaller prediction than \(\xi\) were defined as FN. All instances that could not be assigned to a reference instance were assigned to FP.

### 2.3.2 Rankings

Separate rankings for accuracy and robustness were computed for stage 3 of the challenge in order to address multiple aspects of the challenge purpose. To investigate accuracy, a significance ranking \[14\] as recently applied in the MSD \[19\] and described in Algorithm 1 was computed. The robustness ranking specifically focused on the worst case performance of methods. For this reason, the 5% percentile was computed instead of aggregating metric values with the mean or median. The computation of the mAP naturally included a ranking as the precision values were aggregated across all test cases. This led to a global metric value for each participant which was used to create the ranking. Please note both that the number of test cases and the number of algorithms were generally differed for each task and stage. For the binary and multi-instance segmentation tasks, the rankings were computed for both metrics, namely (MI\_DSC and (MI\_NSD, as shown in Algorithm 1.

#### Algorithm 1: Ranking scheme for the binary and multi-instance segmentation tasks.

1: Let \(T = \{t_1, \ldots, t_N\}\) be the test cases for the given task.
2: \textbf{for all} participating algorithms \(a_i, a_j\) \textbf{do}
3: \quad Determine the performance \(m(a_i, t_j)\) of algorithm \(a_i\) for each test case \(t_j\)
4: \quad \textbf{if} \(m(a_i, t_j) == \text{N/A}\) \textbf{then}
5: \quad \quad \(m(a_i, t_j) = 0\)
6: \quad \textbf{end if}
7: \quad Aggregate metric values \(m(a_i, t_j)\) with the following two aggregation methods:
8: \quad \quad 1. \textbf{Accuracy:} Compute the \textit{significance ranking}. For each pair of algorithms, perform one-sided Wilcoxon signed rank tests with a significance level of \(\alpha = 0.05\) to assess differences in the metric values. The accuracy rank \(r_a(a_i)\) for algorithm \(a_i\) is based on the number of significant test results for each algorithm \[14\]-\[19\].
9: \quad \quad 2. \textbf{Robustness:} Compute the 5\% percentile of all \(m(a_i, t_j)\) to get the robustness rank \(r_r(a_i)\) for algorithm \(a_i\).
10: \textbf{end for}

These procedures produced nine rankings in total, namely four separate rankings (accuracy and robustness ranking for the (MI\_DSC and (MI\_NSD) for the binary and the multi-instance segmentation task respectively and one ranking for multi-instance detection. In every ranking scheme, missing cases were set to the worst possible value, namely 0 for all metrics.

### 2.3.3 Statistical analyses

The stability of the rankings was investigated via bootstrapping as this approach was identified as appropriate for quantifying ranking variability \[14\]. The analysis was performed using the R package \texttt{challengeR} \[24\]-\[25\]. The package was further used to create plots that visualize (1) the absolute frequency of test cases in which each algorithm achieved the different ranks and (2) the bootstrap results for each algorithm.

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6 Please note that an algorithm \(A\) with a higher rank (according to the significance ranking) than algorithm \(B\) did not necessarily perform significantly better than algorithm \(B\), as detailed in \[24\].
2.3.4 Further analyses

For further analyses, the influence of the image artifacts and the size and number of instruments were analyzed. For this purpose, the 100 cases with the worst performance were analyzed to investigate which image artifacts cause the main failures of the algorithms.

3 Results

In total, 75 participants registered on the Synapse challenge website [26] before the submission deadline. Aside from one team that decided to be excluded from the rankings, all teams with a working docker[7] submission were included in this paper. Their participation over the three challenge tasks and the total amount of submissions is summarized in Table 2.

Table 2: Overview of selected participating teams over the three tasks, namely binary segmentation (BS), multi-instance detection (MID) and multi-instance segmentation (MIS).

| Team identifier | BS | MID | MIS | Affiliations |
|-----------------|----|-----|-----|--------------|
| caresyntax      | x  | x   | x   | 1 caresyntax, Berlin, Germany |
| CASIA_SRL      | x  | x   |     | 1 University of Chinese Academy Sciences, Beijing, China |
|                |    |     |     | 2 State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, China |
| Djh             | x  |     |     | 1 SimulaMet, Oslo, Norway |
|                |    |     |     | 2 Arctic University of Norway (UiT), Tromsø, Norway |
|                |    |     |     | 3 Oslo Metropolitan University (Oslomet), Oslo, Norway |
| fisensee       | x  | x   | x   | 1 University of Heidelberg, Germany |
|                |    |     |     | 2 Division of Medical Image Computing (MIC), German Cancer Research Center, Heidelberg, Germany |
| haoyun          | x  |     |     | 1 Department of Computer Science, School of Informatics, Xiamen University, Xiamen, China and School of Mechanical Engineering, University of Electronic Science and Technology of China, Chengdu, China |
| NCT            | x  |     |     | 1 National Center for Tumor Diseases (NCT), Partner Site Dresden, Germany: German Cancer Research Center (DKFZ), Heidelberg, Germany |
|                |    |     |     | 2 Faculty of Medicine and University Hospital Carl Gustav Carus, Technische Universität Dresden, Dresden, Germany |
|                |    |     |     | 3 Helmholtz Association/Helmholtz-Zentrum Dresden - Rossendorf (HZDR), Dresden, Germany |
| SQUASH         | x  | x   | x   | 1 Institute of Information Technology, Klagenfurt University, Austria |
| Uniandes       | x  | x   | x   | 1 Universidad de los Andes, Bogotá, Colombia |
| VIE            | x  | x   | x   | 1 Institute of Digital Media (NELVT), Peking University, Peking, China |
| www            | x  | x   | x   | 1 Department of Computer Science, School of Informatics, Xiamen University, Xiamen, China |
|                |    |     |     | 2 Department of Computer Science Engineering, The Chinese University of Hong Kong, Hong Kong, China |

valid submissions | 10 | 6   | 7   |
invalid submissions | 2  | 1   | 1   |
TOTAL             | 12 | 7   | 8   |

3.1 Method descriptions of participating algorithms

In the following, the participating algorithms are briefly summarized based on a description provided by the participants upon submission of the challenge results. Further details can be found in Table 3.

[7]https://www.docker.com/
Team **caresyntax**: Single network fits all

The **caresyntax** team’s core idea for multi-instance segmentation was to apply a Mask R-CNN [27] based on a single network with shared convolutional layers for both branches. They hypothesized that it would help the network to generalize better if it was only provided with limited training data. The team decided to use a pre-trained version of the Mask R-CNN without including any temporal information from the videos. In their results, they reported that their approach outperformed a U-Net-based model by a significant margin. The team worked out that tuning pixel-level and mask-level confidence thresholds on the predictions played an important role. Furthermore, they acknowledged the importance that the training set size had for improved predictions, both qualitatively and quantitatively. The team participated in all three tasks using the same method. They produced the same output for the multi-instance segmentation and detection tasks and binarized the output of the multi-instance segmentation for the binary segmentation task.

Team **CASIA_SRL**: Dense pyramid attention network for robust medical instrument segmentation

The **CASIA_SRL** team proposed a network named Dense Pyramid Attention Network [28] for multi-instance segmentation. They mainly focused on two problems: Changes in illumination and surgical instruments scale changes. They proposed that an attention module should be used, which was able to capture second-order statistics, with the goal of covering semantic dependencies between pixels and capturing the global context [28]. As the scale of surgical instruments constantly changes as they move, the team introduced dense connections across scales to capture multi-scale features for surgical instruments. The team did not use the provided videos to complement the information contained in the individual frames. The team participated in the binary and multi-instance segmentation tasks. They produced the same output for the multi-instance segmentation and detection tasks and binarized the output of the multi-instance segmentation for the binary segmentation task.

Team **Djh**: A RASNet-based deep learning approach for the binary segmentation task

The **Djh** team only participated in the binary segmentation task. They used the Refined Attention Segmentation Network [29] and put a large amount of effort into data augmentation and hyperparameter tuning. Their motivation for using this architecture was its U-shape design which consists of contracting and expanding paths like the ResUNet++ [30]. The RASNet is able to capture low-level and higher-level features. The team did not use the videos provided to complement the information contained in the individual frames.

Team **fisensee**: OR-UNet

Team **fisensee**’s core idea was to optimize a binary segmentation algorithm and then adjust the output with a connected component analysis in order to solve the multi-instance segmentation and detection tasks [31]. Inspired by the recent successes of the nnU-Net [32], the authors used a simple established baseline architecture (the U-Net [33]) and iteratively improved the segmentation results through hyperparameter tuning. The method, referred to as optimized robust residual 2D U-Net (OR-UNet), was trained with the sum of DSC and cross-entropy loss and a multi-scale loss. During training, extensive data augmentation was used to increase robustness. For the final prediction, they used an ensemble of eight models. They hypothesized that ensembles perform better than a single network. In their report, the team wrote that they attempted to use the temporal information by stacking previous frames but did not observe a performance gain. Additionally, they noticed that in many cases, instruments did not touch thus they used a connected component analysis [34] to separate instrument instances.

Team **haoyun**: Robust medical instrument segmentation using enhanced DeepLabV3+

The **haoyun** team only participated in the binary segmentation task. They based their work on the DeepLabV3+ [35] architecture in order to focus on high-level information. To enrich the receptive fields, they used a pre-trained ResNet-101 [36] with dilated convolutions as encoder. To train their network, the team combined the DSC with the focal loss [37] in order to focus more on less accurate pixels and challenging images. In addition, the team used a 5-fold cross validation to improve both generalization and stability of the network. They did not use the provided videos to complement the information contained in the individual frames.

Team **NCT**: Robust medical instrument segmentation in robot-assisted surgery using deep convolutional neuronal network

The **NCT** team only participated in the binary segmentation task. They used a TernausNet with a pre-trained VGG16 network [38] as TernausNet had already showed promising results in two previous MICCAI EndoVis segmentation challenges from 2017 and 2018 [39]. The team did not use the provided videos to complement the information contained in the individual frames.
Team **SQUASH**: An ensemble of models, combining image frame classification and multi-instance segmentation

Team **SQUASH**’s hypothesis was that they could increase the robustness and generalizability of all challenge tasks simultaneously by using multiple recognition task training. In training their method from scratch, they assumed that the network capabilities were fully utilized to learn detailed instrument features. Based on a ResNet50 \[36\], the team used the video data provided and built a classification model in order to predict all instrument frames in a sequence of video frames. On top of this classification model, they built a segmentation model by employing a Mask R-CNN \[27\] to detect multiple instrument instances in the image frames. The segmentation model was trained by leveraging the preliminary trained classification model on instrument images as a feature extractor to deepen the learning of the task of instrument segmentation. Both models were combined in a two-stage framework to process a sequence of video frames. The team reported that their method had trouble dealing with instrument occlusions, but on the other hand, they were surprised to find that it handled reflections and black borders well.

Team **Uniandes**: Instance-based instrument segmentation with temporal information

Team **Uniandes** based their multi-instance segmentation approach on the Mask R-CNN \[27\]. For training purposes, they created an experimental framework with a training and validation split as well as supplementary metrics in order to identify the best version of their method and gain insight into the performance and limitations. Data augmentation was performed by calculating the optical flow with a pre-trained FlowNet2 \[40\] and using the flow to map the reference annotation on to the previous frames. However, they did not find significant benefits in using the augmentation technique. The team participated in all three tasks. They produced the same output for the multi-instance segmentation and detection tasks and binarized the output of the multi-instance segmentation for the binary segmentation task. The team observed that their approach was limited in terms of finding all instruments in an image frame, but once an instrument was found it was segmented with a high DSC score. Although the team achieved good metric scores they stated that they fell short in segmenting small or partial instruments and instruments covered by smoke.

Team **VIE**: Optical flow-based instrument detection and segmentation

The **VIE** team approached the multi-instance segmentation task with an optical flow-based method. Their hypothesis was that the detection of moving parts in the image enables medical instruments to be detected and segmented. For their approach, they calculated the optical flow over the last five frames of a case by using the OpenCV library and concatenated the optical flow with the raw image as input for a Mask R-CNN \[27\]. The team assumed that this would reduce most of unnecessary clutter segmentation. The team participated in all three tasks. They produced the same output for the multi-instance segmentation and detection tasks and binarized the output of the multi-instance segmentation for the binary segmentation task. The team hypothesized that the temporal data could have been used more effectively.

Team **www**: Integration of Mask R-CNN and DAC block

Team **www** proposed that a framework based on Mask R-CNN \[27\] to handle the three tasks in the challenge. Based on the observation that the instruments have variable sizes, their idea was to enlarge the receptive field and tune the anchor size for the Mask R-CNN. In addition, the team integrated DAC blocks \[41\] into the framework to collect more information. The team participated in all three tasks. They produced the same output for the multi-instance segmentation and detection tasks and binarized the output of the multi-instance segmentation for the binary segmentation task. The team reported that including temporal information might have helped to improve their performance.\[9\]

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\[8\] https://opencv.org/

\[9\] Please note that this team used data from the EndoVis 2017 challenge \[39\] to visually check their performance on a different medical data set. The participation policies (see appendix \[A\]) prohibit the use of other medical data for algorithm training or hyperparameter tuning. The challenge organizers defined this case as a grey zone but noted that the team may have had a competitive advantage in terms of performance generalization.
Table 3: Overview of submitted methods. Abbreviations are as follows: Stochastic gradient descent (SGD) [42], adaptive moment estimation (Adam) [43].

| Team          | Basic architecture | Video data used? | Additional data used? | Loss functions | Data augmentation                                                                 | Optimizer |
|---------------|--------------------|------------------|-----------------------|----------------|----------------------------------------------------------------------------------|-----------|
| caresyntax    | Mask R-CNN [27]    | No               | ResNet-50 pre-trained on MS-COCO [22] | Smooth L1 loss, cross entropy loss, binary cross entropy loss | Applied in each epoch: Random flip (horizontally) with probability 0.5 | SGD [42] |
| CASIA_SRL     | Dence Pyramid Attention Network [28] (backbone: ResNet-34 [36]) | No               | ResNet-34 backbone pre-trained on ImageNet [23] | Hybrid loss: cross entropy $-\alpha \log(Jaccard)$ | Data augmented once before training: Random rotation, shifting, flipping | Adam [43] |
| Djh           | RASNet [29]        | No               | ResNet50 pre-trained on ImageNet [30] | DSC coefficient loss | Applied on the fly on each batch: Crop (random and center), flip (horizontally and vertically), scale, cutout, greyscale | Adam [43] |
| fisensee      | 2D U-Net [33] with residual encoder | No               | No                     | Sum of DSC and cross-entropy loss | Randomly applied on the fly on each batch: Rotation, elastic deformation, scaling, mirroring, Gaussian noise, brightness, contrast, gamma | SGD [42] |
| haoyun        | DeepLabV3+ [35] with ResNet-101 encoder | No               | ResNet-101 pre-trained on ImageNet [23] | Logarithmic DSC loss | Applied on the fly on each batch: Flip (vertically), crop (random) | Adam [43] |
| NCT           | TernausNet [38], replaced ReLU with eLU [44] | No               | VGG16 pre-trained on ImageNet [23] | Weighted binary cross entropy in combination with Jaccard Index | Applied on the fly on each batch: Flips (horizontally and vertically), rotations of $[-10, 10]^\circ$; image contrast manipulations (brightness, blur, motion-blur) | Adam [43] |
| SQUASH        | Mask R-CNN [27] (backbone: ResNet-50 [36]) | Yes, to estimate the probability that last frame of video shows instrument instance | No | ResNet-50: Focal loss, Mask R-CNN: Mask R-CNN loss + cross entropy loss | 35% of total input for classification: Gaussian blur, sharpening, gamma contrast enhancement; additional 35% of images: Mirroring (along x- and y-axes); minority class: Translation (horizontally); non-instrument image frames are not processed | SGD [42] |
| Uniandes      | Mask R-CNN [27] (backbone: ResNet-101 [36]) | Yes, for data augmentation | Pre-trained on MS-COCO [22] | Standard Mask R-CNN loss functions | Applied on the fly on each batch: Random flips (horizontally), propagation of annotation backwards to previous video frames | SGD [42] |
| VIE           | Mask R-CNN [27] (backbone: ResNet-50 [36]) | Yes, calculating the optical flow over 5 frames | No | RPN class loss, MASK R-CNN loss | Applied on the fly on each batch: Image resizing (1024x1024), bounding boxes, label generation | N/A       |
| www          | Mask R-CNN [27] (backbone: ResNet-50 [36]) | No               | Pre-trained on ImageNet [23] | Smooth L1 loss, focal loss, binary cross entropy loss | Applied on the fly on each batch: Random flip (horizontally and vertically), rotations of $[0, 10]^\circ$ | Adam [43] |
3.2 Individual performance results for participating teams

The teams’ individual performances in both segmentation tasks are presented in Figure 2. The dot- and boxplots show the metric values for each algorithm over all test cases in stage 3.

![Figure 2: Dot- and boxplots showing the individual performances of algorithms on the binary segmentation (BS; top) and multi-instance segmentation (MIS; bottom) tasks. The (multi-instance) Dice Similarity Coefficient (MI_DSC; left) and the (multi-instance) Normalized Surface Distance (MI_NSD; right) were used as metrics.](image)

3.3 Challenge rankings for stage 3

As described in section 2.3.2, an accuracy and a robustness ranking were computed for both metrics of the segmentation tasks (resulting in 4 rankings for each task). These are shown in Tables 4 and 6. For the multi-instance detection task, the mAP was computed for each participant (see Table 5). The metric computation already included aggregated values, therefore only one ranking was computed for this task.

To provide deeper insight in the ranking variability, ranking heatmaps (see Figure 3) and blob plots (see Figure 4) were computed for all rankings of both segmentation tasks. Ranking heatmaps were used to visualize the challenge assessment data [24]. Blob plots were used to visualize ranking stability based on bootstrap sampling [24].

The computed rankings for the remaining stages are given in Appendix D.
Table 4: Binary segmentation: Rankings for stage 3 of the challenge. The upper part of the table shows the Dice Similarity Coefficient (DSC) rankings and the lower part shows the Normalized Surface Distance (NSD) rankings (accuracy rankings on the left, robustness rankings on the right). Each ranking contains a team identifier, either a proportion of significant tests divided by the number of algorithms (prop. sign.) for the accuracy ranking or an aggregated DSC/NSD value (aggr. DSC/NSD value) and a rank.

| Team identifier | Prop. Sign. | Rank | Team identifier | Aggr. DSC Value | Rank |
|-----------------|-------------|------|----------------|-----------------|------|
| fisensee        | 1.00        | 1    | haoyun         | 0.52            | 1    |
| haoyun          | 0.89        | 2    | CASIA_SRL      | 0.50            | 2    |
| CASIA_SRL      | 0.78        | 3    | www9           | 0.49            | 3    |
| Uniandes        | 0.67        | 4    | fisensee       | 0.34            | 4    |
| caresyntax      | 0.56        | 5    | Uniandes       | 0.28            | 5    |
| SQUASH          | 0.44        | 6    | SQUASH         | 0.22            | 6    |
| www9           | 0.33        | 7    | caresyntax     | 0.00            | 7    |
| Djh             | 0.22        | 8    | Djh             | 0.00            | 7    |
| VIE             | 0.11        | 9    | NCT             | 0.00            | 7    |
| NCT             | 0.00        | 10   | VIE             | 0.00            | 7    |

| Team identifier | Prop. Sign. | Rank | Team identifier | Aggr. NSD Value | Rank |
|-----------------|-------------|------|----------------|-----------------|------|
| haoyun          | 0.89        | 1    | haoyun         | 0.63            | 1    |
| fisensee        | 0.89        | 1    | CASIA_SRL      | 0.62            | 2    |
| CASIA_SRL      | 0.67        | 3    | www9           | 0.57            | 3    |
| Uniandes        | 0.67        | 3    | fisensee       | 0.45            | 4    |
| caresyntax      | 0.56        | 5    | Uniandes       | 0.32            | 5    |
| www9           | 0.44        | 6    | SQUASH         | 0.26            | 6    |
| SQUASH          | 0.33        | 7    | caresyntax     | 0.00            | 7    |
| VIE             | 0.22        | 8    | Djh             | 0.00            | 7    |
| NCT             | 0.11        | 9    | NCT             | 0.00            | 7    |
| Djh             | 0.00        | 10   | VIE             | 0.00            | 7    |

Table 5: Multi-instance detection: Ranking for the mean average precision (mAP) in stage 3 of the challenge.

| Team identifier | mAP Value | Rank |
|-----------------|-----------|------|
| Uniandes        | 1.00      | 1    |
| VIE             | 0.98      | 2    |
| caresyntax      | 0.97      | 3    |
| SQUASH          | 0.97      | 4    |
| fisensee        | 0.96      | 5    |
| www9           | 0.94      | 6    |
Table 6: Multi-instance segmentation: Rankings for stage 3 of the challenge. The upper part of the table shows the Multiple Instance Dice Similarity Coefficient (\(MI\_DSC\)) rankings and the lower part shows the Multiple Instance Normalized Surface Distance (\(MI\_NSD\)) rankings (accuracy rankings on the left, robustness rankings on the right). Each ranking contains a team identifier, either a proportion of significant tests divided by the number of algorithms (prop. sign.) for the accuracy ranking or an aggregated \(MI\_DSC/MI\_NSD\) value (aggr. \(MI\_DSC/MI\_NSD\) value) and a rank.

| Team identifier | Prop. Sign. | Rank | Team identifier | Aggr. \(MI\_DSC\) Value | Rank |
|-----------------|-------------|------|-----------------|--------------------------|------|
| fisensee        | 1.00        | 1    | www             | 0.31                     | 1    |
| Unianes         | 0.83        | 2    | Uniandes        | 0.26                     | 2    |
| caresyntax      | 0.67        | 3    | SQUASH          | 0.22                     | 3    |
| SQUASH          | 0.33        | 4    | CASIA_SRL       | 0.19                     | 4    |
| www             | 0.33        | 4    | fisensee        | 0.17                     | 5    |
| VIE             | 0.17        | 6    | caresyntax      | 0.00                     | 6    |
| CASIA_SRL       | 0.00        | 7    | VIE             | 0.00                     | 6    |

Figure 3: Ranking heatmaps for the four rankings in the binary segmentation and multi-instance segmentation tasks. Each cell \((i, A_j)\) shows the absolute frequency of test cases in which algorithm \(A_j\) achieved rank \(i\). The plots were generated using the package challengeR [24, 25].
3.4 Comparison across all stages

Figure 5 shows the comparison of the average (MI)_DSC performances of the participating algorithms over the three evaluation stages (see section 2) for both segmentation tasks. For this purpose, boxplots were generated for both tasks over the average metric values per team. A clear performance drop is visible in line with the increasing difficulty of the stages: Average performance produces median values of 0.88 (min: 0.73, max: 0.92) for the binary segmentation task and 0.80 (min: 0.65, max: 0.84) for the multi-instance segmentation task for stage 1. For stage 2, the median metric values decrease to 0.87 (min: 0.76, max: 0.90) and 0.78 (min: 0.64, max: 0.84) and finally, the performance for stage 3 resulted in a median of 0.85 (min: 0.69, max: 0.89) and 0.76 (min: 0.60, max: 0.80).

3.5 Further analysis

For further analyses, we investigated the image frames that produced the 100 best or worst metric values of participating teams. This investigation revealed the strengths and weaknesses of the proposed methods. In general, algorithm performance drops with the number of instruments in the image as illustrated in Figure 6. The algorithms succeeded in images containing reflections, blood, different illuminations and in finding the inside of the trocar. Problems still arose in image frames which contained small and transparent instruments (see Figure 7). False positives (mainly objects that were not defined as instruments) turned out to be a problem for all tasks. Furthermore, algorithm performance was poor for images with instruments, close to another as well as crossing, partially hidden or moving instruments, instruments close to the image border and images containing smoke (see Figure 8).
Figure 5: Boxplots of the variance across all test images for the (a) binary segmentation task with the Dice Similarity Coefficient (DSC) and (b) the multi-instance segmentation task with the Multi-instance Dice Similarity Coefficient (MI\_DSC) for stages 1 to 3. The boxplots show the average algorithm performances (mean over all participant predictions per image) per image.

Figure 6: Boxplots of mean (multi-instance) Dice Similarity Coefficient (MI\_DSC) values of participating algorithms for the binary and multi-instance segmentation tasks for stages 1 to 3 stratified by the number of instruments in the video frames.

4 Discussion

We organized the first challenge in the field of surgical data science that (1) included tasks on multi-instance detection/tracking and (2) placed particular emphasis on the robustness and generalization capabilities of the algorithms. The key insights are:

1. Competing methods: These state-of-the-art methods are exclusively based on deep learning with a specific focus on U-Nets [33] (binary segmentation) and Mask R-CNNs [27] (multi-instance detection and segmentation). For binary segmentation, the U-Net and the new DeepLabV3 architecture yielded an equally strong performance. For the multi-instance segmentation, a U-Net in combination with a connected component analysis was a strong baseline, but a Mask R-CNN approach was more promising overall, especially in terms of robustness.

2. Performance:
Figure 7: Test case with small instruments. The top row shows the raw image frame, the outlined contours of three instrument instances and the reference mask. The bottom row shows the results of four participating teams and their masks and as their respective Dice Similarity Coefficient (DSC) values.

Figure 8: Test case with instruments close to each other. The top row shows the raw image frame, the outlined contours of two instrument instances and the reference mask. The bottom row shows the results of four participating teams and their masks and their respective Dice Similarity Coefficient (DSC) values.

(a) Binary segmentation: The mean performances of the winning algorithms for the accuracy ranking (DSC of 0.88) and the robustness ranking (DSC of 0.89) were similar to that of the previous winners of binary segmentation challenges (winner of the EndoVis Instrument Segmentation and Tracking Challenge 2015\[^{10}\] DSC of 0.84; winner of the EndoVis 2017 Robotic Instrument Segmentation Challenge \[^{39}\]: DSC of 0.88). Given the high complexity of ROBUST-MIS’ data in comparison to previously released data sets, we attribute the fact that the performances are similar to the high amount of training data.

(b) Multi-instance detection: All participants achieved mAP values ≥ 0.94 for stage 3. The winning algorithms featured very high accuracy, robustness and generalization capabilities. The few failure cases were related to the detection of small instruments, instruments close to another or instruments close to the image border.

\[^{10}\]https://endovissub-instrument.grand-challenge.org/
(c) Multi-instance segmentation: The mean $MI_{DSC}$ scores for the winning algorithm of the accuracy ranking were
- 0.82 for cases with one instrument instance,
- 0.71 for cases with two instrument instances,
- 0.62 for cases with three instrument instances,
- 0.45 for cases with more than three instrument instances.

Multi-instance segmentation in endoscopic video data, therefore cannot be regarded as a solved problem.

3. Generalization: All participating methods for the binary segmentation tasks had a satisfying generalization capability over all three stages, with a median drop from 0.88 (stage 1) to 0.85 (stage 3; 3%). The generalization capabilities for the multi-instance segmentation were slightly worse, with a median drop form 0.80 (stage 1) to 0.76 (stage 3; 5%).

4. Robustness: The most successful algorithms are robust to reflections, blood and smoke. The segmentation of small, close positioned, transparent, moving, overlapping and crossing instruments, however, remains a great challenge that needs to be addressed.

The following sections provide a detailed discussion on the challenge infrastructure (section 4.1.1), challenge data (section 4.1.3), challenge methods (section 4.2.1) and challenge results (section 4.2.2).

4.1 Challenge design

In this section, we discuss the infrastructure and the data of our challenge.

4.1.1 Challenge infrastructure

We decided to use Synapse as our challenge platform as it is the underlying platform of the well-known and DREAM challenges and, as such, provides a complete and easy to use environment for both challenge participants and organizers. Furthermore, in addition to helping organizers monitor on how a challenge should be structured, it also helps them to follow current best practices by relying on docker submissions. However, while the overall experience with Synapse was very good, downloading the data was a problem due to slow download rates, which were dependent on the global download location and the size of the data set (about 400 GB). Unlike the data download, the docker upload was very quick and easy to follow.

The submission of docker containers and complete evaluation is already in common usage in other disciplines (e.g. CARLA). However, most of the very recent challenges in the biomedical image analysis community still use plain results submissions (e.g. BraTS, KiTS2019, PAIP 2019). We believe that using dockers for the evaluation is the best way as it can help (1) to avoid test data set overfitting and (2) to prevent potential instances of fraud such as manually labeling the test data [45]. However, using docker containers also means more work for the individual participants (in creating of the docker containers) and for the organizers. In addition to providing the Computing Processing Unit (CPU) and Graphics Processing Unit (GPU) resources, they have to provide support for docker related questions and must have a strategy for dealing with invalid submissions (e.g. allowing re-submission). In our challenge for example, submitted dockers were run on a small proportion of the training set to check whether the submissions worked. For five participants, the first submission failed. They were allowed to re-submit but we manually checked whether the network parameters had changed.

4.1.2 Metrics and Ranking

Following recommendations of the Medical Segmentation Decathlon, we decided to use two metrics for the segmentation task; an overlap measure ($DSC$) and a distance measure ($NSD$). We used a non-global $DSC$ for the multi-instance segmentation, meaning that the $DSC$ values of instrument instances were first averaged to get an image-based score before taking the mean over all images. Another option would have been to use a global $DSC$ measure, which would compute the $DSC$ score globally over the complete data set and all instrument instances. However, we decided to use the non-global metric to give higher weight to small instruments.

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11https://www.synapse.org/
12http://dreamchallenges.org/
13https://carlachallenge.org/
14http://braintumorsegmentation.org/
15https://kits19.grand-challenge.org/rules/
16https://paip2019.grand-challenge.org/
To put a particular focus on the robustness of the methods, we decided to compute a dedicated ranking for the 5% percentile performance of the methods, as summarized in Section 2.3.2. Given our previous work on ranking stability [14], it can be assumed that a ranking based on the 5% percentile would naturally lead to less robust rankings compared to an aggregation with the mean or the median. This is one possible explanation for the fact that the ranking stability for the robustness ranking was worse compared to that of the accuracy ranking, as shown in Figure 4.

4.1.3 Challenge data

In general, we observed many inconsistencies in the initial data annotation, which is why we introduced a structured multi-stage annotation process involving medical experts and following a pre-defined annotation protocol (see appendix B). We recommend challenge organizers to generate such a protocol from the outset of their challenge.

It should be noted that three different surgical procedures were used for the challenge, yet, these three procedures are all colorectal surgeries that share similarities. A rectal resection incorporates parts of a sigmoid resection, for example. It is possible that performance drops will be more radical when analyzing a wider variety of procedures such as biliopancreatic or upper gastrointestinal surgeries.

In the future, we will also prevent the potential side effects which resulting from pre-processing. The fact that we downsampled our video images may have harmed performance. However, due to the fact that (1) all participants had the same starting conditions, (2) the applied CNNs methods had to fit to GPUs and (3) all participants reduced the resolution further, we think that these effects are only minor.

4.2 Challenge outcome

4.2.1 Methods

The variability of all of the methods, submitted for the binary segmentation was vast and ranged from 2D U-Net versions (TernausNet, multi scale U-Net) to different implementations of the Mask R-CNN with a ResNet backbone to the latest DeepLabV3 network architecture. For the multi-instance detection and multi-instance segmentation tasks, however, the range of the underlying architecture was much narrower, with multiple Mask R-CNN variations and one combination of a U-Net, a classical approach and the principal component analysis (see Table 3).

The most successful participating team (haoyun) in the binary segmentation task implemented a DeepLabV3+ architecture which gave them the top rank in three out of the four rankings for the binary segmentation task. A relatively simple approach based on the combination of a U-Net with a connected component analysis by the fisensee team turned out to be a strong baseline and won accuracy rankings in both the binary segmentation task and the DSC accuracy ranking for the multi-instance segmentation task. It was, however, less successful in terms of robustness.

An increasingly relevant problem in reporting challenge results is the fact that it is often hard to understand which specific design choice for a certain algorithm make this algorithm better than the competing methods [14]. Based on our challenge analysis, we hypothesize that data augmentation and the specifics of the training process are the key to a winning result. In other words, we believe that focusing on one architecture and performing a broad hyperparameter search in combination with an extensive data augmentation technique and a well-thought-out training procedure will create more benefit than testing many different network architectures without optimizing the training process. This is in line with recent findings in the field of radiological data science [32].

4.2.2 Results

The key insights have already been summarized at the beginning of the discussion. Methods that tackle the multi-instance segmentation performed worse compared to the binary segmentation task. In fact, when multiple instrument instances were visible in one image, the algorithm performance decreased dramatically from over 0.8 for one instance to less than 0.6 for more than three instances (see Figure 6). This is also reflected in Figure 2 (c) and (d), which show clusters in the boxplots at specific metric values. These clusters correspond to the performance with respect to different numbers of instrument instances. For a single instrument, metric values are high, for multiple instruments the metric values are grouped around lower values. We thus conclude that detection of multiple instances remains an unsolved problem.

By analyzing the worst 100 cases across all of the methods, we found that all methods generally had issues with small, transparent or fast moving instruments. In addition, instruments close to other instruments or the image border, as well as partially hidden or crossing instruments were difficult to detect and segment (see Figures 7 and 8). We also observed that classic challenges [11] such as reflections, blood, different illumination conditions did not pose any great problems. Images acquired when the lens of the endoscope was inside of a trocar were not particularly difficult to process.
It should be noted that only three of the ten methods incorporated the temporal video information provided with the frames to be annotated. One method used the video information to predict the likelihood of instrument presence in a multi-task setting while two approaches used the videos to calculate the optical flow. However, based on the team reports and on the challenge results, none of the teams where able taking a benefit from using the video data, neither for the binary segmentation task, nor for the multi-instance detection/segmentation tasks. Given the way in which medical and technical experts annotated the data, this is surprising, and we speculate that much of the potential of temporal context remains to be discovered.

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[32] Fabian Isensee, Jens Petersen, Andre Klein, David Zimmerer, Paul F Jaeger, Simon Kohl, Jakob Wasserthal, Gregor Koehler, Tobias Norajitra, Sebastian Wirkert, et al. nnu-net: Self-adapting framework for u-net-based medical image segmentation. *arXiv preprint arXiv:1809.10486*, 2018.

[33] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.
Appendix

A Challenge organization

The “Robust Medical Instrument Segmentation Challenge 2019 (ROBUST-MIS 2019)” was organized as a sub-challenge of the Endoscopic Vision Challenge 2019 at the International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI) in Shenzhen, China. It was organized by T. Roß, A. Reinke, M. Wagner, H. Kenngott, B. Müller, A. Kopp-Schneider and L. Maier-Hein. See section A.2 for detailed description. The challenge was intended as a one-time event with a fixed submission deadline. The platforms grand-challenge.org [46] and synapse.org [26] served as websites for the challenge. Synapse served as data providing platform which was further used to upload the challenge participants’ submissions.

The participation policies for the challenge allowed only fully automatic algorithms to be submitted. Although it was possible to use publicly available data released outside the field of medicine to train the methods or to tune hyperparameters, it was forbidden to use any medical data, besides the training data offered by the challenge. For members of the organizers’ departments it was possible to participate in the challenge but they were not eligible for awards and their participation would have been highlighted in the leaderboards. The challenge was funded by the
company Digital Surgery with a total monetary award of 10,000€. As the challenge comprised 9 rankings in total (see section 2.3.2), each winning team was awarded 1,000€ and each runner-up team 125€. Moreover, the top three performing methods for each ranking were announced publicly. The remaining teams could decide whether or not their identity was revealed. One team decided not to be mentioned in the rankings. Finally, for this publication, each participating team could nominate members of their team as co-authors. The method description submitted by the authors was used in the publication (see section 3.1). Personal data of the authors include their names, affiliations and contact addresses. References used in the method description were published as well. Participating teams are allowed to publish their results separately with explicit permission from the challenge organizers once this paper has been accepted for publication.

The submission instructions for the participating methods are published on the Synapse website and consist of a detailed description of the submission of docker containers which were used to evaluate the results. The complete submission instructions are provided in appendix C. Algorithms were only evaluated on the test data set, so no leaderboard was published before the final result submission. The initial training data set was released on 1st July 2019, the final training data set on 5th August 2019. Participants could register for the challenge until 14th September 2019. The docker submission took place between 15th September and 28th September 2019. There were two deadlines, the 21th September for participants, whose methods would require more than 3h of runtime and the 28th September for participants, whose dockers needs less than 3h runtime. Participating teams had to submit a method description in addition to the docker containers.

The data sets of the challenge were fully anonymized (see section 2.2) and could therefore be used without any ethics approval [47]. By registering in the challenge, each team agreed (1) to use the data provided only in the scope of the challenge and (2) to neither pass it on to a third party nor use it for any publication or for commercial use. The data will be made publicly available for non-commercial use.

The evaluation code for the challenge was made publicly available [48] and participants were encouraged to release their methods in open source.

A.1 Conflicts of interest

This challenge is funded by the National Center for Tumor Diseases (NCT) Heidelberg and is/was further supported by UNDERSTAND.AI[17], NVIDIA GmbH[18], and Digital Surgery[19]. All challenge organizers and some members of their institute had access to training and test cases and were therefore not eligible for awards.

A.2 Author contributions

All authors read the paper and agreed to publish it.

- T. Roß and A. Reinke organized the challenge, performed the evaluation and statistical analyses and wrote the manuscript
- P.M. Full, H. Hempe, D. Mindroc-Filimon, P. Scholz, T.N. Tran and P. Bruno reviewed and labeled the challenge data set
- M. Wagner, H. Kenngott, B.P. Müller-Stich organized the challenge and performed the medical expert review of the challenge data set
- M. Apitz performed the medical expert review of the challenge data set
- K. Kirtac, J. Lindström Bolmgrem, M. Stenzel, I. Twick and E. Hosgor participated in the challenge as team caresyntax in all three tasks
- Z.-L. Ni, H.-B. Chen, Y.-J. Zhou, G.-B. Bian and Z.-G. Hou participated in the challenge as team CASIA_SRL in the binary and multi-instance segmentation tasks
- D. Jha, M.A. Riegler and P. Halvorsen participated in the challenge as team Djh in the binary segmentation task
- F. Isensee and K. Maier-Hein participated in the challenge as team fisensee in all three tasks
- L. Wang, D. Guo and G. Wang participated in the challenge as team haoyun in the binary segmentation task

[17]https://understand.ai
[18]https://www.nvidia.com
[19]https://digitalsurgery.com
• S. Leger, S. Bodenstedt and S. Speidel participated in the challenge as team NCT in the binary segmentation task
• S. Kletz and K. Schoeffmann participated in the challenge as team SQUASH in all three tasks
• L. Bravo, C. González and P. Arbeláez participated in the challenge as team Uniandes in all three tasks
• R. Shi, Z. Li, T. Jiang participated in the challenge as team VIE in all three tasks
• J. Wang, Y. Zhang, Y. Jin, L. Zhu, L. Wang and P.-A. Heng participated in the challenge as team www in all three tasks
• A. Kopp-Schneider and M. Wiesenfarth performed statistical analyses
• L. Maier-Hein organized the challenge, wrote the manuscript and supervised the project

B Annotation instructions

B.1 Terminology

Matter: Anything that has mass, takes up space and can be clearly identified.

- Examples: tissue, surgical tools, blood
- Counterexamples: reflections, digital overlays, movement artifacts, smoke

Medical instrument to be detected and segmented: Elongated rigid object introduced into the patient and manipulated directly from outside the patient.

- Examples: grasper, scalpel, (transparent) trocar, clip applicator, hooks, stapling device, suction
- Counterexamples: non-rigid tubes, bandage, compress, needle (not directly manipulated from outside but manipulated with an instrument), coagulation sponges, metal clips

B.2 Tasks

Participating teams may enter competitions related to the following tasks:

Binary segmentation:

- Input: 250 consecutive frames (10sec) of a laparoscopic video with the last frame containing at least one medical instrument.
- Output: A binary image, in which “0” indicates the absence of a medical instrument and a number “>0” represents the presence of a medical instrument.

Multi-instance detection and segmentation:

- Input: 250 consecutive frames (10sec) of a laparoscopic video with the last frame containing at least one medical instrument.
- Output: An image, in which “0” indicates the absence of a medical instrument and numbers “1”, “2”,... represent different instances of medical instruments.

For all three tasks, the entire corresponding video of the surgery is provided along with the training data as context information. In the test phase, only the test image along with the preceding 250 frames is provided.

C Submission instructions

The following section provides the instruction document that challenge participants obtained.
Submission Instructions
ROBUST-MIS 2019 - Part of the Endoscopic Vision Challenge

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General Instructions

Introduction

This document contains instructions on how to access the data, how to create a nvidia-docker image (NVIDIA Container Runtime for Docker) and how to submit it to the synapse portal to participate in our challenge.

Challenge details can be found at our web pages:
https://robustmis2019.grand-challenge.org/
https://www.synapse.org/#!Synapse:syn18779624/wiki/591266

All links in this document are located in the link collection.

Method description

Transparency is a very important prerequisite for high quality work, therefore, we ask you to follow the method write-up template when describing your method. Furthermore, only participants that agree to make their method description public will be considered as co-authors for the challenge publication and are eligible for awards. However, it is still possible to participate in the challenge without publishing the method description (e.g. for industrial participants). A pdf file containing the following contents should be part of your submission:

Title
Authors
Affiliations

Abstract
Please address the following points:

- What was the main motivation of the approach?
- What is the core idea of the approach?
- What are the expected benefits of the approach compared to common methods?

Method description
This section should cover a full description of your methods. Proposals must be well documented and include any references, data, visualizations, or other information that supports the validity of the algorithm.
A full description of your methods should include the following key points for each task you are competing in:
● Describe data pre-processing steps (e.g. filtering, normalization)
● List all additional training data with references
● For those competing for awards/interested in co-authoring the publication on the challenge, describe your method thoroughly so that it can be re-implemented (if possible). At a minimum, it should include:
  ○ Detailed network architecture (if it exists with reference)
  ○ All loss functions
  ○ Hyperparameters
  ○ Optimizer and training procedures
  ○ Further data augmentation techniques

**Conclusion/Discussion**
This section should include any **insights** gained during the challenge, reasons for **choosing/altering parameters** and **adjustments** you wish to make for future challenges. Highlight situations where the algorithm is expected to perform well and situations where the algorithm would be unsuitable, explaining any strategies to overcome these limitations. Briefly discuss the general performance, merits and limitations of your methodology.

**References**
List all method and data references.

**Authors Statement**
Please list all authors' contributions

**Acknowledgements**
Recognition of contributions that do not warrant authorship. Grant funding.
Technical Instructions

Data access

Training phase
1. Create an account at synapse and register for the challenge: https://www.synapse.org/#!Synapse:syn18779624/wiki/591266
2. Download the data as zip or use our download script: https://www.synapse.org/#!Synapse:syn18779624/wiki/592660
The data has the following structure:
   - [surgery type] (e.g. Prokto)
   - [patient no.] (e.g. 1-10)
   - [frame no.] (e.g. 1-n)
   - raw.png: Frame to be segmented
   - 10s_video.zip: 249 previous frames with the same dimensions as raw.png
   - UPDATE: If instruments are visible in the frame: instrument_instances.png: Segmented instrument instances (segmentation masks)

Test phase
Testing data won’t be accessible during testing. To be part of the challenge, you must create a docker file and upload it to the synapse platform. The challenge organizers will perform the complete evaluation. Please follow the instructions in the following sections to install, create and submit docker images.

Creation of nvidia-docker images

Installation of nvidia-docker
Please follow the instructions provided on the NVIDIA docker github webpage to set up nvidia-docker. This is only supported for Linux.

Usage of pre-compiled docker images
This section describes the usage of pre-compiled docker images provided by NVIDIA, Tensorflow and PyTorch.
Standard NVIDIA docker image

Nvidia provides an image containing all relevant drivers etc. to run Cuda applications. No extra libraries are contained. An example can be run with:

```
nvidia-docker run --rm nvidia/cuda:9.0-base nvidia-smi
```

Tensorflow docker image

Tensorflow provides images containing Cuda drivers and different versions of Tensorflow. The stable, GPU-based image can be downloaded and tested in the following way:

```
docker pull tensorflow/tensorflow:latest-gpu
```

```
nvidia-docker run --rm tensorflow/tensorflow:latest-gpu python -c "import tensorflow as tf; tf.enable_eager_execution(); print(tf.reduce_sum(tf.random_normal([1000, 1000])))"
```

PyTorch docker image

Sign up for NGC to download images from Nvidia, and generate your API-KEY:

- **Signup**
- **API-KEY**

**Download and test PyTorch image:**

docker login nvcr.io
  Username: $oauthtoken
  Password: APIKEY

docker pull nvcr.io/nvidia/pytorch:19.06-py3

```
nvidia-docker run --ipc=host --rm nvcr.io/nvidia/pytorch:19.06-py3 python -c "import torch;print(torch.cuda.is_available())"
```

Docker submission preparation

General usage

During testing, the docker image will be run with the following command:

```
nvidia-docker run --ipc=host -v "<input folder>:/input" -v "<output folder>:/output" test-submission /usr/local/bin/run_network.sh
```

In other words, we will **mount two folders**, one at “/input” and one at “/output”.
Then, we will run the script “run_network.sh”, therefore, the “run_network.sh” must be written in such a way that it will run your model automatically.

The folder “/input” will contain the test data set, in the same way as the training data set, with the image dimensions equal to the image dimensions in the training data set. Thus, it will have the following structure:

- /input
  - Stage_1
    - [...] (see below; same structure as described in stage 3)
  - Stage_2
    - [...] (see below; same structure as described in stage 3)
  - Stage_3
    - /[surgery type] (e.g. Prokto)
      - [patient no.] (e.g. 1-10)
        - [frame no.] (e.g. 1-n)
          - raw.png: Frame to be segmented
          - video_frames/ (In testing there is no zip file! Instead all video frames are already extracted in this folder)
            - [1-249].png: 249 previous frames with the same dimensions as raw.png

Your model should process all image frames and create results with the following structure in the “/output” directory:

- /output
  - Stage_1
    - [...] (see below; same structure as described in stage 3)
  - Stage_2
    - [...] (see below; same structure as described in stage 3)
  - Stage_3
    - /[surgery type]
      - [patient no.]
        - [frame no.]
          - output.png

Please be aware of the different output formats depending on your task:

- **Binary instance segmentation**: “output.png” must be a binary image with “1” representing medical instruments and “0” representing the absence of medical instruments. The image dimensions (height, width) should be equal to the input image dimensions. There should only be one image layer (no rgb image).
- **Multiple instance segmentation**: “output.png” should contain multiple instrument instances with “1”, “2”, etc., representing different instances of medical instruments and
“0” representing the absence of medical instruments. The image dimensions (height, width) should be equal to the input image dimensions. There should only be one image layer (no rgb image).

- Multiple instance detection: “output.png” should contain multiple instrument instances with “1”, “2”, etc., representing different instances of medical instruments and “0” representing the absence of medical instruments. The image dimensions (height, width) should be equal to the input image dimensions. There should only be one image layer (no rgb image).

Becoming a certified user

**Important:** In order to use all docker functionality e.g. `docker push`, you must be a certified user. You can become a certified user by filling out the following quiz (attention, the url contains a “:” at the end!): [https://www.synapse.org/#!Quiz](https://www.synapse.org/#!Quiz)

Example submission (based on nvcr.io/nvidia/pytorch:19.06-py3)

1. **Connect to the docker image and open console**

   ```bash
   nvidia-docker run -it --ipc=host nvcr.io/nvidia/pytorch:19.06-py3
   bash
   ```

   ```
   bodenste@B27LP0001-Linux:~$ nvidia-docker run -it --ipc=host nvcr.io/nvidia/pytorch:19.05-py3 bash
   =======
   == PyTorch ==
   =======
   NVIDIA Release 19.05 (build 6411784)
   PyTorch Version 1.1.0a0-928a6e3
   Container Image Copyright (c) 2019, NVIDIA CORPORATION. All rights reserved.
   Copyright (c) 2014-2019 Facebook Inc.
   Copyright (c) 2011-2014 Idiap Research Institute (Ronan Collobert)
   Copyright (c) 2012-2014 Deepmind Technologies (Koray Kavukcuoglu)
   Copyright (c) 2011-2012 NEC Laboratories America (Koray Kavukcuoglu)
   Copyright (c) 2011-2013 NYU (Clement Farabet)
   Copyright (c) 2010-2011 NEC Laboratories America (Ronan Collobert, Leon Bottou, Iain Melvin, Jason Weston)
   Copyright (c) 2006 Idiap Research Institute (Samy Bengio)
   Copyright (c) 2001-2004 Idiap Research Institute (Ronan Collobert, Samy Bengio, Johnny Mariethoz)
   Copyright (c) 2015 Google Inc.
   Copyright (c) 2015 Yangqing Jia
   Copyright (c) 2012-2016 The Caffe contributors
   All rights reserved.
   Various files include modifications (c) NVIDIA CORPORATION. All rights reserved.
   NVIDIA modifications are covered by the license terms that apply to the underlying project or file.
   ERROR: Detected NVIDIA GeForce 940MX GPU, which is not supported by this container
   ERROR: No supported GPU(s) detected to run this container
   NOTE: MOVED driver for multi-node communication was not detected.
   Multi-node communication performance may be reduced.
   ```

2. **Setup proxy (if required)**

   ```bash
   root@91a5c632aedd:/workspace# export HTTP_PROXY=http://192.168.10.29:3128/
   root@91a5c632aedd:/workspace# export HTTPS_PROXY=http://192.168.10.29:3128/
   root@91a5c632aedd:/workspace# ```
3. Install **imageio** and **imageio-ffmpeg** for python (library for reading videos)

```bash
pip install imageio
pip install imageio-ffmpeg
```

4. Exit docker and note container ID

The container ID is highlighted in blue in the screenshot below.

```
root@91a5c632aedd:/workspace# exit
```

5. Copy relevant file to container

```bash
nvidia-docker cp run_network.sh <containerID>:/usr/local/bin/run_network.sh
nvidia-docker cp run_model.py <containerID>:/root/run_model.py
```

6. Commit the docker container

```bash
nvidia-docker commit <containerID> <docker image name>
```

7. Test program

Note that this program will also be run to evaluate the submitted models.

```bash
nvidia-docker run --ipc=host -v <local folder>:/input -v <local folder>:/output <docker image name> /usr/local/run_network.sh
```
Docker submission on the synapse platform

1. Create a new project on synapse
To submit a docker file, you first need to create a new project on the synapse platform with the challenge name and your team:

*Robust Medical Instrument Segmentation Subchallenge Task* <Binary Segmentation, MI Detection or MI Segmentation> <Your team name>

**Note the Synapse ID** (e.g. syn20482334).

Furthermore, once the project has been created, the organizing team of the challenge (*Robust Medical Instrument Segmentation Challenge 2019 ORGANIZERS*) must be given download permissions to the project, as shown in the following screenshots:
2. Login to synapse with docker

docker login docker.synapse.org (Enter synapse username and password)

(base) rost@mb1999:~$ sudo docker login docker.synapse.org
[sudo] password for rost:
Username: schnibi990
Password:
WARNING! Your password will be stored unencrypted in /home/rost/.docker/config.json.
Configure a credential helper to remove this warning. See https://docs.docker.com/engine/reference/commandline/login/#credentials-store
Login Succeeded

3. Tag the submission docker image

Please note the synapse ID highlighted in blue in the screenshot.

nvidia-docker tag <imagename_local>
docker.synapse.org/<SynapseID>/<imagename_synapse>

4. Push the docker image to synapse

docker push docker.synapse.org/<SynapseID>/<imagename>:latest
5. Verify the success of your push
You can verify on the Synapse website if the push was successful. If the download fails, it might be because you are not a **certified user**. Please refer to the upper paragraph “Becoming a certified user”.

6. Submit the docker image

**UPDATE:** To submit the docker, there are two ways to submit:

1) Go to the challenge synapse webpage. Open Submissions and press “Submit”.

Submission instructions for participating in the test phase

1. Transparency is a very important prerequisite for high quality work, therefore, we ask you to follow the method write-up template when describing your method. Furthermore, only participants that agree to make their method description public will be considered as co-authors for the challenge publication and are eligible for awards. However, it is still possible to participate in the challenge without publishing the method description (e.g., for industrial participants). A pdf file containing the contents described in the following document (see 2.) should be part of your submission.

2. Testing data won’t be accessible during testing. To be part of the challenge, you must create a docker file and upload it to the Synapse platform. The challenge organizers will perform the complete evaluation. Please follow the instructions comprised in the following document to install, create and submit docker images.

Submit to challenge

SUBMITTED SUBMISSIONS

| repository/Name | userid | modifiedOn | teamid | name | status |
|-----------------|--------|------------|--------|------|--------|
| docker.synapse.org/syn20482334/example_submission | @technab1990 | 07/10/2019 2:24 PM | syn20482334 | RECEIVED |
2) Click on the docker image. In the next view, select “Docker Repository Tools → Submit Docker Repository to Challenge”.

To submit the docker to the challenge, first click on the docker image you want to submit which brings you to the following screen:

Submit to Challenge

Select the commit below that you would like to submit:
Tag
- latest

Digest:
sha256:f79ad5bc5e590e833f

For each of the three tasks there is an individual submission queue:
- ROBUST-MIS 2019 Submission - Binary Segmentation,
- ROBUST-MIS 2019 Submission - Multi Instance Detection,
- ROBUST-MIS 2019 Submission - Multi Instance Segmentation.

Choose the task for which you want to submit and click “Next”.

If you plan to participate in multiple tasks of the challenge, you need to submit your corresponding docker to each queue individually (e.g. Binary Segmentation Task → ROBUST-MIS 2019 Submission - Binary Segmentation and Multi Instance Detection Task → ROBUST-MIS 2019 Submission - Multi Instance Detection).
Specify if you are entering alone or as a team. The submission pipeline will be checked in regular intervals starting at the beginning of October. You will then be notified whether your submission is invalid (due to wrong format, etc…) or has been accepted.

The committee wishes you much success :-) 

Link Collection

- Challenge webpage hosted at grand-challenge: https://robustmis2019.grand-challenge.org/
- Challenge webpage hosted at synapse (and challenge registration): https://www.synapse.org/#!Synapse:syn18779624/wiki/591266
- Data download: https://www.synapse.org/#!Synapse:syn18779624/wiki/592660
- Synapse certified user quiz: https://www.synapse.org/#!Quiz:
- Nvidia container runtime for docker: https://github.com/NVIDIA/nvidia-docker
- Tensorflow docker: https://www.tensorflow.org/install/docker
- Nvidia NGC:
  - Signup: https://ngc.nvidia.com/signin
  - API-KEY: https://ngc.nvidia.com/setup/api-key
- PyTorch image: https://docs.nvidia.com/deeplearning/frameworks/pytorch-release-notes/running.html
D Rankings for all stages

The ranking schemes described in section 2.3.2 were also computed for stages 1 and 2. To compare the performance of participating teams across stages, stacked frequency plots of the observed ranks, separated by the algorithms, for each ranking of the binary and multi-instance segmentation tasks are displayed in Figure 9 to 16. Observed ranks across bootstrap samples are presented over the three stages. The metric values for the multi-instance detection task are displayed in Table 7.

Figure 9: Stacked frequency plot for stages 1 to 3 with the Dice Similarity Coefficient (DSC) accuracy ranking of the binary segmentation task. The plots were generated using the package challengeR [24, 25].
Figure 10: Stacked frequency plot for stages 1 to 3 with the Dice Similarity Coefficient (DSC) robustness ranking of the binary segmentation task. The plots were generated using the package challengeR [24, 25].

Figure 11: Stacked frequency plot for stages 1 to 3 with the Normalized Surface Distance (NSD) accuracy ranking of the binary segmentation task. The plots were generated using the package challengeR [24, 25].
Figure 12: Stacked frequency plot for stages 1 to 3 with the Normalized Surface Distance (NSD) robustness ranking of the binary segmentation task.

Figure 13: Stacked frequency plot for stages 1 to 3 with (multi-instance) Dice Similarity Coefficient (\( (MI_\text{DSC}) \)) accuracy ranking of the multi-instance segmentation task. The plots were generated using the package challengeR\cite{24, 25}. 
Figure 14: Stacked frequency plot for stages 1 to 3 with the (multi-instance) Dice Similarity Coefficient \((MI_{\text{DSC}})\) robustness ranking of the multi-instance segmentation task. The plots were generated using the package challengeR \cite{24, 25}.

Figure 15: Stacked frequency plot for stages 1 to 3 with the (multi-instance) Normalized Surface Distance \((MI_{\text{NSD}})\) accuracy ranking of the multi-instance segmentation task. The plots were generated using the package challengeR \cite{24, 25}.
Figure 16: Stacked frequency plot for stages 1 to 3 with the (multi-instance) Normalized Surface Distance ((MI)_NSD) robustness ranking of the multi-instance segmentation task. The plots were generated using the package challengeR [24, 25].

Table 7: Results over all stages for the multi-instance detection task.

| Team identifier | Stage 1 | Stage 2 | Stage 3 |
|-----------------|---------|---------|---------|
| Uniandes        | 1.000   | 0.833   | 1.000   |
| VIE             | 0.750   | 0.778   | 0.978   |
| caresyntax      | 0.944   | 0.833   | 0.972   |
| SQUASH          | 0.967   | 1.000   | 0.966   |
| fisensee        | 1.000   | 1.000   | 0.964   |
| www             | 0.900   | 0.833   | 0.944   |

E Challenge design document
Robust Medical Instrument Segmentation Challenge 2019 – Structured description of the challenge design

SUMMARY

1) Title
a) Use the title to convey the essential information on the challenge mission.

Robust Medical Instrument Segmentation Challenge 2019

b) Preferable, provide a short acronym of the challenge (if any).

Robust-MIS 2019

2) Abstract
Provide a summary of the challenge purpose. This should include a general introduction in the topic from both a biomedical as well as from a technical point of view and clearly state the envisioned technical and/or biomedical impact of the challenge.

Intraoperative tracking of laparoscopic instruments is often a prerequisite for computer and robot assisted interventions. Although previous challenges have targeted the task of detecting, segmenting and tracking medical instruments based on endoscopic video images, key issues remain to be addressed:

1. The methods proposed still tend to fail when applied to challenging images (e.g. in the presence of blood, smoke or motion artifacts) and
2. Algorithms trained for a specific intervention in a specific hospital typically do not generalize.

The goal of this challenge is, therefore, the benchmarking of algorithms for medical instrument segmentation with a specific emphasis on robustness and generalization capabilities of the methods. The challenge is based on the biggest annotated data set made (to be made) available in the field, comprising more than 10,000 annotated images that have been extracted from a total of 30 surgical procedures from three different surgery types.

3) Keywords
List the primary keywords that characterize the challenge.
Instrument segmentation, multiple instance segmentation, instrument detection, minimally invasive surgery, robustness, generalization

**CHALLENGE ORGANIZATION**

4) **Organizers**
   a) Provide information on the organizing team (names and affiliations).

   Tobias Roß, Annika Reinke, Lena Maier-Hein
   Div. Computer Assisted Medical Interventions (CAMI), German Cancer Research Center (DKFZ)

   Martin Wagner, Hannes Kenngott, Beat Müller
   Div. General, Visceral and Transplant surgery, Heidelberg University Hospital

   Annette Kopp-Schneider
   Div. Biostatistics, DKFZ

   b) Provide information on the primary contact person.

   Tobias Roß (CAMI, DKFZ), t.ross@dkfz-heidelberg.de

5) **Life cycle type**
   Define the intended submission cycle of the challenge. Include information on whether/how the challenge will be continued after the challenge has taken place.

   A one-time event with a fixed submission deadline.

6) **Challenge venue and platform**
   a) Report the event (e.g. conference) that is associated with the challenge (if any).

   International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI) 2019 (China)

   b) Report the platform (e.g. grand-challenge.org) used to run the challenge.

   Main website: grand-challenge.org
   Docker submission: DREAM platform/synapse

   c) Provide the URL for the challenge website (if any).

   https://robustmis2019.grand-challenge.org/
   https://www.synapse.org/#!Synapse:syn18779624/wiki/

7) **Participation policies**
   a) Define the allowed user interaction of the algorithms assessed (e.g. only (semi-) automatic methods allowed).
Only fully automatic algorithms are allowed.

b) Define the policy on the usage of training data. The data used to train algorithms may, for example, be restricted to the data provided by the challenge or to publicly available data including (open) pre-trained nets.

It is allowed to use publicly available data released outside the field of medicine. In other words, no medical data, besides the training data offered by the challenge, must be used to train the methods or tune hyperparameters.

c) Define the participation policy for members of the organizers’ institutes. For example, members of the organizers’ institutes may participate in the challenge but are not eligible for awards.

Members of the organizers’ departments may participate in the challenge but are not eligible for awards. Furthermore, they will be highlighted in the leaderboards.

d) Define the award policy. In particular, provide details with respect to challenge prizes.

10,000€ are available for the winners and runner-ups of the three tasks (stage 3).

e) Define the policy for result announcement.

The top 3 performing methods will be announced publicly. The remaining teams may decide whether or not their identity should be publicly revealed (e.g. in the publication of the challenge).

f) Define the publication policy. In particular, provide details on ...
   - who of the participating teams/the participating teams’ members qualifies as author
   - whether the participating teams may publish their own results separately, and (if so)
   - whether an embargo time is defined (so that challenge organizers can publish a challenge paper first).

All participating teams that reveal their identity can nominate two members of their team as co-authors for the challenge paper.

The method description submitted by the authors will be used in the publication of the challenge results. Personal data of the authors will include their names, affiliations and contact addresses. References used in the method description may be published in the challenge results as well.

Participating teams may publish their own results separately with explicit allowance from the challenge organizers once the main paper on the challenge has been accepted for publication.

**8) Submission method**

a) Describe the method used for result submission. Preferably, provide a link to the submission instructions.

See separate document.
b) Provide information on the possibility for participating teams to evaluate their algorithms before submitting final results. For example, many challenges allow submission of multiple results, and only the last run is officially counted to compute challenge results.

There will be no leaderboard before the participating teams submit final results.

9) Challenge schedule
Provide a timetable for the challenge. Preferably, this should include
- the release date(s) of the training cases (if any)
- the registration date/period
- the release date(s) of the test cases and validation cases (if any)
- the submission date(s)
- associated workshop days (if any)
- the release date(s) of the results

- Release date of the initial training data set: 1 July 2019
- Release date of the final training data set: by 5 August 2019
- Registration: Until 14 September 2019
- Submission of dockers: 15 September 2019

10) Ethics approval
Indicate whether ethics approval is necessary for the data. If yes, provide details on the ethics approval, preferably institutional review board, location, date and number of the ethics approval (if applicable). Add the URL or a reference to the document of the ethics approval (if available).

According to [Euro2016], the anonymized data can be used for the challenge.

11) Data usage agreement
Clarify how the data can be used and distributed by the teams that participate in the challenge and by others during and after the challenge. This should include the explicit listing of the license applied.

By registering in the challenge, each team agrees (1) to use the data provided only in the scope of the challenge and (2) to neither pass it on to a third party nor to use it for any publication or for commercial use. After the challenge, the data will be made publicly available for non-commercial use.

12) Code availability
a) Provide information on the accessibility of the organizers’ evaluation software (e.g. code to produce rankings). Preferably, provide a link to the code and add information on the supported platforms.

The evaluation code for the challenge will be made publicly available after the challenge.

b) In an analogous manner, provide information on the accessibility of the participating teams’ code.
Participants are encouraged to release their methods in open source.

13) Conflicts of interest
Provide information related to conflicts of interest. In particular provide information related to sponsoring/funding of the challenge. Also, state explicitly who had/will have access to the test case labels and when.

This challenge is funded by the National Center for Tumor Diseases (NCT) Heidelberg and is/was further supported by Understand AI and NVIDIA GmbH.

All challenge organizers and some members of their institute had access to training and test cases.

MISSION OF THE CHALLENGE

14) Field(s) of application
State the main field(s) of application that the participating algorithms target.

Intervention assistance.

15) Task category(ies)
State the task category(ies).

- Binary Segmentation
- Multiple Instance Segmentation
- Multiple Instance Detection

16) Cohorts
We distinguish between the target cohort and the challenge cohort. For example, a challenge could be designed around the task of medical instrument tracking in robotic kidney surgery. While the challenge could be based on ex vivodata obtained from a laparoscopic training environment with porcine organs (challenge cohort), the final biomedical application (i.e. robotic kidney surgery) would be targeted on real patients with certain characteristics defined by inclusion criteria such as restrictions regarding gender or age (target cohort).

a) Describe the target cohort, i.e. the subjects/objects from whom/which the data would be acquired in the final biomedical application.

Patients undergoing minimally invasive surgery.

b) Describe the challenge cohort, i.e. the subject(s)/object(s) from whom/which the challenge data was acquired.

Patients undergoing rectal resection, proctocolectomy or UNKNOWN SURGERY (will be made public after the docker submission deadline).

17) Imaging modality(ies)
Specify the imaging technique(s) applied in the challenge.

Laparoscopic video.

18) Context information
Provide additional information given along with the images. The information may correspond...

a) … directly to the image data (e.g. tumor volume).

A whole surgical video and information on the type of surgery performed is provided for each training case. No additional information is given for the test cases.

b) … to the patient in general (e.g. gender, medical history).

None.

19) Target entity(ies)

a) Describe the data origin, i.e. the region(s)/part(s) of subject(s)/object(s) from whom/which the image data would be acquired in the final biomedical application (e.g. brain shown in computed tomography (CT) data, abdomen shown in laparoscopic video data, operating room shown in video data, thorax shown in fluoroscopy video). If necessary, differentiate between target and challenge cohort.

An abdomen shown in laparoscopic video data.

b) Describe the algorithm target, i.e. the structure(s)/subject(s)/object(s)/component(s) that the participating algorithms have been designed to focus on (e.g. tumor in the brain, tip of a medical instrument, nurse in an operating theater, catheter in a fluoroscopy scan). If necessary, differentiate between target and challenge cohort.

An elongated rigid object put into the patient and then manipulated directly from outside the patient

• Examples: grasper, scalpel, trocar
• Counterexamples: non-rigid tubes, bandage, needle (not directly manipulated from outside but manipulated with an instrument)

Please refer to https://www.synapse.org/Portal/filehandle?ownerId=syn18779624&ownerType=ENTITY&fileName=LabelingInstructions.pdf&preview=false&wikid=592660 for further details.

20) Assessment aim(s)

Identify the property(ies) of the algorithms to be optimized to perform well in the challenge. If multiple properties are assessed, prioritize them (if appropriate). The properties should then be reflected in the metrics applied (see parameter metric(s)), and the priorities should be reflected in the ranking when combining multiple metrics that assess different properties.

• Identify robust methods for instrument detection, binary instrument segmentation and multiple instance segmentation.
• Assess generalization capabilities of the methods proposed.
• Identify which image properties (e.g. smoke, bleeding, motion artefacts) makes images particularly challenging to process.

**CHALLENGE DATA SETS**

21) Data source(s)

a) Specify the device(s) used to acquire the challenge data. This includes details on the device(s) used to acquire the imaging data (e.g. manufacturer) as well as information on additional devices used for performance assessment (e.g. tracking system used in a surgical setting).

Laparoscopic camera Karl Storz Image 1 with a 30° optic. (Karl Storz SE & Co KG). As a light source Karl Storz Xenon 300 was used.

b) Describe relevant details on the imaging process/data acquisition for each acquisition device (e.g. image acquisition protocol(s)).

Data acquisition took place during daily routine procedures with the integrated operating room (Karl Storz OR1 FUSION®). Video data was then anonymized by excluding parts of the video displaying parts outside the abdomen. Image resolution was downscaled from 1920X1080 pixels (HD) in the primary video to 960x540.

c) Specify the center(s)/institute(s) in which the data was acquired and/or the data providing platform/source (e.g. previous challenge). If this information is not provided (e.g. for anonymization reasons), specify why.

Institute: Heidelberg University Hospital, Department of Surgery

d) Describe relevant characteristics (e.g. level of expertise) of the subjects (e.g. surgeon)/objects (e.g. robot) involved in the data acquisition process (if any).

No characteristics available due to fully anonymized data.

22) Training and test case characteristics

a) State what is meant by one case in this challenge. A case encompasses all data that is processed to produce one result that is compared to the corresponding reference result (i.e. the desired algorithm output).

A training case encompasses a 10 second video snippet in form of 250 endoscopic image frames and a reference annotation for the last frame. In the annotated frame a “0” indicates the absence of a medical instrument and numbers “1”, “2”, ... represent different instances of medical instruments.

The test cases are identical in format but do not include a reference annotation.

For training images, the entire corresponding video is provided as context information along with information on the surgery type.

b) State the total number of training, validation and test cases.
Videos from 30 surgical procedures corresponding to three different surgery types (10 rectal resection, 10 proctocolectomy, 10 UNKNOWN SURGERY) served as a basis for this challenge. From these 30 procedures, a total of 10,040 training and test cases were extracted according to the following procedure:

For surgery type \( s \) in \{rectal resection, proctocolectomy, UNKNOWN SURGERY\}

For procedure \( 1 \ldots 10 \) in surgery type \( s \):

Every 60 seconds:

- Extract frame
- If the frame is blue (it means that it has been modified for anonymization reasons) ignore it;
- otherwise add its ID to the IDs of the challenge data set

This resulted in a total of 4456 frames (corresponding to the extracted IDs) to be annotated.

To obtain at least 10,000 annotated frames in total, additional frames, in interesting parts (phase transition), were obtained using the following protocol:

For surgery type \( s \) in \{rectal resection, proctocolectomy, UNKNOWN SURGERY\}

For procedure \( 9 \ldots 10 \) in surgery type \( s \) \((8 \ldots 10 \text{ if } s = \text{rectal resection})\):

For each phase transition in the video:

Every second within the 25 seconds around the phase transition:

- Extract frame
- If the frame is blue ignore it;
- otherwise add its ID to the IDs of the challenge data set

This procedure led to 10,040 frames in total.

The extracted frames were annotated (see parameter 23) and complemented by the 249 preceding frames to form the training and test cases for the challenge.

The performance assessment for the challenge will performed in three stages.

- Stage 1: The test data is taken from the procedures (patients) from which the training data were extracted.
- Stage 2: The test data is taken from the exact same type of surgery as the training data but from procedures (patients) not included in the training data.
- Stage 3: The test data is taken from a different but similar type of surgery (and different patients) compared to the training data.

To achieve this, the data of all 10 procedures from one of the surgery types (UNKNOWN SURGERY) was reserved for testing in stage 3. From the 20 remaining procedures, 80% were reserved for training and 20% (i.e. 2 procedures from each type) for testing in stage 2. More specifically, the two patients with the lowest number of annotated frames were taken as test data for stage 2 (for both, rectal resection and proctocolectomy). For stage 1, every 10th annotated case from the remaining \( 2^*(10-2) = 16 \) procedures was used.
While all training and test cases were used for the multiple instance detection task, cases not showing an instrument in the image were removed from training and test sets for the binary and multiple instance segmentation tasks.

No validation cases are provided by the organizers; hence, it is up to the challenge participants to split the training data into training and validation data.

This all lead to a total of:

- **Training data:** 5,983 cases in total (2,943 cases for the proctocolectomy surgery and 3,040 cases for the rectal resection surgery)
- **Test data:**
  - Stage 1: 663 cases in total (325 cases for the proctocolectomy surgery and 338 cases for the rectal resection surgery)
  - Stage 2: 514 cases in total (225 cases for the proctocolectomy surgery and 289 cases for the rectal resection surgery)
  - Stage 3: 2,880 cases for the UNKNOWN SURGERY

c) Explain why a total number of cases and the specific proportion of training, validation and test cases was chosen.

All data from a specific surgery type were reserved for testing (stage 3) to test generalization capabilities of the methods. The ratio 80%/20% (stage 2) is commonly used in challenges.

d) Mention further important characteristics of the training, validation and test cases (e.g. class distribution in classification tasks chosen according to real-world distribution vs. equal class distribution) and justify the choice.

No further important characteristics.

**23) Annotation characteristics**

a) Describe the method for determining the reference annotation, i.e. the desired algorithm output. Provide the information separately for the training, validation and test cases if necessary. Possible methods include manual image annotation, in silico ground truth generation and annotation by automatic methods.

If human annotation was involved, state the number of annotators.

Each case was annotated according to the following procedure:

1. **Initialization:** The company Understand AI extracted video frames as described in parameter 22b and did an initial segmentation for the extracted frames.
2. **Refinement:**
   a. The challenge organizers analyzed the annotations provided, identified inconsistencies and agreed on an annotation protocol.
   b. A team of 15 engineers analyzed all annotations again and refined them according to the annotation protocol if necessary.
c. In ambiguous/unclear cases, a team of two engineers and one medical student generated a consensus annotation.

3. Quality control:
   a. A medical expert went through the refined segmentations and reported potential errors.
   b. An engineer did the refinement according to the instructions of the medical expert.

4. Final check: After refinement, a medical expert checked the refined annotations together with the engineer for possible final correction.

b) Provide the instructions given to the annotators (if any) prior to the annotation. This may include description of a training phase with the software. Provide the information separately for the training, validation and test cases if necessary. Preferably, provide a link to the annotation protocol.

See separate document:
https://www.synapse.org/Portal/filehandle?ownerId=syn18779624&ownerType=ENTITY&fileName=LabelingInstructions.pdf&preview=false&wikid=592660.

c) Provide details on the subject(s)/algorithm(s) that annotated the cases (e.g. information on level of expertise such as number of years of professional experience, medically-trained or not). Provide the information separately for the training, validation and test cases if necessary.

See parameter 23a for all details.

d) Describe the method(s) used to merge multiple annotations for one case (if any). Provide the information separately for the training, validation and test cases if necessary.

See parameter 23a for all details.

24) Data pre-processing method(s)
Describe the method(s) used for pre-processing the raw training data before it is provided to the participating teams. Provide the information separately for the training, validation and test cases if necessary.

For each frame that had to be segmented, 249 previous frames were also extracted. All frames were saved as .png using the python-opencv2 library. The 249 video frames were then compressed using zip and must be extracted before use. The annotation masks were stored as binary images in .png format. This process was identical for both the training data and the test data.

25) Sources of error
a) Describe the most relevant possible error sources related to the image annotation. If possible, estimate the magnitude (range) of these errors, using inter- and intra-annotator variability, for example. Provide the information separately for the training, validation and test cases, if necessary.

As each case was analyzed by multiple annotators, errors in annotation can mainly be attributed to image quality (i.e. the inherent ambiguity of the problem when relying solely on the image data).
b) In an analogous manner, describe and quantify other relevant sources of error.

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**ASSESSMENT METHODS**

26) **Metric(s)**

a) Define the metric(s) to assess a property of an algorithm. These metrics should reflect the desired algorithm properties described in assessment aim(s) (see above). State which metric(s) were used to compute the ranking(s) (if any).

**Binary Segmentation**

- Dice Similarity Coefficient (DSC) [Dice 1945, MSD 2018]
- Normalized Surface Distance (NSD) [MSD 2018]
- Other metrics will be computed but not used in the ranking scheme.

**Multiple Instance Segmentation**

- Multiple Instance Dice Similarity Coefficient (MI_DSC) [MSD 2018]
- Multiple Instance Normalized Surface Distance (MI_NSD) [MSD 2018]
- Other metrics will be computed but not used in the ranking scheme.

**Multiple Instance Detection**

- The mean average precision (mAP) [Everingham et al. 2010, Hui 2018] will be computed according to the following procedure:
  1. Compute matching matrix: For each instrument instance \( i \) in the reference output (represented by a specific ID > 0) and each instance \( j \) in the participant's output, \( m_{ij} \) is set to the Intersection of Union (IoU).
  2. if \( m_{ij} < 0.3 \): \( m_{ij} = 0 \) ("no match")
  3. Apply the Hungarian algorithm to assign participant's instances to reference instances. Instruments with matches are considered true positives (TP). Reference instances without a match are considered false negatives (FN). Participants' instances without a reference match are considered false positives (FP).
  4. Compute the mAP.

b) Justify why the metric(s) was/were chosen, preferably with reference to the biomedical application.

We based our design choice regarding the metrics (MI,)DSC and (MI,)NSD on the Medical Segmentation Decathlon [MSD] for the BS and MIS tasks. We chose the mAP for the detection task because it was widely used in popular object detection challenges [Everingham et al. 2010, Lin et al. 2014, Russakovsky et al. 2015].

27) **Ranking method(s)**

a) Describe the method used to compute a performance rank for all submitted algorithms based on the generated metric results on the test cases. Typically the text will describe how results obtained per case and metric are aggregated to arrive at a final score/ranking.

**Ranking scheme**

An accuracy ranking and a robustness ranking will be computed for the following metrics in stage 3:
• DSC and NSD for the BS task
• MI_DSC and MI_NSD for the MIS task

Rankings will be computed for each metric m separately as follows:

Let \( T = \{t_1, ..., t_n \} \) be the test cases for the given task.
For all participating algorithms \( a \):
1. Determine the performance \( m(a, t_i) \) of algorithm \( a \) for each test case \( t_i \)
2. If \( m(a, t_i) = \text{N/A} \): \( m(a, t_i) = 0 \).
3. Aggregate metric values \( m(a, t) \) with the following two aggregation methods:
   a. Accuracy: Compute the significance ranking described in [Maier-Hein et al. 2018] and recently applied in the Medical Segmentation Decathlon [MSD 2018]. This yields the accuracy rank \( r_{\text{a}}(a) \).
   b. Robustness: Compute the 5% percentile of all \( m(a, t_i) \) to obtain a robustness rank \( r_{\text{r}}(a) \) for algorithm \( a \).

For the MID task, the computation of the mAP metric already involves an aggregation of the precision values along different recall levels of all test cases. This results in one mAP value per participant which will be used to determine the ranking.

Remark: Please be aware that the number of test cases as well as the number of algorithms generally differ for each task and stage.

This procedure will lead to
• BS: four separate rankings (accuracy and robustness ranking for the DSC and the NSD)
• MIS: four separate rankings (accuracy and robustness ranking for the MI_DSC and the MI_NSD)
• MID: one ranking

b) Describe the method(s) used to manage submissions with missing results on test cases.

Missing cases are set to the worst possible value, namely 0 for all metrics.

c) Justify why the described ranking scheme(s) was/were used.
To address multiple aspects of the challenge purpose, separate rankings for accuracy and robustness will be computed for stage 3 of the challenge. We decided to use a ranking scheme that tends to group algorithms, in case of minor performance differences (see significance ranking that was used for [MSD 2018]). The computation of the mAP already includes an indirect ranking scheme because precision values are aggregated over all test cases; resulting in a global metric value for each participant which is used to create the ranking.

28) Statistical analyses
a) Provide details for the statistical methods used in the scope of the challenge analysis. This may include
• description of the missing data handling,
• details about the assessment of variability of rankings,
• description of any method used to assess whether the data met the assumptions, required for the particular statistical approach, or
• indication of any software product that was used for all data analysis methods.

Stability will be investigated via bootstrapping and hypothesis testing.

b) Justify why the described statistical method(s) was/were used.

Bootstrapping was identified as an appropriate approach to investigate ranking variability in [Maier-Hein et al. 2018].

29) Further analyses
Present further analyses to be performed (if applicable), e.g. related to
• combining algorithms via ensembling,
• inter-algorithm variability,
• common problems/biases of the submitted methods, or
• ranking variability.

Performance gain based on ensembling the algorithms will be investigated.
Common problems of the submitted methods will be identified.

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